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Mitigating Barriers on Artificial Intelligence Pre-adoption in Forecasting:

A case Study in a Manufacturing Firm

Thesis in Industrial Innovation Management, 30 credits

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Abstract

Introduction: To predict the future, how a coming day, week, or month will look has become even more crucial than ever for a firm, due to recent pandemic crises, and wars. Being able to predict the future will enable firms to reduce costs and increase time efficiency. Processes such as forecasting have been at the forefront to aid managers in these matters by improving decision-making and planning. Greater forecasting capabilities have been achieved by adopting technologies such as Artificial Intelligence (AI). As it has shown to aid practitioners in predicting the future with high accuracy. Thus, leading to improved decision making and planning.

Problem discussion: AI is still in its infancy, and technology adoption is a staged-based process. More research is needed to identify the potential barriers a firm faces when looking to adopt AI into their forecasting process. As well as how these barriers are mitigated, and what barriers are relevant depending on the stage of adoption.

Purpose and Research question: The purpose of this study is to investigate the barriers of AI pre-adoption in forecasting and how these barriers are mitigated. To answer the following research question: *How does a manufacturing firm mitigate AI pre-adoption barriers in the forecasting process?*

Method: First, a scoping review is conducted to identify barriers in AI adoption with the support of the TOE framework, (Technological, Organizational, and Environmental). Later, the thesis follows a qualitative approach, conducting a single case study. The primary source of empirical data was collected from five in-depth semi-structured interviews. The data is collected from an international manufacturing firm located in Sweden that is looking to adopt AI-ML into its forecasting process. The findings collected from the firm are later discussed with an expert in the field of AI and forecasting to further bring validity and input to the findings.

Findings: Organizational readiness, Top management, Poor data, Inappropriate technology infrastructure, and Partnership were identified as key barriers in the AI-ML pre-adoption for the forecasting process. The barrier could be mitigated by building a strong business case, creating managerial awareness and understanding, interactive data platform, comprehensive dataset, and incentives.

Conclusion: The study provides theoretical contributions as well as managerial implications. By shedding light on the barriers in the pre-adoption phase and providing insight as to how to mitigate the barriers. Future research is recommended to study the same phenomena at another firm.

Keywords: Technology adoption, Artificial Intelligence, Machine Learning Barriers, TOE Framework, Operation Management, Forecasting

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Table of Abbreviations

AI	Artificial Intelligence
AGI	Artificial General Intelligence
ANI	Artificial Narrow Intelligence
ASI	Artificial Super Intelligence
DOI	Diffusion of Innovation
ERP	Enterprise Resource Planning
ML	Machine Learning
MPS	Master Production Planning
OM	Operation management
PM	Production Management
TAM	Technology Acceptance Model
TOE	Technology-Organizational-Environmental Framework

1. Introduction

Uncertainties surrounding the future of what is to come can be both intriguing as well as present various challenges for firms (Petropoulos et al., 2022). Thus, firms are looking into various techniques to be able to predict future scenarios and mitigate unforeseen challenges.

Processes such as forecasting have been at the forefront to aid firms to mitigate uncertainties as sufficient forecasting has been seen to aid in decision making, and the planning to predict future scenarios (Praveen et al., 2019). Forecasting is a process associated with and utilized in fields such as operation management, supply chain, and production management (Bag et al., 2021; Petropoulos et al., 2022; Sohrabpour et al., 2021). The prediction of the forecasting is based on past and current data that is used as input, which later produces the output (Petropoulos et al., 2022). The importance of forecasting competence has in recent years become even more important due to emergent events such as pandemics and wars (Nikolopoulos et al., 2021). To improve the forecast outcome, manufacturing firms are exploiting digital technology such as Artificial Intelligence (AI) with the ambition to enhance accuracy and performance (Emrouznejad et al., 2016).

Artificial intelligence is defined as "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"*(Kaplan & Haenlein, 2019, p. 5). Different AI techniques have grown tremendously, in the era of industry 4.0 (Wamba-Taguimdje et al., 2020). Recent literature reviews indicate that AI and specifically the subbranch of machine learning (ML) in the forecasting process, can improve decision making and provide more accurate predictions for production planning, leading to reduce costs and time savings (Emrouznejad et al., 2016). Furthermore, adopting AI creates a unique competitive edge for firms (Bag et al., 2021). A successful example of adopting Artificial Intelligence and Machine Learning (AI-ML) in forecasting is seen in the retail industry (Choi et al., 2018). optimizing inventory, reducing cost, as well time saving.

However, due to the complexity surrounding AI-ML technology manufacturing firms are still struggling in adopting technology into their production processes (Kinkel et al., 2021). The struggles emerge due to the lack of adequate resources and competence to handle AI-ML (Bag et al., 2021; Kinkel et al., 2021). As well as the research on AI-ML adoption can still be seen to be in its infancy, and practitioners and scholars lack knowledge and techniques as to how AI-ML can be adopted, and how the barriers in AI adoption can be mitigated (Jöhnk et al., 2021). The literature provides a long list of barriers that in AI-ML adoption such as poor data, firms having a lack of digital infrastructure, top management support, and involvement, as well the partnership with different actors (Chatterjee et al., 2021; Enholm et al., 2021; Mahmud et al., 2022; Mikalef & Gupta, 2021).

1.1. Problem statement and Research gap

The research on technology adoption has been studied for decades, thus, the literature provides several different theoretical frameworks to best suit the context of the study and to help the researcher identify the enablers and barriers of technology adoption (Kamble et al., 2021; Kinkel et al., 2021). Technology adoption is seen as a stage-based process consisting of more than one stage (Hameed et al., 2012; Yu & Tao, 2009). However, studies do not in most cases narrow down and focus on a specific phase, rather the research shows a focus on a more holistic approach focusing on the factors that act as enablers and barriers (Chatterjee et al., 2021; Neumann et al., 2022). The research conducted by Hameed et al (2012), analysed over 100 studies of technology adoption, and the revisit made by Caron-Fasan et al. (2020) to Hameed et al. (2012), showed that the pre-adoption stage is underrepresented. Furthermore, technology adoption is studied in either the individual or organizational setting, where in the case of this thesis, organizational is referred to as a firm setting. The research on technology adoption at the firm level is less researched than compared to the individual level (Alsheibani et al., 2019; Bag et al., 2021). Thus, the first gap addressed in the thesis will be to focus on a specific phase in the technology adoption, such as the pre-adoption phase and at the firm level.

Furthermore, the studies on AI adoption in manufacturing are scarce, in which studies today have mostly focused on the potential benefits there is to be had by adopting the technology (Kinkel et al., 2021). Stornelli et al., (2021) further claim that research on technology adoption, of advanced technologies, has primarily focused on the enablers and less on the barriers. Barriers related to AI adoption can consist of poor data quality and inappropriate technology infrastructure (Mikalef & Gupta, 2021). The lack of management support and partnership between the firm and internal and external actors are a few of the barriers identified in the literature (Bag et al., 2021; Kinkel et al., 2021; Merhi, 2021; Stornelli et al., 2021). Furthermore, as stated by Jöhnk et al. (2021) given that research on AI adoption is still in its infancy, practitioners and research lack mitigation actions to deal with the supposed barriers. Thus, the research aims to fill a second gap by identifying the barriers in a manufacturing firm when looking at the pre-adoption phase of AI and how to mitigate these challenges.

Notably, AI is considered an umbrella term consisting of several different subbranches (Mutasa et al., 2020; Taylor et al., 2018). Research has shown that adopting AI technology and specifically the subbranch of machine learning (ML) to aid in managerial tasks in the operation management (OM) field, such as forecasting has been seen to be beneficial, dues highly sought to research further (Bag et al., 2021; Choi et al., 2018; Dhamija & Bag, 2020). Forecasting has been at the forefront of decision-making and planning for production (Petropoulos et al., 2022). Furthermore, due to the recent pandemic crisis and wars, the interest and need to possess great forecasting capabilities have grown (Nikolopoulos et al., 2021).

To enable great forecasting prediction the utilization of a large amount of data needs to be provided (Fattah et al., 2018; Kilimci et al., 2019). Due to that in recent decades, the accessibility of data has increased greater possibilities with AI-ML adopted in the forecasting process can be had (Enholm et al., 2021). As previously stated, AI-ML adoption in the forecasting process has led to greater decision-making capabilities. As well as increase the firm's efficiency, reducing cost and leading to leverage competitive advantage (Anil Kumar & Suresh, 2008; Choi et al., 2018). However, Petropoulos et al. (2022) state that more research is needed to investigate the usefulness of forecasting using AI-ML.

Given the considerable benefits previously mentioned there are to be had when utilizing an effective forecasting process. Additionally with the increased relevance and need for accurate forecasting, due factors such as the recent pandemic crises and wars. As well as the need for further investigation of AI-ML's usefulness in forecasting. One would consider it intriguing to investigate the AI pre-adoption barriers faced in a manufacturing firm, and how the identified barriers can be mitigated. This type of research can be done by conducting a single case study at a manufacturing firm that is currently in the pre-adoption phase of AI.

1.2. Research delimitations

As previously stated, Artificial Intelligence is considered an umbrella term, that includes different subbranches of technologies, in which depending on the task one technology may be best suited for that specific task. The thesis will give the reader an overview of AI technology and focuses on the most prominent subbranch of AI adopted in the forecasting process known as machine learning (ML). Furthermore, the research focus will be on a specific phase in the technology adoption study (pre-adoption), due to the early firm collaboration as well of the lack of research earlier identified. Additionally, one specific industry is focused on (manufacturing) and a specific process (forecasting). This is due increase the research on AI adoption in manufacturing firms, while focusing on a hot topic forecasting.

The firm chosen needs to fit these criteria, as the research aims to gain insight into the phenomena of AI pre-adoption in the forecasting process. To answer the research question, I have chosen a case study dealing with a specific firm. For privacy reasons I cannot give the name of the firm, so I will simply refer to it as "firm X" throughout this thesis.

1.3. Purpose and Research Question

The purpose of this thesis is to first, research the barriers that a manufacturing firm encounter in the AI pre-adoption phase focused on the operation management field based on the literature. What barriers are relevant in the forecasting process for the specific firm, and how the firm would mitigate the identified barriers for the forecasting process.

Thus, from the introduction, problem statement, research delimitation, and purpose the following research question is created:

RQ: How does a manufacturing firm mitigate AI pre-adoption barriers in the forecasting process?

1.4. Thesis Layout

In chapter 1 the reader got an introduction to the topic studied in the thesis, furthermore, what the gap, purpose, and the question the research aims to answer. In chapter 2 the reader will dive into the literature part of the research as well as what will be the theoretical framework utilized in this thesis. Chapter 3 provides the reader with the method chosen to answer the research question as well as the data collection, and the quality of the research. Chapter 4 presents the empirical findings and Chapter 5 the analysis and discussion of the study. Furthermore, Chapter 6, draws the thesis to an end with a conclusion, showing the key findings, followed by the theoretical and managerial implications, as well as the limitations of the study conducted and the suggestion for further research.

2. Scoping Literature Review

The following section aims to provide an in-depth explanation and understanding of the phenomenon studied in the thesis regarding pertinent pre-adoption barriers within AI-ML implementation and its use in the forecasting process.

The first section will explain the basics of AI followed by a deeper explanation of the subbranch of AI machine learning. The next section focuses on the technology in the context of operation management (OM) and provides the reader with a brief explanation of what OM implies and the process of forecasting.

After the chapter about AI-ML in the context of operation management. The topic of technology adoption in the context of AI is described. Presenting the different frameworks existing when studying technology adoption. This is followed by an in-depth explanation of the chosen framework (TOE) utilized in the thesis, followed by a brief definition of what the pre-adoption phase means in the context of this thesis. Ending the literature part with the barriers discovered of AI adoption, in which the barriers are categorized following the theoretical framework TOE.

It is important to note particular attention will be drawn to the forecasting process. Furthermore, this research centers on the pre-adoption phase which implies that other phases are not deeply investigated in this thesis.

2.1. Artificial Intelligence (AI)

Artificial intelligence is not considered a new technology, the technology was introduced as early as the 1950s by John McCarthy (Lee et al., 2019). However, due to the emergence of industry 4.0 and the recent accessibility to massive amounts of data often referred to as big data, new opportunities for the technology have come forth, due to that data can be considered to be the core that drives AI (Enholm et al., 2021; Govindan, 2022; Kinkel et al., 2021). Thus researchers, as well as firms, have found a new interest in studying the phenomena of AI (Bag et al., 2021; Chatterjee et al., 2021; Enholm et al., 2021; Kinkel et al., 2021)

Despite the technology of AI existing for a long time as well as the increased interest in the field in the recent decade, the lack of all-around accepted definition regards to Artificial intelligence still exists (Enholm et al., 2021; Mikalef & Gupta, 2021). Table 1 gives an overview of some of the definitions of AI identified in the literature.

Table 1. Definitions of Artificial Intelligence.

Definition of Artificial Intelligence	**Sources**
"Define AI as an assemblage of technological components that collect, process, and act on data in ways that simulate human intelligence"	(Canhoto & Clear, 2020, p. 184)
"A *system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"*	(Kaplan & Haenlein, 2019, p. 5)
"Computer and applications that sense, comprehend, act and learn"	(Kolbjørnsrud et al., 2017, p. 1)
"Artificial intelligence (AI) Intelligent systems created to use data, analysis and observations to perform certain tasks without needing to be programmed to do so"	(Lee et al., 2019, p. 1)
"*The endeavour to mimic cognitive and human capabilities on computers"*	(Schmidt et al., 2020, p. 2)

However, to fully grasp the notion of AI Enholm et al. (2021) state that each word needs to be looked at separately. Thus, the word Artificial can be described as something that is created by humans and does not come into being naturally (Enholm et al., 2021; Shrestha et al., 2019). While on the other hand, the word Intelligence refers to the notion of different mental activities that include learning, reasoning, and understanding (Cao et al., 2021; Enholm et al., 2021; Shrestha et al., 2019). For the context of this thesis, the following definition is seen as most appropriate; AI is "*a system's ability to interpret external data correctly, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation"*(Kaplan & Haenlein, 2019, p. 5). The definition is utilized as it captures the essence of what AI is, and what the thesis is focusing on. The definition does this by bringing up the notion of data that it can learn from data, as well as the adoption of AI is used to achieve a specific goal, in this case, to be adopted into the forecasting process.

Furthermore, AI technology can be divided into different stages such as weak/narrow AI (ANI), general/deep AI (AGI), and super AI (ASI) (Riahi et al., 2021; Shrestha et al., 2019). The term Artificial general intelligence refers to AI machines that can perform any type of task successfully equal to a human, while ASI refers to a computer system that can outperform even the most talented humans (Núñez-Corrales & Jakobsson, 2021; Riahi et al., 2021; Shrestha et al., 2019). However, this type of AI does not exist, and research implies that the stage of AGI will take several years to mature (Riahi et al., 2021; Shrestha et al., 2019). Therefore weak/narrow AI (ANI) is the current stage that is active today in the industry. Artificial narrow intelligence can be described as goal-orientated, which is designed to execute only singular tasks extremely well (McLean et al., 2021; Riahi et al., 2021; Shrestha et al., 2019).

