From Investment to Payoff: Exploring the Cost Implications of AI Adoption in Inventory Management Across the Different Phases

A multiple case study of how the adoption of AI in inventory management can affect logistics and manufacturing companies costs during each phases

**BACHELOR THESIS WITHIN:** Business Administration, 15 credits  
**PROGRAM OF STUDY:** International Management (B.Sc.)  
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**JÖNKÖPING DECEMBER 2023**
**Abstract**

**Background and problem discussion:** In recent years, there has been increasing recognition of Artificial intelligence (AI) and its benefits in various sectors, including inventory management, which is a significant component of company expenses. However, adopting AI in inventory management also comes with challenges and expenses before businesses can fully reap its benefits. Although extensive research has been carried out in the field of inventory management in areas like the benefits of AI adoption, the road map on AI implementation, and the generalized challenges of AI, a research gap is identified. No single study has addressed the financial cost associated with different phases of AI adoption that companies need to evaluate before adopting AI and the potential benefits associated with adopting AI within their inventory management. Hence, this thesis addressed this research gap.

**Research Purpose:** The purpose of this study is to explore how the adoption of artificial intelligence (AI) can affect organizational costs associated with inventory management at each phase of adoption, offering insights into both the cost implications and the benefits that companies will realize. This will equip businesses with the necessary knowledge to make informed decisions, allowing them to strategically implement AI to maximize efficiency, cost-effectiveness, and the overall benefits of their inventory management processes.

**Method:** These thesis philosophical assumptions are guided by a relativist ontology and social constructionist epistemology. The abductive approach was used where Qualitative data was collected through semi-structured interviews where we studied the perceptions of managers who were a part of AI adoption in inventory management.

**Conclusion:** it becomes evident from our study that organizations face significant costs in the pre-adoption phase, these costs are associated with readiness for AI adoption, which involves evaluating needs, commitment, and hiring experts. As they transition into the adoption phase, companies also face costs associated with enhancing the workforce skills to effectively utilize AI. Also, there are costs associated with Hardware equipment and training AI models. In the Post-adoption phase, companies start to experience cost-related benefits, these benefits include automation of repetitive tasks and complex data handling, improved forecasting, reduction in human error, and potentially reduced employee costs, leading to overall cost savings and enhanced business operations.
Acknowledgments

We want to use this opportunity to express our sincere gratitude and acknowledgment to the people who have supported and guided us throughout this research process.

First and foremost, we would love to show our gratitude towards our supervisor, Emma Stendahl, whose guidance, feedback, and encouragement were impeccable in the entire thesis process.

Secondly, we also offer our gratitude to our research participants who generously shared their valuable time and knowledge. Without whom this research would not have been completed and easygoing.

Thirdly, we would like to thank the fellow students of our seminar group for their insights and suggestions for improvement.

Lastly but certainly not least, we extend our heartfelt thanks and gratitude to our families and friends for their remarkable support throughout this thesis journey.

Jonkoping, December 2023

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1. Introduction

The objectives of this chapter are to provide the research background, purpose, and problem of this thesis and to deliver an overview of the topic of supply chain management and artificial intelligence in today’s world.

1.1 Research background

Artificial intelligence (AI) stands at the forefront of computer science today, a domain where high-tech is all about. According to Schroer (2023), AI is a part of computer science that deals with the creation of an intellectual system that can perform tasks that usually require human intelligence. By combining machine learning, data analysis, and sophisticated algorithms, it draws from an array of disciplines. Noticeably enough, AI has gained widespread recognition in various sectors. It's easy to see why, given its capacity to reshape systems and processes that organizations readily exploit for enhanced efficiency and lower costs. If there is one area that calls for such intricacy more than anything else, it's got to be inventory management, where inventory-carrying costs represent 20% to 30% of total inventory value (McCue, I, 2020). The main reason why inventory management is very important in organizations is to avoid cases of stockouts, minimize the cost involved, and ensure that the industry meets the objective of full manufacturing (Jenkins, A, 2020). In order to make things easier in organizations, management must have a strategy rolled out on how to control inventory. It involves the coordination and monitoring of the supply of goods from the manufacturers all the way to the point of sale to the end user (Hayes, 2023).

Incorporating AI into inventory management Exceeds the predefined constraints by utilizing machine learning, predictive analytics, and natural language processing to overcome the problems of traditional inventory systems. The efficiency of the AI techniques ranges from immediate data access to efficient demand forecasting. The importance of AI in inventory management includes mitigating issues related to stock discrepancies, order delays, and excess inventory (Dhaliwal, 2023). AI adoption in inventory management is not as easy as it looks. It necessitates a thorough understanding of technology, strategic planning, and adaptation to organizational needs and processes. The impact of AI adoption on organizational costs during
different phases is a critical area of study, as it provides insights into the investment required, the potential return on investment, and the long-term sustainability of AI-driven inventory management solutions.

There is significant importance in this research due to its multifaceted nature concerning the correlation between the adoption of AI and the effect on the cost of inventory management. This effect is looked at across the stages of adoption. Companies more and more are realizing the need to invest in leading-edge technologies to help keep in the race (Smaje, K. 2020); however, whether to adopt the use of AI is a careful decision since the costs involved with such a decision are significant.

1.2 Problem formulation

In today's rapidly changing world, the adoption of artificial intelligence in inventory management in the supply chain has gained significant attention. There is a growing body of literature that recognizes the importance of AI adoption in the inventory management of SCM, with a focus on understanding how AI technologies can improve efficiency and reduce costs in the inventory management process. (Bughin et al., 2017; Schaeffer et al., 2018). The literature regarding inventory management in artificial intelligence has been frequently discussed, and the concept of efficiency in inventory management is a highly relevant topic within existing literature today (Praveen et al., 2020). According to Sharma et al. (2021), efficiency in businesses with AI is important for industries because it can lead to certain benefits such as reducing operational costs, increasing production speed, improving product quality, and lastly, enhancing decision-making processes. Liu et al. (2022) stated that efficiency in the manufacturing industry is critical since it directly affects productivity and profitability in companies. Nasution et al. (2022) highlighted that AI can improve efficiency, reduce manual errors, and enhance the convenience of warehouse operations.

Another aspect that has received attention in the field of artificial intelligence in inventory management is the use of artificial intelligence techniques, mostly machine learning, artificial neural networks (ANN), and expert systems, to manage production. According to Pournader et al. (2021), machine learning algorithms can help analyze data on 14 inventory levels, helping in demand forecasting, reducing waste, and minimizing cost. Also, Sustrova (2016) highlighted that artificial neural networks (ANN) examine data for underlying trends and enhance stock
optimization through AI in inventory management. Moreover, Min (2010) highlighted that the Expert system can also help in optimizing production schedules through the provision of suggestions for process improvement and the analysis of data. Another interesting research phenomenon increasing in the literature today is the processes, stages, and mapping applications of artificial intelligence in various supply chain fields. Reim et al. (2020) created a roadmap with four key insights that are essential when implementing AI in a business. Similarly, Gamoura et al. (2020) proposed the five core processes of AI implementation: 'plan', 'source', 'make', 'deliver', and 'return'. Which has been widely used as a model for existing literature in SCM.

However, even though the use of AI in inventory management has grown, current AI theories cannot be used to fully understand the financial implications that organizations may face when they adopt AI within the different phases of implementation. This is because most research has been focused on the technology's general benefits and uses, with fewer in-depth studies on how these adoptions have a cost impact on organizations. Hence, a research gap is identified. For instance, Liu et al. (2022) pointed out that AI can be used to optimize production processes, reduce the need for human labor, and minimize downtime. Also, Pannu (2015) highlighted that AI has the potential to revolutionize several industries by lowering costs, increasing productivity, and enhancing decision-making. Similarly, Pech et al., (2021) found that machine learning can be used to prevent costly repairs through predictive maintenance. Hence, all these previous authors limited their research to the operational benefits of AI implementation in terms of reducing cost and increasing productivity, omitting the financial cost implications, for example, expenses related to the installation of AI technology, hiring professionals, or maintenance of adopting AI in organizations during different adoption phases.

This means that we need a better understanding of the full range and possible effects of the financial costs that organizations face when they first start using AI in their inventory management and the benefits that may arise after adopting AI completely. Several scholars have mentioned this need. For instance, Dhaliwal et al. (2023) stated the need for future investigation on the impact of AI in inventory management and its role in driving cost efficiency; likewise, Mohsen (2023) claimed that existing literature has offered limited investigation on the ROI (return on investment) of adopting AI in supply chain management, making it challenging for organizations to analyze the value of their AI investments. He also highlighted the need for a precise assessment of the cost of the complex integration of AI and the costly investment into a business for organizations. Hence, this paper addresses this gap by further exploring the costs
associated with AI integration during these different phases of inventory management, which are currently unaddressed in past literature.

1.3 Purpose and research question

The research question of this study is: *How does the adoption of AI into inventory management impact the costs of organizations during each phase of adoption?*

To completely address this research topic, we will investigate the three phases of integrating artificial intelligence in inventory management from a financial standpoint—post-adoption, adoption, and post-adoption. We will analyze and give insights into the different impacts of AI on inventory management costs as it is adopted. This study will provide more knowledge of the implementation of AI in inventory management and the potential impact on organizational costs. Furthermore, the implications of AI adoption in the different stages will be examined to offer useful information for managers, practitioners, and researchers in the field of AI applications in supply chain management.

1.4 Delimitation

It is important to note that the scope of this study includes limitations. This thesis is solely limited to financial cost in terms of monetary expenses associated with hiring experts, customization, and maintenance of AI systems within the three phases of AI adoption in inventory management; it does not explore other types of cost, like non-financial cost or opportunity cost, that are non-relevant for AI adoption. Moreso, since the field of our study is AI adoption, we will engage with technology industries for some vital information relevant to this study. However, this research is mainly focused on two industries, which are logistics and manufacturing companies. It is restricted to other sectors like construction, transportation, or the agricultural industry to maintain a focused and accurate research study.
2. Frame of references

This section presents a theoretical background on the adoption of artificial intelligence and inventory management in the supply chain. Firstly, it explains the derivation of how the relevant literature was achieved. Secondly, it explains a comprehensive review of previous research concerning the merging theme of AI and inventory management and to conclude, it gives a theoretical explanation of this paper.

2.1 Method for literature search

A thorough examination of the literature was conducted with the objective of identifying and analyzing significant scholarly studies on the given phenomena about artificial intelligence in supply-chain management field as well as to present evidence from previous studies. Prior literature was researched to develop our theoretical basis because this thesis attempted to explore how the integration of artificial intelligence technologies impacts the cost of manufacturing and logistics organizations during the phases of adoption into their inventory management. The literature review approach utilized several academic journals from the database: Research Gate, Science Direct, Semantic Scholar, and Scopus. However, Google Scholar and Web of Science was used as the main database since it provides comprehensive scholarly literature across an array of discipline and includes most peer-reviewed journals. using “artificial intelligence and Inventory management” as keywords and focusing on search results of peer-reviewed journal articles, yielded 319,000 results from Google Scholar and yielded 272 results from Web of Science using the year range from 2018-2023. The year range was preferred in order to attain a more relevant and up-to-date research review based on our topic. The general literature search was only limited to 2010-2023 and this range was essential to understand the growing body of knowledge in Artificial intelligence on our field of study and tracking up to date performance of previous studies. similarly, we focused on using highly cited articles. In order to perform the literature search accurately, we obtained results merging from our keywords by scanning through the title and abstract and using other boolean operators like “OR” and “NOT” to search for our keywords.

