Implementing Artificial Intelligence in Supply Chain Management

A Qualitative Study of How Manufacturing Companies Can Implement AI to Improve Supply Chain Management

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Abstract

The emergence of new technologies, such as artificial intelligence (AI), is transforming society and changing fundamental beliefs about money, value judgments, and enterprise implications. AI is becoming increasingly prevalent, serving as an exceptional advisor and an omniscient informant. While AI offers great potential to tackle serious global issues, such as climate change, food security, and healthcare, there are also potential hazards and ethical concerns that require careful consideration.

The manufacturing industry is grappling with the complexities of improving efficiency, but there is hope in the form of AI. The industry's intricate nature, with variations and interactions among system members, presents challenges in streamlining processes. However, the rapid transformation brought about by new technologies like AI offers opportunities to enhance competitiveness and efficiency. AI can automate operations, optimise production processes, and provide valuable insights that humans may struggle to generate alone. By implementing AI in supply chain management (SCM), companies can mitigate risks and reduce errors, delays, and wastage. AI can also contribute to predictive maintenance, minimising downtime and costly repairs, while process optimization can streamline operations and maximise productivity. Embracing AI in the manufacturing sector holds immense potential for increased productivity, profitability, and overall success. It is crucial to develop specific knowledge and understanding about AI to ensure effective implementation and high-quality decision-making in the future.

Providing guidance for the future of AI is crucial, as it holds the promise of solving significant problems and driving innovation. However, its implementation can also present challenges for companies. Accurate forecasting and understanding the implications of AI are essential for navigating this landscape. The successful usage of AI hinges on effective implementation, particularly in complex environments like the supply chain (SC). Therefore, the aim of this thesis is to provide insights and deeper knowledge on how integrating AI into SCM can enhance its operations. By using a qualitative method and the grounded theory in order to analyse the data collection, we have discovered how the implementation of AI can improve SCM as well as its drawbacks. The implementation of AI has the potential to revolutionise production processes, streamline operations, and improve decision-making and forecasting, leading to increased prosperity and cost savings for companies. However, it is important to acknowledge and address several challenges and considerations to ensure the successful implementation of AI. Mainly, the implementation of AI comes at the cost of complex integration, time consuming strategizing and costly investments into the system.

Our results highlight the importance for companies to not only implement AI, but integrate it, in order for successful utilisation. Unlike prior research, this study highlights the dynamic nature and variations in SCM operations and the challenges practitioners encounter. In addition, the study confirms previous findings on the positive impacts of AI, such as enhanced productivity, cost reduction, and improved decision-making. However, it emphasises the significant costs and time commitments involved in implementing AI, creating decision-making obstacles for companies. This underscores the importance of thoroughly evaluating the anticipated benefits of AI in relation to the initial investment and time constraints.

Keywords: Supply Chain Management, Artificial Intelligence, Manufacturing Industry, Artificial Intelligence Implementation Process.

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Glossary

To facilitate understanding and simplify for the reader, we have included a glossary of the abbreviation we have used throughout our thesis.

AI	**Artificial intelligence**
SCM	**Supply Chain Management**
SC	**Supply Chain**
IoT	**Internet-of-Things**
ES	**Expert System**
GA	**Genetic Algorithm**
ML	**Machine Learning**
GDP	**Gross Domestic Product**
JIT	**Just-in-Time Principle**

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1.0 Introduction

To commence the degree project, the problem background concerning the implementation of AI and its potential impact on the manufacturing industry will be presented. This will be followed by a discussion on the emergence of the research problem, which will lead to the formulation of the research question. Lastly, the purpose of the degree project will be presented, along with the focus, delimitations, and limitations that the thesis will entail.

1.1 Problem background

The widespread implementation of Artificial Intelligence (AI) in society has become increasingly prevalent. The digitalization of currencies and the workforce further complicates the future civilization, combined with other force such as the aging population and climate change, making it difficult to predict with certainty. Nonetheless, it is clear that technology's significance in our daily lives is increasing (Colbert et al., 2016, p. 731). The socio-materiality of money, value judgments, and their implications for businesses are being transformed by technology, resulting in a shift in our fundamental beliefs (Dodgson et al., 2015). Harari (2017, p. 354) labels this phenomenon "Dataism," which he characterises as a new religion that extols the rising importance of technology. This highlights the extent to which technology has replaced outmoded faiths, values, and worldviews. AI plays a vital role in this context, serving as both an exceptional advisor and an all-knowing informant. AI has the capacity to supplant human intuition, which has traditionally informed our decision-making processes (Harari, 2017, p. 354; Glikson & Woolley, 2020, p. 627). According to several authors (Goralski & Keong Tan, 2020; Vinuesa et al., 2020, p.6), AI is expected to play a crucial role in addressing some of the world's most pressing issues, including climate change, food security, and healthcare. However, as emphasised by Jobin et al. (2019), the future of AI also presents potential risks and ethical concerns, such as biases, privacy, and accountability, that must be considered to ensure ethical development and implementation. Therefore, despite AI's enormous potential, it is essential to approach it with care and thoughtfulness to assess and mitigate any potential consequences.

The potential of AI is significant, as noted by Cheatham et al. (2019, p.1). Intelligent systems are increasingly assuming various aspects of organisational decision-making, including using AI to improve strategic decisions (Rimol, 2022). In the manufacturing industry, significant investments have been made towards AI and automation of processes, presenting an opportunity to increase efficiency (Schaeffer et al., 2018, p.4-5; Bughin et al., 2017, p. 13). The primary goal of AI is to develop intelligent machines and establish a definition of intelligence (Schank, 1987, p.60). In practice, AI is a scientific discipline that enables programs to improve by learning from their experiences and behaving intentionally, intellectually, and adaptively (Schank, 1987, p. 64; Shubhendu & Vijay, 2013, p.28).

Intentionally, AI gathers information from multiple sources using sensors, digital data, or remote inputs, analyses the data instantly, and acts on the insights obtained (Shubhendu & Vijay, 2013, p.29; West & Allen, 2018, p.2). Due to significant advances in storage systems, computing power, and analytic approaches, AI systems can perform complex analyses and make informed decisions (West & Allen, 2018, p.2). From an intellectual perspective, AI including machine learning (ML), examines data for underlying trends and if it detects relevant patterns, software designers can use that information to evaluate specific issues (Brynjolfsson & McAfee, 2017). The key requirement for ML is the availability of robust data that algorithms can use to detect valuable patterns. Finally, AI systems can learn and adapt as they make decisions (West & Allen, 2018, p.3; Brynjolfsson & McAfee, 2017). Semi-autonomous vehicles, for instance, have features that alert drivers and vehicles of approaching traffic congestion, potholes, highway construction, or other potential traffic obstacles. Vehicles can leverage the experience of other vehicles on the road without requiring human involvement, and the entirety of their gained "experience" is instantly and fully transferable to other similarly constructed vehicles. Therefore, the manufacturing industry widely believes that AI will benefit both individual corporations and the industry as a whole (Schaeffer et al., 2018, p.4).

Moreover, the widespread adoption of AI raises concerns about the displacement of human workers, particularly in industries that are easily automated (Cheatham et al., 2019, p. 2; Howard, 2019, p.921). As AI technology advances, it becomes increasingly capable of performing complex tasks that previously required human expertise (Shubhendu & Vijay, 2013, p. 28). For example, Merantix, a German company, uses deep learning to solve medical problems and can identify lymph nodes in the human body in Computer Tomography pictures (Rothe, 2017). Furthermore, AI systems can carry out complex tasks like driving a car and creating an investment portfolio without active human intervention or supervision (Scherer, 2015, p. 363). Some researchers argue that AI's decision-making accuracy and logic are designed to mimic or even surpass those of humans (Wirtz & Müller, 2018, p. 1085-1086; Grace et al., 2018, p. 729), which has led experts to warn that AI could result in significant job losses and increased economic inequality (Sharma et al, 2021, p.3). Moreover, some believe that AI will outperform various fields in the future decades (Grace et al., 2018, p. 731), while others claim that AI will create new job opportunities, but the number of jobs lost will outweigh the new job creation. These developments raise questions about accountability and transparency, as well as the potential for unintended consequences (Scherer, 2015, p. 364).

In order to implement AI, a sizable network of linked computing units must be able to process massive amounts of data using ML techniques (Wirtz & Müller, 2018, p. 1085). The enforcement of AI within a corporation, according to Scherer (2015, p. 364 et seq.), results in a loss of control on a number of fronts. A loss of control can occur through a variety of methods, including: a malfunction, such as a corrupted file or physical damage to input equipment; a security breach; the superior response time of computers over humans; or defective programming (Scherer, 2015, p. 366). The fourth possibility poses the most significant difficulties since it implies that a loss of control could be a direct but unexpected consequence of a conscious design choice (Scherer, 2015, p. 366). If the AI is built with capabilities that allow it to learn, adapt and act autonomous, it could be challenging to maintain control if it is lost (Scherer, 2015, p. 366). Implementing AI may therefore pose a risk to the general public and society (Scherer, 2015, p. 366). Due to the requirement for nearly flawless modelling of highly nonlinear processes in a fast environment, applications of AI in the manufacturing industries have proven to be particularly difficult (Kim et al., 2021, p.125).

Despite being in its initial stages, AI has enormous potential as a modelling, analysis, and automation technique that can shift the manufacturing paradigm in the near future, according to the vast amount of recent literature investigating AI in related manufacturing industries (Kim et al., 2021, p.125). AI has received extensive research attention in the fields of medical image analysis, bioinformatics, drug discovery, recommendation systems, financial fraud detection, processing of works of art, and military (Kim et al., 2021, p.125). Moreover (Pannu, 2015, p.79) claim that AI has the potential to revolutionise a number of industries, including health care, finance, and transportation, by increasing productivity, lowering costs, and enhancing decision-making. Which might explain why financial services, information and communication technology, healthcare and life sciences are all sectors that are ahead of the race towards AI in comparison to the manufacturing industry (Schaeffer et al., 2018, p.6).

1.2 Arriving at the research problem

The manufacturing industry has emerging challenges with increasing its efficiency due to complexity. Complexity refers to the variations and interactions of system members. Industrial manufacturing can have complexity in both products and production, with the level varying based on industry, product type, and operational strategies (Park & Okudan Kremer, 2015, p.216). Additionally, the manufacturing sector is currently undergoing a rapid transformation as new technologies such as AI are being developed and used to add efficiency and competitiveness in the business. In this instance, efficiency is economic and is determined by comparing actual costs, revenues, and profits to what the production unit would ideally want to achieve, subject, of course, to the relevant quantity and price restrictions. According to Sharma et al. (2021, p.3) efficiency in businesses with AI is important for the manufacturing sector 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, p.1) continues that efficiency in the manufacturing industry is critical due to the fact that it directly affects the productivity and the profitability in companies. By productivity we mean the ratio of input to output. Assuming the unit produces a single output via a single input, thus this ratio is simple to determine (Knox Lovell, 1993, p. 3). Even though the industry is heavily dependent on efficiency, they still have trouble increasing it, due to its very complex process to streamline because the process involves multiple stages (Park & Okudan Kremer, 2015, p.215).

The manufacturing industry relies on a complex network of suppliers and distributors, which can contribute to inefficient supply chain management (SCM). Based on Coyle's et al., 2017) book, SCM aims to examine and manage supply chain (SC) networks. An essential goal is to increase a company's competitiveness in the global marketplace in the face of fierce competition and rapidly changing client requirements (Coyle et al., 2017). Some also argue that the goal is to increase throughput while simultaneously reducing both inventory and operating expenses (Hugos, 2018, p. 7). Additional scholars contribute to the definition of SCM, saying that SCM is essentially an ensemble of procedures designed to coordinate and manage the whole SC, from the suppliers of raw materials to the final consumer (Heikkilä 2002, p. 749; Melo et al., 2009, p. 401). SCM focuses on improving processes as a whole rather than local optimization of specific business units (Heikkilä, 2002, 749). However, due to the complexity within SCM, there is a higher likelihood of errors, delays, and wastage, which can all impede productivity. Reducing complexity can help to integrate the production processes, minimise errors and lead to lower costs and increased efficiency (Liu et al., 2022, p.2). Naturally, when SCM is inefficient, it can lead to setbacks, increased costs, and reduced customer satisfaction (Clarke-Potter, 2019).

SCM can mitigate these possible risks through five areas: production, inventory, location, transportation, and information (Hugos, 2018, p. 7). *Production* refers to a SC ability to produce and store goods. Factories and warehouses serve as production facilities and companies can therefore work with a lean production approach in order to increase efficiency in the production (Fairris & Tohyama, 2002, p. 529). The same goes for *inventory* efficiency, the lean inventory philosophy (Mishra et al., 2013, p. 300) can increase efficiency, since it views excess inventories as waste and focuses on fostering inventory efficiency in companies. Companies' inventories reflect their locked-up capital. As a result, increased inventory efficiency can minimise the working capital required by companies to continue their operations, resulting in stronger cash flow situations (Mishra et al., 2013, p. 301). Furthermore, companies with low inventories, i.e., high inventory efficiency, are less susceptible to inventory write-offs due to obsolescence (Hendricks & Singhal, 2009). For *Location* a common facility limited location problem involves a collection of geographically scattered clients and a collection of facilities to meet customer requests (Melo et al., 2009, p. 401). Furthermore, companies can use a given metric to measure the distances, timeframes, or expenses between consumers and facilities and therefore promote a better view of efficiency. The following questions should be addressed by companies in order to improve their efficiency regarding location: (i) Which facilities should be utilised? (ii) Which consumers should be served by which facility (or facilities) in order to reduce total costs? (Melo et al., 2009, p. 401). Regarding company *transportation*, it may play a critical integrative role in the structure of SC when companies strategically compete on the basis of cost, service, or time (Morash & Clinton, 1997, p. 5). Here companies work mainly with being reliable and just-in-time principle (JIT) for the purpose to increase efficiency (Morash & Clinton, 1997, p. 5; Aityassine et al., 2021).

Lastly, *information* within SCM serves as an essential approach for the survival of companies as well as an enabler for them to integrate (Lotfi et al., 2013, p. 298). Sharing information in a SC can be advantageous for a company in several ways (Lotfi et al., 2013, p. 300). For example, the products more closely fit customer demand, and market shifts may be predicted. Currently, companies share information through the following categories: (1) Inventory Information; (2) Sales Data; (3) Sales Forecasting; (4) Order Information; (5) Product Ability Information; (6) Exploitation Information of New Products (Lotfi et al., 2013, p. 300). However, further research is needed to determine how and what information should be provided, as well as the advantages of improvements in quality (Lotfi et al., 2013, p. 300; Boussehaib & Belhsen, 2023). Thus, companies struggle with the underlying areas that companies work with to mitigate inefficiency. Within the areas SCM can improve the efficiency can technology be implemented to enhance their capability (Fairris & Tohyama, 2002; Mishra et al., 2013, p. 298; Melo et al., 2009).

The manufacturing sector is one of the key industries that can benefit significantly from AI, particularly in areas such as SCM (Sharma et al, 2021, p.5). Despite AI being a widely accepted tool to help in decision-making, SCM has applied AI very limited (Min, 2010, p. 20). Additionally, relevant SC literature is also limited, despite some recent efforts to include current AI methodologies into its research, in comparison to other organisational fields (Pournader et al., 2021, p. 1). Often, SC Managers are interested in assessing the practicality and the applicability of the suggested AI technology (Min, 2010, p. 19). However, approximately 37 % of companies, looking at all industries, are searching to outline their strategies with AI, and 35 % are struggling to find the right application of AI (Pournader et al., 2021, p. 2). For SCM this plays a huge role, mainly because a single item of inventory might cost between 15 % to 35 % of its product value annually for a company to store (Timme & Williams-Timme, 2003). As a result, a company's performance in a competitive market frequently depends on its capacity to manage and organise inventory at the lowest possible cost while having it constantly accessible to customers (Min, 2010, p. 20). This capacity can be strengthened by having precise, real-time information about predicted client requests, inventory quantity and type, and order cycle time to fulfil the customer order (Min, 2010, p. 20). Traditional decision criteria based on mathematical models, such as economic order amount, cannot, however, capture the core of inventory management since this type of information is frequently difficult to assess, predict, and get (Min, 2010, p. 20). That is, a tool like AI, which can substitute experienced inventory managers' strong judgement and intelligence and deal with the unexpected, is more suited to handle inventory control and planning choices. Hence, AI should be implemented within SCM in order for the manufacturing industry to increase their margins and become even more competitive.

Various AI techniques can be applied to reduce complexity and increase efficiency, such as process optimization (Waltersmann et al., 2021, p.22). AI has the potential to simplify complex processes and provide insights that would be difficult or impossible for humans to generate alone (Azzam & Beckmann, 2022, p.4). If companies have a well-planned AI and is implemented accurately it can develop and advance ways to manage daily operations and improve the efficiency in the company (Sharma et al, 2021, p.12). Therefore, effective implementation of AI in the manufacturing sector can bring significant improvements in productivity and profitability and contribute to the industry's overall growth and success. Further, with the significant attention AI is receiving and the significant investment being made in it, its implementation becomes crucial (Strohm et al., 2020, p. 5530; Schaeffer et al., 2018, p.4-5; Mishra et al, 2013, p. 298). Some applications of AI have failed to achieve widespread adoption. Previous literature claims this is due to low technical performance, whereas other authors (Strohm et al., 2020, p. 5526; Frank et al., 2019, p. 80) say that we should look at additional implementation barriers, such as organisational or social characteristics, to better understand the reason behind failure implementations. If underutilisation would appear, Boucher (2020) argues that it may stem from public and business mistrust of AI, poor infrastructure, lack of initiative and low investment, or, as AI's ML relies on data, from a fragmented digital market. The factors behind successful implementation as well as failed implementation are therefore not evident.

To optimise AI within the manufacturing industry, more specific knowledge about the subject needs to be developed. AI is a general term for machines that have the ability to perceive, logic and learn. ML is a branch of AI and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy. It addresses the question of how to build computers that improve automatically through its experience (Jordan & Mitchell, 2015, p. 255). In the concept of ML, the machine, after processing the data, intelligently extracts the patterns in them, learns them and turns them into knowledge (Ghahremani Nahr et al., 2021, p. 38; Glikson & Woolley, 2020, p. 628). To conclude, ML is the study of how a computer may learn directly from data and so learn to solve problems (Ratner, 2000). Because of the sheer volume of data generated by both humans and machines, it is impossible for humans to comprehend, understand, or make complicated judgments using this data (Reim et al., 2020, p. 183). ML is therefore one of the most essential parts of AI, since it enables machines to ease the burden humans currently have with processing large volumes of data.

However, the range of AI research is very wide and not that specific (Ghahremani Nahr et al., 2021, p. 38). AI is the facilitator to making difficult decisions in the future (Ghahremani Nahr et al., 2021, p. 45). Therefore, the evolution in AI, ML and new knowledge of automatisation is essential for business decisions. ML can improve efficiency through predictive maintenance which means that ML algorithms can analyse data from sensors and machines to predict when equipment is likely to fail, allowing maintenance to be performed proactively before a breakdown occurs (Pech et al., 2021, p.1). This reduces downtime and prevents costly repairs. It can also be through process optimization where AI can be used to optimise production processes and minimise downtime (Weichert et al., 2019, p.1893). AI (and indirectly ML) has the potential to automate numerous commercial operations, drastically reduce the need for human labour, boost an organisation's productivity, and save both time and money (Ghahremani Nahr et al., 2021, p. 45; Pech et al., 2021, p.1; Rimol, 2022). One must therefore develop more specific, applicable comprehension about AI in order to ensure high quality decisions will be made by machine in the future.

1.3 Research question

Given the identified research gaps and the background information on the topic, the primary research question that this degree project seeks to address is:

- *How can implementation of Artificial Intelligence improve Supply Chain Management?*

1.4 Purpose

The purpose of this study is to contribute with guidance regarding the future of AI. AI is expected to solve large issues and facilitate new innovation, but will also result in challenges for companies, therefore accurate forecasting regarding AI can be highly beneficial (Scherer, 2015, p. 358; Grace et al., 2018, p. 729). The implementation is the catalyst for successful usage of AI, therefore the goal is to provide insights and deeper knowledge of how implementation of AI within a complex environment like the SC, can improve its SCM. As already mentioned, organisations usually lack the skills and knowledge necessary to deploy and use AI and underutilisation can hamper a company largely (Grace et al., 2018, p. 733). Our essay therefore also aims to help businesses become more knowledgeable so they can handle any problems that come up when implementing AI. As a result, we aim to increase successful implementations of AI within the manufacturing industry and focus our research on minimising the potential challenges AI might bring during implementation. In addition, we also aim to establish a contribution to the long-term benefit implementation of AI has, as well as challenges. Alternatively, debate potential solutions and shed light on the societal difficulties that may come from this.

1.5 Focus, delimitation, and limitation

This thesis will exclusively focus on analysing and researching the manufacturing industry due to its potential for significant growth and development with the implementation of AI. This choice was made based on the fact that according to Accenture, AI will boost the industrial sector by over US$3.7 trillion by 2035 (Schaeffer et al., 2018, p.5). Further this sector was selected in order to capture an industry that is still in the experimental stage regarding leveraging AI (Schaeffer et al., 2018, p.6) compared to other sectors like the healthcare sector and the transportation sector that already has wider research and also are the leaders in the AI race.

Furthermore, we have delimited this degree project to analyse only the implementation of AI and not the maintenance or reconstructing part that might follow after one has implemented AI. This is mainly because the implementation part of AI is crucial and complex for companies to do (Strohm et al., 2020, p. 5526) and we wanted to gain deeper knowledge and understand how companies in the manufacturing industry are facing this challenge when implementing AI. Numerous articles and authors explore the manufacturing process and mention the implementation part of AI as an important step to take to stay competitive (Sharma et al, 2021, p.3; Strohm et al., 2020, p. 5526; Thun et al., 2021, p.727). Due to the considerable attention and investment AI is receiving, its adoption has become increasingly significant (Strohm et al., 2020, p. 5530; Schaeffer et al., 2018, pp. 4-5). However, these analyses usually emphasise that implementation is crucial and an important future tool and rather than delving into the specifics of how the current adoption of AI can enhance SCM and the methods utilised to achieve it.

Furthermore, there is an absence of scientific evidence supporting the impact that the implementation of AI has regarding SCM. Our aim is to bridge this gap by offering insights that can be extended to other industries beyond our chosen sector, thereby contributing to the broader understanding of the subject.

