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Artificial Intelligence and Firm Performance in Norway

"Which Norwegian firms are adopting Artificial Intelligence, and how does the adoption of AI affect firm performance?"

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Abstract

This thesis investigates firms' adoption of artificial intelligence technology and its effects on firm performance. Due to the rapid technological advances of artificial intelligence, this field of research is still largely unexplored, especially in Norway. The research question guiding this study is: "Which Norwegian firms are adopting AI, and how does this adoption affect firm performance?"

To estimate and analyze the adoption of AI, we employ web scraping-based methodology and conduct textual analysis of company websites. This approach taps into an underutilized source of information for research purposes. However, it is important to note potential concerns related to endogeneity due to the limitations of our cross-sectional data.

Based on our analysis of approximately 53,000 Norwegian companies, we find that several factors influence the likelihood of having adopted AI. Generally, companies located in urban areas, startups, those with more employees, and those with male CEOs are more likely to have a positive AI Know-how score. However, we also identify nuanced variations. Specifically, the number of employees positively affects the AI score in the computer programming industry but does not exhibit the same relationship in the advertising or transportation sectors. This suggests that the number of employees positively relates to AI adoption in industries where value is driven by employee capabilities and complementary resources.

Furthermore, within our sample, we observe that 2.7% of Norwegian firms utilize AI technology. Notably, the "Telecom, IT, and Media" industry group exhibits the highest proportion of positive AI Know-how scores, with 11.87%. We find that firms adopting AI experience a lower return on their assets, a lower operating margin, and lower sales per employee than their non-adopting counterparts, indicating that today's Norwegian firms' AI capabilities do not lead to higher performance. However, we see increased sales growth in AI adopters, indicating a focus on future growth for these firms.

These findings contribute to the growing literature on AI adoption and offer insights into the Norwegian context. Additionally, our thesis can serve as a valuable starting point for future research employing similar methodologies.

Keywords – Artificial intelligence, adoption, firm performance, resource-based view

Acknowledgments

This master's thesis is written as part of our Master of Science in Economics and Business Administration at the Norwegian School of Economics in collaboration with the research center Digital Innovation for Growth, and we are thankful for all the support we have received. This thesis aims to investigate the adoption of artificial intelligence amongst Norwegian firms and explore the potential of using data from company websites for organizational research.

Although challenging at times, writing this thesis has been rewarding. Writing this thesis has given us more insights into applications of artificial intelligence and the state of the technology in Norway.

We thank everyone who contributed and provided great insights. Particularly, we want to thank Christoph Gschnaidtner for his ideas and insights regarding the use of our AI data. Finally, we want to express our most tremendous gratitude to our supervisors, Lasse B. Lien, and Bram Timmermans, who have demonstrated deep knowledge and enthusiasm about the topic and helped us navigate the extensive process of writing this thesis.

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1 Introduction

The adoption of Artificial Intelligence (AI) has witnessed a remarkable surge across various industries and businesses, extending its reach to Norwegian firms as well. With the rise of the World Wide Web and the explosion of big data, AI has undergone significant advancements. Stanford University's recent report indicates a staggering 20-fold increase in papers about artificial intelligence between 2010 and 2019 (Grosz & Stone, 2018). Despite the widespread attention surrounding AI, there continues to be a scarcity of research that investigates adoption and its effects in an organizational setting.

This thesis aims to examine the adoption of AI and its impact on firm performance. To provide a comprehensive understanding, this introductory chapter establishes the necessary context and background for our thesis. We begin by discussing the current challenges and gaps in the existing literature and underscoring the relevance and significance for further research. Subsequently, we articulate our research question, outline the limitations, and provide an overview of the structure of our thesis.

1.1 Background

In recent years, there has been a surge of hype and excitement surrounding artificial intelligence, captivating both professional communities and society at large. One notable example is the introduction of ChatGPT, a language model that showcased the impressive ability to generate human-like responses (Kelly, 2022). This development sparked widespread fascination and speculation about AI's potential applications and implications in various domains. Other groundbreaking advancements like AlphaGo, the AI program that defeated world champion Go players, shook both the gaming and AI communities, emphasizing the remarkable capabilities of AI systems (Chen et al., 2018). Such achievements have propelled the dialogue on AI's transformative potential and ignited a sense of wonder about its future possibilities. In this thesis, we want to delve deeper into Norwegian firms' adoption of AI technology and its effect on firm performance.

Despite the current spotlight on AI, the research field has a rich history spanning several decades. The term "artificial intelligence" was first coined during a seminal workshop at Dartmouth in 1956 (McCarthy et al., 2006). Moreover, the roots of AI can be traced back to early human attempts at automation as far back as the first century BC (Fanti et al., 2022).

However, the advancement of AI has not always been linear and straightforward. The field has encountered significant setbacks, often referred to as “AI winters,” characterized by periods of reduced enthusiasm and progress (Crevier, 1993). Nonetheless, despite these challenges, the recent remarkable breakthroughs in AI have propelled the field forward, opening up new possibilities and opportunities.

Even after more than fifty years since the inception of the term AI, a widely accepted definition of the term remains elusive (Mikalef & Gupta, 2021). Mikalef and Gupta (2021) delve into the concept and propose their definition, aiming to establish clarity in distinguishing AI activities within organizational contexts. According to their definition, AI encompasses the system’s capability to identify, interpret, draw inferences, and learn from data to accomplish predetermined goals at the organizational and societal levels. Their definition is valuable to understanding AI and provides a framework for discerning AI-related activities from other endeavors.

The adoption of big, new technologies brings exciting possibilities. AI technology has received much spotlight this year, making research regarding adoption most compelling. Regardless, AI adoption is still in a relatively early stage, and empirical research concerning Norwegian firms' AI adoption is scarce. We build on AI and technology adoption research and utilize the resource-based view framework (Barney, 1991) to investigate why some AI adopters achieve superior profits while others struggle to see payoffs from their AI investments. We build on the AI capability term formed by Mikalef & Gupta (2021) and explore the topic further for Norwegian companies. Firms' AI capabilities reference firms' ability to leverage their AI-specific resources and could help create sustained competitive advantages for firms adopting AI. In this thesis, we aim to investigate what types of firms are adopting AI technology in Norway, as well as how the AI-adopting firms’ performance differs from non-adopters.

AI has developed significantly in the last few years. Hence, the research focus on the topic has also dramatically increased. AI is rapidly becoming relevant for several different research subjects, making the AI literature diverse and assorted. We use the research on AI capabilities, further built on the resource-based view (hereby referred to as the RBV), to link literature from AI- and technology adoption and explain potential performance differences. These subjects are largely new and unexplored, making this research exciting and noteworthy. Additionally, empirical research on Norwegian AI adoption and performance effects is also a novel subject. As such, this study offers empirical insights and sheds light on intriguing relationships that warrant further investigation, both in the Norwegian setting and in the literature as a whole.

1.2 Research Question

Despite the rapid advancements in AI technology, the adoption of AI and its effects on firm performance in Norwegian firms remain largely unknown. Therefore, this thesis aims to contribute to the growing literature on AI with findings about the adoption of AI and its effects on firm performance amongst Norwegian firms. Specifically, we want to investigate firm characteristics of firms adopting AI and how adoption affects firm performance. Based on established theory, we have formulated the following research question:

"Which Norwegian firms are adopting Artificial Intelligence,
and how does the adoption of AI affect firm performance?"

Another key objective of our research is to examine the feasibility and applicability of utilizing data from company websites for research purposes. In Chapter 3, we delve into the specifics of the data collection process, which involved web scraping techniques and conducting textual analysis of Norwegian companies' websites. This dataset was acquired by the research center Digital Innovation for Growth at NHH, and our supervisors displayed a strong enthusiasm for exploring the potential utility of this dataset for further research.

1.3 Structure

We have structured our thesis around six chapters, starting with the introduction and research question in Chapter 1. In Chapter 2, we present the relevant literature and the basis for our hypotheses. Furthermore, in Chapter 3, we discuss the research methodology and data employed. In Chapter 4, we present the results of our analysis. We discuss the findings and answer our hypotheses in Chapter 5 before we conclude our thesis in Chapter 6.

2 Literature Review

In this chapter, we explore the relevant literature on the adoption of artificial intelligence and artificial intelligence related to firm performance. We discuss the essential concepts and definitions needed to develop our knowledge on the topic. Furthermore, we use a deductive approach and develop hypotheses from relevant literature.

The literature review is organized such that we begin with defining and outlining critical concepts related to artificial intelligence, then move on to relevant theories regarding the adoption of AI technology. Further, we discuss the theory on firm performance and strategic resources, and finally, we draw connections between the topics with literature on the effect of AI on firm performance.

2.1 Artificial Intelligence

Artificial Intelligence is a rapidly growing field of technology that has become an integral part of our modern lives. Nevertheless, the applications and implications of this technology are still being explored. What does it mean to be intelligent, and what does it mean to be artificial? While these questions are still being debated and examined, one thing is clear: AI has made incredible advances over the past few decades and continues developing rapidly. This chapter will review the history of AI, its definitions, and current advances. We will explore the implications of this technology on business and strategic management.

2.1.1 The history of artificial intelligence

The very beginning of artificial intelligence can be traced back to humans' first attempts to automate human activities (Fanti et al., 2022). According to Bedini (1964), one of the first recorded attempts at automation was that of Heron of Alexandria in the first century BC, like the design of a statue that pours wine. Later, in the Iliad, written in the sixth century BC, Homer presented the automata of the Greek god Hephaestos (McCorduck, 2004). As time progressed, other historical figures conceptualized automation, such as R. Llull in 1309, who denotes the first attempt to create a mechanical calculator capable of performing computations like humans (Fidora & Sierra, 2011). Another noteworthy early contributor to automation and technological advancements that paved the way for artificial intelligence was Leonardo da Vinci. Between the 15th and 16th centuries, da Vinci designed several robotic devices, referred to as the automata, such as a mechanical knight and a self-propelled cart (Price, 1964; Nilsson, 2009). Finally, Babbage (1837) has been credited by many as the inventor of the computer (Simon & Newell, 1958; Fanti et al., 2022)

Before we reached the age of computation and information and communication technologies (ICTs), significant accomplishments were made in statistical and probabilistic theory. Fanti, Guarascio, and Moggi (2022) highlight Legendre's Least Square method (1806), the formalization of the "Bayes theorem" by Laplace (1802), and finally the introduction of "Markov chains" (1913) as significant advances that laid the foundation for the computational theory. With this foundation laid, Alan Turing started the known beginning of intelligent machines and artificial intelligence. Alan Turing's celebrated "Turing machine" is said to represent the beginning or direct ancestor of modern computers (Fanti et al., 2022; Turing, 1936). In 1956, AI saw a massive breakthrough when the term artificial intelligence was first coined during a seminal workshop at Dartmouth by J. McCarthy and other computer scientists (McCarthy et al., 2006). Newell and Simon (1956) created the "logic theory machine", also called the LT program, based on the seminal workshop. This program could use mathematical theorems to imitate a type of "reasoning." The LT program is also considered one of the first attempts to mimic human cognitive processes. From 1950 to the start of the 1970s, the topic of AI emerged as a proper research field. Moreover, we started seeing real applications and experiments with machine learning (ML) and reinforcement learning (RL), such as the first machine playing checkers (Samuel, 2000; Fanti et al., 2022) and machines that were able to play Tic-Tac-Toe (Michie, 1963).

Following the great uses of probabilistic theory in machine learning in the 1960s, the period known as the first AI winter followed (Fanti et al., 2022; Crevier, 1993). The AI winter first started in 1973 when a report by James Lighthill described the development within AI as disappointing (Pan, 2016). Lighthill's report formed the basis for the decision by the British government to stop funding for all AI research in all but two universities (Russel & Norvig, 2022). Disappointment is a term that resurfaces amongst other setbacks the development of AI has faced. The grand ambition and enthusiasm for the technology have created periods of excitement, ambition, overpromise, and some have even called it greed (Newquist, 2020).

After about ten years, the first AI winter ends recapitulated as a decade of stories of both tremendous success and failure. In the 1980s, we saw a resurgence in research on Artificial Neural Networks (ANN), and we saw commercial adoption of AI from large US companies

(Fanti et al., 2022; McDermott, 1982). Overall, the industry grew from a few million in the early 80s to several billion in 1988 (Russel & Norvig, 2022). However, the industry tanked shortly after. Pan (2016) argues that the second setback for AI development started with the investments made by the Japanese government into an intelligent computer in 1981. However, this machine's development failed, costing the Japanese government over 850 million US dollars. In many ways, the trigger for the second AI winter was the same as the first AI winter in the 70s; hype and overly ambitious goals and targets. The industry failed to deliver on ambitious and exaggerated promises. One of the most significant hurdles that contributed to the underdevelopment was how expert systems broke down when facing uncertainty. Despite less funding and interest, research on artificial intelligence continued (Crevier, 1993).

In the late 80s, we started to see another resurgence in the field of artificial intelligence. In 1986 four separate groups reinvented the original neural network algorithms of the early 60s (Russel & Norvig, 2022; Fanti et al., 2022). Moreover, AI's experienced weaknesses in handling large amounts of data prompted new research into probabilistic reasoning and machine learning. Between the 1990s and early 2000s, AI applications based on machine learning took a leap from academics to applied solutions within the IT sector (Fanti et al., 2022). Along with the enormous growth of the Internet and the World Wide Web in the early 2000s, we saw immense advances in computing power and the use of big data technology. The new availability of large amounts of training data helped AI recover its commercial attractiveness, referred to as AI Spring by Melanie Mitchell (2019). Google quickly took advantage of artificial intelligence and machine learning techniques and launched Google Translate in 2006 (Mitchell, 2019). Later, in 2011 methods involving deep learning gained traction, leading to applications with speech recognition and visual object recognition. Since 2011 deep learning has evolved to surpass human capabilities; for example, AlphaGo's achievements in beating world-leading Go Players. Moreover, Stanford University's report AI100 shows that papers about artificial intelligence increased 20-fold between 2010 and 2019 (Grosz & Stone., 2018). Additionally, they report that AI is now the most popular specialization in Computer Science courses in higher education.

A common theme we see is waves of hype and enthusiasm followed by not being able to achieve what was perceived to be the future. James Hendler has previously warned about the possibility of another "AI winter" (Hendler, 2008). Moreover, Belik and Neufeld (2022) tell us that "History […] teaches us that optimism and heightened interest in AI technologies are sure to be followed by a period of frustration and decline in investments in AI – in other words, an AI winter". Considering the recent advances in artificial intelligence, with the widely known OpenAI's ChatGPT (Kelly, 2022), DeepMind's AlphaGo and AlphaFold (Chen et al., 2018; Senior et al., 2020), we wonder if we face another wave of over-excitement, enthusiasm, and impossible goals of AI.

2.1.2 Defining artificial intelligence

As mentioned earlier, it can be argued that the rise of artificial intelligence started with Alan Turing in 1936 (Fanti et al., 2022); however, the term "artificial intelligence" was not coined until 20 years later during a seminal workshop at Dartmouth College. The term was then defined as the problem of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy et al., 2006). Since then, we have seen tremendous advances in AI technology. The authors behind the widely known book "Artificial Intelligence: A Modern Approach" define AI as "Systems that mimic cognitive functions generally associated with human attributes such as learning, speech, and problem-solving" (Russel & Norvig, 2003). Both McCarthy et al. (2006) and Russel & Norvig (2022) describe artificial intelligence as the ability of a machine to behave in ways that are associated with human intelligence, such as learning, problem-solving, and communication. The main difference between the two descriptions is that McCarthy et al. (2006) focus on the idea that AI machines mimic the behavior of intelligent humans, while Russel and Norvig (2003) focus more on the cognitive functions of AI, such as learning and problem-solving.

However, there is still lacking a universally accepted definition of the term (Mikalef & Gupta, 2021). In their paper about artificial intelligence, Mikalef and Gupta (2021) discuss the term artificial intelligence. They start by dismantling the term into two notions: Intelligence and Artificial. Building on the definition of intelligence by Legg and Hutter (2007), the term artificial by Cambridge university press (Walter, 2008), and other earlier studies, they provide the following definition: "AI is the ability of a system to identify, interpret, make inferences, and learn from data to achieve predetermined organizational and societal goals" (Mikalef & Gupta, 2021). Mikalef and Gupta's definition diverges from other definitions because they purposefully avoid inferring human-like abilities. The purpose behind their definition was to make it easier to determine which activities in an organizational setting are artificial intelligence and which are not. Based on the rapid growth of artificial intelligence and the increasing scope of the term, we have chosen to use Mikalef and Gupta's recent definition of the term artificial intelligence.

2.2 Firm Adoption of AI

The adoption of new technology brings exciting new possibilities. Studies show that using AI in organizations can increase productivity and help people make quick decisions (Duan et al., 2019). Other studies argue that AI will play a significant role in the economic growth of countries such as the US (Makridakis, 2017), India (Vempati, 2016), and China (Li, 2017). The recent development of AI technology has made AI increasingly accessible to firms and people. From virtual assistants to predictive analytics, AI arguably transforms our lives and work. However, there are challenges regarding firms adopting AI, as many industries are not ready to adopt the new technology (Alsheibani et al., 2018). In light of these developments, we will in this chapter explore the factors that drive the successful adoption of AI technology in firms. Drawing on our literature review findings, we will develop a set of hypotheses that we test using empirical data.

The adoption of AI technology is in a relatively early stage. A report from McKinsey and Company (Bughin et al., 2017) surveyed over 3,000 respondents from companies that were aware of AI and showed that only 20% had adopted one or more AI-related technologies on a larger scale or as a core part of their business. Generally, few companies have incorporated AI on a larger scale, with most of the companies that were AI-aware still in the experimental or pilot phase. These numbers may also overstate the current commercial demand for AI. A review of more than 160 global use cases across different industries showed that only 12% had progressed past the experimental stage (Bughin et al., 2017). Further, the report points to poor and uncertain returns as the main reason companies are not adopting the technology. The report claims the uncertainty in results is predominantly why smaller firms are not adopting AI. A more recent report states that AI adoption globally has increased by 150% since 2017 but has leveled off over the recent years (Chui et al., 2022). Further, the authors find indications that high AI performers are expanding their competitive advantage rather than the majority catching up.

For firms to be capable of adopting new innovations, a combination of complementary resources is critical. Mikalef and Gupta (2021) argue that the collection of resources needed to leverage firms' AI-specific resources is essential to create lasting competitive advantages. The authors refer to this collection of complementary resources as AI capabilities, which we will delve into more thoroughly later in this paper. Their article shows that firms that want to adopt AI need additional specific capabilities and cannot rely solely on their technological resources. This finding is consistent with existing literature on the adoption of innovations. A substantial body of empirical research has demonstrated that organizations possessing adequate technological, organizational, and human resources are more likely to adopt new innovations (Aboelmaged, 2014; Chatterjee et al., 2021; Wang & Cheung, 2008). A report from McKinsey and Company (Bughin et al., 2017) shows that the early adopters of AI are firms using AI in their core activities and have high digital adoption, further showing the importance of access to complementary resources when adopting AI.

Rogers (2003) states that the organization's size directly influences the adoption of innovations. Larger organizations generally have more financial and technical resources, enabling them to adopt new technology more easily (Aboelmaged, 2014; Chatterjee et al., 2021). The generally higher accessibility to critical resources coheres with the logic regarding AI capabilities' importance for AI adoption. Larger organizations could also have access to a higher number of skilled employees within AI, which can help build more complementary capabilities internally for the firm. In the existing body of theory, the organization's size generally correlates with higher technology adoption (Alsheibani et al., 2018). Contradictory, other studies indicate that smaller businesses are more flexible in adopting innovative technologies (Chatterjee et al., 2021). This displays that there likely are contours regarding firm size and AI adoption. It seems logical that newer start-ups with AI ingrained in their business model will be able to adopt the technology. However, for existing smaller businesses, adopting AI will likely not be prioritized when it is unnecessary to deliver customer value. According to relevant theory, larger firms should be more likely to adopt the technology if they believe AI can provide them with a competitive advantage and have the required capabilities (Chatterjee et al., 2021).

Nonetheless, AI has developed much in recent years. We are curious how firm size affects AI adoption in Norwegian firms, as there are some dissimilarities within relevant theory regarding firms adopting AI technology and new technology in general. Ultimately, most of the evidence points towards organization size increasing the adoption of AI. We choose to include measurements for firms' size in two ways; in terms of the number of employees that can build internal complementary capabilities and the total assets that can provide other critical resources. We form the following hypotheses:

H1: The number of employees positively affects the adoption of AI.

H2: Total assets have a positive effect on the adoption of AI.

The role of top management in facilitating the adoption of innovative technologies has been widely recognized in both academic literature and industry practice. Numerous studies have emphasized the importance of top managerial support in successfully implementing new technologies like artificial intelligence (Oliveira & Martins, 2011; Chatterjee et al., 2021; Yang et al., 2015). Chatterjee et al. (2021) state that without strong leadership support for implementation, organizations' adoption of any innovative technology will be unsuccessful. Their article displays how management support moderates the intention to adopt AI technology through changes in their "AI ease of use" and "AI perceived usefulness" variables. The moderating trait of leadership support aligns with the existing theory of RBV (Wade & Hulland, 2004). A lack of leadership support fails to improve a firm's competitive position and decreases its ability to adopt an innovation. If strong leadership support exists in an organization, the adoption of AI will be accelerated (Chatterjee et al., 2021). Unfortunately, we do not have access to the data needed to test these relationships.