AI can be considered an umbrella term consisting of several different subbranches (Ikumoro & Jawad, 2019; Mahmud et al., 2022; Mikalef & Gupta, 2021; Riahi et al., 2021). These subbranches consists of different technologies and techniques that are connected to the AI term. In which the user chooses the technology best suited for the specified task. Thus, the different technologies and techniques within AI that can be implemented in organizations to aid in a variety of different functions (Kinkel et al., 2021; Mahmud et al., 2022; Rodríguez-Espíndola et al., 2022). Figure 1 provides a classification of the different technologies associated with AI.

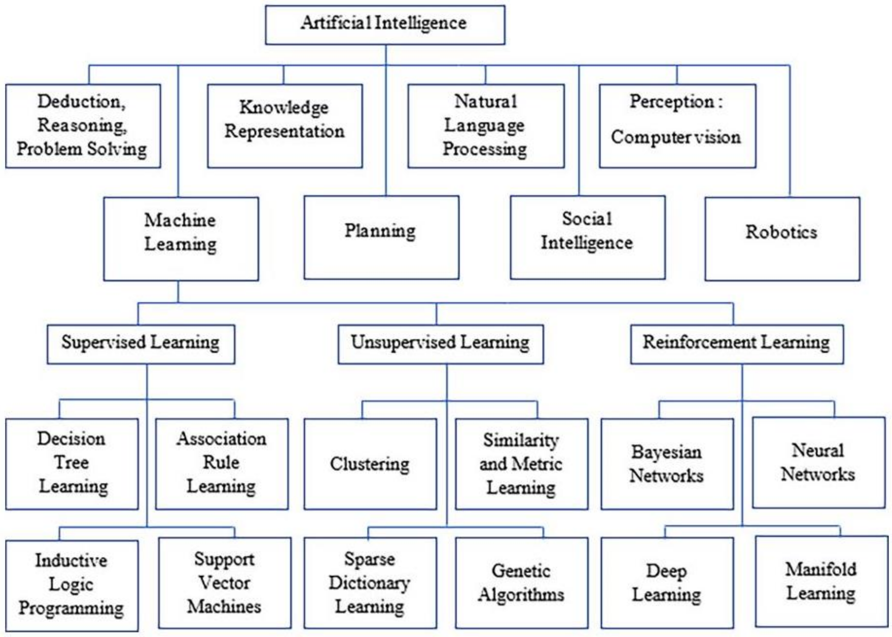

Figure 1. Shows Artificial Intelligence Classification.

Note. From *Artificial intelligence applications in supply chain: A descriptive bibliometric analysis and future research directions* (p.13), by Y. Riahi., T. Saikouk., A. Gunasekaran., & I. Badraoui, 2021, Expert Systems with Applications (https://doi.org/10.1016/j.eswa.2021.114702). Copyright 2021 by International Journal Expert Systems with Applications.

Figure 1 displays several AI technologies. The term machine learning (ML) is considered by far as one of the most utilized technologies associated with AI (Allen, 2019; Chatterjee et al., 2021; Enholm et al., 2021; Kinkel et al., 2021).

2.1.1. Machine Learning (ML)

To emphasize a single definition of machine learning is difficult as it also encompasses several different aspects (Bertolini et al., 2021). Table 2 presents three definitions of ML.

Table 2. Definitions of Machine Learning.

Definitions of Machine learning	**Sources**
"Machine learning is a type of artificial intelligence; in machine learning, computers learn patterns from data"	(Allen, 2019, p. 38)
"A set of methods that can automatically detect patterns in data, and then use the uncovered patterns to predict future data, or to perform other kinds of decision making under uncertainty"	(Hutchinson, 2021, p. 631)
"Machine learning is automatic learning: machines learn' from the datasets offered to them"	(Wamba-Taguimdje et al., 2020, p. 5)

Furthermore, as previously stated ML is a subset of AI, in which in the case of this thesis ML can be referred to as computer systems that can utilize different methods to learn, predict and aid in the decision making processes under uncertain conditions (Allen, 2019; Bag et al., 2021; Bertolini et al., 2021; Chatterjee et al., 2021; Cubric, 2020; Hutchinson, 2021; Kinkel et al., 2021; Lee et al., 2019; Mahmud et al., 2022; Wamba-Taguimdje et al., 2020). According to Lee et al. (2019) ML uses different algorithms to improve its learning capabilities to complete its specific set of tasks. These algorithms work to mimic the human brain (Lee et al., 2019; Mathews, 2019). Furthermore, there are different types of ML such as supervised, unsupervised, and reinforcement learning (Canhoto & Clear, 2020; Kinkel et al., 2021; Lee et al., 2019). Supervised learning utilizes label-trained data to train the ML model, while unsupervised learning refers to one data system that does not require label data or the involvement of human intervention (Kinkel et al., 2021; Lee et al., 2019). Reinforcement learning is founded on the actions that gain positive or negative reinforcement for the desired goal put on by the organization, this type is usually utilized to improve production processes (Haefner et al., 2021; Kinkel et al., 2021; Lee et al., 2019).

Furthermore, machine learning requires a large amount of data to complete the different tasks and to provide accurate and trustworthy results (Bag et al., 2021; Kinkel et al., 2021; Roh et al., 2021). The word describing different types of data is often associated with big data and access to this type of data is a strong driving force for adopting AI-ML in firms (Bag et al., 2021; Kinkel et al., 2021). When describing big data it is commonly associated with the 3Vs, Velocity, Variety, and Volume (Bag et al., 2021; Merhi, 2021; Rodríguez-Espíndola et al., 2022). Velocity is associated with the speed of the data generated (Kitchin & McArdle, 2016; Merhi, 2021). Variety displays the complexity and the models behind the data, and finally, volume refers to the amount of data (Buhl et al., 2013; Merhi, 2021). In the paper written by Allen, (2019) he provides five lessons for adopting ML. While also indicating what data factors firms need to look for when adopting ML such as *"Is the data accessible?", "Is the data sizeable enough?", "Is the data useable?", "Is the data understandable?",* and finally *"Is the data maintainable?"*(Allen, 2019, p. 40). These factors can be considered adoption barriers for AI-ML and will be explained in more detail in section 2.6.

On a final note, AI has been seen to be prominent in a variety of different fields such as education, governmental, healthcare, manufacturing, digital imaging, supply chain, and operation management as well as several other fields (Bag et al., 2021; Chatterjee et al., 2021; Grover et al., 2022; Kinkel et al., 2021; Mikalef & Gupta, 2021; Rodríguez-Espíndola et al., 2022; Sohrabpour et al., 2021; Wamba-Taguimdje et al., 2020).

2.2. Artificial Intelligence and Operation Management

Operation management (OM) can also be referred to as production management (PM) (Holstein, 2022). OM can be defined as *"end-to-end organizational management activities service chains"* (Grover et al., 2022, p.2) OM/PM is in charge of various tasks that can be considered both challenging and complex (Dhamija & Bag, 2020; Dubey et al., 2020). Some of these activities are product design, production processes, producing goods, planning, and scheduling (Grover et al., 2022; Lee et al., 2019). The production process can include many different tasks such as the master production planning (MPS), which is a schedule showing each week what must be produced to meet the demand forecast (Anil Kumar & Suresh, 2008). When performing a MPS factors such as the resource requirements, material requirements, and capacity requirements are looked at (Anil Kumar & Suresh, 2008; Ernani Vieira & Ribas, 2004). However, even if the production planning is done to the last minute, it is still next to impossible to achieve 100% perfect execution according to the set plan As various unforeseen factors can come to impact the planning. (Anil Kumar & Suresh, 2008).

AI-ML adoption in OM has proven to be extremely fruitful and beneficial for organizations (Bag et al., 2021; Chatterjee et al., 2021; Kinkel et al., 2021). Fields included in the OM such as forecasting, inventory, finance, logistics, and supply chain management has seen to benefit greatly from the adoption of AI technology (Bag et al., 2021; Chatterjee et al., 2021; Dubey et al., 2020). Due to that the technology can help managers in their decision-making process, optimize time and inventory planning. The adoption of AI-ML in these various fields is due to the recent accessibility of data (Chatterjee et al., 2021; Choi et al., 2018). Processes such as forecasting rely heavily on historical data and given the recent access and data increase, It has allowed for improved forecasting capabilities when adopting AI-ML (Choi et al., 2018; Sohrabpour et al., 2021).

2.2.1. Artificial Intelligence on Forecasting

The thesis focuses on a specific process when it comes to AI-ML adoption. Thus, the following section will provide the reader with the purpose and definition of forecasting. Furthermore, its relation forecasting has to OM and AI-ML technology

The purpose of forecasting is defined as to "inform the process of planning future actions" (Ord et al., 2017, p. 3). Where planning is defined as "develop a course of action so that current activates don't just continue based on a no-change forecast" (Ord et al., 2017, p. 3). The purpose is further described by Emrouznejad et al. (2016), as the term forecasting is as a way to help decision makers such as managers to make plans in the present that can predict possible future scenarios. The traditional means of conducting forecasting is using statistical models or a judgemental approach, where the statistical approach utilizes data and the judgemental approach is more human-based (Fattah et al., 2018; Ord et al., 2017). When it comes to utilizing technical tools, today there exist several sophisticated forecasting techniques such as machine learning and data mining (Emrouznejad et al., 2016; Lalmuanawma et al., 2020). However, it is important to note before choosing a more sophisticated method such as ML, one must ask themselves "do we have the necessary data?" or will it be more beneficial to go for the judgemental approach, if so, is the decision group based or individual. Furthermore, The choice of the method is commonly based on one critical criterion, such as what enables the highest accuracy of result (Emrouznejad et al., 2016). To make the predictions forecasting utilizes a significant amount of data and most commonly historical data (Fattah et al., 2018; Kilimci et al., 2019).

Good forecasting is highly sought after in firm-related fields such as operation management, supply chain, and production management. Firms that lack adequate forecasting capabilities have been seen to create unnecessary costs to arise and lowered customer satisfaction (Petropoulos et al., 2022). Firms improving their forecasting capabilities have also been shown to create greater competitive advantage (Kinkel et al., 2021). Furthermore, due to recent pandemic crises such as Covid-19 strong forecasting capabilities are becoming even more crucial (Nikolopoulos et al., 2021). As it helps to better plan and predict the necessary resources and demands needed to meet for example consumer demands.

As previously discussed in section 2.1 the most common subbranch associated with AI is ML. Firms looking to improve their forecasting processes are using AI technology such as ML and big data to make more sufficient and accurate predictions and to aid OM and the supply chain in their various challenges (Bueno et al., 2020; Petropoulos et al., 2022; Riahi et al., 2021).

A case that shows the successful use of forecasting can be seen in the example of the retail industry from the firm Rue La La, which has benefited from AI-ML adoption in its demand forecasting process. This leads to inventory and price optimization as well as increased revenue and stronger predictions by aiding in the decision-making process (Choi et al., 2018).

Thus, having AI-ML adopted in areas such as forecasting will aid OM in creating more accurate production planning, reducing cost, and allowing the firms to efficiently make use of various resources (Bag et al., 2021; Choi et al., 2018; Dhamija & Bag, 2020).

2.3. Technology innovation adoption of AI-ML

The primary focus of this thesis is to explore the barriers manufacturing firms face when adopting innovative technologies such as AI into specific OM tasks such as forecasting production planning and how a firm can mitigate these barriers. It is considered important to give a clear definition of what technology adoption refers to in the context of this research.

The definition of technology adoption in the context of this thesis is derived from the following authors (Connally & Morris, 2017; Hassan, 2018; Tatnall & Burgess, 2009; Umapathy, 2009), which say; that technology adoption is a decision process of which an organization in the end commits, utilizes, implements, and invests to help in core business activities.

The literature on technology adoption in the context of AI has primarily focused on the specific characteristics that influence the adoption (Kinkel et al., 2021). However, there are several other factors needed to be taken into consideration, when looking at technology adoption of new and advanced technologies (Chatterjee et al., 2021; Kinkel et al., 2021). Today there is an extensive amount of different technology adoption theories such as the Technology Acceptance Model (TAM), Diffusion of Innovation (DOI), and Technological-Organizational-Environmental framework (TOE) (Baker, 2011; Kinkel et al., 2021). All of these theories have proven to be a great asset in the study of technology adoption for advanced digital technologies (Al Hadwer et al., 2021; Bag et al., 2021; Ikumoro & Jawad, 2019; Kamble et al., 2021; Kinkel et al., 2021)

Furthermore, technology adoption can be studied at different levels. Research on technology adoption at the individual level uses theories such as TAM (Baker, 2011; Kinkel et al., 2021). The TAM model was developed by Davis (1989) *"to understand the factors influencing the intention and use of technology"* (Chatterjee et al., 2021, p. 2). However, researchers indicate the study of AI technology adoption in the individual setting is considered more common and well researched compared when looking at technology adoption at the firm level (Enholm et al., 2021; Kinkel et al., 2021). As this research focuses on the firm level and the intentions as to why the technology wants to be adopted are already defined in the thesis, the TAM framework is not seen as suitable for this research.

When it comes to studying technology adoption at the firm level the most-used adoption framework has been the Technology-Organizational-Environmental framework (TOE) (Baker, 2011; Chatterjee et al., 2021; Enholm et al., 2021; Ikumoro & Jawad, 2019; Kinkel et al., 2021). As well as the Diffusion Of Innovation (DOI) (Baker, 2011; Kinkel et al., 2021). However, there exist certain aspects in which the two frameworks differ. According to Al Hadwer et al., (2021) the TOE framework was created by Tornatzky & Fleischer (1990) to explain the different organizational elements that affect the decision to adopt new technology. This is done by dividing it into three different factors technological, organizational, and environmental. While the DOI theory introduced by Rogers (2003) focuses primarily on specific attributes that enable the possibility for adoption and what the perceived benefits of adopting the technology (Al Hadwer et al., 2021). Furthermore, the DOI theory is used to explain the diffusion process (Correia Simões et al., 2020). The TOE framework shows to be more prominent and strong already on its own (Al Hadwer et al., 2021; Baker, 2011; Hradecky et al., 2022; Kinkel et al., 2021). Due to that it already takes into consideration several of the aspect already discussed in the DOI theory while also indicating and emphasizing on the environmental factors that influence the adoption (Al Hadwer et al., 2021; Baker, 2011; Kinkel et al., 2021).