Lastly we limit our study to a certain geographical area, Sweden. This is mainly because the manufacturing industry in Sweden is extensive and contributes significantly to the national economy. According to Armelius (2022), this sector alone accounts for nearly 20 percent of the business Sweden's value added, which is included in the gross domestic product (GDP). We also chose Sweden in order to maximise the number of shared factors among participants to be able to analyse and evaluate their response based on their common background.

2.0 Scientific methodology

In this chapter, we will begin by discussing how we chose our topic and our prior knowledge on the subject. Then, we will delve into research philosophy and explore our philosophical beliefs. Finally, we will examine our research approach and design to provide a better understanding of how our degree projects have taken shape.

2.1 Choice of subject

The selection of this subject mainly comes from management courses at civilekonomprogrammet at Umeå University. From these courses, we sparked interest in how management works in different industries to make companies better and felt the need to dive into the subject more. We started to search about this subject in order to find a gap in the literature. We found an interest in AI and that it is an emerging trend that has developed as a transformative technology in recent years, with the potential to revolutionise many industries and management in industries, including manufacturing. Therefore, the selection of AI as a subject in our thesis reflects the importance and the potential benefits it can offer to the manufacturing industry. By examining how the implementation of AI can improve SCM in the manufacturing industry, we aim to contribute to a better understanding of this technology and provide valuable insights for businesses looking to adopt it. Furthermore, as we delved deeper into the subject of AI and its potential applications in manufacturing, we realised the need for more research in the SC. The SC is characterised with complexity and touch upon several business areas within a company. By improving SCM, hopefully companies will be able to improve the organisation at large. Finally, it is interesting and significant to contribute to the advancement of this field at both an individual and societal level.

2.2 Pre-understandings

Preunderstanding refers to the knowledge, insights, and experience that are retrieved beforehand and prove to be beneficial when interpreting new research and contexts (Ryan, 2011, p. 220). Moreover, pre-understanding can improve the quality of research as it facilitates greater visibility, transparency, and proximity to the phenomenon being studied (Stenbacka, 2001, p. 554). Our education has equipped us with some relevant pre-understandings related to the selected field and have given us both an interest in management. Nevertheless, our pre-understandings connected to the subjects relevant to this thesis are mainly indirect, derived from secondary sources such as literature, rather than originating from first-hand experiences (Stenbacka, 2001, p. 554).

Furthermore, our knowledge about AI is limited and no one of us have experience working with this in a company. Therefore, it is important for us to acknowledge our limited pre-understanding of the specific topic of AI in a business context. However, our general knowledge and interest in the field of management, combined with our willingness to learn and explore new concepts, will allow us to approach this research with an open mind and a willingness to expand our pre-understanding through the analysis of primary sources and firsthand experiences.

2.3 Research philosophy

In philosophical inquiry, there are two primary assumptions: ontology and epistemology. Each of these assumptions has distinct perspectives that shape our understanding of research questions, methodologies, and findings (Aliyu et al., 2015, p.12; Brand, 2008, p.432). In this context, we will examine these assumptions and determine which perspectives are best suited to our study.

2.3.1. Ontology

Regarding ontology, researchers must choose between two opposing views of reality which is objectivism and subjectivism. For our thesis, we have adopted subjectivism as our ontological view because it is aligned with our research area. Subjectivism is an ontological view that suggests that reality is constructed by individuals through their interactions and experiences (Brand, 2008, p.447). This view holds that reality cannot be separated from the subjective experiences of the individuals involved, and therefore researchers should seek to understand these subjective realities in order to fully understand the nature of the phenomenon they are studying (Brand, 2008, p. 436; Marsh, & Furlong, 2002, p.22). The other view is objectivism which regards the social reality under investigation as something that exists independently of social actors and is not constructed by them (Brand, 2008, p.436).

We chose subjectivism as our ontological view because we believe that respondents play an active role in constructing their own reality and have the potential to influence it in various ways. We do not find the objectivist assumption appropriate, as objectivists seek to uncover universal facts and assume that there is only one social reality that all humans experience in a similar way, which is independent of human influence. Because of the fact that this study seeks to understand how the implementation of AI takes place within the manufacturing industry, specifically to improve SCM, we want to gain deeper understanding about the subject from our respondents personal realities and experiences, implying that we need to acknowledge the existence of several realities (Alharahsheh & Pius, 2020, p.42). Subjectivism is therefore the most suitable view for our thesis.

Finally, based on the subjective assumption concerning ontology, we adopt the interpretive approach. The interpretivist perspective maintains that since reality is subjective and does not exist externally, the experiences encountered by individuals will vary from one person to another (Aliyu et al., 2015, p.3).

2.3.2. Epistemology

Epistemological assumption pertains to the principles of what can be seen as acceptable valid knowledge as well as how the acquisition of facts affects assumptions based on collected knowledge (Laverty, 2003, p.26). Positivism and interpretivism are the two viewpoints that come from the epistemological assumption. There exists a significant contrast in approach and knowledge management between the two concerning social science mechanisms and structures, resulting in observable phenomena that cannot always be explicable through natural science methods. In the interpretivist paradigm, intricate and unique perspectives on reality, along with the significance of various contexts, are assumed acceptable forms of knowledge (Marsh, & Furlong, 2002, p.19). Such views are even preferred, as the researcher aims to attain a more profound comprehension of the relevant subject matter (Aliyu et al., 2015, p.5). Thus, the best approach for this study would be the interpretivist perspective. Our contention is that this approach is necessary as we aim to understand our respondents emotions and experiences to gain insight of how the implementation of AI can improve SCM. Thus, we consider our participants' individual and contextual experiences and realities as valuable forms of knowledge in this study.

The other belief, positivism, on the other hand focuses instead on using scientific methods to explain social reality. The aim of this is to examine facts, causality, and develop testable hypotheses to obtain objective and systematic explanations (Brand, 2008, p.432). As positivists seek to explain human behaviour rather than understand it (Aliyu et al., 2015, p.11), interpretivism is deemed more fitting. In conclusion, we maintain that comprehending each person's experience is critical to gain a complete understanding of our research inquiry. This reasoning further underscores why an objective and positivistic philosophy, on the other hand, is deemed unsuitable for our objectives and to address our research question.

2.4 Research approach

The thesis desires to answer the research question by using an inductive approach. This starts with empirical observation, and then attempts to identify a pattern within the appropriate subject for research. This technique is consistent with the thesis's objective of generating broad generalisations. There are two basic research methods: deductive and inductive (Bamberger, 2018, p.2). These two techniques are completely contradictory, describing the most extreme regions of the spectrum and starting their reasoning logic from different ends of the spectrum. Nonetheless, it should also be mentioned that a mixed approach, including both deductive and inductive procedures during the research, has been more widely accepted, referred to as an abductive approach (Bamberger, 2018, pp.3-4). Ultimately, the inductive approach is suitable for our circumstances, making a abductive and deductive inapplicable.

We believe that the inductive approach is more suited to our thesis. The inductive approach is a way of reasoning that begins with empirical fact and progresses to a generalisation. As a result, the inductive approach might be defined as progressing from the specific to the universal (Bamberger, 2018, p.2). As previously said, the inductive approach is better suited to our research because the objective of our thesis is to provide insights into the initial phases of AI in organisations that operate in the manufacturing industry. As a result, the conclusions should be generalisable, moving from experience to theory and then applying the theory to other businesses or regions. When the deductive approach contradicts the inductive, we consider it inapplicable.

We discovered several difficulties in quantifying the data in the deductive technique in our study, potentially missing out important aspects of the research due to knowledge discrimination in social science. Natural science typically conducts its studies using the deductive technique, which bases empirical research on a theory and better captures the data (Bamberger, 2018, p.2). Using deduction, the created theoretical frameworks are compared to the empirical data (Bamberger, 2018, pp. 3-4), establishing initial hypotheses that serve as the basis for the study, and based on the empirical results, accepting or rejecting those assumptions. In our research, hypothesis testing is not preferred, and so neither is the deductive or abductive technique. Furthermore, Collis and Hussey (2014, p.47) state that when performing a study with the previously given interpretivism assumptions, the inductive approach is the best choice.

2.5 Research design

Our research aims to answer a question of ‘how’, indicating that we want to better understand the implementation of AI in manufacturing organisations (Clancy, 2002, p.548). Therefore we have designed our thesis as analytical research, often referred to as explanatory research. The study's goal and the research question we want to answer are related by way of the research design that was established (Clancy, 2002; Shmueli, 2010, p. 291). This study analyses and explains the phenomena being researched rather than just documenting their characteristics (Clancy, 2002, p. 548), since we aim to learn *how* Swedish manufacturing companies can apply AI to enhance their SCM, this fits well with the study question we've chosen.

First off, exploratory research is less appropriate than analytical research because the topic we intend to explore already has a solid basis regarding the definition of AI and how AI is structured. Hence, exploratory is ideally suited when researchers strive to get a basic understanding of a phenomenon for which there have been few or no prior investigations (Bryman, 1984, p. 84). Furthermore, if we had a different perspective on our subject, the descriptive method might have been suitable. In our case, the descriptive approach will not provide as much depth as the analytical research will because it leaves out the "how," which is essential to our research (Sandelowski & Barroso, 2003, p. 783). The last type of research is predictive research, which is more detailed than all the others. By creating and elaborating on future predictions based on speculated and general relationships, predictive research goes beyond the analytical (Shmueli, 2010, p. 291-292). The future might start making advantage of this. Yet, because AI is currently evolving and changing rapidly, it is challenging to generalise it to a prediction that is meant to be applicable elsewhere in the future. Conclusion: by studying the additional approaches further demonstrates that the analytical design is the optimal one to choose for our research.

2.6 Summary for chosen scientific methodology

Table 1: Summary for chosen scientific methodology.

Philosophical assumptions 1. Ontology 2. Epistemology	1. Subjectivism 2. Interpretivist
Research approach	Inductive
Research design	Analytical/Explanatory

3.0 Theoretical framework

The theoretical framework created for the thesis focuses on understanding and analysing the impact of Artificial Intelligence (AI). It includes four key areas: (1) AI technology, (2) AI implementation processes, (3) potential effects on SCM, and (4) potential effects on the manufacturing industry. The literature was thoroughly evaluated, and gaps were identified. The chapter was structured to align with research objectives and a connection was established between AI and SCM. The context of the manufacturing industry was also considered. Overall, the theoretical framework provided a comprehensive understanding for the thesis.

3.1 Breaking down the concept of Artificial Intelligence

In 1955, John McCarthy introduced the term "artificial intelligence" to explore whether machines could solve problems and use language as effectively as humans (Helm et al., 2020, p.69; Min, 2010, p.14; Pournader et al., 2021, p.2). AI involves developing computer systems that can perform tasks that typically require human intelligence, including learning, reasoning, problem-solving, and decision-making. To achieve this, AI is equipped with the ability to learn and understand new concepts, learn from experience, engage in reasoning, draw conclusions, and interpret symbols in context (Pournader et al., 2021, p.2-3). These capabilities have enabled AI's successful use in various domains such as game playing, human performance modelling, machine learning, data mining, genetic algorithms, and expert systems (Min, 2010, p.14). Additionally, AI has found extensive use in robotics, where it helps create machines capable of performing dangerous or difficult tasks beyond human capacity. For instance, AI-powered robots can be used in manufacturing, healthcare, and research environments for tasks such as data collection, surveying, and patient care (Min, 2010, p.14).

By harnessing the power of AI, organisations can automate complex tasks, improve efficiency, and gain valuable insights into their data. As AI technology continues to develop and improve, we can expect to see even greater benefits and applications in the years to come. In fact, the manufacturing industry is already experiencing the advantages of AI. It is evident that AI is contributing to increased productivity, reduced costs, and improved decision-making processes within the industry (Pannu, 2015, p.79). However, the adoption of AI is still limited, compared to other industries. The use of AI technologies such as expert systems (ES), machine learning (ML), and genetic algorithms (GA) is becoming increasingly prevalent in various applications in the manufacturing industry (Zeba et al., 2021, p.2; Min 2010, p.20; Wuest et al., 2016, p.24).

3.1.1 Expert System

One of the most important techniques that are used when implementing AI in the manufacturing industry is ES (Zeba et al., 2021, p.2). ES is referring to computer programs that have their own decision-making abilities to address a specific problem. ES is a powerful tool for maintaining the vital knowledge necessary for manufacturing competitiveness. They are commonly used in organisations for knowledge dissemination and training purposes. ES enables a simplified transfer of knowledge, which results in minimal costs (Leo Kumar, 2018, p.4767). In the manufacturing industry, ES can be used to make decisions related to quality control, scheduling, and process control. For example, an ES can be used to detect defects in products on the production line and suggest corrective actions to operators. ES can also help in optimising production schedules, by analysing production data and providing suggestions for process improvements (Min, 2010, p.16-17).

Additionally, ES can aid in predictive maintenance, by analysing data from sensors to predict when maintenance is required. According to research, ES demonstrates high performance in domains where human intelligence can be effectively formalised and structured (Pournader et al., 2021, p.4). An ES is usually composed of four main components. The first one is knowledge base, which is a collection of rules, facts, and knowledge that has been acquired from a human expert. This repository of information is essential for the ES to make decisions (Min, 2010, p.17). The second component is the inference engine and is considered the "brain" of an ES as it is responsible for coordinating the search, reasoning, and inference processes based on the rules and information in the knowledge base. The third one is the scheduler and is the component that is responsible for coordinating and controlling the sequencing rules within the ES. The final component of an ES is the user interface, which allows for communication and interaction between the system and its user through a course of user queries (Min, 2010, p.17). ES are particularly useful in practical SC problems because they operate using concepts and terminology that are familiar to the user. This makes the system more easily accepted by practitioners and therefore more applicable to real-world situations (Min, 2010, p.17). Incorporating ES into the manufacturing processes can offer significant support to operational workers when executing and managing crucial and significant tasks.

3.1.2 Genetic Algorithms

The use of genetic selection principles in optimising search tools for complex problems is referred to as a GA (Min, 2010, p.17; Katoch et al., 2020, p.8094). GA not only serves the purpose of optimization, but also aids in ML, research, and development (Lambora et al., 2019, p.380). GA is a type of AI method that uses a search process to find a solution and is useful in finding the shortest path in a graph by encoding the path as chromosomes. For the algorithm to work, Lima et al. (2020, p.2) states that two things should be defined. The first is a fitness function that calculates the best solution to the given problem. The second definition is a function that can represent "DNA" for the selected solutions. GA is a method of solving complex problems by mimicking the process of natural selection, where the "fittest" individuals are selected and their traits are combined and mutated to create new, potentially better solutions. Using genetic algorithms can provide an optimal solution with high accuracy and in a very short time (Lambora et al., 2019, p.380). The GA generally consists of five components, *(1) A genetic representation of potential solutions to the problem, (2) A way to create a population, (3) An evaluation function measuring the fitness of solutions to see whether they will survive, (4) Genetic operators that alter the genetic composition of offspring* and *(5) parameter values that determine population size* (Min, 2010, p.17-18). The five components of a GA work together to optimise solutions to a given problem. Overall, using a GA can provide highly accurate solutions in a short amount of time, making it a valuable tool in research, development, and ML.

3.1.3 Machine learning

ML has proved to be effective in optimising processes, monitoring and controlling operations, and enabling predictive maintenance across various industries, particularly in the manufacturing sector and it is one of the most promising improvements in the industry (Dogan & Birant, 2021, p.2; Wuest et al., 2016, p.27). Successful appliance of ML is contingent on a change of task characteristics and contextual factors of work activities (Brynjolfsson et al., 2018, p.45). The majority of advancements and applications in AI are attributed to a type of algorithms referred to as ML, which also includes deep learning (Brynjolfsson et al., 2018, p.43). Considered a subset of AI, ML exhibits the experiential "learning" associated with human intelligence, while also having the capacity to learn and improve its analyses through the use of computational algorithms (Helm et al., 2020, p.69). ML algorithms can analyse data on inventory levels, demand forecasts, and other factors to ensure that the right materials are available when they are needed, minimising waste and reducing costs (Papageorgiou, 2009, p.1931-1932; Pournader et al., 2021, p.7). For example, based on data, the algorithm predicts that there will be a surge in demand for the product in the next month. The algorithm also analyses the availability of raw materials needed for production and predicts that there may be a shortage in the coming weeks. Using this information, the company takes proactive measures to order more raw materials and adjust their production schedule to ensure that they have enough stock to meet the demand without overstocking and wasting materials. By leveraging ML, manufacturers can identify patterns and anomalies in data that humans may miss, leading to more efficient and effective decision-making (Pournader et al., 2021, p.7). As such, it is no surprise that the market for ML in manufacturing is expected to grow significantly in the coming years (Pournader et al., 2021, p.7). In addition, deep neural networks, also known as deep learning systems, have been the driving force behind much of the recent progress in ML performance (Brynjolfsson et al., 2018, p.44). Deep learning techniques have made it possible for machines to surpass humans in different tasks, such as image and speech recognition, natural language processing, and predictive analytics.

Furthermore, ML techniques can be divided into several categories based on their learning method (Min, 2010, p.16). These categories include *(1) concept learning*, which aims to identify relevant concepts for future decision-making through inductive learning, *(2) decision tree learning*, which involves testing object properties and composing a decision tree for classification, *(3) perceptron learning*, which minimising errors and solves decision obstacles using a single perceptron layer, *(4) bayesian learning*, which educate computers to learn probabilistic functions and lastly *(5) reinforcement learning*, which uses feedback in the form of rewards to educate computers to perform at high levels. Although these techniques differ in their approach, they all seek to replicate natural learning based on human knowledge and experience accumulated over time (Min, 2010, p.16). The various categories of ML techniques provide a wide range of approaches for solving problems and achieving goals. Each method has its own strengths and weaknesses, and selecting the appropriate technique depends on the specific problem at hand. For example, decision tree learning may be more suitable for problems with discrete variables, while bayesian learning may be better suited for problems with probabilistic data. The process of machine learning can aid in comprehending the driving force behind collaborative behaviour among SC partners, leading to the sharing of critical information and enhancing the partnership through the organisational learning process (Min, 2010, p.16).

In summary, while the scope of tasks that can be achieved through ML may be more constrained and definable, it is important to recognize that this is just one aspect of the broader field of AI, and that the capabilities of ML are constantly expanding and improving and is needing more research (Brynjolfsson et al., 2018, p.47). One promising area of research is the application of ML techniques for SCM. As SC becomes more complex and global, the need for effective management strategies is becoming increasingly important. ML algorithms can be used to analyse large amounts of data to identify potential risks and help managers make informed decisions. Therefore, there is a need for further research in this area (Pournader et al., 2021, p.11). Although there are lots of different techniques and solutions through AI, the implementation process and how to introduce this to a business is a challenge.

3.2 The Implementation Process

3.2.1 Implementation Challenges

Large changes are anticipated as a result of AI, but according to Strohm et al. (2020, p. 5526) the implementation of AI has quite the complex character. It is a fact that implementing AI in the manufacturing sector can be challenging due to issues such as data availability, data quality, cybersecurity concerns, and protection to change from human workers (Sharma et al, 2021, p.3; Strohm et al., 2020, p. 5526). For example, AI and automation can be seen as a threat to job security, and workers may be resistant to changes in their work processes or the introduction of new technologies (Sharma et al, 2021, p.3). Despite these challenges, it is still important to adopt AI in this sector to remain competitive in the global market (Sharma et al, 2021, p.7-9). Further, with the significant attention AI is receiving and the significant investment being made in it, its implementation becomes crucial (Strohm et al., 2020, p. 5530; Schaeffer et al., 2018, p.4-5). As mentioned, some AI applications have failed to gain popular acceptance and there is a debate whether the failed implementation is caused by poor technical performance or organisation and/or social characteristics (Strohm et al., 2020, p. 5526; Frank et al., 2019, p. 80). If underutilization occurs, according to Boucher (2020), it might be due to public and commercial fear in AI, weak infrastructure, a lack of initiative, and low investment, or, because AI's ML relies on data, a fragmented digital market. As a result, the causes underlying successful and unsuccessful implementation are hidden. Underutilization of AI is viewed as a serious concern since it could, for instance, result in the EU's failure to implement important initiatives like the EU Green Deal, loss of comparative advantages over other regions, economic stagnation, and reduced possibilities for citizens (Boucher, 2020). One must therefore ensure the catalysts behind a successful implementation in order to secure the large investment that a large part of the society has carried out.

This shows that implementing AI in the manufacturing industry can be difficult. However, to meet the industry and market standards, digitalization is crucial (Thun et al., 2021, p. 727). Some other challenges that can be faced for companies during the implementation is trust in the systems, transparency, analogue processes, and the misunderstandings people can have of AI (Reim et al, 2020, p. 182). Trusting the system is not easy to solve and to do so companies must ensure compatibility with existing systems, deal with network speed and stability issues, and address data security concerns (Thun et al., 2021, p. 736). Put simply, people are less likely to trust an AI application if they don't comprehend how it functions. Trust can be influenced not only by the technology itself, but also by the company behind it and its ability to convey information (Reim et al., 2020, p. 182).

Further, ensuring transparency in AI systems involves providing clarity on their operations and decision-making processes. However, as AI comprises a dimension of technologies, it becomes challenging to understand its decision-making mechanisms. Establishing transparency in intelligent systems poses an important challenge (Reim et al., 2020, p. 182). The concept of explainability is often mentioned in the literature when discussing transparency in the context of AI. Explainability encompasses both interpretability and the trustworthiness of the systems. For instance, recent studies on users' trust in applied AI assume that transparency needs to be assessed in a way that considers how the average person comprehends explanations and evaluates their relationship with a service, product, or company (Larsson & Heintz, 2020, p. 7). Another challenge that is mentioned is analogue processes. Analog processes refer to manual or physical methods of collecting and managing data that are not digital. For example, filling out paper forms or using spreadsheets to track information. In order to effectively implement AI, it is important to have digital processes in place, which allow for the efficient collection and storage of data (Reim et al., 2020, p. 182). The last challenge that Reim et al. (2020, p. 183) mentions is the misunderstanding of AI. Developing a better understanding of AI and its potential to enhance current operations is likely to lead to a more positive attitude towards the changes it brings (Reim et al., 2020, p. 185). Understanding the benefits with the implementation and highlighting barriers to implementing new digital tools is a challenge for companies. The old tools can become a hindrance to implementation, and new tools need to have the entire focus. However, due to problems with reliability, response time or login challenges, coexistence between new and old tools can make the application more powerful and less exposed to flaws in the digital technology (Thun et al., 2021, p. 737).

