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AI in Supply Chain Risk Management

A study on how artificial intelligence can be applied on supply chain risk management and its effects on decision-making using Technology-Task Fit Theory

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Abstract

Supply chains have become increasingly complex and demanding. Yet, supply chains play a vital role for almost all companies regardless of industry. Previous research and literature have proposed AI as a powerful business tool with the ability to increase visibility and to perform supply chain management (SCM) activities. But despite the fact that AI has shown promise in the area of SCM, its application to supply chain risk management (SCRM) and its effects to decision-making remains underexplored and lacking context. Through the lens of a theoretical framework based on Technology-Task Fit (TTF) theory and using a qualitative research approach this thesis investigates how AI can be applied to SCRM, what factors impact its utilization and the effects its utilization will have on SCRM decision-making.The findings indicate that AI can be applied both to automate and to augment SCRM tasks throughout the different phases of SCRM. However, the thesis identified the fit between AI and SCRM tasks and the degree of utilization as playing an important role in determining the performance and the effects on decision-making.

Keywords: Supply Chain Risk Management, Artificial Intelligence, Applicability, Decision-making, Technology-Task Fit Theory

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Abbreviations

Full-text	Abbreviation
Artificial Intelligence	AI
Supply Chain Management	SCM
Supply Chain Risk Management	SCRM
Supply Chain Resilience	SCRes
Key Performance Indicator	KPI
Minimum Order Quantity	MOQ
Multi-Criteria Decision Making	MCDM
Machine Learning	ML
Artificial Neural Networks	ANN
Bayesian Networks	BN
Deep Learning	DL
Multi-Agent Systems	MAS

1. Introduction

This section presents the reader with the background of the thesis as well as its research problem, its purpose and the two research questions that it aims to answer. The aim of this introduction is to introduce and provide the background knowledge necessary for the reader to understand the subject's foundations, the problems and the scientific significance of the thesis. Finally the reader is introduced to any delimitations for the thesis and an overview of the thesis contents.

1.1 Background

Artificial intelligence (AI) is transforming and changing how companies and organisations are operating through increased employee productivity, guiding decisions and enabling more complex analysis of business problems (Halaburda et al. 2024). AI has characteristically been used for managing and generating insights from huge sets of data, detecting patterns hidden to humans themselves (Helm et al. 2020). Being described as a source for continued economic growth and financial development, AI has attracted a lot of interest from companies and organisations in a relatively short amount of time (Grashof and Kopka. 2023). Supply Chain Management (SCM) is one area that has received a lot of interest previously by other researchers and where AI has shown great promise (Mohsen, 2023). With its quickly evolving nature, AI is nowadays often regarded as a powerful business tool (Narasimha Rao Boinapalli, 2020), and within SCM AI has been described as an enabler for improved warehousing, demand management, distribution planning and manufacturing (Mohsen, 2023). SCM is made up of several areas, one being Supply Chain Risk Management (SCRM) that aims to improve supply chain resilience and reduce uncertainty and risk within the supply chain (Gani et al. (2023), ultimately lowering the risk of disrupted operations (Schroeder and Lodemann, 2021). SCRM has become a strategic necessity for many companies due to the challenges brought by outsourcing, offshoring and foreign market expansion, resulting in a more complex and challenging supply chain environment (Blome and Schoenherr, 2011).

The term AI was originally used to describe machines that exhibited human intelligence but since then the term has evolved. Today AI is being used for managing and generating insights from large sets of data, detecting patterns hidden to humans themselves (Helm et al. 2020) and as aforementioned, this has generated interest from companies and organisations

(Grashof and Kopka, 2023). The market size for AI applications is projected to reach 243 billion USD by 2025 and is not expected to slow down, but instead increase by 27% annually until 2030 (Statista, 2024). This growth allows for both organisational development and innovation, as well as generating financial value for organizations. Companies have been quick to notice this and have already begun to leverage AI in order to enhance their business processes through improved productivity, scalability and potential for cost reduction (Dsouza, 2024; Accenture 2016). This could also be noted by the increased rate of AI adoption amongst companies and organizations (Statista, 2024). Ultimately, it can be said that AI has become a force that drives radical changes across industries and that it is showing great promise in the area of SCM (Mohsen, 2023). This has not gone unnoticed, as SCM and SCRM are vital parts of companies operations and strategy, allowing for competitive advantages through decreased costs, improved flexibility, lowered exposure to operational risk and improved service levels (Wisner, Leong, and Tan, 2019) (Narasimhan and Talluri, 2009). There are large amounts of data that can be collected about events and variables that SCRM is concerned about and there are many different factors that interact with each other. Since successful SCRM often requires decisions to be made on a rapid and adaptive basis, the proposition of using AI has shown promising results (Baryannis, et al. 2019).

1.2 Problem description

SCRM plays a vital role in a company's efforts to ensure a supply chain that is resilient and flexible enough to handle potential disruptions as it has a direct link to the company's operational reliability (Wisner, Leong and Tan, 2019) and there are many aspects of SCRM that overlap well with the potential usage of AI (Baryannis, et al. 2019). The increasingly complex and demanding environment SCRM practitioners are exposed to has made for increasingly challenging decision-making. At the same time, AI has shown great promise in enabling decision-making (Steyvers, and Kumar, 2022). Therefore, managers and executives interested in applying AI into their decisions and processes would gain practical value by understanding whether or not AI could be a solution and addition to their current SCRM practices.

Despite this, AI in SCRM remains underexplored especially in specific problems to industry applicability (Toorajipour et al., 2021). Previous research has focused primarily on mathematical programming as well as the results of using these mathematical constructs (Baryannis et al. 2019). This indicates that researchers are more inclined to look at mathematical techniques rather than the applicability of AI. As such there is a gap in SCRM research and literature on the applicability, utilization and effects of AI in SCRM. Given this and the potential use of AI in SCRM, there is a clear need for research on the applicability and utilization of AI that this thesis aims to fill. AI has not received an adequate amount of attention amongst SCRM practitioners while it could be beneficial to them and to the organisation to take a holistic approach on the subject. This since AI opens up the possibility for proactive, rather than reactive decisions and actions to be taken in an effort to improve the risk exposure of the company (Meng and An, 2024).

To summarize, there is a gap in the current understanding amongst both practitioners and researchers regarding the feasibility and usefulness of applying AI to SCRM. SCRM is becoming increasingly complex and the amount of factors that need to be taken into consideration is growing along with the number of risks that could cause disruptions. AI has shown promise, but the area is still underexplored. Furthermore, the impact of AI utilization on decision-making in SCRM is not yet thoroughly covered by research. Decision-makers' ability to make good decisions is hindered by increasing complexity, and AI with its capabilities and strengths could aid in these endeavours. Before it can be applied, there needs to be an understanding of how its utilization will affect the decision-making process, both positively and negatively.

1.3 Research purpose and significance

There is a need for this thesis as there are research gaps of qualitative research, of AI application in SCRM and how its utilization could impact SCRM decision-making. As such the purpose of this study is to analyse how AI could be applied within SCRM and to analyse how the use of AI in SCRM affects the decision-making process. This is done using a case study and semi-constructed interviews to gather qualitative and empirical data to study AI in SCRM, a technology that very well could disrupt the current way of working within SCRM. Understanding how AI could be applied and used is important as it provides a foundation to understand the opportunities and limitations of the technology as well as the effects of said technology in an industry that is becoming ever so more reliant on technology to continuously improve. Therefore the purpose of this study is to further the understanding how AI could be applied to SCRM, which tasks it could apply to, what factors impact the utilization and how applying it would impact the decision-making in SCRM. The results of this study should be of interest both to other researchers that are interested in AI and SCRM.