We do, however, possess data related to top management attributes, such as the gender of the CEO and chairperson, which could prove interesting to explore. We do not have any reason to believe any gender effect exists on firms' adoption of AI. Because of this, we include a hypothesis with a two-tailed test.

H3: The gender of the CEO has no effect on the adoption of AI.

From our research into firms' adoption of AI, we have proposed several hypotheses from studies on AI adoption and technology adoption in general. The existing theory shows that AI technology is still in a relatively early stage, with some profiting from the technology. We expect firms' size to affect their adoption of AI positively. Top management support is stated as utmost importance for the adoption of AI. However, we are unable to test this relationship for our Norwegian sample. Next, we look further into AI adoption and link it with findings regarding AI capabilities and firm performance.

2.3 AI Capabilities and Firm Performance

Jay B. Barney proposed the resource-based view in the article *Firm Resources and Sustained Competitive Advantage* back in 1991. The resource-based view has been widely adopted and developed by management scholars and practitioners. It has become one of the most influential perspectives in strategic management. Following the RBV, firms achieve a sustained competitive advantage and superior profits by owning or controlling strategic assets (Michalisin et al., 2020). In this chapter, we will first present relevant literature regarding firm performance. Then we introduce the AI capability resource from a resource-based view. Lastly, we explore the theory considering the relationship between AI capabilities and firm performance.

2.3.1 Firm performance

From our research into firm performance, it has been surprising to see how many different measures have been used to operationalize the variables of performance, firm performance, and organizational performance. Richard et al. (2009) report that few studies use the same consistent measures. Moreover, March and Sutton (1997) find that performance has become so common in management research that its definitions are rarely justified. Even two decades after the original article from March and Sutton (1997), Jay Barney (2020) discusses the need to develop empirically tractable measures of firm performance. Because of this, we found it imperative to research and map out how different studies measure performance. Combs et al. (2005) suggest that organizational performance can be dimensionalized into accounting returns, stock market returns, and growth measures. Hamann et al. (2013) find support for four rather than three dimensions of organizational performance: Stock market performance, growth, profitability, and liquidity. In this subchapter, we delve deeper into the literature on firm performance and, more specifically, on competitive advantage, firm size, age, and geographic location.

Two main perspectives explain competitive advantage in the academic literature on strategic management. Firstly, we have the structural approach, which states that competitive advantage is the degree a firm can defend its position over competitors (Porter, 1985). Porter highlighted primarily two types of competitive advantage: cost leadership and differentiation. Secondly, we have the resource-based view (Barney, 1991). RBV proposes that the firm’s unique resources are the sources of competitive advantage. However, Ma (2000) addresses three observations regarding competitive advantage; competitive advantage does not equate to performance, competitive advantage is a relational construct, and that competitive advantage is context specific.

Further, Ma (2000) visualizes the relationship between competitive advantage and firm performance, explaining that discrete competitive advantage affects compound competitive advantage that ultimately leads to firm performance, see Figure 2.1. Regarding the relationship between firm performance and competitive advantage, Lakhal (2009) finds that higher levels of competitive advantage may lead to increased organizational performance. They also find that competitive advantage affects organizational performance more than quality.

Figure 2.1 Competitive advantage: From "Competitive Advantage and Firm Performance" by Ma, H., 2000, *Competitiveness Review*, 10 (2), pp. 15-32, Copyright American Society for Competitiveness 2000, reproduced with permission.

Moreover, the study on the effects of firm size has been researched for many decades. Baumol (1959) hypothesizes that entrepreneurs sacrifice current profits to maximize growth. In a later study on this topic, Hall and Weiss (1967) find support that firm size does tend to result in higher profit rates, as Baumol suggested. One possible answer for this correlation is that large capital requirements create barriers to entry that generate higher effects on profit margins. Moreover, Hall and Weiss (1967) discuss the concept of firm size and its meaning. They argue that total assets are a better approximation for firm size than sales or employment because the complexity of financing large sums of assets limits entry and creates barriers. Beck et al. (2005), who examine the relationship between firm size, growth, and perceived growth barriers, measure firm size according to the World Bank's definition (Schiffer & Weder, 2001). The World Bank's definition in 2001 assigns firms into categories based on the number of employees. One possible reason researchers use different measures for firm size is the implication of intercorrelation between them. However, Shalit and Sankar (1977) argue that different measurements of firm size are not automatically interchangeable. From what we have managed to find in the literature, there does not seem to be a one-for-all solution; some researchers use market value, while others use sales or the number of employees (Hall & Weiss, 1967; Rogers, 2004; Bates, 1965; Ghasemaghaei et al., 2017).

The relationship between firm age and performance has also been the subject of exciting research. First, some data suggests that company age positively affects the likelihood of superior organizational outcomes (Argote, 1999; Coad et al., 2016). However, Sørensen and Stuart (2000) find two effects of firm age on innovation – learning- and obsolescence effects. Sørensen and Stuart also find support for the notion that as organizations age, they generate more innovations. Related to Sørensen and Stuart's findings, Majumdar (1997) note that older businesses are more liable to experience inertia, or "bureaucratic ossification," that reduces overall learning effects.

Further research by Balasubramanian and Lee (2008), where they use patent data from Compustat firms, reveal a negative correlation between firm age and technical quality. The effect is more significant in areas with higher technological activity. Coad et al. (2018) further highlight how the literature seems to have mixed results regarding firm age and innovativeness, referencing two specific studies. Bianchini et al. (2018) argue that young companies prefer short-termism and value preservation over long-term risky innovation strategies. Conversely, Acemoglu and Cao (2015) find that new entrants engage in more "radical" innovations to replace incumbents. We then hypothesize that the adoption of AI is highly correlated with overall innovation and that we should find similar findings in our research. It would be interesting to explore the effect of age on AI adoption and if there are any significant differences across industries or regions in Norway. From the literature, we formulate the following hypothesis:

H4: Firm age has a negative effect on AI adoption.

Furthermore, the connection between geographic location and economic performance has been thoroughly studied. Back in 1998, Michael Porter defined the term clustering as "[…] geographic concentrations of interconnected companies and institutions in a particular field. Clusters encompass an array of linked industries and other entities important to competition." (Porter, 1998). Since then, many researchers have studied the effects of clustering on firm performance. Wennberg and Lindqvist (2010) find that firms located in strong clusters create more jobs, higher wages, and tax payments, as well as higher chances of firm survival. Another study by Diez-Vial (2011) on Iberian ham clusters shows that as the number of neighboring firms increases, so does firm performance. Similar results have been displayed in studies on firms in the biotechnology industry (Folta et al., 2006; McCann & Folta, 2011).

Interestingly, Folta et al. (2006) get results suggesting that agglomeration diseconomies also play a role when clusters evolve. In the follow-up study on biotechnology firms, McCann and Folta (2011) report strong evidence that firms benefit asymmetrically from clusters, whereas younger firms and firms with higher knowledge stocks benefit more from agglomeration. Isaksen (1997) researched the effects of clustering in Norway from 1970 to 1990 and, from his analysis, finds that regional clusters experience relatively more considerable job growth than industry averages. The findings on clustering and firm performance indicate that firms participating in geographic clusters experience better chances of survival and higher job growth.

According to Delgado et al. (2014), strong regional clusters may lead to agglomeration economies and externalities across firms within individual industries, such as learning, innovation, and spawning entrepreneurs. Agglomeration may also lead to larger pools of skilled employees, knowledge spillovers, and growth of specialized institutions, such as educational programs and trade groups. Clusters and robust regional hubs can serve as valuable sources of complementary externalities, fostering the adoption of new technologies such as AI as well as assisting in creating sustained competitive advantage. These findings support the idea of the importance of complementary AI capabilities for the adoption of AI technology (Mikalef and Gupta, 2021). In contrast to other segments, this capability stems from external complementarity. As critical capabilities could better evolve in clusters, AI adoption could also increase in these more urban areas. In our research, it would be interesting to investigate the relationship between clusters and the adoption of artificial intelligence.

H5: Firm municipality centrality has a positive effect on AI adoption.

From our research into firm performance, it is evident that different studies measure performance in different ways. The literature suggests that competitive advantage is one of the main drivers of performance, with firm size, age, and geographic location also impacting. Studies have found that firms located in strong clusters create more jobs, higher wages, and higher chances of firm survival. In the next chapter, we look further into AI as a resource and its role in the RBV framework.

2.3.2 The AI technology in the RBV framework

Jay B. Barney proposed the resource-based view in the article *Firm Resources and Sustained Competitive Advantage* back in 1991. The resource-based view (hereby referred to as the RBV) has been widely adopted and developed by management scholars and practitioners. It has become one of the most influential perspectives in strategic management. Following the RBV, firms achieve a sustained competitive advantage and superior profits by owning or controlling strategic assets (Michalisin et al., 2020).

The RBV is one of the most widely adopted theoretical frameworks for elucidating how a firm's resources can impact its performance within a given industry (Barney, 2001). The RBV has demonstrated its durability in crafting theoretical propositions and conducting empirical research on the impact of organizational resources on firm performance, as evidenced by more than three decades of testing (Mikalef & Gupta, 2021). Additionally, the RBV has been a central theoretical perspective in several studies addressing how AI could affect firm performance (Mikalef & Gupta, 2021; Chen et al., 2022). Given the goal of examining how AI impacts firms' performance, applying the RBV framework seems fitting. Research has demonstrated that the RBV is an appropriate framework for analyzing dynamic and rapidly evolving business environments. This is because the complementarity of resources and the creation of unique and difficult-to-replicate resources have consistently been associated with competitive success (Dutta et al., 2005). The rapid advancements in the field of AI over the past year(s) suggest that utilizing the RBV as a framework is a sensible approach, given its potential for future expansion.

In this paper, we define firm resources as "all assets, capabilities, organizational processes, firm attributes, information, and knowledge, controlled by a firm that enables the firm to conceive of and implement strategies that improve its efficiency and effectiveness" (Daft, 1983). In other words, firm resources can refer to both tangible and intangible assets, as well as human skills that can create value (Grant, 1991). Barney (1991) discusses the conditions under which firm resources can be a source of sustained competitive advantage. He argues that for a resource to hold the potential for a sustained competitive advantage, it must be valuable, rare, inimitable, and non-substitutable. Further, these attributes of firm resources can be seen as indicators of how heterogenous and immobile the resources are and how useful they are in creating sustained competitive advantages. Firm resources that fulfill the criteria as sources of sustained competitive advantage and superior profits can be called strategic firm resources (Barney, 1991).

As an extension of this, Barney (1991) also discusses the difference between competitive advantage and sustained competitive advantage and how this can change over time. He describes a competitive advantage as when a firm implements a strategy that not simultaneously are being implemented by existing or potential competitors. A sustained competitive advantage transpires when this strategy's *benefits* additionally is un-duplicatable for the competitors. Further, Barney explains that even if a competitive advantage is sustained, this does not imply it will last perpetually. Unanticipated changes in the economic structure - "Schumpeterian shocks" (Schumpeter, 1983) might alter firms' previous position of sustained competitive advantage. As a firm's position may change over time, it must continuously monitor and adapt its resources to maintain its sustained competitive advantage.

Intangible resources such as AI capabilities will generally be more strategic assets than their tangible counterparts because of their increased heterogeneous and immobile nature. In their context analysis study of American firms, Michalisin et al. (2000) find that intangible resources can be a source of sustainable competitive advantage due to their nature of being more difficult for competitors to imitate or acquire. The authors find that intangible resources, such as reputation, brand, intellectual property, and human capital, play a significant role in determining a firm's performance. They discovered that intangible assets could provide a competitive edge by creating barriers to entry, enabling the firm to diversify its products and services, and supporting the development of new products and services. Human capital, which refers to the firm's employees' knowledge, skills, and experience, can also be a source of competitive advantage by enabling the firm to develop and implement new products and services and respond to changing market conditions (Michalisin et al., 2000).

Several authors have discussed AI's role in the resource-based theory framework, herby RBT (Chen et al., 2022; Mikalef & Gupta, 2021; Chowdhury et al., 2023). Through the view of the RBT, firms gain improved competitive performance gains by building valuable, unique, hard-to-imitate, and non-substitutable capabilities (Mikalef and Gupta, 2021). These capabilities arise when complementary firm resources are combined and deployed. In their article, Mikalef and Gupta define AI capabilities as "The ability of a firm to select, orchestrate, and leverage its AI-specific resources." The firms' AI capability is, therefore, dependent and developed based on the firms' organizational resources. The strength of the AI capability will, in turn, depend on the resources they are developed. This AI capability has gained attention as it can potentially increase the competitive advantages of firms (Obschonka and Audretsch, 2020).

Different authors' use of the terms "strategic firm resources" and "firm capabilities" will vary, but the purpose will often correlate. What is critical is the terms describing valuable, rare, difficult to imitate, and non-substitutable elements. A firm capability is more strategic in nature than a simple firm resource due to its increased complexity and, in turn, likely being more valuable, rarer, more complex to imitate, as well as harder to substitute. However, some authors could describe the capability as a strategic firm resource. A firm capability will imply a strategic resource, but a strategic resource will not always signify a firm capability. Amit and Schoemaker (1993) define resources as tradeable non-specific firm assets, while capabilities are non-tradeable firm-specific abilities to deploy, integrate and utilize resources within the firm. The authors consider AI an influential firm resource but insufficient to develop an AI capability (Mikalef and Gupta, 2021). This implies that AI technology alone is unlikely to deliver any competitive gains, as the resource is relatively mobile and can be replicated or acquired on the market. Leading firms' reports on AI adoption emphasize that combining physical, human, and organizational resources is necessary for creating an AI capability that can generate value through differentiation from competitors (Davenport and Ronanki, 2018). Similarly, Chen et al. (2022) provide a model of AI capability composed of Tangible, Intangible and human resources, which is the same recipe that Grant proposed in 1991.

2.3.3 The effect of AI on firm performance

As established, an AI capability requires additional complementary resources to bring sustained competitive advantages to a firm. When investigating the impact of AI on firm performance of E-commerce firms, Chen et al. (2022) finds that for firms to improve their performance, they must recognize the actual business value of AI technology and cannot solely depend on software, hardware devices, technical resources, or data resources. However, they explain that these complementary resources should be allowed to naturally build the firm's superior competitiveness. In their article, they find three variables composing E-commerce firms' AI capability. These variables are "basic" (tangible resources), "skill" (human resources), and "proclivity" (intangible resources). Furthermore, they find that firms' AI capability indirectly influences firm performance and AI-driven decision-making through firm creativity and AI management. AI-driven decision-making strongly and positively affects firm performance. Their results also suggest that innovation culture and environmental dynamism are relevant moderating variables in the research model.

In their industry survey, Ransbotham, Kiron, Gerbert, and Reeves (2017) report that despite high expectations of AI, the adoption of AI technology is at a very early stage. Their article looks at the current state of AI technology and how it can improve decision-making processes and make businesses more efficient. The authors discuss the potential benefits of AI and how it can be used to improve decision-making, such as enhanced data analysis, automation of repetitive tasks, and improved customer service. Furthermore, they discover that only about one in five companies have implemented AI in some processes, even though 85% of respondents believe the technology will help their businesses gain or sustain a competitive advantage.

In their study, Wamba-Taguimdje et al. (2020) aim to investigate the effect of artificial intelligence on firm performance. The authors review 500 case studies from different organizations and find that implementing AI-based projects significantly positively impacts firm performance in terms of efficiency, innovation, and customer satisfaction. Further, they find that the benefits of AI are not limited to specific industries or company sizes and that organizations with a clear strategy and well-defined objectives for their AI projects tend to achieve better results. The study highlights that AI can help companies streamline processes, reduce costs, and improve decision-making, increasing efficiency and profitability. However, findings in the article suggest that AI is best used to optimize existing processes. Therefore, having the right resources, skills, and leadership is essential to make the most of the technology. These results support the findings of other studies which ascribe that the AI resource itself might not be sufficient for firms to achieve sustained competitive advantage (Mikalef and Gupta, 2021). Firms will also need other complementary resources as well as a suitable strategy to be able to achieve higher performance.

Chen et al. (2022) find support for AI capability positively impacting firm performance. By positively impacting firm performance, we mean an increase in market share growth, financial resources, and the ability to introduce new products and services to a market. Their findings are based on a cross-sectional survey targeting e-commerce entrepreneurs. The authors' results show that firms' AI capability impacts firm performance through better AI-driven decision-making, which in turn comprises the quality of the firms' creativity and AI management. They also identify innovation culture and environmental dynamism to be positively moderating variables in the model. Interestingly, they also find firm age to correlate with firm performance in their AI capability-focused dataset negatively, contradicting other research findings (Argote, 1999; Coad et al., 2016). However, we do not want to read too heavily into the difference in results, as they may be attributed to dissimilarities in data.

In their paper about AI adoption and R&D strategy, Lee et al. (2022) show that the adoption of AI at lower levels does not significantly increase revenue growth. However, they report that sufficient investments in AI may lead to an increase in revenue growth. Moreover, they find that the benefits of adopting AI are greater at firms that also invest in complementary technologies, such as cloud computing and database systems.

In a newer study on the effects of AI capabilities, Mishra et al. (2022) find that a focus on AI is associated with increases in net profitability, net operating efficiency, and return on market-related investments. Moreover, they report that increased AI focus may lead to reduced ad spend and more job creation. In their study, they examined 10-K reports of companies in the COMPUSTAT database against a detailed list of words associated with the term artificial intelligence. From this analysis, they developed a variable called AI focus that they investigated against measures for firm performance. Furthermore, Mishra et al. (2022) call for further research and proposes the potential to examine the relationship of AI focus on small and medium-sized businesses. This is something we are interested in doing, and it could be relevant to replicate some of the variables they employ. In their research model, they use measures of size, growth, leverage, liquidity, tangible and intangible assets, risk, and sales ratios such as sales to the number of employees and sales to total assets. From Mishra et al. (2022), Lee et al. (2022), and Chen et al., 2022), we formulate the following hypotheses:

H6: AI adoption has a positive effect on sales growth.

H7: AI adoption has a positive effect on return on assets.

H8: AI adoption has a positive effect on net operating efficiency (Sales per employee).

There is no question that AI can bring firms significant value and provide competitive advantages. As mentioned in our AI adoption chapter, the adoption of AI is in an early stage. Chowdhury et al. (2023) show that organizations are yet to experience the anticipated benefits of AI technology. The absence of experienced benefits remains consistent regardless of whether firms invest time, effort, and resources. Chowdhury et al. (2023) find that firms need to look beyond their technical resources and develop non-technical ones, such as human skills and competencies, as well as leadership and team coordination. Further, the authors state the importance of developing an innovation mindset and AI-employee integration strategies to benefit from AI technology. These results build on previous findings stating the importance of AI capabilities where complementary resources are combined and deployed (Mikalef and Gupta, 2021). Furthermore, the results support firms' need for AI capabilities to gain sustained competitive advantages. We want to investigate the Norwegian landscape of firms' AI adoption to see whether adopting the technology positively affects their performance.

Table 2.1 Hypotheses: Summary and description of all hypotheses formulated from the literature review.

	Hypotheses	Sources
H1	The number of employees positively affects the adoption of AI.	(Aboelmaged, 2014; Chatterjee et al., 2021)
H2	Total assets have a positive effect on the adoption of AI.	(Aboelmaged, 2014; Chatterjee et al., 2021)
H3	The gender of the CEO has no effect on the adoption of AI.	
H4	Firm age has a negative effect on AI scores.	(Acemoglu & Cao, 2015; Coad et al., 2018; Majumdar, 1997)
H5	Firm municipality centrality has a positive effect on AI Score.	(McCann & Folta, 2011; Wennberg & Lindqvist, 2010)
H6	AI score has a positive effect on sales growth.	(Wamba-Taguimdje et al., 2020; Lee et al., 2022; Chen et al., 2022)
H7	AI score has a positive effect on return on assets.	(Wamba-Taguimdje et al., 2020; Mishra et al., 2022; Chen et al., 2022)
H8	AI score has a positive effect on net operating efficiency (Sales per employee).	(Mishra et al., 2022)

3 Methodology

In this chapter, we will explain the methodological choices we have made so that we can adequately investigate our research question. This chapter starts by describing the research approach, design, and strategy. Furthermore, we present how the data has been acquired, structured, and analyzed. Finally, we assess the strengths and weaknesses of our study, including considerations of ethical concerns.

3.1 Approach, Design, and Strategy

The research design can be considered a “roadmap” or systematic plan that guides the process of collecting data to answer the research question (Saunders et al., 2019; Krishnaswami & Satyaprasad, 2010; Kothari, 2004). This includes describing the research approach and chosen methods for collecting and analyzing data.

3.1.1 Research approach

When selecting a research approach, it is important to consider current and relevant literature on the subject of interest. Depending on the amount of theory employed at the start of the research, a research approach can be classified as inductive, deductive, or abductive (Saunders et al., 2019). Deductive research seeks to assess existing theories in the light of reality, while inductive research seeks to generate new theories from the exploration of a novel phenomenon (Saunders et al., 2019). Abductive research combines inductive and deductive research, where one begins by exploring and collecting data and generates theories we can test through additional data collection. Our study utilizes a deductive approach, starting with theory regarding the adoption of AI and theories of the relationship between AI and firm performance based on current and relevant academic literature. Based on relevant literature, we have proposed hypotheses and premises we aim to test.