By using the same keyword search performed in the database, the search was narrowed down by adding the key term “Cost-efficiency” to the previous search word resulting in 2,542 from Web of Science and 18,600 results from Google Scholar. To narrow down the results of relevant
articles, the language of the articles was restricted to the English language. Also, To ensure that the articles used meet the required level of quality, most of the articles used in the literature review were published in association with business school list (ABS) journals, the relevant articles used was between a rank of 3-4* which is considered to be the highest rank and guarantee the relevancy of the paper, using such articles gives our literature more credibility (collins & Hussey 2014). The following figure below shows the keywords situated from our topic focus.

2.2 Literature review

2.2.1 Defining artificial intelligence

AI as a domain within computer science, is dedicated to crafting systems that can undertake tasks that traditionally require human cognitive abilities (Pournader et al., 2021). The inception of the term "artificial intelligence" can be traced back to 1955 when John McCarthy introduced it, emphasizing the potential of machines to process language and tackle challenges typically associated with human cognition (Pournader et al., 2021). Delving into the multifaceted realm of AI, it can be categorized into distinct branches based on their core functionalities. One such branch focuses on the ability to sense and interact across various mediums, including text, audio, and video, encompassing areas like speech recognition, computer vision, and Natural Language Processing (NLP) (Pournader et al., 2021).

The surge in AI's popularity can be attributed to various organizational and environmental factors, including dynamic customer expectations, heightened global competition, comprehensive digitalization in companies, and a swiftly evolving technological landscape (Helo & Hao, 2021). Such advancements have enabled AI to transcend traditional computational boundaries, offering capabilities like machine learning and artificial neural networks that can process vast datasets and continually refine their performance with minimal human intervention (Helo & Hao, 2021).

2.2.2 AI in supply chain management

SCM traditionally, has been a complex web of activities that involve the planning, control, and execution of product flow from sourcing to manufacturing and distribution to the end customer.
With globalization and the digital revolution, these processes have become even more intricate (Christina, A., 2020). AI, with its ability to process vast amounts of data and provide actionable insights, has emerged as a game-changer in this domain (Dhaliwal et al., 2023).

Amidst technological advancements, the role of AI in SCM has become increasingly pivotal (Helo & Hao, 2021). The rapid evolution of AI has significantly impacted various sectors, including supply chain management, introducing a plethora of terminologies and concepts that have reshaped traditional processes, and highlighting its role in demand forecasting, inventory planning, and supplier selection, offering enhanced efficiency, accuracy, and predictive capabilities (Sharma et al., 2022). During the fourth industrial revolution, characterized by the convergence of disruptive technologies like AI and robotics, the traditional boundaries between humans and machines are becoming increasingly indistinct (Sharma et al., 2022). AI, with its capabilities in interoperability, data storage, and business analytics, emerges as a pivotal catalyst for transformations in supply chain management (Sharma et al., 2022). Supply chain management is becoming increasingly information-centric, with a shift from relying on assets like inventory and transportation equipment to leveraging information (Min, H., 2010).

Recognizing the paramount importance of information for supply chain success, professionals in the field have been exploring various methods to manage and capitalize on this information, with AI being one such method (Min, H., 2010).

The integration of AI in supply chain management has been posited as a solution, with AI tools offering the potential to streamline sourcing, production, and delivery processes. These tools can enhance predictive maintenance, planning, and scheduling, and mitigate the bullwhip effect, a phenomenon in forecast-driven distribution systems (Hangl et al., 2022). Despite the evident potential of AI in optimizing these specific aspects of supply chains, there remains a scarcity of comprehensive studies that thoroughly explore the breadth and depth of AI's applications in the broader context of supply chain management (Riahi et al. 2021).

Supplier selection is another area that has attracted a lot of attention to its substantial impact on effective supply chain management, (Chai et al., 2013). According to Carrera and Mayorga (2008), Supplier selection is the procedure by which the optimal option is determined from among various alternatives and supplier attributes. When faced with multiple options and supplier characteristics, the wisest course of action is to select one. In recent years, many manufacturers have been downsizing their operations moving away from vertical integration. (Carrara and Mayorga, 2008). Most organizations, according to the author, have tried to gain a
competitive edge by enhancing the capabilities and technology of their suppliers. Kannan and Tan (2002) highlighted that supplier selection can take two approaches to be descriptive and prescriptive. Supplier selection decisions are frequently made in a context characterized by uncertainty, opposing goals, and insufficient information (Carrera and Mayorga, 2008), the author further claimed that one can anticipate enhancements in product quality, streamlined technology integration, and decreased delays for new products through the utilization of suppliers' capabilities. An important study on the topic was conducted by Zhang et al. (2016), who investigated the use of artificial intelligence in supplier selection. According to their findings, AI technology can sort through a company's supplier portfolio and eliminate those that don't meet the order's specifications. They also recommended AI to businesses with a large pool of potential suppliers. Nissen and Sengupta (2006) found that AI can automate several operations, including exploring online catalogs for potential suppliers, rating vendors based on several attributes, selecting qualifying suppliers, and processing purchase orders. In addition to being one of the most essential and crucial decisions a company can make, supplier selection is also one of the most challenging and critical owing to the growing complexity of the decision-making process (Carrera & Mayorga, 2008).

2.2.3 AI in inventory management

Inventory management can be defined as a continuous process that involves planning, organizing, and controlling to minimize inventory investment and maintain a balance between supply and demand (Verma & Sigh 2018). Perez et al (2021) conducted a study, they highlighted that Inventory management is crucial for efficient supply chains, cost control, and timely customer delivery, and is closely linked to supply chain management. Verma and Sigh (2018) highlighted various factors that are included in inventory management such as visibility of stocks, forecasting, delivery time, shipping costs, valuation, physical space, quality management, returns, and demand forecasting.

AI has been utilized to send alerts for stock reordering and aid in creating manufacturing schedules that account for demand fluctuations, including seasonal surges, with high precision Yashoda (2018). A study conducted by Rushton et al. (2014) found that cash tied for company warehouses accounts for around 20-30% of logistics costs, while holding inventory makes up about 18-20%. According to Eliamani (2021), implementing inventory management techniques
offers several benefits such as cost reduction, improved customer satisfaction, enhanced supply chain, and increased employee knowledge.

According to Kvartalnyi (2021), the author explores the advantages offered by AI in the realm of inventory management. It was found that AI offers several benefits in inventory management. These include minimizing errors, improving inventory and item tracking, predicting and planning through machine learning, and reducing errors through forecasting. Kvartalnyi, 2021 further argues that AI-powered forecasting was found to decrease errors by 30-50% in supply chain networks. This results in improved accuracy and a 65% reduction in lost sales primarily caused by out-of-stock inventory. Additionally, warehousing costs decrease by 10-40%. As demand forecasting and inventory planning can be seen to be significant in the area of inventory management.

Demand forecasting has been an emerging concept arising from the concept of inventory management (Nasution et al., 2022). Demand Prediction and Reinforcement Learning are the two main AI methodologies mentioned in papers (Praveen K B, 2020; Nasution et al., 2022). Demand forecasting focuses on predicting future demand for inventory products with greater accuracy by using a variety of ML approaches and external data sources (Praveen K B, 2020). The capacity of AI to improve demand forecasting is one of the major benefits of using it in inventory management. According to a paper named "Inventory management using Machine Learning," AI-based predictive models may considerably increase the accuracy of demand forecasting, which in turn improves inventory management (Praveen K B, 2020). Abiodun et al. (2018) carried out a survey on the most recent uses of artificial neural networks (ANNs) and discovered that AI tools like predictive analytics and machine learning may improve data accuracy, productivity, and decision-making, which can save costs, according to their findings. A study by Nasution et al., 2022 stresses that AI-driven forecasting of demand not only helps inventory management, but it also boosts consumer satisfaction by guaranteeing items are accessible when and where they are required. This is consistent with the conclusions of the (Praveen K B, 2020) paper, which highlights how precise demand forecasting results in greater raw material cost reductions and enhanced strategic planning. By looking at previous data, AI-driven models may find trends and variables that affect demand, reducing the possibility of overstocking and stockouts and eventually, saving money (Nasution et al., 2022). The potential for AI to save costs related to excess inventory or lost sales opportunities is highlighted by this.
Inventory planning has been seen to be an important aspect of AI when it comes to inventory management since inventory deals with a large cash flow (Song et al., 2020). Min 2010 stated that the success of a firm's competitiveness is the ability to control and plan inventory at a minimum cost. The core difficulty of inventory management begins with establishing parity between operational efficiency, cost of capital, and other related costs while optimizing inventory holding levels (Mor et al., 2021), therefore inventory planning is essential to minimize the total inventory ordering, and shortage costs Song et al., (2020) claimed this necessity in his literature. By considering a number of elements, such as historical data and outside variables, AI systems have been used to improve inventory levels (Nasution et al., 2022). According to Sustrova, (2016), AI may have a substantial influence on inventory control and planning. AI-enabled expert systems, for example, may reduce errors and improve inventory management by 8-18%. This demonstrates how crucial AI is as a tool for preserving the ideal quantities of inventory. According to Abu Zwaida et al. (2021), their research revealed that inventory levels can be optimized via AI-powered algorithms. Additionally, it may enhance cargo placement layout and optimize storage techniques, which will increase operational efficiency, claim (Davarzani & Normann, 2015). Lowering the expense of maintaining inventory and avoiding stockouts, can help companies cut expenditures.

Summary of the literature review

Previous researchers have shown significant findings and discussions in the area of artificial intelligence having a strong impact on supply chain management, with a major focus on the benefits of its implementation and contribution to businesses, such as improved efficiency and productivity (Sharma et al., 2022; Pournader et al., 2021). Moreover, numerous studies of artificial intelligence in inventory management have been carried out, identifying areas like demand forecasting, inventory planning, and supplier selection. Despite the evidence of artificial intelligence advancement in these various fields of study, half of the studies failed to examine the different cost impacts, like the financial effects, of adopting AI in this area. Researchers have not treated the cost of adopting this new technology in much detail. Therefore, our conceptual lens aims to address these aspects through the theory of the adoption phases of AI. This will help businesses make strategic decisions by navigating the complexities associated with each phase, allocate resources effectively at each step, and realize the full benefits of AI in inventory.
management. This theory will explain the various costs related to the application of AI during the different phases of its implementation.

2.3 Conceptual lens

The adoption of AI into inventory management can impact the costs of organizations during each phase of adoption. Although there are numerous conceptual lenses composed of the theory of adoption of AI technologies, none has directly offered a structured framework for understanding the organisational cost in the process of adopting these AI technologies over time which has been identified as a gap in the literature review. This conceptual lens was developed based on combining existing theories and insights from data and this will enable us to be flexible in refining and adjusting our lens by moving back and forward between the empirical data and existing theories. Therefore, the conceptual lens developed will enable us to identify various factors influencing costs at different stages of adoption of AI technologies. and it’s important for this study because it serves as a road map for organizations to evaluate their decision based on the cost implication at each phase of adopting AI.

2.3.1 Pre-Adoption phase of AI in inventory management

The concept of pre-adoption by Lesca et al., (2015) refers to a phase characterized by the acknowledgment and understanding of a specific requirement, the collection of relevant information, and the assessment of whether information technologies (ITs) possess the capability to address the identified need. Therefore, this stage is regarded as the preliminary phase of the adoption process. This could include a number of things that affect the stages of the adoption process, such as researching and developing different artificial intelligence systems, doing a feasibility study, and checking to see if they are compatible, Himang et al. (2020). The factors in the pre-adoption phase include:

**Complexity and capability check**

The pre-phase of this study involves an investigation into the firm's readiness to implement artificial intelligence, Jöhnk et al. (2021). AI readiness, during the pre-adoption phase, centers on evaluating an organization's requirements, dedication, and existing resources necessary for the implementation of AI technology. Financial resources, specifically a designated budget (Pumplun et al., 2019), are crucial to consider Consequently, organizations must carefully
evaluate their readiness and assess their capacity to effectively manage the expenses associated with AI adoption in this phase.