3.2.2 The Roadmap for possible Implementation Success

Even though literature regarding AI implementation within SCM is very limited, SCM and the manufacturing industry might be able to apply established theories. Reim et al. (2020, p. 186) created a roadmap with four key insights that can be good to know when implementing AI in a business to best succeed. The roadmap is connected to the challenges that have been identified earlier, such as transparency issues, lack of trust in AI among employees, use of analogue processes, and misunderstandings about AI. The main lessons learned can be summarised as follows, *(1) gaining an understanding* of both AI and the organisational capabilities required for digital transformation; *(2) comprehending the current business model,* potential for business model innovation, and the role of the business ecosystem; *(3) acquiring and improving the necessary capabilities for AI implementatio*n; and *(4) achieving organisational acceptance and building internal competencies* (Reim et al., 2021, p. 186).

The first initial step in the plan is gaining an understanding of both AI and the organisational capabilities required for digital transformation. It is a plan to produce a conceptual framework for the management of AI and to assess the firm's potential (Reim et al., 2020, p. 187). The authors suggest that successful implementation of AI is dependent on data acquisition and infrastructure. It is important to use AI in the right way, with the right language and to understand it before the implementation process begins. The other step in the roadmap is comprehending the current business model, potential for business model innovation, and the role of the business ecosystem. This step suggests that before making any changes, it is essential to understand how the business currently creates, captures, and delivers value to its customers and how technology can be utilised to exceed their expectations (Reim et al., 2020, p. 187). The third step is acquiring and improving the necessary capabilities for AI implementation which address that to initiate further development of these capabilities, it is essential to have a proper understanding of the current business model, internal and external capabilities, and customer needs (Reim et al., 2020, p. 188). Introducing AI into a business often involves significant changes to core operations and capabilities, leading to uncertainty and risk. Firms have two options when undergoing these transformations which is being the first developer or first follower. To inspire the development of both technical and strategic solutions, firms can perform benchmarking activities and evaluate surrounding companies. The last step in the roadmap that Reim et al. (2020) is mentioned is achieving organisational acceptance and building internal competencies. In this context it is important to explore collaboration with partners in order to establish a better understanding for AI applications. It is also highlighted that feedback and evaluation during the process is extremely important when implementing AI (Reim et al., 2020, p. 188).

Furthermore, to ensure the success of the application of AI, organisations should enhance their planning and monitoring processes. Currently, some organisations take little action to keep an eye on present practices and/or the effects of adding new technologies. Strohm et al., (2020, p.

5528) believes the unstructured character of implementation processes can be explained by the absence of established regulations or best practices. Having an unstructured planning and monitoring regarding AI implementation tends to restrain the implementation (Strohm et al., 2020, p. 5528; Sun & Medaglia, 2019, p. 378). There are two main reasons why planning and monitoring the process should be enhanced. First off, if the benefits or organisational goals that using AI might achieve, are not clearly articulated, it becomes challenging to assess the implementation's performance afterward (Strohm et al., 2020, p. 5528). Secondly, if implementation plans do not outline how AI should be included into the workflow, it causes substantial variances in how the technology is used between departments (Strohm et al., 2020, p. 5528). Additionally, having an unplanned implementation facilitates risk appearing, which has proven to implicate in exceeding budget and postpone schedule (Hoon Kwak & Dixon, 2008, p. 553). Hence, by planning and monitoring the implementation process more thoroughly, companies can assess the success of the implementation further and save both time and costs.

3.3 The outcome of AI

3.3.1 Outcomes of AI in Supply Chain Management

3.3.1.1 Potential advantages from implementing AI in the Supply chain

The implementation of AI in SCM has been advocated by several researchers even though theories to support it are narrow (Dash et al., 2019; Bughin et al., 2017; Reim et al.,2020, p. 186). One of the primary objectives of supply chain optimisation is to ensure the efficient operation of manufacturing and distribution activities, which involves the optimal positioning of inventory, and the minimization of manufacturing, transportation, and distribution costs (Sithole et al., 2016, p. 18). Sithole et al. (2016) highlighted the potential for AI to improve SCM. The study found that ongoing cross-functional optimizations that make use of new technologies, such as AI and Internet-of-Things (IoT), can lead to significant improvements in supply chain optimization. This can lead to increased productivity and competitiveness for companies. Given the common driving forces of reducing costs, accurate forecasting, and gaining a competitive edge within the SC, there is a growing appreciation for implementing technologies that can help achieve these objectives.

Several studies have highlighted the potential advantages of implementing AI in the SC. Bughin et al. (2017, p. 22) found that AI-based approaches are expected to reduce forecasting errors by 30 to 50 percent compared to conventional approaches. This can lead to significant cost savings, as it enables more accurate inventory management and reduces waste. Additionally, the study found that AI can reduce inventory costs by 20 to 50 percent and costs associated with storage, transportation, and SCM by 5 to 10 percent and 25 to 40 percent, respectively. Another potential advantage of implementing AI is real-time visibility into the SC. According to a study by Kohli et al. (2021a), AI-based systems can provide real-time tracking of inventory levels, monitor supplier performance, and identify potential issues before they become problems. This enhanced visibility can help improve customer satisfaction and reduce waste. Overall, the implementation of AI in the SC can bring numerous advantages, including cost savings, increased productivity, improved forecasting accuracy, personalised customer offerings, and enhanced visibility. These benefits make AI an attractive option for companies looking to improve their SC operations.

Despite the potential benefits that AI can offer and the driving forces behind it, its implementation in SCM remains uncommon due to the high complexity of SCM and the limited exploration of AI's potential applications in this field (Min, 2010, p. 20). SCM involves managing relationships across various industries such as marketing, logistics, and production, and requires a comprehensive understanding of interconnected decision-making processes and the development of intelligent knowledge bases for collaborative problem-solving (Dash et al., 2019, p. 44). The control base of SCM is characterised by networking and process integration across functional, regional, and organisational interfaces (Van Hoek, 1998). Hence, although many are aware of the potential benefits that AI can provide along with the driving forces mentioned above, its implementation remains rare due to the high level of complexity.

In conclusion, while the potential advantages of AI in SCM are numerous, its implementation remains uncommon due to the high complexity of SCM and the limited exploration of AI's potential applications in this field. However, as companies strive to reduce costs, improve forecasting accuracy, and gain a competitive edge, there is a growing appreciation for the potential of AI in the SC. With ongoing cross-functional optimizations and the use of new technologies such as AI and IoT, significant improvements in SC optimization can be achieved. As AI continues to evolve, it is likely to play an increasingly important role in SCM, helping companies to achieve greater efficiency, productivity, and competitiveness. Therefore it is essential for companies to also evaluate the disadvantages with it.

3.3.1.2 Potential disadvantages from implement AI in the Supply chain

Since the SCM is such an important part of a company, it is crucial to be able to rely on it. Many experts argue that SCM is the most critical aspect of management for a company to succeed (Dash et al., 2019, p. 43; Hult et al., 2007, p. 1036). Implementing AI in the SC can also have potential disadvantages. Developing and implementing AI systems require a significant investment of time and money, which can be a barrier for some companies, particularly smaller ones with limited resources (Huang et al., 2018). There is also a risk of overreliance on AI systems, which can lead to complacency and a lack of human oversight (Kohli et al., 2021b). Additionally, AI systems may not always perform as intended, and errors can occur. In some cases, these errors can have serious consequences, such as SC disruptions or incorrect inventory management (Kumar et al., 2019a). Finally, implementing AI systems may require significant changes to existing processes and systems, which can cause disruption and resistance from employees (Huang et al., 2018). Therefore, companies need to carefully weigh the potential benefits and drawbacks of implementing AI systems in the SC and be prepared to address any issues that may arise.

Implementation cost is one of the disadvantages with implementing AI within the SC. AI systems require a significant investment of time and money, and while the potential benefits of AI are significant, the cost of it and maintaining it can be a major challenge, particularly for small- and medium-sized enterprises (SMEs) (Schmidt et al., 2021, p. 170). Additionally, SMEs also have more limited resources and access to financing, which can make it even further difficult for them to invest in AI technology (Schmidt et al., 2021). The implementation cost is especially high within SCM, since the integration of AI requires a new level of technical complexity (Kohli et al., 2021b). The cost of implementing AI includes purchasing AI technology, hiring experts to implement and maintain it, and training employees to use it, and was found to be one of the top barriers for companies.

Another disadvantage of implementing AI in the SC is the potential for *errors and malfunctions*. Although AI systems can enhance SC operations, they may not always function as intended, leading to overreliance on these systems by humans, as noted by Kohli et al. (2021b). This overreliance can lead to serious consequences such as incorrect inventory management or SC disruptions. Kumar et al. (2019a) emphasise the importance of companies being vigilant in monitoring and addressing any issues that arise with their AI systems to mitigate potential negative impacts. Here, Gharehgozli et al. (2021) suggested that companies should develop contingency plans to address such risks and ensure that their employees have the necessary skills and knowledge to intervene if necessary.

Lastly, AI technology is still relatively new, and many individuals may not understand how it works or how it can benefit the SC. Additionally, there may be a lack of trust in the accuracy and reliability of AI systems. Wang et al. (2021) found out that individuals who *lack understanding of AI* may be sceptical of its capabilities and reluctant to adopt it in their SC operations and therefore highlighted the importance of education and training to increase understanding and trust in AI systems. Actually, lack of trust in AI systems is a significant barrier to adoption, therefore education employees should prioritise in order to increase implementation of AI (Hasija & Esper, 2022, p. 389; Nagurney et al., 2021, p. 400). Nagurney et al. (2021) suggested that companies should work to build trust in AI systems by ensuring their accuracy and reliability and communicating their benefits to stakeholders. Moreover, implementing AI systems may lead to significant changes in current processes and systems, resulting in both resistance and disruptions from employees (Huang et al., 2018).

In conclusion, implementing AI in the SC can bring numerous benefits, such as increased efficiency and improved decision-making. However, it also comes with potential drawbacks, including high implementation costs, the risk of errors and malfunctions, and the need for employee education and trust-building. To successfully implement AI in the SC, companies need to carefully weigh the potential benefits and drawbacks and be prepared to address any issues that may arise. They should develop contingency plans, ensure the accuracy and reliability of AI systems, communicate their benefits to stakeholders, and prioritise employee education and training. By doing so, companies can maximise the potential benefits of AI while minimising the potential drawbacks.

3.3.2 Outcomes of AI in the Manufacturing industry

3.3.2.1 Potential advantages when implement AI in the Manufacturing industry

The use of AI might improve the manufacturing sector. According to Elomri et al. (2020), artificial intelligence may increase efficiency by streamlining production times, preventing interruptions and identifying equipment faults prior to they arise. Furthermore, as mentioned by Kumar et al. (2019b), AI may be utilised for predictive maintenance, assisting manufacturers in reducing maintenance costs and avoiding unexpected downtime. Kumar et al. (2019b), continues and argues that AI may help improve quality control by evaluating data from sensors, cameras, and other sources to discover faults and quality concerns. Moreover, AI can enhance safety in the manufacturing industry by monitoring working conditions and alerting workers to potential hazards (Kumar et al., 2019b). Finally, Li et al. (2020) claim that artificial intelligence (AI) may assist manufacturers in identifying new product opportunities and improving existing goods by studying consumer input, market trends, and other data sources.

Increasing efficiency is one of the key benefits of using AI in the manufacturing industry. AI-controlled machines and robots can perform repetitive and labour-intensive tasks faster and more accurately than humans, allowing workers to focus on higher-value tasks that require human expertise (Li et al., 2020). AI can also optimise manufacturing processes by reducing waste and minimising downtime, leading to higher productivity and efficiency. It is noticeable that the benefit of AI within SCM will also be beneficial for the manufacturing industry, since SCM is an essential aspect of it (Piplani et al., 2021). AI algorithms can analyse data from multiple sources, such as weather forecasts, customer demand and supplier availability, to make real-time decisions that minimise costs and lead times. For example, a study published in the International Journal of Production Research examined the effectiveness of implementing AI algorithms in a SC network. The researchers found that AI reduced overall logistics costs by 9.3% and improved delivery performance by 21.7%, resulting in a significant improvement in overall SC efficiency (Piplani et al., 2021).

Predictive maintenance is another advantage of implementing AI within the manufacturing industry. By using machine learning algorithms to analyse sensor data from devices, AI can predict when machines are likely to fail, enabling proactive maintenance and reducing the risk of costly outages (Kumar et al., 2019b). Lin et al., (2021, p. 218) investigated the influence of predictive maintenance on a semiconductor manufacturing process using machine learning techniques. They discovered that implementing predictive maintenance reduced downtime by 30% and boosted overall equipment effectiveness by 5%, resulting in a 5% gain in output and a 10% decrease in maintenance expenses. Additionally, Yang et al. (2019, p. 1338) investigated the effectiveness of an artificial intelligence-based predictive maintenance system in a plastic injection moulding machine. Results showed how the predictive maintenance system minimises downtime by 30% and increases productivity by 6%, leading to a 12% increase in machine utilisation Yang et al. (2019, p.1340). Lastly, predictive maintenance can also improve inventory management, since managers can, in a more precise way, plan maintenance activities and reduce the need for expensive spare parts (Cai et al., 2021). Specifically, it can reduce inventory costs by 13 % and improve inventory turnover by 25%, leading to significant cost savings (Cai et al., 2021, p. 1135). All together, AI-powered predictive maintenance can improve maintenance efficiency, minimise downtime and optimise inventory management. Manufacturers can perform proactive maintenance by predicting machine failures before they occur, resulting in higher asset utilisation, production output and cost savings.

AI can detect faults and abnormalities in real-time by analysing data from sensors, cameras, and other sources with machine learning algorithms, allowing for early detection and remedial action. Therefore, improved *quality control* is an additional area where the manufacturing industry would benefit from implementing AI (Kumar et al., 2019b). Gao et al. (2020) found out how the implementation of an AI-based quality control system reduced the defect rate by 60% and increased the production yield by 4%, leading to significant cost savings. Another study investigated the effectiveness of using AI for surface defect detection in the manufacturing of steel products (Wu et al., 2020) and found out that the AI-based system achieved an accuracy rate of 95% in detecting surface defects, outperforming traditional detection methods. Lastly, AI can streamline the inspection process by reducing the need for manual inspections and increasing accuracy. One study found that the implementation of an AI-based inspection system reduced inspection time by 60% and improved defect detection accuracy by 20%, resulting in a significant improvement in overall product quality (Wang et al., 2019, p. 1475). In summary, quality control based on artificial intelligence has the potential to dramatically improve product quality, reduce defect rates and increase production output. Manufacturers can save money and increase customer satisfaction by detecting defects and anomalies in real time.

AI can *enhance safety* in the manufacturing industry by identifying potential safety hazards and predicting when accidents are likely to occur through the use of predictive analytics. For instance, AI can also be used to monitor worker behaviour and ensure that safety protocols are being followed. Then, computer vision systems can be used to monitor workers and identify unsafe practices, such as workers not wearing required safety equipment or standing too close to dangerous machinery (Huang et al., 2020). Additionally, implementation of AI-based safety management systems have shown a reduction in the number of safety incidents and increased worker safety awareness in manufacturing plants (Huang et al., 2020, p. 73). In summary, AI can be used to enhance safety in the manufacturing industry by identifying potential safety hazards, preventing accidents, and monitoring worker behaviour to ensure safe practices are being followed.

Lastly, *innovation and product development* is another area that can benefit companies after implementing AI. By analysing data from multiple sources, including customer feedback and product usage patterns, AI can provide insights that enable manufacturers to develop and improve products more effectively (Li et al., 2020, p. 258). AI-implementation can reduce the time required for product development by 30 % and increase the success rate of new product launches by 20 % (Kwak et al., 2019). Hence, AI can provide insights that enable manufacturers to develop and improve products more effectively, leading to more efficient product design, faster time-to-market, and increased customer satisfaction.

In conclusion, the manufacturing industry can benefit greatly from the implementation of AI. By improving efficiency, predictive maintenance, quality control, safety, and innovation, AI can increase productivity, reduce costs, and improve customer satisfaction. With the continued advancement of AI technology, it is likely that more benefits will emerge, making AI an increasingly important tool for manufacturers looking to stay competitive in today's fast-paced business environment. However, companies should also evaluate the potential drawbacks of incorporating AI systems in their operation. Therefore, in order to implement AI successfully, one must require careful consideration and planning to ensure that the benefits of AI are balanced against its potential costs and risks.

3.3.2.2 Potential disadvantages when implement AI in the Manufacturing industry

Numerous scientific publications have emphasised the possible drawbacks of using AI to the manufacturing industry. According to Li et al. (2020), the expenses and complexity of creating and integrating AI systems might be a substantial barrier for many manufacturers. There is also a possibility of employment losses as a result of some traditionally performed functions by humans possibly becoming automated (Li et al. 2020). Furthermore, security risks are another concern, since the use of AI in manufacturing increases the risk of cyberattacks (Delshad & Safaei, 2021). Fourthly, Kumar et al. (2019a) examines how the lack of transparency in AI systems might be problematic in the manufacturing industry, as decision-making processes can have a substantial influence on production processes and outcomes. Elomri et al. (2020) explore how the usage of AI might result in a dependency on technology and open the door to SC risks. Therefore, before incorporating AI into their processes, manufacturers need to thoroughly assess any potential drawbacks.

Similar to SCM, the implementation of AI in the manufacturing industry requires high investments and is associated with complexity. However, to bring in a new perspective, the following drawbacks are more significant for manufacturing than the previously mentioned drawbacks. First, the use of AI in manufacturing can lead to *employment losses* as some tasks traditionally performed by humans are automated (Li et al., 2020, p. 349; Kohli et al., 2021a). Companies introducing AI systems need to carefully consider the impact on their employees and develop strategies to mitigate any negative consequences (Kohli et al., 2021a). This raises ethical concerns. For example, there are concerns about the use of AI to monitor and track employees, which could be seen as an invasion of privacy.

Security risks are another drawback of using AI in manufacturing. The use of AI in manufacturing can also pose security risks as these systems can be vulnerable to cyber-attacks (Delshad & Safaei, 2021, p. 131; Gunasekaran et al., 2019). With AI comes the collection and analysis of large amounts of data. Ensuring the security and privacy of this data is critical, and companies need to take the necessary measures to protect their data (Gunasekaran et al., 2019). The large amounts of data required for AI systems to function effectively must be collected, stored and processed in a secure manner. If this data is compromised, it can have serious consequences, such as data breaches or loss of confidential information. Therefore, Delshad and Safaei, (2021) emphasise that manufacturers need to ensure that their AI systems are secure and protected from potential cyber threats.

Furthermore, the *lack of transparency* is a significant drawback to the adoption of AI in the manufacturing industry. While AI has the potential to improve production efficiency, quality control and predictive maintenance, its lack of transparency can introduce risks such as errors, bias and safety concerns. Lack of transparency in the development and training of AI algorithms can lead to biassed decisions (Kang et al., 2020). This can be particularly problematic in the manufacturing industry, where decisions made by AI systems can have a significant impact on worker safety, production efficiency and product quality. Furthermore, a lack of transparency in the decision-making process of AI systems can make it difficult for manufacturers to understand how the system arrived at a particular decision (Guo et al., 2020, p. 152). This can be a problem when manufacturers need to fix problems with the AI system or make changes to improve its performance. In addition, the lack of transparency in the data used to train AI systems can lead to inaccurate predictions and decisions. According to Song et al. (2020, p. 3447), this can be particularly problematic in the manufacturing industry, where AI systems are often used to predict equipment failures or detect quality defects in products. Researchers suggest that addressing the lack of transparency requires a multidisciplinary approach that includes incorporating transparency into the design and development of AI systems, providing transparency to end users, and setting regulations and standards for AI (Guo et al., 2020; Song et al., 2020; Kang et al., 2020). Failure to address transparency issues can lead to mistrust, legal and ethical problems, and unintended consequences.

Finally, *technology dependency* is a potential drawback to implementing AI in the manufacturing industry (Elomri et al., 2020). According to Jäger et al. (2021), heavy use of AI can lead to a decline in creativity and innovation among workers who become overly dependent on technology to perform tasks. This can lead to a lack of employee engagement and lower job satisfaction, which in turn can lead to higher turnover rates. In addition, this reliance on technology can lead to significant production disruptions when malfunctions, system failures or hacking occur, and raise ethical concerns. According to Brown and Wilson (2019), increasing reliance on AI and automation may reduce the capabilities of the human workforce, leading to a situation where workforce diversity is limited and workers cannot respond to unforeseen events. This could also lead to job losses and potential economic inequality. In addition, the inability of the workforce to respond appropriately to new situations can have a negative impact on innovation and growth. Therefore, manufacturers need to carefully manage their integration of AI to mitigate these risks and ensure that they are not overly dependent on the technology.

In conclusion, while AI has the potential to revolutionise the manufacturing industry, there are several drawbacks that need to be carefully considered before integrating AI systems into manufacturing processes. These include the potential for job losses, security risks, lack of transparency, and technology dependency. To overcome these challenges, manufacturers need to develop strategies to mitigate the negative impact of AI on their employees, ensure the security and privacy of their data, increase transparency in the development and training of AI algorithms, and manage their integration of AI to avoid over-reliance on technology. By doing so, manufacturers can unlock the benefits of AI while minimising its potential drawbacks and creating a sustainable future for their business and workforce.

4.0 Practical methodology

Our practical methodology outlines the methods used when retrieving our data for our thesis. Specifically, it includes our data collection, data analysis and ethical consideration. Initially our data collection comprises our sampling techniques, description of how the interviews were conducted and the transcription of data. Thereafter, our data analysis is described step by step to provide transparency. Lastly, the ethical consideration we took into account when collecting our data is displayed.

4.1 Data collection methods

In order for us to ensure that the research question is answered, and our purpose is being fulfilled, we aimed to recognize the data collection method and choose a method that is consistent with our philosophical assumptions (Howard-Grenville et al., 2021, p. 1315). In our study, our research question is focused on how the implementation of AI can improve SCM within the manufacturing industry, and we believe that existing data is insufficient to answer this question. Therefore, we have gathered primary data to increase our chances of answering the research question.