As well as for professionals who are interested in the application of AI in SCRM and who are looking to understand how they could apply it.

1.4 Research questions

The research questions that this thesis aims to answer are the following:

- RQ1: How can AI be applied in supply chain risk management and what impacts its utilization?
- RQ2: How does AI's utilization impact supply chain risk management decision-making?

These two research questions require two different approaches to be taken. In order to answer the first question, it first needs to be established whether or not companies are able to apply AI in their SCRM process. This area has been studied in previous research however it has mainly looked at SCM in general and not risk management in particular. Therefore, this premise needs to be researched and verified using both primary and secondary data.

The second research question expands on the first research question. The research field of decision-making, and how it is carried out in organisations, has prior literature examining it. However, since the question is directed towards how the utilization of AI affects the decision-making process within SCRM there is a need to gather more evidence that is specific to SCRM. This will be done using primary and secondary sources.

1.5 Delimitations and structure of the thesis

With the risk of having too wide of a scope for this thesis the authors made the decision to make some delimitations. As such, the following delimitations were made;

First of all, the authors decided to only focus on SCRM and thus any other parts of SCM are excluded from the scope of this study. This was in order in order to not have too broad of a scope and to accurately provide answers to the research questions.

A second delimitation that the authors made was that this thesis only brings up and considers the AI types of machine learning, deep learning, generative AI, multi-agent systems and Fuzzy programming. There are many functions within SCM that AI has the potential to perform. However this thesis will only focus on their application in SCRM and only the aforementioned AI types are included in this thesis. This to maintain a coherent research logic and to allow for greater depth.

This concludes the introduction to the thesis. The structure of the remaining parts are as follows:

- Next follows the *literature review* of the report where the reader will be presented with relevant frameworks and previously written literature on the subjects of SCRM, AI, decision-making and technology-task fit theory. The theoretical framework the authors will use is also presented under the second chapter.
- After this the reader will be presented with the methodology the authors have used for this thesis. Under *methodology* the authors will detail the research approach and design, as well as discuss the limitations to this study and how it might impact the research quality of the thesis.
- Next the results of the interviews and data collection will be presented to the reader under *empirical findings.*
- After this follows the *analysis and discussion*, in which the authors combine previous literature, theoretical frameworks and the data collected in order to discuss and answer the research questions presented earlier.
- Finally, under *conclusion* the reader is presented with the conclusions of the thesis. The authors theoretical and practical contributions, proposals for future research on the subject and any reflections from the authors are also summarised.

2. Literature review

This section of the thesis will present the literature review, covering key aspects of SCRM, AI and decision-making. It will cover strategies and frameworks for managing risks, the role and application of AI in SCRM, and how decision-making is influenced by these based on the findings of previously written literature. The chapter also covers technology-task fit theory and the theoretical framework developed by the authors.

2.1 Supply Chain Risk Management

SCRM has been defined as: *"an inter-organizational collaborative endeavor utilizing quantitative and qualitative risk management methodologies to identify, evaluate, mitigate, and monitor unexpected macro and micro level events or conditions, which might adversely impact any part of a supply chain"* (Ho et al. 2015:5036). Essentially it refers to identifying, assessing, mitigating and monitoring any risks that could disrupt the flow of goods, services, information or capital across the supply chain. But SCRM also includes a part that focuses on proactive strategies aimed at minimizing risks and ensuring resilience in the supply chain operations (Qiao and Zhao, 2023). Today supply chains are increasingly global and complex. While the interconnectivity within the supply chain network enables businesses to optimize costs, enter foreign markets and enhance efficiency, it also exposes supply chains to a broader range of risks. As a result, the demand and need for SCRM has grown in the last decade (Choudhary et al., 2022). By applying SCRM, organizations can defend and adjust against a broader range of risks while building resilience to future risks (Choudhary et al., 2022). This section of the literature review will explore definitions, different categories of supply chain risks and frameworks within SCRM.

2.1.1 Definitions

There are several definitions to terms widely used in the literature review. This section aims to introduce and evaluate what previous research and literature has found.

2.1.1.1 Supply Chain Risk

The definition of supply chain risk has changed a lot during the years which have made risks hard to clearly define and quantify, however a recent definition is that *"Supply chain risk is the potential loss for a supply chain in terms of its target values of efficiency and effectiveness evoked by uncertain developments of supply chain characteristics whose changes were caused by the occurrence of triggering-events"* (Heckmann, Comes and Nickel, 2015:130). A more general approach to defining supply chain risk is that: *"the risk is* *quantified as the product of its probability of occurrence and consequences"* (Deiva Ganesh and Kalpana, 2022:2).

2.1.1.2 Supply Chain Resilience

Supply Chain Resilience (SCRes) has become an important area of research as many industries have become increasingly complex and competitive (Ponis and Koronis, 2012), due to factors such as financial instability, ongoing crises, natural hazards and increased customization demands. This has led to an increased focus on SCRes as a key component within SCRM (Ponomarov and Holcomb, 2009). Like many other concepts, SCRes has several definitions that have changed over time. According to Pires Ribeiro and Barbosa-Povoa (2018), the definition of SCRes is not clearly established and there can be differences in elements between different authors. Based on this, Pires Ribeiro and Barbosa-Povoa (2018:116) created a framework intended to clarify the relevance and scope of SCRes. This led them to the following definition: *"A resilient supply chain should be able to prepare, respond and recover from disturbances and afterwards maintain a positive steady state operation in an acceptable cost and time"*.

2.1.1.3 Supply Chain Disruption

According to Wagner and Bode (2006) a supply chain disruption happens when an unexpected event occurs, causing problems that disrupt the flow of materials and interfere with normal business operations. The risk of these disruptions has grown over the past years due to globalization, outsourcing and the increased focus on efficiency (Stecke and Kumar, 2009).

2.1.2 Goals of SCRM

While previous literature have pointed to it being difficult to define SCRM (Ho et al. 2015), it is possible to align and agree on the overarching goals. The aim of SCRM, much like that of traditional risk management, is to ensure that the risks that the company is exposed to are identified and managed to a level which is manageable and reasonable by the organisation (Gurtu and Johny, 2021). There are other benefits than just lowered risk exposure that previous research has identified. For example, by collaborating and lowering the likelihood of disruptions the need for safety stock decreases along with warehousing costs (Chopra and Sodhi, 2004). When centralising production, lowering the likelihood of having redundant capacity, which makes for greater economies of scale (Chopra and Sodhi, 2004). Furthermore, previous research has pointed to the fact there is a positive correlation between the effectiveness and practices of well managed SCRM and the ability to lower uncertainty and reduce the vulnerability of the supply chain network (Chowdhury and Quaddus, 2016). As such the effects of decisions related to SCRM have positive effects following the lowered risk exposure (Gurtu and Johny, 2021; Munir et al. 2020). A requirement of SCRM's goal of managing and reducing risks to tolerable levels is that there is a satisfactory level of visibility throughout the supply chain and that way provide the opportunity to prevent disruptions from occurring (Nooraie and Mellat Parast, 2015). Extending a bit further, SCRM is a critical part of the company's general SCM performance (Oliveira et al. 2019)

2.1.3 Phases of SCRM

Understanding the process of SCRM can be challenging due to the complexity and unpredictability of today's supply chains. To ease this, Devia Ganesh and Kalpana (2022) developed the "Implementation Framework". This framework gives the SCRM process a holistic view by breaking it down into four clear phases: *Risk Identification, Risk Assessment, Risk Mitigation* and *Risk Monitoring* (See Fig.1)

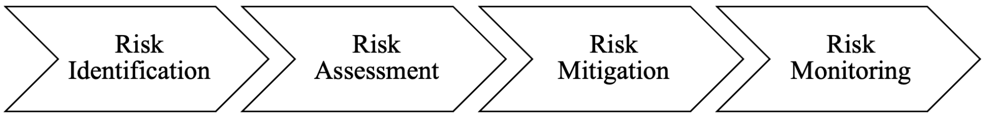

Fig. 1: "Implementation Framework" copied from the works of Deiva Ganesh and Kalpana (2022).