3.1.2 Research design

We have chosen to employ a quantitative research design, as it is well suited for studying relationships, predicting, and explaining phenomena (Saunders et al., 2019). Sukasmolson (2007) defines quantitative research as "… the numerical representation and manipulation of observations for the purpose of describing and explaining the phenomena that those observations reflect". Our research question aims to determine what firms adopt AI technology and what the effects are on firm performance. With a quantitative design, we can take advantage of statistical and graphical techniques to analyze and present the data. Moreover, quantitative data is particularly well suited for hypothesis testing, allowing us to explore and explain differences between groups of firms.

3.1.3 Purpose and objectives

The purpose behind our research question can be described as following a descripto-explanatory format. Descripto- explanatory studies are studies with a dual purpose, based on descriptive and explanatory purposes (Saunders et al., 2019). Firstly, a descriptive approach allows us to gain an accurate profile of the adoption of AI amongst Norwegian firms, providing invaluable insights and familiarity with the phenomena that could lead to interesting hypotheses. In a sense, we use the descriptive purpose as a forerunner to the main explanatory study. Explanatory research aims to study a situation to establish causal relationships between variables (Saunders et al., 2019). In our study, we want to see what organizations adopt AI technology and explain the relationship between firm performance and the adoption of artificial intelligence. Additionally, an explanatory approach is logical due to the depth of prior literature on strategic resources and firm performance. Drawing on prior literature, we have been able to formulate propositions and hypotheses about possible relationships.

3.1.4 Research strategy

We have decided to use a documentary research strategy, which is also known as documentary research. This type of strategy allows us to collect data from a wide array of secondary sources, including financial statements and companies' web pages. Document secondary data can be defined as existing data initially collected for other purposes (Saunders et al., 2019; Lee, 2012). Michaud (2017) summarizes document research eloquently with the title "Words fly away, writings remain." From secondary sources, such as web pages, we can compile data for our study. Furthermore, Michaud states that document research often provides ready-to-code data in a nonintrusive manner, which are important strengths we hope to take advantage of when we collect and analyze data. In Chapter 3.2, we further detail our methods for data collection.

3.2 Data Collection

The purpose of this chapter is to explain the data collection process used in our research. In this chapter, we will provide an overview of the main data sources used in our study, discuss how we acquired and accessed this data, and explain the steps taken to ensure data quality. We will also provide an in-depth look at the two major data sources used in our research: an acquired dataset with AI scores and additional accounting data. By providing a comprehensive clarification of our data collection process, we hope to demonstrate the robustness of our research and the validity of our findings.

3.2.1 AI score data

We aim to explore various issues related to companies' adoption of AI technology. Therefore, it is desirable to quantify and measure companies' use of AI. Our data utilizes company websites to measure their use of AI technology. Firms that are active in the artificial intelligence field, have businesses geared to it, or offer products and services with a direct link to AI usually communicate this (Dehghan, 2022). The more central the topic is for the company, the more the firm will communicate it externally. The data is acquired by the research center Digital Innovation for Growth at the Norwegian School of Economics. The data was obtained from the team behind Istari.ai, a company founded as a scientific spin-off specializing in AI-created market research. The data is based on company websites and, hence, falls under the category of document secondary data (Saunders et al., 2019).

Using artificial intelligence, Istari.ai has gone through a type of content analysis for analyzing text, allowing for quantitative analysis. First, several AI-related keywords are identified to measure which companies use AI. Industry standards, online dictionaries, and a Natural Language Processing (NLP) analysis of research articles are used to identify relevant words that can measure companies' use of AI (Dehghan, 2022).

Second, web scraping[1] technology is used to collect and analyze the contents of the company websites. A WebAI uses the keywords that have been identified earlier to determine which companies have websites where AI is centrally utilized. The WebAI has been trained to determine which websites meet the requirements for adopting AI technology.

Then, the WebAI provides the companies with two different scores. The first is the "Information Intensity score", and the second is the "Know-how Intensity score". The WebAI not only counts relevant keywords on the pages. It finds relevant words and analyzes the paragraphs around them to see how the firms describe the technology's use. The “Information Intensity Score” measures how intensively the company provides information on the topic of AI without having its products and services integrated with AI or personnel with AI skills. A newspaper that writes about different technology can achieve an informational intensity score even though the company does not have relevant AI capabilities in place.

The “Know-how Intensity Score” measures the degree to which products and services are integrated with AI or personnel with AI skills. The resulting numerical indicator reflects how centrally the topic of artificial intelligence is communicated on the company’s website and presented as essential for its business model. We have discussed the term AI capabilities in Chapter 2.3.2, and we believe the Know-how Intensity Score will sufficiently measure firms’ AI capability. The fact that our dataset can differentiate between companies that inform or write about AI and those that use AI in their business strategy allows us to investigate some interesting issues that would otherwise be difficult to distinguish. This is particularly relevant as we want to use the resource-based view to see if AI (know-how) acts as a strategic resource that can explain financial performance differences.

From the RBV, better AI capabilities should lead firms to better performance by being valuable, unique, hard-to-imitate, and non-substitutable. As the AI Know-how Intensity Score measures products and services with integrated AI or personnel with AI skills, this should be an appropriate variable to measure firms’ AI capabilities. However, our findings should be interpreted cautiously, as the AI score data is limited to what is available on company websites. By focusing on websites, we did not consider any other forms of verbal or written expressions of AI by the firms in our sample, such as promotional materials or internal documents which

[1] Web scraping refers to extracting information or data from websites, and exporting this to data formats useful for analysis, for example spreadsheets. Web scraping can be done either manually or with automated programs.

might express views and efforts toward AI. In Chapter 5, we will discuss the limitations of our findings in greater detail.

3.2.2 Accounting and financial data

Supplying our study on the adoption of artificial intelligence, we collected accounting and financial data about the companies in our sample. Through the Centre for Applied Research at NHH (SNF), we got access to their comprehensive database, “Norwegian Corporate Accounts,” consisting of high-quality financial and corporate information on Norwegian companies. This database was constructed specifically for research and now holds more than six million firm-year observations for legal entities (Mjøs & Selle, 2022). Getting access to this database requires all users to sign a declaration of loyal data usage, pledging to use the data for research or educational purposes.

The database of Norwegian Corporate Accounts by SNF gets its primary financial data from the Accounting Register of Norway, which is maintained by the Brønnøysund Register Centre (Mjøs & Selle, 2022). In Norway, all private and public limited liability companies must create and make public their yearly financial records, which must include a profit statement, a balance sheet, and additional notes. The database gets access to this information through Bisnode D&B Norway AS in cooperation with Menon Economics AS. According to SNF, all sources are used from “renowned and well-established organizations, of which most are governmental institutions that collect administrative data for tax, transparency, and analytical reasons” (Mjøs & Selle, 2022, p.5).

The database offers a wide array of variables to sample, including income statements, balance sheet information, industry data, and shareholder information. Moreover, the database now provides geographical variables that measure the centrality of the municipality where the companies are based. These variables can be interesting to incorporate into our study as a proxy for clustering or as control variables for our analyses. The data we access can be categorized as multiple source, longitudinal secondary data (Saunders et al. 2019). Our study's most central information comes from the income statement and balance sheet. We have identified the following metrics from academic literature as relevant to our research: the number of employees, net income, total assets, return on assets leverage, operating margin, and sales growth.

3.3 Data Preparation

In this chapter, we discuss in greater detail the methods used to prepare, organize, and analyze the data we have collected. As we conduct quantitative, descripto-explanatory research, we rely more on statistical methods to describe, explore, and test the chosen variables. This section contains definitions and information about our variables, methods for preparing the data, and a discussion about models used for our analysis. We hope that providing in-depth insights into data preparation will make the results more valuable and reliable.

3.3.1 Selected variables

It is crucial to carefully select and construct critical variables for the study to thoroughly analyze the adoption of AI and its effects on firm performance. In this subchapter, we provide detailed descriptions and definitions of the variables we use and have constructed from the data we have accessed. Understanding the variables' characteristics and definitions is essential for properly interpreting the study's results. By the end of this chapter, we hope readers will clearly understand the variables we will be using and how they contribute to our overall research question. Following this chapter, in Chapter 3.3.2, we detail the data preparation process for analysis.

Firstly, from the acquired AI dataset, we keep the following variables: Name, Company identifier, URL-address, Max AI Score, AI Know-how Intensity Score, and AI Information Intensity Score. The AI dataset also has data about the number of employees, industry classification, and postal code. However, this is data we also have through the Norwegian Corporate Accounts dataset, which is ultimately the most reliable source for this information. The company identifier represents the organizational identification number, which is a unique identifier administered and issued by the Brønnøysund Register Centre. The firm identifier variable is the crucial variable for merging the AI scores dataset with the Norwegian Corporate Accounts data, as it uniquely identifies each firm. We kept the variables for the company names and URL-address for purposes related to quality assurance, control, and testing, as will be discussed in Chapter 3.3.2. The AI score variables are fascinating, and it is essential to note their differences. We communicate more details on the AI scores in Chapter 3.2.1. In short, the AI Know-how Intensity score measures firms' AI capability. By this, we mean firms' ability to leverage their AI-specific resources. This variable is a derivate of AI's role in products, services, and workforce. On the other hand, The AI Information Intensity Score is simply informative and measures how intensively a firm provides information on the AI topic. These variables are both valuable, but their use cases will differ.

Secondly, we access corporate data of over 220 variables from the Norwegian Corporate Accounts database. This includes everything related to income statements, balance sheet information, as well as firm characteristics. Based on earlier studies and our research objectives, we decided to keep roughly 35 variables. See Table 3.1 for a detailed list and descriptions. From these 35 variables, we were able to construct new variables useful for our analysis. Based on the variable "Date of establishment," we created the variables "Age in days" and "Age in years." Moreover, we constructed the following variables "Debt Ratio," "Return on Assets," "Sales CAGR," and "Operating Margin."

Table 3.1 Selected variables: Definitions and description of variables and data types. For even more information variables and data sources, see Mjøs and Selle (2022).

Variable	Description	Data type
AI Know-how Intensity Score	This item represents how centrally the topic of AI is communicated on the company's website regarding how essential the AI technology is for the firm's own business model. Therefore, the variable should also be more closely related to the company's AI capabilities.	Numerical, Continuous
AI Information Intensity Score	This item represents the degree to which a company is communicating AI technology that is of informational character. A high AI Information Intensity Score does not necessarily mean the firm has AI capabilities.	Numerical, Continuous
Main industry code	This item represents the NACE code. The code indicates the firm's primary business activity. Read more from the Brønnøysund Register Centre (The Brønnøysund Register Centre, 2022).	Categorical, Nominal
Region of Norway	This item represents the name of the region in which the company is registered. The data is from the Centre of Applied Research (SNF), which follows the official NUTS-2 standard for regional classification by Statistics Norway.	Categorical, Nominal
Municipality Centrality	This variable represents the centrality of the municipality where the company is located. The centrality score is based on travel times to workplaces and service functions. The centrality score index takes a value between 0 and 1000, where the higher score indicates the more central municipalities. For more information, see Høydahl (2020).	Numerical, Continuous
Number of Shareholders	This variable represents the number of unique shareholders reported.	Numerical, Continuous
Number of employees	This variable represents the number of employees reported.	Numerical, Continuous
Sex of CEO	This item represents a dummy variable of the sex of the CEO or general manager. 1 = Female, 0 = Male. Data from the Centre of Applied Research at NHH (Mjøs & Selle, 2022), information based on the National Population Registered that is maintained by the Norwegian Tax Administration.	Categorical, Dichotomous

Variable	Description	Data type
Sex of chairperson	This item represents a dummy variable of the sex of the chairperson. 1 = Female, 0 = Male. Data from the Centre of Applied Research at NHH (Mjøs & Selle, 2022), information based on the National Population Registered that is maintained by the Norwegian Tax Administration.	Categorical, Dichotomous
Firm age	This item represents the age in years of the companies in our sample. The variable was estimated based on the date of establishment and the last date of the fiscal year, which is 31 December for most Norwegian firms.	Numerical, Continuous
Startup	This item represents a dummy variable that turns 1 if the company was established in 2016 or later.	Categorical, Dichotomous
Net income	This variable represents the net income and is calculated by the Centre of Applied Research at NHH as follows: *Net income = Result before tax – total taxes*	Numerical, Continuous
Total assets	This variable represents the total assets and is calculated by the Centre of Applied Research at NHH as follows: *Total assets = Fixed assets + Current assets*	Numerical, Continuous
Debt ratio	This variable represents the debt ratio and is a variable constructed based on data from the Centre of Applied Research at NHH. The debt ratio is calculated as follows: *Debt ratio = total liabilities / Total assets*	Numerical, Continuous
Liquidity, or Current Ratio	This variable represents a measure of liquidity. The liquidity, or current ratio, is calculated as follows: *Liquidity = Current assets / Current liabilities*	Numerical, Continuous
Operating margin	This variable represents the operating margin and is calculated by the Centre of Applied Research at NHH as follows: *Operating margin = Operating profit / Total operating income*	Numerical, Continuous
Return on assets	This variable represents the firm's return on assets and is constructed based on data from the Centre of Applied Research at NHH. The debt ratio is calculated as follows: *Return on assets = Net income / Total assets*	Numerical, Continuous
CAGR sales	This variable represents the firm's Compounded Average Growth Rate in sales. We calculate for several time periods but mainly use the five-year variant in our analysis. We keep the value in decimal form. $CAGR = \left(\frac{Ending\ value}{Starting\ value}\right)^{\frac{1}{periods}} - 1$	Numerical, Continuous
Research and development	This variable represents the capitalized parts of innovative activities where the focus is to produce knowledge, new products, or improvements. May be reliability concerns regarding the capitalization.	Numerical, Continuous

3.3.2 Data preparation and investigation

One of the main disadvantages of utilizing secondary data is that the data is collected primarily for other purposes (Saunders et al., 2019). A potential consequence is that the data might be structured or compiled in ways that require research into its reliability and usability. Secondly, with secondary data, we have no accurate control over the data quality (Saunders et al., 2019). This indicates that researchers need to exercise extra caution when assessing the data quality and when preparing the data for analysis. In this subchapter, we divide the discussion about the preparation into two parts: one part about the AI data and another part about the accounting data.

3.3.2.1 AI score data

In the original AI dataset, there were data from a total of 142,549 Norwegian firms. However, there were a substantial number of firms with missing AI scores. There were 46,602 companies where the program failed to identify a website, leading to missing data. Because the program could not identify a website, it failed to estimate these companies' AI scores. This is an important limitation of the representativeness of our sample.

Moreover, from the remaining 95,947 companies where the program identified a website, the dataset returned 10,965 NAs for the AI score variables. This indicated that some identified websites either had solutions to combat web scraping or were not functioning. This was not further analyzed in the original dataset, so we had to look into this ourselves. We collected a sample of 200 random companies from the original data, 100 with an AI score and 100 without one. From this, we could manually investigate the websites that were reported. We reported our findings into categories based on the status of the websites, for example, “functioning,” “empty page,” “page under development, and “website not functioning/loading.” From our random sample, we find that for those with an AI score, 87% were functional, while those with NA scores were only 56% functional. Those with an AI score had a standard deviation of 0.338, and those with NA scores had 0.499. Based on this, we got the hypothesis that the average functionality of those with a score was statistically different from those without a score. Following this, we did a hypothesis test for two means. With a 5% significance level, we get a test statistic of 5.144, a critical t-value of ±1.97368, and a p-value of approximately 0.000. We then reject the null hypothesis and conclude that there is a statistically significant difference between the two samples.

Furthermore, we conducted two other analyses to investigate the differences between those with AI scores and those with missing values. We created a dummy variable where those without a score turned one and those with a score turned zero. With this, we could see differences through descriptive statistics and regressions with the dummy. With the dummy as the dependent variable, we can quickly see if there are any significant changes between those without scores and those with scores; see Figure 3.1. There are some differences; however, the differences are minimal. Based on this, we argue that adjusting the sample based on firms with NA AI scores is reasonable. One potential weakness of our investigations is that we investigated the websites at a later date than when the Istari.ai calculated the AI scores.

Exploring the original data, we also became increasingly suspicious about the firms with foreign domain suffixes. From the original data, 12,136 companies had a ".com" domain suffix. Based on an initial investigation of a handful of observations with a ".com" suffix, we saw that most of these were not the actual Norwegian companies' websites, but American companies not affiliated with Norway in any capacity. Again, this was not commented on in the original data, so we did our own investigation. We collected a sample of 80 random companies from the original data, 40 with a ".com" suffix and 40 with a ".no" suffix. Manually we investigated the websites and categorized the findings based on whether the company was Norwegian or not. Our sample shows that those with a ".no" suffix were Norwegian 100% of the time, while those with a ".com" suffix were Norwegian only 40% of the time.

Again, we conducted hypothesis testing of two independent means. With a 5% significance level, we get a test statistic of 5.099, a critical t-value of ±2.02269, and a p-value of approximately 0.00001. We reject the null hypothesis and conclude that there is a statistically significant difference between the two samples. Furthermore, we constructed a dummy variable for the domain suffixes that turned one if the URL ended with ".com" and zero otherwise. With this dummy, we ran regressions with the dummy as the dependent variable. With this, we could identify any significant difference between the two groups. In Figure 3.1, we show the regression results. There are some differences: however, the differences are minimal. Based on this information, we concluded to exclude companies with a ".com" suffix in our study. Including these observations would lead to inaccurate data as the AI scores would be based on different companies than intended.

Figure 3.1 Testing NA AI scores and .com URLs: We created dummy variables of the variables AI Score and URL. The dummy for score turns one if the company had NAs for AI score, and the dummy for URL turns one if the domain ended with a ".com" suffix.

	Dependent variable:	
	Dummy Scores	Dummy URLs
	(1)	(2)
Municipality Centrality	0.00002^{*}	0.0002^{***}
	t = 1.930	t = 20.677
Gender Chairman	0.001	0.001
	t = 0.195	t = 0.295
Gender CEO	-0.007^{*}	-0.020^{***}
	t = -1.861	t = -5.318
Number of Employees	-0.00000	-0.00002
	t = -0.469	t = -1.605
Number of Shareholders	0.00000	0.00001^{***}
	t = 0.456	t = 4.083
Age in Years	0.001^{***}	-0.002^{***}
	t = 6.339	t = -17.305
Total Assets	-0.00000^{***}	0.00000^{***}
	t = -4.006	t = 12.772
Debt Ratio	0.004^{**}	-0.003
	t = 2.285	t = -1.464
R&D	-0.00000	0.00000
	t = -1.381	t = 0.615
Return on Assets	-0.006^{*}	-0.030^{***}
	t = -1.839	t = -7.776
Constant	0.094^{***}	-0.004
	t = 11.679	t = -0.489
Observations	73,026	73,026
R^2	0.001	0.017
Adjusted R^2	0.001	0.017
Note:	*p<0.1; **p<0.05; ***p<0.01	

The issue of corporate groups and observations with the same website domain was also prevalent in the original dataset. Initial investigation showed that the dataset did not make adjustments to this. The problem was that the dataset had several observations using the same domain for estimating the AI scores. This could skew the data in either favor or against bigger firms. One example we identified was a large Norwegian bank. The dataset included observations of some smaller local affiliations and divisions of the corporation, where everyone's AI score was based on the same domain. First, we adjusted for this by omitting the observations with the lowest reported number of employees, based on our assumption that the largest entity reported was the parent company. This was mostly correct, but it happened to be other large corporations that were structured such that all the employees were employed in a subsidiary of the parent company. To correct this, instead of omitting based on the number of employees, we adjusted based on total assets.

Finally, we constructed several dummy variables for the AI scores. This allows us to conduct logistic regression models with binary dependent variables of the dummies. We will come back to this in Chapter 3.4, but this allows us to investigate who are the adopters of AI technology.

3.3.2.2 Financial and accounting data

The original dataset from the Centre for Applied Research at NHH (SNF) had 369.593 rows of data, each representing a legal entity. After merging with the smaller AI dataset, we were left with 56.251 rows of data. In this subchapter, we will discuss further adjustments made based on variables from the financial and accounting data.

We decided to limit our sample to companies with one or more employees. This is for several reasons. For one, these firms are often inactive or not operational, making it more difficult to draw valid conclusions. Secondly, with certain statistical models and variables of efficacy, such as sales per employee, it may not be possible to include firms with zero employees, as this would result in undefined values. Moreover, adjusting for firms with zero employees, we can use logarithmic formats if we believe there is a non-linear relationship between employees and selected dependent variables. From the first merged dataset of AI scores and accounting data, we have 56.251 observations, where a total of 3.182 had zero employees. From the same dataset, 102 companies that had above zero in the AI Know-how Intensity score had zero employees. After final adjustments, we were left with 52.964 observations.

Furthermore, we investigated potential outliers in the dataset. An outlier is defined as a data point that deviates significantly from the other values in the sample to the extent that ignoring it and keeping it unadjusted can lead to inaccurate estimates (Chambers, Hentges, & Chao, 2004). Researchers, in particular, are interested in avoiding results that could be inaccurate and based on outliers (Sullivan, Warkentin, & Wallace, 2021). Sullivan, Warkentin, and Wallace (2021) present different methods of detecting and adjusting for outliers. Some of these methods include trimming, winsorizing, and using standard deviations or interquartile ranges. We used the winsorizing method, which involves replacing extreme values with less extreme ones. The advantage of using the winsorizing method is that it is a simple adjustment. Furthermore, in contrast to trimming, we keep all observations. One disadvantage, however, is that winsorizing does not consider the overall representativeness of outliers; it just adjusts them.