It is important to note a common practice within the literature is to combine the TOE framework with other adoption theories as this can act as a complement to each other (Al Hadwer et al., 2021; Chatterjee et al., 2021). Integrating for example the TOE and DOI, or TOE and TAM theory into one framework may be beneficial in some cases (Al Hadwer et al., 2021; Chatterjee et al., 2021; H. Chen et al., 2021; Kamble et al., 2021; Nilashi et al., 2016). However, Firstly, due to the simplicity, flexibility, and categorization of the three essential factors affecting adoption, the TOE framework can be seen as suitable for this research. Secondly, the thesis aims to firstly the barriers associated with AI adoption in the firm level, The TOE frameworks provide a base line as how the scholar can categorize factors related to adoption in a simplistic way, additionally help with the structure of the question formulated in a later stage. Furthermore, as previously stated the TAM model is communally utilized in the individual setting, and this thesis focus on the firm level. Furthermore, the TOE framework already takes into account several of the factors in the DOI, and therefore TOE is sufficient enough for the context of this thesis.

2.4. The TOE Framework

The Technology – Organizational- Environmental-framework (TOE) was first introduced in the book published by Tornatzky & Fleischer (1990). The framework is seen as a firm-level theory that discusses technology adoption focused on three different types of factors; technology, organization, and environmental (Chatterjee et al., 2021; Kinkel et al., 2021; Pillai et al., 2021; Wang et al., 2010). The technological context refers to both the external and internal technologies that are of interest or have an impact on the firm (Al Hadwer et al., 2021; Dwivedi et al., 2012; Wang et al., 2010). The organizational context focus on what attributes or resources an organization has that can either be seen as a potential enabler or barrier to new technology adoption (Al Hadwer et al., 2021; Nilashi et al., 2016; Wang et al., 2010). The Environmental context of the framework focus on the external factors that can impact technology adoption (Pillai et al., 2021). It's important to note that the TOE framework does not explicitly name the potential factors that influence technology adoption instead it organizes it to fit within the three different contexts previously stated. A generic structure of the TOE framework is given in figure 2.

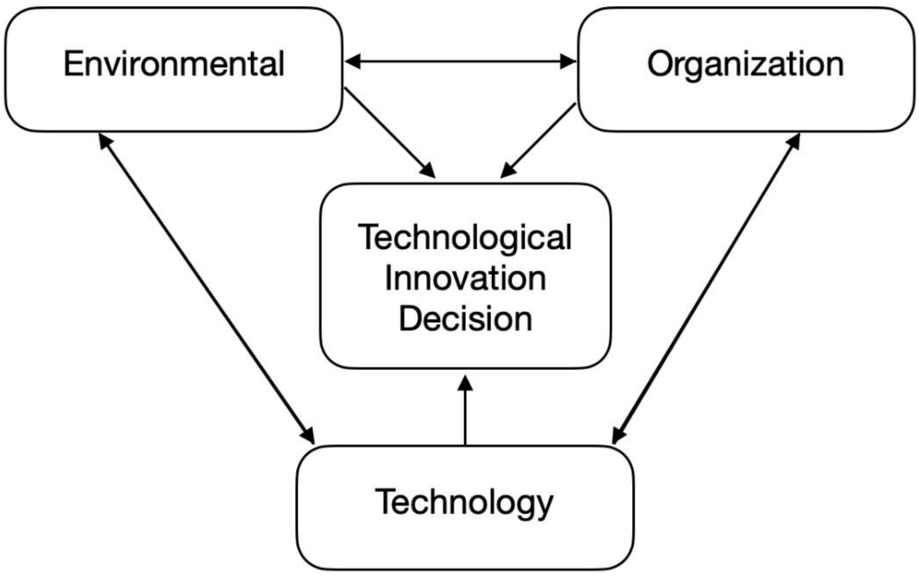

Figure 2. Shows the TOE-Framework, adopted from Tornatzky & Fleischer (1990).

Utilizing the TOE framework has proven to be fruitful when studying the adoption of highly advanced technologies (Chatterjee et al., 2021). The framework has been applied in the context of cloud-based technology adoption, Radio frequency Identification, blockchain adoption, e-commerce, and several other contexts (Al Hadwer et al., 2021; Ikumoro & Jawad, 2019; Kamble et al., 2021; Wang et al., 2010). Additonally, and most importantly the TOE framework has also proven to be useful in different contexts when studying AI adoption, such as digital manufacturing, telecom industry, organizational AI adoption, and value creation in the supply chain

(Chatterjee et al., 2021; D. Q. Chen et al., 2015; H. Chen et al., 2021; Kinkel et al., 2021).

Thus, utilizing the TOE framework for the context of this thesis is suitable. As it has a proven track record for its useability in the study of technology adoption and it focuses on the primary factors studied in the thesis.

2.5. Pre-Adoption phase in technology innovation adoption

As the thesis focuses on a specific phase in the adoption process, hence the pre-adoption phase. The following section will explain and define the pre-adoption phase in the case of this thesis.

According to Sohn & Kwon (2020), intelligent products such as artificial intelligence can be classified as innovative IT products. When studying IT adoption, the literature indicates it to be widely recognized and studied as a three-stage process (Baker, 2011; Caron-Fasan et al., 2020; Pierce & Delbecq, 1977).

The three stages are described as phase one *initiation*, phase two *adoption-decision*, and phase three *implementation*. These phases also go under different names such as *pre-adoption*, *adoption-decision*, and *post-adoption* (Hameed et al., 2012). In the case of IT adoption, Hameed et al (2012) defined the following pre-adoption stage to include activities such as; recognizing a need, acquiring knowledge or awareness, formulating an opinion of the innovation, and finally proposing the innovation for adoption. However, it can be equally important to also assess factors such as the financial aspect in the pre-adoption phase (Quagli et al., 2021). Hameed et al. (2012) stated it is more an aspect in the second stage called adoption decision.

Research conducted by Stornelli et al. (2021) investigate the different enablers and barriers and their association with the different stages of an innovation adoption process. In the pre-adoption phase factors referring to both the technological, organizational, and environmental aspect was found to be important. Factors such as technology issues, economical constraints, and partnership to name a few were seen as relevant factors in the pre-adoption phase.

As this research studies AI-ML adoption in manufacturing firms utilizing the TOE framework, in which the barriers are classified into three different factors. A broader perspective of the pre-adoption phase will be taken into consideration. Factors such as resource allocation will also be taken into consideration in the pre-adoption phase described by Hradecky et al. (2022), studying AI readiness and adoption utilizing the TOE framework.

On a final note the research conducted by Hameed et al. (2012), showed that out of the 111 analysed studies only five focused on the pre-adoption stage.

2.6. Key factors influencing the adoption of AI technology in manufacturing firms.

As previously stated, there exist different frameworks that are being utilized to study the technology adoption of AI in different settings.

This study focuses on identifying the barriers a manufacturing firm is faced with when it comes to the adoption of AI-ML technology and how these barriers are mitigated. Performing a scoping literature review enables one to find out the potential challenges that are currently being discussed regarding AI-ML technology adoption. From the information gathered from the literature review, a new table can be created displaying the key factors that influence AI adoption in the context that is being studied in the thesis. The scoping literature review is done by utilizing two databases Scopus and Google Scholar. The data bases are utilized to find relevant articles on the matter of AI-ML adoption.

Furthermore, the different barriers are split and categorized following the TOE Framework. Thus, in the newly developed Table 3 appropriate names have been chosen to enable the clustering of different definitions. Table 3 presents an overview of the identified adoption barriers in the literature related to AI adoption.

Following the summary of Table 3. Each context will be presented with its own table of identified barriers followed by an in-depth explanation of each barrier.

Table 3. Presents barriers for AI adoption in accordance with the TOE - Framework.

Technological	Organizational	Environmental
T1. Poor Data • Quality • Access • Volume **T2. Inappropriate technology infrastructure** • Computing power • Digital platform • Digital infrastructure • Interoperability • Algorithms	**O1. Organizational Culture** • Flexibility • Goal compatibility **O2. Top Management** • Involvement • Support **O3. Organizational Readiness** • Economic • Competence **O4. AI Acceptance** • Trust in the technology **O5. Compatibility** • Compatibility between the technology and organization	**E1. Partnership** • IT collaboration • Supplier collaboration **E2. Regulations** • Industrial policies • Governmental regulations

2.5.1. Technological Context

T1. Data

According to Enholm et al. (2021), data can be seen as the core of AI and the lack of data has been proven to be a significant barrier when it comes to firms aiming to adopt AI technology (Cubric, 2020; Kinkel et al., 2021; Lee et al., 2019; Mahmud et al., 2022; Merhi, 2021; Mikalef & Gupta, 2021; Rodríguez-Espíndola et al., 2022; Stornelli et al., 2021; Wamba-Taguimdje et al., 2020, 2020).

The term T1. describes data and refers to the following; Quality, access, and the amount of data (Allen, 2019; Enholm et al., 2021; Merhi, 2021; Mikalef & Gupta, 2021). Quality data focus on the useability and the degree to which the data is understandable (Enholm et al., 2021; Merhi, 2021). Mikalef & Gupta, (2021) states that having access to high-quality data is critical as it is used to train the AI system. Access to data can be defined in two ways internally and externally. Mikalef & Gupta, (2021) state that access to internal data can be referred to as all the data created in the organization such as accounting, sales, human resources management, manufacturing, and production. The external data is seen as the data that is not necessarily needed to be connected to the firm's operation but data that can create novel and deeper insight (Mikalef & Gupta, 2021). However, to create quality data, the authors Mikalef & Gupta (2021), and Kshetri (2021) state, that data needs to be labelled appropriately and filtered otherwise, the results may become biased.

Tools such as machine learning (ML) require a massive amount of data to perform and aid in managerial challenges (Allen, 2019; Bag et al., 2021; Kinkel et al., 2021). By providing ML tools with a high amount of low-quality data the accuracy, reliability, and useability of the result become questionable. Thus, being able to filter the noisy data and manage a large amount of data to create none bias, high accuracy, and reliable results is a significant barrier faced by the organization and effective strategies are needed in the quest for AI adoption (Mikalef & Gupta, 2021).

T2. Inappropriate technology infrastructure

The next barrier that influences AI adoption is the inappropriate technology infrastructure, which refers to a firm's lack of the appropriate digital platform and infrastructure that can facilitate the necessary computing power, large storage space for the massive amount of data, as well as the communication between different datasets (Allen, 2019; Cubric, 2020; Enholm et al., 2021; Kinkel et al., 2021; Merhi, 2021).

A digital platform can be described as *"a set of digital resources-including services and content-that enable value-creating-interactions between external producers and consumers"*(Constantinides et al., 2018, p.381). This means that the digital platform does not necessarily have to contain physical assets, rather the digital platform can be seen as an ecosystem model which contains several different systems that communicate with each other (Constantinides et al., 2018; Merhi, 2021).

Furthermore, Constantinides et al., (2018) state that digital platforms are built on top of digital infrastructures, which can be described as *"the computing network and resources that allow multiple stakeholders to orchestrate their service and content needs"*(Constantinides et al., 2018, p.381). As in the case of AI technology adoption, the integration with other computing systems can be seen as vital as it will allow the user to collect and share data from different institutions more sufficient (Merhi, 2021).

AI-ML uses different algorithms to solve a variety of tasks (Allen, 2019; Enholm et al., 2021; Kinkel et al., 2021). To provide accurate and reliable results/output these algorithms can start to become highly complex requiring a massive amount of computing power and space for the data sets (Allen, 2019; Enholm et al., 2021; Hutchinson, 2021; Kinkel et al., 2021; Mahmud et al., 2022; Wamba-Taguimdje et al., 2020). Firms utilizing an appropriate digital platform and infrastructure can meet these demands as they can communicate, share data, and knowledge, and free up access to store a large amount of data (Enholm et al., 2021; Merhi, 2021). However, knowing how to facilitate an organization with the appropriate infrastructure is a significant barrier faced by manufacturing firms, as well as how the different data sets will be able to communicate with each other (Enholm et al., 2021; Kinkel et al., 2021; Merhi, 2021; Wamba-Taguimdje et al., 2020).

In Table 2 all the authors mention the barrier of poor data, and inappropriate technology infrastructure referring to the technological context is presented.

Table 4. Presents the Technological AI adoption barriers identified in the literature.

Technological barrier	Sources
T1. Poor Data • Quality • Access • Volume	• Allen (2019) • Cubric (2020) • Dhamija et al. (2019) • Enholm et al. (2021) • Kinkel et.al. (2022) • Lee et al. (2019) • Mahmud et al. (2022) • Merhi (2021) • Mikalef & Gupta (2021) • Rodriguez-Espindola et al. (2022) • Stornelli et al. (2021) • Wamba-Taguinmdje et al. (2020)
T2 Inappropriate technology infrastructure • Computing power • Digital platform • Digital infrastructure • Interoperability • Algorithms	• Allen (2019) • Cubric (2020) • Enholm et al. (2021) • Hutchinson (2021) • Kinkel et al. (2022) • Lee et al. (2019) • Mahmud et al. (2022) • Merhi (2021) • Wamba-Taguinmdje et al. (2020)

2.5.2. Organizational Context

O1. Organizational Culture

According to the literature, the culture of the organization is another important influenceable factor when it comes to AI adoption (Bag et al., 2021; Chatterjee et al., 2021; Enholm et al., 2021; Fountaine et al., 2019; Kinkel et al., 2021; Merhi, 2021; Mikalef & Gupta, 2021; Rodríguez-Espíndola et al., 2022; Stornelli et al., 2021; Wamba-Taguimdje et al., 2020).

Culture refers to the flexibility, willingness, and values shared between the employees and the organization (Fountaine et al., 2019; Kinkel et al., 2021; Merhi, 2021). Organizational flexibility refers to a firm's ability to quickly adapt and integrate highly sophisticated technologies to respond to ever-changing business environments (Bag et al., 2021; Stornelli et al., 2021). As AI is seen as an innovative technology firm lacking an innovative culture is said to have it more difficult when trying to adopt digital technologies such as AI (Fountaine et al., 2019). This is due to those firms not possessing an innovative culture usually lacking employees that are more eager and willing to learn and utilize new and advanced technologies (Bag et al., 2021; Fountaine et al., 2019). Furthermore, organizations and employees not sharing the same values and goals will create significant barriers when it comes to adopting highly advanced technologies such as AI (Bag et al., 2021; Fountaine et al., 2019; Merhi, 2021). Thus, firms face significant barriers to facilitating the right organizational culture for successful AI adoption.

O2. Top Management support

A major barrier discussed in the literature when it comes to the adoption of AI in manufacturing firms is the lack of involvement and support from top management (Bag et al., 2021; Cao et al., 2021; Chatterjee et al., 2021; Enholm et al., 2021; Kinkel et al., 2021; Mahmud et al., 2022; Merhi, 2021; Mikalef & Gupta, 2021; Xing et al., 2021). Top management is said that it can influence different functions, such as the hiring and training of employees to possess the skills required to successfully use AI tools for managerial decisions making (Bag et al., 2021). Furthermore, top management can influence the structure of the organization as well as by allocating different resources and freeing up capital for the investment of AI (Bag et al., 2021; Enholm et al., 2021; Merhi, 2021). Thus, the lack of leadership support and involvement is seen as a significant barrier in the quest for technology adoption.