2.1.3.1 Risk Identification

Risk identification is the first phase in the SCRM process and involves identifying potential disruptions to the supply chain. By finding risks, organizations can take proactive measures before disruptions occur (Devia Ganesh and Kalpana 2022). This phase is important, as it makes SCRM possible (Kleindorfer and Saad, (2005). Previously this has been a difficult part of SCRM (Rao and Goldsby, 2009). However, with the advancement of technology and access to larger amounts of data this has changed. It is now possible to identify risks much more easily using advanced and predictive analysis (Deiva Ganesh and Kalpana, 2022). Furthermore, with the advent of control towers, regarded as centralized hubs, there is now greater focus and visibility on disruptions and risks (IBM, 2021).

2.1.3.1.1 Classification of Risks

In order to effectively identify risks, organizations must analyse various sources of potential disruptions. According to Bandaly et al. (2012), risk classification is an important part of identifying risks. There are different approaches to classifying the risks within a supply chain and researchers have different strategies. In order to simplify this, Deiva Ganesh and Kalpana (2022) have summarized the different categories of risks in one framework in Figure 2.

Fig. 2: "Categorization of risks" copied from the works of Deiva Ganesh and Kalpana (2022).

(1) *Demand risk* refers to the volatility of demand, product life cycles and competitors actions (Deiva Ganesh and Kalpana 2022). Volatility and uncertainty in customer demand is common in many supply chains (Liagkouras and Metaxiotis, 2023). It risks disrupting supply flows and the operations of the company. Demand risk could originate from a large range of different sources. For example, new product introductions, seasonality of products and new market entrants (Selvaraj and Wesley, 2020). (2) *Supply risk* relates to the network of suppliers, quality and management issues with supply as well as off-shoring and sourcing related decisions (Deiva Ganesh and Kalpana 2022). There are many examples of risks that fit the category. For example, poor supplier service or disrupted supply flows.What they have in common is that they affect the flow of incoming deliveries to the focal company (Ho et al. 2015). (3) *Process risk is* used to categorize risks that relate to equipment reliability, bottlenecks and inflexible processes (Deiva Ganesh and Kalpana 2022). Process risks have the ability to impact the company in many ways, such as severely affecting the quality of the goods or services that the company offers, but also lower production yields and higher product costs (Tummala, Schoenherr and Xie, 2011). (4) *Environmental risks* relate to natural disasters, terrorism, regulatory risks and strikes (Deiva Ganesh and Kalpana 2022). This

category has become increasingly important as sustainability has become important to stakeholders such as shareholders and regulators (Freise and Seuring, 2015). Companies that are not acting according to the expectations held against them are at risk to receive harsher legislation, increased costs and disruptions in the flow of products (Freise and Seuring, 2015).

(5) *Information risks* can be described as cyber threats, intellectual property breaches and data management risks (Deiva Ganesh and Kalpana 2022). There are several examples of cyber threats and the risk of being exposed has been increasing during the last years, having the potential to cause both disruptions to operations as well as causing severe financial harm to the company (Pandey et al. 2020). (6) *Control risk* refers to the visibility in the supply chain, the extent of collaboration and planning and bullwhip effects (Deiva Ganesh and Kalpana 2022). Modern logistics is not all about goods and services, but is also dependent on the movement and transparency of information in order to achieve a high level of efficiency (Choi, Wallace and Wang, 2016). Sharing information within the supply chain can reduce some of the uncertainty that exists within it, and as such lower the control risk (Qiao and Zhao, 2023b; Liagkouras and Metaxiotis, 2023).

2.1.3.2 Risk Assessment

The next step of SCRM is to assess the risks in order to determine their potential impact on the organization's performance. When assessing risks there are two important variables. The first variable is seen as the "*likelihood of occurrence of an adverse event"*. The second is referred to as the "*magnitude of the impact on the supply chain's performance should the event occur"* (Bandaly et al., 2012:253). Accurately assessing risks is important because it influences how effective the mitigation actions will be. Traditionally, businesses relied on forward-thinking analysis and past experiences to assess risks. However, with the increasing unpredictability of disruptions, there is a need for stronger and more reliable assessment methods (Kumar Sharma and Sharma, 2015).

As of today there are many different techniques for assessing risks within supply chains. Choudhary et al. (2022) conducted an extensive analysis of over 100 of these techniques, with the aim to find the most commonly applied techniques in risk assessment. The technique that appeared the most in their sample was Fuzzy set theory. This theory was according to Zadeh (1988) introduced in 1965 and is a multi-valued logic approach that handles imprecise reasoning and uncertainty. Making it a suitable technique for risk assessment in SCM, as supply chains often involve subjectivity and unpredictability. Fuzzy theory helps decision-makers to quantify these often very vague parameters such as risk severity and the likelihood (Choudhary et al., 2022). Continuing, there are several other techniques such as Grey sets, ANP, Bayesian Network, Fault-Tree Analysis, Mean-Variance, CVaR, DEA, ISM, Structural Equation Modelling and DEMATEL. All of these decision-making techniques in risk assessment have their own characteristics and applicable areas. According to Choudhary et al., 2022, risk assessment consists of five dominant characteristics in uncertainty, hierarchy, propagation, expected impact and cause-effect relationships. By selecting the right technique based on the dominant characteristics of the risk, organizations can make better decisions in managing supply chain risks (Choudhary et al., 2022).

2.1.3.3 Risk Mitigation

Risk mitigation is the process of managing and reducing the impact that disruptions to the supply chain will have (Deiva Ganesh and Kalpana, 2022). During this phase, the results and findings from the risk assessment are reviewed in order to identify which risks can be addressed or not. Based on this review, appropriate strategies are then developed to eliminate the risks or minimize their impact (Vishnu, Sridharan and Kumar, 2019). Sometimes a strategy used to reduce risk can itself become a source of risk. For example, an organization can choose single sourcing to improve their relationship with a supplier which can reduce risks brought by poor supplier quality and long lead times. However, it would also make for a larger impact if the single supplier would face any disruptions. The effectiveness of a mitigation strategy depends on to what extent the strategy is implemented, meaning that the impact varies based on execution (Bandaly et al., 2012). Hence, there are many factors to consider when selecting a mitigation strategy and there is no “one size fits all”. According to Vishnu, Sridharan and Kumar (2019), there are in general nine attributes that could help in determining the selection of mitigation strategies, that are listed in table 1.