Moreover, we decided to make log format adjustments for some of the variables in our regression analyses. The main reason to use log formats is if we believe or have identified a possible nonlinear relationship. Mishra et al. (2022) adjust the number of employees to log format when studying the relationship with AI focus. We created plots to visualize the relationship between employees and the AI Know-how score, and we identified a nonlinear relationship. Moreover, comparing regression models, we found that the ones with the log format of employees had a better fit. Another advantage of using log formats is to improve model fit, as we reduce the effects of extreme values and outliers.

3.4 Research Models

As we are doing descripto-explanatory research, it is important to select the most appropriate models and methods for the analysis of the data. In this chapter, we will discuss two types of research models we utilize: models for descriptive statistics and regressions.

3.4.1 Descriptive models

With appropriate models for descriptive statistics, we can describe the characteristics of our dataset. We will also be able to present and investigate factors of who adopts AI technology in Norway. With descriptive statistics, we hope we can obtain a clear and concise picture of the data we have acquired, which aids the process of identifying potential relationships between firm characteristics, performance, and AI adoption. Moreover, accurate data descriptions will increase transparency, credibility, and external reliability.

Firstly, Tukey's (1977) Exploratory Data Analysis approach will be helpful in the initial stages of data exploration. Tukey's method uses graphs and charts to explore the data. Tukey's approach also allows for certain flexibility for new, unplanned analyses. Additionally, we want to use geographical maps to show the distribution and adoption of AI across Norway.

Furthermore, we intend to utilize more common models for describing the dataset. We want to include tables showing the distribution of variables in our analysis, displaying the number of observations, the range, median, mean, and standard deviation. With the more classic descriptive statistic, we can filter based on firms with positive AI scores and show the differences between the groups. Finally, we want to show a correlation matrix of our variables. This helps identify potential problems with multicollinearity.

3.4.2 Regression models

In this chapter, we will describe the regression models we run for analyzing what firms adopt AI technology and its effects on firm performance.

Firstly, Mishra et al. (2022) argue that a variable with AI focus, or score, might be endogenous, which leads to concerns about overall causality. The AI Score variable might have a simultaneous relationship with other variables, such as the number of employees. Simultaneity bias, also known as reciprocal causation, is a bias that occurs when the relationship between the dependent variable and one or more dependent variables is bidirectional (Stock & Watson, 2020). This bidirectionality is a concern as simultaneity bias may lead to inaccurate and biased estimates. Previous studies use lag values of endogenous values to correct this (Mishra et al., 2022; Bhagat & Bolton, 2008). Because of the nature of the AI data we have accessed, and the time constraint for our thesis, we have not been able to get appropriate lag values to adjust for potential simultaneity bias. In our research, the accounting data is from 2020, while the AI scores were estimated in 2022. This would essentially indicate that our models build on time-series regressions where we assume unidirectionality between AI score and other variables, for example, that number of employees affect AI scores and not the other way. Other solutions we investigated for correcting this issue were using instrumental variables such as research papers on AI, the value of patents, and R&D spending. Testing for relevancy, we got F-statistics under 10 for both R&D and patents, so we concluded that those would not work. Our main limitation is that we only have cross-sectional data for AI scores. For others to be building on our thesis, with panel data and lagged values for AI score, would be interesting. For now, we conclude that some fundamental limitations and weaknesses reduce the overall causality.

Next, we divide this chapter in two, focusing on who adopts AI and the effects on firm performance.

3.4.2.1 Adoption of AI

As previously described, we employ a descripto- explanatory research design. Part of our thesis is to investigate what Norwegian firms are adopting AI technology. For this, we run models with the AI Know-how Intensity variable as the dependent variable. As the scores are difficult to interpret, and it is unclear what different levels of AI score indicate, we create dummy variables of firms that receive scores over zero and 0.5, respectively. With binary dependent variables, there are three main methods for regression analysis, linear probability, logit, and probit (Stock & Watson, 2020). After testing several specifications, we opt for using logistic methods with logit. Moreover, to investigate what firms are adopting AI, we first conduct more general regressions on all firms and industries before we conduct specialized regressions on three select industries based on the degree of knowledge intensity. We perform these more specialized regressions to see if there are differences between the different categories of knowledge intensity within sectors.

In the first regression, we use a continuous variation of the AI Know-how variable as the dependent variable. This regression follows a standard Ordinary Least Squares (OLS) specification. We also adjust for heteroskedasticity robust standard errors. We also include industry-fixed effects. The equation is then:

$$\begin{aligned} AI\ Knowhow_{continous} &= \beta_0 + \beta_1 Centrality + \beta_2 Age + \beta_3 Startup \\ &+ \beta_4 \log(Employees) + \beta_5 \log(Shareholders) + \beta_6 Gender\ CEO \\ &+ \beta_7 Gender\ Chairperson + \beta_8 Total\ Assets + \beta_9 Net\ Income \\ &+ \beta_{10} R\&D + \beta_{11} RoA + \beta_{12} Debt\ Ratio + \beta_{13} Liquidity + u \end{aligned} \tag{1}$$

In the second and third regressions, we use the dummy variables of the AI Know-how variable as the dependent variable. This model uses a logistic logit specification. We include industry-fixed effects. We get the following equations:

$$\begin{aligned} Prob(AI\ Know-how_{>0} = 1|x) &= \Lambda(\alpha + \beta_1 Centrality + \beta_2 Age + \beta_3 Startup \\ &+ \beta_4 \log(Employees) + \beta_5 \log(Shareholders) + \beta_6 Gender\ CEO \\ &+ \beta_7 Gender\ Chairperson + \beta_8 Total\ Assets + \beta_9 Net\ Income \\ &+ \beta_{10} R\&D + \beta_{11} RoA + \beta_{12} Debt\ Ratio + \beta_{13} Liquidity) \end{aligned} \tag{2}$$

$$\begin{aligned} Prob(AI\ Know-how_{>0.5} = 1|x) &= \Lambda(\alpha + \beta_1 Centrality + \beta_2 Age + \beta_3 Startup \\ &+ \beta_4 \log(Employees) + \beta_5 \log(Shareholders) + \beta_6 Gender\ CEO \\ &+ \beta_7 Gender\ Chairperson + \beta_8 Total\ Assets + \beta_9 Net\ Income \\ &+ \beta_{10} R\&D + \beta_{11} RoA + \beta_{12} Debt\ Ratio + \beta_{13} Liquidity) \end{aligned} \tag{3}$$

In the fourth, fifth, and sixth models, we use the same specification as in (2) and (3). However, we filter the sample based on three industries based on the degree of knowledge intensity activities (KIA). Eurostat defines activities as knowledge intensive "… if employed tertiary educated persons […] represent more than 33% of the total employment activity" (Eurostat, 2020). Among others, they list computer programming as a knowledge-intensive activity, and we use that as our high KIA industry. For medium and low KIA industries, we use advertising and market research and land transportation and transport via pipelines. Here we do not include industry-fixed effects, and we get the following equation:

$$\begin{aligned} &Prob\left(AI\ Know-how_{y_{KIA},\ >0.5}=1\middle|x\right)\\ &\quad= \Lambda(\alpha+\beta_1 Centrality+\beta_2 Age+\beta_3 Startup\\ &\quad+\beta_4\log(Employees)+\beta_5\log(Shareholders)+\beta_6 Gender\ CEO\\ &\quad+\beta_7 Gender\ Chairperson+\beta_8 Total\ Assets+\beta_9 Net\ Income\\ &\quad+\beta_{10}R\&D+\beta_{11}RoA+\beta_{12}Debt\ Ratio+\beta_{13}Liquidity) \end{aligned} \quad (4), (5), (6)$$

3.4.2.2 Effects of AI adoption on firm performance

For the explanatory part of our research question, we run regression on selected variables for firm performance as the dependent variable, with the dummy variable AI Know-how > 0 as the main independent variable. Again, we conduct two different sets of regressions, one more general purpose with all firms and one set based on the three industries we selected based on the degree of knowledge intensity. Both sets of regressions are based on OLS methodology, and we adjust for heteroskedasticity robust standard error.

In the seventh equation, we have the variable return on assets as the dependent variable. We include industry-fixed effects and get the following equation:

$$\begin{aligned} &\left(\frac{Net\ Income}{Total\ Assets}\right)\\ &\quad= \beta_0+\beta_1 AI\ Know-how_{>0}+\beta_2 Centrality+\beta_3 Age\\ &\quad+\beta_4 Startup+\beta_5\log(Employees)+\beta_6\log(Shareholders)\\ &\quad+\beta_7 Gender\ CEO+\beta_8 Gender\ Chairperson+\beta_9 R\&D\\ &\quad+\beta_{10}Debt\ Ratio+\beta_{11}Liquidity\ +u \end{aligned} \quad (7)$$

In the eighth equation, we have the variable net income per employee (net operating efficiency) as the dependent variable. We include industry-fixed effects and get the following equation:

$$\begin{aligned}\left(\frac{Net\ Income}{Employees}\right) &\\ = \ \beta_0 + \beta_1 AI\ Know - how_{>0} + \beta_2 Centrality + \beta_3 Age &\\ + \beta_4 Startup + \beta_5 \log(Shareholders) + \beta_6 Gender\ CEO &\\ + \beta_7 Gender\ Chairperson + \beta_8 Total\ Assets + \beta_9 R\&D &\\ + \beta_{10} Debt\ Ratio + \beta_{11} Liquidity\ + u &\end{aligned} \tag{8}$$

In the ninth equation, we use the operating margin as the dependent variable. We include industry-fixed effects and get the following equation:

$$\begin{aligned}\left(\frac{Operating\ Profit}{Operating\ Income}\right) &\\ = \ \beta_0 + +\beta_1 AI\ Know - how_{>0} + \beta_2 Centrality + \beta_3 Age &\\ + \beta_4 Startup + \beta_5 \log(Employees) + \beta_6 \log(Shareholders) &\\ + \beta_7 Gender\ CEO + \beta_8 Gender\ Chairperson + \beta_9 Total\ Assets &\\ + \beta_{10} R\&D + \beta_{11} Debt\ Ratio + \beta_{12} Liquidity\ + u &\end{aligned} \tag{9}$$

Finally, the tenth equation uses five year compounded average sales growth rate (CAGR) as the dependent variable. This removes companies founded in the last four years as they do not have a five-year CAGR. However, it still lets us see the potential effects of older firms that have gone through the process of adopting AI instead of being founded based on AI technology. We include industry-fixed effects and get the following equation:

$$\begin{aligned}\left(\left(\frac{Sales_{2020}}{Sales_{2016}}\right)^{\frac{1}{5}} - 1\right) &\\ = \ \beta_0 + +\beta_1 AI\ Know - how_{>0} + \beta_2 Centrality + \beta_3 Age &\\ + \beta_4 Startup + \beta_5 \log(Employees) + \beta_6 \log(Shareholders) &\\ + \beta_7 Gender\ CEO + \beta_8 Gender\ Chairperson + \beta_9 Total\ Assets &\\ + \beta_{10} R\&D + \beta_{11} Debt\ Ratio + \beta_{12} Liquidity\ + u &\end{aligned} \tag{10}$$

3.5 Research Quality

In this chapter, we will evaluate the strengths and weaknesses of the collected data and chosen research design. To assess the quality of research, it is vital to consider the clarity of the design and methods, as well as how robust the findings and conclusions are when subjected to critical analysis. In quantitative research, reliability and validity are frequently the primary determinants of research quality (Saunders et al., 2019). In addition, we will also discuss ethical concerns regarding our study and data.

3.5.1 Reliability

The term reliability refers to consistency and replicability (Saunders et al., 2019). We consider research reliable if the findings, methods, and design are replicable by others and the initial results are consistent with new research. In this subchapter, we will explore reliability in the context of our study on the adoption of AI and firm performance. By examining the concepts of consistency and replicability, we ensure transparency about our research strengths and weaknesses and provide a stronger fundament for further research. In this chapter, we discuss internal reliability, such as consistency, before examining replicability and external reliability.

3.5.1.1 Internal Reliability

Internal reliability refers to the consistency of a research project. Ensuring a project is consistent may be done using multiple researchers, getting third-party verification and insights, and taking notes of progress and changes (Saunders et al., 2019). Throughout our research, we have ensured consistency by continuously logging changes, taking notes of ideas and plans, and getting insights from other students and researchers. Moreover, we wrote the code in R separately and then discussed methods and outcomes. By writing the code separately, we ensured that we had inspected the data material, econometric models, and frameworks comprehensively. Even though it might have increased the workload, as opposed to doing it alone, it increased the consistency of our research. We seek to limit threats such as researcher bias and error by taking notes and getting insights from other researchers.

3.5.1.2 External Reliability

According to Saunders et al. (2019), external reliability is the extent to which a study's data collection and analysis methods would yield consistent results if repeated by the same researcher or another researcher in the future. Focusing on the two primary data sources, company websites, and government-mandated accounting statements, is crucial to examine the replicability of this study.

A potential weakness regarding replicability is methods and access for getting AI scores from company websites. Our research builds on data gathered with artificial intelligence and web mining techniques. We accessed structured data through the research center Digital Innovation for Growth at NHH, which in turn received data from the AI-based analytics company Istari.ai. While we utilize data from Istari.ai, others can recreate our study with different methods for gathering measures for AI capabilities. Using textual analysis techniques, one can create estimates of AI capabilities. While our study uses company websites as references for textual analysis, other studies use company reports, such as 10-K filings and IPO filings (Mishra et al., 2022; Hanley & Hoberg, 2010). However, the weakness and potential threats to the overall replicability are instrumentation and the definition of what constitutes AI capabilities. In Chapter 3.2.1, we discussed the AI data in more detail. Our goal is for this discussion to ensure greater replicability.

The financial and accounting data that we employ in our study take the basis of the Accounting Act of 1977 and the newer Accounting Act introduced in 1998 (Mjøs & Selle, 2022). All private and public limited liability companies in Norway must publish yearly financial statements that include a balance sheet, a profit statement, and notes. Through the Centre for Applied Research at NHH, which uses data from the Accounting Register of Norway, we access accounting data for all companies required to report statements. Therefore, we argue that our accounting and financial data is strong and robust to the overall replicability.

Finally, it is also vital that methods for analyzing the data are transparent and replicable. Chapter 3.4 thoroughly detailed the models we employ in our study. Some of these methods will also be discussed further in Chapter 3.5.2 regarding the validity of this study, along with some limitations and potential solutions for further research. Moreover, we detail definitions and formulas for crucial variables in Chapter 3.3 and Figure 3.1. Disclosing weaknesses and limitations further increases the transparency and replicability of our research.

3.5.2 Validity

Conversely, validity refers to a study's relevancy, causality, and generalizability (Saunders et al., 2019). In this subchapter, we will examine validity in the context of our research on the adoption of AI and firm performance. Specifically, we will focus on internal and external validity concepts and how they relate to our research design and data analysis. We will also discuss the weaknesses and limitations of our study, as presented in Chapter 3.4.

3.5.2.1 Internal validity

Internal validity describes the degree to which we can attribute observed effects on firm performance to the adoption of AI. In other words, internal validity refers to the causality and whether our findings are correct and trustworthy. As stated in Chapter 3.4, other researchers explain that variables such as AI focus or score might be endogenous (Mishra et al., 2022). This endogeneity may come from the potential simultaneity bias of AI scores and other variables. As we stated earlier, a possible solution for correcting this endogeneity issue is to use lag values of AI score, R&D, or patents as instrumental variables. However, we are limited by the data available and are unable to use panel data and lag values of AI, which has been the more traditional method. After testing other options, such as R&D or patents, for their relevance, we found they were not viable. This was due to weak instruments, as indicated by the F-statistic of the first-stage regression being below ten. Considering our limitations, we concluded there are concerns regarding causality, and it would be necessary to account for them in future research. One of the main threats to internal validity is ambiguity about causal direction (Saunders et al., 2019). In our analysis, we cannot be entirely sure about the directionality and relationship between AI scores and employees. We also tried to limit potential omitted variable bias, but with cross-sectional data, we could not control for time effects.

Furthermore, we tested for multicollinearity with the variance inflation factor (VIF) method by investigating the correlation between variables in the regressions. Multicollinearity is when one of the regressors is an exact function of other regressors, which leads to significant inaccuracies and standard errors. According to Vittinghoff (2005), a VIF level above ten is considered problematic. However, some researchers suggest that lower levels, even as low as 2.5, can pose issues (James et al., 2013; Menard, 2001, Johnston et al., 2018). After analyzing the regression models, we discovered no significant problem with multicollinearity in all models except for model (6), where we observed a VIF value of 6.4 for the Total Assets variable. This finding indicates that there might be a higher degree of multicollinearity in the transportation industry than in the other industries we examined. To address this issue, we removed the Total Assets variable from the model because it was both statistically and economically insignificant. This action increased the model's overall robustness while maintaining our analysis's validity.

3.5.2.2 External validity

External validity concerns the generalizability of research findings to populations beyond the specific sample studied. In the context of our study on the adoption of AI and firm performance, external validity is crucial to ensure that our findings are extendable to other Norwegian limited liability companies beyond our sample of 53,000 companies. However, using AI scores based on companies' websites may limit the generalizability of our study's results. Similarly to Mishra et al. (2022), we do not include other verbal, written, or internal information from companies that could indicate the level of AI adoption. Moreover, we had to make a couple of adjustments to increase the overall quality of the data. For example, we found out that companies with a ".com" domain suffix were more likely to be wrong, i.e., Norwegian companies with a ".com" suffix had gotten an AI score from unrelated American companies. We adjusted for this by removing observations with a ".com" domain. By eliminating companies whose AI scores are based on other firms, we ensure the data used in the analysis accurately reflected the adoption of AI by the companies in the sample rather than being influenced by errors in data collection or input. This adjustment ensures that the data accurately reflects the population of interest to a higher degree. To conclude, our findings may not accurately reflect the adoption of AI in other countries or companies without an online presence.

3.5.3 Ethical considerations

The general rule of research ethics is that the design and methods should not subject the research population to embarrassment, harm, or other disadvantages. Moreover, research ethics includes the appropriateness of one's choices and behavior as a researcher, especially regarding the study's subjects and those affected by it. Because research ethics compromises all parts of the study, it is essential to consider ethics throughout the research process (Saunders et al., 2019).

We thoroughly explored the quality of already acquired data for the data collection. Moreover, we explored other potential sources and methods that could get us the data needed in case it turned out that previously acquired data was not ethically responsible or unsuitable for our study. Firstly, starting our thesis, we received the data of AI scores obtained from Istari.ai. We conducted several randomized samples to examine the data's strengths, weaknesses, and suitability. As described in Chapter 3.3., we tested certain aspects of the data concerning observations with NA scores and differences between companies with different domain suffixes. Based on internal and external discussions about our findings, we concluded that the data acquired was suitable for our study, with some minor adjustments based on our tests.

Secondly, we investigated possible solutions for gathering accounting and financial data. From our research into available databases and sources for this, we ended up with two potential sources for this information. We got access to data from the Centre of Applied Research at NHH (SNF), which was the more robust and ethical solution we had identified. This data is specifically designed for research and educational purposes. Before getting access to the data, we had to sign a declaration to use the data responsibly and not redistribute or use the data for commercial purposes.

4 Results

In this chapter, we present our findings and results. Firstly, we provide an overview of general descriptive statistics, graphs, tables, and visualizations, which will be followed by our regression analyses. The results presented in this chapter form the foundation for our discussion and conclusions in Chapters 5 and 6. The section on regression results is divided into two parts, one for regressions with AI know-how as the dependent variable and the other for firm performance indicators as the dependent variable. This division allows us to examine the two separate aspects of our research question more precisely: which firms are adopting AI and how it affects their performance.

4.1 Descriptive Analyses

This subchapter focuses on the descriptive results that shed light on the adoption of artificial intelligence among Norwegian firms. The chapter begins by discussing descriptive statistics for our sample, followed by a correlation matrix. Additionally, we provide a variety of figures and graphs that illustrate the distribution of firms with positive AI scores, as well as trends in newly established firms with positive AI scores. Finally, we utilize maps to visually represent the geographic distribution of firms with positive AI scores across Norway. By utilizing these descriptive techniques, we aim to provide a comprehensive overview of the adoption of AI among Norwegian firms.

4.1.1 Descriptive statistics

In this subsection, we present the descriptive statistics used to summarize and analyze data on the adoption of artificial intelligence among Norwegian firms. Our analysis reveals that 2.6% of our sample have a positive AI Know-how Intensity score, while approximately 1.7% have a positive AI Information Intensity score. These findings are consistent with data obtained by Istari.ai for the DACH region (Germany, Austria, Switzerland), where 2.0% of surveyed companies had an AI Intensity score above zero (Dehghan, 2022). Additionally, we identified 200 companies in our sample with an AI Know-how score above 0.5 and 177 with an AI Information score above 0.5. See Appendix 1 for a boxplot of the AI scores.

Now, Table 4.1 provides an overview of our sample's descriptive statistics. Table 4.2 and Table 4.3 display statistics for subgroups of firms with positive AI Know-how Intensity and positive AI Information Intensity scores, respectively. Firstly, companies with positive AI scores (Both Know-how and Information) have a higher mean and median municipality centrality score than the entire sample.

Furthermore, we could not detect any apparent differences between firms with and without positive AI scores when examining the median values for the year established, the number of employees, and the number of shareholders. However, the mean values indicate that companies with positive AI scores tend to have a higher number of employees. The entire sample has a mean number of employees of 18, whereas those with positive AI Know-how have a mean of 45, and those with positive AI Information have a mean of 54. The larger firms in our sample may belong to the positive AI category, thereby skewing the mean values.