O3. Organizational readiness

Organizational readiness refers to the financial barriers and lack of employee competencies required for successful AI adoption (Bag et al., 2021; Chatterjee et al., 2021; Dhamija & Bag, 2020; Hutchinson, 2021; Kinkel et al., 2021; Lee et al., 2019; Merhi, 2021; Mikalef & Gupta, 2021; Stornelli et al., 2021; Wamba-Taguimdje et al., 2020). As AI is still in its development phase, integrating highly advanced technologies such as AI is costly and may not yield direct results when put in a short time frame (Bag et al., 2021; Kinkel et al., 2021).

Furthermore, as stated earlier AI is an innovative technology and requires a specific set of skills to understand, how to deal with and use the technology. Having a restricted budget hinders the exploration and time it takes to develop and adopt highly advanced technologies such as AI (Bag et al., 2021; Kinkel et al., 2021; Merhi, 2021; Stornelli et al., 2021). Furthermore, the hire and development of employees possessing the right skill set will be shut down due to budget constraints (Stornelli et al., 2021). This will impact the success of AI adoption, as successfully adopting AI technology into the organization the necessary skill set is seen as vital (Bag et al., 2021; Kinkel et al., 2021; Mikalef & Gupta, 2021). These skills include digital and soft skills (Kinkel et al., 2021). Which could be referred to as employees being able to deal with the AI algorithms and deal with the organizational infrastructure to facilitate these initiatives (Mikalef & Gupta, 2021).

Thus, organizations face significant barriers in the form of budget conflicts to free up the capital needed for investing in the possibility of AI adoption as well as the lack of competencies needed.

O4. AI acceptance

This barrier refers to the trust in the supposed outcome of the result using the AI system to operate and perform different tasks. As stated earlier adopting AI systems to aid in operations and supply chain tasks has proven to lead to more efficient and accurate results (Bag et al., 2021; Kinkel et al., 2021; Riahi et al., 2021; Sohrabpour et al., 2021). However, the data quality and quantity put into the AI machine has direct effects on the output (Cubric, 2020; Enholm et al., 2021; Kinkel et al., 2021). Firms face challenges when it comes to employees and managers being able to trust the supposed outcome produced by the highly advanced technology (Enholm et al., 2021; Merhi, 2021; Stornelli et al., 2021). Thus, employees and managers displaying distrust towards the technology create barriers for organizations looking to adopt the supposed technology and is an important obstacle that needs to be overcome.

O5. Compatibility

This barrier refers to the lack of existing suitability between the organization and the desired use of the technology, causing issues in its ability to early on create value and satisfy the need of the adopters (H. Chen et al., 2021). Chatterjee et al., 2021; Enholm et al., 2021; Merhi, 2021) state that firms that lack existing compatibility between the advanced digital technology and the task it is related to solving, find it less desirable to adopt the technology. This is due to the that the process of adopting highly advanced technology can lead to a change in business processes as well as the organizational design (Chatterjee et al., 2021; H. Chen et al., 2021; Kinkel et al., 2021, 2021; Pillai et al., 2021; Rodríguez-Espíndola et al., 2022). Furthermore, Chen et al., (2021) state that having the right IT environment compatible with the AI technology will reduce the cost and time involved for the adoption of the technology leading to that it is more desirable to adopt the innovative technology. Thus, firms knowing how to possess the right type of compatibility that suits the AI technology is considered a significant barrier in the quest for AI adoption.

In Table 3, all the authors mentioning the barriers related to the organizational context are presented and categorized according to its barrier.

Table 5. Presents the Organizational AI adoption barriers identified in the literature.

Organizational Barriers	Sources
O1. Organizational Culture • Flexibility • Goal compatibility	• Bag et al. (2021) • Chatterjee et al. (2021) • Enholm et.al. (2021) • Fountaine et al. (2019) • Kinkel et.al. (2022) • Merhi (2021) • Mikalef & Gupta (2021) • Rodriguez-Espindola et.al. (2022) • Stornelli et.al. (2021) • Wamba-Taguinmdje et.al. (2020)
O2. Top Management • Involvement • Support	• Bag et al. (2021) • Cao et al. (2021) • Chatterjee et al. (2021) • Enholm et al. (2021) • Kinkel et al. (2022) • Mahmud et al. (2022) • Merhi (2021) • Mikalef & Gupta (2021) • Rodriguez-Espindola et al. (2022) • Xing et al. (2021)
O3. Organizational Readiness • Economic • Competence	• Bag et al. (2021) • Chatterjee et al. (2021) • Chatterjee et al. (2021) • Chen et al. (2021) • Dhamija et al. (2019) • Hutchinson (2021) • Kinkel et.al. (2022) • Mahmud et al. (2022) • Merhi (2021) • Mikalef & Gupta (2021) • Stornelli et al. (2021) • Wamba-Taguinmdje et al. (2020)
O4. AI Acceptance • Trust in the technology	• Chatterjee et al. (2021) • Cubric (2020) • Enholm et al. (2021) • Fountaine et al. (2019) • Mahmud et al. (2022) • Merhi (2021) • Rodriguez-Espindola et al. (2022) • Stornelli et al. (2021)
O5. Compatibility • Compatibility between the technology and organization	• Chatterjee et al. (2021) • Enholm et al. (2021) • Kinkel et al. (2022) • Merhi (2021) • Pillai et al. (2021) • Rodriguez-Espindola et al. (2022)

2.5.3. Environmental Context

E1. Partnership

This barrier refers to firms lacking the necessary collaboration needed for successful AI adoption. Firms usually do not possess the needed number of technical requirements to understand and deal with sophisticated algorithms, Thus, external help from IT firms comes into the mix to aid in the adoption of technology (Chatterjee et al., 2021; H. Chen et al., 2021; Kinkel et al., 2021; Rodríguez-Espíndola et al., 2022). Furthermore, the lack of a good supplier relationship is also seen to be a barrier faced by firms looking to adopt AI technology (Chatterjee et al., 2021). As the suppliers can provide firms with quality and a large amount of data to feed the technical tools associated with the AI technology (Chatterjee et al., 2021; H. Chen et al., 2021). Thus, bad partnership collaboration can be seen as a considerable barrier faced when it comes to AI adoption.

E2. Regulations

Regulations refer to the governmental and individual industrial policies that affect the access to gather quality and necessary data amount needed for AI-ML adoption. AI can cause several conflicts when it comes to data security, and privacy (H. Chen et al., 2021). This means that AI requires either good legislation or a regulatory environment (H. Chen et al., 2021). This is further that Governments can reinforce new protection laws such as; The General Data Protection Regulation which affects access to public data (GDPR) (Constantinides et al., 2018). However, manufacturing firms may also face internal challenges in data access due to internal policies affecting the accessibility of data sharing (Bag et al., 2021; Stornelli et al., 2021). As stated, earlier AI requires a massive amount of quality data to produce trustworthy results. These issues are mentioned throughout the literature and mean having favourable governmental and internal industrial policies is thus considered a significant barrier in the AI-ML adoption process (Bag et al., 2021; H. Chen et al., 2021; Kinkel et al., 2021; Lee et al., 2019; Rodríguez-Espíndola et al., 2022; Stornelli et al., 2021; Xing et al., 2021).

In Table 4, all the authors discussing barriers related to the environmental context are presented. Categorized into each barrier.

Table 6. Presents the Environmental AI adoption barriers identified in the literature.

Environmental Barriers	Sources
E1. Partnership • IT collaboration • Supplier collaboration	• Chatterjee et al. (2021) • Chen et al (2021) • Kinkel et al. (2022) • Rodriguez-Espindola et al. (2022) • Stornelli et al. (2021)
E2. Regulations • Industrial policies • Governmental regulations	• Bag et al. (2021) • Chen et al. (2021) • Lee et al. (2019) • Rodriguez-Espindola et al. (2022) • Stornelli et al. (2021) • Xing et al (2021)

3. Method

The following chapter aims to provide the reader with an in-depth view of the method utilized to answer the following research question.

RQ: How does a manufacturing firm mitigate AI pre-adoption barriers in the forecasting process?

3.1. Research approach and case selection

3.1.1. Exploratory

Studies on AI technology has primarily focused on the potential benefits and value there is to be had by utilizing advanced digital technology (Kinkel et al., 2021). Not much research has been done exploring the barriers and enablers that influence AI adoption in manufacturing firms (Kinkel et al., 2021). Stornelli et al, (2021) state that the research on technology adoption has mostly focused on the enablers and less on the barriers. Jöhnk et al. (2021) state given that AI adoption is still considered to be in its infancy more research is needed to understand the phenomena, as well as find ways to mitigate AI adoption barriers. As this study focuses on a specific process in which to adopt AI technology, an exploratory study can be useful as it helps to clarify the understanding of the problem as well as if there is a point in pursuing it (Saunders et al., 2009). The study is exploratory in some respects due to the fact that the early collaboration with firm X and because of their specific needed, one needed to explore the literature and assess whether there was a point in pursuing the phenomena and as well gain an in-depth understanding of the problem and research field. From the exploration of the literature it was found that the literature had identified several barriers associated with AI adoption, but less on ways to mitigate these adoption challenges.

3.1.2. Qualitative study

A qualitative study is chosen as it was seen as most sufficient for the research being conducted in the thesis and effective study to follow to answer the research question. Due to that the research is a single case study that focuses on a specific firm in a specific process. The study conducts semi-structured in-depth interviews with the main participants involved in the forecasting process at the firm. To gain initial data to answer the research question and later a similar approach is used to validate the findings with an outside AI expert in the field of forecasting the needed data was collected. Quality data is also collected due to that following a qualitative study allows for more flexibility (Maxwell, 2009; Mills et al., 2010). The flexibility is important as it allows the participants to further develop their response to the interview questions as well as ask questions that arise from the participants. Furthermore, the question was asked in an open matter enabling the participants to explain their own experiences as to how they experience their current barriers and how they would be mitigated. Thus, new questions will be formed to further elaborate on the participant's response. It is worth note that it still followed the barriers identified within section 2.6.

In short, the semi-structured in-depth interviews were done to identify the relevant barriers associated with the pre-adoption of AI in the forecasting process and how they can be mitigated.

3.1.3. Single case study

Today, there exist several different research strategies such as case study, grounded theory, survey, action research, archival, and ethnography research (Saunders et al., 2009). A research strategy is utilized to aid the research to describe how the supposed to research question will be answered. To answer the proposed research question for this study a case study approach was adopted. The following chapter explains what a case study is a why it was seen as the most appropriate research strategy.

A case study is described as a research that focuses on a specific phenomenon in a real-life context (Denzin & Lincoln, 2011; Saunders et al., 2009). As the research was conducted in collaboration with a manufacturing firm looking to adopt AI-ML into their forecasting process. Furthermore, due to the recent pandemic process such as good forecasting has become even more relevant (Nikolopoulos et al., 2021). As well that forecasting has been at the forefront of decision making and planning (Petropoulos et al., 2022). Thus, the research is seen as to fulfils the criteria of studying a phenomenon in a real-life context.

When it comes to case study strategies they can be distinguished between four different dimensions (Saunders et al., 2009). The dimension is divided into a single-case design focusing on one specific case, a multiple-case design containing several different contexts, or an embedded single, and multiple-case design (Yin, 2014). The case study strategy I have chosen is to conduct a single case study, which can be considered one of the most frequently used strategies (Yin, 2014). The single case study approach was chosen firstly, due to the early collaboration made with the manufacturing firm. Secondly, the single case study approach was seen as most suitable as the thesis focused on a specific process such as forecasting, which allowed the researcher to fully emerge and get a deeper understanding of the components that affect the adoption of AI-ML in forecasting at a specific firm. As forecasting methods can vary depending on the firm (Ord et al., 2017). Thirdly, the study focuses on the pre-adoption stage of AI-ML technology, and how a firm in the following stage mitigates the identified barriers. It was seen as difficult to find other manufacturing firms being in the pre-stage, and also focused on the specific process, as the research that was conducted in given a short time horizon.

According to Saunders et al. (2009), a single case study is also utilized when representing a critical or unique case, and when conducting exploratory research. The choice of selecting a single case study instead of multiple cases is that a *"single case can represent the critical test of significant theory"*(Yin, 2014, p. 51). As well as a single case study can confirm, challenge or broaden the theory, increasing the possibility of further investigating the field of research (Yin, 2014). As the first part of this research is to investigate the critical AI pre-adoption barriers. The research can either challenge or confirm the barriers identified, which the research will also broaden the knowledge of how the identified barriers can be mitigated.

Yin (2014)**,** states that a single case study is also an appropriate choice of strategy under several different conditions, five of which he defined as, *critical, unusual, common, revelatory, or longitudinal* cases. In the case of the five-condition presented by Yin (2014), The research is seen as *critical*, firstly because it investigates a relevant topic such as AI technology, which as previously stated has in a recent decade become a more relevant and intriguing field for scholars and practitioners alike (Bag et al., 2021; Kinkel et al., 2021). Secondly, as stated by Jöhnk et al (2021) given that AI technology and the research on adoption is still in its infancy, the research on how firms mitigate AI adoption barriers is scarce and needs to explore. Thirdly, as stated by Kinkel et al (2021) the research on AI adoption in manufacturing firms is limited. Forth, the process of forecasting has been described as being at the forefront of decision making and planning (Petropoulos et al., 2022). As well as the potential benefits of adopting AI-ML technology in forecasting have had (Choi et al., 2018). It is critical to further extend the knowledge of what firms can do to mitigate the obstacles that come with AI-ML adoption in the forecasting process.

The case is seen as *unusual* as its focus on a specific industry (manufacturing), from a specific perspective (OM), and a unique process (forecasting). As well as the firms showed interest at the start of the project, due to that they saw the relevance and potential benefits there was to be had with the project. This enabled unique access into how firms conduct their current forecasting process being able to discuss with the people directly involved in the process and collecting data on how they think when it comes to mitigating the pre-adoption barriers of AI and the relevance of the barriers. With access to an AI expert that possesses expertise in forecasting will lead to deeper insight and confirmation of the findings.

It is *revelatory* as the research has had a long-lasting relationship, due to prior work experience at the firm enabling an in-depth view into the firm's processes. Enabling access to data that is not accessible by outside actors. Given that research on AI adoption in manufacturing firms is limited (Kinkel et al., 2021). As well as studies on the pre-adoption phase (Hameed et al., 2012). It will contribute to deeper insights into a real-world context.

3.1.4. Case selection

The selected firm was picked for several reasons. Firstly, as the master thesis focuses on the manufacturing industry it was important to conduct the research with a firm in this specific field. Secondly, the case needed to have access to a firm interested in the topic of AI adoption and be in the pre-stage of the adoption process. Thirdly, the firm needed to have some interest in the support from people in academia in this matter.