1. *Cost of implementation*	6. *Change management required for implementation*
2. *Involvement of other firms in the strategy implementation process*	7. *Level of improvement required after implementation*
3. *Relevance of risk factor addressed by the strategy*	8. *Benefits to other firms in the supply chain*
4. *Level of impact on the identified risk factor i.e., prevention, mitigation of effects, etc.*	9. *Evidence of successful implementation of the strategy in other firms*
5. *Level of impact on other risk factors (positive/negative)*	

Table 1: Attributes determining the selection of mitigation strategies. Based on Vishnu, Sridharan and Kumar (2019).

Building on these attributes, organizations can choose from a range of different mitigation strategies to address their supply chain risks. The strategies have varying complexity, scope and impact depending on the specific risk being faced and its operational context. The different risk mitigation strategies have been identified in previous literature, with each addressing different aspects of SCRM. According to Diabat, Govindan and Panicker (2012) some of the most common risk mitigation strategies are preventing risk by understanding, minimizing their impact, and transferring the risk through insurance or contracts. Furthermore, organizations can diversify their product assortment or use risk pooling to spread risk exposure. There are also several other strategies that have proved successful to mitigate supply chain disruptions, such as physical backups, standardization of process, multi-location sourcing and pricing strategies (Tang, 2020). There are many additional strategies, but the point is that the choice of strategy is much dependent on the context of the risk and its complexity. All of the mentioned strategies have an effect on risk reduction, however their performance can be difficult to measure unless the organization has experience of risk mitigation strategies (Vishnu, Sridharan and Kumar, 2019).

2.1.3.4 Risk Monitoring

Risk monitoring is the last step in the SCRM process and plays an important role as it ensures that the mitigation strategies remain effective over time. As previously stated, supply chain risks are often unpredictable and tracking the supply chain performance allows organizations to take proactive measures (Tummala and Schoenherr, 2011). The key part to risk monitoring is evaluating how well the mitigation strategies are working. By regularly assessing the progress and effectiveness, organizations can identify areas for improvement.

Although research is somewhat limited, there are some proven risk monitoring methods. One effective way to monitor risks through failure data analytics (Vishnu, Sridharan and Kumar, 2019). First, disruptions are recorded in a computer database where details regarding time of incident, impact potential and recovery time are stored. This data is then used to calculate reliability parameters, which then provides a clear picture of the supply chain's health. With these insights, organizations can develop early warning systems which help to detect and respond to risks more efficiently (Zhang et al., 2011). With the advent of big data, some researchers have pointed to the future use of risk monitoring systems that leverage large amounts of data and advanced monitoring systems to create more intelligent SCRM systems

(Zekhnini et al., 2020). Additionally, researchers suggest an IoT-driven risk management system that uses IoT applications and AI to enhance risk monitoring (Tsang et al., 2018).

2.2 Artificial Intelligence

As aforementioned, AI was originally a term used to describe machines that exhibited human intelligence (Helm et al. (2020) but the term has since changed. Now AI could be defined as *"the imitation by computers of the intelligence inherent in humans"* (Sheik, Prins and Schrijvers, 2023:15). Previous literature have pointed to two different prerequisites for a human or machine, to be regarded as intelligent; *(1) "the ability to carefully choose their actions in a way that leads to success or profit, in terms of some kind of objective or goal"* and *(2) "the ability to deal not with a fully known environment, but with a range of possibilities which cannot be wholly anticipate, through learning and adaptation"* (Baryannis et al. 2019:7).

It is sometimes said that the world has entered the fourth industrial revolution where different disruptive technologies, AI being one of them, disrupt and break down the barriers between man and machine (Sharma et al. 2022). AI has already had an impact on companies and organisations, allowing them to pursue and improve on SCM strategies such as LEAN, changing how companies organise and structure themselves as well as how they interact with other companies (Fanti, Guarascio and Moggi, 2022). From a more practical perspective, AI has been applied for several different purposes by companies and organisations, with examples ranging from optimising production scheduling, component utilization and defect detection (Brunello et al. 2025). SCM is in other words not exempted from the use of AI, and instead seen as one of the sectors where AI can bring the most benefit to companies and organisations (Sharma et al. 2022). Developing further on this, the area of SCRM is no different and AI has been theoreticized to have an applicability both in terms of improving and automating decision-making (Mahama et al. 2024; Baryannis et al. 2019b), improving the supply chain agility (Belhadi et al. 2022) and to predict future risks and events (Baryannis et al. 2019a). Previous literature has also pointed to deploying AI for tasks that are characterised as more operational, with increased efficiency as a benefit that could be achieved through the use of AI in these instances (Hendriksen, 2023).

2.2.1 Types of Artificial Intelligence

The definition earlier mentioned for AI describes it as providing computers with humanly equivalent intelligence, and there are different approaches or perhaps more aptly, types, that AI can take the form of in the area of SCM and SCRM. Considering how AI is defined, there are several different methods through which AI could be applied to (Baghalzadeh Shishehgarkhaneh et al. 2024).

Type of AI	Citations	Potential area of usage
Machine learning	Baryannis, G. et al. (2019), Baryannis, G. et al. (2019b), Deiva Ganesh and Kalpana (2022), Baghalzadeh Shishehgarkhaneh. M et al. (2024) Meng, X. and An, N (2024)	production risk assessments, supplier selection, fleet management, vendor selection, product quality, forecast prediction, supply chain visibility,
Fuzzy programming	Baryannis, G. et al. (2019), Deiva Ganesh and Kalpana (2022), Baghalzadeh Shishehgarkhaneh. M et al. (2024), Wu, D.D. et al. (2010).	risk identification, supplier rating, forecast prediction
Deep Learning	Janiesch, C., Zschech, P. and Henrich, K. (2021), Hosseinnia Shavaki, F. and Ebrahimi Ghahnavieh. A. (2023)	Inventory forecasting, forecast prediction, price forecasting
Generative AI	Richey, R.G. et al. (2023), Anantrasirichai and Bull (2021), Samuel Fosso Wamba et al. (2023), Shen et al. (2023), Vinay Yandrapalli (2023)	Sourcing assessments, procurement assessment, inventory management
Multi-Agent Systems	Baryannis, G. et al. (2019b), Deiva Ganesh and Kalpana (2022), Giannakis, M. and Louis, M. (2011)	inventory management, order planning, order fulfillment

Table 2. Summary of the five different types of AI and their respective potential area of usage according to previous literature.

The choice of "AI type" is an important one, since their success depends on which task they are applied to perform, as such companies interested in choosing an AI method must be sure that they select the best one and that there is an appropriate amount of data for the chosen method to use (Baryannis et al. 2019).

2.2.1.1 Machine Learning

Machine learning (ML) has been described as very useful for SCRM. (Baryannis et al. 2019b; Baryannis et al. 2019). In ML, the algorithm is provided with large datasets that it analyses and learns from (Baryannis et al. 2019). Resulting in the requirement of access and availability to data to allow the model to analyse trends and find patterns that otherwise would be very difficult to find (Meng and An 2024). Access and amount of data is positively correlated with improved accuracy of ML models as it allows ML to better understand the association between the different variables (Baryannis et al. 2019b; Panch, Szolovits, and Atun, 2018).