Notably, we observed that firms with positive AI scores had higher median and mean values for both total assets and net income. Regarding total assets, the entire sample had a median of NOK 3,458,500.00, while those with positive AI Know-how scores had a median of 7,167,000.00, and those with positive AI Information scores had a median of NOK 7,516,000.00. Although the median value of capitalized R&D was similar across all groups, firms with a positive AI Know-how score had a mean value of NOK 555,000.00 higher.

Furthermore, we discovered that firms with positive AI scores had a higher median five-year sales growth rate but similar medians for return on assets and operating margin. Specifically, the median five-year sales growth rate was 2.8% for the entire sample and 4.6% for both positive AI Know-how and Information score companies. However, the mean value for the same variables was higher for firms with positive AI scores. Notably, the mean value of return on assets was 3.5% lower for positive AI Know-how firms than the entire sample, which we further discuss in the upcoming discussion chapter.

Lastly, we observed no apparent difference in either the median or mean values for the liquidity and debt ratio variables among all groups.

Table 4.1 Descriptive statistics for all firms

All firms in sample	N	Min	P25	Median	Mean	P75	Max	St. Dev.
AI Knowhow Intensity Score	52,964	0.000	0.000	0.000	0.007	0.000	2.999	0.073
AI Information Intensity Score	52,964	0.000	0.000	0.000	0.005	0.000	2.757	0.065
Municipality Centrality Score	52,921	295.000	756.000	860.000	834.980	916.000	1,000.000	131.560
Year Established	52,964	1852	2000	2011	2006.443	2016	2020	13.178
Number of Employees	52,964	1.000	2.000	5.000	18.097	13.000	12,411.000	115.465
Number of Shareholders	52,411	1.000	1.000	1.000	2.903	2.000	86.000	7.576
Gender Dummy CEO	52,964	0.000	0.000	0.000	0.192	0.000	1.000	0.394
Gender Dummy Chairman	52,964	0.000	0.000	0.000	0.167	0.000	1.000	0.373
Net Income (in thous.)	52,964	-18,549.710	-8.000	228.000	2,043.334	1,050.250	112,257.800	10,473.660
Total Assets (in thous.)	52,964	33.000	1,067.000	3,458.500	36,889.370	11,865.250	2,072,866.000	183,643.900
Research and Development	52,964	0.000	0.000	0.000	101.065	0.000	9,546.250	839.863
Operating Margin	52,631	-8.524	-0.001	0.054	-0.040	0.128	0.707	0.795
5-yr Sales CAGR	38,250	-0.839	-0.028	0.028	0.070	0.100	8.518	0.263
Return on Assets	52,964	-2.683	-0.005	0.080	0.051	0.195	0.936	0.360
Debt Ratio	52,964	0.016	0.447	0.664	0.757	0.869	6.841	0.697
Liquidity (Current Ratio)	52,964	0.009	1.066	1.518	2.374	2.365	38.161	3.721

Table 4.2 Descriptive statistics for firms with AI Know-how > 0

Firms with AI Know-how > 0	N	Min	P25	Median	Mean	P75	Max	St. Dev.
AI Knowhow Intensity Score	1,383	0.072	0.086	0.114	0.278	0.303	2.999	0.362
AI Information Intensity Score	1,383	0.000	0.000	0.000	0.143	0.089	2.757	0.339
Municipality Centrality Score	1,382	330.000	808.000	891.000	874.930	1,000.000	1,000.000	125.692
Year Established	1,383	1886	2000	2011	2006.557	2017	2020	13.713
Number of Employees	1,383	1.000	3.000	8.000	45.307	19.000	6,920.000	261.136
Number of Shareholders	1,374	1.000	1.000	2.000	5.421	4.000	86.000	12.211
Gender Dummy CEO	1,383	0.000	0.000	0.000	0.116	0.000	1.000	0.321
Gender Dummy Chairman	1,383	0.000	0.000	0.000	0.098	0.000	1.000	0.297
Net Income (in thous.)	1,383	-18,549.710	-69.500	395.000	4,153.613	2,192.000	112,257.800	16,362.820
Total Assets (in thous.)	1,383	33.000	2,098.000	7,167.000	80,827.570	25,026.000	2,072,866.000	288,074.600
Research and Development	1,383	0.000	0.000	0.000	656.580	0.000	9,546.250	2,155.149
Operating Margin	1,367	-8.524	-0.036	0.049	-0.233	0.133	0.707	1.338
5-yr Sales CAGR	908	-0.541	-0.007	0.046	0.111	0.137	2.993	0.293
Return on Assets	1,383	-2.683	-0.031	0.074	0.016	0.192	0.936	0.424
Debt Ratio	1,383	0.016	0.435	0.648	0.722	0.836	6.841	0.673
Liquidity (Current Ratio)	1,383	0.009	1.105	1.489	2.467	2.357	38.161	3.895

Table 4.3 Descriptive statistics for firms with AI Information > 0

Firms with AI Information > 0	N	Min	P25	Median	Mean	P75	Max	St. Dev.
AI Knowhow Intensity Score	902	0.000	0.000	0.000	0.241	0.276	2.999	0.438
AI Information Intensity Score	902	0.070	0.087	0.166	0.322	0.372	2.757	0.380
Municipality Centrality Score	901	351.000	851.000	914.000	900.900	1,000.000	1,000.000	109.096
Year Established	902	1922	2001	2012	2007.010	2017	2020	13.391
Number of Employees	902	1.000	2.000	7.000	54.010	22.000	6,719.000	312.927
Number of Shareholders	888	1.000	1.000	1.000	5.687	4.000	86.000	12.547
Gender Dummy CEO	902	0.000	0.000	0.000	0.133	0.000	1.000	0.340
Gender Dummy Chairman	902	0.000	0.000	0.000	0.126	0.000	1.000	0.332
Net Income (in thous.)	902	-18,549.710	-67.000	371.500	4,898.808	2,589.000	112,257.800	18,447.070
Total Assets (in thous.)	902	33.000	1,471.750	7,516.000	108,571.900	34,772.000	2,072,866.000	358,791.000
Research and Development	902	0.000	0.000	0.000	713.169	0.000	9,546.250	2,282.403
Operating Margin	886	-8.524	-0.037	0.054	-0.201	0.150	0.707	1.231
5-yr Sales CAGR	560	-0.541	-0.016	0.046	0.117	0.149	2.310	0.319
Return on Assets	902	-2.683	-0.023	0.081	0.022	0.205	0.936	0.423
Debt Ratio	902	0.016	0.441	0.651	0.748	0.873	6.841	0.719
Liquidity (Current Ratio)	902	0.009	1.032	1.422	2.686	2.332	38.161	4.971

Table 4.4 presents the correlation matrix for the variables analyzed in this study. The correlation between AI Know-how and AI Information variables is 0.536, indicating a moderately positive relationship. We observe a similar correlation between the dummy variables for gender CEO and gender Chairperson, with a correlation of 0.548. This can be attributed to small businesses where the CEO, founder, and chairperson may be the same person. Net income and total assets have a strong positive correlation of 0.670, which was a concern for multicollinearity in our regression analyses, as discussed in Chapter 3.5.2.

We also find a moderate correlation between the variables that function as measures for firm size. We find that the number of employees has a correlation of 0.3 with net income and 0.403 with total assets. This correlation is likely contributing to explanatory power being moved within variables.

Moreover, the Debt ratio has a moderate negative correlation of -0.399 with return on assets, suggesting that an increase in the debt ratio is associated with a decrease in return on assets. However, correlation does not necessarily imply causation; other factors may affect this relationship. Additionally, the liquidity, or current ratio, has a moderate negative correlation of -0.250 with the debt ratio, indicating that leverage tends to decrease as liquidity increases. This is consistent with our expectation that increased liabilities decrease liquidity and increase the debt ratio.

Table 4.4 Correlation matrix

	Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1)	AI Knowhow Intensity Score	1.000															
(2)	AI Information Intensity Score	0.536	1.000														
(3)	Municipality Centrality Score	0.044	0.046	1.000													
(4)	Age in years	0.000	0.000	0.005	1.000												
(5)	Number of Employees	0.019	0.031	0.049	0.076	1.000											
(6)	Number of Shareholders	0.040	0.035	-0.013	0.109	0.026	1.000										
(7)	Gender Dummy CEO	-0.014	-0.014	0.001	-0.068	0.000	-0.012	1.000									
(8)	Gender Dummy Chairman	-0.012	-0.009	0.005	-0.073	-0.013	-0.024	0.548	1.000								
(9)	Net Income (in thous.)	0.022	0.039	0.054	0.145	0.300	0.059	-0.045	-0.036	1.000							
(10)	Total Assets (in thous.)	0.025	0.041	0.044	0.158	0.403	0.128	-0.037	-0.033	0.670	1.000						
(11)	Research and Development	0.105	0.085	0.030	0.015	0.091	0.145	-0.033	-0.027	0.068	0.139	1.000					
(12)	Operating Margin	-0.011	-0.006	-0.010	0.002	0.008	-0.113	0.014	0.010	0.024	-0.060	-0.075	1.000				
(13)	5-yr Sales CAGR	0.030	0.027	0.022	-0.176	-0.002	0.048	-0.030	-0.022	0.020	0.021	0.058	0.086	1.000			
(14)	Return on Assets	-0.011	-0.006	0.026	0.020	-0.002	-0.026	-0.007	-0.003	0.136	-0.002	-0.033	0.315	0.083	1.000		
(15)	Debt Ratio	-0.006	-0.005	0.042	-0.109	-0.002	-0.035	0.033	0.033	-0.059	-0.034	-0.013	-0.079	0.003	-0.399	1.000	
(16)	Liquidity (Current Ratio)	0.000	0.002	-0.015	0.058	-0.037	0.007	-0.007	-0.003	0.010	0.020	-0.029	-0.128	-0.074	0.034	-0.250	1.000

4.1.2 Industry distribution and proportion of firms with a positive AI score

Figure 4.1 displays the distribution of firms across industry categories in our sample. The plot shows that the majority of observations are from industries such as trade, retail, general services, construction, and public sector and culture. Our results align with the overall population as reported by Statistics Norway (2023a), where retail and trade represented 20% of all businesses in Norway, with more than one employee in 2022, while health and social services, as well as construction, represented 13% each.

Figure 4.2 illustrates the proportion of firms with a positive AI Know-how intensity score in each industry category, using the data from Figure 4.1 as a baseline. As expected, the telecom, IT, and media sector have the highest proportion of firms with a positive AI Know-how score, at 11.87%. From our sample, this corresponds to roughly 411 companies in this sector. In addition, we observe that 10.13% of research and development companies and 6.53% of finance and insurance companies have a positive AI Know-how score. However, this may be biased due to the small number of companies in these industries in the sample. Conversely, the oil and gas and transportation industries have the lowest percentage of firms with a positive AI Know-how score.

The telecom, IT, and media industry have the highest proportion of firms with a positive AI Know-how score. This category comprises 3,462 companies, with the "computer programming activities" subcategory accounting for 196, or approximately 30%. Within the "computer programming activities" subcategory, 196 companies (18.72%) have a positive AI Know-how score. Moreover, this subgroup contributes 48% of the observations with positive AI Know-how scores in the primary industry grouping, which means that 30% of the group accounts for nearly 50% of the observations with positive AI Know-how scores. We examined subcategories in media: "Publishing activities", "Motion picture, television, and broadcasting", and "Programming and broadcasting activities". These subcategories contain 1,054 companies, but only 34 (3.2%) have a positive AI Know-how score. Thus, despite representing 30% of the primary industry grouping, the media category contributes only 8% of observations with positive AI Know-how scores.

In Appendix 3 and 4, we show the same as Figures 4.1 and 4.2, but with a sample consisting only of companies established in 2016 or later. Moreover, Appendix 2 shows the percentages of firms with positive AI Information scores.

Figure 4.1 Industry distribution of sample: Categories are based on the industry grouping created by the Centre for Applied Research at NHH with support from Statistics Norway (Mjøs & Selle, 2022).

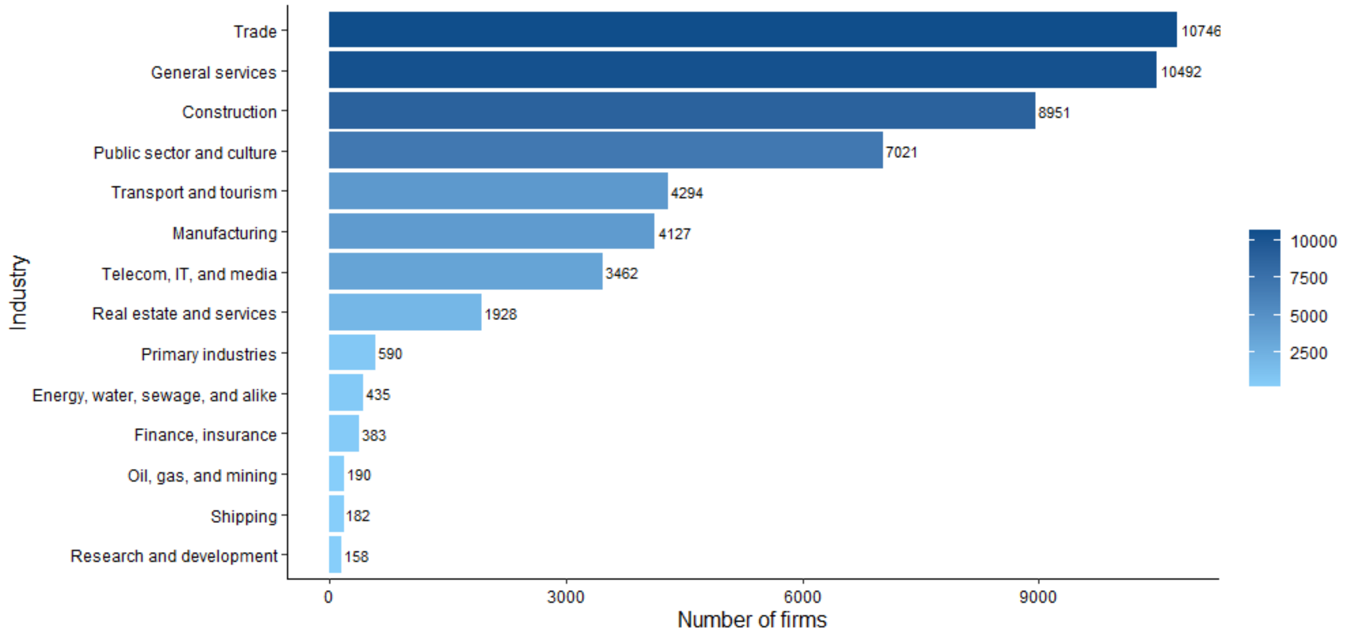
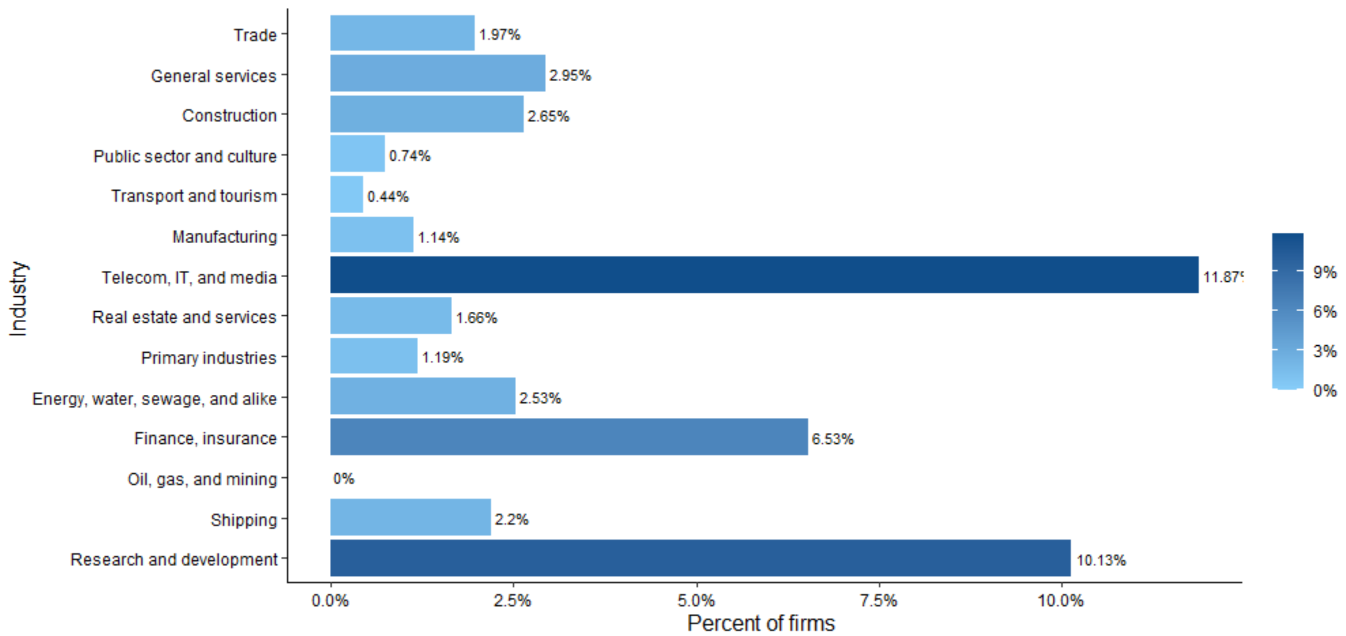


Figure 4.2 Percentage of firms with positive AI Know-how scores by industry: Here, we visualize the percentage of firms with an AI Know-how score over zero in each industry - the same categories and ordering as Figure 4.1.



4.1.3 Firms by year established with positive AI scores

Figure 4.3 displays the count of firms founded each year with AI scores greater than zero as of collecting the data in 2022. For explanation, in the year 2000, we show firms established in the year 2000 that have positive AI scores when collecting the data in 2022. However, since our sample only consists of active and operational firms, the graph alone does not provide much information. According to Statistics Norway (2023b), only 26.6% of companies established in 2016 survived for five years, and our sample reflects this trend, with fewer observations as firm age increases. Additionally, Figure 4.3 shows a sharp decrease in the number of newly established firms with positive AI scores in 2020, which might be related to the covid-19 pandemic.

Figure 4.4 displays the percentage of firms founded each year with positive AI scores as of 2022, which provides insight into the adoption and trend of AI. However, as firm age increases, the number of observations decreases, leading to less reliable and more ambiguous older observations. Surprisingly, the percentage of newly established firms with a positive AI score remains stable at 1.5 to 3%, without any clear trend toward increasing adoption. Both graphs show a nearly horizontal trend line when running a linear regression. This finding is unexpected as we anticipated indications of more startups utilizing AI technology. However, a possible reason for not detecting a trend is the time it takes to adopt and develop AI technology. Additionally, there is a possibility that companies established in 2019 and 2020 have not been able to fully develop their websites, which would result in a downward bias.

From Figure 4.4, we also see a spike in the year 2000, which might indicate that the firms that survived the .com bubble have been the firms with a higher degree of resilience, adaptability, and flexibility to incorporate new technology, which has resulted in that these companies have a higher percentage with positive AI scores.

We also see that older firms that have survived have a higher percentage of positive AI scores. From this, we theorize that there is a type of U-curve regarding the age and size of firms that adopt AI. In other words, the bigger and older firms, along with new startups, are the best at adopting and utilizing new technology, especially AI.

Figure 4.3 Number of firms with AI scores over 0 by year established: Here, we visualize the number of firms founded each year in our sample with an AI score over zero. Keep in mind survivorship bias.