For this study, we used semi-structured interviews to collect primary data. This approach is aligned with our interpretivist research design, which aims to gain an in-depth understanding of the subjective experiences and perceptions of respondents regarding how implementing and managing AI within the manufacturing industry can improve SCM. Semi-structured interviews were the most suitable and is a commonly used method for obtaining qualitative data in an interpretivist study. It offered flexibility in terms of question order, while maintaining a natural flow and direction to the conversation (Kallio et al., 2016, p. 2960). Open-ended questions were used in our semi-structured interviews to encourage the respondents to provide detailed and personal answers beyond a simple 'yes' or 'no' response, providing us with extensive insights based on respondents' experiences (Bearman, 2019, p. 4). Probing questions, such as 'why', 'how', and 'can you provide examples', has also been used to further develop respondents' answers. Additionally, the semi-structured format eliminated the need for follow-up interviews, enabling us to continuously confirm or clarify responses during the interview without deviating from the interview guide (Kallio et al., 2016, p. 2960-2961).

Structured and unstructured interviews are common options for data collection, but neither were suitable for our study. Structured interviews ask the same questions in the same order, leaving little room for deviation from the planned interview guide and possibly missing important information (Blouin et al, 2011, p. 517). This type of interview is also associated with the positivist paradigm, which does not align with our interpretivist approach. On the other hand, unstructured interviews do not have pre-planned questions, making it difficult to take notes and capture all the information provided by the respondent. This approach may also fail to elicit crucial information from the respondent unless the interviewer asks the right questions (Blouin et al., 2011, p. 517).

4.1.1 Sampling technique

As our research focuses on a specific topic, it was not feasible for us to study the entire population. Therefore, we opted to use a sample of participants with relevant experience and knowledge, which is a common practice in analytical qualitative studies (Gill, 2020, p. 579). To ensure that our sample was relevant to our research question, we employed purposeful sampling as our primary sampling method. This method involves using our judgement to select participants who we believe can provide insightful answers to our research question. Purposeful sampling allowed us to actively include participants who met our selection criteria (Gill, 2020, p. 580). These criteria were based on three factors that we deemed essential to uphold.

To begin with, we limited our sample to companies operating in Sweden, as the manufacturing industry is a significant contributor to the Swedish GDP. This allowed us to collect comparable data from companies operating in the same market. Secondly, we only included participants who were knowledgeable about AI, meaning that they had been part of organisational discussions or were proficient regarding the implementation of this technology. Furthermore, since we aimed to investigate activities concerning how the implementation of AI can benefit SCM, it was essential that our respondents were actively involved in SCM. This approach enabled us to gather information from an environment that is highly engaged with AI. All the interviewees were either SC managers or members of manufacturing companies, providing us with a holistic view of how they operate and enabling us to develop the theory presented in subsequent chapters.

We obtained information about organisations that met our criteria by initiating research through searching websites. We contacted suitable companies and individuals via email and LinkedIn, and provided them with an information form (see appendix one) outlining our research project and the criteria they needed to fulfil. Through this contact, we confirmed their eligibility and ability to participate in an interview. If we did not initially contact the appropriate manager, we requested that the manager forward our request to individuals they believed had knowledge and experience regarding risk identification in pharmaceutical projects. We obtained a total of two interviews, thanks to forwarding. Individuals who agreed to participate in our study, contacted us to arrange a time and place for the interview, and signed a consent form (see appendix three) agreeing to the terms of participation.

We chose purposeful sampling, which is a type of non-random sampling, for several reasons. First, since we did not aim to generalise our findings to the whole population, it was more appropriate to directly contact participants who could provide relevant data (Benoot et al., 2016, p. 2). Random sampling is typically used in positivist studies, where the goal is to generalise from the population (Taherdoost, 2016, p. 20). Second, purposeful sampling allowed us to identify participants who met our criteria. Lastly, non-random sampling techniques are particularly relevant to the interpretive paradigm, which focuses on participants' experiences and knowledge in depth of the phenomenon under study (Benoot et al., 2016, p. 3). Therefore, this sampling technique was best suited to our research purpose of providing insights on how the implementation of AI can benefit SCM in the manufacturing industry.

Snowball sampling has been used in conjunction with purposeful sampling to ensure inclusion of individuals with relevant experience in the study (Taherdoost, 2016, p. 20). This involves asking participants if they know anyone with similar knowledge or experience who could be included in the study. Given the extensive networks that managers or employees within SC typically have, snowball sampling was deemed appropriate for our study (Larson & Gray, 2021, p. 11).

Determining the appropriate sample size for a qualitative research study involves various factors. Saturation, where new interviews yield minimal or no new information, is one such factor that may guide sample size (Aldiabat & Le Navenec, 2018, p. 247). However, Gill (2020, p. 581) suggests that it cannot be predetermined, and therefore, specifying a sample size may not be necessary. He mentions that to justify the findings in qualitative studies, the authors need to demonstrate to the reader that the sample size and selection were appropriate and adequate for addressing the research questions (Gill, 2020, p. 581). Conversely, not achieving saturation may indicate further research opportunities. Given our time constraints for the degree project, achieving saturation was our ideal aim, but we were aware that it may not have been feasible. Instead, we focused on obtaining a comprehensive understanding of the topic, which was realistic given our limitations. Furthermore, Hagaman and Wutich's (2016, p. 205) study suggests that conducting six to sixteen interviews is a reasonable approach. Our study included a sample of six interviews, which according to Magnusson and Marecek (2015, pp. 36-37) should be fine, since in an interpretivist study, the amount of interviews is less relevant than the quality of them.

4.1.2 Conducting the interviews

In a qualitative study like ours, face-to-face interviews are the most suitable method as they allow participants to see each other and build trust, leading to higher participation rates (Krouwel et al., 2019, p. 7). However, since our participants were located throughout Sweden, we conducted videoconference interviews via platforms such as Zoom to avoid time-consuming travel (Basch et al., 2020, p. 926). Remote interviews have their benefits, including increased participation from geographically distant areas (Solarino & Aguinis, 2021, p. 663). Videoconference interviews are preferable over phone calls, as they allow for non-verbal expressions to be observed and analysed (Basch et al., 2020, p. 922). However, phone calls may reduce biases stemming from the lack of visual contact, which can be a relief for participants. In light of these factors, we determined that videoconference interviews were the most suitable option for our thesis.

Effective planning and time management were crucial for our thesis due to the limited timeframe we had. To respect the participants' time and energy, we scheduled predetermined 45-minute interviews. Unstructured interviews can be very time-consuming, whereas structured interviews with closed questions are the most time-effective option, with semi-structured interviews falling somewhere in the middle (Mueller & Segal, 2015, p. 1). It is common to underestimate the time needed for an interview. We found 45 minutes to be a suitable time frame for the interviews, as well as for the transcription and analysis of the data, within our timeframe for the thesis. While most interviews were within the predetermined time frame, some were shorter or longer, for more detailed duration of each interview, see table three. Semi-structured interview has the tendency to exceed time frames, however some interviews of ours where quite short. The reason behind this was due to the participants differences in knowledge and elaboration skills. For instance, our shortest interview was conducted within 28 minutes, this participant had long elaborations which resulted in several questions being answer at once. Meanwhile we did not want to interrupt our participants. Overall, the data collected through our interviews aimed to seek saturation which we believe it has.

We followed a semi-structured approach in our interviews by using an interview guide that contained prepared questions and themes (Mueller & Segal, 2015, p. 2). All interviews followed the same structure, and we shared the questions with the participants beforehand to allow them to prepare for more thoughtful and developed answers (Collis & Hussey, 2014, p. 133). Our open-ended questions encouraged participants to provide detailed answers (Gill et al., 2008, p. 292). However, it was important for the interviewer to actively engage and encourage the participants during the interview to become more integrated with them and encourage elaboration (Kallio et al., 2016, p. 2955). Asking follow-up questions was crucial to gain insights, but it was essential to do so gently to avoid interrupting the participants (Kallio et al., 2016, p. 2960). We aimed to strike a balance between the questions and themes while also receiving advanced questions that contributed to insightful data analysis.

To ensure ethical research practices, we began each interview by informing the participants of the confidentiality of their information during and after the study. We also received explicit consent from them to record the interview for transcription purposes. Moreover, all participants had previously signed a consent form that detailed the research ethics and their right to withdraw or decline to answer any questions, see appendix three. The interview guide provided structure to the conversation and helped us stay on track while adhering to the allocated time frame. Following Solarino and Aguinis' (2021) recommendation, at the end of the interview, we invited participants to share any additional comments or information they deemed relevant, as this can provide valuable insights to the research.

4.1.3 Interview guide

The semi-structured interviews that were conducted were guided by our interview guide. The guide is composed of five main themes, all relevant to our research question (refer to table two). Once the themes were established, we proceeded to formulate questions for each theme, taking into account the research question, theoretical framework, and purpose. As researchers, we strived to strike a balance in formulating questions that are brief and uncomplicated, non-leading, but still capable of eliciting sufficient data to answer the research question (Kallio et al., 2016, p. 2960).

Table 2: Themes for our interview guide

Introduction
Background
Artificial Intelligence
SCM Efficiency
Concluding remarks - Ending thoughts

The interview guide is provided in two versions, one in English and one in Swedish, as shown in appendices five and six. This is to ensure that the interviews are conducted in a language that both parties are proficient in, reducing the risk of translation issues or other language-related barriers (Squires, 2009, p. 277). If any participant preferred to conduct the interview in English, we were flexible and willing to accommodate their preference. This is because we aimed to use a language that was understandable and relevant to the participants (Squires, 2009, p. 285). However, the interviews were conducted in Swedish since both the researchers and all participants are native Swedish speakers, allowing for the collection of more insightful and in-depth data.

Each interview had a standardised structure, starting with an introduction that explained the study's purpose, introduced us, and informed the participants of their rights. The researchers aimed to establish a positive atmosphere and build trust by creating a comfortable setting, as the beginning of the interview is critical (Gill et al., 2008, p. 292). The interview followed a specific sequence of themes and began with background questions to provide context. All questions were asked neutrally to avoid any biases or confusion. This approach enabled participants to express their perspectives on the phenomenon being studied and describe environments or processes as they experienced them, which is crucial for conducting successful semi-structured interviews (Gill et al., 2008, p. 292-293). Short follow-up questions were used to clarify answers and gather more in-depth data. Towards the end of the interview, probing and specific questions were asked to encourage exploration in particular areas (Gill et al., 2008, p. 293). The interviews concluded with a summarising question, followed by an opportunity for participants to provide additional data or express their opinions on implementation of AI within SCM in the manufacturing industry.

4.1.4 Recording and transcription

In order to improve the quality of the interviews, we made the decision to record the audio of each interview. This allowed us to focus on the conversation and follow-up on any unclear points, without the distraction of taking notes (Harvey, 2011, p. 436). Of course, we made sure to inform participants of our intentions to record, and we obtained their consent beforehand, in line with our research ethics. However, if a participant was uncomfortable with being recorded, we respected their wishes and was ready to take detailed notes instead. Luckily, all our participants allowed recording. To ensure we had a backup recording, we used two devices (our mobile phones and Zoom/Teams) throughout all the interviews, mitigating the risk of technical difficulties leading to lost audio recordings.

We took measures to ensure the respondents were comfortable with the recording process, such as reminding them of their anonymity and company name confidentiality and emphasising it throughout our communication with them. However, some respondents may still have hesitations despite these efforts (Harvey, 2011, p. 436). To transcribe the audio recordings, we first used a transcription tool, Microsoft Word's own transcription tool, to save time and then reviewed and made any necessary amendments to ensure accuracy. The purpose of transcription was to use grounded theory to analyse the data we collected, which is essential for answering our research question.

4.2 Data analysis

We have selected grounded theory as our data analysis method because our project aims to generate theories based on observations in reality rather than testing pre-existing theories. Grounded theory involves breaking down collected data into its key components through a series of coding cycles, resulting in a theory that is highly rooted in the original data (Saldaña, 2013, p. 51).

The two alternative approaches for content analysis are inductive and deductive, as described by Elo and Kyngäs (2008, p. 109). In our study, we have chosen the inductive approach because we aim to generate new theoretical insights and gain a deeper understanding of how the manufacturing industry implements AI within SCM. Therefore, we will be going from the specific to the general in our content analysis.

The coding process is rarely accurate on the first try, as noted by Saldaña (2013, p. 10). Therefore, we have implemented the coding process multiple times and conducted it separately between researchers to gain diverse perspectives on the collected data. This, in combination with a repetitive coding process, aims to increase the reliability of the data. Throughout the coding and recoding process, we have aimed to refine our codes and categories to become more conceptual and abstract, thereby creating a more robust foundation for theory building (Saldaña, 2013, p. 11). Additionally, we compared our coding and discussed any discrepancies to comprehend each other's interpretations of the data. Furthermore, the data analysis format is based on a four-step process, which is presented in the following section.

Step 1. Developing initial codes

To develop concepts and formulate a theory, we begin by analysing the transcribed interviews and creating the initial codes. These codes represent our first impressions of the data, as described by Saldaña (2013, p. 5). We use questioning as a valuable tool to search for answers within the interviews, as recommended by Grodal et al. (2020, p. 593), specifically we broke down our research question that aims to answer 'how' something is conducted into more detailed questions when identifying initial codes with 'what', 'when' and 'where' the implementation of AI can improve the SCM. The objective here was to gain a general understanding of the data by reading through it. This process yielded in 314 initial codes from the six interviews, which are listed in table three below.

Table 3: Overview of initial codes

Case	***Role of respondent***	***Duration of interview***	***Pages transcribed***	***Number of initial codes***
Interview 1	*Digitalization manager*	*37 min*	*9 pages*	*73 codes*
Interview 2	*Supply chain planner*	*42 min*	*10 pages*	*81 codes*
Interview 3	*Logistic manager*	*34 min*	*6 Pages*	*28 codes*
Interview 4	*Logistic manager*	*28 min*	*8 Pages*	*42 codes*
Interview 5	*Digitalization manager*	*45 min*	*8 Pages*	*58 codes*
Interview 6	*Production planning manager*	*30 min*	*7 Pages*	*32 codes*
Total			***48 pages***	***314 codes***

Step 2. Developing first-order codes

Secondly, we gathered the initial codes from the previous session. The process here included an analysis of all interviews, aiming to establish which initial codes were of similar characteristics and of interest to our topic, AI implementation to improve SCM. Generating categories that could serve as the basis for new theoretical insights was the essence of our analysis process (Grodal et al., 2020, p. 594). By coding, we could categorise our gathered data on shared beliefs and opinion (Saldaña, 2013, p. 9). To create categories, we grouped similar components, elements, or quotes into a first-order code. To preserve the authenticity of the data collected from the interviews and avoid misinterpretation, we always used the data within its proper context and quoted it verbatim from the respondents' words. Our first-order code was the initial step for us to depart from a specific and detailed perspective and approach a more general finding (Grodal et al., 2020, p. 594). In total, we identified 15 first-order codes, which are presented in table four below.

Table 4: Overview of first-order codes

First-order codes
1.a.1 Creating scenario analyses to facilitate business decisions
1.a.2 Generating feedback and evaluation to move forward
1.b.1 The current situation
1.b.2 Improving administrative work to gain time
1.b.3 Improving companies' competitiveness
1.b.4 Preventing disruption to maintain production
2.a.1 Decreasing contingencies to improve data quality
2.a.2 Creating an 'even flow'
2.b.1 Keeping inventory to an appropriate level
2.b.2 Saving the most out of resources
3.a.1 Planning and restructuring
3.a.2 Creating similarity in work to diminish deviation
3.b.1 Growing the accuracy and live up to expectations
3.b.2 Increasing the transparency in order to reduce suspicion
3.b.3 Simplifying the road-map in order to see the end-goal

Step 3. Developing second-order codes

Thereafter, we compared the first-order codes with our theoretical framework and the existing literature that we had previously noticed. We found that comparing emerging concepts, theories, or hypotheses with existing literature was a critical aspect for us and the theory-building we aim to contribute with (Eisenhardt, 1989, p. 544). We leveraged literature from the theoretical framework to interpret the collected data. Therefore, the second-order codes are the results of combining the first-order codes and representative literature, which can be found in table five below.

Table 5: Overview of the development of second-order codes

First-order codes	**Second-order codes**
1.a.1 Creating scenario analyses to facilitate business decisions	1A. Increasing accuracy of forecasts to enable success

1.a.2 Generating feedback and evaluation to move forward	
1.b.1 The current situation	1B: Refining methods and processes in order to sustain
1.b.2 Improving administrative work to gain time	
1.b.3 Improving companies' competitiveness	
1.b.4 Preventing disruption to maintain production	
2.a.1 Decreasing contingencies to improve data quality	2A: Enhancing the allocation of resources
2.a.2 Creating an 'even flow'	
2.b.1 Keeping inventory to an appropriate level	2B: Optimising the supply chain
2.b.2 Saving the most out of resources	
3.a.1 Planning and restructuring	3A: Reducing complicated transformation
3.a.2 Creating similarity in work to diminish deviation	
3.b.1 Growing the accuracy and live up to expectations	3B. Working on increasing trust to the AI-system
3.b.2 Increasing the transparency in order to reduce suspicion	
3.b.3 Simplifying the road-map in order to see the end-goal	

Step 4. Developing aggregate dimensions

Lastly, we reviewed our second-order codes and analysed how they concurred with each other. Especially during this stage, we took into account the research question we have, to ensure that the emerging concepts and theories would address the research question. In addition, alongside with the process of scrutinising how the second-order codes co-occur, we kept relevant literature in our mind, highlighting the significance of comparing emerging theories with existing literature (Eisenhardt, 1989, p. 544). We then organised and structured the concepts and theories, into a more condensed and abstracted form, creating three aggregate dimensions, which can be viewed in table six.

Table 6: Overview of the development of aggregated dimensions

Second-order codes	Aggregated dimensions
1A. Increasing accuracy of forecasts to enable success	1. Automating the production for more prosperity
1B. Refining and automating in order to sustain	
2A. Allocating resources to improve contingency management	2. Conserving financial funds
2B: Optimising the supply chain	
3A. Reducing complicated transformation	3. Integrating previous approaches to mitigate emerging challenges
3B. Working on increasing trust to the AI-system	

4.3 Research ethics

The adherence to ethical principles ensures equitable treatment of all research participants in accordance with widely recognized standards upheld by the research community (Bryman & Bell, 2007; Saunders et al, 2019; Collis & Hussey, 2014).

Throughout our research, we have made a conscious effort to uphold academic ethics both in conducting our research and in handling the data collected from respondents. To demonstrate our commitment to ethical research practices, we have followed Bryman and Bell (2007, p. 71) recommendations, which outline how we have treated our respondents and their participation, as shown in the table seven below.

Table 7: Ethical research principles

Ethical principles (Bryman & Bell, 2007, p. 71)	The researchers' ethical approach to research during this study:
Harm to participants It is essential to safeguard the mental and physical health of both the researchers and participants to avoid causing any harm to any of the individuals involved.	We maintained an open-minded attitude during the interviews to create a welcoming atmosphere for the participants. Additionally, we allowed them to choose between conducting the interview in the comfort of their own home or at their workplace, a familiar and comfortable environment for them.
Dignity Respect for the dignity of both the respondents and researchers is necessary to prevent any participant from experiencing discomfort or anxiety.	During the interviews, we made sure to demonstrate respect to our respondents by acknowledging and affirming their statements. This reassured them that we were actively listening and that their insights were highly valued.

Privacy The confidentiality of the respondents must be protected by the researchers.	We ensured that the questions asked were strictly related to the respondents' professional roles and did not include any personal questions that may have made them uncomfortable.
Informed consent The researchers have the responsibility to ensure that the respondents fully comprehend the ethical research principles that are being followed during the study before obtaining their consent.	The respondents were given an information form and a consent form to ensure they were fully informed about the interview process and to clarify the expectations of both the researchers and the participants.
Anonymity The researchers assured the respondents that their participation in the study would not result in their identity being disclosed or made identifiable to anyone.	The respondents were repeatedly informed about the guarantee of their anonymity throughout the study, using various methods such as the consent form, information form, emails, and a statement made before recording the interview.
Confidentiality The confidentiality of research data for the participants and the organisations they represent was ensured by the researchers.	To ensure the confidentiality of research data for the respondents and the organisations they represent, we provided them with both an information form and a consent form that they had to sign. These forms reassured them that their data would be kept confidential as promised.
Deception, Honesty and transparency The research process can be disrupted by dishonest or misleading responses from the respondents, as well as misrepresentations of data by the researchers. Therefore, it is essential for all participants involved in the research to demonstrate honesty, trustworthiness, and openness.	We made every effort to encourage our respondents to provide truthful information during the interviews. However, we acknowledge that there is a possibility of deception or misinformation, which can undermine the research process. We remain hopeful that our respondents have shared their genuine perceptions and experiences to the best of their knowledge and memory.
Affiliation The researchers have an ethical responsibility to disclose any sources of funding, sponsorship or professional affiliations related to the research.	We disclosed our professional affiliation and provided our personal information and our supervisor's contact details to the respondents. Although our research was not sponsored, we made sure to be transparent about our university affiliation.
Reciprocity It is important to ensure mutual benefits for both researchers and respondents during the research process, and active participation and collaboration from all parties involved is necessary.	We ensured mutual benefits for both researchers and respondents throughout the research process by having active participation and collaboration from all participants. Our respondents were willing to answer our questions, and if they didn't know the answer or felt they didn't have a good answer, they were honest about it. Additionally, we offered to send the thesis to our respondents once it was finished, if they wished to receive it.
Misrepresentation To ensure accurate reporting of research findings, researchers must avoid any presentation of data that is misleading or misrepresentative, and that may lead to misunderstandings	It is important to report the findings in a clear and concise manner, using appropriate language and avoiding any manipulation of data to support preconceived notions or biases. The goal is to present the findings in a way that is honest, transparent, and informative, while avoiding any potential harm or confusion to the readers. To ensure that the research findings were reported accurately, we transcribed the audio from the

	interviews and conducted separate coding of the data multiple times. This allowed us to determine the most appropriate coding and minimise the risk of presenting data outside of its relevant context. Both authors reviewed and compared their coding to ensure accuracy and appropriate representation of the data.

4.4 Quality criteria

Maintaining high standards of quality and veracity is imperative in the realm of research. To uphold these standards, we will define two criteria that we have incorporated into our degree project. These two criteria are trustworthiness and authenticity and are normally used in research that is qualitative.

4.4.1 Trustworthiness

The trustworthiness criterion is subdivided into Credibility, Transferability, Dependability, and Confirmability (Amin, 2020, p. 1473; Cope, 2014, p. 89).