As firm X is a manufacturing firm and showed an early interest in this matter, resources were made available to study the topic at hand. As the thesis focus on the prior adoption of AI-ML in the forecasting process. A discussion was held to create a so-called win-win for both the academic and practitioners. Firm X in Sweden was looking to improve its capacity planning, which is a related task in the operation management and forecasting process previously discussed in the literature section. The firm is interested in adopting AI-ML technology to handle capacity planning. The research conducted and the problem of the firm were able to correlate well. Thus, suiting the statement held by Van De Ven, (2013), emphasizes the importance of both parties engaging in the project and seeing meaning in the study. Furthermore, it was also discovered in their annual report of 2021 that investments were being made in the research field of AI. In discussions with the top management at the location of Sweden, it was noted that a part of the US facilities, was already conducting research in introducing AI into the forecasting processes and could be seen to be at the forefront compared to their Swedish counterparts. Given that the production processes and products differ across each sector of the firm. The Swedish sector needed to build a better foundation to understand what potential barriers there are to be faced when adopting AI into the forecasting processes, and plan how to mitigate these challenges. The barriers need to be understood as this will help the firm to accelerate the adoption processes of adopting AI-ML technology.

3.1.5. Case firm

Firm X is an international firm founded in 1917 and is considered to be the global leader in motion and control technologies, Firm X employs around 60 thousand people and is located all over the world. The following thesis is conducted with one of the firms located in Sweden.

Firm X located in Sweden is a manufacturing firm that employs around 70 people, in which majority of employees are involved in the production and assembly of their quick coupling products. Firm X in Sweden is exploring new ways to improve its production processes and is curious about adopting an AI-based approach instead of their traditional means of conducting its forecasting process and specifically in the capacity planning for production. The capacity planning is done every Thursday in which the top management associated with the operation, production, and supply chain management are included in the meeting. Their goal is to plan, predict, and allocate the right amount of workforce and resources needed to produce the demanded couplings to their customers.

Their current method collects data from their Enterprise Resources Planning (ERP) system called JDE in which they base their prediction by utilizing the data gathered from JDE together with their data analysis tools such as excel calculations combined with some professional assumption-making based on their previous experiences and historical data. The current system can predict the results with high accuracy when looking at a day apart. However, the accuracy and trust in the results are significantly lowered when trying to forecast further into the future. This is due to several different factors such as illnesses among staff, unpredicted delays in the material supply, breakdowns of assembly machines, and other problems in the assembly line. As well as several parameters affecting the accuracy of the prediction are not documented in their current forecasting process.

By adopting an AI-based approach they hope to improve their decision-making capabilities. It will provide them with a stronger method to forecast their capacity planning over a longer period and with high prediction accuracy.

As previously discussed in section 2, it is noted that AI is indeed a viable solution to help managers in the decision-making process. The technology has been seen to be adopted to aid in different forecasting processes such as demand forecasting (also previously discussed in section 2). Adopting an AI-based approach can utilize a massive amount of historical data to identify trends and learn from the previous prediction. Thus, improving the accuracy of the results over time.

Additionally, as previously stated AI is a complex technology, and firms looking to adopt the technology are faced with different barriers that need to be mitigated. With this research, I aim to identify the pre-adoption barriers of AI-ML in forecasting and how a firm would come about mitigating these challenges. By looking at previous research conducted in the literature combined with empirical data provided by the firm and AI expert in forecasting.

3.1.6. Time horizon

According to Saunders et al. (2009), it is important to ask oneself whether the research should be conducted looking at a specific point in time, which is referred to as a "*snapshot*" also more specifically called cross-sectional. Or over a longer period following a dairy format consisting of several" *snapshots*" described as longitudinal (Saunders et al., 2009). Given that the study focuses on what influences AI-ML adoption in the current presence of time of a manufacturing firm. Furthermore, given the time restrictions of the master thesis, it is deemed more appropriate to follow a cross-sectional design.

3.2. Data Collection

To accomplish a high amount of quality data produced for the study, the data collection was done in three separate steps:

- Pre-study
- Scoping Literature Review
- Qualitative data collection

3.2.1. Pre-study

To understand the topic studied in the thesis and to comply with the firm's demands an exploratory pre-study was conducted. Utilizing two main databases Scopus and Google scholar. This is done to support the argument of the supposed topic and to see if it was worth pursuing. Thus, the pre-study enabled the formulation of the purpose and research question. The pre-study consisted of a wide range of different articles such as literature reviews which help one get a holistic overview of the field. The pre-study aimed to also identify the supposed theoretical framework to be adopted in the master thesis and identify the literature to enable the initiation of the literature review.

3.2.2. Scoping Literature review

The second stage of the data collection process was conducting the literature review. which firstly, had the purpose of identifying a theoretical framework suitable for the adoption of digital technologies such as AI. Secondly once the theoretical framework was established, extensive research to identify barriers faced in the AI pre-adoption process is conducted.

Due to that, the academic papers on AI have increased in recent years (Bag et al., 2021; Kinkel et al., 2021). Inclusions and exclusions criteria are set to handle the increase of academic papers. Drawing inspiration from other articles such as Stornelli et al. (2021). Restricting the period of articles to be set between 2017-2022 to suffice that the articles are relevant and up to date. Furthermore, to start by including only journals from the ABS Academic Journal Guide (ACG) and not accepting journals with only one rating. Once the main articles have been identified some criteria were let go to allow the existence of a mix of articles to gain a different perspective and accomplish a full overview of the literature. To identify if the articles were relevant or not. The title and abstract were first looked at followed by an in-depth reading. The scoping literature review enables one to identify the adoption barriers relevant to the context of this study. In total 19 articles were included, mixing both top ABS Academic journals and articles from lower ranks. The articles with a lower ranking included also in the list were appropriate due to their similarities and similar data to top journals with some small modifications. The adoption barriers identified in the literature review are further used to formulate the initial questions for the data collection of the interviewees.

3.2.3. Qualitative data collection

When gathering empirical data, it is vital to consider the different types of data collection methods best suited for the field of research. Performing either a qualitative or quantitative data gathering method yield different benefits depending on the study. Quantitative can be seen as a synonym that refers to collecting data in the form of such techniques as questionaries or data analysis processes such as graphs or statistics. In short, the data generated is in the form of numerical data (Saunders et al., 2009).

While qualitative data collection can be referred to as data that is none numerical data, such as pictures, video clips, and words (Saunders et al., 2009). The strategies included in qualitative data collection are done by performing interviews or data analysis which is done by categorizing data that produce non-numerical data (Saunders et al., 2009).

According to Saunders et al. (2009), interviews can be categorized in the following way such as structured interviews, semi-structured interviews, and unstructured or in-depth interviews. Structured interviews are used to collect quantifiable data, and are mostly used in quantitative data collection

(Saunders et al., 2009). While semi-structured, and in-depth (unstructured) interviews are commonly associated with qualitative data collection/analysis and are referred to as *non-standardized* (Saunders et al., 2009). Semi-structured interviews can be explained as the researcher creating a list that has different themes and questions and depending on the interviewee the theme and question may vary (Saunders et al., 2009). The order of the questions can also vary depending on the atmosphere in the room to create a good flow in the interview. Furthermore Bryman & Bell (2015) state, that interviews are popular and commonly adopted in qualitative studies as they can be highly flexible.

For this thesis, it was deemed most appropriate to collect primary and secondary data using qualitative methods.

The primary data was collected using semi-structured interviews. The interviews were conducted in April of 2022. To ensure high-quality data the interviews were conducted with managers associated with the forecasting process. The interviews conducted with the managers associated with the forecasting processes gave deep insight into the manufacturing industry and the process of forecasting. Thus, connections were enabled concerning the adoption barriers identified in the literature from the perspective of operation management and how these barriers can be mitigated. The first findings provided by the firm's participants were later discussed with an AI expert with further expertise in forecasting.

As the firm is still in the pre-adoption stage of AI. The interviewees may present new ideas not thought of or presented by the authors. This gives new insight into how it can be planned to mitigate adoption barriers and if there are any, they believe will be crucial and needs to be prioritized to make the adoption possible. Semi-structured interviews are appropriate way to collected data as even though it follows an interview guide it allows for flexibility and enables the researcher to address problems not included in the guideline (Bryman & Bell, 2015). The managers were new to the technology of AI, having semi-structured interviews creates a greater atmosphere due to its flexibility allowing the interviewee to more easily ask questions that can arise in the interview.

Before the interview, a presentation was held for the managers at the Sweden location associated with the forecasting process. The presentation introduced the topic of AI, discussing its usage in the manufacturing industry and what different types of AI technologies exist. Providing the participant's insight towards the phenomena as the term AI is considered an umbrella term previously stated and discussed in section 2.1. The presentation discussed the current stage of AI. Following the presentation, a discussion was held about the technology and question that came to mind during the presentation.

A few weeks later interviewees were held with the people that participated in the presentation. Participants A-E are associated with dealing with the forecasting of capacity planning. Followed the interviews with participants A-E, an interview with an AI expert was held to discuss the findings. Table 5 shows the participants of the interviewees.

Table 7. Presents the participants list of the interviews.

Person	Position	Date	Time
A	Manufacturing Supervisor	2022-04-08	70 min
B	Supply Chain Manager	2022-04-13	60 min
C	Manufacturing and Logistics Supervisor	2022-04-13	60 min
D	Material Manager	2022-04-13	60 min
E	Plant-Manager	Continues discussion	-
F	AI Expert - Forecasting	2022-04-28	60min

The interviewees with participants A-D started by explaining the setup and how the processes of the interview would work to make the participant understand the context and the reason for the interview. This led to the interviewee being able to provide the necessary data needed to answer the supposed research questions. The interviewee started by presenting themselves with their background and experience at the firm as well as their knowledge of data analytics and AI as well as how long they have been a part of dealing with the forecasting of their capacity planning. Once the background had been established the questions were discussed in the contexts correlating with the TOE framework, Technological, Organizational, and Environmental. Asking open questions to the participants A-D makes it possible for them initiate an answer, in which follow-up questions are asked enabling the participant to explain in-more depth giving a solid foundation to answer the question. Furthermore, as participants A-D had different functions in the firm some of the questions were modified in minor ways to best suit the person being interviewed. Following guidelines provided by Saunders et al. (2009), which states that the researcher utilizes a list consisting of different themes and questions that will be covered during the interview, however, these questions may be different depending on the person being interviewed. The foundation of the questions where kept the same to achieve the necessary amount of empirical data to answer the proposed research questions. The interview questions were the primary source of data. The questions were based on the articles presented in section 2.6. That discusses the barriers related to AI adoption. In Table 6 an extract of the questions from the interview guide is provided. The reader can see the full question guidelines in chapter 8 appendices.

Table 8. Presents a sample of the interview guideline.

Barrier	**O2. Management Support**
Description	A major barrier discussed in the literature when it comes to the adoption of AI in manufacturing firms is the lack of involvement and support from top management (Bag et al., 2021; Cao et al., 2021; Chatterjee et al., 2021; Enholm et al., 2021; Kinkel et al., 2021; Mahmud et al., 2022; Merhi, 2021; Mikalef & Gupta, 2021; Xing et al., 2021). Top management can influence different functions such as the hiring and training of employees to possess the skills required to successfully use AI tools for managerial decisions making (Bag et al., 2021).
AI question (Barrier related)	How do you perceive the top management's support and involvement in various projects?
Challenge	Can you describe a scenario where you were met with difficulties due to a lack of management involvement and support and how you dealt with it?

Once the data was collected from participants A-E a table of the findings was created see Table 8 in chapter 4. The table of the first findings was then later discussed with an AI expert to confirm and further provide insight into the findings to answer the supposed research question.

The secondary data is collected for 4 months by participating in meeting related to the capacity planning being able to observe as well as ask questions during meetings to fully grasps their forecasting processes. Understanding the difficulties that are met, what data is used, and how they make their decisions based on the data. As well as continuous meetings with my firm supervisor provided me with clarification limiting the misperception and allowing deeper insight into the processes. Several discussions with participant A are also done as they were able to provide the researcher with deep knowledge understandable to the researcher. It is important to note that previous knowledge of the organization of the firm is held by the researcher of the thesis as the researcher have over two years of experience working at the firm as a Product Development Engineer possessing somewhat insight into the organization and the way how business is being conducted.

3.3. Data Analysis

This thesis aims to investigate the AI pre-adoption barriers manufacturing firms face in the forecasting process and understand how to mitigate these challenges from the perspective of operation management. The identified barrier found in the literature review was addressed in the interviews and coded to compare to the theoretical framework. The data analysis is theory-guided, in which it follows the concept of sensitizing (Bowen, 2006). The sensitizing concept can according to Bowen (2006) be beneficial as it takes a more general approach. As well as it may aid the researcher to focus on the appropriate direction to collect data (Gama et al., 2017). When utilizing a sensitizing concept it is common to examine the data by following a thematic data analysis approach (Bowen, 2006). The data analysis method is structured and utilized following a thematic approach described by Braun & Clarke (2006). Including the six phases shown in Table 7.

Table 9. Presents the six phases in a thematic analysis, described by Braun & Clarke (2006).

Phase 1	*Familiarizing yourself with your data*
Phase 2	*Generating initial codes*
Phase 3	*Search for themes*
Phase 4	*Reviewing themes*
Phase 5	*Defining and naming themes*
Phase 6	*Producing the report*

Following the transcription of the data, it is seen as the first stage of the thematic method in which you familiarize yourself with the data (Braun & Clarke, 2006). As the questions asked during the interview are based on the barriers identified in the literature and structured following the TOE framework these were used as coding guidelines to identify the proper theme and extract the important data that is needed to be transcribed. Furthermore, as the interviews are recorded continuous rewatching was done to extract important findings from the interviews and to avoid missing crucial information as well as identify what was seen as relevant to extract.

The second phase described by Braun & Clarke (2006) is where the actual coding takes place. However, as the coding already started with the familiarization phase the interviews were transcribed during the familiarization phase, as the interviewees were conducted in Swedish. The interviews were first transcribed in Swedish and then later translated into English where further familiarization and coding were done simultaneously. It can be deduced that phases one and two can be seen as intertwined. As Braun & Clarke (2006) states a good way to familiarise yourself with the data is by transcribing it and writing it down if a qualitative study was the choice of the method where the researcher for example records the interviews.

Once all the data has been collected phase three begins (Braun & Clarke, 2006). During phase three the main priority is to identify the themes that fit into the respective part. As the question was based on the adoption barriers presented in section 2.6 and early categorized following the TOE framework the themes were easily identified as they related well to each question during the interview, already during phase one, phase three was initiated. Phase four specifies that the researcher focuses on checking that the supposed theme works in relation to the code (Braun & Clarke, 2006).

This process was also somewhat done in the familiarization phase as the data was transcribed and rewatched, enabling one to make sure that the proper data fits into the specific factor. Phase five focuses on defining and naming the themes (Braun & Clarke, 2006). The themes already had set names as the TOE framework is utilized firstly categorizing it based on the context and, secondly key names are given due to the context of each barrier. Once phases one to five are done, the final phase can be initiated, which is phase six *producing the report*.

In phase six, once all the data was collected and analysed a similar format was used that has echoed in recent publications on innovation sciences presented by van Giffen et al. (2022). To display the findings first shown in chapter 4, see Table 8, to help answer the supposed research question. Followed by Table 9, which is the AI response, with regards to the findings of Table 8.