**Hiring consultants for feasibility check**

In the pre-adoption phase, there are financial expenses associated with doing a feasibility analysis (Enhom et al., 2021). Kinkel et al. (2021) stated that adopting AI technology needs the help of consultants or personnel who are very good at developing software and hardware and also know a lot about data science. Organizations will also be required to allocate financial resources for the recruitment of external experts or consultants who possess specialized knowledge in AI technologies. This underscores the importance for organizations to maintain a flexible budget, as advanced AI technologies represent a long-term investment (van Dewell, 2022).

**Data collection and processing**

Organizations that hold high-quality data are more likely to adopt artificial intelligence (AI) as they rely on such data to train AI systems (Mikalef & Gupta 2021). According to Allen (2019), organizations may face expenses related to data acquisition and the integration of new data sources during the process of forecasting. These costs include activities such as data cleansing, organization, and assuring the quality and integrity of the data during the adoption phase.

**Compatibility analysis**

The concept of compatibility refers to the extent to which an innovation is seen to align with the prevailing values, requirements, and historical encounters of potential adopters (Luo et al., 2010). This integration has the potential to yield cost reduction and time savings in the respective phase under consideration. However, Chen et al. (2021) and Kinkel et al. (2021) assert that many businesses have challenges during the early phase of comprehending the suitable kind of compatibility with artificial intelligence (AI) technology, which can result in increased costs associated with investigating and exploring pre-adoption of AI.

**2.3.2 Adoption phase of AI in inventory management**

The adoption phase is the point in the implementation process that enterprises move from the phase of decision-making and planning into the actual deployment of AI technology in their
inventory management systems. From theoretical thought to actual execution, this step represents an important transition (Karahanna et al. 1999). It is crucial to address the financial element of AI deployment during the adoption phase, even if the pre-adoPTION phase predominantly concentrates on its conceptual components. Financial considerations that are relevant at this point should be assessed, according to Quagli et al. (2021). This may include the costs of customizing the existing inventory management system and incorporating AI, as well as the cost of staff training and expert hiring. The factors in the adoption phase include:

**Hiring new experts/training employees**

The ability to properly use and operate the AI system depends on personnel having the right knowledge and skills. Bughin et al. (2018) highlight the importance of skillset evaluation in detecting skill shortages and deciding how much training or recruiting is required during AI adoption. In line with this Vepsäläinen (2023) states that addressing the skills gap requires strategic actions such as retraining, redeploying, contracting, and releasing employees if necessary, emphasizing the importance of considering the financial burden and time commitment associated with training initiatives (Vepsäläinen, 2023).

By evaluating the skill sets of the workforce, training initiatives may be tailored to the specific requirements of the company. Machine learning, data analytics, and AI system operation are just a few of the topics that the training programs may cover. Workshops, online classes, and collaborations with educational institutions are some of the ways they might be implemented (Kuna et al., 2022).

**Customization and integration cost**

Effective AI adoption additionally requires seamless integration with the organization's current data infrastructure, bringing together data sources from different departments such as sales, procurement, and logistics. To guarantee a seamless transition and leverage the advantages of AI, organizations should carefully plan and manage their resources (Diaferia et al., 2022). Furthermore, Tang et al., (2021) emphasize the need for long training sessions and a thorough assessment of the customization and integration costs of the AI model during the adoption phase. In order to ensure an affordable yet complete AI system. They also focus on providing a comprehensive view of model complexity, computational cost, and convergence rate.
2.3.3 Post-adoption phase of AI in inventory management

According to Shaikh, A, 2015, “Continuous usage (or post-adoption) refers to the individual’s decision to embrace the Technology and System well beyond its first use and continuously exploit and extend the functionality built into it”. The post-adoption phase in the integration of AI into inventory management pertains to the period following the adoption of AI technology. In that phase, organizations focus on realizing and optimizing the benefits of the new system (Shaikh A, 2015). This phase involves maintaining the new system and managing the workforce. The factors in the post-adoption include:

**Efficiency increases**

Businesses start to realize Efficiency increases in inventory operations in the post-adoption phase. (Helo & Hao, 2021) argued that AI can do the repetitive tasks that usually need a human to do, which will allow humans to focus on the creative side of the business. That will cause a minimization of human errors in picking and warehousing operations (Min, H., 2010). Additionally, (Praveen. 2019) argued that AI can give more accurate results than humans in demand forecasting by around 3%, and this improvement will lead to an increase in overall efficiency.

**Cost reduction**

This is another financial aspect to consider in the post-adoption phase. As AI systems automate several inventory management tasks, there may be a reduction in the need for human intervention in these processes (Hangl & Joy. 2022) which in turn, can lead to a reduction in labor costs. Additionally, Min, H (2010) argued that AI can reduce carrying costs by addressing the problem of determining the optimal lot size to order over multiple time periods for a single item. This approach aims to satisfy a certain demand pattern while minimizing the sum of ordering and inventory carrying costs.

**Summary of the conceptual lens**

The adoption phases theory we developed examines various ways costs evolve throughout the process of adopting AI in an organization. It highlighted the costs related to the pre-adoption phase such as feasibility analysis, data collection, and processing. Also, there are costs related to
the adoption phase like the hiring of new experts, and integration. However, the potential benefits are related to the post-adoption like cost reduction and efficiency increases. This theory shows the potential barriers by categorizing different cost perspectives in the pre-adoption and adoption phases and the potential benefits that can arise in the post-adoption phase. This model can be further used to address empirical data.

Figure 1: Conceptual framework of the phases of the adoption process: created by authors.
3. Methodology and method

This chapter presents the methodological framework of our research. We will describe the philosophy guiding our research and then describe the data collection process and provide an overview picture of how the data is analyzed, finally, we will present some ethical implications of our research study.

3.1 Research philosophy

Ontology

This refers to the beliefs regarding “the nature of reality and existence” (Easterby-Smith et al., 2018 pg 66). The ontological categories of realism, internal realism, relativism, and nominalism provide different perspectives on perceiving and interpreting the world (Easterby-Smith et al., 2018). Different points of view are included in the idea of ontology, from realism, which says the existence of reality is independent of our perceptions, to nominalism, which says truth is subjective and depends on how it is understood (Easterby-Smith et al., 2018). In the realm of research philosophy, there is also a position called internal realism, which posits that truth does indeed exist but cannot be directly accessed. On the other end of the range lies relativism, which acknowledges the existence of multiple truths based on individuals' unique experiences and perspectives (Easterby-Smith et al., 2018).

This study adopts a philosophical stance of relativism in its applied ontology. The perspective of relativism maintains that there isn't a singular reality. Various perspectives exist regarding the "truths" surrounding this topic (Easterby-Smith et al. 2018). The adoption process of AI in organizations is influenced by various circumstances, which differ across different organizational contexts. The diverse experiences and interpretations of logistics and manufacturing companies result in varying perceptions of cost impact, suggesting that there is no singular truth that is in contrast to the other three categories since interpretations are vast in different contexts. Thus, our research questions demonstrate this ontological perspective. Our primary goal is to investigate how AI integration can affect the costs incurred by manufacturing and logistics organizations during the adoption phases and to obtain insight from their various points of view regarding their experiences, and therefore this ontology is found suitable as our philosophical position.
**Epistemology**

Epistemological assumption is seen as a principle of what constitutes valid knowledge as well as how the acquisition of facts affects assumptions based on collected knowledge (Laverty, 2003). These are two divergent perspectives: positivism and social constructionism (Easterby-Smith et al., 2018). Positivism says that the social world exists on its own and can be understood through objective methods and observations. On the other hand, social constructionism states that reality is constructed and perceived by individuals, instead of through external and objective aspects (Easterby-Smith et al., 2018).

Social constructionism more closely aligns with our philosophical view regarding the effects of integrating AI in inventory management on the costs incurred by organizations during different phases of adoption. This is because a deeper comprehension of the costs involved can be obtained through various social interactions, interpretations of the distinct cost impacts during different phases, and the exchange of meaning among logistics and manufacturing companies. Social constructionism informs our research because the research question seeks to investigate the phenomenon through narratives and subjective interpretations of the cost of AI integration within this organization. This allows us, the researchers, to gain a deeper understanding of the subject matter through their unique perspectives.

In summary, by embracing ontological relativist and epistemology social constructionism worldview, we gain a broader view of how our participants constructed their meanings and perspectives regarding the cost impact of integrating AI at various stages of adoption within their organizations. This has also provided us, the researchers, with a more comprehensive understanding of the phenomenon.

**3.2 Research approach**

The selection of a reasoning approach in research is crucial. According to Saunders (2019), researchers can use inductive, deductive, or abductive approaches. The objective of the deductive approach is to prove that if the premises are true, the conclusion cannot be false. This approach is based on the idea that, if the premises that support a conclusion are true, then certain conclusions must follow. Conversely, the objective of inductive reasoning is to arrive at a knowledge claim where, given the validity of the premises, there is little chance that the conclusion is incorrect. Focusing on establishing likely generalizability based on situational facts, it emphasizes the
formation of wider generalizations from particular observations (Bamberger, p., 2018), while the
abductive approach, which is a mix between deductive and inductive approaches and focuses on
identifying appropriate theories to explain empirical observations (Kovács, G., & Spens, K. M.
2005). In our research, we are using the abductive approach as it allows the theoretical
framework to be continuously refined based on unexpected empirical findings and insights
gained during the research process (Dubois & Gadde, 2014), and it will allow us to observe the
interactions between technology, processes, and human factors and provide insights that can help
develop the theory about how AI adoption can lead to cost reduction, and as AI is a new
technology in inventory management, the abductive approach helps in making the best possible
interface with the available information.

Researchers have the option to use qualitative, quantitative, or mixed methods in their research
(Williams, C., 2007). Quantitative research is characterized by its focus on measurement and
counting, garnering scientific credibility through its capacity for quantification. This approach is
typically reductionist, aiming to convert complex phenomena into measurable units, and is
predominantly utilized in the natural sciences, emphasizing objectivity, reductionism, and
reproducibility (Lakshman et al., 2000). On the other hand, qualitative research adopts a holistic
perspective, preserving the intricacies of human behavior. It is especially adept at addressing the
"why" and "how" questions, making it particularly suitable for delving into human experiences
and behaviors. Qualitative research employs methods such as structured or open-ended
interviews, and external observation proving to be highly effective in situations where variables
are ill-defined or situational, thus allowing for a deeper understanding of complex, nuanced
aspects of human life and interactions (Lakshman et al., 2000). For our abductive approach
study, we are using the qualitative approach where we study the experience of inventory
managers who worked with AI systems in their organizations, and the managers who did not
adopt AI in their inventory system to explore how human mistakes can be avoided by AI impact
companies profitability, as well as companies that provide AI systems for inventory
management, that will give us a deeper understanding of the benefits and challenges companies
face when implementing AI in their inventory management process.
3.3 Research design

The present study is ideally suited for multiple case study research due to the unique needs and characteristics of the study. First of all, it enables a thorough analysis of the experiences and procedures of several businesses aligning with our research philosophy grounded in ontological relativism and epistemology social constructionism. This approach is useful in identifying shared difficulties and chances related to the application of AI in inventory management which is important for our research (Stake, 1995). Second, this design allows for targeted examination making it possible to evaluate and compare the strategies of other businesses and the results they have, which may be useful in identifying best practices and possible areas for development.

Ultimately, unlike single-case studies, multiple-case studies provide a broader empirical foundation, reducing the risk of findings being idiosyncratic to a single case. This enhances the credibility and replicability of the research (Eisenhardt & Graebner, 2007). Furthermore, multiple case studies make it possible to comprehend the various factors that affect the adoption and efficiency of AI in inventory management with greater depth, which may help in the creation of more focused and successful implementation plans in the future.