Credibility

Credibility pertains to the veracity of the data or the viewpoints of the participants, as well as how the researcher has interpreted and presented them (Cope, 2014, p. 89). We have exerted considerable efforts to attain transparency and establish credibility. To guarantee that the phenomenon truly reflected reality, we employed triangulation by incorporating multiple sources of information (Amin et al., 2020, p. 1475). Multiple researchers employing the same methodology should ideally yield similar outcomes. Nonetheless, in reality, this is not always the case. If any disparities arose regarding the interpretation of the data, we deliberated the discrepancies and subsequently arrived at a mutual understanding for a novel interpretation that was more appropriate. Furthermore, we have ensured that the respondents were adequately informed prior to the interview by sending out an information letter. During the interviews, we made sure to establish a comfortable and secure atmosphere, which helped the respondents feel at ease and facilitated a more natural and productive conversation. Our efforts led to the collection of rigorous data. Additionally, we guaranteed anonymity, which allowed the participants to delve deeper into their experiences. This aligns with the idea of prolonged engagement (Amin et al., 2020, 1473). Lastly, we followed a practical methodology that involved a thorough and systematic coding process. Through persistent observation, we combined theories with the data to develop a model that answered our research question. To create authentic codes, we repeatedly reviewed the data and processed it in a systematic manner. By following these rigorous procedures, we aimed to enhance the credibility of our study and ensure the accuracy of our findings.

Transferability

The transferability criterion in a study is about how general conclusions can be drawn
the results in other social environments and situations (Korstjens & Moser, 2018, p. 121). Incorporating transferability is crucial, as it is ultimately up to the reader to determine whether the findings are applicable beyond the specific context of the study (Cope, 2014, p. 89). We acknowledge that our sample size was relatively small, consisting of only six participants. However, it was not our intention to make generalised claims. Nonetheless, we have confidence that data saturation has been achieved and therefore our findings can be applicable to comparable settings. We believe that our result can be applicable to other manufacturing

companies around the world as well as other industries in Sweden. Schaeffer et al. (2016, p. 6) mention that industries that are behind in the implementation of AI are for example the agriculture industry, metals & mining industry and the food & beverages industry. These industries can benefit from this result and incorporating AI into their SCM could potentially lead to similar improvements in efficiency. It is important to note that the transferability criterion in a study is about how general conclusions can be drawn from the results in other social environments and situations (Korstjens & Moser, 2018, p. 121).

Dependability

The dependability criterion refers to the extent to which the research findings are consistent and stable over time and across conditions (Cope, 2014, p. 89). Dependability is attained when a different researcher conducts a study with comparable features and arrives at the same conclusions, or at least concurs with the conclusions drawn by the original researchers (Cope, 2014, p. 89). In our thesis, we aim to ensure that the research process is defined and presented clearly, enabling the reader to easily follow the decisions made by us. Moreover, to ensure dependability, we have regularly presented our work in progress to a supervisor and peers, receiving feedback and making changes accordingly. Based on these measures, we assert that our study fulfils the requirements for the dependability criterion.

Confirmability

The last criterion of trustworthiness is confirmability. The concept of confirmability pertains to the researcher's capacity to demonstrate that the collected data accurately reflect the responses of the participants and are not influenced by the researcher's personal biases or perspectives (Cope, 2014, p. 89). In order to attain a large degree of objectivity and confirmability, we have opted to provide a comprehensive display of our coding process, culminating in the aggregate dimension. However, in business research, it can be challenging to completely detach oneself from personal values (Cope, 2014, p. 89). To mitigate this potential interference, we ensured that both researchers were involved in the data collection and analysis stages, allowing for a dialogue when interpreting the responses of the participants. In addition, we have provided quotes from respondents that portray every new and developing theme to ensure that we fulfil this criterion as well (Cope, 2014, p. 89).

4.4.2 Authenticity

Authenticity is divided into five components, Fairness, Ontological authenticity, Educative authenticity, Catalytic authenticity, and Tactical authenticity (Amin, 2020, p. 1479-1480; Phillips et al., 2014, p. 8).

Fairness

Among all the authenticity criteria, fairness holds the most significance. Fairness pertains to whether the research has accounted for the diverse experiential realities of the participants when relaying the responses obtained from the conducted interviews (Amin et al., 2020, p. 1479; Phillips et al., 2014, p. 10). It means that the researcher should avoid any form of favouritism or discrimination towards any individual, group, or community involved in the research. By interviewing individuals with a range of roles within each company, we were able to obtain a more comprehensive understanding of the perspectives and experiences of the participants, thus avoiding any potential bias or discrimination towards any particular group or individual. For example, some of the respondents were logistic managers and others were supply chain planners or digitalization managers. This gave us the opportunity to approach the process from several lived realities of our respondents.

Ontological authenticity
The concept of ontological authenticity criterion is particularly important in studies that involve people as participants. This criterion ensures that participants gain a better understanding of their social context and receive something valuable in return for their participation in the study (Amin et al., 2020, p. 1480; Phillips et al., 2014, p. 10). By examining the implementation of AI in the manufacturing industry and its impact on SCM, this study not only contributes to the knowledge of practitioners and researchers but also meets the ontological authenticity criterion by providing participants with valuable insights into the social situation in which they live and work. Therefore, this study offers a win-win situation for both participants and the wider community by generating knowledge that benefits all stakeholders involved.

Educative authenticity
The third criterion, educational authenticity, pertains to the extent to which study respondents develop a deeper awareness and comprehension of individuals foreign of their own stakeholder group (Amin et al., 2020, p.1480; Phillips et al., 2014, p. 10). Upon the completion of the study, the final version was made available to the participants. By granting access to the study's respondents, they can learn about the various strategies used by other companies with the implementation of AI including their views on how to improve SCM. Additionally, the study's conclusions are presented, providing participants with valuable insights into the topic.

Catalytic authenticity
Catalytic authenticity refers to how much a research study inspires and enables action towards clarifying the issue at hand, improving or solving the problem, or strengthening values related to the issue. The idea behind catalytic authenticity is that simply gaining knowledge through research is not enough to effectively address the various issues that participants may raise during the research process. Instead, the study should encourage and facilitate action towards addressing those issues in a meaningful way (Amin et al., 2020, p. 1480; Phillips et al., 2014, p. 10). The aim of our study was not only for us as writers to enhance our understanding of the subject matter, but also for study participants and readers to gain a deeper and broader understanding and knowledge of the topic. We hope that those who take part in the study will find useful insights that can inform the development of their implementation of AI or other relevant areas.

Tactical authenticity
Tactical authenticity refers to the degree to which all participants in a research inquiry are given the power and agency to take the necessary actions that are implied or proposed by the research (Amin et al., 2020, p. 1480; Phillips et al., 2014, p. 10). To achieve tactical authenticity, several useful procedures and techniques can be employed, including confidentiality, negotiations regarding the types of data that will be collected and how they will be interpreted and reported and the use of clear and detailed consent forms (Amin et al., 2020, p. 1480). We have fulfilled this criterion by sending out clear consent forms to all our respondents which can be seen in appendix three and have been careful with confidentiality throughout the whole process. In addition, our contention is that this standard has been met, as our model provides respondents and stakeholders with valuable insights into the process of implementing AI in the manufacturing industry in order to improve SCM. Specifically, it offers participants the chance to engage with the framework of our thesis when approaching the process.

4.5 Summary over practical methodology

Table 8: Summary of practical methodology

Data Collection methods	Primary data through interviews
Sampling technique	Purposeful and snowballing
Conducting the interviews	Semi-structured interviews Through video conference calls.
Research ethics	Table 7. Ethical research principles
Analysis method	Inductive Grounded Theory
Quality criteria	Trustworthiness and Authenticity

5.0 Empirical findings and analysis

This chapter will present the results of our data collection efforts. Firstly, we will provide a summary of the findings. Then, we will delve into a detailed analysis of the aggregated dimensions, in order to break down both the first-order and second-order codes that constitute them.

5.1 Findings and data structure

The objective of our thesis project is to develop a comprehensive understanding of *How implementation of AI can improve SCM.* We adopted an inductive approach to perform thematic analysis of the collected data, specifically grounded theory, as mentioned earlier. Furthermore, we structured our analysis into three levels, namely aggregate dimensions, second-order codes, and first-order codes, which will be elaborated upon in the following sections. Figure one illustrates the data structure of the analysis and shows how the three aggregated dimensions were developed.

The first aggregate dimension, (1) **Automating the production for more prosperity,** is composed of two elements, (1A) Increasing accuracy of forecasts to enable success and (1B) Refining methods and processes in order to sustain.

Moving on, the second aggregate dimension, (2) **Conserving financial funds,** comprises two elements, (2A) Enhancing the allocation of resources and (2B) Optimising the supply chain.

The third and the last aggregate dimension, (3) **Integrating previous approaches to mitigate emerging challenges,** is built on two components, (3A) Reducing complicated transformation and (3B) Working on increasing trust to the AI-system.

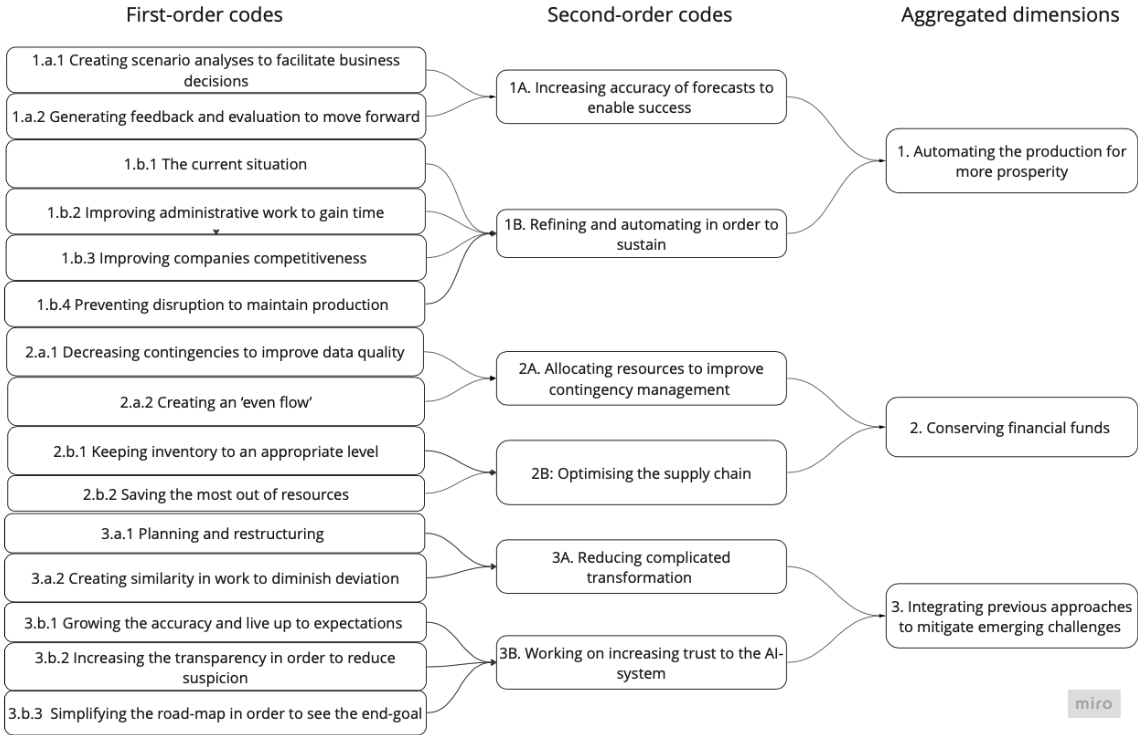

Figure 1: Overview of the data structure

5.2 Aggregate dimension 1: Automating the production for more prosperity

For companies to improve their SCM, our data analysis means they need to automate production in order to create more accurate forecasts. Forecasting is being used by employees and managers as a prediction-tool to estimate possible supply and demand on the market. By predicting the demand, companies arrange their organisation and thereafter will be able to know what they can supply. These forecasts proved to be the basis for crucial decisions, decisions that determine the success or failure of the future. With AI, more accurate forecasting becomes apparent, thus by implementing AI forecasting, prosperity is therefore enabled (1A). Additionally, the respondents answer indicates that AI has the capacity to refine and automate companies, which can be crucial for them to sustain within the industry (1B).

5.2.1 Second-order code 1A: Increasing accuracy of forecasts to enable success

When companies work within SCM, a large part is about accurate forecasting (1A). Accurate refers to how precise the estimation of the future demand and supply was being made, when comparing the approximation with the actual result. When conducting forecasting, participants explained how they often ask themself 'what if?', making up scenarios and estimating about the future, in order to increase potential achievements and increase the accuracy (1.a.1).

Forecasting was a crucial part of the SCM, both when predicting potential demand from the market and when estimating what supply their production could generate. In order to do forecasting in a more profitable way, using AI, the system can create scenario analyses faster and more specific with using less amount of time (1.a.1).

"*So forecasting is the part where **we work a lot with AI, to be able to calculate demand & supply** for the following 24 months"* - Respondent 1

"*When you are in a supply chain role, [...] **you want AI to be able to generate scenarios** because those are the ones that take the most time*." - Respondent 2

"*It is an incredibly volatile market **[...]. To get an analysis which may have generated that "now it looks like this",** "then you can expect that the prices should start going up". I think that would be something good, I can spontaneously feel **that it would be something good for us"*** - Respondent 4

Subsequently, the scenario analysis and its forecast works as the foundation for business decisions (1.a.1). Therefore implementing AI to create scenario analyses both is beneficial but above all, should be accurate in order for companies to rely on it and enable success through it. Accordingly, companies who implement AI which will generate successful estimation from their scenario analysis, generate more prosperity in the long run.

*"Above all, from my side then, is that **we must get better forecasting**. Everything that we produce during pre-season, **we produce based on forecasting**"* - Respondent 1

As already touched upon, an essential part of forecasting to enable success is to also evaluate the outcome, to gain experience for the future (1.a.2). Our respondents indicated that an evaluation between the expected outcome and the actual outcome is a great feedback and something that AI needs to to be able to produce, since it's used widely (1.a.2). By doing evaluation and providing feedback, the AI-system also learns from it in order to gain secure success through forecasting.

"There are a lot of meetings, a lot of follow-ups and then also a lot of scouting, workshops, ***how do we proceed? Where are we going? What kind of projects*** *do we have that we will run? and* ***how do we ensure that we solve problems*** *in our production"* - Respondent 1

*"****AI will probably be a recurring thing*** *during the summer and at weekly meetings, what should be changed and done."* - Respondent 2

To conclude, by implementing AI, companies strive to achieve accurate forecasting, they will then be able to learn from their mistakes and plan for the future in a more profitable way. This was proven through our data to both be of high demand within SCM and to be a profitable option than previous methods used.

5.2.2 Second-order code 1B: Refining methods and processes in order to sustain

Refining in order to sustain (1B) refers to how the implementation can improve certain general areas within the SCM. However, in order to truly be transparent with our data, and give context to our findings, we have also included how our respondent has explained their current situation (1.b.1). Firstly, a lot of administrative work can be replaced with AI and the employee can therefore focus their time on more fulfilling assignments (1.b.2). Additionally with AI and in combination with SCM, companies are able to gain competitiveness (1.b.3), which is of importance since they need to stay relevant in the manufacturing industry. Lastly, our respondents expressed the importance of their production, which the implementation of AI can aid with predicting disruption or interference more in detail (1.b.4).

Our respondents provided diverse perspectives on their current situations (1.b.1) regarding AI implementation, which can be displayed in figure two. Some participants were in the process of implementing AI and had recently witnessed the positive outcomes of their implementation efforts. Others had made more significant progress along the AI spectrum. By considering these varied viewpoints, we have gained valuable insights into the specific areas within SCM where AI has demonstrated improvements.

The accumulation of knowledge gathered from these different perspectives spans across the industry. Consequently, we have been able to identify the specific domains within SCM that have benefited from AI implementation. It is worth noting that those who have fully established AI within their operations recognize its significant advantages and believe that the benefits outweigh any potential drawbacks. Conversely, participants who have not made as much progress in AI development often perceive more obstacles than opportunities, which is demonstrated in figure two.

Overall, our research has allowed us to comprehend the contrasting experiences and perspectives related to AI implementation in SCM. This comprehensive understanding enhances our ability to assess the benefits and challenges associated with AI adoption and provides valuable insights for organisations considering or currently undertaking AI initiatives in their supply chain management processes.

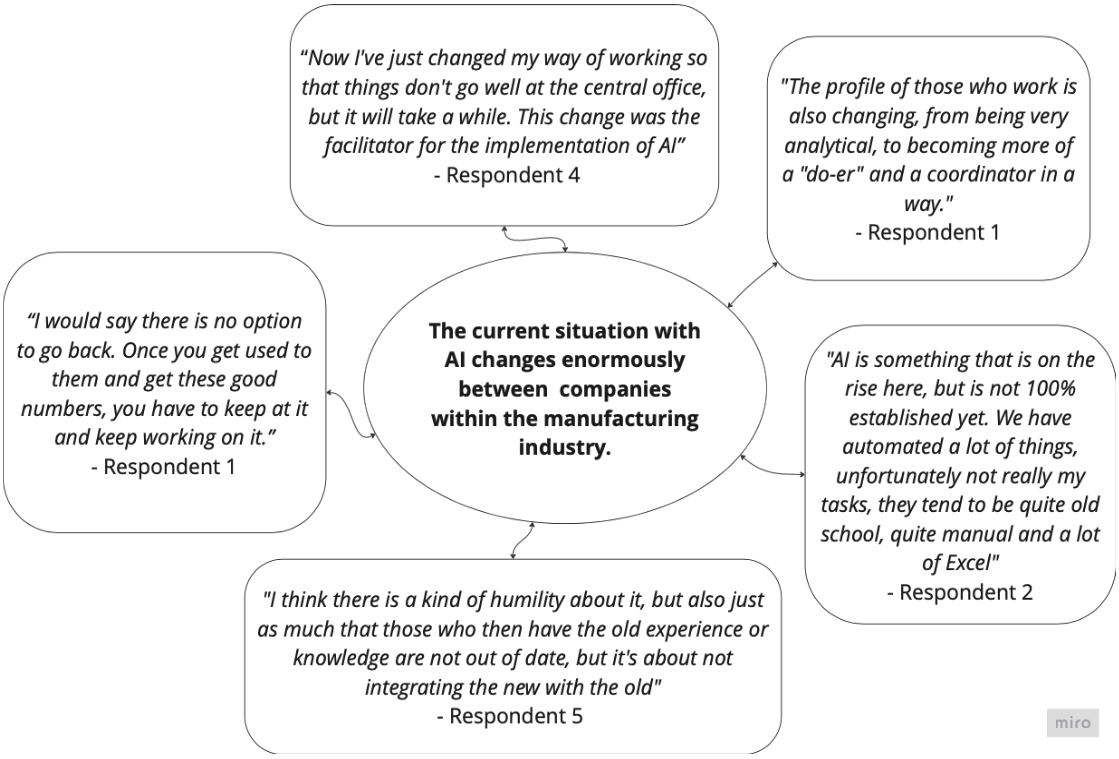

Figure 2: Illustrative image of the current situation

According to our participants in the supply chain management field, AI has played a significant role in completing or has the potential to complete a substantial amount of their administrative work (1.b.2). This use of AI technology serves as a valuable support for employees, allowing them to save time on tedious assignments and redirect their focus towards more rewarding and strategic work.

By automating administrative tasks through AI, SCM professionals can streamline their workflow and increase overall productivity. Time-consuming activities such as data entry, documentation, and repetitive data analysis can be efficiently handled by AI systems. This enables employees to dedicate their time and expertise to more complex decision-making, problem-solving, and relationship-building aspects of their roles.

The ability to offload administrative work to AI not only enhances efficiency but also contributes to employee satisfaction and engagement. By relieving employees from mundane and repetitive tasks, they can engage in more intellectually stimulating and fulfilling work, leading to increased job satisfaction and higher morale within the SCM team. Furthermore, leveraging AI for administrative tasks minimises the potential for human error and improves accuracy and consistency in data processing and analysis. This, in turn, enhances the overall quality of SCM operations and decision-making.

Overall, the integration of AI technology in SCM has the potential to significantly alleviate the burden of administrative work, allowing employees to focus on higher-value activities. This not only improves operational efficiency but also enhances employee satisfaction and the overall effectiveness of SCM processes

"***AI makes the efficiency greater****, because I can polish my data and wait for the result, I don't have to sit and work with my excel sheets. [...]* ***Sitting and doing laboratory work and picking***

***takes a lot of time**, and then you get less time to analyse what it was you got out and work on those deviations."* - Respondent 1

"From a Supply Chain perspective, I think AI is good, when you have more than one site and you have several assumptions you have to make, then AI can help a lot because it's something that previous tools can't help with at all. ***Without AI, you have to do manual calculations.*** *"* - Respondent 2

"Mainly when it comes to efficiency, ***it's about lost working hours due to inefficient working methods*** *that we have today* ***without the AI tool"*** - Respondent 2

In addition to making employees more time-efficient, AI implementation within supply chain management (SCM) has the potential to enhance working methods and increase competitiveness (1.b.3). By leveraging AI technologies, SCM professionals can optimise processes, improve decision-making, and gain a competitive edge in several ways.

AI can analyse vast amounts of data and provide valuable insights and recommendations that can inform strategic decision-making within SCM. It can identify patterns, trends, and anomalies in data that may not be readily apparent to human analysts. These insights can enable more informed and data-driven decision-making, leading to improved operational efficiency, cost reduction, and better resource allocation. As previously mentioned, companies can improve their forecasts by using AI and therefore provide more success for the company. Further, they will also be able to use AI to improve their competitiveness, targeting markets that they previously have not intended to, polishing current methods to become more efficient and improving their margins to be able to provide greater customer service in terms of price and time-frame.

"*Since we work with such incredibly large sums and incredibly large volumes,* ***AI is almost something that's necessary****, to continue* ***to stay relevant in the world market****."* - Respondent 2

"If we don't have an idea on how AI can help more in a business and don't do AI, then we won't survive against competitors. It's not just fun and games for the geeks, but ***it's really business critical that we implement it"*** - Respondent 6

"Therefore, I mean that AI is competitive because… ***You want to be faster, better quality and better trust, have a higher trust"*** - Respondent 5

By embracing AI and leveraging its capabilities within SCM, companies can transform their working methods, optimise operations, and enhance their competitiveness in the marketplace. The ability to make data-driven decisions, streamline processes, and leverage predictive insights positions organisations for success in a rapidly evolving business landscape.