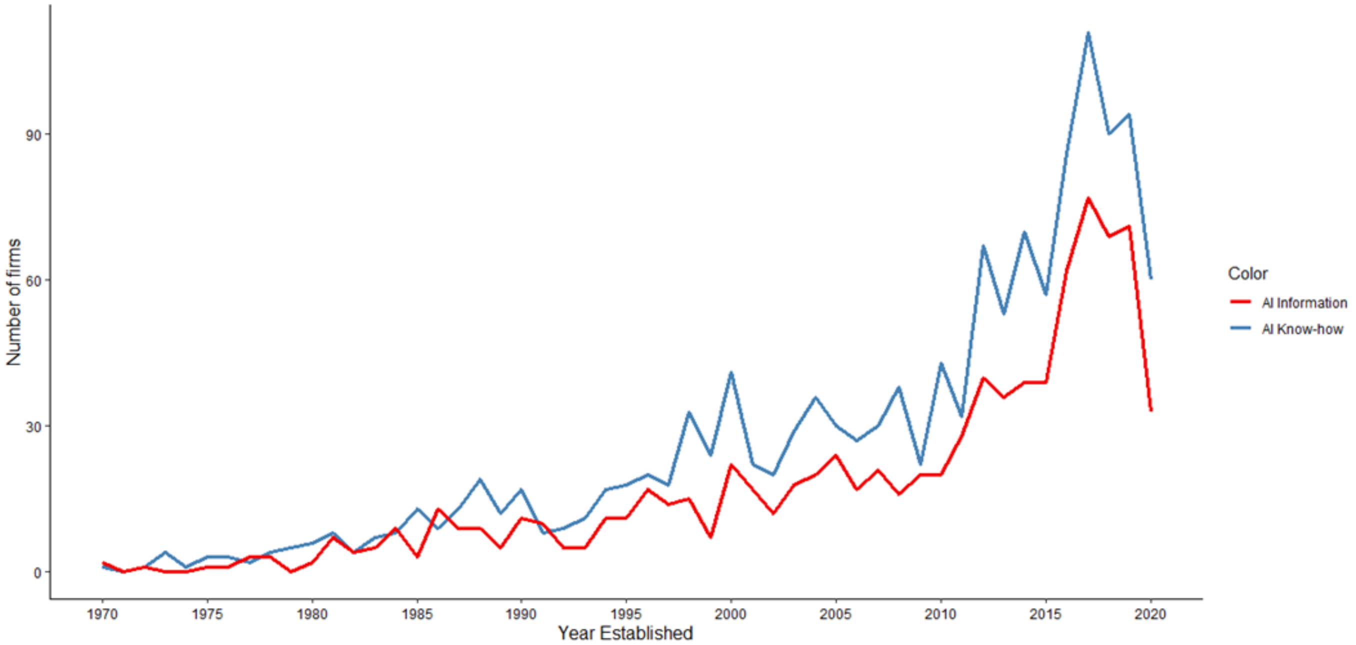
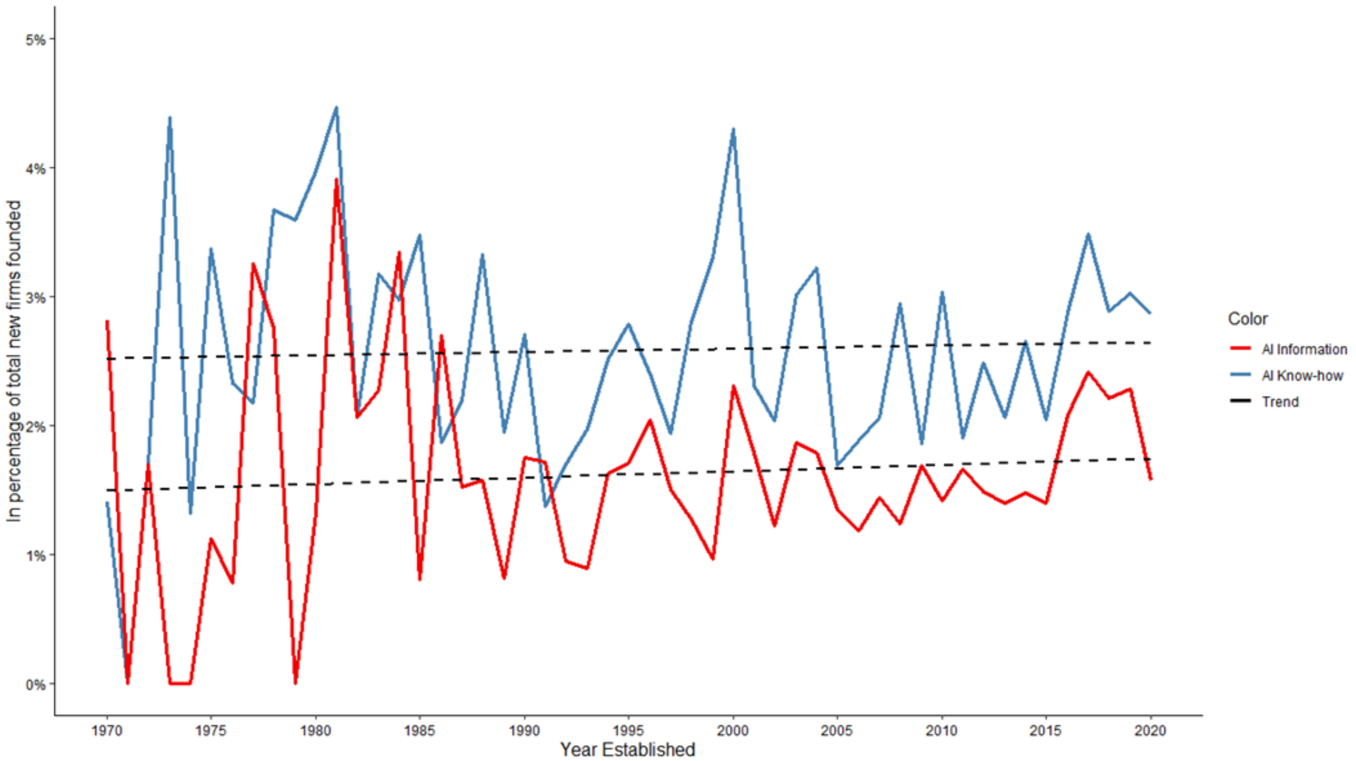


Figure 4.4 Percentage of firms founded each year with AI scores over 0: In this graph, we visualize the percentage of firms founded each year in our sample with an AI score over zero in 2022. Keep in mind survivorship bias.



4.1.4 Geographical mapping of companies with positive AI scores

Figures 4.5 and 4.6 show the distribution of companies with positive AI scores across the 19 regions of Norway. Although the Norwegian government reduced the number of counties from 19 to 11 in 2020, we use the original 19 counties for our analysis to provide greater detail (Kommunal- og distriktsdepartementet, 2019). We also exclude island groups, such as Svalbard.

Figure 4.5 shows two maps displaying the number of companies with positive AI scores in each region, one for AI Know-how score and one for AI Information score. We find that the regions with the largest cities have a higher number of companies with positive AI scores. The region of Oslo has the highest number of firms with positive AI scores, followed by Akershus, Rogaland, Trøndelag, and Hordaland. In Oslo, there are 420 companies with a positive AI Know-how score and 332 companies with a positive AI Information score. On the other hand, the regions Finnmark and Sogn og Fjordane have the lowest number of firms with positive AI scores. The average and median values of the number of firms with positive AI Know-how scores for all regions were 77 and 43, respectively. The average and median values of firms with positive AI Information scores for all regions were 50 and 21.

The maps in Figure 4.6 display the percentage of companies in each region with positive AI scores, one for AI Know-how and one for AI Information. Oslo has the highest proportion of positive AI scores, with 4.6% for AI Know-how and 3.7% for AI Information. Following Oslo, we have the regions Rogaland, Akershus, and Trøndelag. Interestingly, Hordaland, the region where Bergen is located, has a lower percentage of positive AI Know-how companies, with 2.15%. As stated in Chapter 4.1.1, the national average for firms with positive AI Know-how scores is 2.61%, and the average AI Information score is 1.7%. The median percentage for AI scores across all regions is 2.16% for AI Know-how and 1.13% for AI Information.

Figure 4.5 Map of the number of firms with AI scores over 0 by region

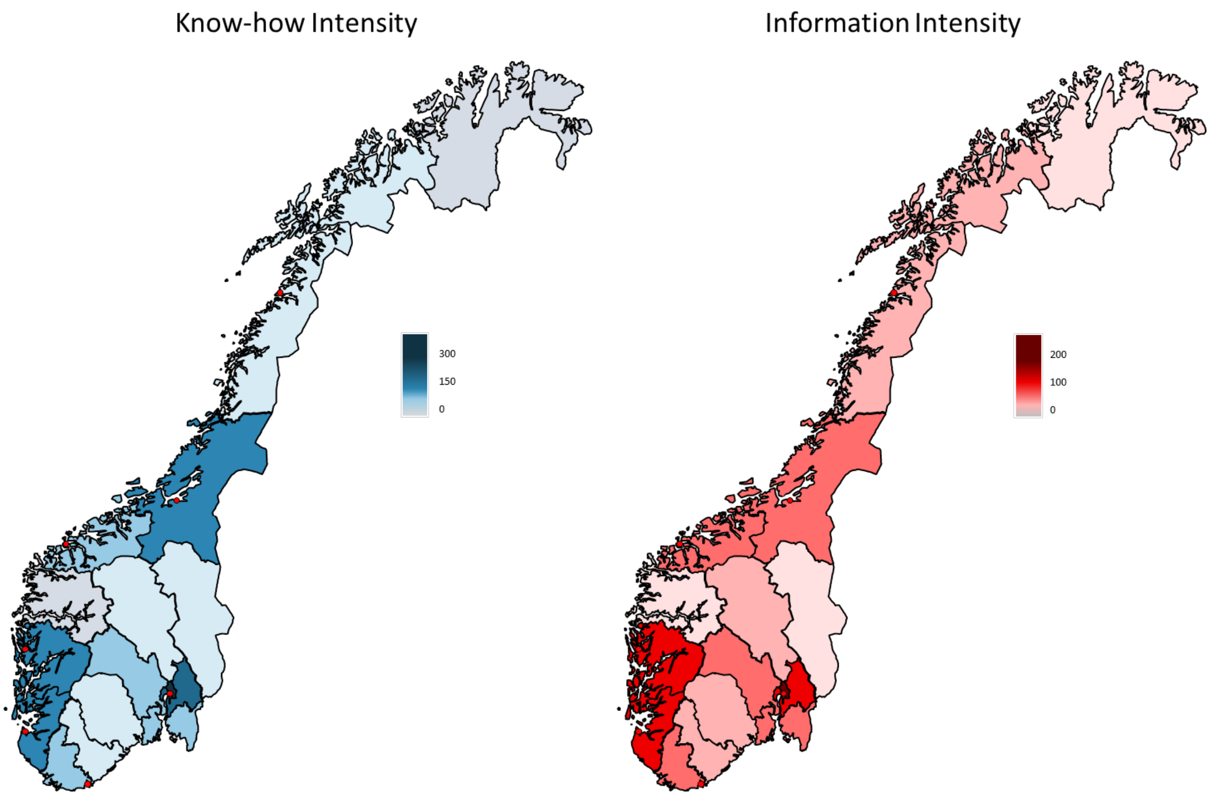
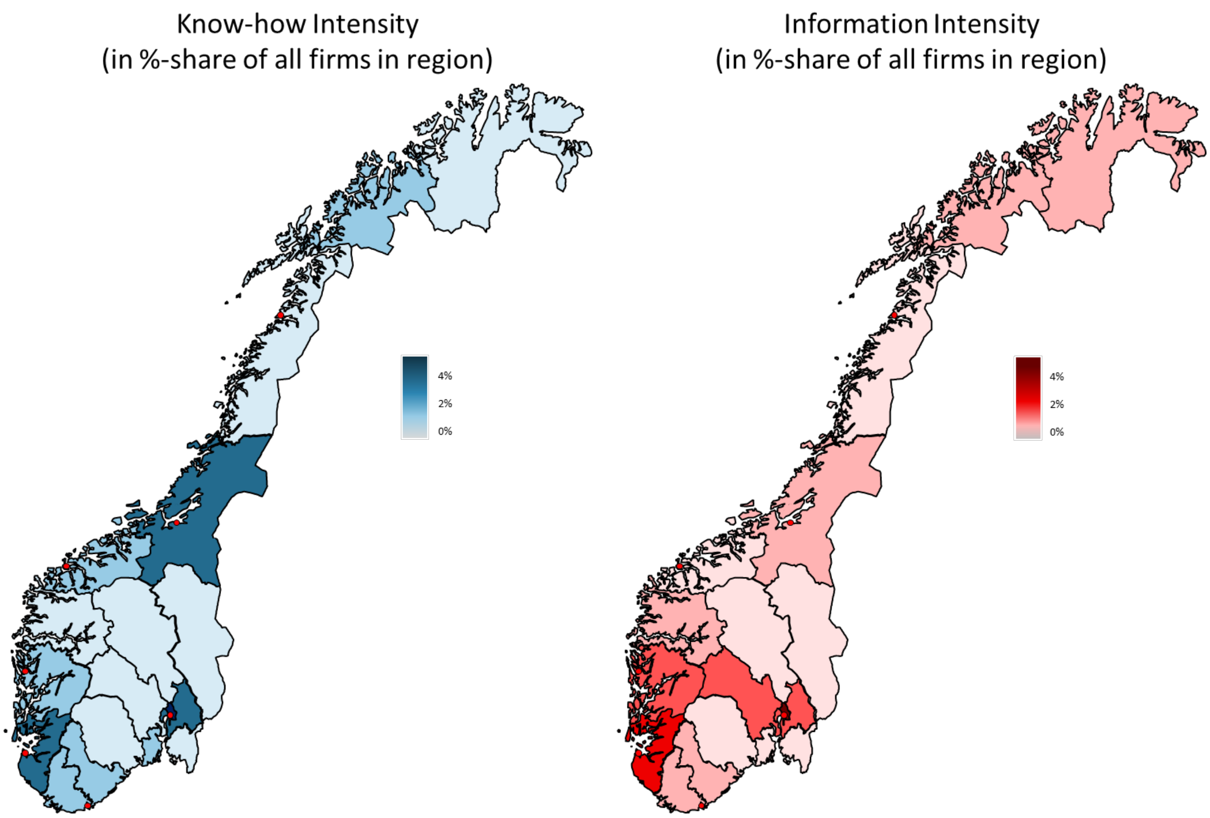


Figure 4.6 Map showing the percentage of firms in each region with an AI score over 0



4.2 Regression Analyses

This subchapter presents the results from three sets of regression models. Firstly, we conduct three regression models with variations of the AI Know-how Intensity variable as the dependent variable to gain insights into the characteristics of firms adopting AI. Secondly, we run three regression models with the dummy variable AI Know-how above zero, focusing on three industries: computer programming, advertisement and market research, and land transportation. Lastly, we conduct four different regressions with firm performance indicators as the dependent variable and the dummy variable AI Know-how above zero as the main independent variable. This subchapter presents the regressions with the AI Know-how scores as the dependent variable.

4.2.1 AI score as the dependent variable

In Figures 4.7 and 4.8, we present the findings of our regressions where we use the AI Know-how Intensity score as the dependent variable. Figure 4.7 show regression models (1), (2), and (3) as presented in Chapter 3.4.2. Here we test different versions of the AI Know-how variable; one continuous version, a dummy that turns one for positive AI Know-how, and another dummy variable for AI Know-how over 0.5. Figure 4.8 run regressions with the positive AI Know-how dummy as the dependent variable for different industries based on the degree of knowledge intensity. For more information about the model specifications, see Chapter 3.4.2.

4.2.1.1 General regressions

In Figure 4.7, we find that, generally, firms that are more urban, are a startup, have more employees, and have a male CEO are more likely to have a positive AI Know-how Intensity score. The variables municipality centrality, dummy startup, dummy gender CEO, and R&D are all statistically significant at the 1% level for all models. The variable log(employees) is statistically significant at the 1% level for models (1) and (2) and significant at the 10% level for model (3). Interestingly, we find no statistical significance for the variables age in years, total assets, or net income. The variables return on assets and the debt ratio are statistically significant only in model (2), at the 1% level. Furthermore, we find moderate to low statistical significance for liquidity and log(shareholders).

Among the three models in Figure 4.7, model (3) show indications of having the better fit or quality. Model (1) has an Adjusted R-squared of 0.036, while model (2) and (3) has a Pseudo R-squared of 0.10 and 0.16, respectively. Moreover, comparing the log-likelihood, we see that model (3) has a higher value which indicates a better fit for the data. The Akaike Information Criterion (AIC) also indicate that model (3) has a better fit, as it has the lowest value of model (2) and (3).

Furthermore, we estimate the economic significance of the variables in model (2). The marginal effect at the mean (MEM) for the variable municipality centrality is 0.278%. This indicates that for a one-unit increase in the municipality centrality score, keeping all other variables constant, the probability of having a positive AI Know-how score increase by 0.278%. The municipality centrality variable is a score that ranges between 0 and 1000, so a change of 100 points would then increase or decrease the probability of having a positive AI Know-how score by 2.78%.

Moreover, we get a MEM of 0.723% for the dummy startup variable, which indicates that if the firm were established in 2016 or later, they have an increased probability of having a positive AI Know-how score by 0.723%. We also have a MEM of negative 0.498% for the dummy gender CEO variable, which indicates that if the firm has a female CEO, the predicted probability of having a positive AI Know-how score is decreased by 0.498%, keeping all other variables constant.

Figure 4.7 Relationship between AI Know-how and firm characteristics: Relationship between AI Know-how Intensity and selected firm characteristics. We include industry-fixed effects. (1) Show a linear OLS model, (2) show a logit model with a binary AI Know-how > 0 dummy, (3) show a logit model with a binary AI Know-how > 0.5 dummy. All relevant variables are winsorized at the 1% level. Gender CEO and Chairperson are dummies that turn one if female. (1) includes heteroskedasticity robust standard errors. Dummy Startup turns one if established in 2016 or later.

	Dependent variable:		
	Continuous AI	AI > 0	AI > 0.5
	OLS	*logistic*	*logistic*
	(1)	(2)	(3)
Municipality Centrality	0.00001^{***}	0.002^{***}	0.003^{***}
	t = 5.662	t = 6.196	t = 4.278
Age in Years	0.00002	0.003	0.002
	t = 0.543	t = 1.045	t = 0.247
Dummy Startup	0.005^{***}	0.363^{***}	0.759^{***}
	t = 4.880	t = 4.925	t = 4.020
log(Employees)	0.001^{***}	0.215^{***}	0.110^{*}
	t = 3.433	t = 9.024	t = 1.709
log(Shareholders)	0.002^{**}	0.208^{***}	0.066
	t = 2.476	t = 7.082	t = 0.912
Dummy Gender CEO	-0.002^{***}	-0.296^{***}	-0.797^{***}
	t = -2.665	t = -3.037	t = -2.678
Dummy Gender Chairperson	0.0004	-0.243^{**}	-0.142
	t = 0.355	t = -2.331	t = -0.516
Total Assets	0.000	0.00000	0.00000
	t = 0.245	t = 0.185	t = 0.908
Net Income	-0.000	0.00000	-0.00000
	t = -0.198	t = 1.547	t = -0.444
R&D	0.00001^{***}	0.0001^{***}	0.0002^{***}
	t = 4.745	t = 6.673	t = 5.009
Return on Assets	-0.002	-0.362^{***}	-0.292
	t = -1.465	t = -4.228	t = -1.533
Debt Ratio	-0.0004	-0.155^{***}	-0.110
	t = -0.352	t = -2.685	t = -0.839
Liquidity	0.0003^{**}	0.014^{**}	0.022
	t = 1.967	t = 2.025	t = 1.349
Constant	-0.015^{***}	-6.676^{***}	-22.455
	t = -5.380	t = -15.501	t = -0.064
Industry Fixed Effects	Included	Included	Included
Observations	52,265	52,265	52,265
Adjusted R^2	0.036		
Log Likelihood		-5,668.821	-1,068.273
Akaike Inf. Crit.		11,383.640	2,182.547
Note:			*p<0.1; **p<0.05; ***p<0.01

4.2.1.2 Industry specific regressions

In Figure 4.8, we show the results of regression models (4), (5), and (6). In these models, we use the dummy variable AI Know-how above zero as the dependent variable, with the same independent variables as in the regression models (1), (2), and (3). However, we run the same regression model on three industries. As detailed in Chapter 3.4.2, these are computer programming, advertisement and market research, and land transportation and transport via pipelines. For clarification, these industries are not the same industry groupings we see in Chapter 4.1.1.

We do not find a lot of statistically significant variables in the models in Figure 4.8. The only statistically significant variable at the 1% level is the log(employees) for the programming industry. In contrast to advertising and transportation, this might indicate that AI capabilities and knowledge stem from the employees. We find that the number of employees positively affects the computer programming industry, whereas we do not see the same relationship for advertising or transportation. These findings might suggest that the adoption of AI is positively correlated with the number of employees in sectors and activities where the adoption of AI is driven by employee capabilities and knowledge rather than by the purchase of AI products.

We do not find any statistical significance for the gender of the CEO dummy. However, it was interesting to see the difference in the coefficient for the transportation industry. In contrast to advertisement and programming, transportation has a positive coefficient for gender CEO. These results would typically indicate that having a female CEO increases the likelihood of having a positive AI Know-how score. However, in this case, we believe it has more to do with the fact that the transportation industry is male-dominated, and we thus have very few female CEOs. From our sample, we find that 19.2% of firms have a female CEO, but in the transportation industry, only 4.82% of CEOs are female.

Net income was negatively statistically significant for the transportation industry. However, we found no economic significance or marginal effects at the mean for this variable. We only found an economic significance for the programming industry's variable log(employees). The marginal effect at the mean for this variable was 5.79%.

Additionally, we find that model (3) had the highest log-likelihood, highest Pseudo R-squared, and lowest Akaike Information Criterion (AIC). This indicates that model (3) had the best fit out of the three models.

Figure 4.8 Relationship between AI and firm characteristics for KIA firms: Relationship between firm characteristics and the dummy AI Know-how > 0. Here we run regression models of three industries based on the degree of Knowledge Intensity Activities (KIA). Model (4) show results for high KIA industry Programming, (5) medium KIA Advertising, and (6) low-intensity transportation. All relevant variables are winsorized at the 1% level. Gender CEO and Chairperson are dummies that turn one if female. Dummy Startup turns one if established in 2016 or later.