Using this methodology, several cases are thoroughly analyzed in order to find trends, themes, and insights that might help draw more general conclusions about the subject of the study. Information was gathered from logistics and manufacturing organizations through a range of techniques, including document analysis and interviews (Yin, 2009; Stake, 1995).

Although the multiple case study method provides perspective and depth, it is important to recognize its limits. Findings from specific cases might not be applicable to all situations, which raises questions about generalizability. In order to address this, we have made sure that there are differences in size (Startup, Medium-sized companies, large and global companies) and geographical presence (Sweden, USA, Norway, and Italy) of the selected companies for a variety of viewpoints and some similarities in technological infrastructure (Deep-tech, partly automated and AI exploration/ or early stages) and shared challenges (AI provider companies, logistics companies, and factories) for insightful comparisons during the case selection process.

Moreover, we recognize that while case studies cannot give a perfect answer, they can provide insightful information that can guide theory development and future research (Yin, 2009).
Data triangulation was used to improve the study's credibility by merging several data sources such as interviews and document analysis. To validate interpretations, we used member checking, in which the participants examined and verified the findings. Transparency is also maintained in the research by recording the research method, decisions, and any changes made during the study.

3.3.1 Case description:

In this section, we will go in-depth regarding our cases, we will refer to the companies we interviewed with alphabets, the criteria we used to make the cases relevant to our study are: 1) companies that adopted AI in their inventory system, 2) companies that provide AI systems to inventories, 3) companies in the pre-adoption phase.

**Company A**

Company A is a deep-tech startup that is located in Sweden. The company was established in 2020, it provides different kinds of AI solutions and services helping businesses to speed up their AI deployment. They are active in healthcare, logistics, manufacturing, and ESG Support sections.

**Company B**

It is an AI provider company that makes software models for the entire supply chain and identifies the best, most profitable plan in minutes. The company was founded in 2008 with a head office in Colorado. Now they have over 200 employees and they operate in Europe, Asia, South America, and Australia.

**Company C**

Company C is a Swedish retail logistics and purchasing company. It employs 1,001–5,000 and was founded in 1974. They streamlined assortment, inventory purchase, and distribution. Since 2018, the company has operated automated digital technologies like palletizing and stacking machines for goods, and for transport tasks.

**Company D**

Company D is one of Sweden's major wholesalers of brands and concept solutions for grocery retail, logistics, bakeries, consumer goods, and services. It employs around 3000 people and
operates 15 manufacturing units. It was formed in 1838, and it currently implements AI-based sales and operations planning software offered by company B.

**Company E**
Company E is a Norwegian logistics company that operates in the Nordic countries and entered Sweden in 2018, they offer services in e-commerce to pharmaceutical transport, and they also handle packages, couriers, and goods, and they have around 13000 employees. At the beginning of 2023, they started using an AI-based robot hand with scanners, the robot can recognize the size of each box and move the boxes from the pallets to the belt that going to take the boxes to the next stage.

**Company F**
Company F represents itself as a market leader for high-quality seating solutions in Europe. They have many branches in Sweden and Norway, and they produce several furniture brands. Their factory in Sweden produces around 240000 units annually. The company has an integrated warehouse within the same building as the factory. About 3 years ago they started using an AI-based robot for transporting pallets within the factory.

**Company G**
Company G was founded in 2011 in Italy, and with around 30,000 employees and operations in 50 countries, they describe themselves as the global leader in the energy and telecom cable systems industry. The company is still in the pre-adoption phase of AI adoption in its inventory system.
Table 1: Overview of Case Descriptions

<table>
<thead>
<tr>
<th></th>
<th>Company A</th>
<th>Company B</th>
<th>Company C</th>
<th>Company D</th>
<th>Company E</th>
<th>Company F</th>
<th>Company G</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Industry</strong></td>
<td>Technology</td>
<td>Technology</td>
<td>Logistics</td>
<td>Manufacturing &amp; Logistics</td>
<td>Logistics</td>
<td>Manufacturing</td>
<td>Manufacturing</td>
</tr>
<tr>
<td><strong>Year AI Integrated</strong></td>
<td>-</td>
<td>-</td>
<td>2018</td>
<td>-</td>
<td>2023</td>
<td>2020</td>
<td>-</td>
</tr>
<tr>
<td><strong>Number of Employees</strong></td>
<td>Fewer than 100</td>
<td>Over 200</td>
<td>1,001–5,000</td>
<td>Around 3000</td>
<td>Around 13,000</td>
<td>1,800</td>
<td>30,000</td>
</tr>
<tr>
<td><strong>Business Size</strong></td>
<td>Small</td>
<td>Medium</td>
<td>Large</td>
<td>Large</td>
<td>Large</td>
<td>Large</td>
<td>Global</td>
</tr>
<tr>
<td><strong>Origin</strong></td>
<td>Sweden</td>
<td>Colorado, USA</td>
<td>Sweden</td>
<td>Sweden</td>
<td>Norway</td>
<td>Norway</td>
<td>Italy</td>
</tr>
</tbody>
</table>

3.4 Data collection methods

3.4.1 Primary data

Semi-structured interviews
We employed semi-structured interviews since this strategy aligned with our qualitative research design and philosophical lens. Primary data is information that we have obtained, giving us some influence over the research design and direction (Easterby-Smith, 2018). Semi-structured interviews were used since they allowed for flexibility in question order while retaining a natural flow and direction to the conversation (Kallio et al., 2016). In our semi-structured interviews, some probing questions, such as 'why,' 'how,' and 'can you provide instances,' were utilized to
further develop respondents' responses; also, follow-up questions were posed during the interview. We generated our interview questions using the theoretical lens and the research gap. Initially, before conducting the interviews, we categorized the questions into four sessions based on (1) background information, (2) pre-adoption, (3) adoption, and (4) post adoption which can be found in the interview guide, as Easterby-Smith et al., (2021) also stated the significance for grouping interview questions for more clarity and logical flow of interview questions. We ensured that our interviewees met one of our criteria to provide us with information regarding our research question.

**Sampling techniques**

We used an intentional sampling technique to ensure accurate and high-quality data for our study objectives. This sampling strategy permits respondents who meet or match the selection criteria to participate (Gill, 2020). To begin, we did not limit our sample to simply logistics and manufacturing enterprises based in Sweden, but rather globally, because several AI technologies are widely used in larger organizations based outside of Sweden in the same industry. Second, we only interviewed participants who were more adept in the field of AI, implying that they were fully involved in organizational matters; all of the respondents were largely senior managers or technical administrators from logistics and manufacturing businesses.

We sought information about organizations that met our criteria by searching websites, contacting suitable companies via email, LinkedIn message, and phone calls, and providing them with a brief description of the scope of our research project and the interview process. We checked their eligibility and ability to engage in an interview this way. We also asked for assistance from university professors in seeking companies that best fit our interview requirements. Employers who consented to participate in our study contacted us to set up a time and location for the study and completed a consent form (see appendix) accepting the terms of participation. Given the time limits for the degree projects, we received 8 interviews, which is a sufficient sample size. As Gill (2020) explains, it cannot be predicted, and hence defining a sample size may be unnecessary. We had two participants from 1 company and one participant from the rest of the 7 companies (see Table 2).

**Conducting the interviews**

Krouwel et al., 2019 claimed that face-to-face interviews were the most appropriate technique for conducting interviews because they allow participants to see each other and create trust, resulting in a greater participation rate. We used face-to-face interviews with one company
because they were located in the same city in Sweden where we are currently based and permitted us to meet physically with them. In addition, we performed videoconference interviews with the remaining 7 companies using Zoom and Microsoft Teams. Due to the short time frame and the participants' time and energy, time management was a significant aspect of our project. We schedule interviews for 30-45 minutes. While most interviews took place within the predetermined time range, others were shorter or longer; see Table 2 for further information on each interview's duration. To ensure ethical research practices, we began each interview by advising the participant of the confidentiality of their information and obtaining their permission to record and transcribe the conversation.

**Recording and transcription**

To increase the quality of the interviews, we obtained consent to record them ahead of time following our research ethics. This allowed us to focus on the conversation and follow up on any unclear points with less distraction. We used three devices for all of the interviews to ensure we had a backup recording, reducing the possibility of technical difficulties or recording loss. We took precautions to protect the respondent's comfort during the recording process by reminding them of their anonymity and the confidentiality of their company name throughout the interview. To save time, we utilized a transcription program called Transcriptor to transcribe the audio recordings, and then we reviewed them for correctness. This method is critical because it serves as a grounded theory for data analysis (Harvey, 2011).

**3.4.2 Secondary data**

This includes information gathered from current sources such as publications, internal documents, articles, and so on (Collis & Hussey, 2014). As a result, it could come from sources such as industry data and statistics, company reports, and databases. Secondary data was gathered to supplement our original data. One of the companies contacted supplied an internal document. The document featured information regarding the many AI technologies that the company has used, as well as the obstacles associated with their use. We also acquired extra secondary data by searching for firms' annual reports on search engines such as Google to obtain more information about the various financial costs in their company to evaluate the cost efficiency of adopting AI. Another source of secondary data was stories about how logistics and industrial companies have integrated AI into their value chains. Furthermore, we receive some information about the company's business descriptions and new insights on their AI technology
from their website. Finally, all of this secondary data was gathered to support our research findings.

Table 2. Overview of primary data collection

<table>
<thead>
<tr>
<th>Case companies</th>
<th>Interviewee ID</th>
<th>Position within the company</th>
<th>Duration of interview</th>
<th>Pages transcribed</th>
</tr>
</thead>
<tbody>
<tr>
<td>Case 1: Company A</td>
<td>1.1</td>
<td>CEO of the company</td>
<td>38min</td>
<td>7 pages</td>
</tr>
<tr>
<td>Case 2: Company B</td>
<td>2.1</td>
<td>Product manager/Demand prediction</td>
<td>48min</td>
<td>12 pages</td>
</tr>
<tr>
<td>Case 3: Company C</td>
<td>3.1</td>
<td>Transportation manager</td>
<td>35min</td>
<td>6 pages</td>
</tr>
<tr>
<td>Case 4: Company D</td>
<td>4.1</td>
<td>Logistics manager</td>
<td>38min</td>
<td>7 pages</td>
</tr>
<tr>
<td>Case 5: Company E</td>
<td>5.1</td>
<td>Administration manager</td>
<td>60min</td>
<td>11 pages</td>
</tr>
<tr>
<td>Case 6: Company F</td>
<td>6.1</td>
<td>Production Manager</td>
<td>30min</td>
<td>6 pages</td>
</tr>
<tr>
<td>Case 7: Company F</td>
<td>6.2</td>
<td>Inventory manager</td>
<td>30min</td>
<td>6 pages</td>
</tr>
<tr>
<td>Case 8: Company G</td>
<td>6.3</td>
<td>Supply chain manager</td>
<td>36 min</td>
<td>8 pages</td>
</tr>
</tbody>
</table>
3.5 Data analysis

After conducting the semi-structured interviews and transcribing the recorded conversations, we wanted to get fresh knowledge and understanding of the managers who participated in our study's perspectives and experiences with the adoption of AI and its phases. We started the coding process that involves developing groups, themes, and patterns from the raw data, and codes that are descriptive labels for the groups of data (Miles et al., 2014). This pattern coding is connected to our multiple-case explanatory study since it allows for the analysis of shared themes across the cases while acknowledging the unique aspects of each case (Miles et al., 2014). The process starts by grouping the 63 pages of transcribed data under each question that was asked in the interviews for the 8 participants. We started extracting the empirical data by highlighting the key sections to help speed up the coding process and to avoid complexity. We conducted that step individually followed by collaborative discussions to help identify the most prominent codes. This step was important since we have eight cases which allowed us to explore and identify shared themes and patterns throughout the multiple cases (Miles et al., 2014).