The final aspect highlighted by our respondents (1.b.4) is how AI aids in preventing issues within the manufacturing industry. Given the industry's heavy reliance on production, AI plays a crucial role in enabling SCM to operate proactively. By utilising AI technologies, companies can predict potential machine shutdowns, identify when machines require maintenance or repairs, and plan ahead accordingly. This proactive approach leads to improved efficiency and mitigates production disruptions.

Through AI-driven predictive maintenance, SCM professionals can leverage historical and real-time data from sensors and equipment to anticipate potential failures or breakdowns. AI algorithms can analyse patterns and indicators of machine performance, providing early warnings and insights into when maintenance or repair activities should be scheduled. This allows companies to prevent unexpected production downtime and optimise the utilisation of their manufacturing resources.

By effectively managing machine maintenance and repairs, companies can reduce unplanned disruptions, optimise production schedules, and minimise the associated costs of downtime. AI's predictive capabilities enable better resource allocation, ensuring that maintenance activities are performed at the most opportune times, avoiding unnecessary interruptions to production.

"During production, where you can also use AI in many ways, *where you can see how machines work, when they will break down and when I need to do maintenance.* ***Cause no factory feels good on stand by"*** - Respondent 1

"What we can't do is that ***we can't cause production in an industry like this to stop,*** *because then it won't be fun."* - Respondent 3

"Actually ***implementing AI*** *is because you* ***want to maintain control over your production*** *[...]"* - Respondent 2

Therefore, by leveraging AI to predict and prevent potential issues, companies can optimise their SCM processes, reduce downtime, enhance production efficiency, and ultimately improve their competitiveness within the manufacturing industry. The proactive nature of AI-enabled SCM allows companies to stay ahead of potential disruptions and operate more efficiently, ultimately benefiting both the company and its customers.

5.3 Aggregate dimension 2: Conserving financial funds

In order for manufacturing companies to have the opportunity to improve the SCM through the implementation of AI, our data analysis shows that it is important to strive to save money by effectively distributing the resources you have available. Instead of wasting or overusing resources, it can be crucial to try to use them in a strategic and efficient way to reduce costs and maximise value. What has been seen is that by implementing AI, (2A) resources can be allocated in a better way so that one can improve their contingency management and to (2B) preserve financial resources by optimisation in the SC.

5.3.1 Second-order code 2A: Enhancing the allocation of resources

When dealing with the SC, allocate the resources property can pose challenges and one approach that has been shown from our data collection is that by applying AI (2.a.1), it can decrease contingencies to improve data quality, and (2.a.2) a more consistent and even flow can be fostered. In conclusion, companies therefore try to solve these challenges and allocate resources better by implementing AI.

What our data analysis showed us was that within the SC, the occurrence of unexpected events is normal. Unplanned incidents appear that the employees or manager needs to handle. Often, they manage to do so, but the "abnormal event" makes their data quality poor. What AI then has been able to aid, is to prevent unpredictability by reducing contingencies. Therefore by implementing AI, the SCM will be able to improve their data quality since they have less contingencies (2.a.1) and provide better control and planning over it. With improved data quality, they can allocate their resources more appropriately to the operational organisation. By allocating their resources correctly, the financial resources can be saved.

"Throughout 2021 and large parts of 2022 there were problems with deliveries in, mainly due to Asia and China closing and opening, closing and opening. So no goods came out of there. ***It makes the history look very strange, if you compare it to a normal season.*** *[...] that's our biggest challenge now, to 'clean' our data and check 'What was the abnormality?'"* - Respondent 1

"If you ***throw in bad data****, then you get* ***bad data out****, it's that simple."* - Respondent 4

"With data quality then, to do it well ***you have to have control over your data*** *and you* ***have to have high quality****. What is meant by high quality then? Well, you have to know what it means, where it comes from and what it is supposed to fulfil."* - Respondent 6

"We make a plan and then something happens a week in the future and then we have to throw the whole plan away, ***the whole plan becomes invalid*** *and we* ***start over from scratch****. There I think that AI would have a good role [...]"* - Respondent 2

Our respondents has emphasised the importance of establishing an even flow within the SC to enhance efficiency (2.a.2). Our data analysis findings strongly support the notion that companies with a consistent and smooth flow of operations can achieve higher levels of efficiency. This efficiency, in turn, translates into several benefits, including the ability to allocate more time and resources to other critical activities, ultimately resulting in cost savings for the company.

"We win when we can ***automate the simple flow****"*- Respondent 3

"*....and that's probably the first efficiency I miss - that I make time for a formal, manual thing, instead of* ***evaluating*** *and* ***optimising my team's goods flow*** *as well as possible"* - Respondent 2

"Instead of having an operator there who works 6 shifts and there is a new guy or girl every shift who thinks differently from the other. ***AI becomes a simple flow*** *that is fairly standardised, and in this way it becomes more efficient and saves money."* - Respondent 3

The goal to create an even flow can be effectively achieved through the utilisation of AI. The 'even flow' that our respondents refer to are the processes and changes from when goods enter production, until they are shipped, where they want to reduce any large variations and deviations. This will create an even flow, making it more predictable and therefore manageable. By leveraging AI technologies and algorithms, companies can optimise the allocation of resources, minimise disruptions, and ensure a consistent and smooth flow of materials, products, and information throughout the SC and also to save more money.

5.3.2 Second-order code 2B: Optimising the supply chain

The respondents emphasise the importance of preserving financial resources within the SC. They suggest that one effective approach to achieve this is by maintaining inventory at an appropriate level (2.b.1), which can greatly enhance inventory management and streamline processes. This strategy offers several benefits, including cost reduction and improved operational efficiency. Moreover, saving the most out of resources due to financial considerations (2.b.2) becomes crucial as it enables substantial cost savings.

According to our respondents, the management of inventory at an appropriate level (2.b.1) is a critical aspect of SCM. This is particularly significant in manufacturing industries, where inventory levels tend to represent a substantial portion of the balance sheet. SCM endeavours to optimise this aspect by ensuring that the required inventory is available while avoiding the accumulation of unnecessary stocks, which can have a detrimental impact on financial resources. By carefully controlling inventory levels, SCM aims to strike a balance between meeting demand and avoiding excessive storage costs. It recognizes the importance of having the right amount of inventory on hand to fulfil customer orders promptly and efficiently. However, according to our respondents, AI holds the potential to revolutionise inventory management within SCM.

*"**It costs a lot of money to sit on too much inventory**, so there is a need for AI, to get a better forecast model, so that we see that we are at **reasonable inventory levels**, and above all when inventory optimization, that we have **proper safety stock**."*
- Respondent 1

*"it always has to do with this **balance between inflow** from a process that in theory should run 24/7 **and then balance the flow out** with cost parameters [...] and then we theoretically optimise inventory after that"* - Respondent 3

The advent of AI presents remarkable opportunities to enhance inventory management. AI's predictive capabilities, coupled with its ability to assist with demand planning and supply planning, enable organisations to regulate and maintain optimal inventory levels more efficiently. Additionally, AI can automate numerous processes, resulting in reduced time and effort expended by employees.

Furthermore, our respondent also indicated that in order to preserve financial resources it is crucial to optimise the general SC (2.b.2). The SCM always aims to save as much as possible, to enhance their financial resources. Efficiently optimising the general supply chain is a critical strategy for organisations to maintain a competitive edge and financial stability. By streamlining processes, reducing waste, and eliminating inefficiencies, SCM aims to achieve cost savings and resource optimization. The respondents mean that this can be accomplished through AI.

*"Our industry is quite old school, we don't have fixed market prices, so of course I want to **optimise as much as possible** because **otherwise the margin will be far too low** and we won't make it around, [...]. There you want the AI to think for itself in a suggestion perspective, you want to be able to receive suggestions"* - Respondent 2

*"But it has to do with all that, **save, become efficient** and if you save money, maybe **resources have been saved**, that you don't need to have had an extra man, an extra operator, or an extra truck"*. - Respondent 3

To conclude, by leveraging AI algorithms and advanced analytics, the companies can gain valuable insights and make data-driven decisions to enhance overall SC performance. They will have the opportunity to save the most of the resources and conserve financial funds.

5.4 Aggregate dimension 3: Integrating previous approaches to mitigate emerging challenges

The last theme that has been developed from our data collection is previous approaches challenging the acceptance of AI. This theme has been developed due to the fact that a lot of the respondents have experienced challenges with both the implementation and the acceptance of AI. The theme has therefore been developed into two parts, which is that different approaches can make the transformation difficult (3A) and that it can be difficult to trust the AI-system (3B).

5.4.1 Second-order code 3A: Reducing complicated transformation

Our data analysis has revealed that transitioning and switching systems to AI can be a challenging endeavour, as indicated by our respondents. The process of adopting AI is considered a complex internal process, presenting significant obstacles for companies aiming to embrace AI successfully. Integrating AI into existing systems and workflows requires careful planning, coordination, and technical expertise (3.a.1), which can make the process daunting. Moreover, the nature of work within the respondent's domain adds another layer of difficulty (3.a.2). The continuous variation in their work poses unique challenges when it comes to transforming their operations with AI. The dynamic nature of their tasks and responsibilities may necessitate adaptability and flexibility in integrating AI solutions. The need to accommodate diverse workflows and ever-changing demands further complicates the transformation process. Therefore AI

Implementing AI involves several key challenges, including selecting appropriate AI technologies, integrating them with existing systems, ensuring data compatibility and quality, and addressing organisational and cultural barriers. These complexities can result in difficulties in achieving a smooth and successful integration of AI within the company's operations. Overcoming these challenges requires careful planning, dedicated resources, and a comprehensive understanding of the organisation's unique requirements and goals (3.a.1). Companies must invest in the necessary expertise, training, and change management processes to navigate the complexities of AI implementation and ensure a successful transformation.

The results indicate that the existing internal logistics or organisational structure can act as a barrier to the successful implementation of AI. This suggests that simply implementing AI into an unchanged structure may not yield the desired improvements in SCM. Instead, a new structure and planning procedure may be necessary to fully leverage the benefits of AI in SCM.

By introducing AI, companies have an opportunity to reevaluate and redesign their internal logistics and processes. AI can provide insights, recommendations, and automation capabilities that enable more efficient and effective planning, coordination, and execution of SCM activities. This may involve redefining roles and responsibilities, optimising workflows, and aligning the organisational structure to better support AI-enabled SCM practices.

Implementing AI-driven solutions often requires a holistic approach that encompasses not only technological aspects but also organisational and cultural changes. This includes fostering a data-driven culture, promoting collaboration across departments, and providing training and support for employees to adapt to the new ways of working. By reimagining the structure and planning procedures within the company, organisations can harness the full potential of AI in improving SCM. The integration of AI as an organiser can help untangle complicated internal processes and pave the way for enhanced operational efficiency, better decision-making, and improved competitiveness.

*"It is **our internal logistics** that makes it **complicated**."* - Respondent 3

*"If we throw in **a bad sales plan, it doesn't matter how much we look at all the generated parameters**, we have to have a good plan in as well and a well-crafted plan."*
- Respondent 1

*"When it **gets too complicated**, usually, **then the automation doesn't help much**. It will not be as easy to achieve something good, if it happens all the time, or for complicated parameters."*
- Respondent 2

Based on our analysis, we have identified a common challenge faced by many manufacturing companies operating in SCM when it comes to integrating AI. This challenge arises from the substantial day-to-day variations and deviations encountered in their operations (3.a.2).

The dynamic nature of SCM operations introduces complexity and unpredictability, making it more challenging to seamlessly integrate AI solutions. These variations can stem from factors such as fluctuating customer demands, changing market conditions, supplier disruptions, and evolving production requirements. These fluctuations pose significant obstacles when attempting to implement AI systems that rely on consistent and stable data inputs.

To effectively integrate AI into SCM operations, companies must account for these variations and deviations. They need to develop AI models and algorithms that can adapt and respond to real-time changes, making use of available data to generate accurate and relevant insights. This may involve incorporating machine learning and advanced analytics techniques that can dynamically adjust to the evolving conditions of the manufacturing environment.

Furthermore, companies must ensure that their data collection processes capture the necessary information to account for variations and deviations. Robust data management practices, including data cleansing, normalisation, and validation, become essential to handle the diversity and variability present in SCM operations. Addressing these challenges requires a comprehensive understanding of the specific variations and deviations encountered in SCM processes. By incorporating AI technologies that can effectively handle these dynamics, companies can harness the full potential of AI to optimise operations, improve decision-making, and enhance overall supply chain performance.

*"There are **no normal days for me**, I can think I will do one thing when I come to work and then it becomes something else entirely"* - Respondent 1

*"So the optimization that we do, which says that 'this is how we should always do it'. **But that "always" doesn't exist**. Of course, we have a plan to try to put that product on one site and the next product somewhere else. But, two, five or eight times, we put something else there, because we had to."* - Respondent 3

*"Above all, you can see that **the work from day to day is changing**."* - Respondent 1

While the process of transitioning AI into SCM can be demanding, it also presents opportunities to leverage technology. Companies that effectively address these challenges can unlock the immense potential of AI to optimise operations, including managing and adapting to the day-to-day variations and deviations. In addition they will be able to improve decision-making, and gain a competitive advantage in their industry.

5.4.2 Second-order code 3B: Working on increasing trust to the AI-system
Another challenge of accepting AI is the lack of trust in the system (3B). It has emerged that when implementing AI, it does not always live up to the expectations as thought (3.b.1). Also, if there is no transparency people are starting to be suspicious and uncertain (3.b.2), why is this good for us? This lack of openness results in employees and managers still using old systems and methods. Additionally, certain respondents have reported encountering challenges during the implementation of AI, which include factors like maintenance demands, time commitments, and heightened complexity. The objective is to streamline the roadmap to ensure a clear vision of the end goal (3.b.3).

Implementing AI can bring about high expectations for organisations seeking to leverage its potential benefits. However, some respondents have found that the reality of AI implementation does not always align with their initial expectations (3.b.1). Challenges have arisen when the companies have encountered situations where AI does not perform as they anticipated which has led to that they feel some annoyance towards AI.

*"[...] it happens quite often that **something starts spinning**, then we don't get all the data in on time and **you experience a frustration** when you come to work and these runs are not finished and then you get a little discouraged."* - Respondent 1

"*I take out a sort of laser-read volume and still fact-check it, because **AI has been wrong so many times**. "* - Respondent 2

So even though AI has its upside, frustration and negative experience has emerged when using the system. Therefore in order for the implementation to be beneficial for SCM, more contributions to developing the system's accuracy are acquired, so expectations from employees and users are encountered.

Moreover, the aspect of transparency has emerged as a significant concern among some of the respondents and they therefore are suspicious towards the AI-system (3.b.2), as its absence creates an environment of uncertainty within companies. This suspicion makes employees hold onto old methods and techniques, which work against the integration of AI. Due to a lack of basic understanding or familiarity with the new AI system, employees are facing challenges in trusting the system. As a result, they find themselves working twice as hard to correct and verify the data generated by the system, aiming to ensure its accuracy.

*"People **don't trust data**, especially not data they don't understand how it came about. You can implement very advanced models, which spit out a result, but **if you don't understand where the result comes from**, then you have uncertainty."* - Respondent 1

*"Do I just want to go in and trust those numbers without knowing how it's happened behind it? [...] **I want to know the background**. [...] if I have a forecast this week that changes to next*

week, I have to ***be able to understand, explain and defend*** *the differences between them, to the other departments."* - Respondent 2

What our respondents have expressed is their need for transparency and more communication regarding what AI produces, in order for them to understand and grasp the decision-process the AI-system has explored.

It's very much a communication issue as well, not just how you should know techniques or something but a lot of communication. And ***trust each other and the technology****.* - Respondent 5

For the companies and employees to place trust in an AI system, it becomes essential that they have a clear understanding of its underlying principles. Without comprehending the system's background, establishing trust becomes a challenge. Working on increasing trust becomes therefore crucial when integrating previous approaches with AI.

The last building-block for 3B revolves around the respondents' shared experience regarding the complexity involved in introducing AI, as it demands considerable time and maintenance commitments for companies. People tend to see the barriers of implementing AI due to the complexity, instead of what AI can contribute in the long run. (3.b.3). So there is a challenge of acceptance in AI for the respondents.

The final component of 3B revolves around the collective experience of respondents concerning the complexity associated with the adoption of AI. Implementing AI requires significant time and ongoing maintenance commitments, which companies often perceive as barriers rather than recognizing the long-term benefits AI can provide (3.b.3). Consequently, there is a challenge of acceptance among respondents regarding AI. To address this challenge, a clearer roadmap is necessary to guide companies in integrating AI into their systems. Our earlier analysis of aggregated dimensions reveals that AI can bring substantial advantages to companies, such as time savings, reduced complexity, and cost savings. However, despite these benefits, respondents currently hesitate to implement AI due to concerns about complexity, time investment, and financial costs which presents a problem that needs to be addressed.

"In this particular department, it's too early now, in 5 years - absolutely, but ***now we let everyone else test AI first****. We can see with the kind of manufacturing that we have, we're not going to benefit because it's too complex."* - Respondent 6

"perhaps that AI is ***not as easy to implement*** *in this industry"* - Respondent 3

"This is ***too complex for us now*** *to invest in because it doesn't have the short-term impact because our business is not that mass-produced."* - Respondent 5

"I think that if we look at continuous production, it would ***take time before setting up such a system.*** *You would have to feed it with basic data and only know which data is relevant to the system and to obtain in order to then be able to process it. I think that would be* ***a pretty complicated task."*** - Respondent 4

"I can imagine ***that AI can be quite a lot of work*** *to get to the basics, so to speak."* - Respondent 2

"People have understood what AI is now and ***you have to invest time in it****, in order for it to work."* - Respondent 5

In conclusion, the adoption of an AI system presents a significant barrier for companies aiming to transform their operations. The uncertainty and the complex investment that this requires makes it not worth it because they don't know if it will be good or if you can trust that it will work. To overcome this obstacle and facilitate a smoother transition, it is crucial to establish a streamlined roadmap that provides a clear vision and goals. Such a roadmap ensures that the company can place trust in the transformation process and navigate the complexities of integrating AI effectively.

6.0 Discussion and Theory Elaboration

In this chapter, we have undertaken a comprehensive discussion of the previously presented findings. The chapter is structured into individual discussions for each aggregate dimension, which are then compared to the existing literature, revealing both similarities and differences. Moreover, the combination of these discussions will contribute to the elaboration of a theory. Through this theory elaboration, we will present a proposed theory that addresses the research question, how the implementation of AI can improve the SCM.

6.1 Automating production for more prosperity

Consistent with prior research, our findings reinforce the notion that AI holds promise in enhancing the SCM (Sithole et al., 2016, p. 18). Both existing literature and our own study underscore the advantages of AI in optimising production through the analysis of production data and offering recommendations for process enhancements (Min, 2010, pp. 16-17). Additionally, AI aids in predictive maintenance by analysing sensor data to anticipate maintenance requirements (Min, 2010, pp. 16-17). Being able to forecast potential circumstances has shown to be of great advantage from both our results and literature (Bughin et al., 2017, p. 22; Li et al., 2020; Piplani et al., 2021). It becomes reasonable why the manufacturing industry strives to automate and implement AI. By implementing automation within SCM, manufacturing companies gain the ability to swiftly adapt to evolving market demands and customer preferences, they can create both potential demands and supply from the market. Through accurate scenario analyses and forecasting, automation empowers companies to make informed decisions and respond effectively to changes. Integrating automation in production and SCM, coupled with receiving feedback and evaluations, has enhanced companies' adaptability. This increased adaptability has the potential to drive prosperity by enabling companies to proactively meet customer needs, optimise operations, and capitalise on emerging opportunities. Hence, the driving forces from manufacturing companies to reduce costs, accurate forecasting and fainting competitive edge within the SC can all be pursued by implementing AI (Sithole, 2016, p. 18; Thun et al., 2021, p. 727).

What previous studies have failed to highlight is the importance of feedback and evaluation even after the implementation of AI. Reim et al., (2020, p. 188) emphasise how feedback and evaluation during the process of implementation is extremely important. What our study has shown is that feedback and evaluation is something that is required in SCM, not as a tool to increase the AI-system, but as an instrument within AI to improve SCM. AI should be able to generate feedback and evaluation, not only receive it, in order for SCM to be improved.

In addition, there appears to be a potential disparity between the existing literature and our own results. Prior studies (Bughin et al., 2017, p. 22) assert that AI-based approaches can lead to quantifiable reductions in errors and cost savings. However, our findings do not provide specific numerical evidence to support such claims. While our study acknowledges the advantages of AI, it remains uncertain to what extent it has improved production, reduced errors, increased savings, and saved time. Consequently, the return on investment (ROI) for AI implementation remains indefinite. Given the substantial investments being made into AI (Schmidt et al., 2021, p. 170; Strohm et al., 2020, p. 5530; Schaeffer et al., 2018, p. 4-5), the ROI becomes increasingly crucial, especially considering the significant implementation costs associated with AI (Schmidt et al., 2021, p. 170). This contradiction between the literature and the practical implementation of AI arises from the fact that while AI can refine and automate processes to enhance a company's competitiveness (Thun et al., 2021, p. 727), the true impact behind increased competitiveness and prosperity remains unclear, even though everything points towards AI.

6.2 Conserving financial funds

The implementation of AI systems offers manufacturing companies the opportunity to streamline their SC operations, but effective resource management and cost-saving measures are crucial for success. Our data analysis emphasises the significance of this aspect. Existing literature supports the idea that AI development and implementation in the industry can lead to increased productivity, cost reduction, and improved decision-making processes (Pannu, 2015, p. 79). However, the literature also acknowledges the high costs and time-consuming nature of AI implementation. It is recognized as a significant investment and a potential barrier for companies (Huang et al., 2018). Additionally, within SCM, the technical complexity further adds to the implementation costs (Kohli et al., 2021b). Our respondents and the literature agree that implementing AI has the potential to yield long-term time and cost savings. However, previous research also highlights the substantial financial and time requirements involved in AI implementation. This creates a decision-making barrier, as companies must carefully evaluate whether the expected benefits of AI in terms of future time and cost savings outweigh the initial investment and time commitments.