2.2.1.1.1 Artificial Neural Networks

ML is not only one single type of AI, instead consisting of several methods. One of these methods is Artificial Neural Networks (ANN) (Baryannis et al. 2019b). ANN could be described as an algorithm that works like a human brain, being composed of linkages between nodes and neurons that transmit information and process information. Each connection between these nodes and neurons have weights that are assigned to each factor which are then adjusted based on the learnings from the data (Janiesch, Zschech and Henrich, 2021; Soori, Arezoo and Dastres, 2023). Learning from the data it analyses, ANN's apply these learnings in order to anticipate events and decide on actions (Soori, Arezoo and Dastres, 2023). The choice of ANN when implementing AI into a process has gained popularity and ANN's have been successfully tested on a number of different applications within SCM and SCRM (Xie, Liu and Wang, 2024). Examples of this range from *supply chain optimization,* with demand forecasting, supplier selection and risk management where ANN's help by finding patterns in both internal and external factors, historical sales and industry trends (Soori, Arezoo and Dastres, 2023).

2.2.1.1.2 Bayesian Networks

Another method connected to ML is through Bayesian Networks (BN). A BN consists of several different nodes, connected to one another in a network. The probabilities of different outcomes or events are then assigned to each node and by analysing the probability of a certain combination of outcomes or events, a BN could be used to calculate the likelihood of a supply chain disruption (Witten, Frank and Hall, 2011). Building on this, BN's can also be used in order to perform root cause analysis and to find interdependencies in the supply chain, where an event might impact a larger, or smaller, portion of the supply chain and the company's operations. Such insights have a large potential for the managers and decision makers within SCRM (Baghalzadeh Shishehgarkhaneh et al. 2024; Cao, Bryceson and Hine, 2019). However, a BN is dependent on data in order for the algorithm to assign probability values to the different events. Otherwise there is a risk of misjudging the causal relationships within the network, resulting in a false output (Qazi et al. 2018).

2.2.1.1.3 Decision Trees

Decision trees are a type of ML. The reasoning of the decision tree method is comparatively easy to understand for a human observer as they use decision rules, allowing the human to see the reasoning and the logic behind each decision. Such as; *the decision was made due to the fact that the following conditions, X1, X2 and X3, were found to be true.* Decision trees as such are programmed procedures that look at the outcome of certain defined functions. (Blockeel et al. 2023). Decision-trees have shown promise in SCRM in several different ways (Er Kara et al. 2020). One has been through risk prediction, where the method has been applied in predicting cyber attacks against supply chains and quality risks, detecting defects in manufacturing lines (Lee, Cheang and Moslehpour, 2022), this while still remaining interpretable for the human supply chain practitioner (Baryannis, Dani and Antoniou, 2019).

2.2.1.2 Deep Learning

As was noted previously, the terminology within the field of AI is not characterised by strict guidelines as to what "only" constitutes ML and how that is different compared to other AI methods in a SCM context. Previous literature has attempted to differentiate Deep Learning (DL) from other methods. DL can be described as; *"a machine learning concept based on artificial neural networks"* (Janiesch, Zschech and Henrich, 2021:685). Developing further on this, in the case of ANN's the "neurons" or "nodes" that are connected to each other are often joined in networks with different layers. One layer often collects the input from the data and another layer produces the conclusion of the module. Between these layers are what is referred to as *hidden layers* and deep neural networks. DL typically consists of more than one of these hidden layers, as well as more advanced neurons or nodes that are able to carry out more advanced mathematical operations. As such DL models can be fed with data and automatically learn itself, a difference compared to ML. (Janiesch, Zschech, and Henrich, 2021). A similarity between the two however relates to the fact that DL can also be applied through several different methods. Examples of which are *deep neural networks, convolutional neural networks* and *recurrent neural networks*, which prior literature have found being applied in a SCM and SCRM context (Hosseinnia Shavaki and Ebrahimi Ghahnavieh, 2023).

DL models have in previous research been applied to a number of different SCM and SCRM areas and applications. One area where DL has been argued to be of good value to companies and supply chains is within *forecasting.* DL could be applied to a range of different forecasting scenarios such as inventory forecasts, demand planning and price forecasting (Hosseinnia Shavaki and Ebrahimi Ghahnavieh, 2023). There are several different methods within DL that could be used for forecasting and improving the visibility throughout the supply chain, however these are dependent on the organisation being able to maintain a high quality of data and a sufficient amount of data (Douaioui et al. 2024). As with many other AI types, DL also faces certain challenges, with implementation and application. First of all, DL requires access to a large amount of training data that has been created by humans, and obtaining such data can be very difficult for a company. With DL there is also the risk of overfitting, which is explained as ”*perform well on the training data but fail to generalize to unseen data*” (Talaei Khoei, Ould Slimane and Kaabouch, 2023:23119). There is also a challenge in understanding the output of DL models. The models themselves quickly become extremely complex, resulting in a lack of transparency for any human observer, which also makes it more difficult to judge the validity and quality of the DL models output (Talaei Khoei, Ould Slimane and Kaabouch, 2023)

2.2.1.3 Generative AI

Generative AI is an AI type that can create various types of content, ranging from text, images, audio and even synthetic data. It learns by analyzing real examples and recognizing patterns to understand structures within the data. The content it produces is then based upon the data it has been trained on (Anantrasirichai and Bull, 2021). The main difference between generative AI and the more traditional AI is that generative AI can create new content, whereas the traditional AI analyzes existing data and makes its decisions based on that (Samuel Fosso Wamba et al., 2023). Different from other AI types, generative AI can create content through interactions. However, despite these differences generative AI is still powered on the core technologies within AI, like neural networks and DL. An example of this is ChatGPT, which uses large language models based on various parameters to learn the relationship between data and what type of content that should be produced (Shen et al., 2023).

In terms of implementation of generative AI within SCM, researchers believe that there are several potential benefits to be gained. According to Richey et al. (2023) the key benefits are better sourcing assessment, risk mitigation, procurement and inventory management and customer relations. There are also challenges related to the implementation of generative AI. One major challenge is managing and ensuring the quality of different data sources (Vinay Yandrapalli, 2023). Supply chains consist of different nodes and the data from each of these nodes needs to be consolidated and validated. This is a very complex task, especially as the data comes from multiple systems. Furthermore, the complex structure of supply chains makes the scalability of generative AI solutions challenging. Apart from these technical challenges, the use of AI also needs a cultural shift and effective change management as many people within organizations lack AI expertise (Brock and von Wangenheim, 2019). There are also challenges with both the training data and the operational data, as it risks introducing biases to generative AI models, which in the end results in a non-factual output (Banh and Strobel, 2023). Generative AI also characteristically requires a large amount of computational capacity, which is not only expensive but also makes it difficult to implement (Bandi, Adapa, and Kuchi, 2023).

2.2.1.4 Multi-Agent Systems

Another form of AI that previous research has described as useful for companies in a SCRM context is known as Multi-Agent Systems (MAS). (Baryannis, et al. 2019b; Deiva Ganesh and Kalpana 2022). To understand the basics of MAS, it is good to first understand what an agent is. An agent can be defined as *"a computer system that is situated in some environment, and that is capable of autonomous action in this environment in order to meet its design objectives."*(Nitsche et al. 2023:896). When several of these agents are grouped into one, a MAS starts to take form, as they are systems with several agents grouped together (Nitsche et al. 2023).