It is important to note, that even though the same approach in analyzing the data was done for all the participants interviewed. In the case of the AI expert, the question asked was related to the findings from participants A-D, see Table 8.

3.4. Quality of the research

When conducting a study, the researcher must make sure to retain a well-structured research design that is planned and performed in a high-quality matter. This is due to ensure trustworthiness and to answer the supposed research question. To ensure the reader that the study can be trustworthy and contains high-quality research. The following section seeks to demonstrate this to the reader by following the guidelines of Bryman & Bell (2015). The author states that the criteria of trustworthy research can be based upon four criteria: *Credibility, Transferability, Dependability, and Confirmability.*

3.4.1. Credibility

According to Bryman & Bell (2015) enabling credibility to a researcher’s work is to ensure that the research has followed a set of rules that exist. As well as reducing the chance of getting the wrong answer(Saunders et al., 2009). The research is sent to be validated by an expert in the supposed field. To ensure that the research of this master thesis has been able to accomplish a good sense of credibility The following approaches have been taken; Firstly, good communication with my supervisor. The continued discussion with my supervisor has provided me with feedback regards to my manuscript. Pointing out flaws and problems with the thesis allows the possibility for appropriate changes to follow the guidelines needed to produce a sufficient thesis.

Secondly, the close collaboration with the firm, as well as prior knowledge of the firm’s organization. Due to the researcher’s prior relationship with the firm, enabled the researcher to gain access to data and deep insight into the organization as well as validate the data found with the people working in the organizations. Thirdly, observations were done to collect secondary data and the participant was allowed to ask questions as well in-depth knowledge of the processes was able to be collected.

Fourth, to ensure credibility a common approach utilized in research is triangulation (Saunders et al., 2009). Triangulation is defined as collecting data from two or more independent sources (Saunders et al., 2009). Triangulation was achieved by interviewing all the partners associated with the forecasting process. Following the findings provided by participants A-E associated with the forecasting, the result was validated and discussed with an AI expert, further increasing the credibility of the research.

3.4.2. Transferability

According to Bryman & Bell (2015), qualitative research focuses on studying a small group of individuals. Furthermore, transferability refers to dealing with the question of the supposed findings that can be applied to other situations. This research follows the purposed ways of Lincoln & Guba (1985) described in the book by Bryman & Bell (2015), which states that the research should provide a rich database to enable other researchers to assess if the findings could be applied to other contexts. As this research is a single case study focusing on a narrow subject, and with an extensive scoping literature review. The collection of high amounts of rich data was collected and it is up to other researchers to assess if it can be useful for future research.

3.4.3. Dependability

According to Bryman & Bell (2015) dependability is reassured when the researcher can provide in-depth information regarding the research process and data collected. This is necessary as it allows other researchers to perform the same study, even though it may not yield the same outcome (Bryman & Bell, 2015). To make sure that dependability has been established in the following research. Documentations has been made in the different decision-making process as well as the interviews are recorded, which enables one to go back and listen to the data collected.

3.4.4. Confirmability

Confirmability can be described as the researcher's tension acting in good faith to create trust in the research (Bryman & Bell, 2015). This means that the research is conducted from an objective perspective, and the findings are established from the data derived in the study, not by the researchers’ values (Bryman & Bell, 2015; Shenton, 2004). To ensure confirmability for the study, the interviews were recorded and transcribed as previously mentioned, which enables strong statements to be validated and documented in an objective matter. The recordings allowed for repeated listening and studying the person's facial expression and different gestures. The main findings were discussed with an AI expert with expertise in forecasting creating sufficient clarification about the subject studied.

4. Empirical Findings

The purpose of this thesis is to seek answers as to how a manufacturing firm mitigates AI pre-adoption barriers in the forecasting process. The following section presents the empirical data findings that have been collected for the study that will be utilized to fulfill the purpose of this research and answer the research question. The first Table 8 gives an overview of the main findings from respondents A-D. A similar format of recommendation has been echoed in recent publications on innovation science (van Giffen et al., 2022). While Table 9 presents the AI expert (respondent F) response regards to Table 8. The two tables are split according to the TOE framework: Technological, Organizational, and Environmental, which shows the main findings.

Following the two Tables 8 and 9, the empirical findings are explained in more detail. The data has been collected by observations such as participating in meetings, and semi-structured in-depth interviews. The empirical findings present the identified barriers for AI-ML in the pre-adoption for the forecasting process as well as the planned mitigation action to deal with the identified barriers. Following each section, another table is collected showing the main exemplary quotes used in the coding for each context.

Table 10. Presents a summarized table of the main findings from the empirical data analysis from interviews A-D.

Context	Adoption Barrier	Example from case	Recommended Action
Technological	T1. Poor data - Quality - Access - Volume	The prediction related to the forecasting is purely based on the data input and has a direct effect on the output. However, several other factors also affect the accuracy and reliability of the result that is not yet taken into consideration when performing the forecasting. Some of these factors are sickness and sales trends. As well as how sufficient each assembly team is.	Create a comprehensive dataset including team efficiency, sickness records, documenting sales trends, and break down time on machines and tools. Allow that their main data source contributor the suppliers are granted access early on as they provide the most data.
	T2. Inappropriate technology infrastructure - Digital platform - Infrastructure - Interoperability	Prior experience shows that we have had difficulties in different technologies being able to communicate with our main data system. As the forecasting data is collected from various sources sufficient communication and integration between various datasets are of concern.	Design an interactive data platform, prior to adoption, that grants access to the different actors associated with providing the data for the forecasting.
Organizational	O2. Top management - Support - Involvement	The top management shows support and involvement once the project is ongoing. However, clear justifications as to why the project is important and need to be done before taking it up with the top management.	Increase the managerial awareness and understanding of AI-ML technology and the potential benefits and value there is to be created.
	O3. Organizational Readiness - Economical - Competencies	Allocating resources such as hiring new personnel is difficult unless that person directly generates sales revenue. We have specific protocols that we follow to justify an investment Furthermore, we usually have a specific timeframe as to when the investment is supposed to generate profit. The prework has proven to take up most of the time when it comes to allocating resources and bringing the required competencies	Approve a compelling business case and have different protocols depending on what type of technological uncertainty exists. This may help speed up the process of allocating needed resources. Train the employees to achieve the needed skills or have an outside hire possessing the needed skills. As well as take the help from students.
Environmental	E1. Partnership - Collaboration IT - Collaboration Suppliers	We have about 30 suppliers across the world of which the majority is based in Europe, we also utilize our subsidiary partners in the US to supply us with parts. Without suppliers, we don't get the needed parts. The in-house IT is allocated in Germany. The IT used in Sweden is provided by an external actor that deals with hardware and some software updates. In one of our new projects ongoing, we see the need to expand our IT resources. Furthermore, experience regarding IT support in Germany has been proven to be less sufficient.	Have a continuous good relationship with the supplier, informing them of their interest in investing in AI-ML technology and explaining their needs that need to be met by the suppliers. Expanding the partnership with the external IT or allocating adequate resources such as a dedicated IT in-house. This will help foresee potential bottlenecks in the early stage of AI pre-adoption. As well as educate the IT utilized to understand the organization.

Table 11. Presents the AI expert in forecasting response and perspective regards to Table 8.

Context	Adoption Barrier	Relevance of barrier	Reaction to the recommended actions
Technological	T1. Poor data - Quality - Access - Volume	Poor data quality impacts the accuracy and reliability, but poor data does not affect the pre-adoption phase. As the modular can still work with poor data.	The recommended actions displayed in Table 8 are a sufficient way to deal with poor data. However, it is more important to ask themselves, what are the main parameters not yet considered that affect the forecasting.
	T2. Inappropriate technology infrastructure - Digital platform -Infrastructure - Interoperability	Infrastructure is an important factor to look at. Having the right inputs of the data prior adoption.	The recommended action is sufficient to create a comprehensive dataset allowing the different actors to put in the data. However, it is instrumental to justify the reasons for creating a comprehensive dataset, otherwise, it won't be done.
Organizational	O2. Top management - Support - Involvement	I agree with your identified barrier as top management being a key factor.	Increasing awareness for the managers and the potential value to be created is sufficient action. I would also add the notion of creating an understanding of the expectation of the technology.
	O3. Organizational Readiness - Economical - Competencies	You need to have a dedicated modular. That handles the structuring of the data to be used for the forecasting. Furthermore, one of the greatest challenges is having investment freedom to acquire the needed expertise.	Building a strong business case is a sufficient way to deal with the justifications of investments and training competencies. However, in the case of forecasting, we have numbers that make it easier to justify an investment. Furthermore, I would recommend that a new hire would be more a sufficient investment than training or hiring a consultant as they will possess the skills as well as be able to learn the business perspective of the organization in-depth.
Environmental	E1. Partnership - Collaboration IT - Collaboration Suppliers	Collaborations are an important factor.	The recommended action is a good way to mitigate the barrier in the early stage of adoption. However, an important aspect to take into consideration is not just to inform, but also to create incentives for the supplier that gives the motivation to be created. For example, in the form of more capital for the supplier's work of informing and adding the information to the joint data sources information. If the supplier does not see why when it comes to adding information they won't comply. Furthermore, IT collaboration is important but may not be considered a barrier as they probably do not have the required skills to deal with AI due to it being a complex technology

4.1. Technological Context

4.1.1. Barrier T1. Poor data and Mitigation action

All respondents emphasized the importance of data on the pre-adoption of AI in forecasting. The respondents stated that the decision-making process for the prediction is based primarily on the data in the forecasting. While respondents A, B, and D state that the prediction is based primarily on data 70% and 30% on “gut feeling”. Respondent C describes that the prediction is purely based on data and that the gut feeling is referred to as the historical data. Respondent C continued explaining that while performing the current forecasting is quite easy it is the prework of structuring the data and making sure that all the data is collected which is the hard part.

The respondent’s notions regard to the current data they possessed were seen as sufficient for making predictions one to two days ahead. Presented by respondent A their current forecasting is supposed to be sufficient for at least one week ahead. Further, explain that the data was not seen as sufficient emphasizing that there is high insecurity towards the data due that several other parameters not taken into consideration that also impact the forecasting.

Even though it was made clear from respondents A-D that data is a vital aspect of the forecasting this would not be seen as too much of a barrier in the early stages of AI adoption. To mitigate the insufficient possession of data respondents A-D suggested that parameters affecting the forecasting can be documented to fill the gap of having poor data such as “sufficient data set containing data on, efficiency in the team, sickness, and sales estimation”.

The response from the AI expert stressed the relevance of the data and confirmed recommended action suggested by participants A-E. Explained while poor data is an important factor to consider it is not as important in the pre-adoption phase. Due to that, the modular that handles the structuring of the data can work with poor data as well. The recommended action that was considered to be taken to include several other parameters was stated by the AI expert to be a sufficient way to deal with poor data quality. The AI expert noted that it is important to first focus on what are the most important parameters impacting the reliability and accuracy of the prediction of the forecasting.

Table 12. Presents exemplary quotes from the data analysis regards to barrier T1.

Adoption barrier	Respondent A	Respondent B	Respondent C	Respondent D	AI Expert
T1. Poor data - Quality - Access - Volume	"It is an important factor; however, it is not as relevant in our current adoption phase".	“As the prediction is based on data… access to the needed data is one of my major concerns".	"We base our prediction 100% on data and the data has a direct effect on the output".	Good question I would say it would have an impact, but maybe not right now as we are still exploring".	“It is not about having poor data it is about having the right data”.

4.1.2. Barrier T2. Inappropriate technology infrastructure and Mitigation action

The respondent's A-D response to the barrier of adopting a proper digital infrastructure in the pre-adoption stage was somewhat mixed. Facilitating a proper digital infrastructure is supposed to enable sufficient communication between the different datasets to make it possible to create a comprehensive data set to feed the AI-ML. From respondent B a statement was given concerning that "this would be one of the biggest challenges and interesting factors towards the end of the adoption". While respondent D described early scenarios in which "this problem of adopting other technologies has already been seen as a problem and is something that needs to be made sure to work early in the stage of adoption to avoid major costs and bottlenecks".

The AI expert confirms that interoperability and facilitating a proper digital infrastructure are important aspects to look at. The AI expert pointed out that the recommended action provided is a sufficient way to deal with the perspective of allocating all the right inputs. However, while it is important the respondents also need to create motivation as to why the different actors should comply to input their data into this system.

Table 13. Presents exemplary quotes from the data analysis regards to barrier T2.

Adoption Barrier	**Respondent A**	**Respondent B**	**Respondent C**	**Respondent D**	**AI Expert**
T2. Inappropriate technology infrastructure - Digital platform - Infrastructure - Interoperability	"This is one of the biggest challenges towards the end of the adoption in my mind".	**N/A**	**N/A**	"I see this as a big problem, as from previous experience this is something that has occurred, and will cause significant damage if not dealt with prior".	"Yes, it is an important factor. However more importantly they need to find ways to motivate the actors to comply, so they interact with the platform".

4.2. Organizational Context

4.2.1. Barrier O2. Top Management and Mitigation action

Overall, the participants A-D shared a mutual agreement that supportive management and involvement are one of the most significant factors that can either be seen as a great enabler or a strong barrier when it comes to various projects. A statement given by participant A stated "as our top management is in charge of allocating resources needed to make things happen. "By not having the management onboard it becomes incredibly difficult to make sure that the adoption of new technology can take place as they have the final say". The participants further, explained that the top management is both supportive and involved once the project is ongoing. Additonally to mitigate the issue of lack of management support and involvement the participant discussed that this issue could be dealt with by increasing awareness and understanding regards to AI-ML.

From the AI expert, it was discussed that sufficient management support is a barrier to consider and that needs to be streamlined in the pre-adoption phase. Furthermore, the recommended action of creating awareness and understanding regarding AI-ML is a beneficial response to deal with the identified barrier.

Table 14. Presents exemplary quotes from the data analysis regards to barrier O2.

Adoption Barrier	**Respondent A**	**Respondent B**	**Respondent C**	**Respondent D**	**AI Expert**
O2. Top management - Support - Involvement	“The management support is for sure there once the project is initialized”.	“Well if we don’t have management on board, it is, of course, difficult, but if they see the investment as useful it won't be an issue”.	“I see the top management as very supportive… once the project is invested in the management support is good”.	“Clear justifications need to be made why to invest in the project…. It takes time to get approval from management…. once the project is ongoing the management supports us”.	“The management plays a key role in the adoption”.

4.2.2. Barrier O3. Organizational readiness and Mitigation action

From the interviews with participants, A-D regards the previous barrier top management support and involvement it was discussed that the prework in creating awareness and understanding was considered quite time-consuming.