We used Saldaña's (2013) framework that helped us divide the coding process into cycles. The first cycle started by capturing the core of the data by grouping the quotes under first-order descriptive codes that are close to the language used by participants in the raw data, and that is to help us better understand their perspective when we analyze the data. From the first cycle, we got 17 first-order codes that we then grouped into fewer second-order themes in the second cycle. In this step, we link two to three first-order codes to each second-order theme, where we found seven themes that are more theoretical and have more connection to the current literature. Moreover, these second-order themes were then aggregated into third-order dimensions—post-adoption phase, adoption phase, and post-adoption phase—presenting a more organized and conceptual version of the data.

From there, we developed the full coding table that shows the hierarchy of first-order codes, second-order themes, and aggregate dimensions and the relationship between them. This systematic approach resulted a structured and transparent representation of the data that helps to ensure that our findings align with the participant's perspectives and with the theoretical framework.
Figure 2: Coding Tree

"There have been preliminary discussions about adopting AI, but it seems that, from the logistics perspective, the company is not yet ready to initiate the process."
"A lot of people are afraid of the machine."

"One factor hindering AI adoption might be financial considerations. We are just starting to look at AI opportunities, and there's still a long way to go. The negative side of a big company is that decisions and adoption of good tools take a longer time, which affects the costs."

"Smaller and often immature AI companies face challenges in understanding where to initiate their AI journey."
"When you implement new tools, it takes a lot of time and effort to get them running smoothly."

"Whenever we implement new technologies, we spend money on hiring consultants for the operation."
"They are quite expensive to hire, but we do that for more guidance in the operation since they are professional."

"The significant cost in AI implementation is associated with training the model, which involves the program learning and recognizing patterns. The training phase can incur substantial costs, depending on the complexity and volume of data, ranging from hours to weeks."

"We find it costly since it also entails vast processes when implementing the model."
"Of course, it will cost a lot for such a big company, but I think they already see that benefit as well."
Companies must bridge the knowledge gap to be able to use AI fully."

"Our journey highlighted the need for specialized knowledge. Integrating AI into our logistics required not only technical expertise but also employees who have a real understanding of the industry."

"The size of the organization plays a big role but having the right resources is important."

"Training the model includes huge time commitment which adds to labor hours."

"Additional costs may arise when integrating the new system related to the need for additional technical adjustments."

Specialized Skills Are Needed For Effective AI Adoption

Expertise and Costs Associated with AI Adoption

AI Deployment Requires Resource And Infrastructure

Costs Related To AI Customization

Challenges in AI Customization and Operational integration

Costs of Integrating The Models Into The Existing Systems

Aggregated dimension

Adoption Phase of AI
Ongoing costs related to AI use include subscription fees and continual updates to the software, reflecting a need for maintenance and updating.

"Regarding the AI system, there's an ongoing subscription cost per user. Additionally, support from the AI tool provider is managed case by case."

"A major focus in manufacturing is predictive maintenance, aiming to predict when machines need maintenance to prevent breakdowns and ensure continuous operation."

"We started using the AI transportation system at the beginning of 2020. This system plans our routes to be more efficient in driving and eco-driving. It always plans the route according to eco-driving principles to save fuel, money, and hours, thereby increasing our efficiency."

"Reorganization and using robots reduced the time lost in moving pallets, previously done by coworkers."

"AI and machine learning enable managing more complex planning solutions with the same organizational structure."

"The AI systems help in making real-time decisions on how to cut and package these items, considering factors like current stock and rapidly changing market demands."

"Another significant aspect is optimizing energy consumption, where AI helps identify opportunities to turn off machines or equipment when not in use, leading to substantial energy savings."

"We observed a significant reduction in the workforce after implementing the method, decreasing from around 75-80 employees to almost sixty, reflecting a substantial percentage decrease."

"AI can help in the optimization of logistics transportation."

"AI can help in the optimization of logistics transportation."

"Improvement in Operational Efficiency"

"Efficiency Increasing and Minimizing Errors"

"Post-adoption phase of AI"

"Maintenance and Updating of AI Technology"

"2nd order code"

"1st order code"

"Necessitating recurring costs and maintenance"

"Enhancing complex planning and decision-making with AI"

"AI Optimizes Energy Saving which will Saves Costs"

"Workforce Optimization through AI is Cost-Efficient"
3.6 Trustworthiness

Credibility
Credibility in qualitative research is about producing reliable representations of the research subject, characterized by rich, thick, and truthful accounts of participants' stories (Stewart & Gapp, 2013). During this research, we collected data by conducting interviews with managers who were a part of the adoption of AI into inventory management to get the greatest insight on the adoption process. Also, (Sandelowski, M., 1986) argued that a qualitative study gains credibility when its descriptions of human experiences resonate strongly and are immediately identifiable by others who have shared those same experiences. the authors of this study made sure that other respondents could instantly identify and relate to the experiences of one interviewee when they were described by the authors. Additionally, many sources were used in this study to enhance triangulation, like internal company documents, statistics, and articles.

Transferability
In qualitative research, transferability is equivalent to external validity, also known as generalizability, the concerned question is: “Can a study’s research findings be generalized to other relevant contexts?” (Saunders et al., 2019). To ensure transferability In this research, we have thoroughly described various aspects of their research. This includes an in-depth background of the study in section 1.1, the purpose and research questions in section 1.3, the design of the research detailed in section 3.2, as well as comprehensive explanations of data collection and analysis in sections 3.5 and 3.6 respectively (Saunders et al., 2019). Also, the purpose of this study was to examine the cost-related implications of AI adoption in inventory management, so a generation attempt was made to find similarities between companies that have undergone similar experiences.

Dependability
Dependability relates to the reliability and consistency of research findings (Shenton, 2004). To ensure dependability in this research, we employed semi-structured interviews for primary data collection to ensure reliability, and this raw data was recorded and transcribed into 63 pages. We also remained consistent in our methodological approach throughout the investigation. Following an organized process for gathering and analyzing data allowed us to make sure that our methods could be repeated in comparable circumstances.
Confirmability
Within qualitative research, confirmability pertains to the extent to which the findings are influenced by the participants and the study environment, as opposed to the prejudices, incentives, or personal preferences of the investigator. In quantitative research, this idea is similar to objectivity (Shenton, 2004). To ensure confirmability in this study, we avoided the leading questions during the interviews to avoid taking the interview in the wrong direction. Also, as mentioned above, triangulation was used for collecting data, it has been done by using multiple resources (Nowell et al., 2017).

3.7 Ethical considerations

We are devoted to keeping the highest levels of ethics in our research to guarantee the reliability, quality, and accuracy of our findings. The guidelines provided by Bell and Bryman (2007) serve as a reference for our ethical concerns in order to protect participant interests.

To foster an honest atmosphere, participants were given clear and understandable information about the study's goal and methods before they participated in the research. Participants were allowed to ask questions and were told that their participation was fully voluntary. To build confidence, a consent form explaining the General Data Protection Regulations (GDPR), their rights, the extent of their engagement, and the possible uses of the acquired data was sent out. Prior to conducting interviews with the participants, the consent form was signed and submitted to us, and before recording the interviews, an oral confirmation was acquired.

We provided the participants with the opportunity to do the interview anonymously if they preferred to keep their personal information private in order to preserve their privacy (Bell & Bryman, 2007). There was no pressure on participants to provide any information they did not feel comfortable discussing, and the interview questions were limited to the research issue. Following data security protocols, including safe storage and secure platforms for data exchange so that only researchers could access the obtained information was handled with the highest confidentiality.
A non-harmful setting was created for the participants, taking into account their physical and mental health. Some interviews were performed online to offer a comfortable environment, while others were conducted in person following an invitation from the participants. By keeping lines of communication open and swiftly addressing any worries or discomforts, as well as informing them that their participation was entirely optional and that they may withdraw at any time or choose not to answer any questions in particular, a pleasant attitude was maintained.

Throughout the investigation, transparency has been maintained to prevent misrepresentation of any kind. The goal of the study is explained to participants in a truthful and simple manner, and any potential findings are offered openly. According to Bell and Bryman (2007), truthful and open reporting is essential to preserving the research's credibility. To prevent misrepresentation and preserve credibility, any possible misconceptions were addressed right away. To prevent misinterpretations and inaccurate reporting, all researchers participated actively in every interview. We created a supportive environment by actively listening to the participants and minimizing interruptions.

In order to guarantee that participants profited from their participation in the research, the reciprocity principle was highlighted. Participants were given the option of receiving summaries of the research findings, enabling them to get insight into the study's overall outcomes. Our study attempts to provide businesses with useful management insights as well as important insights for the academic community.
4. Empirical findings

In this section, the empirical findings are presented and analyzed through quotations and comments from both primary and secondary data.

4.1 AI influence on the pre-adoption phase

Our empirical data shows that companies incurred various costs pertaining to the usage of AI technologies in the pre-adoption phase. This includes costs associated with financial feasibility and the complexity of navigating technological advancement, the cost associated with AI technology investment data collection processes.

4.1.1 Complexity and concerns in navigating technological advancements and financial feasibility

The empirical findings indicate that a majority of participants express feelings of insecurity when it comes to incorporating technological advancements such as AI into their business. This insecurity stems from their perceived lack of readiness. As one transport manager of Company C stated, "The company invests in various areas, but there's uncertainty about the timing and readiness for AI investments." (ID 3.1). The participant explained one major concern that influences the reason why companies may feel insecure or lack the readiness to adopt AI may be because of lack of technical know-how, This indicates that employees' resistance to the adoption of AI technology can be attributed to a lack of necessary skills, this view is consistent with the words from the administrative manager of Company E "People feel like they're not ready, they don't feel that they can handle the new technology." (ID 5.1).

Similarly, our research data shows that the complexity of implementing technological advancements in AI is influenced by limited knowledge regarding their application and usefulness within the organizational value chain, as the logistic manager of Company D “The primary barrier seems to be the company's technological immaturity and a lack of awareness regarding the potential benefits and how AI solutions can benefit or provide support." (ID 4.1). similarly, the administrative manager of Company E's internal documents aligns this by saying: “In warehousing and logistics, circumstances can change on an hour-to-hour basis. So, predicting what the warehouse will look like in five years can seem daunting” (Archival material, company report n.d). This shows that being equipped with the knowledge of how the
technology can influence the organizational process since integrating such advanced AI technology is costly is significant. As the product manager of Company B discussed: “Apart from financial considerations, a significant barrier is the lack of understanding about what AI implementation entails. This uncertainty and lack of domain knowledge can make organizations hesitant to adopt AI technologies.” (ID 2.1). The findings show that regardless of the cost associated with other operational factors, the knowledge and competence needed can be challenging because it also aligns with the company's understanding of the effectiveness of applying these technologies and having the right personnel to handle them effectively. The findings were supported by the words from the CEO of Company A "The primary hurdle in AI adoption lies in understanding its applications and effective utilization. While costs are a consideration, competence and knowledge are paramount.” (ID 1.1).

Another important finding in terms of the pre-adopter phase shows that most companies feel insecure about the cost and return on investment of this technology. A significant majority of the participants shared a similar perspective on the financial resources required for adopting AI. They acknowledged the challenge of evaluating the potential investment in utilizing these technologies due to the associated operational expenses. As the transport manager of Company C stated, "The company expresses concern about the extended timeline needed to recover the investment in AI implementation, taking anywhere from 5 to 10 years." (ID 3.1). Similarly to the internal document from Company E underlines this finding “Full automation may be on the horizon, but businesses are not rushing towards it blindly. Instead, they are strategically investing in technologies that offer immediate returns and seamlessly integrate with their existing operations” (Archival material, company report 2023). Therefore, this implies the need for financial consideration regarding its return on investment pertaining to adopting AI technologies.