One of the features of MAS is that they are able to solve complex problems by breaking them down into several less complex problems (Nitsche et al. 2023). In modern day SCRM complexity is no shortage. MAS as a result of its autonomy, social ability, reactivity and ability to be proactive could therefore be increasingly useful (Giannakis and Louis, 2011). For example, MAS could be used for inventory management, order fulfilment and order planning (Giannakis and Louis, 2011). MAS models are quick to adjust and react to changes, which is useful in an uncertain environment (Baryannis et al. 2019b). However, using MAS in an SCRM context comes with some challenges. Since the agents are interdependent of each other the system requires a large amount of computational resources or the company will have to accept that computational times will be long. Furthermore, previous research has pointed to the fact that they are cumbersome to implement and require a large amount of monitoring, which is costly (Nitsche et al. 2023).

2.2.1.5 Fuzzy Programming

Fuzzy programming is a mathematical programming approach to AI that can assist in decision making with unknown variables (Baryannis et al. 2019) Fuzzy programming works by assigning each element of the model with a value that is located somewhere in between the interval of 0 and 1. This is a difference that sets fuzzy programming apart from boolean models that would assign the element a 0 or a 1 depending on if it is false or true. The fact that the element can be assigned with any value between 0 and 1, allows fuzzy models to account for a broader range of variations (Sakawa et al. 2013). One of the advantages and reasons why Fuzzy Programming has been applied is due to the fact that it allows the model to bring nuance to risk identification and assessment (Baghalzadeh Shishehgarkhaneh et al. 2024).

Fuzzy programming allows for greater flexibility and can tackle uncertainty in its parameters, which makes it suitable for risk identification and for decision support systems (Baryannis et al. 2019). Fuzzy Programming is no different from other models and algorithms in the sense that multiple factors can be taken into consideration, such as demand and supply risks, supplier ratings and costs for example (Wu et al. 2010). It can also deal with certain issues of data quality, where there are uncertainties with the data that the company has been collecting (Wang, Xu and Pedryc 2017). However there are also challenges with fuzzy programming that needs to be taken into consideration. Similar to other types of AI, there is a need for large amounts of data to be collected. Processing such large datasets requires a large amount of resources. The velocity and value of the data are also two other challenges which fuzzy programming depends on (Wang, Xu and Pedryc 2017). Fuzzy programming models are also characteristically difficult to interpret (Baryannis et al. 2019b).

2.2.2 Advantages of AI

As mentioned earlier, there are many advantages of using AI in SCM. One of the benefits according to Sharma et al. (2022) is the ability of AI to improve transparency and enable end-to-end visibility. This helps organizations to make more accurate decisions in a shorter amount of time. Additionally, AI can make it easier to also identify potential bottlenecks before they cause disruptions. An example of this is the fusion of AI and blockchain, by combining these two organizations can gain deeper insights into their supplier performance, demand trends and overall logistics. Ultimately, making smarter decisions like adjusting inventory levels, improving supplier relations and choosing the most efficient transportation route (Chang, El-Rayes and Shi, 2022).

Another advantage is the improved forecasting accuracy that can be leveraged by using AI-driven systems. AI has the ability to help organizations with anticipating seasonal fluctuations and thereby also reduce the potential bullwhip effect. This leads to better inventory management, less waste and better supply-demand balance (Sharma et al. 2022).

Apart from this, AI has also been linked to advantages such as cost reductions, lower losses and improved performance (Riahi et al., 2021). An industry example of this is Goodyear's AI-powered sensors which they combined with IoT to create their Smart Tyre technology. These sensors could monitor the tire conditions in real time, which allowed for proactive maintenance and performance optimization (Wamba et al., 2021).

Looking beyond operational efficiency, AI is also able to transform supply chain structures with the use of adaptive models that help to increase collaboration and the responsiveness of the supply chain (Getto, 2021). This is further supported by Ma and Chang (2024) who state that AI has the power to improve both speed and ability in information processing for organizations. The result of this is that organizations can adjust their supply chain structure in order to handle changes in the external environment. Continuing, AI also has the capacity to improve an organization's ability to sense, adapt and respond to disruptions (Belhadi et al., 2021). This is also underscored by Wamba et al. (2021) who states that AI could support activities regarding disruptive events. This can be achieved as AI-driven innovations have the potential to drive adaptability and innovation within SCRM. According to Deiva Ganesh and Kalpana (2022) AI is well-suited for SCRM as it supports risk mitigation strategies that depend on fast, data-driven decision making. Furthermore, AI also holds potential to improve the SCRes.

It can be concluded that AI presents various advantages within SCM and its different fields, such as improved efficiency, agility, transparency, forecasting, decision making and ability to respond to disruptions. All of these advantages contribute to an increased competitive edge for the organization. This is also supported by leading consulting firms such as McKinsey and Deloitte, who state that AI has the potential of driving business value and creating competitive advantages (Spaul, M. 2023; Chui, M. et al., 2023). However, simply applying AI does not guarantee success. Organizations must implement strategic approaches based on the field of application, as well as deciding which type of AI to use.

2.2.3 Challenges of AI

Despite the many advantages of AI, there are still many challenges that organizations must address in order for AI to be successful. These are challenges such as data quality, transparency, security, integration, costs, regulations and ethical concerns. Understanding and exploring the challenges is important, as it allows organizations to understand the full potential of AI as well as being able to withstand its challenges (Richey et al., 2023). One of the biggest challenges with AI adoption are issues related to data. The reason for this is due to the large amounts of high quality data needed in order for the AI to function properly. The data from supply chains are often fragmented or difficult to access which makes the data collection process much harder. Additionally, this is something that limits the accuracy and effectiveness of AI models (Samuel Fosso Wamba et al., 2023).

Another issue could be that the current data structures and standards may not be suitable for the newer AI applications, which makes it harder to implement and process the information. Without standardised data, it is more difficult to build a successful AI framework (Sun and Medaglia, 2019). In order to tackle this challenge, new technologies are needed to manage, analyse and store large amounts of data (Deiva Ganesh and Kalpana, 2022). However, there are also technological challenges. As the amount of data grows, so does the computing demands of the technology. AI, ML and DL require powerful processors that can handle high levels of computation speed. Hence addressing the challenges around advanced system structures and architecture becomes crucial for the implementation process (Tizhoosh and Pantanowitz, 2018). Furthermore, there are also cost related challenges linked with AI. According to Sun and Medaglia (2019) many small and medium-sized organizations struggle to adopt AI due to the large investment costs.

Implementing AI also comes with its management challenges, such as infrastructure development and network connectivity. As previously mentioned, AI systems require advanced approaches to improve the human to computer interaction, as well as being able to ensure a seamless information flow (Tizhoosh and Pantanowitz, 2018). However, the problem is that many organizations struggle with the lack of infrastructure, skilled labor and data algorithms which makes it more difficult to adopt AI (Deiva Ganesh and Kalpana, 2022). Without the right knowledge, the use of AI can result in costly mistakes like overstocking or stockouts (Richey et al., 2023). Organizational barriers also bring its implementation challenges. Barriers consist of a general lack of understanding of AI, unclear project goals and ownership responsibilities, and misaligned strategies among stakeholders. Additionally, AI implementation depends on strong top management which can be disturbed by lack of trust in AI, not identifying the right problems and poor commitment to AI (Shrivastav, 2022). In order to overcome these challenges organizations need effective change management, structured organizational development and commitment to AI implementation (Hangl, Behrens and Krause, 2022).