	Dependent variable:		
	AI Know-how > 0		
	logistic		
	Programming	Advertising	Transportation
	(4)	(5)	(6)
Municipality Centrality	0.001	0.002	-0.002
	t = 1.497	t = 0.822	t = -0.441
Age in Years	-0.007	-0.073	0.023
	t = -0.498	t = -1.469	t = 0.949
Dummy Startup	0.479^{**}	0.281	-0.961
	t = 2.136	t = 0.430	t = -0.782
log(Employees)	0.421^{***}	0.006	-0.781^{**}
	t = 4.751	t = 0.025	t = -2.197
log(Shareholders)	0.166^{**}	0.399	-0.573
	t = 2.148	t = 1.235	t = -0.866
Dummy Gender CEO	-0.567	-1.392^{*}	2.684^{**}
	t = -1.589	t = -1.657	t = 2.100
Dummy Gender Chairperson	0.722^{**}	0.638	-1.549
	t = 2.030	t = 0.992	t = -0.904
Total Assets	0.00000	-0.00001	
	t = 0.640	t = -0.540	
Net Income	-0.00000	0.0001	-0.0004^{***}
	t = -0.249	t = 1.065	t = -3.450
R&D	0.00004	0.004^{***}	-0.434
	t = 1.306	t = 2.667	t = -0.005
Return on Assets	-0.258	-0.483	2.686^{*}
	t = -1.452	t = -0.838	t = 1.953
Debt Ratio	0.041	0.056	0.262
	t = 0.354	t = 0.192	t = 0.550
Liquidity	0.009	0.015	-0.829
	t = 0.399	t = 0.324	t = -1.251
Constant	-3.696^{***}	-4.543^{**}	-1.946
	t = -4.795	t = -2.216	t = -0.630
Industry Fixed Effects	Not Included	Not Included	Not Included
Observations	1,045	646	953
Log Likelihood	-461.496	-92.328	-27.758
Akaike Inf. Crit.	950.993	212.657	81.517
Note:			*p<0.1; **p<0.05; ***p<0.01

4.2.2 Firm performance indicators as dependent variables

In Figure 4.9, we present our regression models' findings, using firm performance indicators as the dependent variables. Figure 4.9 show regression models (7), (8), (9), and (10) as presented in Chapter 3.4.2.2.

In model (7), the dummy for a positive AI Know-how is statistically significant at the 1% level for the dependent variable return on assets. The AI Know-how dummy has a negative coefficient of -0.037, which indicates that firms with positive AI Know-how scores have a lower return on assets. As we will come back to in Chapter 5, some unobserved effects might come from the covid-19 pandemic. Firms with a higher share of intangible assets are more vulnerable to financing constraints (Knudsen & Lien, 2014). For model (7), we have a difference in mean, and coefficient, of -3.619%. This result indicates that firms with a positive AI Know-how have, on average, 3.619% lower return on assets than those with an AI Know-how score of zero.

The dummy for a positive AI Know-how is not statistically significant in model (8) for our measure of net operating efficiency or sales per employee. The coefficient indicates that firms with a positive AI Know-how score have a predicted NOK 50,654,000.00 fewer sales per employee than those with a score of zero. The difference in mean indicates that firms with a positive AI Know-how score have, on average, NOK 109,011,400.00 fewer sales per employee than firms with a score of zero.

In model (8), the dummy for a positive AI Know-how is statistically significant at the 1% level for the dependent variable operating margin. The AI Know-how dummy has a negative coefficient of -0.096. The coefficient indicates that firms with a positive AI Know-how have a predicted operating margin of 9.6% less than those with a score of zero. The difference in mean is higher and indicates that firms with a positive AI Know-how score have, on average, 19.773% lower operating margin than those with a score of zero.

Furthermore, model (9) shows that the positive AI Know-how dummy is statistically significant at the 10% level. The AI Know-how dummy has a positive coefficient of 0.015. This indicates that a positive AI Know-how score increases the five-year compounded average sales growth rate by 1.5%. The difference in mean shows that firms with positive AI Know-how scores have a 4.213% higher sales growth rate on average.

We also see that the dummy startup has a positive and statistically significant coefficient for the sales growth rate in model (10). One possible interpretation is that startups, and firms that focus on AI, are more inclined to target growth and expansion than cost-cutting and profitability. Moreover, the startup dummy has a negative, statistically significant coefficient for return on assets, sales per employee, and operating margin, again reinforcing the idea that startups focus less on profitability and more on growth.

Interestingly, we note that the coefficients and the difference in means do not match. There are a few possible explanations, for example, issues with missing data, non-linearity, or multicollinearity. With the variance inflation factor (VIF), we do not get any values that indicate multicollinearity. However, as discussed in Chapter 3.5, we are aware of possible endogeneity and limitations to overall causality.

Figure 4.9 Relationship between firm performance and AI Know-how Intensity: Firm performance indicators as dependent variables. Relevant variables are winsorized at the 1% level. (9) has fewer observations due to missing values from the accounting data, (10) has fewer observations as we only regress companies who report five years of sales. We include industry-fixed effects. All regressions use heteroskedasticity robust standard errors. Gender CEO and Chairperson are dummies that turn one if female. Dummy Startup turns one if established in 2016 or later.

	Dependent variable:			
	ROA	Sales/Emp	Op. margin	5-yr CAGR sales
	OLS	*OLS*	*OLS*	*OLS*
	(7)	(8)	(9)	(10)
AI Know-how > 0	-0.037***	-50.654	-0.096***	0.015*
	t = -3.782	t = -0.629	t = -4.502	t = 1.658
Municipality Centrality	0.0001***	1.591***	-0.0001***	0.00005***
	t = 5.236	t = 16.923	t = -4.273	t = 4.586
Age in Years	-0.001***	3.062**	0.0001	-0.003***
	t = -6.276	t = 2.008	t = 0.379	t = -27.223
Dummy Startup	-0.029***	-267.257***	-0.070***	0.345***
	t = -7.101	t = -7.662	t = -7.846	t = 29.835
log(Employees)	0.005***		0.048***	0.012***
	t = 4.422		t = 16.033	t = 9.858
log(Shareholders)	-0.020***	-69.720***	-0.126***	0.023***
	t = -10.449	t = -3.160	t = -27.483	t = 8.559
Dummy Gender CEO	-0.004	-420.092***	0.0003	-0.011***
	t = -1.013	t = -11.230	t = 0.034	t = -2.941
Dummy Gender Chairperson	0.005	-380.250***	0.020*	-0.005
	t = 1.198	t = -10.181	t = 1.810	t = -1.188
Total Assets		0.003***	-0.00000***	0.00000
		t = 13.863	t = -16.485	t = 1.497
R&D	-0.00002***	0.026	-0.0001***	0.00001***
	t = -14.303	t = 1.329	t = -24.419	t = 3.908
Debt Ratio	-0.269***	-233.598***	-0.156***	-0.013***
	t = -36.008	t = -21.227	t = -30.917	t = -5.134
Liquidity	-0.007***	-28.573***	-0.035***	-0.004***
	t = -18.056	t = -5.354	t = -34.667	t = -8.796
Constant	0.227***	1,373.895***	0.231***	0.100***
	t = 17.936	t = 8.214	t = 6.898	t = 5.630
Industry Fixed Effects	Included	Included	Included	Included
Observations	52,265	52,265	51,948	37,770
Adjusted R^2	0.262	0.116	0.079	0.134
Note:				*p<0.1; **p<0.05; ***p<0.01

5 Discussion

In this chapter, we will interpret our findings and situate them in the context of existing literature. First, we will address the hypotheses we formulated in the literature review and determine whether our results support or contradict them. We will then examine how our findings compare and contribute to the literature on the adoption of AI and firm performance.

5.1 Hypotheses

In this subchapter, we present and summarize the results of our study that address the hypotheses formulated in Chapter 2. We divide this subchapter into further subchapters based on our hypotheses. We begin by discussing the hypothesis and provide a comprehensive summary of our findings, drawing on the data and analyses that we conducted.

When testing our hypotheses, we examined the t-values, z-values, and p-values of the variables' coefficients. The null hypothesis is that the coefficients equal zero, and we set the significance level at 1%.

5.1.1 H1: The number of employees positively affects the adoption of AI.

For hypothesis one, we aim to investigate if the number of employees positively affects the firm adoption of AI. Therefore, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

In model (1), we get a t-value of 3.422 and a p-value < 0.00004. We reject the null hypothesis and conclude that log(employees) positively affect the AI Know-how score in model (1). In model (2), we get a z-value of 9.024 and a p-value < 0.0001. Therefore, we reject the null hypothesis and conclude that log(employees) positively affect the AI score in model (2). Moreover, we get a z-value of 1.709 and a p-value of 0.0435 for model (3). Hence, we keep the null hypothesis for model (3).

Moreover, we conduct tests for models (4), (5), and (6), where we perform regressions for three different industries. In model (4), a subsample for computer programming, we get a z-value of 4.751 and a p-value < 0.0001. We reject the null hypothesis and conclude that the log(employees) coefficient for computer programming positively affects the AI Know-how score. In model (5), the subsample for advertising, we get a z-value of 0.025 and a p-value of 0.490. We keep the null hypothesis and conclude that the advertisement subgroup's log(employees) coefficient does not affect the likelihood of firms having a positive AI Know-how score. For the transportation industry, model (6), we get a z-value of -2.197 and a p-value of 0.014. We keep the null hypothesis and conclude that the log(employees) coefficient equals zero in model (6). Interestingly though, the transportation industry has a negative z-value that indicates, to some degree, a negative effect. However, we cannot conclude anything further with the significance level we set.

In conclusion, we get different results for our various regression analyses. Two of our general regression models utilizing the entire sample, models (1) and (2), indicate that the number of employees positively affects the adoption of AI. However, other analyses point to the concept of AI adoption being more complex. We find that the number of employees positively affects the computer programming industry, whereas we do not see the same relationship for advertising or transportation. Based on these results, we argue that the number of employees has a positive relationship with the adoption of AI in industries and activities where AI adoption derives from the capabilities and knowledge of employees rather than from purchasing AI solutions.

5.1.2 H2: Total assets have a positive effect on the adoption of AI.

For hypothesis two, we aim to investigate if the variable "total assets" positively affects firm adoption of AI. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

From our hypothesis tests, we do not get any p-values under our significance level for any of our regression models. Therefore, we keep the null hypothesis and conclude that total assets do not have a significant positive effect on the AI Know-how variable. The descriptive statistics presented in Chapter 4.1.1 reveal a notable contrast in the median total assets between the overall sample and firms with positive AI scores. However, it is worth noting that the correlation between the number of employees, net income, and total assets may mitigate the relationship between total assets in isolation and AI scores.

5.1.3 H3: The gender of the CEO has no effect on the adoption of AI.

For hypothesis three, we aim to investigate whether the gender of the CEO affects the firm adoption of AI. Thus, we conduct a two-tailed hypothesis test to determine whether the results are statistically significant.

We keep the null hypothesis that there is no effect for models (1), (4), (5), and (6). However, in models (2) and (3), we get p-values of 0.0023 and 0.0074, respectively. We then reject the null hypothesis and conclude that the gender of the CEO does influence the AI Know-how score in models (2) and (3). Moreover, the t-value and z-values for all but model (6) are negative, which indicates that having a female CEO decreases the likelihood of having a positive AI Know-how score.

These findings are not unexpected, as most technical expertise comes from graduates with technological degrees. According to the Norwegian Directorate for Higher Education and Skills (2023), 77.8% of applicants for technological degrees were male. They also reported that 65.6% of applicants for degrees within information technology were male.

5.1.4 H4: Firm age has a negative effect on AI adoption.

For hypothesis four, we investigate if firm age negatively affects firm adoption of AI. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

Based on our hypothesis tests, none of the p-values observed in our regression models are below the significance level we set a priori. Consequently, we retain the null hypothesis that the firm's age does not influence the AI Know-how dummy variable. It is essential to note that a startup status dummy has been incorporated into our analysis. As a result, it is possible that the startup dummy variable may capture certain effects of firm age. Moreover, from the descriptive statistics in Chapter 4.1.1, we find no significant differences between the entirety of the sample and firms with positive AI scores.

5.1.5 H5: Firm municipality centrality has a positive effect on AI adoption.

For hypothesis five, we investigate if firm municipality centrality positively affects firm adoption of AI. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

Upon testing hypothesis five, we obtained a p-value of < 0.0001 for models (1), (2), and (3). As a result, we reject the null hypothesis and infer that firm municipality centrality affects the AI Know-how score. Additionally, the positive t-value and z-values show a positive effect. However, we fail to discover a statistically significant relationship for models (4), (5), or (6).

5.1.6 H6: AI score has a positive effect on sales growth.

For hypothesis six, we investigate if the dummy variable AI Know-how above positively affects the 5-year sales CAGR. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

From model (10), we get a t-value of 1.776 and a p-value of 0.3788. Therefore, we keep the null hypothesis and conclude that we do not find a significant positive effect between the AI Know-how variable and the dependent variable sales growth rate. Even though we do not find a statistically significant relationship, we do find a significant economic difference between those with positive AI Know-how scores and those with a score of zero, see Chapter 4.2.2. It is also essential to be aware of the limitations of overall causality, as discussed in Chapter 3.5.2.

5.1.7 H7: AI score has a positive effect on return on assets.

For hypothesis seven, we investigate if the dummy variable AI Know-how above zero positively affects the return on assets. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

Upon testing hypothesis six with model (7), we get a t-value of -4.222 and a p-value of < 0.0001. From this, we reject the hypothesis that the AI Know-how variable positively affects the return on assets. Instead, we find evidence that the AI Know-how variable has a negative relationship with the dependent variable return on assets. From Chapter 4.2, we also find that those with positive AI Know-how scores have a 3.619% lower return on assets than those without a score.

5.1.8 H8: AI score has a positive effect on net operating efficiency (Sales per employee).

For hypothesis eight, we investigate if the dummy variable AI Know-how above positively affects the net operating efficiency or sales per employee. Thus, we conduct a one-tailed hypothesis test to determine whether the results are statistically significant.

From model (8), we get a t-value of -0.598 and a p-value of 0.27495. Therefore, we keep the null hypothesis and conclude that we do not find a statistically significant positive relationship between the AI Know-how score and the dependent variable net operating efficiency, or sales per employee. Interestingly, the t-value and coefficient were negative, indicating a negative relationship. However, we do not have statistical significance for this relationship.

5.2 Theoretical discussion

In this subchapter, we discuss our findings against the existing theory. We split our discussion into two parts. First, we compare our results with existing literature regarding firm adoption of AI. Second, we compare our results regarding AI's effect on firm performance with relevant theory. We introduce our hypotheses and discuss how our findings align with existing studies.

5.2.1 Firm adoption of AI

Hypothesis one to five pertain to firms' adoption of AI technologies. From previous theory, we learn that AI technology is in an early stage for most firms (Bughin et al., 2017; Chui et al., 2022). From our sample, we find that 2.6% of firms have a positive AI Know-how intensity score. We, therefore, categorize these 1,383 firms as AI adopters and assume they possess adequate AI capabilities. We retain information on the degree to which firms' products and services are integrated with AI or personnel with AI skills. However, we avoid focusing on the exact degree of capabilities/scores as this would represent a layer of uncertainty. Instead, we primarily compare companies with positive scores to those without a score. We see that degree of Norwegian firms adopting AI is on par with results published by Istari for the DACH region (Dehghan, 2022). This information does not in itself signify much. Regardless, it would be interesting to see other studies looking closer at this relationship or this development over time.

Our first two hypotheses aim to investigate firms' size and its effect on their adoption of AI. The first hypothesis examines whether the number of employees positively affects firms' adoption of AI, while the second hypothesis examines the relationship between total assets and AI adoption. From the literature, we expect the firm size to correlate with AI adoption as bigger firms generally have more financial and technical resources, enabling them to adopt new technology easier (Aboelmaged, 2014; Chatterjee et al., 2021; Alsheibani et al., 2018). We find support for our first hypothesis regarding the number of employees' effect on adoption.

However, we do not find support for the total assets affecting firms' adoption of AI. Unsurprisingly, our results show a significant correlation between firm size variables (see Table 4.4). Because of this correlation, the explanatory effect is likely being shifted from one variable to another, which could limit their statistical significance. We theorize that the number of employees might be a better-suited size measurement regarding the theory of AI adoption because of the importance of capabilities. Further, we reason that the number of employees has a positive relationship with the adoption of AI in industries and activities where AI adoption derives from the capabilities and knowledge of employees. In summary, we support the existing theory and find that firm size generally affects AI adoption positively.

Our third hypothesis concerns the gender of the CEO's effect on firms' adoption of AI. From our theory section, we learn that top management backing is essential for any technology adoption. Initially, we expected that the gender of the CEO would have no discernible impact on the firm adoption of AI. However, our results show a clear correlation between male CEOs and AI adopters. We do not find this correlation surprising, as most technical expertise stems from graduates with technological degrees, most of whom are male (Norwegian Directorate for Higher Education and Skills, 2023). Our data sample shows that sectors like programming are significant contributors to AI adoption. These industries also have a higher number of male CEOs. We do not believe a causal relationship exists where male CEOs lead to higher adoption. Instead, we think firms with AI capabilities are more likely to have a male CEO (and generally more male employees) as more men have the competency to develop AI capabilities, as they overrepresent the technical degree programs. Hence, they experience higher participation in the field. We theorize that men will overrepresent AI-related startups, where the CEO often is the founder, which could further explain our results. Our presented theory explains how management support moderates the effect of ease of use and AI's perceived usefulness. It would be interesting to investigate whether any attitudinal differences between men and women could potentially lead to differences in AI adoption. In summary, however, our results show that AI adopters are more likely to have a male CEO.

Our fourth hypothesis aims to explore the influence of firm age on AI adoption. Studies exhibit somewhat conflicting results regarding firm age and technology adoption in our presented theory. Some studies suggest that company age positively influences superior organizational outcomes and generates more innovations over time (Argote, 1999; Coad et al., 2016; Sørensen and Stuart, 2000). Other research points to contrasting effects. Older businesses may experience inertia or "bureaucratic ossification", limiting overall learning effects (Majumdar, 1997).

Balasubramanian and Lee (2008) also find a negative correlation between firm age and technical quality, particularly in areas with higher technological activity. The relationship between firm age and innovativeness remains mixed, with some studies suggesting that younger companies prioritize short-termism and value preservation, while others highlight the inclination of new entrants toward "radical" innovations (Coad et al., 2018; Bianchini et al., 2018; Acemoglu and Cao, 2015). Further, some studies indicate that smaller businesses are more flexible in adopting new technology, such as AI (Chatterjee et al., 2021). Initially, we do not find a significant effect from firm age on AI adoption in our regression analyses. However, we see substantial results when including a dummy that signifies whether the firm is a startup, which is determined by firm age. Hence, we argue that, generally, firm adopters are younger firms.

Additionally, we find figures 4.3 and 4.4 intriguing. Surprisingly, the percentage of newly established firms with a positive AI score remains stable between 1.5 to 3.0%, without any clear trend toward increasing adoption. We recognize that the graphs have issues and biases, as we discuss in Chapter 4.1.3. Initially, we expected a higher degree of adoption from newer firms, but we also see that older firms that have endured have a higher percentage of AI adoption. We theorize a U-curved shape concerning the age and size of firms that adopt AI. We should note that we cannot correct for non-active and non-operational firms. We argue that older, non-adopters of new technology are likelier to go out of business. In this case, we have an under-representation of older non-adopters in our sample, which could understate the relative adoption of newer firms compared to older ones. In summary, our results indicate that bigger and older firms and new startups are the most suitable adopters of AI.

Our fifth and final hypothesis regarding AI adoption examines the effect of firm municipality centrality on firms' adoption of AI. From the theory, we learn that firms located in strong clusters experience can benefit from increased job creation, higher wages, greater chances of survival, and improved overall performance (Wennberg and Lindqvist, 2010; Diez-Vial, 2011). Strong regional clusters can create agglomeration economies and externalities that promote learning, innovation, knowledge spillovers, and growth in specialized institutions (Delgado et al., 2014). Clustering can nourish valuable complementary externalities that can facilitate the adoption of new technologies such as AI. These factors can contribute to developing complementary AI capabilities, resulting in a sustained competitive advantage. Our regression analyses show a significant correlation between our firm centrality variable and firm adoption of AI when testing the entire sample. However, our sub-samples do not show the same statistically significant results. We believe this result is due to the smaller samples. Figures 4.5 and 4.6 displays a clear association between regions with cities with technological competencies and higher AI adoption. We argue that urban areas tend to offer a more favorable environment for evolving critical capabilities necessary for AI adoption (Mikalef and Gupta, 2021). They provide access to a larger pool of skilled employees and knowledge exchange and create a supportive ecosystem that can encourage the integration of AI into business operations. In summary, we find that centrality positively affects AI adoption.

5.2.2 AI adoption's effect on firm performance

Hypothesis six to eight aim to explore the relationship between AI and its effect on firm performance. We learn from the theory that AI can significantly benefit firms. Contrarily, reports and newer studies demonstrate that not all organizations experience the anticipated benefits of AI technology (Bughin et al., 2017; Chui et al., 2022; Chowdhury et al., 2023). Chowdhury et al. state that the absence of experienced benefits remains consistent regardless of time, effort, and resource investments. The presented theory points to developing and deploying complementary resources in the form of AI capabilities as key for firms' success in adopting and implementing AI. Building valuable, unique, hard-to-imitate, and non-substitutable AI capabilities can help create sustained competitive advantages for firms (Mikalef and Gupta, 2021). The quality of firms' AI capabilities should be a defining factor in AI's effect on firms' performance. Wamba-Taguimdje et al. (2020) also note that the benefits of AI are not limited to specific industries or company sizes. They argue that having a clear strategy and well-defined objectives for AI projects is crucial for achieving better results.

Different studies point to various ways AI can benefit firms' performance. Chen et al. (2022) highlight that firms' AI capability, consisting of tangible, human, and intangible resources, indirectly influences firm performance and AI-driven decision-making through firm creativity and AI management. AI-driven decision-making positively affects firm performance, and factors such as innovation culture and environmental dynamism moderate this relationship. Wamba-Taguimdje et al. (2020) find that implementing AI projects significantly positively impacts firm performance regarding efficiency, innovation, and customer satisfaction. Lee et al. (2022) note that adopting AI, particularly when accompanied by investments in complementary technologies, can lead to increased revenue growth. Mishra et al. (2022) find that focusing on AI is associated with increased net profitability, net operating efficiency, and return on market-related investments. Our results contradict many of the findings from studies presented in our literature review. Our findings show that Norwegian firms' adoption of AI correlates negatively with various performance indicators. We find that firms adopting AI experience a decrease in their return on assets, lower operating margins, and lower sales per employee compared to non-adopting firms. However, these AI adopters demonstrate increased sales growth, which suggests their emphasis on future expansion and development.