4.1.2 AI technology investment and challenges in implementation

The empirical findings of our study reveal compelling evidence regarding the comprehensive investment required in various aspects of the development process when integrating AI, such as the necessity of seeking expertise. Our data reveals that the presence of AI competence in both hardware and software development has been observed to potentially result in financial expenses. As stated by the CEO of Company A, "the initial cost involves acquiring AI competence, either by hiring professionals or seeking consultancy to understand how AI capabilities can be applied to their company." (ID 1.1). The findings show that in the pre-adopter stage, companies may
have experienced costs associated with the recruitment of AI experts proficient in both hardware and software development.

Another significant finding was the challenges encountered during the data acquisition and system development process. The participant reveals a significant correlation between the adoption of AI technology and the subsequent expenses incurred during the integration process of the new AI model into the existing organizational system. Additionally, an internal document from company B underlines these findings: "With machine learning, data from events like Covid-19 and sales promotions can be used to predict future sales better, and therefore the replenishment needs for each storage location and sales outlet." (archival material, company document, 2023). Also, we find that many participants express the same concern about acquiring the ability to learn and identify patterns in the program thereby contributing to the overall cost of AI implementation. These findings align with the words from the supply chain manager of company G "The challenge lies in building AI solutions, which includes obtaining and cleaning data, and identifying problems." (ID 6.3) and the product manager of company B company document: "We knew we had to really understand how each individual manufacturing operation worked and interrelated in order to define this in our AI system and to subsequently drive Optimity. This was perhaps the hardest part of the project" (Archival material, company document, 2023). This implies that during stages of filtering and data acquisition, it has been observed that numerous processes are undertaken, which can result in financial implications for the organization.

4.2 AI influence on the adoption phase

Based on the research's empirical findings, it is suggested that the adoption phase of implementing AI in inventory management is crucial since it includes the practical integration of AI solutions into existing systems, with the focus on skills acquisition, financial considerations, and the complex process of customization and integration.

4.2.1 Expertise and costs associated with AI adoption

The empirical findings suggested that hiring new experts and training employees were critical parts of the adoption phase of AI as the CEO of company A stated "Currently, companies require expertise, either through hiring consultants or skilled employees, for effective AI implementation." (ID 1.1). The product manager of Company B stressed the need to ensure that the employees of the adopting company are properly trained on how to effectively utilize the new
technology in order to maximize its advantages. During that time, the expenses of recruiting experts and providing training are critical concerns. "The final stage involves training end-users (users of the AI system) on the integrated system. This incurs additional costs associated with educating users about the system's existence and functionality to ensure effective adoption." (ID 2.1).

Moreover, findings suggest that an integrated strategy that combines technical expertise with business intelligence is necessary to understand how AI capabilities can be applied to their company. Company A highlighted the critical need for specialized skills, whether through training current employees or hiring external consultants skilled in the complex nature of AI applications. “In the realm of AI implementation, the shift has moved beyond mere technical management of applications to a profound understanding of complex business environments. This evolution signifies an urgent need for either extensive training of current staff or the recruitment of experts” (ID 1.1). In addition, the COO of Company D emphasized the importance of skills and knowledge in managing the complicated processes of integrating new technology throughout the company: “We need smart, knowledgeable people more than we ever did. With so much complexity, but also the vast amount of supporting technology that’s available to us, it is important to have people who can connect the dots across the business, identify priorities and successfully navigate the opportunities presented by new technologies.” (archival material company document, interview COO Company D, 2023).

We also found that after the initial investment, there were other financial factors to take into account during the adoption period and that understanding these components is important for businesses to efficiently estimate and allocate resources. The CEO of Company A stated the importance of careful financial planning when asked about the resources and infrastructure required for AI deployment. “Significant costs include the cost of the applications themselves, hardware expenses, employee training, and change management. Additionally, the transition to advanced applications is often gradual, which can lead to costs associated with running parallel systems, such as double hardware expenses.” (ID 1.1). He also explained that the total costs can vary according to the size of the organization and its prior application updates experience. Big companies with prior exposure can find it easier to handle these adjustments. “The total costs vary depending on the company's size and its prior experience with application changes.” (ID 1.1). This conclusion emphasizes the necessity of understanding each organization's unique environment when implementing AI.
In addition, Company B stated that the amount of infrastructure and resources needed depends heavily on the size of AI initiatives. "For more specific and smaller AI solutions, the need for computing power can be addressed by purchasing cloud services. However, for larger and more complex projects like those seen in renowned AI models, the costs can escalate into tens of millions of dollars." (ID 2.1).

4.2.2 Challenges in AI customization and operational integration

Based on our findings, the customization of AI models is a time-consuming and resource-intensive process that necessitates continuous computer activity over an extended period of time. Company A stressed that running computers continuously for weeks not only consumes a lot of energy but also increases computing expenses. "The customization process involves continuous computer operation for weeks, resulting in high energy consumption and compute costs." (ID 1.1).

Furthermore, training AI models constitutes a significant portion of the costs during the adoption phase. The complexity and volume of this data can influence the duration and, consequently, the costs associated with the training process. As our respondent from Company B indicated when questioned about what factors can influence AI model training costs, "The significant cost in AI implementation is associated with training the model, which involves the program learning and recognizing patterns. The training phase can incur substantial costs, depending on the complexity and volume of data, ranging from hours to weeks." (ID 2.1).

This process of integrating the trained AI model must be seamless, ensuring that the numerical outputs generated by the AI model can be effectively processed within the organization’s existing infrastructure ensuring a smooth transition that does not disrupt the existing workflow. As the product manager from Company B noted: "The result of the trained model, typically numerical outputs, must be seamlessly integrated into existing systems. For instance, in an inventory system, it should be capable of processing AI inputs and alerting users about impending orders and timelines." (ID 2.1).

4.3 AI influence on the post-adoption phase
The fourth part identified by our empirical findings is the post-adoption phase of AI implementation in inventory management. Throughout the collection of empirical data from different industries, it became clear that organizations observed a significant improvement in inventory efficiency and cost savings, but at the same time, they faced some costs to maintain the AI system in their process.

4.3.1 Maintenance and updating of AI technology

Our interviewees observed that the maintenance of AI technology in inventory requires consistent updates and improvement. The administration manager in Company E pointed out the difficulties encountered in maintaining the operational efficiency of AI-driven automating equipment and he stated the following: “Maintaining the speed of the robot is challenging due to constant human intervention – someone needs to feed it with pallets. Any interruption, whether due to blocked sensors or issues with the logic in the underlying code, can halt its operation.” (ID 5.1).

In addition, Company E encountered a challenge with its AI-based robot functionality, it occasionally failed to recognize the boxes, that problem was attributed to deficiencies in its scanners or the recognition system, and that issue required human intervention for the robot to continue operating effectively as represented in the following quote “The robot needs a better recognition system, better scanner because it doesn't always recognize the boxes.” (ID 5.1) and that underscores the necessity to update and improve the AI robots to ensure reliability and efficiency.

Also, our empirics found that the adoption of AI can sometimes come with financial commitments unlike traditional investments, the product and demand prediction manager in Company B stated: “Companies face ongoing costs associated with the use of AI applications. These costs are not one-time investments but are continuous” (ID 2.1).

4.3.2 Efficiency increasing and minimizing errors

A significant factor that motivates companies to adopt AI in their inventory system is to increase their efficiency and minimize errors made by humans. It became obvious through our data that companies that use AI in their inventory system are satisfied with the results they achieved, for example, Company F reported a significant improvement in operational efficiency after integrating the AI-based robot in their operations, as their production manager and inventory
manager stated: “We went from 25% available time to maybe 85% available time just because we're using robots for material handling.” (ID 6.1).

Also, Company F observed a transformative impact on their processes after integrating AI technology. They moved from a system that is heavily reliant on humans to one where machines autonomously make decisions, this shift not only improved their efficiency but also reduced their need for manual corrections, and that is represented by the following data "The machine autonomously makes decisions and streamlining processes. Previously, manual corrections were required for every issue." (ID 6.2), and that is also outlined by a document from company A “Inventory management can be made more effective and productive by using AI image analysis. AI can detect defects, categorize, and label the inventory. Doing this manually is a cumbersome and time-consuming task.”.

Furthermore, our interviewees agreed that AI has a critical role in managing and interpreting the vast amounts of data typical in modern inventory systems. By using AI to handle the data processing, companies can make more informed decisions, and reduce risks associated with human errors and data overload, the quote by the logistics manager of company D depicts this: "The necessity for decisions based on data is evident, and handling large amounts of data is challenging for an individual. AI systems can process and organize extensive data sets, ensuring decisions are based on accurate and comprehensive information rather than assumptions or limited data." (ID 4.1) Also, The participant from company B stated: “We think AI is used to manage increasing complexity in supply chains, reducing the risk of human error in planning and decision-making processes.” (ID 2.1).

The CEO of Company A emphasizes that AI has the potential to significantly enhance inventory levels and minimize space required by businesses to store their goods and it can accurately forecast demand, enabling companies to keep inventory levels closely aligned with actual need. That will lead to a decrease in the required storage area and that became clear in the following statement: "AI minimizes storage needs, reducing the square footage required to store goods, and optimizing inventory levels. (...)Highlighting the relevance of AI in inventory management, the solution aims to address the challenges of predicting stock levels and optimizing restocking processes.” (ID 1.1).
4.3.3 Cost reduction

Our interviewees who used AI in their inventory management process agreed that there was a tangible reduction in costs as a result of incorporating AI. For example, Company C noted a trend in cost reduction since 2019. This reduction in costs is primarily attributed to the downsizing of their workforce, with around 50 employees being let go. This significant reduction in personnel has directly contributed to the decrease in operational expenses. This was underlined by the statement from the participant: "There has been a noticeable cost reduction since 2019 when we started using the new system, especially with a reduction of around 50 employees, leading to improvements in efficiency and cost savings." (ID 3.1)

Another company foresees that the adoption of AI will lead to significant cost reductions in the future. This perspective highlights the focus on the strategic value of AI in improving operational efficiency and effectiveness, which will lead to financial benefits in the long term, as stated by the participant from Company D: "The implementation of AI is acknowledged to involve financial costs. But despite those initial costs, there is recognition that AI implementation is going to result in long-term savings." (ID 4.1).

Participant Company B highlighted the potential of Artificial Intelligence (AI) in achieving cost-effectiveness and operational efficiency, similar to Company D’s focus on using AI for accurate inventory management and reducing labor hours on non-essential tasks. He stated: "Adopting AI could positively impact costs by optimizing production processes, ensuring accurate inventory levels, and reducing labor hours spent on unnecessary tasks.” (ID 2.1). Company documents underline these findings: “The result is better customer service and resource utilization with less inventory - all helping to boost the bottom line. These instant benefits are why optimization implementations offer such an attractive ROI.” (Archival material, company B whitepaper, 2021).

To summarize, the quotations mentioned above capture the experience of managers who have been through the adoption phases. We found that there are costs associated with pre-adoption phase like the costs of expertise. Additionally, there are costs associated with the adoption phase like the costs of customization of the AI system to fit the company's needs, and some costs for the maintenance of the AI systems, and benefits that companies realize in the post-adoption phase like increasing efficiency and minimizing costs. The findings outlined above form the basis of our subsequent analysis.
5. Analysis

This chapter analyzes and integrates empirical findings with the literature. This serves as the foundation for developing our conceptual framework on the phases of adopting artificial intelligence in inventory management and costs associated with these adoptions.