Moreover, our findings reveal that it is crucial to allocate the resources to manage contingencies and by incorporating AI, the SCM can enhance the quality of their data as it reduces the number of contingencies they encounter. This aligns with existing literature that argues that predictive maintenance is an advantage of implementing AI within the manufacturing industry (Kumar et al., 2019b). Through the utilisation of ML algorithms to analyse sensor data from various devices, AI has the capability to anticipate potential machine failures or other unforeseeable events. However when it comes to data quality, the literature and our results contradict each other. According to Kumar et al. (2019b), literature indicates that AI can assist in identifying abnormalities. However, our findings reveal that manufacturing companies encounter challenges in SCM that are related to this issue. Instead of relying on AI alone, companies in the manufacturing industry need to provide input to the system, specifying faults or abnormalities. Unfortunately, this process degrades the data and renders it ineffective.

Our findings also indicate that the respondents in our study recognize the significance of having an even flow within the SC to ensure efficiency and the utilisation of AI enables the attainment of this objective as a viable goal. This finding is consistent with existing literature, which suggests that the adoption of AI-based systems can play a crucial role in achieving such a smooth flow (Gao et al., 2020). By leveraging AI technology, companies can optimise various aspects of their supply chain operations and overcome potential bottlenecks or disruptions. Additionally, as Wang et al. (2019) discovered, implementing an AI-based inspection system can reduce the inspection time by 60% and improve defect detection accuracy by 20%, ultimately improving the overall quality of products and the flow in the system. Overall, the convergence of our study's findings with the existing literature underscores the importance of an even flow in the supply chain and highlights the potential role of AI-based systems in achieving this objective. By streamlining processes, reducing inspection time, and improving defect detection accuracy, AI technologies have the capacity to enhance operations and facilitate a smooth flow throughout the supply chain. However, previous evidence from our result demonstrates that when the initial data quality is inadequate, predictive maintenance may provide erroneous indications, rendering AI unable to generate or establish a consistent flow.

Furthermore, the literature highlights the significance of utilising ML algorithms for optimising inventory management as a means to conserve financial resources. By leveraging these algorithms, companies can analyse inventory levels and accurately forecast demand, allowing them to ensure the availability of the right materials at the right time. This optimization leads to cost reduction and minimization of waste, aligning with the goals of improving the SCM (Papageorgiou, 2009, p. 1931-1932; Pournader et al., 2021, p. 7). The findings from our respondents further reinforce the importance of effective inventory management within SCM, particularly in the context of manufacturing industries. Maintaining the appropriate inventory levels becomes crucial for balancing supply and demand, as excessive stocks tie up financial resources and can lead to unnecessary costs. Conversely, inadequate inventory levels can result in stockouts and customer dissatisfaction. Therefore, SCM strives to achieve the optimal balance, ensuring the availability of required inventory while minimising the storage of surplus stocks. In this regard, AI emerges as a valuable tool to help attain the goals of effective inventory management. In addition, Pournader et al. (2021, p. 7) is also saying that ML algorithms can analyse the availability of raw materials needed for production and predicts that there may be a shortage in the coming weeks which can solve the problem with both mange unforeseeable events, creates an even flow and optimise inventory.

Lastly, according to our respondents, optimising to save money is also essential for the companies. They discuss the importance of allocating resources and optimise the SC with AI in order to enhance their financial resources. Existing literature is highlighting that when you streamline the SC with AI and the production quality, reduce defect rates and increase production output the manufacturing companies can achieve cost savings and improve customer satisfaction simultaneously (Wang et al., 2019, p. 1475). This streamlining of operations leads to cost reduction and improved utilisation of resources. Overall, optimising the SC with the aid of AI can have significant financial benefits for manufacturers according to both existing literature and our findings. Efficient allocation of resources and strategic adoption of AI can lead to cost savings and enhanced financial resources for companies. However, challenges related to data quality and the need for manual input in AI systems should be addressed to ensure their effectiveness.

6.3 Integrating previous approaches to mitigate emerging challenges

Numerous studies have emphasised the complexity associated with applying AI in SCM (Dash et al., 2019, p. 44; Van Hoek, 1998). However, it is important to note that the definition of complexity found in the existing literature may not align with the definition derived from our own research findings. While prior studies have likely explored various dimensions of complexity in AI-based SCM, the specific context and scope of our research may have uncovered unique aspects of complexity. The complexity expressed by our respondents primarily revolves around the variation and dynamic nature of their work, where no two days are alike. In contrast, the existing literature portrays SCM as a cross-functional department, to highlight its inherent complexity. This difference in perspectives can be attributed to the specific context of our research and the experiences shared by the respondents. The day-to-day operations within SCM can involve managing multiple stakeholders, coordinating various activities, and navigating uncertainties, which contribute to the perceived complexity described by our participants. While the literature may emphasise the cross-functional nature of SCM (Dash et al., 2019, p. 44), it is essential to recognize and incorporate the real-world experiences and perspectives of practitioners. By acknowledging the unique complexities encountered by individuals within SCM, we gain a more comprehensive understanding of the challenges and intricacies involved in effectively managing supply chains. This divergence could be attributed to differences in research methodologies, data sources, or the specific industry or supply chain under investigation. Therefore, it is crucial to consider and acknowledge the potential variance in defining complexity in AI-SCM. By recognizing this distinction, we contribute to the broader understanding of the multifaceted nature of complexity in SCM and highlight the need for further investigation and refinement of the concept in future studies.

In addition, implementing AI systems has shown to meet a certain resistance from the industry, within SCM, underlined by both our results and by literature (Huang et al., 2018; Sharma et al, 2021, p. 3). According to literature the resistance is mainly from the employees due to the significant changes to existing processes and systems that AI brings with it. However, our results did not indicate that the employees had resistance towards the changes, more that it is the previous processes and systems that are hard to transform into AI, while the employees outlook was positive towards change and streamlining with AI. Our results explained how previous procedures and internal logistics makes the adaptation or the integration more difficult.

Our findings align with the viewpoints expressed by Sharma et al. (2021, p. 3) and Kumar et al. (2019a), who argue that the implementation of AI can be challenging, particularly due to issues related to data quality and its impact on outcomes. These studies suggest that AI may not always perform as intended and that errors in AI-driven processes can have serious consequences, such as disruptions in the SC or incorrect inventory management. The disappointment expressed by respondents in our study regarding AI's failure to meet initial expectations is consistent with the concerns raised by Sharma et al. (2021) and Kumar et al. (2019a). One key factor highlighted by these studies is the critical role of data quality in AI's performance. If the data used to train AI models is incomplete, biased, or of poor quality, it can significantly impact the accuracy and reliability of the outcomes. The disappointment expressed by respondents when AI fails to meet initial expectations highlights the need for careful consideration of data quality, realistic expectations, and ongoing monitoring and improvement of AI systems.

Furthermore, what our study showed, similar to literature, was that there is a suspicion towards AI and when its been implemented into a company (Wang et al., 2021; Nagurney et al., 2021, p. 400; Reim et al, 2020, p. 182; Thun et al., 2021, p. 736). Our results indicated that the reason why employees are suspicious is because of the lack of transparency that AI holds. Literature often explains that transparency is one of the challenges when it comes to AI (Reim et al., 2020, p. 182; Hasija & Esper, 2022, p. 389). Often when a process has been executed by AI, the user of the system gets no insight to why and/or how AI has generated the outcome. What literature then argues for is that transparency and explainability is a combination of being able to interpret the knowledge as well as trustworthiness of the systems (Reim et al., 2020, p. 182). What our result demonstrated was that the lack of transparency and explainability results in employees returning to old methods and processes, to assure AI has considered everything and computed correctly. Due to the frequent involvement of suppliers and customers in supply chain decisions, the external visibility and associated risks of AI outputs are generally higher (Hasija & Esper, 2022, p. 390). Which we argue is why there is a higher level of suspicion surrounding AI in supply chain management compared to other areas in business.

As explained previously by Thun et al. (2021, p. 736), addressing the challenge of establishing trust in AI systems is a complex task that necessitates several considerations. Companies aiming to instil trust in AI systems must focus on ensuring compatibility with existing systems, resolving network speed and stability issues, and addressing concerns related to data security. People will not be able to trust the system, if they can not understand the background (Hasija

& Esper, 2022, p. 389), which our result also indicated. This result shows how literature's estimation of overreliance on AI might be mistaken. Kohli et al. (2021b) explains that a risk with implementing AI, is that individuals might over-rely on AI, resulting in complacency and a lack of human oversight, which is the complete opposite to our result.

Continuously, the lack of popular acceptance of certain AI applications has sparked a debate regarding the factors contributing to their failed implementation. Some argue that poor technical performance is the primary cause, while others point to organisational and/or social characteristics (Strohm et al., 2020, p. 5526; Frank et al., 2019, p. 80). Trust is influenced not only by the technological aspects but also by the company responsible for its implementation and its effectiveness in communicating relevant information (Reim et al., 2020, p. 182). Our results align with this observation. Respondents often expressed two key aspects: (1) working in parallel with the system or (2) controlling the outcome of AI. This is primarily due to their lack of basic understanding or knowledge of the new AI system in comparison to the familiar old system. Additionally, respondents emphasised the importance of collecting all relevant data required for the AI system to function effectively. That is why we argue that companies implementing AI lack the action of actually integrating AI. Our findings suggested, as well as literature, that there might be both a social and organisational aspect to the implementation of AI (Strohm et al., 2020, p. 5526; Frank et al., 2019, p. 80). To manage that, we argue that investments need to be done towards integrating AI, not only implementing it.

Lastly, our findings indicate that companies within the manufacturing industry aspire to adopt AI technology in order to streamline their everyday operations and simplify their systems, resulting in cost reduction and time savings. However, as mentioned before, the implementation of AI presents challenges in terms of complexity, time commitment, and increased costs (Huang et al., 2018). These factors create a sense of indecisiveness among companies regarding the suitability of AI for their specific needs. This uncertainty stems from the need for careful consideration of factors like the company's resources, technical capabilities, and readiness for change. Furthermore, our result shows that companies in the manufacturing industry believe that SCM in this industry is far too complex to do anything about it now. You can see that the respondents think it's something good and will probably come in the future, but right now it doesn't work because it's because it's a far too complex industry. This is contrary to previous literature that indicates the urgency of implementing AI in order to maintain market presence and competitiveness (Sharma et al., 2021, p. 7-9; Pournader et al., 2021, p. 7). Pournader et al. (2021, p. 7) also indicates that ML in manufacturing is expected to grow a lot in the coming years. Interestingly, despite this recognition, there seems to be a prevalent wait-and-see mentality among companies. Many are hoping that someone else will pioneer the solution, making it easier for others to follow suit. Consequently, those with sufficient capital are poised to seize the opportunity early, securing market share and gaining a competitive edge.

6.4 Automating for more prosperity and conserving financial funds, comes at the cost of integrating previous approaches

Our discussion in combination with our empirical findings have facilitated the elaboration of a theory. The inductive approach has faced criticism for its perceived lack of starting close enough to the phenomenon being studied, as pointed out by Shepherd and Sutcliffe (2011, p. 363). However, in the context of our research on how the implementation of AI can improve SMC, we have employed a thoughtful data analysis using a grounded theory approach. This approach has allowed us to develop a theory that is closely aligned with the data collected. Throughout our findings we have distinguished two aggregated dimensions which point towards how the implementation of AI improves SCM, whereas the third aggregated dimension portrays the gloomy side of AI. The pursuit of automating processes in order to achieve prosperity and conserve financial resources through the implementation of AI does come with the challenge of integrating previous approaches. While AI offers significant potential for improvement, it often requires companies to navigate the complexities of incorporating this new technology into their existing systems, culture and workflows.

Integrating AI involves considering the compatibility and cohesiveness of the new AI systems with the pre-existing processes and technologies. This may require modifications or adaptations to ensure seamless integration and minimise disruptions. Companies must assess the impact of AI implementation on their current operations, data infrastructure, and workforce to identify potential gaps or conflicts that need to be addressed. The integration process can involve challenges such as data compatibility, system interoperability, and the need for retraining or upskilling employees. Companies may need to invest in new infrastructure, update their data management practices, or establish communication protocols between AI systems and existing tools. This integration process requires careful planning, effective change management, and collaboration across departments.

Further, organisations must consider the cultural, social and organisational aspects of integrating AI. Resistance to change and the need for cultural adaptation can pose hurdles to successful integration. Efforts should be made to involve employees in the process, communicate the benefits of AI integration, and provide training and support to ensure a smooth transition and increase trust towards the AI-system. It is evident that employees recognize the long-term improvements that can be achieved through AI implementation. They understand the potential benefits and advantages that AI can bring to their work processes and overall organisational performance. However, our research also indicates that there are significant challenges that hinder the successful implementation of AI. One of the key challenges identified is the volume and complexity of the tasks involved in implementing AI. The process of integrating AI into existing systems and workflows can be complex and time-consuming. It requires careful planning, coordination, and technical expertise to ensure a smooth and effective implementation. This challenge can pose a barrier to organisations seeking to adopt AI, as the resources and efforts required may be substantial.

Additionally, the successful implementation of AI often entails significant investments. Companies need to allocate financial resources for acquiring AI technologies, developing customised solutions, and providing training and support for employees. The costs associated with implementing AI can be a deterrent for organisations, especially for those with limited budgets or competing investment priorities. While integrating AI may require adjustments and investments, the potential benefits it offers, such as increased efficiency, improved decision-making, and cost savings, can outweigh the challenges. Organisations that approach integration with a strategic mindset and a focus on aligning AI with their existing approaches can pave the way for a successful and prosperous transformation.

Addressing these challenges may involve strategic planning, setting realistic expectations, and developing a phased approach to AI implementation. It is important to prioritise key areas where AI can have the most significant impact and to allocate resources accordingly. Additionally, organisations may explore partnerships or collaborations with AI solution providers or leverage external expertise to mitigate the challenges and accelerate the implementation process. By acknowledging the challenges and taking proactive measures to address them, organisations can overcome the barriers to successful AI implementation and reap the long-term benefits and improvements that AI offers. This may involve building a supportive organisational culture, providing training and upskilling opportunities for employees, and establishing clear communication channels to manage expectations and facilitate the adoption of AI technologies.

In summary, while there are challenges associated with integrating previous approaches when implementing AI, a thoughtful and comprehensive approach to integration can lead to long-term prosperity by harnessing the full potential of AI technology while leveraging existing strengths and resources.

7.0 Conclusion and contributions

Within this chapter, we will present the conclusion that aims to answer our research question and fulfil the objectives of this degree project. Furthermore, we will elucidate the theoretical contributions combined with the practical and social recommendations that have emerged from our study. Subsequently, we will outline the limitations encountered during our research journey and provide valuable suggestions for future research.

7.1 Conclusion

Our purpose for the thesis was to contribute with guidance regarding the future of AI. We aspired to provide guidance and insights for the future of AI by examining its implementation and development within the complex environment of SCM. AI is expected to offer solutions to significant challenges and drive innovation, but its implementation presents its own set of challenges for organisations. Furthermore, since accurate forecasting regarding AI can be highly beneficial in navigating this transformative technology landscape, we have intended to provide beneficial insights to establish accurate forecasting. Through our grounded theory analysis conducted on the data collected from qualitative interviews, we have detected findings that serves as the basis for answering the research question of this thesis, being:

- **How can implementation of Artificial Intelligence improve Supply Chain Management?**

Our study and the existing literature highlight the potential improvements of implementing AI into supply chain management (SCM) within the manufacturing industry. The study and existing literature support the idea that implementing AI can lead to significant improvements in various aspects of SCM. One key advantage of AI in SCM is its ability to automate production processes. By leveraging AI technologies, manufacturers can enhance the accuracy of their forecasts, enabling them to better anticipate customer demands and adjust their production accordingly. This helps in avoiding overproduction or underproduction, leading to optimized inventory levels and reduced costs.

Moreover, AI can refine and optimize existing processes within the supply chain. By analysing vast amounts of data, AI algorithms can identify inefficiencies and areas for improvement. This allows companies to streamline their operations, minimize waste, and enhance overall productivity. Financial savings are another notable benefit of implementing AI in SCM. With AI's resource allocation and optimization capabilities, companies can effectively manage their resources, such as raw materials, machinery, and labour. By optimizing these resources, manufacturers can reduce costs and avoid unnecessary expenditures. Furthermore, AI empowers decision-making within the supply chain. AI can provide valuable insights and recommendations for strategic decision-making. This enables companies to make informed choices regarding production planning, inventory management, transportation logistics, and more. With improved decision-making, manufacturers can drive prosperity and achieve significant cost savings. In summary, the integration of AI in SCM within the manufacturing industry can automate production processes, increase forecast accuracy, refine existing processes, conserve financial resources, and enhance decision-making capabilities. These advantages contribute to increased efficiency, reduced costs, and overall competitiveness in the market.

However, what our study further explains is the several challenges and considerations that need to be addressed for successful implementation. Firstly, feedback and evaluation are crucial within AI systems to improve SCM. While previous studies have overlooked this aspect, our study conclude the need for AI to generate feedback and evaluation, rather than just receiving it. This feedback loop ensures continuous improvement and enhances SCM effectiveness. In addition, effective resource management and cost-saving measures are crucial for successful AI implementation. While AI can optimise production, streamline SC operations, and improve decision-making, the high costs, complexity, and time requirements associated with implementation pose challenges. The complexity associated with applying AI in SCM can vary depending on the context and perspectives of practitioners. The unique complexities encountered by individuals within SCM, such as managing multiple stakeholders and navigating uncertainties, need to be considered to gain a comprehensive understanding of the challenges involved. In addition, companies need to carefully evaluate the expected benefits of AI and consider whether they outweigh the initial investment and time commitments. Even though effective inventory management through AI can lead to cost reduction and minimise waste. AI algorithms can analyse inventory levels and accurately forecast demand, helping to achieve the optimal balance between supply and demand. However, challenges related to data quality should be addressed to ensure the effectiveness of AI in inventory management.

AI can contribute to achieving an even flow in the supply chain by streamlining processes, reducing inspection time, and improving defect detection accuracy. However, initial data quality and the integration of AI with existing processes and systems can pose difficulties. Data quality is a significant factor in AI performance. Poor data quality can lead to errors and disruptions in SCM. While AI has the potential to analyse sensor data and anticipate maintenance requirements, challenges related to data quality and the need for manual input should be addressed for effective implementation.

Moreover, resistance to AI implementation exists, but it may not necessarily stem from employees' resistance to change. Instead, the resistance lies in the difficulty of transforming previous processes and systems into AI-compatible ones. Transparency and explainability of AI systems are crucial in building trust and addressing suspicions. Trust in AI systems requires compatibility with existing systems, addressing concerns related to data security, and effective communication of relevant information. Over-reliance on AI and complacency should be avoided, and human oversight should be maintained.

In summary, while AI holds promise in improving SCM within the manufacturing industry, careful consideration of feedback and evaluation, cost-benefit analysis, data quality, complexity, resistance, and trust is necessary for successful implementation and reaping the full benefits of AI.

7.2 Theoretical contributions

The conclusions of the study offer several theoretical contributions to the understanding of AI implementation in SCM. Firstly, they highlight the unique complexities associated with applying AI in SCM operations. Unlike previous research that has explored complexity from a cross-functional perspective, this study emphasises the variation and dynamic nature of SCM operations, and the challenges faced by practitioners. By delving into these complexities, the conclusions contribute to a more comprehensive understanding of the intricacies involved in AI-based SCM and call for further investigation and refinement of the concept.

Secondly, the study emphasises the importance of feedback and evaluation in the AI implementation process within SCM. While previous studies have overlooked this aspect, our research underscores the need for AI systems to generate feedback and evaluation to drive improvements in SCM. This perspective expands our understanding of AI implementation in SCM by highlighting the role of feedback and evaluation as critical instruments for SCM enhancement.

Moreover, the study shed light on the significance of effective resource management and cost-saving measures in the implementation of AI systems in SCM. The research supports prior literature's assertions that AI can lead to increased productivity, cost reduction, and improved decision-making processes. However, it also highlights the high costs and time commitments associated with AI implementation, which present decision-making barriers for companies. This underscores the need for careful evaluation of the expected benefits of AI against the initial investment and time requirements. In addition, the study addresses challenges related to data quality and the need for manual input in AI systems. While literature suggests that AI can identify abnormalities and predict maintenance requirements, the research findings reveal challenges faced by manufacturing companies in SCM regarding data quality. The need for manual input to specify faults or abnormalities degrades the data and renders it ineffective. This contributes to the understanding of the challenges associated with data quality and manual input in AI-based SCM systems.

Lastly, the thesis highlights the importance of trust and transparency in AI implementation within SCM. The research findings indicate that employees in SCM may not resist AI implementation itself, but rather the transformation of existing processes and systems into AI-driven ones. Lack of transparency in AI systems, particularly concerning the interpretation of outcomes and trustworthiness, can lead to suspicion, causing employees to revert to old methods. This underscores the need to address transparency, explainability, and trust in AI systems to ensure successful implementation.

Overall, these theoretical contributions enhance our understanding of AI implementation in SCM. Mainly by shedding light on the complexities involved, emphasising the role of feedback and evaluation, exploring the uncertainty surrounding impact, underscoring the importance of resource management and cost savings. Together with, addressing challenges related to data quality and manual input, and emphasising the significance of trust and transparency. These contributions provide valuable insights for future research in the field and contribute to a more nuanced understanding of the role of AI in SCM.

7.3 Practical recommendations

Based on our empirical findings, we present practical recommendations derived from this study to provide valuable insights for organisations currently involved or anticipating involvement in the implementation process of AI in the context of SCM. These recommendations may also be relevant for other industries than just the manufacturing industry.

Our first recommendation is to embrace change management and to make a cultural adoption. In the context of implementing AI in SCM, embracing change management and fostering cultural adoption are crucial steps for success. Change management is essential to ensure a smooth transition and acceptance of new processes. Some practical steps to embrace change can be to educate stakeholders about the benefits of AI in SCM, highlighting the potential improvements in efficiency, cost reduction, and decision-making capabilities. Communicate the need for change and the rationale behind it. Another step can be to create a comprehensive plan outlining the steps, timelines, and resources required for AI implementation. Clearly define roles and responsibilities, and establish communication channels to keep everyone informed throughout the process. Cultural adoption can be achieved through Fostering a collaborative environment where teams from different departments work together to integrate AI into SCM processes. Encourage knowledge sharing, open communication, and cross-functional collaboration to maximise the potential of AI.