Organizational readiness is referred to as the barrier to allocating the needed resources to make the adoption possible. Aspects such as the financial constraints and having access to the required competence to enable the adoption was considered a significant barrier to the adoption of AI -ML technology. From the interviews, it was noted that the economical barrier and allocating the needed resources such as justifying new hires, and investments in IT are significant challenges in the adoption of new technology. Participant A stated that “the investment of a new hire is difficult to justify unless it is an assembler that directly generates profit”. Similar responses were held by participants B, C, and D. Participant A also stated that “the plant manager of the location is given a certain budget in which he/she is allowed to make new investments otherwise he/she needs to discuss with even higher-ups such as corporate”

Participant C stated” If we see there is a lack of competence, we are more likely to hire in consultants that educate our employees on the matter, rather than open up the position for new hires when it comes to acquiring the knowledge to deal with AI”. Furthermore, participant A stated that “we have a timeframe usually of 3 years in which we need to start seeing results in the form of profit, investments expected to take longer than this is significantly difficult to get funding for".

Allocating IT resources to help with the adoption of various technologies seemed to be a primary challenge participant C stated, "when we introduce a new software or technology a common problem occurring is the lack of IT support, to help with the integration of new technologies". Participant C continued the concern regarding that even though being a large firm "I have doubt we have IT that possess the right skills to help us in the implementation". Addiotnally, agreements were held regarding the capabilities according to participant A "I believe we possess strong IT competence in the firm able to deal with AI, however, not in Sweden".

Participant A-D stated to mitigate the financial constraints, a clear justification needs to be formed to make the allocated resources possible. The notion of building a compelling business case was seen as a beneficial action to take regarding this matter. From the discussion with the AI expert the action of building a sufficient business case to mitigate the following adoption barrier was seen as beneficial. Stating that this is something he has aided firms in the past.

The lack of competencies to mitigate the barrier of lack of competencies. It was discussed with participants A-D that the most likely action would be to train their current employers to possess the necessary skills required to deal with AI-ML or have an outside hire. The response from the AI expert regards to this mitigation action was seen as somewhat mixed. Stating that this mitigation action of training employees to possess the required skill can be beneficial as they would know how the organization worked from a business perspective, but the process of achieving this skill would take time and the employer might not show interest. The AI expert regards the other mitigation actions of taking on a consultant possessing the required skills were seen as a good way as well but the consultant would have difficulty understanding the business perspective. Hiring people to possess the required skills is the best notion to take from the expert perspective.

Table 15. Presents exemplary quotes from the data analysis regards to barrier O3.

Adoption Barrier	Respondent A	Respondent B	Respondent C	Respondent D	AI Expert
O3. Organizational Readiness - Economical - Competence	"Making sure that we are profitable is the main goal of the firm. Thus, making it difficult to justify an investment that may not generate profit".	" Hiring new personal that does not directly generate sales revenue, makes it very difficult to invest in".	"Allocating resources to help us with integrating something new is difficult" We have historical and even now bad support from our central IT. We try not to rely too much on IT if we can…. I am unsure if we have the IT resource to deal with AI".	"We really must motivate why, this new hire should be included, as we see it as a cost, and it needs to generate profit…. We have a history of having issues with IT, I believe this will make it difficult to make the adoption possible".	"Not having investments in the right expertise is a barrier".

4.3. Environmental Context

4.3.1. Barrier E1. Partnership and Mitigation action

The overall findings provided by participants A-D found that the key factor in the environmental context. Having sufficient partnership between IT and suppliers early in the adoption process will mitigate problems that would otherwise arise later in the adoption process. As previously discussed, the data provided by the supplier is significant in making the predictions of the forecasting. Participant B explained that currently, they utilize around 30 suppliers all over the world, of which the majority is in Europe. One of their main suppliers is their subsidiary in the US. Additonally, a major problem that kept recurring is the change of delivery dates regards to components creating difficulties in making an accurate and reliable prediction. This statement was held by participant C "The supplier may give us a date when we will receive our components to build the product. However, the expected date on delivery change frequently, in which we may only get ahead up a day in advance at best."

The mitigation actions of dealing with the barrier of the partnership were too early on to seek ways to improve the collaboration between the suppliers. Such as by informing their needs suppliers, and their plans of adopting the AI-ML technique to deal with their forecasting as well as allowing the suppliers to put in the information themselves. The findings provided by the AI expert confirm that good collaboration between suppliers is an essential part of successful AI adoption, it is an important factor to find ways to mitigate early in the adoption process. However, the AI expert added to the recommended action stating that the notion of "motivation" puts empathizes as to "why". Meaning that to create a good supplier relationship the firm needs to provide the supplier with something that motivates them to help them, an example was in the form of more financial backing. The AI expert stated, "if the supplier doesn't understand, why, they should engage in aiding the firm, they won't do it or they will just leave information to have something there”.

To continue with the findings regarding the collaboration with IT, it was noted to be one of the bigger challenges currently for the organization of Sweden. Discussing that while the resources may be adequate to meet their needs. The collaboration with the main sources of IT in Germany has proven to be insufficient and lacking in many areas and their current resources used in-house is not engaged enough to deal with the bigger parts of the organization as it is an outside hire.

To mitigate the barrier regarding the IT collaboration respondent D stated ‘‘we are looking to expand our collaboration with the external IT”. Suggesting that this will accompany a way to create a way to improve the relationship. Participant C explained that to create sufficient collaboration with the central IT in Germany a planned visit from the top management in IT is to visit the Swedish location where they can present their needs and concerns. From the AI expert, it was found that IT collaboration is an important aspect to mitigate the AI adoption process. This support won’t be as significant in the early stages due to, they would probably not possess the required skills to deal with AI adoption due to the complexity of the technology. Referring to the earlier barrier of organizational readiness.

Table 16. Presents exemplary quotes from the data analysis regards to barrier E1.

Adoption Barrier	Respondent A	Respondent B	Respondent C	Respondent D	AI Expert
E1. Partnership - IT collaboration - Supplier collaboration	**N/A**	"We have about 30 supplier’s majority being in Europe. We also work closely with our subsidiary in the US" If we don’t get the parts, we cannot produce our products”.	“The supplier may not keep their promise, they are set to deliver on Thursday, but we get an update on Wednesday saying it won’t be delivered on time” We have external IT Support, but they only deal with small IT issues and are here once a week”.	“We are looking to expand our collaboration with our external IT resource in Sweden”.	“Suppliers can be a problem if they do not provide sufficient data even if you have the best software”.

5. Analysis and Discussion

The first section of the chapter presents an analysis of the literature and empirical data collected as well as a discussion regards to each finding and the connections to the research question. Following the discussion and the analysis, a final table is created to answer the supposed research question.

5.1. Technological context

5.1.1. Poor data

The importance and relevance of the barrier poor data are based on the authors presented in Table 2 in section 2.6

According to Enholm et al. (2021) data is considered to be the core of AI. The data is considered essential as it is used to increase the reliability and accuracy of the output (Bag et al., 2021; Merhi, 2021; Mikalef & Gupta, 2021). Possessing the proper data will lead to stronger predictions. Furthermore, Mikalef & Gupta (2021) stated that firms possessing quality data increase the likely hood of the adoption.

Therefore, it was deemed vital to investigate the relevance of the barrier in the pre-adoption phase and how a firm would mitigate in dealing with poor access to a high volume of quality data.

The empirical findings indicated that data plays a major role to achieve accurate prediction as respondents A-D all stated that the majority of the forecasting prediction is based on the data. Additionally, the relevance of considering it as a barrier that needs to be looked at in the early stages is somewhat mixed. While the literature indicated that data plays a key enabler in leveraging AI (Allen, 2019; Mikalef & Gupta, 2021). The respondents stated that this is something that won't affect their current adoption process. Respondents, A-D did not see poor data to be a barrier in the early stage of the adoption but rather something to be looked at later in the process. The claim is further backed up by the AI expert that stated that the modular can still build the AI model using poor data. Still emphasizes the importance of the data.

To mitigate and deal with poor data it was suggested by Mikalef & Gupta (2021), that proper labelling of the data and filtering needs to take place as well as providing the AI with a high amount of data used to train the AI modular. The respondent's A-D focus to mitigate the challenge of having poor data was more focused on the aspect to add more parameters that could have an impact on the forecasting. While the AI expert indicated that adding a parameter that can affect is good. They should rather find out first what are the most important parameters that are not yet considered.

The respondent's A-D concerns with the adoption barrier and the recommended action may have some flaws in it as the participants, A-D has had little interaction with the technology and only possess a basic understanding of AI-ML technology. Thus, this can impact the way the managers think about dealing with the barrier related to technology.

Additionally, based on the data analysis it can be understood that while data is an important element in AI-ML adoption it may not be a significant barrier in the pre-adoption phase. Furthermore, the mitigation actions to add in several other parameters associated with forecasting may be beneficial the respondents A-D first need to identify the most critical parameters.

In summation, the data is considered a barrier to the adoption of AI-ML technology. Additionally, it may not be a critical barrier in the pre-adoption phase. As from the empirical findings both from participants A-D as well as the AI expert in forecasting all indicated that this is not seen as a barrier as of now. While the recommended actions from respondents A-D have a good base they need to explore and confirm the main parameters missing in their current forecasting.

5.1.2. Inappropriate Technology Infrastructure

The adoption barrier of inappropriate technology infrastructure is first presented in section 2.6, which is referred to a firm possessing the appropriate digital infrastructure and digital platform to be able to facilitate the high computing power, algorithms, and large storage space that needs to be provided to utilize AI-ML technology (Enholm et al., 2021). Furthermore, the old data system can collaborate and communicate with a newly implemented data system to accomplish a comprehensive data set (Merhi, 2021).

The participant's A-D response regards to the barrier of inappropriate technology infrastructure can be seen as somewhat mixed as to seeing it as a barrier or not in the pre-adoption phase. While the response from respondent A pointed out the importance of the factor it plays, respondent A referred to seeing this as something to be the biggest worry towards the end of the adoption phase. While respondent D stated due to prior experience this is something to be looked at early at the start to avoid bottlenecks in the future.

The mitigation action to deal with the supposed barrier from the participants was to create an interactive data set where different actors were also able to interact with the platform and provide them with the data needed. This, correlates well with the definition provided by Constantinides et al (2018), as to what facilitating a good digital and infrastructure platform indicates. A digital platform can be described as *"a set of digital resources-including services and content that enable value-creating interactions between external producers and consumers"* Constantinides et al., 2018, p.381). Digital infrastructures *"as the computing network and resources that allow* *multiple stakeholders to orchestrate their service and content needs"*(Constantinides et al., 2018, p.381). As pointed out by the AI expert an interactive data platform where the different actors can integrate external and internal data may be a good way to make sure that needed data is facilitated. Motivation needs to be considered as to why should the external actors use this system to provide them with information. Thus, the integrated network should also be able to communicate the external actor's needs and not just the firm looking into the AI-ML adoption. Furthermore, the suggested mitigation is also discussed by (H. Chen et al., 2021)**.**

To summarize based on the findings the barrier of inappropriate technology infrastructure can be seen as a barrier in needs to mitigate early in the pre-adoption phase of AI-ML as it will reduce the risk of creating bottlenecks in the future. The mitigation actions of creating an interactive dataset. Motivation needs to be facilitated that underlines a motivation as to why it should be used.

In short, the barrier of inappropriate technology infrastructure is truly a barrier that affects AI-ML adoption. Additionally, whether it is relevant in the pre-adoption stage may still be questioned. As it might not be an immediate threat to AI-ML adoption. It will act as a bottleneck in the future if actions are not taken to facilitate an appropriate infrastructure where sufficient interoperability between the different actors can occur. The recommended action to mitigate the barrier of inappropriate technology infrastructure can be seen as sufficient as the forecasting data is collected from various sources. Allowing different actors associated with providing the forecasting data will create faster updates and create fewer bottlenecks as the data is continuously updated.

5.2. Organizational Context

5.2.1. Top Management Support

The barrier concerning lack of top management support and involvement in the adoption and utilization of innovative technology such as AI-ML is mentioned extensively throughout the literature on AI adoption. According to Bag et al. (2021), top management can influence different functions such as the hiring and training of employees to possess the skills required to successfully use AI-ML tools for managerial decisions making. Merhi (2021) adds to this notion by indicating that top management is an essential factor as they allocate resources needed for a project to continually move forward. Thus, having top management support can be seen as a huge enabler for an adoption process.

From the empirical finding, it can be clearly stated that top management support and involvement plays a crucial role in projects. From respondents, A-D confirms that top management oversees and is responsible for allocating the needed resources to support a project and has the final say if a project should be continued or not. Furthermore, the participant all indicated that top management support and involvement is sufficient, but it is the pre-stage in the project that makes it difficult to get them on board and support the project. It can be considered a barrier that needs to be mitigated early in the stage of AI-ML adoption. The importance of top management support was confirmed by the AI Expert expressing similar claims as to the literature and respondent A-D. By studying the literature and the data collected it can be concluded that top management plays an essential role in the successful adoption of innovative technologies such as AI-ML.

The mitigation actions suggested by respondents A-D to deal with the lack of management support and involvement. Was that stronger managerial awareness and understanding of new and innovative technologies need to be built as this will reduce the amount of prework that goes into building a sufficient business case as the manager already possesses an understanding of the technology and is aware of the potential benefits and value there is with the technology.

In summary, having top management support and involvement is crucial, and having an absence in this matter will act as a massive barrier to the AI-ML adoption. Due to the nature of what managers can bring to a project such as a resource allocation. Thus, creating managerial awareness and understanding is essential and sufficient mitigation action to handle the lack of top management support and involvement.

5.2.2. Organizational Readiness

The economical aspect and the competencies needed to deal with AI-ML technology is seen as a barrier in the pre-adoption phase, and thus sufficient mitigation actions are essential to deal with the challenge. According to Bag et al. (2021), the lack of employee skills has prevented the progression of industry 4.0. In which firms need to find ways to mitigate the barrier (Bag et al., 2021). The importance of employee skill is significant and backed up by several authors (Kinkel et al., 2021; Merhi, 2021; Mikalef & Gupta, 2021). The empirical data concerning the lack of employee skills to affect the adoption of AI was seen as a significant fact by respondents A-D and the planned mitigation action was to train the employees to acquire the needed skills to deal with AI-ML. According to the respondents, A-D hiring new personnel was difficult and it was more likely that either training would take place or hire in a consultant. However, as denoted by the AI expert training people to acquire this type of skill takes time, and hiring a consultant that does not understand the business presents other obstacles. Therefore, it is better to acquire the skills by hiring new personnel. The claim seems relevant as according to Kinkel et al. (2021) dealing with AI technology the most critical skills required are people possessing skills in software and hardware development skills, and having data scientists. Thus, the recommended action of just training employees can be a questionable suggestion.

The financial barrier to AI-ML pre-adoption was also seen as important to look at as indicated by (Enholm et al., 2021; Mikalef & Gupta, 2021; Stornelli et al., 2021). Firms having a strict budget can have a significant impact on the success of adopting highly advanced digital technologies as it usually requires a very flexible budget, that AI is a long-term investment. The barrier can be relevant in the pre-adoption phase as stated by Stornelli et al. (2021) the economic barriers are multiphase being important throughout the whole adoption process. From the empirical data, it can be noted that the financial factor is seen as a relevant barrier. As the financial aspect was a reoccurring theme throughout the interviews. In which the respondents A-D claim that significant justification needs to be done to enable the financial investments of new technologies and especially hiring new personnel.