5.1 The evaluation and consideration of costs throughout the three phases of AI adoption

In the present field of study, where every goal of logistics and manufacturing companies is to be profitable and cut down on expenses, therefore, becoming innovative with their technological advancement in the business and adopting trending digital technology like AI becomes crucial to evaluate the cost implication of integrating AI technology into their inventory management. We found that integrating AI during each phase of adoption (pre-adoption, adoption, and post-adoption) had a variety of challenges and costs associated with it, however, we found that there are also potential benefits after the post-adoption of AI. These findings are further discussed and analyzed in-depth with the existing theory to explore more extensively of our data.

5.1.1 Evaluating pre-adoption cost dynamics of AI

The pre-adoption phase possesses the need for a variety of assessment and capability checks for adopting AI, as it is supported by our findings. Lesca et al. (2015) in the same view elaborated more on this pre-adoption phase cost like understanding of the technology, the gathering of relevant data, and the complexity of the AI system in this phase to be crucial for the organization to check before further proceeding with the full implementation of AI technology. One of our participants expressed this phase to be challenging in terms of assessing the organizational readiness for adopting AI due to the perceived cost associated with the process. These interesting findings could be the reason why companies resist the utilization of AI as it was mentioned by our participant that the lack of AI readiness and financial consideration are reasons for their resistance to AI adoption. Existing literature underlines this by arguing that this AI readiness focuses on the assessment of an organization's needs, commitment, and available resources that are essential for the successful implementation of AI technology in the pre-phase (Bag et al. 2021; Jöhnk et al. 2021; Kinkel et al. 2021). This implies that for organizations to initiate the
adoption of AI, it is crucial to thoroughly evaluate their preparedness in terms of the
commitment, and the resources needed for an effective management of the costs associated with
this phase.

Another interesting finding from the interviews was the expression of concerns about the
assessment of the time frame and technical knowledge during the initial stage of implementing
AI. Many of our participants expressed challenges understanding the compatibility of AI
technology in their operation when fully adopted and the time frame needed for this entire
process. The findings corroborate with the study of Chen et al. (2021) regarding the importance
of businesses analyzing and selecting an appropriate type of AI technology that aligns with their
existing business model. Therefore, in order to effectively implement AI technology, it is
imperative for companies to comprehensively analyze its impact on their business strategy. This
assessment is crucial in determining the feasibility of adopting AI and identifying the specific
areas in which it can enhance operations. One participant stated that this pre-adoption phase
increases their level of uncertainty due to the time – frame and the new system modification with
AI. This means that companies at this phase carefully need to assess the compatibility of the
technology and as Kinkel et al (2021) similarly also stated the significance of employing AI
technology accurately with the existing inventory system to avoid recurring costs of insulations.

The majority of our participants also highlighted the necessity of seeking guidance from experts
to be another financial consideration in this pre-adoption phase and such practice incurs certain
expenses too. This statement aligns with our conceptual framework on the evaluation of
feasibility checks through hiring consultants, as Enhom et al (2021) added that in this pre-
adoption phase, companies require a feasibility check for such advanced technology either by
hiring professionals with expertise in AI or by seeking consultancy services to gain a better
understanding of how AI capabilities can be applied effectively within their organization.  such
as its cost pertains to it, these findings are seen to be vital in AI integration as it emerges for both
the pre-adoption and adoption phases in our empirical data and existing literature. This implies
that for the pre-adoption phase of AI adoption, companies must engage professionals or seek
guidance from experts to assess their capabilities and the resultant business value however it is
important to consider the cost incurred in recruiting these professionals.  This also underlines the
significance for organizations to maintain a more flexible budget during the initiation of adopting
AI as van Dewell (2022) supported this to be important in terms of financial consideration. Our
participant expresses that such financial consideration from hiring this consultant is the initial cost incurred in the pre-adoption phase.

We also find that the collection and processing of data also has a cost implication, which emerged as a critical factor during the pre-adoption stage. Notably, the CEO of company A emphasized that "The significant cost in AI implementation is associated with training the model, which involves the program learning and recognizing patterns. The training phase can incur substantial costs, depending on the complexity and volume of data, ranging from hours to weeks." (ID 1.1) The present findings align with the results of a prior study conducted by Allen (2019), which highlights the challenges encountered by organizations during the data collection and processing phase. These challenges include costs associated with activities such as data labelling, filtering, cleansing, and the integration of new data sources into existing systems. Therefore, our data emphasize the significance of considering multiple factors that impact organizational expenses. It is essential for companies to thoroughly assess the return on investment before fully embracing AI adoption. This phase emphasizes the importance of conducting a comprehensive feasibility assessment and carefully evaluating the associated costs and benefits prior to proceeding with the implementation.

5.1.2 Evaluating adoption cost dynamics of AI

Our empirical findings show that workers with the necessary knowledge and abilities are essential for efficiently utilizing AI, and the lack of specialist expertise and technical competence can emerge as a significant obstacle. Kuna et al., (2022) emphasize the significance of funding employee training and hiring specialists, which aligns with the findings that highlight the significance of human capital in transformations and the essential role of expertise for successful AI deployment, which we found that can be obtained through the hiring of consultants or skilled employees during the adoption phase.

Additionally, we found that it is important for companies to conduct a thorough evaluation of the current workforce's skill set and concentrate on workforce improvement and skill acquisition, emphasizing the critical importance of employee readiness and abilities. This is consistent with insights from Bughin et al. (2018) that stress the need for a strict skillset evaluation to identify shortages, evaluate present abilities, and determine the level of training or recruiting required.
Vepsäläinen (2023) discusses the need to address the costs and time obligations that are connected to the training initiatives. The study highlights strategic measures like retraining, redeploying, contracting, or discharging people if needed to meet the skills shortages. This aligns with our findings that showed the need to address the costs associated with hiring professionals, offering training, and change management as well as the necessity for careful financial planning to cover these costs.

The findings advocate that businesses mostly turn to other sources to bridge the talent gaps, such as AI providers, educational institutions, and training programs that can provide assessment. The findings highlight the importance of customized training programs to ensure that staff members gain the expertise needed to operate AI systems effectively and that the training programs should be a regular measure, to keep the employees informed about the opportunities that the new technologies offer (Quagli et al., 2021). The training courses that Kuna et al., (2022) recommend may be performed through online courses, workshops, and partnerships with educational institutions. They could include a wide range of subjects, such as data analytics, machine learning, and AI system operation (Kuna et al., 2022).

The findings stress the need for seamless integration of the new AI system with the existing infrastructure to avoid conflicts and delays in the company's operations, which requires careful resource planning and management. It also highlighted the need for long training sessions for the model which implies the costs of the applications, running parallel systems as well as hardware costs. This suggests that organizations need to invest considerable resources in training AI models during the adoption phase, contributing to customization and integration costs.

Tang et al. (2021) argue that the costs involve not only the acquisition of the technology but also the costs of tailoring it to fit the organization's needs. Companies need to ensure that the new AI solutions meet the company's needs and the needs of its operations which add another layer to complexity and customization costs. This aligns with the empirical findings that stressed the importance of understanding the unique business environment and characteristics of each company in the adoption phase. Diaferia et al. (2022) added a conceptual framework that includes a set of activities for companies to align the AI model with their business needs. His framework shows that customization can happen in different layers or areas including data, models, algorithms, and infrastructure. And that unique business problems may necessitate customizing one or more of these layers (Diaferia et al., 2022).
We also found the long system training sessions and detailed assessment of the costs of customizing and integrating the system reflect the complex nature of the process. Companies emphasized the significance of understanding the AI model's complexity, computing cost, and convergence rate. This is consistent with Tang et al.'s (2021) approach, which adds depth to the topic by highlighting the need to establish an affordable yet complete AI system.

5.1.3 Evaluating post-adoption cost dynamics of AI

From our empirical findings, the maintenance and updating of AI technology was seen to be one significant aspect of the post-adoption process of AI technology since it entails continuous management and investment for companies. This statement aligns with existing literature which states that this ongoing cost incurred in this phase comes from factors like regular updates of the software and managing new technology systems to prevent breakdowns (Shaikh A, 2015). Although from the empirical findings, many participants highlighted that these various operational maintenance of AI systems can be challenging for them since it affects their finances, some companies contradict these aspects to be difficult rather reckon on its effective maintenance of their AI technology to still be beneficial to them. For example, the product manager of Company B stated that: “we’ve ended up with an almost completely standard installation. We run the system in the cloud and on a subscription basis, so we don’t have to worry about upgrades and new releases. We get all the benefits at minimum cost and with zero hassle.” (archived material company document, 2023). Therefore, this implies that the cost related to these phase amount less compared to the potential benefit companies get after adopting AI. These findings have not been discussed properly in the reviewed literature however are seen to be significant based on the empirical data.

5.2 The potential benefit after adopting AI

Our findings reveal that the adoption of AI in the inventory management process will cause a significant increase in efficiency in the post-adoption phase. Most of our interviewees agreed that this increase in efficiency is primarily due to the automation of repetitive routines and tasks, which will give more time for the employees to focus on the creative side, and that aligns with the existing literature of (Helo & Hao, 2021) where they argued that machines are not a replacement for humans but they can do the repetitive tasks that became possible after the advent
of new AI technologies, allowing humans to focus on more complex and creative aspects of work.

Additionally, our study found that AI is not only good with repetitive tasks but also with decision-making processes, where AI can help with demand forecasting and it can give better predictions for future sales. (Praveen. 2019) found an increase in demand accuracy when they used AI-based system called Artificial Neural Network (ANN). While the average accuracy of demand forecasting in supply chain networks is around 72%, the AI-based system achieved an accuracy of approximately 75% to 80%. This improvement will lead to an overall reduction in the operational costs which include storage and transportation costs. In this context, we find that AI has the potential to increase transportation efficiency and route planning, as one of the participants stated: “We started using the AI transportation system at the beginning of 2020. This system plans our routes to be more efficient in driving and eco-driving. It always plans the route according to eco-driving principles to save fuel, money, and hours, thereby increasing our efficiency.”. This aligns with the findings of Rihai, Y. (2021), who noted that AI-driven models offer highly effective solutions for various routing challenges, thereby ensuring timely deliveries and enhancing the efficiency of goods transportation.

Another interesting aspect that we uncovered is the role of AI in handling vast volumes of data and managing complexity. Using AI in that role can help companies make more insightful and strategic decisions which will enhance their efficiency and accuracy and minimize the risks linked to human errors. Existing literature underlines this by arguing that integrating the power of AI in the supply chain can automate complex tasks and extract meaningful insights from their data (Norgren & Janzon, 2023). Hangl & Joy (2022) discussed in their study a system known as “expert system” which is a computer-based application copying the decision-making ability of a human expert. It is capable of resolving issues by utilizing extensive knowledge which can lead to a reduction in human errors and increase customer satisfaction. Also, we find that AI can help in the process of supplier selection, where Nissen and Sengupta (2006) argued that AI can create higher quality consideration sets than Humans, and it also can support the choice process by providing multi-attribute evaluation, which includes non-price product attributes like product capability, supplier reputation, and lead time.

Furthermore, a significant observation was the reduction in employee expenses. One of our participants stated that they let go of 50 employees after adopting AI which led to a significant
cost reduction. This finding is consistent with Hangl & Joy (2022) study which noted that AI implementation could lead to the elimination of certain job roles. The study highlighted that positions involving manual labor are particularly vulnerable, and jobs in the lower-income bracket are more likely to be supplanted by machines. Also, Helo & Hao (2021) argued that By integrating AI into condition-based maintenance and spare part procedures, which are emphasized as ways to enhance the life-cycle of assets and lower operational expenditures and life-cycle costs, AI can also lower operational expenses and life-cycle costs.
6. Conclusion

This chapter will present a brief summary of our research purpose and provide answers for our research question. We will also provide theoretical contributions and practical implications, furthermore, outline the research limitations and suggestions for future research within the context of Artificial Intelligence integration in inventory management.