Unlike humans, AI have difficulties in understanding and interpreting complex situations which can lead to AI not being able to fully grasp the meaning of some results. This is because AI systems process inputs and outputs without true understanding. The risk with this is that AI becomes more vulnerable to cyber attacks and security threats (Mitchell, 2019). To prevent this there need to be strong regulations in order to ensure that AI is developed and applied responsibly. However, the problem is that AI operates in a legal gray area with unclear regulations. Without oversight, organizations could rush AI development which could lead to negligence of safety to protect consumers from harm or bias (Dogru and Keskin, 2020). Bias is a major concern as it can reinforce discrimination based on several factors. In a SCM context, biased AI models could lead to unfair prioritization or systemic inequalities (Richey et al., 2023). Apart from this there is also the risk of job displacement, however important to note is that this can be balanced by the creation of new job opportunities (Dogru and Keskin, 2020).

2.2.4 Factors impacting AI applicability

It is, as hinted to previously, much easier to say that a company should implement and use AI compared to actually applying AI to a business process. There are several different factors that act as enablers for AI usage in companies, and in extension impact the applicability of AI to a . Previous literature has pointed to three different categories of AI enablers, which are *(1) technological, (2) Organizational* and *(3) Environmental* (Enholm et al. 2022).

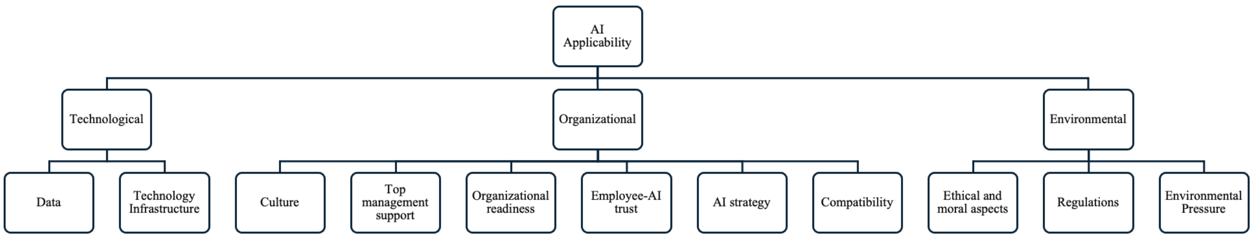

Figure 3; Based on the framework developed by Enholm, I.M. et al. (2022)

Within the technological category there are several different sub-factors that impact whether or not AI can be applied. *Data* is one such subfactor (Enholm et al. 2022). Data has been described as fundamental in the application of AI, but also the quality of it as the data directly influences the way that the AI behaves and the analysis that it may perform (Galaz et al. 2021). In an SCRM context predictive analysis plays a large part and many types of AI such as ML uses historical data to make predictions on demand and potential disruptions. In many ways without a sufficient amount of data, the company would not be able to apply AI. (Riad, Naimi and Okar, 2024). The data in the company that is going to be used by the AI needs to be available, have a high level of integrity to ensure that the quality is sufficient and in cases when it has an impact on the company, confidential (Chehri, Fofana, and Yang, 2021). *Technology infrastructure* is the second subfactor within the technological category that has the possibility to either act as an enabler or an inhibitor for companies attempting to apply AI on business processes (Enholm et al. 2022). AI infrastructure refers to the software, hardware and data and a good infrastructure would allow the company the possibility to deploy its IT resources in an effective way. The infrastructure has an impact on the computing power and as such the analysis carried out (Wamba-Taguimedje et al. 2020). Data, and large amounts of data, is very important in the context of AI, since it impacts the performance of the models. The data that is going to be used needs to be produced, collected and valued as well as be of a good enough quality for the algorithm or models purpose (Malerba and Pasquadibisceglie, 2024). This can at times prove to be a challenge, since data is not readily available during the prototyping and development phases of AI models (Pan, Mason and Matar, 2022).

Continuing with the category of *Organizational* factors, the previous literature had pointed to six different sub-factors that either act as enablers or inhibitors, which are culture, top management support, organizational readiness, employee-AI trust, AI strategy and compatibility (Enholm et al. 2022). The *culture* that exists in the organisation has an impact on how well AI can be applied in an organisation, where organisations that are more innovative are more likely to embrace the concept of AI. Vice versa, an organisation with a culture that is resistant to change is less likely to embrace AI and hence the applicability of AI decreases (Enholm et al. 2022). Culture could also impact on that of collaboration and data sharing in the supply chain, which has the potential to positively impact the application of AI (Riad, Naimi and Okar, 2024). The next sub-factor that has an impact on the applicability of AI is *top management support,* which is described as the support the AI implementation will receive from more senior executives as well as the overall culture in the organisation. This is one of the top determinants of a successful AI adoption as it is a challenging process that has a large impact on the organisation (Enholm et al. 2022). The attitude amongst executives and top management has a large impact on the decision to apply AI on a process. Where a supportive top management could aid the application of AI by providing resources, ensure alignment with the company's strategy and to reduce the resistance to the AI implementation within the organisation (Chen, Zhou and Frankwick, 2023). Continuing with the sub-factor *organizational readiness* which refers to the amount of resources, both human, technological and financial, that are available to the process or project of applying AI to a business process (Enholm et al. 2022). Since AI is in some aspects a radical change, the company needs to ensure that they have the resources necessary in the form of technical skillset (Alsheibani et al. 2020).

Employee-AI Trust is the fourth sub-factor that is defined, and it refers to the impact on the organisation, fulfillment of tasks once human and changes to responsibilities amongst employees (Enholm et al. 2022). Previous research into the area of how employees perceive whether AI is a threat or not have shown that amongst employees who are resistant to the change could even go as far as leaving the organisation altogether, which presents the organisation with several business problems (Zhu, Corbett and Chiu, 2021). Especially big within the sub-factor of Employee-AI Trust is the belief that AI will "steal" responsibilities and ultimately jobs from human employees (Mirbabaie et al. 2022) and companies should be wary of this fear. On the other hand, employees who are more eager to apply AI in their processes are more supportive of the implementation, which would be beneficial to the attempt at applying AI (Zhu, Corbett and Chiu, 2021).

AI-strategy as a subfactor is dependent on whether or not the company has developed and adopted a strategy for its AI usage. This strategy should reflect the organisation's goals with its AI usage and align it with the overall business strategy of the company (Enholm et al. 2022). In a tangible way, the company should aim to align the goals and usage of AI with the KPIs which the company believes as strategic. Strategies are used in order to set a direction on what the company expects to achieve and how it should achieve that, the AI strategy should be seen as an enabler of this "overall" strategy (Kiron and Schrage, 2019). *Compatibility,* the final sub-factor within the organizational category, refers to the fit between chosen AI technology and the problem that it is intended to solve for the organisation. A good fit between the chosen AI technology and the process that it is going to be applied on, will ultimately result in a better result that has a positive impact on the adoption rate within the organisation (Enholm et al. 2022).

Finally, there is the *Environmental* category. Within this category the sub factors that impact the applicability of AI are ethical and moral aspects, regulations and environmental pressure (Enholm et al. 2022). *Ethic and moral aspects* as an enabler or inhibitor reflects the fact that with the impact AI and its usage has, it should not include any bias. By having ethical and moral aspects included in the overall the company can lower their risk exposure to criticism and wrongful decision-making by the AI (Enholm et al. 2022). Next, there is the sub-factor known as *regulations* which refers to the fact that regulators form and shape the continued development of AI. Companies and the people in charge of applying AI will need to take this into consideration as it acts as an external factor impacting the way that the organisation may apply AI (Enholm et al. 2022). Finally, there is *Environmental Pressure* which as a sub-factor can either enable or inhibit the application of AI and is related to the competitive pressure that exists in the industry or market that the company is active on. Companies need to achieve and maintain competitive advantages over their competitors and the threat of losing competitive advantages could push the company in the direction of applying AI (Enholm et al. 2022).