Our second recommendation is to overcome complexity through strategic planning. To navigate the complexities of AI integration in SCM, organisations should invest in strategic planning to ensure a smooth implementation process. By dedicating time and financial resources to develop well-defined strategies, organisations can effectively address the unique challenges associated with AI adoption in SCM. Organisations should formulate comprehensive strategies that encompass all aspects of AI implementation in SCM. These strategies should outline specific objectives, timelines, and resource allocation, taking into account the complexities of SCM operations. The strategic planning should also involve a thorough analysis of potential risks and challenges associated with AI integration in SCM. Organisations should proactively identify and address these risks through contingency plans and mitigation strategies. This may involve considering data security, privacy concerns, system integration complexities, or regulatory compliance.

We strongly advise prioritising investments in data management as our third practical recommendation. The significance of high-quality data cannot be overstated when it comes to effectively implementing AI in SCM. To ensure the accuracy, completeness, and consistency of data, organisations should establish robust data governance practices. This entails implementing processes for data cleansing, employing data validation techniques, and formulating data integration strategies. Furthermore, allocating resources towards advanced technologies and infrastructure that facilitate streamlined data collection, storage, and retrieval is crucial.

Our final recommendation is to establish clear performance metrics in order to evaluate the impact of AI implementation in SCM, organisations should define clear performance metrics aligned with their strategic objectives. These metrics may include cost savings, productivity improvements, customer satisfaction, and supply chain responsiveness. By regularly monitoring and analysing these metrics, organisations can assess the effectiveness of AI integration and identify areas for further improvement. Furthermore, it is crucial for organisations to establish a feedback loop that facilitates continuous improvement. By regularly monitoring and analysing the defined performance metrics, organisations can gather valuable insights into the effectiveness of AI integration in SCM. This ongoing evaluation allows them to identify strengths, weaknesses, and areas for further improvement. It also enables them to adapt their strategies and optimise AI systems to maximise benefits and align with their evolving strategic objectives. Moreover, organisations should foster a culture of data-driven decision-making, where insights derived from performance metrics are used to inform future actions and drive continuous advancements in their AI-driven supply chain processes.

In conclusion, this study provides practical recommendations for the successful implementation of AI in SCM. These recommendations are derived from empirical findings and aim to offer valuable insights to individuals involved or anticipating involvement in the AI implementation process in SCM, regardless of the industry.

7.4 Societal recommendations

The successful implementation of AI in SCM has the potential to revolutionise operational efficiency and decision-making processes. To ensure the maximisation of societal benefits, several recommendations can be followed according to us.

Firstly, fostering collaboration among stakeholders such as businesses, government entities, and academic institutions promotes knowledge sharing and joint projects, tailored to the unique needs of SCM. As far as we know, AI seems to only be accessible for companies who have large funds and financial resources, since they have the money and time that AI requires. This can jeopardise the future market for companies, since only the largest entities will be able to increase their competitiveness through AI, leaving SME behind or acquired by the larger ones. Therefore by fostering collaboration, the chances of SMEs developing more successful implementations of AI might increase.

Thereafter, we believe investing in training programs and educational initiatives would enhance the digital literacy and AI skills of SCM professionals, empowering them to leverage AI technologies effectively. As for now, the definition of what AI is and how AI can be applicable within SCM seems unclear. Often during the sampling, individuals we got in contact with, had to check if AI truly was the system they used. Therefore, training programs and education would not only be beneficial when the system is in place, but even before, in order to increase the interest towards AI and fasten the acceptance of it.

Thirdly, we reckon that promoting ethical AI practices through guidelines and standards ensures transparency, fairness, and accountability in AI development and deployment in SCM. Ethical AI practices involve adhering to principles that prioritise the well-being and rights of individuals, address potential biases and discrimination, and mitigate the risks associated with AI implementation. Transparency is an essential aspect of ethical AI. Organisations should provide clear and understandable explanations of how AI systems are designed, trained, and utilised within the SC. This includes disclosing the data sources used, the algorithms employed, and the decision-making processes involved. Transparent AI systems enable stakeholders to understand and evaluate the basis for decisions made, fostering trust and accountability. Accountability is a critical aspect of ethical AI practices. Organisations should establish mechanisms to take responsibility for the actions and decisions made by AI systems. This includes establishing clear lines of responsibility and accountability for AI-related outcomes. In case of errors or unintended consequences, organisations should have processes in place to rectify and learn from the mistakes, while providing avenues for affected parties to seek redress.

Lastly, prioritising data quality and integration, and investing in robust data management systems, facilitates accurate and timely data analysis. Encouraging pilot programs and experimentation enables organisations to assess the feasibility and effectiveness of AI applications in SCM before scaling up. Effective change management strategies, employee engagement, and communication about the benefits of AI implementation help address concerns and ensure a smooth transition. A culture of continuous improvement, adaptability, and responsible deployment should be embraced to assess the impact of AI, seek feedback, and address societal implications such as employment and sustainability.

By following these recommendations and integrating AI into SCM with ethical considerations, organisations can unlock numerous benefits and contribute to societal advancement. Firstly, the implementation of AI can lead to more efficient and resilient supply chains. AI technologies can optimise inventory management, demand forecasting, and logistics, resulting in streamlined operations, reduced lead times, and improved responsiveness to customer needs. This increased efficiency contributes to cost savings and minimises waste within the supply chain.

7.5 Limitations and future research

Despite making a valuable contribution to the field of the implementation of AI in order to improve SCM, it is important to acknowledge the limitations of this thesis. First of all, a significant limitation arises from the time constraints imposed on the study. With only a brief period of approximately one and a half months for conducting the research, certain chapters had to be prioritised over others. Consequently, some areas of the thesis could have been explored in greater depth, and the analysis may not have been as comprehensive as desired. Given more time, a larger volume of data could have been collected, allowing for a more robust and extensive analysis. Additionally, the sample size of six respondents may be considered relatively small. However, this choice was deliberate, as it allowed for a more in-depth exploration of each participant's perspective and facilitated a comprehensive understanding of their viewpoints. Drawing meaningful conclusions from the available data was not compromised by the sample size.

Furthermore, it is essential to note that the thesis focused solely on the implementation phase of the process, neglecting the maintenance and reconstruction aspects. Consequently, to gain a holistic understanding of the respondents' perception of the AI process as a whole, it would be valuable to investigate and incorporate insights from these other phases. By assembling knowledge from all stages of the process, the industry can enhance their understanding and make informed improvements in their own AI-system. A deeper understanding of these factors can help guide organisations in making informed decisions about AI implementation and maximise its potential benefits.

Furthermore, the discussion acknowledges the potential inconsistency between the literature and the findings of the study. However, it is important to recognize that the realm of AI and its integration into supply chain management is an ever-evolving field. With advancements in AI technologies and increasing organisational expertise in implementation, it is plausible that future studies will offer more definitive proof concerning the precise advantages and ROI associated with AI in SCM. In essence, the present passage effectively emphasises the prevailing disparity and raises significant points to ponder concerning the implementation and assessment of AI in SCM.

9.0 Reference list

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10. Appendices

Appendix 1 Information form in English

Information form for participants

AI implementation in Supply Chain Management within the manufacturing industry

We are currently working on a degree project that studies the implementation and management of artificial intelligence (AI) within manufacturing companies in Sweden, specifically for supply chain management (SCM). You have been invited to participate in the project.

Before you decide whether or not you want to participate in our thesis, please take the time to carefully read the following information about what it means to participate in this study.

What is the purpose of the study?
Our degree project is part of the Business Administration program at Umeå School of Business, Economics and Statistics, Umeå University. Within the program we have explored several different management areas and therefore touched on SCM. The purpose of this study is to provide insights and deeper knowledge about how the implementation and management of AI has taken place or should take place, especially within a complex environment such as SCM. In addition, we would like to investigate whether the implementation of AI can or has improved the effectiveness of SCM. By exploring which strategies and methods are successfully useful for manufacturing companies, we want to add value to future research and practices as they implement AI. AI is expected to solve big problems and facilitate new innovation, but will also result in challenges for businesses, therefore accurate forecasts regarding AI can be very beneficial. As a result, we aim to increase successful implementations of AI in the manufacturing industry and focus our research on minimising the potential challenges AI can

bring during implementation. Which in turn will generate higher efficiency for the manufacturing companies.

Why have I been chosen?
We aim to interview people involved with (a) Supply Chain Management (b) within the manufacturing industry (c) in Sweden.

Do I have to participate?
Your participation is voluntary-based. Once you agree to participate, you will be given this information sheet to keep and be asked to sign a consent form. Even though you decide to take part, you can still decide to withdraw from the study at any time without an explanation if you do not wish to explain.

If you wish to withdraw from the research after some data have been collected, you will be asked if you are content for the data collected to be retained and included in the study. If you prefer, the data collected can be destroyed and not included in the study. However, you cannot withdraw the data from the study when the research has been completed and data analysis has begun on May 10th 2022.

If I take part in the research, what do I have to do?
If you decide to take part, we would like to conduct 1 to 2 interviews with you, ideally on Zoom/Teams. You will be asked a number of questions regarding (1) yourself and your role within your organisation (2) your take on AI implementation in Supply Chain Management (3) your organisation's implementation processes.

We aim to ask open-ended questions and we can provide the questions in advance if you wish. Each interview will last for around 45 minutes.

What will happen to the information I provide the researchers?
Personal details including your name and contacts will be kept confidential and not revealed to third parties in compliance with academic research ethics and the rules and regulations of processing personal data at Umeå University. More information can be found at:
https://www.umu.se/en/about-the-website/legal-information/processing-of-personal-data/
The consent forms we retrieve from the participants will be preserved in Umeå University OneDrive with password protected. Each participant's identity will be coded so the information remains confidential and anonymous. Researchers in our research project are the only ones who possess access to the data. The data we collect from interviews i.e audio files, transcripts and observation notes will be encrypted and saved similar as the consent form, in a Umeå University OneDrive account, protected by password. Researchers in our research program are the only ones who have access to this data.

Quotes from the interview transcripts will be included in the thesis that we author. Your and your organisation's identities will remain anonymous in the interview quotes that will be used in our papers.

Umeå University will be the organisation processing your personal information. In accordance with the General Data Protection Regulation (GDPR) of the European Union, you have the right to request information once a year, concerning what personal data Umeå University holds on you. If the data that is collected about you is incorrect, you are entitled, as a data subject, to correct it. Additionally, you are authorised to have personal data concerning you erased when it is no longer needed for the purpose for which it was collected. However, the personal data might not always be allowed to be erased due to other legislation that supersedes this rule. Furthermore, you are entitled that the processing of personal data regarding you is limited to a certain specific purpose only. You may complain about the processing of your personal data. If there are no compelling reasons for the university to continue processing the personal data, the university will stop processing.

If you have any request for your personal data, please contact Alva Norgren or Wilma Janzon Hägglund. Our contacts are listed below.

You can also contact the Data Protection Officer at Umeå University, at pulo@umu.se.
If you have any concerns about the university's personal data rights practises you can lodge a complaint to the supervisory authority, Datainspektionen. Information on how to proceed with a complaint is available on their website, www.datainspektionen.se

What if something goes wrong?
Do not hesitate to contact us if you have any concerns or questions. Our contacts are provided below.

How do I get access to the results of the study?
Please feel free to contact the responsible researchers if you have any questions regarding publications or results of the study. If you wish to, we can provide the link or the finished copy of our degree project to you when available.

What happens next?
If you agree to participate in this study, you will find a copy of the consent form below that needs to be signed. You can keep this document and the consent form. We will keep another copy of the consent form.

Thank you for your time!

For further information, please contact:
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Appendix 2 Information form in Swedish

Informationsformulär för deltagare

AI-implementering i Supply Chain Management inom tillverkningsindustrin

Vi arbetar just nu med ett examensarbete som studerar implementering och hantering av artificiell intelligens (AI) inom tillverkande företag i Sverige, specifikt för supply chain management (SCM). Du har blivit inbjuden att delta i projektet.

Innan du bestämmer dig för om du vill delta i vårt examensarbete eller inte, ta dig tid att noggrant läsa igenom följande information om vad det innebär att delta i denna studie.

Vad är syftet med studien?
Vårt examensarbete är en del av Masterprogrammet i Handelshögskolan vid Umeå universitet. Inom programmet har vi utforskat flera olika management-områden och därför berört SCM. Syftet med denna studie är att ge insikter och djupare kunskap om hur implementering och hantering av AI har skett eller bör ske, speciellt inom en komplex miljö som SCM. Dessutom skulle vi vilja undersöka om implementeringen av AI kan eller har förbättrat effektiviteten för SCM. Genom att utforska vilka strategier och metoder som framgångsrikt är användbara för tillverkningsföretag vill vi tillföra värde för framtida forskning och praktiker när de implementerar AI. AI förväntas lösa stora problem och underlätta ny innovation, men kommer också att resultera i utmaningar för företag, därför kan korrekta prognoser gällande AI vara mycket fördelaktiga. Som ett resultat av detta strävar vi efter att öka framgångsrika

implementationer av AI inom tillverkningsindustrin och fokusera vår forskning på att minimera de potentiella utmaningar AI kan medföra under implementeringen. Vilket i sin tur kommer att generera högre effektivitet för de tillverkande företagen.

Varför har jag blivit utvald?
Vi strävar efter att intervjua personer som är involverade i (a) Supply Chain Management (b) inom tillverkningsindustrin (c) i Sverige.

Måste jag delta?
Ditt deltagande är frivilligt. När du samtycker till att delta kommer du att få detta informationsblad att behålla och ombeds att underteckna ett samtyckesformulär. Även om du bestämmer dig för att delta kan du när som helst välja att avbryta studien utan förklaring om du inte vill förklara.

Om du vill dra dig ur forskningen efter att viss data har samlats in kommer du att tillfrågas om du nöjer dig med att den insamlade informationen behålls och inkluderas i studien. Om du föredrar det kan de insamlade uppgifterna förstöras och inte inkluderas i studien. Du kan dock inte dra tillbaka data från studien när forskningen är klar och dataanalysen har påbörjats den 10 maj 2022.

Om jag deltar i forskningen, vad måste jag göra?
Om du bestämmer dig för att delta vill vi genomföra 1 till 2 intervjuer med dig, helst på Zoom/Team eller via telefonsamtal. Du kommer att ställas ett antal frågor om (1) dig själv och din roll inom din organisation (2) din inställning till AI-implementering inom SCM (3) din organisations implementeringsprocesser.

Vi strävar efter att ställa öppna frågor och vi kan tillhandahålla frågorna i förväg om du så önskar. Varje intervju kommer att pågå i cirka 45 minuter.

Vad kommer att hända med informationen jag ger forskarna?
Personuppgifter inklusive ditt namn och dina kontakter kommer att hållas konfidentiella och inte avslöjas för tredje part i enlighet med akademisk forskningsetik och reglerna för behandling av personuppgifter vid Umeå universitet. Mer information finns på:
https://www.umu.se/en/about-the-website/legal-information/processing-of-personal-data/

De samtyckesformulär vi hämtar från deltagarna kommer att bevaras i Umeå universitet OneDrive med lösenordsskydd. Personlig information som lämnas under intervjuerna såsom personens namn, platser, namn på projekt och sysselsättning kommer att anonymiseras i intervjuutskrifter. Specifikt kommer vi att tilldela pseudonymer till personers namn som nämns i intervjuerna. Samma pseudonymstrategi gäller för platser och företag. Yrke kommer att ersättas av allmänna termer som att Andrews jobb som forskare blev "jobb inom utbildning". Forskare i vårt forskningsprojekt är de enda som har tillgång till data. De data vi samlar in från intervjuer, t.ex. ljudfiler, utskrifter och observationsanteckningar, kommer att krypteras och sparas på samma sätt som samtyckes formuläret, på ett OneDrive-konto vid Umeå universitet, lösenordsskyddat. Forskare i vårt forskningsprogram är de enda som har tillgång till denna data.

Citat från intervjuerna kommer att ingå i den avhandling som vi skriver. Din och din organisations identiteter kommer att förbli anonyma i de intervjucitat som kommer att användas i våra arbeten.

Umeå universitet kommer att vara den organisation som behandlar dina personuppgifter. I enlighet med Europeiska unionens allmänna dataskyddsförordning (GDPR) har du rätt att, en gång per år, begära information om vilka personuppgifter Umeå universitet har om dig. Om uppgifterna som samlas in om dig är felaktiga har du som registrerad rätt att korrigera dem. Dessutom har du rätt att få personuppgifter om dig raderade när de inte längre behövs för det ändamål för vilka de samlades in. Det kan dock hända att personuppgifterna inte alltid tillåts raderas på grund av annan lagstiftning som ersätter denna regel. Vidare har du rätt att behandlingen av personuppgifter om dig är begränsad till endast ett visst specifikt ändamål. Du kan klaga på behandlingen av dina personuppgifter. Om det inte finns några vägande skäl för universitetet att fortsätta behandlingen av personuppgifterna kommer universitetet att upphöra behandlingen av dina personuppgifter.

Om du har någon begäran om dina personuppgifter, vänligen kontakta Alva Norgren eller Wilma Janzon Hägglund. Våra kontaktuppgifter finns nedan.

Du kan också kontakta data skyddsombudet vid Umeå universitet, på pulo@umu.se.
Om du har oro kring universitetets praxis för rätten om personlig information kan du lämna in ett klagomål till tillsynsmyndigheten Datainspektionen. Information om hur du går tillväga med ett klagomål finns på deras hemsida, www.datainspektionen.se

Vad händer om något går fel?
Tveka inte att kontakta oss om du har några funderingar eller frågor. Våra kontaktuppgifter finns nedan.

Hur får jag tillgång till resultaten av studien?
Kontakta gärna ansvariga forskare om du har frågor angående publikationer eller resultat av studien. Om du vill kan vi tillhandahålla länken eller den färdiga kopian av vårt examensarbete när det är tillgängligt.

Vad händer härnäst?
Om du samtycker till att delta i denna studie hittar du en kopia av samtyckeformuläret nedan som måste undertecknas. Du kan behålla detta dokument och samtyckeformuläret. Vi kommer att behålla ytterligare en kopia av samtyckesformuläret.

Tack för din tid!

För ytterligare information, vänligen kontakta:
Wilma Janzon Hägglund
Forskare

Handelshögskolan i Umeå
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Appendix 3 Consent form in English

Consent form for participants

AI implementation in Supply Chain Management within the manufacturing industry

Please complete this form after you have been informed about the research project.

Name of the participant:

I hereby confirm that I am over 18 years old and…

I agree to take part in this research,

I have read and understood the study information form and been given the opportunity to ask questions before agreeing to take part in the project, I understand that I can withdraw from the study at any time without having to give an explanation,

I understand that the interview will be audio-recorded and give permission for the researchers to do so,

I give permission for direct quotes from the interview to be used for academic purposes under the condition that I remain anonymous.

By signing this consent form, you understand and agree to the terms stated above.

Date:

Sign:

Appendix 4 Consent form in Swedish

Samtyckesformulär för deltagare

AI-implementering i Supply Chain Management inom tillverkningsindustrin

Fyll i detta formulär efter att du har blivit informerad om forskningsprojekt.

Namn på deltagaren:

Jag bekräftar härmed att jag är över 18 år och...

Jag går med på att delta i denna forskning,

Jag har läst och förstått information-formuläret och fått möjlighet att ställa frågor innan jag tackar ja till att delta i projektet,

Jag förstår att jag kan dra mig ur studien när som helst utan att behöva ge en förklaring,

Jag förstår att intervjun kommer att spelas in på ljud och ger tillåtelse för forskarna att göra det, Jag ger tillåtelse att direkta citat från intervjun används för akademiska syften under förutsättning att jag förblir anonym.

Genom att underteckna detta samtyckesformulär förstår och godkänner du villkoren som anges ovan.

Datum:

Signatur:

Appendix 5 Interview Guide in English

Introduction

- Introduce ourselves and the study.
- Ask for permission to record
- Review how their data is handled. (GDPR+anonymous)
- Age, gender

Background

- Can you tell us a little about your role and the company you work for? Where in the supply chain are you active?
- What are your responsibilities? What does a typical day look like for you?
- When do you come into contact with AI? In which situations do you work with AI?
- What type of AI do you use in your everyday tasks?

Artificial Intelligence (AI)

- When was AI introduced as a new tool to the company? How did it happen?
- Why do you believe the company decided to introduce AI tools? Was there any upside/downside of introducing AI?

- Would you say that AI has solved the purpose of why the company implemented it?

- When you have worked with AI, have any new challenges emerged?

SCM Efficiency

- Did you experience challenges with efficiency within your part of the supply chain, before AI was introduced?

- Have you seen evident improvements with efficiency after AI was implemented?

- Have you seen evident challenges with efficiency after AI was implemented?

- When have these improvements/challenges emerged?

Ending thoughts

- If you were to summarise what we have talked about in the interview, what would you say are the three most important things when it comes to AI implementation?

- How would you summarise that AI affects the SCM and indirectly the manufacturing industry?

- Do you have anything else you would like to add?

Appendix 6 Interview Guide in Swedish

Introduktion

- Presentera oss själva och studien.

- Be om tillåtelse att spela in

- Gå igenom och förklara hur deras data hanteras. (GDPR+anonym)

- Ålder, kön

Bakgrund

- Kan du berätta lite om din roll och företaget du jobbar på? Var i försörjningskedjan är du aktiv?

- Vad har du för ansvar? Hur ser en vanlig dag ut för dig?

- När kommer du i kontakt med AI? I vilka situationer arbetar du med AI?

- Vilken typ av AI använder du i dina vardagliga sysslor?

Artificiell Intelligens (AI)

- När introducerades AI som ett nytt verktyg för företaget? Hur hände det?

- Varför tror du att företaget bestämde sig för att introducera AI? Fanns det någon upp- och baksida med att introducera AI?

- Skulle du säga att AI har löst syftet med varför företaget implementerat det?

- När du har arbetat med AI, har det dykt upp några nya utmaningar?

SCM Effektivitet

- Upplevde du utmaningar med effektivitet inom din del av försörjningskedjan, innan AI introducerades?

- Har du sett uppenbara förbättringar med effektivitet efter att AI implementerades?

- Har du sett uppenbara utmaningar med effektivitet efter att AI implementerades?

- När har dessa förbättringar/utmaningar dykt upp?

Avslutande tankar

- Om du skulle sammanfatta det vi har pratat om i intervjun, vad skulle du säga är de tre viktigaste sakerna när det kommer till AI och dess implementering och hantering?

- Hur skulle du sammanfatta att AI påverkar SCM och indirekt tillverkningsindustrin?

- Har du något mer du vill tillägga?

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