6.1 Answer to research question

The research question for this thesis is:

*How does the integration of AI into inventory management impact the costs of organizations during each phase of adoption?*

Throughout this research, a deeper understanding of costs associated with the adoption of AI into inventory management for each phase of the adoption was gained. Also, knowledge was developed about the potential benefits of adopting AI in the post-adopter phase. Firstly, during the pre-adopter phase, there are substantial costs and challenges that often contribute to resistance to the adoption of AI. In general, the existing literature argues that these costs and challenges primarily revolve around assessing the organization's readiness, and that includes evaluating needs, commitment, and available resources, which is crucial for successful AI integration (Bag et al. 2021; Jöhnk et al. 2021; Kinkel et al. 2021). We also found that there is a significant cost associated with hiring experts with specialized expertise in developing AI technology software and hardware. (Kinkel et al., 2021). Additionally, there are costs and challenges related to data collection such as data labeling, filtering, cleansing, and the integration of new data sources into existing systems (Allen, 2019).

The adoption phase is also characterized by significant investment in AI. Companies need knowledgeable workers for effective AI utilization, and the lack of specialized expertise is a significant hurdle. This expertise is often acquired through hiring consultants or skilled employees during the adoption phase. Additionally, companies must evaluate and improve their
current workforce's skills, focusing on employee readiness and ability development (Bughin et al. 2018). Also, we found that there are costs associated with running the AI model such as hardware and training the model costs. These costs are essential for long-term efficiency and cost-saving benefits.

Post-adoption phase is where the biggest changes become noticeable and companies start to realize the cost-related benefits, either by increasing inventory efficiency or by direct cost reduction. (Helo & Hao. 2021) argued that AI machines can do repetitive tasks that usually require human labor which will allow humans to focus on the more creative side of the business. We also found that AI can increase the forecast efficiency which will give better predictions for future sales (Praveen. 2019). Another interesting aspect that this study uncovered is the ability of AI to automate complex tasks and handle large amounts of data (Norgren & Janzon, 2023). That can help companies minimize costs related to human errors and increase customer satisfaction. The direct cost reduction benefit we found is cutting employee costs, where AI implementation could lead to the elimination of certain job roles (Hangl & Joy 2022). To conclude, there are significant costs associated with the pre-adoption and adoption phases, but these costs are essential to realize the significant cost reduction in the post-adoption phase.

6.2 Theoretical contributions

This study offers four contributions to the theory of inventory management and AI adoption. First, we developed a framework that outlines the pre-adoption, adoption, and post-adoption stages of AI adoption in inventory management. It expands our understanding of the cost elements that influence the successful integration of AI and carefully breaks down the difficulties, expenses, and advantages unique to each stage. This framework assists with strategic planning and decision-making by offering a structured approach for companies thinking about adopting AI. Previous research by Mohsen (2023), Dhaliwal et al. (2023), and Norgren & Hägglund (2023) frequently falls short of providing a thorough analysis of the unique benefits and obstacles that arise at every phase of AI deployment. This framework closes an important knowledge gap on AI deployment methods by providing a systematic breakdown of the complexity involved at each stage, enhancing the theoretical landscape and making it a valuable tool for businesses looking to adopt AI based on informed decisions after fully understanding the expenses involved.
Second, this thesis offers contribution to the existing literature by emphasizing the cost of hiring specialists and providing tailored training initiatives during the adoption phase. We highlight that the AI integration process can be regarded as successful by having experienced employees who are capable of running the new system. For that, we provided practical insight for strategic investment in employee training and hiring professionals with particular AI experience for organizations aiming to bridge the talent gap. The study also adds depth by emphasizing the importance of human capital during the adoption phase drawing from Bughin et al. (2018), Kuna et al., (2022), and Van Dewell, (2022).

Third, the research particularly contributes by offering real examples of operational cost savings, improved logistical procedures, and improved demand forecasting accuracy, as well as the experience of multiple cases that adopted AI in their operations. We added a theoretical contribution by comprehensively exploring the costs and benefits involved, emphasizing the efficiency gains in the post-adoption period. Thereby enriching the existing literature such as Helo & Yuqiuge (2022), Praveen (2019), Hangl & Joy (2022), Sharma et al. (2022), and Nasution et al. (2022) by providing an in-depth examination of the transformative impacts and the potential benefits associated with AI implementation.

Fourth and last, this study contributes to the organization's understanding of AI readiness in the pre-adoption phase. The study highlights that before integrating AI, firms must assess their needs and the resources available with an emphasis on the value of a comprehensive assessment and the financial challenges encountered in the early phases, adding insights to previous studies such as Jöhnk et al. (2021), Bag et al. (2021), Kinkel et al. (2021), Chen et al. (2021), and Pumplun et al. (2019). This contributes to the current literature by offering empirical evidence and a more thorough understanding of the complexities of AI preparation.

6.3 Practical implications

Based on our research, we provide practical implications for organizations that are already or plan to be involved in the AI adoption process in the context of inventory management. These may be relevant to industries other than manufacturing and logistics. AI use in organizational environments has been fast evolving in recent years. Understanding how digital technology may be integrated into inventory management is critical. Our research contributed to a better understanding of how logistics and manufacturing organizations should conduct effective strategic planning to ensure a smooth integration process, such as specifying the steps,
timetables, and resources needed for AI adoption. This research will also assist firms in being aware of the problems and costs associated with each phase and taking necessary strategies to overcome or reduce them.

Furthermore, our research contributes to a better understanding of the costs associated with artificial intelligence not only for firms in supply chain management but also for companies in other industries such as hospitality and healthcare. This is especially significant because most industrial sectors throughout the world attempting to improve efficiency and cut costs by gradually pushing into the usage of digital advancements like AI to accomplish this goal. Because of our emphasis on AI adoption, other industrial sectors can leverage the theory from our research to design a plan for applying it. Organizations in this industry might use it to carefully assess their readiness to integrate AI while dealing with unknown financial concerns.

Another practical implication of our research is that logistics organizations can better understand the elements that influence the cost of implementing AI. Our research contributes to this by providing an overview of the adoption phases of integrating AI, as well as the costs and problems that may be connected with these phases, and by providing support through detailed elaboration of integrating AI. Through this understanding, firms will be able to successfully embrace AI and make smarter decisions, as well as build a collaborative environment in which teams from all departments can share expertise, communicate openly, and collaborate to maximize the potential of AI.

6.4 Limitations and future research

Firstly, this study was conducted using a multiple case study design and was examine with a qualitative research method, which may have overlooked other important factors. To address this limitation, future research endeavors could consider adopting a single case study and explore the research question using a quantitative approach to provide a more comprehensive assessment of the diverse cost impacts associated with AI adoption. This will facilitate a more comprehensive understanding of the different cost implication in integrating into AI.

Secondly, one notable limitation that emerged in this thesis was the limited interview and time scope. Given the limited timeframe of around six months allocated for the study endeavor, it became necessary to assign priority to specific chapters over others. As a result, certain aspects
of the thesis may have been further examined more comprehensively. With an extended time frame, a greater quantity of data might have been gathered, hence facilitating enhanced transparency and the acquisition of higher-quality information. Nevertheless, the data extracted from a sample size of only 7 interviews was insufficient. Future studies should conduct more interviews and a lot more time or study to get data that is more accurate.

Finally, our study solely focused on the different phases of AI adoption and the different organizational cost associated with each phase which was connected to both our empirical data and theoretical lens, however, in the post-adoption phase, the cost of maintenance and updating of AI technology was found significant based on the empirical findings but has not been properly researched in the reviewed literature, Future research should focus on conducting more in-depth investigations into the cost implications on maintenance and updating of AI technology in the post-adoption phase. such studies would aim for more insight for organizations make informed decisions on the adoption of AI and effectively leverage its potential benefits.
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Appendix
**Consent form**

**What is the purpose of the collected personal data within this study?**
This research is conducted for the thesis within the Bachelor of International Management at Jönköping International Business School. The duration of the research is four months, from August to December 2023. The goal of the research is to create a better and deeper understanding of the organizational costs and benefits associated with each adoption phase of AI into inventorn management.

**Data Protection Privacy Note**
Taking part in this research is completely voluntary. Therefore, when you choose to be a participant in this research, you will be asked to sign this form of consent. Furthermore, all the information we conduct during the research is strictly confidential and will only be used for the purpose of this study. You will have the choice to remain anonymous, which means your name will not be visible in the published articles.

**Data Storage**
The collected data will be stored within a secured file, whereas only the researchers are able to access the document. When the thesis is completed, the data will be deleted permanently immediately. Under the GDPR you have the following rights:

- The right to be informed. You have the right to be informed when and where your personal data is being used.
- The right of access. You have the right to ask for a copy of the gathered data. You can do this by making a ‘subject access request’.
- The right of rectification. You have the right to ask for your data held to be corrected.
- The right to erasure. You have the right to ask for your data to be deleted.
- The right to restrict processing. You have the right to limit the way an organization uses your personal data if you are concerned about the accuracy of the data or how it is being used.
- The right to data portability. You have the right to get your personal data from an organization in a way that is accessible and machine-readable. You also have the right to ask an organization to transfer your data to another organization.
- The right to object. You have the right to object to the use of your personal data in some circumstances. You have an absolute right to object to an organization using your data for direct marketing.
- The right against automated decision-making and profiling. You have the right not to be subject to a decision that is based on automated processing if the decision affects your legal rights or other equally important matters; to understand the reasons behind decisions made about you by automated processing and the possible consequences of the decisions, and to object to profiling in certain situations, including for direct marketing purposes.

Moreover, in case you have any doubts or questions, do not hesitate to contact us with the following contact details.

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Participant:  
________________  ________________  ________________  _________

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**Email to the participants**

Greetings! My name is Bashir, and I am a postgraduate student at Jönköping University, Sweden. Along with my colleagues Lilas Khalil and Linda Offor, I am currently working on a research thesis focused on
"How does the integration of AI into inventory management impact the costs of organizations during each phase of adoption”.

Our aim is to understand and quantify the benefits, challenges and costs associated with the integration of AI technologies in inventory and logistics management. We believe that the insights from leading companies like yours would be invaluable in shedding light on this subject, and it would greatly benefit the academic and business communities.

To this end, we are kindly seeking an opportunity to interview a representative from your organization who has expertise or involvement in this domain. We assure you that any information shared will be used strictly for academic purposes and can be anonymized upon request.

The interview will be conducted at a time convenient for you and will last approximately 30-45 minutes.

Participating in this study will not only contribute to the academic literature but also provide your organization with an opportunity to reflect upon its own practices and potentially discover new avenues for optimization.

Please let us know if your company would be interested in participating or if you have any questions about our research. We would be more than happy to provide additional details or address any concerns.

Thank you for considering our request. We genuinely hope for a positive response and look forward to the possibility of collaborating with you.

Warm regards,
Bashir Kattan, Lilas Kalil, Lina Offer

Interview Guide

Introduction
● Brief introduction of ourselves and the purpose of the interview.
● Introduction of the participant
● Assure confidentiality and consent for recording.

1- Background Information

Respondent’s Background:
● Name, position, and organization.
● Experience with AI technologies.

Organization's Profile:
● Type of industry
● Current use of AI technologies (if any).

2- Pre-Adoption Phase

What sources of information did you rely on for AI tech exploration?
What were the perceived cost implications of adopting AI at this stage?

3- Adoption Phase

Who were the key decision-makers in adopting AI?
What were the major considerations (cost, efficiency, etc.)?
What were the initial costs involved in implementing AI?
Were there unexpected costs or budget overruns?

4- Post-Adoption Phase

What are the ongoing operational costs associated with AI usage?
Did your company recognize any efficiency increasing or costs reduction after the adoption?
Figure 3: Example of Company E AI-based robot