As our analysis is limited to cross-sectional data, we should note some significant limitations to these results. We acknowledge a vital issue with endogeneity. As we cannot correct for the endogeneity problem using lag variables or other instruments, we recognize that our results regarding AI adoption's effect on firm performance can be inaccurate. However, as it stands, our results indicate that Norwegian firms to this day do not possess the AI capabilities needed to provide them with benefits to their firm performance. Our findings support the findings of Chowdhury et al. (2023), which show that most organizations are yet to experience the anticipated benefits of AI technology. As adopters of AI seem to focus on growth, it would be exciting to see how the firms' performance evolves in the future years. We know that AI capabilities can take time to build and should naturally develop over time (Chen et al., 2022). We theorize that AI adopters' capabilities will evolve in the coming years, and their performance will follow.

5.3 Theoretical Contribution

In this subchapter, we place our findings in the existing body of research. Our thesis contributes to existing research on AI adoption and AI's effect on firm performance. We recognize that our data has weaknesses that limit our confidence in stating unproven relationships. However, our results signify interesting relationships and point to areas where future research is needed.

By examining the AI adoption patterns of Norwegian firms, this study offers empirical insights and sheds light on intriguing relationships that warrant further investigation. Firstly, our results provide empirical insights into the AI adoption of Norwegian firms. We find that Norwegian AI adopters generally are situated in more urban areas, aligning with the theory regarding external complementarity. Closely related, our results indicate that the number of employees positively correlates with AI adopters. Moreover, our findings suggest that this is amplified in higher knowledge-intensive sectors such as programming. These findings align with the existing theory, explaining that firm size facilitates technology adoption. We only find support for the number of employees variable out of all variables used to measure firm size. This can suggest that the number of employees could best measure firm size when it comes to AI adoption. Further, our analyses show that being a startup increases the likelihood of being an AI adopter, even though firm age's effect on adoption proved convoluted. Lastly, our results show that firms with male CEOs are more likely to adopt AI technology. This is not surprising, as the study programs related to AI and programming are predominantly male.

We build on the work of several studies which investigate AI's role in the resource-based view framework (Chen et al., 2022; Mikalef & Gupta, 2021; Chowdhury et al.,2023). We draw upon the work of Mikalef and Gupta (2021), who define AI capabilities, and we explore the topic further with our data from Norwegian firms. Our results suggest that Norwegian firms' capabilities and AI adoption do not correlate with higher performance. Contrarily, our findings suggest an inverse relationship between AI adoption and firm performance indicators. As previous studies show, AI capabilities can lead to sustained competitive advantages. However, our findings align with reports claiming that today's average firm's AI capability does not lead to higher performance even though firms are investing in the technology. We find that firms adopting AI experience a lower return on their assets, a lower operating margin, and lower sales per employee than their non-adopting counterparts. However, we see an increase in sales growth in AI adopters, indicating a focus on future growth for these firms.

5.4 Limitations and Future Research

In this subchapter, we address the limitations of our study and outline potential avenues for future research. We begin by discussing how we measure the adoption of AI, acknowledging the strengths and weaknesses of utilizing textual analysis of websites. Additionally, we highlight certain restrictions and limitations regarding validity and reliability. Lastly, we point to areas where future research efforts could be focused.

Firstly, our findings should be interpreted cautiously as we base our analysis on estimating AI scores from textual analysis and keywords associated with AI as of 2022/23. Given the nature of Artificial Intelligence and the massive growth in popularity of AI applications, there might be words that reflect recent advances that are not reflected in the AI scores in our data. In our analysis, we only had cross-sectional data. However, if future iterations of similar research are to be compared, we must be cautious of the possible effects of increasing the list of AI-related keywords.

Additionally, even though we have gathered data from a substantial sample of around 53,000 companies, it is important to acknowledge the possibility that we might have overlooked firms that have adopted AI but have not explicitly mentioned it on their websites. Our measure of AI adoption is derived exclusively from company websites. We do not include material from internal documents or other reports that indicate whether a firm has adopted AI technology. Moreover, there are certain limitations to the generalizability. We removed observations with a ".com" domain suffix, NA scores, and companies with zero employees to increase robustness and overall quality. We also adjusted for corporate groups. Even though we have good reasons to make these adjustments, it is important to be aware of the changes, especially when comparing findings.

Additionally, it is crucial to highlight certain aspects discussed in Chapter 3.5 concerning causality and endogeneity. Firstly, as emphasized by Mishra et al. (2022), it is plausible that the AI variable is endogenous. This endogeneity may arise from simultaneous bias and confounding effects, such as the relationship between the AI variable and the number of employees. In situations involving endogeneity, the estimated relationships may suffer from bias and inconsistency, thus posing challenges in establishing causal relationships. Common approaches to address endogeneity include the utilization of instrumental variables, as employed by Mishra et al. (2022), who used lag values as instruments. Due to the nature of our cross-sectional dataset, we could not incorporate lag values. Moreover, alternative options for instrumental variables proved unsuccessful. Future research should consider incorporating panel data and lag values to estimate more robust and accurate relationships.

Our thesis explores a novel research area. Future research could build on our methodology and findings by constructing a more complete measure of AI adoption. In this thesis, we utilize a more general measure of AI using the AI Know-how Intensity score. However, there might be elements we have not captured and uncertainties with the variable itself. Moreover, our study covered various analyses, from descriptive to explanatory. Future research should take a more in-depth look at either the descriptive part of the adoption of AI, such as how companies are using AI, or look more closely at the effects of AI on firm performance.

Our thesis provides areas that warrant future research. As mentioned, this study uses cross-sectional data. For future research, collecting AI data at several different times would be beneficial. Using panel data would increase the results' overall quality substantially. The added time element would also reduce other problems and biases regarding endogeneity, as lag variables would be able to adjust for several issues.

We know that firms' AI capabilities take time to accumulate. Therefore, seeing how our results would change when newer AI data is collected in the coming years would be interesting. As firms' capabilities improve over time, their results are also expected to improve. Further, we have begun to explore the field of AI adoption and firm performance for Norwegian firms, which opens a variety of future study directions. For example, it could be exciting to look further into different levels of knowledge-intensive sectors and see what well-performing firms are doing right and what less-performing firms could do better. We have outlined elements that existing theory generally finds impactful, but as AI technology advances, these could change.

6 Conclusion

In the final chapter of our master thesis, we summarize the main findings and purpose of our research. We look back at our research objectives, purpose, and research question, followed by a brief summarization of our main findings and contributions.

Our thesis had multiple purposes and objectives. Firstly, we aimed to explore the feasibility of utilizing the underlying data for research purposes. Secondly, we sought to examine the adoption of Artificial Intelligence among Norwegian firms. Lastly, we aimed to investigate the impact of AI adoption on firm performance. To address these objectives, our study focused on the following research question:

"Which Norwegian firms are adopting Artificial Intelligence,
and how does the adoption of AI affect firm performance?"

Our thesis employs a quantitative methodology with a descripto- explanatory purpose, utilizing a documentary research strategy. The initial dataset for our study consisted of AI scores from approximately 96,000 Norwegian companies obtained from Istari.ai. These AI scores were derived by analyzing the words and paragraphs found on companies' websites. Additionally, we incorporated accounting and financial data from "Regnskapsdatabasen – Norwegian Corporate Accounts", provided by the Center for Applied Research (SNF) at NHH. After merging and carefully refining the dataset, we narrowed our analysis to approximately 53,000 Norwegian firms.

To answer our research question, we have reviewed the current literature on the adoption of artificial intelligence, artificial intelligence's role in the resource-based view, and its effect on firm performance. We place significant emphasis on the term AI capabilities to unite the relevant literature that builds our hypotheses and analysis. Existing theory states that firms could achieve competitive advantages by adopting technology such as AI. However, the impact of firms' AI capability is complex. As reports regarding AI adoption show, we also find that the average Norwegian firm's AI capability, to this day, has not increased their firm performance.

In our sample, we find that 2.6% of companies have a positive AI Know-how Intensity score, and approximately 1.7% have a positive AI Information Intensity score. These findings are consistent and comparable to data obtained by Istari.ai for the DACH region. Examining the descriptive statistics, we found that companies with positive AI scores exhibited higher mean and median municipality centrality scores than the overall sample. Notably, we also uncovered that firms with positive AI scores displayed a higher median five-year sales growth rate while maintaining similar medians for return on assets and operating margin. Specifically, the median five-year sales growth rate for the entire sample was 2.8%, whereas it reached 4.6% for companies with positive AI Know-how and Information scores.

Furthermore, we found that the industry group telecom, IT, and media had the highest proportion of companies with positive AI Know-how scores, with 11.87%, followed by research and development, and finance and insurance. Looking even deeper at the telecom, IT, and media category, we find that computer programming companies represent 30% of the industry group, where 18.72% of this subgroup had positive AI scores. We also find that media companies represent approximately 30% of the industry group and that 3.2% of these have positive AI Know-how scores.

Interestingly, we find that the percentage of firms established each year with positive AI scores remains around 1.5% to 3%, without any clear trend towards increased adoption, see Figure 4.4. From Figure 4.4, we theorize that there is a type of U-curve regarding the age and size of firms that adopt AI. In other words, the bigger and older firms, along with new startups, are the best at adopting and utilizing new technology, especially AI.

Based on our regression analyses, we find that, generally, companies that are more urban, are a startup, have more employees, and have a male CEO are more likely to have a positive AI Know-how score. However, there are some nuances. We find that the number of employees has a positive effect on the AI score for the computer programming industry, whereas we do not see the same relationship for advertising or transportation. From this, we argue that the number of employees has a positive relationship with the adoption of AI in industries where AI adoption derives from the capabilities and complementary resources in firms, such as the knowledge of the employees.

Moreover, we fail to find a statistically significant relationship between the AI Know-how variable and total assets, firm age, sales growth rate, and sales per employee. We do, however, find support for a negative relationship between return on assets and the AI Know-how variable. We do see a statistically significant relationship for municipality centrality score. Even though we do not find statistical significance for all variables, we report interesting findings for economic significance in Chapter 4.

Despite gathering data from a substantial sample of approximately 53,000 companies, we must acknowledge potential limitations in our study. One limitation is the reliance on AI adoption information solely obtained from company websites, which may have resulted in overlooking firms that have adopted AI but did not explicitly mention it online. This limited scope may not capture the full extent of AI adoption within the sample.

Addressing endogeneity and establishing causal relationships also present challenges. Previous research highlights the potential endogeneity of the AI variable, suggesting that estimated relationships may suffer from bias and inconsistency. Due to our dataset's cross-sectional nature, we could not incorporate lag values as instrumental variables to address endogeneity. Future research should explore the use of panel data and lag values to provide more robust estimations of the relationships.

Moving forward, future research could expand on our methodology and findings. A more comprehensive measure of AI adoption could be developed, capturing elements and uncertainties not accounted for in our study. Additionally, conducting more focused analyses, such as exploring how companies utilize AI or delving deeper into the effects of AI on firm performance, would provide valuable insights. Collecting AI data at multiple time points using panel data would enhance the validity of results and allow for a better understanding of the evolution of AI capabilities and their impact on firm performance.

Through the completion of this thesis, we have delved into the exploration of AI adoption in Norway, uncovering valuable insights into its applications and the current state of the technology. We hope that our findings and analysis will serve as a valuable resource for researchers, professionals, and organizations interested in understanding the landscape of AI adoption and its implications for firm performance. This study has allowed us to contribute to the existing body of knowledge in the field, shedding light on the potential benefits and challenges associated with AI implementation.

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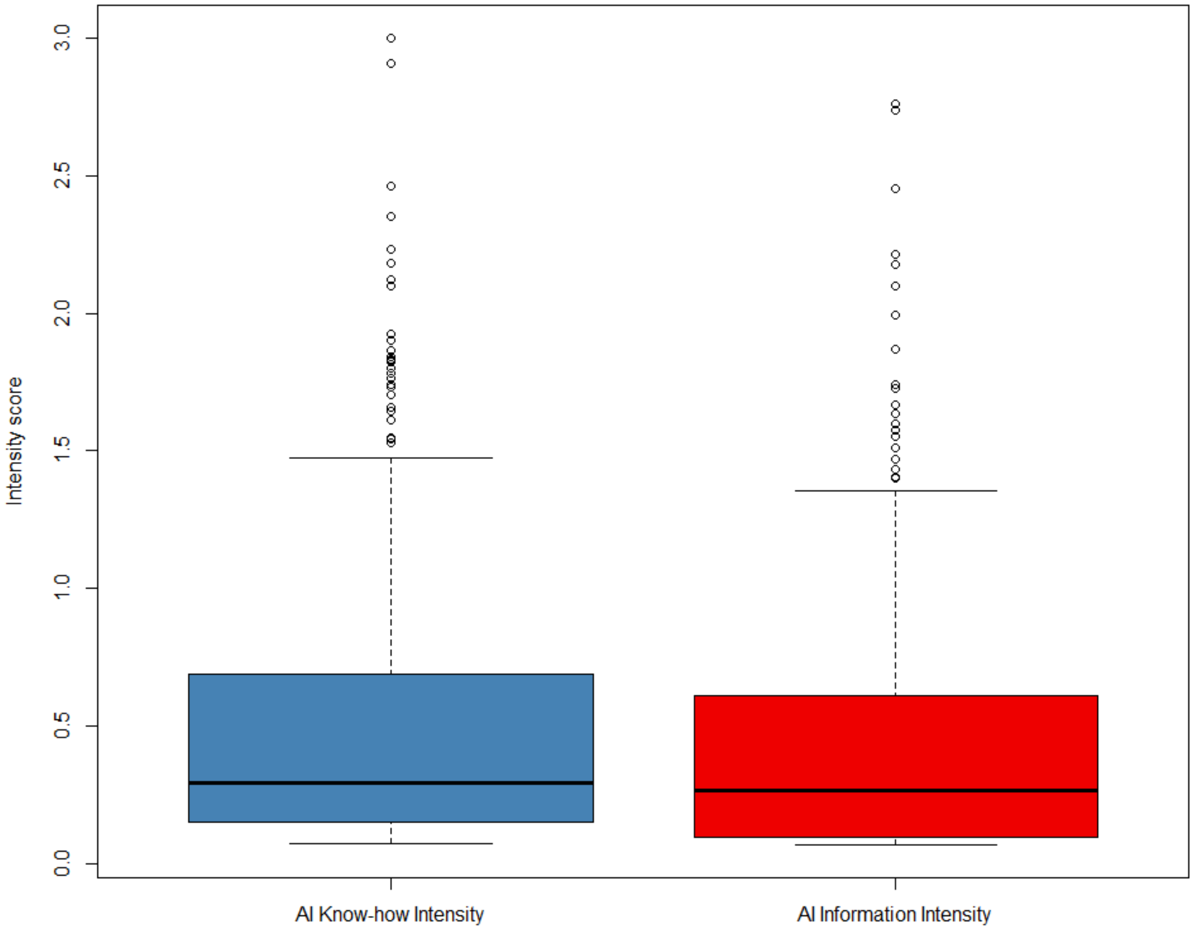
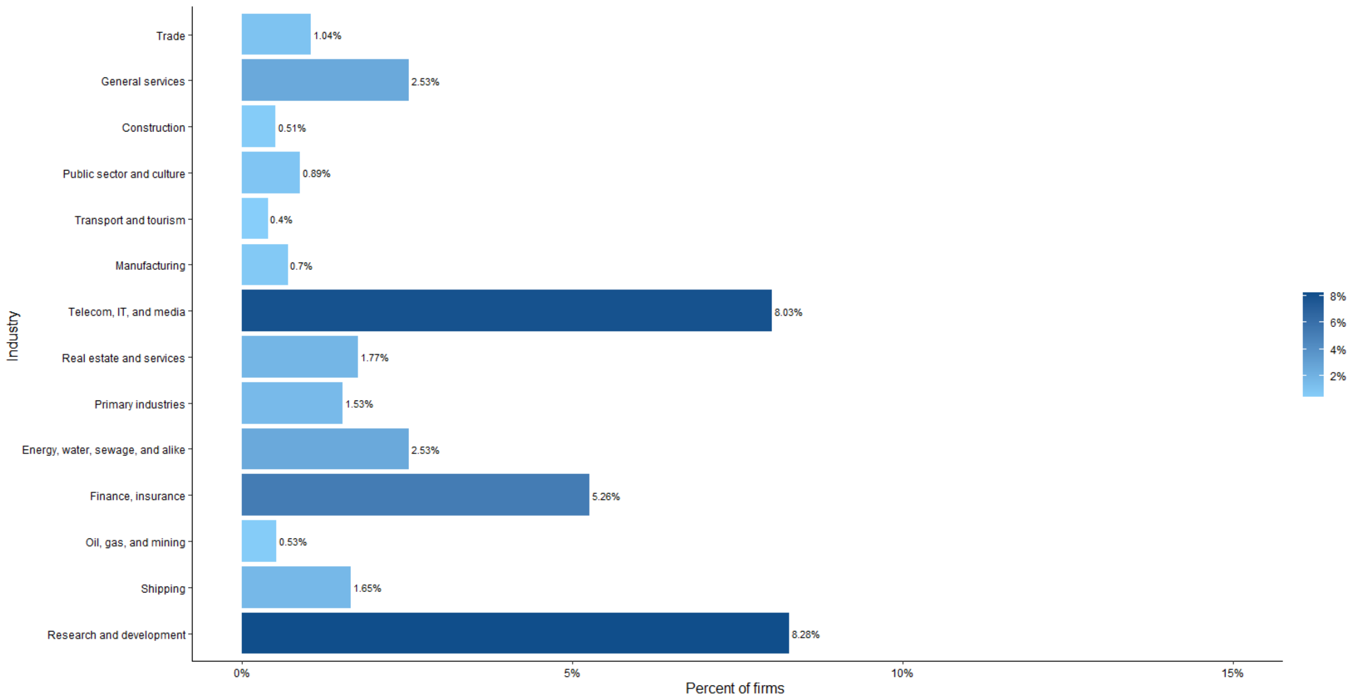
Appendix

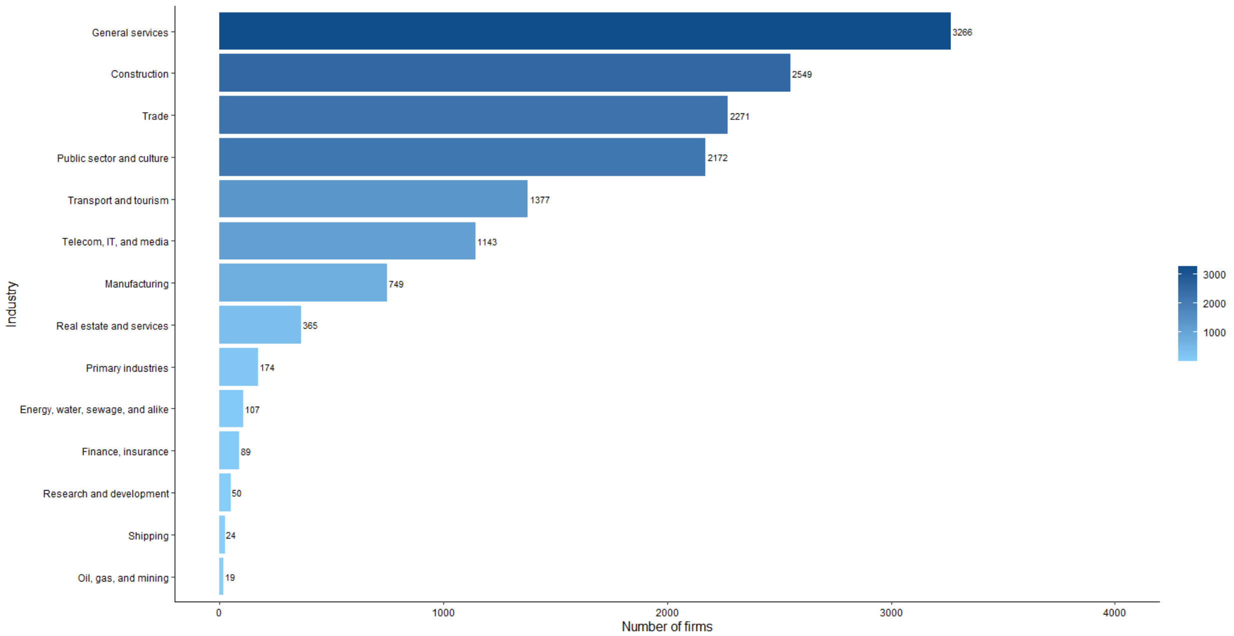
Appendix 1 Boxplot of AI scores for those with > 0 scores



Appendix 2 Percentage of firms with positive AI Information scores by industry : In addition to figure 4.2 about the percentage in our entire sample with positive AI Know-how, we visualize the percentage with positive AI Information scores.



Appendix 3 Industry distribution for startups in sample: Categories based the industry grouping created by the Centre for Applied Research at NHH with support from Statistics Norway (Mjøs & Selle, 2022). Here we add insights to figures in Chapter 4.1.2, with data for only companies established in 2016 or later.



Appendix 4 Percentage of firms with positive AI Know-how scores by industry for startups : Here we add insights to figures in Chapter 4.1.2, with data for only companies established in 2016 or later.