The suggested mitigation action to deal with the barrier of organizational readiness by respondents A-D is to build a sufficient business case that can justify the needed investments. The AI expert input towards the recommended action was seen to be sufficient as this is a common mitigation action used, in which AI expert had its own experience in helping firms build sufficient business cases to deal with AI-ML adoption. However, according to Sjödin et al. (2018) if the technology is complex it can create difficulty in creating a convincing case that presents sufficient justification for the investments. Given that AI is considered a complex technology (Kinkel et al., 2021). The firm, therefore, needs to invest time in building its case. However, according to the AI expert, it was seen that building a sufficient business case for AI-ML adoption for the forecasting process may be simpler than first thought due to that they will have access to numbers to help with the justifications.

In short, the economical aspect, as well as the lack of skills, are a barrier that needs to be mitigated in the pre-adoption phase of AI-ML. Due to the complexity of AI-ML technology having a restricted budget will lessen the chance of successful AI adoption as having a restricted budget can lead to those not having enough resources allocated as well as the required skills are acquired that can deal with AI-ML technology. Thus, the mitigation action suggested by participants A-D will be sufficient, as building a strong business case containing the benefits and the value there is to be had will create strong arguments as to why to invest in the technology. The recommended action was also confirmed by the AI expert giving further validity to the recommended action.

5.3. Environmental Context

5.3.1. Partnership

The lack of sufficient partnership both internally and externally is a relevant barrier in the pre-adoption phase of AI-ML in the forecasting process. As stated by Mikalef & Gupta (2021) data is collected both internally and externally. From the empirical data collection, it was found that the firm currently utilizes 30 suppliers all over the world, in which the data provided by the supplier is significant as the data is utilized to predict the forecasting for the firm's capacity planning. The key role of good supplier collaboration was first noted by the author (H. Chen et al., 2021), in which they stated the unique part good supplier relationship has in AI adoption. Furthermore, the notion of good supplier collaboration and its importance was also backed up by the AI expert emphasizing it as a necessity in AI-ML adoption for forecasting. Creating good collaboration with one supplier will act as a great enabler for AI adoption.

The suggested mitigation action by respondents was to seek ways to improve their collaboration presenting their needs and reasons for adopting AI-ML. From the AI expert regards to the suggested mitigation action it was noted that the firm just stating their needs may not prove to be beneficial, moreover that there also needs to be created incentive given motivation for the supplier to work towards a better relationship and supply them with the resources needed with the data system.

The other aspect of having good collaboration with IT firms is also seen as important early on in the adoption phase as firms do not usually possess the full technical skill capacity to deal with the sophisticated technology of AI (Chatterjee et al., 2021; H. Chen et al., 2021). From the empirical data, it can be noted that the IT issue was a reoccurring theme, in which the participant explained their main inhouse IT is allocated in a different country as well the collaboration with the external IT partnership is not significantly invested in.

Thus, the suggested mitigation action provided by participants A-D was to either expand their current collaboration with their external IT. As well as the main IT management were to plan a visit to the location in which the employees could state their concern. However, while the AI expert agreed to the suggested mitigation action. The expert did not see IT playing a significant role in the AI pre-adoption part due to that they may not possess the needed skills.

In summary, making sure that good collaboration is withheld with different actors is important for the success of AI-ML adoption as in the case of the supplier they provide vital data used to make the predictions. Creating different incentives to improve the collaboration may be seen as sufficient mitigation action and hopefully can yield good results in the end.

5.4. Outcome from the discussion and analysis

From the analysis and discussion between the literature and empirical data, it can be noted that some supposed barriers were of larger concern than others. In the interviews, a large chunk of focus held by the participants was on the organizational context suggesting that this may be the most important factor. As well as indicated by the literature and AI expert regard the top management, and organizational readiness.

Furthermore, as the participant discussed that without the top management support the project won't have the opportunity to start. As the management is the one that either acts as a great enabler or barrier when it comes to the organizational readiness. Thus, prioritizing creating managerial awareness and understanding suggests that it will allow for some flaws in the business case as the top management already have some understanding and awareness of the potential benefits.

The environmental aspect was put third due to the strong statements held first by the AI expert, and secondly by the participants involved in the forecasting process. Due to the reliability, the firm has on both the supplier to provide them with data and IT for its support.

The technological context was put last in this case due to the participant involved in the forecasting process, and AI expert. Showed less worried about the following barriers in the pre-adoption stage.

Thus, based on the discussion and analysis a new table is created displaying the mitigation actions to answer the supposed research question. See Table 15. The barriers are ordered following what was seen as the most relevant barrier in the pre-adoption from respondents A-D, the AI expert, and literature.

Table 17. Presents the recommended actions for the AI pre-adoption barriers identified for the forecasting process.

Priority to be addressed	Context	Adoption barrier	Recommended action
1.	**Organizational**	O2. Top management - Lack of Support - Lack of Involvement	Create managerial awareness and understanding of AI-ML technology.
2.	**Organizational**	O3. Organizational Readiness - Economical constraints - Lack of competence	Build a strong business case including, the benefits and economical value it can create. Hire the personnel already trained in the matter of dealing with AI technology, for example, data sciences.
3.	**Environmental**	E1. Partnership - Supplier collaboration - IT collaboration	Seek ways to improve the supplier relationship. By creating incentives that establish motivation for the supplier to want to build the relationship. Increase the collaboration with the external IT actor. Allow the IT to learn and understand the organization.
4.	**Technological**	T2. Inappropriate Technology Infrastructure - Digital platform - Infrastructure - Interoperability	Create an interactive data platform, that allows the different actors associated with forecasting to input their data.
5.	**Technological**	T1. Poor Data - Quality - Access - Volume	Comprehensive dataset, that includes the most significant parameters associated with forecasting.

It is important to note that even though some of the barriers may be seen as more critical. The mitigation to handle the supposed barriers may vary greatly in both time and effort. Therefore, the reader and firm need to keep this in mind. In this case, the priority to be addressed for the firm was purely based on the data collected from the literature, and primarily the data provided by participants A-F.

6. Conclusion

The following chapter aims to conclude the thesis and to create clarification for the reader regards the proposed research question. Followed by the theoretical and managerial contributions. Ending the chapter with the limitations of the thesis and suggestions for future research.

6.1. Answer to the research question

The following research is a single case study, which investigates the barriers associated with AI adoption in the pre-adoption phase in the forecasting processes, and how these barriers are mitigated. The barriers are identified through a scoping literature review identifying the main barriers connected to AI adoption and the mitigation action is answered with the help of empirical data collection. Thus, enabling the following research question to be answered:

RQ: How does a manufacturing firm mitigate AI pre-adoption barriers in the forecasting process?

The first part of the research question identifying the relevance of the barriers associated with AI adoption is seen to connect well to the literature and empirical data collection. With only minor differentiation such for example making sure that sufficient data is established early on at the start of the adoption phase. This did not seem to have a significant effect and require immediate mitigation in the AI pre-adoption phase. Table 16 shows the main findings summarized to answer the proposed research question in a categorized manner based on the empirical data findings and literature. It can be noted that the organizational context may be seen as the most influential aspect impacting AI-ML adoption in the pre-adoption phase. Due to that without the lack of managerial support and involvement the project will not be able to progress at all.

Table 18. Presents a summarized version of the mitigation for the pre-adoption barriers of AI in forecasting.

Adoption Barrier	**Recommended Action**
Top management	Create managerial awareness and understanding.
Organizational Readiness	Strong business case. Hire personnel possessing the needed skills.
Partnership	Communicate needs, as well as create incentives that initial motivation for increased collaboration.
Inappropriate technology infrastructure	Interactive data platform, allowing access to the different actors associated with the forecasting.
Poor data	Comprehensive dataset, comprising the most important parameters associated with forecasting.

6.2. Theoretical Contribution

The following research contributes to the literature by first addressing the gap identified concerning the lack of studies on the pre-adoption phase (Caron-Fasan et al., 2020; Hameed et al., 2012), discussing the barriers in the context of manufacturing firms, and the recommended actions to deal with these barriers (Jöhnk et al., 2021; Kinkel et al., 2021). By conducting the research at a firm that is in the pre-adoption phase of AI-ML technology and with the validation from the AI-forecasting expert. The findings from the research can be seen as significant as the data is collected in the right context.

Secondly, the research highlights the barriers that can be most significant in the pre-adoption phase of AI-ML in a specific manufacturing process (forecasting). Creating new insight as to how to mitigate the challenges associated with different elements of the TOE framework brings specificity and assists scholars in innovation science to explore particular aspects. Furthermore, what context and factors can be considered to focus on in the pre-adoption phase. From the literature, the concern and importance of data were highly regarded to be a core to enabling AI adoption (Enholm et al., 2021). However, in the pre-adoption, the empirical analysis suggests being less of a significant barrier.

Finally, the research reduces the lack of studies when it comes to studying barriers associated with technology adoption (Stornelli et al., 2021). As the study primarily focuses on the barriers associated with technology adoption, and how the identified barriers are mitigated.

6.3. Managerial Implications

The study can be insightful for practitioners looking to understand the potential challenges there are in the pre-adoption stage of AI-ML technology. As well as provide them with practical recommended actions to mitigate these barriers. The insight provided by the AI expert adds to the validity as well as enriches regards to the mitigation action and relevance of the adoption barriers. Thus, practitioners currently in the pre-adoption of AI-ML that are interested in utilizing the technology will provide them with knowledge as to barriers associated with AI-ML adoption in the forecasting process and ways to mitigate the difficulties.

Secondly, the research provides managers with insight as to the power they possess to drive or halter projects. Emphasizing, that creating managerial awareness and understanding of technology is a crucial factor in the pre-adoption phase. Furthermore, creating managerial awareness and understanding will help mitigate some of the other barriers such as the economical and competence barriers. Thirdly, the study highlights the hire of new competence was seen to be the more prominent mitigation action to deal with the lack of competence instead of just training current personnel to possess the necessary skillset.

6.4. Limitations and Suggestions for future research

As with any research, limitations are set at the start, and more are found once the study nears its end. In the case of this study, several limitations were met. The first limitation to take into consideration is that the study is a single case study. Meaning the researcher focused on the perspective of one specific firm. Thus, to further confirm and add to the findings future research is recommended to perform a similar study at another firm that can also validate or add to the result.

Secondly, even though the firm is a multinational firm, the view on AI adoption is based exclusively on the Swedish perspective, in which the firm's knowledge of AI has shown to be scares, as the adoption of AI is still in the early stages compared to its counterpart in the US. Thus, future studies with the firm are recommended to investigate the mitigation actions on the part of the firm, which is further ahead in the adoption phase of AI-ML in the forecasting process. As well as conduct more interviews with the firm.

Thirdly, the findings suggest that the greatest challenge of AI-ML adoption in the pre-adoption faced by the firm is the organizational factor. Thus, it would be interesting to study the perspective of another manufacturing firm. To further validate the challenges, and if the mitigation actions to deal with the pre-adoption barriers would be dealt with differently.

7. References

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8. Appendices

Background questions:

1. What is your educational background?
2. How long have you worked at the firm?
3. Have you held many different titles during your time at the firm?
4. What is your current title?
5. How long have you been a part of the forecasting process?
6. What is your main function during the forecasting process?
7. What is your experience with data analytical tools?

Tables 19-21 present the initial questions asked in the semi-structured interviews divided following the TOE framework.

Technological:

Table 19. Technological context initial question asked in the interview.

Barrier	**T1. Poor data**
Description	Tools such as machine learning (ML) require a massive amount of data to perform and aid in managerial challenges (Allen, 2019; Bag et al., 2021; Kinkel et al., 2021). By providing ML tools with a high volume of low-quality data the accuracy, reliability, and useability of the result become questionable.
AI question (Barrier related)	How important is the data when it comes to forecasting?
Challenge	How would you make sure that enough data is supplied to support a sufficient forecasting prediction?
Barrier	**T2. Inappropriate technology infrastructure**
Description	Refers to the firm's lack of the appropriate digital platform and infrastructure that can facilitate the necessary computing power, large storage space for the massive amount of data, as well as the communication between different datasets (Allen, 2019; Cubric, 2020; Enholm et al., 2021; Kinkel et al., 2021; Merhi, 2021).
AI question (Barrier related)	Is it difficult to collect the needed data used in forecasting to enable your predictions?
Challenge	How would you like to make the data more accessible and easier to collect?

Organizational:

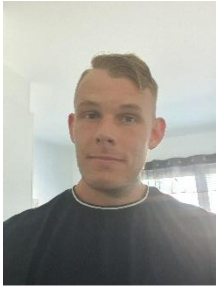
Table 20. Organizational context initial question asked in the interview.

Barrier	O2. Top management
Description	A major barrier discussed in the literature when it comes to the adoption of AI in manufacturing firms is the lack of involvement and support from top management (Bag et al., 2021; Cao et al., 2021; Chatterjee et al., 2021; Enholm et al., 2021; Kinkel et al., 2021; Mahmud et al., 2022; Merhi, 2021; Mikalef & Gupta, 2021; Xing et al., 2021). Top management can influence different functions such as the hiring and training of employees to possess the skills required to successfully use AI tools for managerial decisions making (Bag et al., 2021).
AI question (Barrier related)	How do you perceive the top management's support and involvement in various projects?
Challenge	Can you describe a scenario where you were met with difficulties due to a lack of management involvement and support and how you dealt with it?
Barrier	**O3. Organizational Readiness**
Description	Organizational readiness refers to the financial barriers and lack of employee competencies required for successful AI adoption (Bag et al., 2021; Chatterjee et al., 2021; Dhamija & Bag, 2020; Hutchinson, 2021; Kinkel et al., 2021; Lee et al., 2019; Merhi, 2021; Mikalef & Gupta, 2021; Stornelli et al., 2021; Wamba-Taguimdje et al., 2020).
AI question (Barrier related)	Is it difficult for the firm to make justifications for financial investments?
Challenge	1. What does the process look like to make sure that you achieve the finical investments? 2. How does your firm deal with a need such as when you see that there is a lack of employee competence?

Environmental:

Table 21. Technological context initial question asked in the interview. Environmental context initial question asked in the interview.

Barrier	E1. Partnership
Description	This barrier refers to a firm lacking the necessary collaboration needed for successful AI adoption. Firms usually do not possess the needed number of technical requirements to understand and deal with sophisticated algorithms, Thus, external help from IT firms comes into the mix to aid in the adoption of technology (Chatterjee et al., 2021; H. Chen et al., 2021; Kinkel et al., 2021; Rodríguez-Espíndola et al., 2022). Furthermore, the lack of a good supplier relationship is also seen to be a barrier faced by firms looking to adopt AI technology (Chatterjee et al., 2021).
AI question (Barrier related)	1. How does your IT work in the firm at the Swedish location? 2. Are the suppliers an important relationship to the firm to collect data for the forecasting?
Challenge	1. How would you like to improve your IT partnership? 2. Can you describe a scenario where you had difficulty due to a lack of collaboration with your external partners?



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