2.3 Decision-making

As established earlier AI has the potential to enhance the decision-making process. This part of the literature review will delve deeper into the decision-making process, decision models, how decisions are made within organizations and SCM. Furthermore, the role of AI in decision-making will be explored. There are several ways which a decision can be defined as and many of the definitions miss out on the important aspect, what exactly is a decision? According to Eilon (1971:172) a suitable and straightforward definition is the one from Ofstad (1961). According to him, *"to make a decision means to make a judgment regarding what one ought to do in a certain situation after having deliberated on some alternative courses of action."*. The key components of this definition are that the decision-maker is presented with multiple options and must compare them by evaluating their respective outcomes (Eilon, 1971).

Decisions are made by all sorts of different actors in organizations every day. The decision-making process is important to the company since it allows them to act or work in a way that allows them to hopefully achieve a goal or added-value (Kunc and Morecroft, 2010). By making the right decisions, a company or an organization is able to seize opportunities and gain new advantages and benefits (Driouchi and Bennet, 2012). The decisions that are made and that set the direction are often about achieving some type of goal that the decision-maker or the organization could have, which results in that the decision-making process has an influence and an impact on the performance, be it financial or organizational, of the organization (Kunc and Morecroft, 2010). However, the quality of the decisions and the decision-making process is an important factor to take into consideration of this. By having well-motivated and well-informed decision makers the company can improve its decision-making (Miller and Lee, 2001). Building on this, the quality of the information that decision-makers have at their disposal has a heavy influence on the actual quality of the decisions that are made. The information could come from a lot of different directions and is in turn dependent on many factors such as cooperation, visibility and efficiency (Moshood, Rotimi and Shahzad, 2025).

2.3.1 Decision-making process

A decision consists of a sequence of steps which is generally referred to as the decision-making process. This process outlines the mental stages a person goes through before reaching a conclusion (Eilon, 1971). The decision-making process covers eight steps starting with Information input and followed by Analysis, Performance measures, Model, Strategies, Prediction of outcomes, Choice criteria and then the Final decision (See Fig. 4)

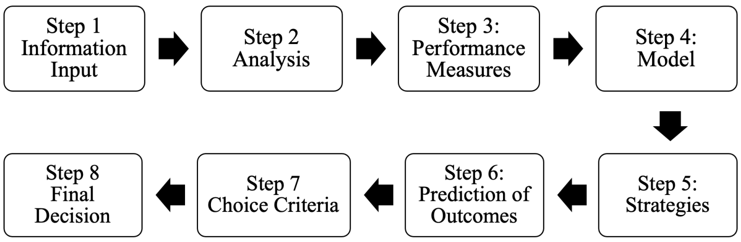

Fig. 4: Decision-making process. Based on Eilon, S (1971).

Information is one of the most important aspects of the decision-making process as it shapes how we analyse situations, define performance metrics and in the end what our final decision will be. But raw data alone is not enough, the data needs to be processed and structured in order for us to grasp it fully. According to Eilon (1971) there are three key stages in data processing and they are data storage, data handling and data presentation. Data storage refers to the collecting and maintaining relevant information, whereas data handling is the organizing process and refining of data for the analysis. Finally, data presentation is about displaying the insight in a way that helps the decision-making process.

2.3.2 Decision-making in SCRM

SCRM is generally characterized by uncertainty and complexity, which makes for a challenge in decision-making (Colocchia, Strozzi and Wilding, 2012; Bode and Wagner, 2015). Complexity and uncertainty as factors in SCRM, can come from several different directions and origins. One source of greater complexity is related to the amount of and distance to and from suppliers, as it creates a more complex supply chain network (Guntuka, Corso and Cantor, 2024). Another source of complexity stems from the growing number of actors or the trend of customization and variation (Tachizawa and Wong, 2015; Yang and Yang, 2010). Uncertainty is no different and can come from a number of different directions, both downstream from customers and upstream from suppliers (Liagkouras and Metaxiotis, 2023; Vilko, Ritala and Edelmann, 2014). Previous literature on how the uncertainty in SCRM impacts decision-maker has put forward the following *"decision making situations in the supply chain in which the decision maker does not know definitely what to decide as he is indistinct about the objectives; lacks information about (or understanding of) the supply chain or its environment; lacks information processing capacities; is unable to accurately predict the impact of possible control actions on supply chain behaviour; or, lacks effective control actions (non-controllability)"*(van der Vorst and Beulens, 2002:413). As such, there is a dependence on accessible data, information and knowledge. Where an easier access provides less uncertainty and easier decision-making (Vilko, Ritala and Edelmann, 2014).

2.3.3 AI and decision-making

With the rise of AI, the way we humans make decisions has changed. We have moved from relying on human reasoning and past experiences, to a world where AI can process large amounts of data in no-time. This has given AI the potential to enhance human decision-making by offering recommendations and relevant information to assist decision makers (Steyvers and Kumar, 2022). This is further underscored by Kaggwa et al. (2024), who also states that this is not only a technological advancement but a complete transformation in how organizations think, plan and execute their strategies. Having the ability to analyze large datasets while also finding hidden patterns has helped organizations to develop new products, enter new markets and remain competitive. El Namaki (2019) highlights this in his study where he provides real examples of AI as a tool and component in strategic planning across industries.

There are many different "tools" that have been employed to assist the decision-making process within research. According to Baryannis et al. (2019b) researchers have implemented MCDM into SCRM. MCDM is a decision-making tool which is used to evaluate multiple conflicting criterias and by doing this helps to make decisions within complex scenarios. The most common MCDM methods are AHP, TOPSIS, DEA and FMEA. However, these methods can be quite complex to understand and as a result of this AI has become more common in order to improve accuracy and efficiency. By combining AI with MCDM, organizations have the potential to make smarter decisions in complex and dynamic situations (Deiva Ganesh and Kalpana, 2022). This is exemplified by Belhadi et al. (2021a) who proposes a MCDM framework built on AI algorithms such as the previously mentioned Fuzzy systems. The aim with their framework is to strengthen SCRes by identifying patterns in AI and then develop the most suitable strategy. Another example is from Rajesh (2020), where grey theory was combined with layered analytic network processes with the aim to create a decision support model for risk mitigation strategies. The model helped organizations with their decision-making regarding resilience strategies.

Despite providing companies with many opportunities, there are also aspects that need to be considered when implementing AI into the decision-making process. Firstly, there is the cognitive side of AI assisted decision-making that relates to how humans interact with AI in decision-making scenarios. According to Tejeda et al. (2022) AI has become a trusted assistant in many business processes, however it is crucial to understand how much people rely on AI and when they should question its decisions. Some AI systems perform better than humans in specific tasks, whereas in other cases human intuition and experience add value. According to Steyvers and Kumar (2022) studies have shown that humans usually either over-rely on AI or ignore AI recommendations completely, resulting in reduced overall performance. In order to avoid this, organizations must carefully balance the efficiency of AI with human intuition.
Steyvers and Kumar (2022) continues by talking about the importance of designing effective human-AI interaction. Even when AI provides useful recommendations, it is still important to consider how and when these suggestions are presented as this affects the decision quality. The timing and volume of information provided by AI is crucial. If AI delivers insights at the wrong moment or overwhelms users with information it can lead to cognitive overload which reduces decision-making effectiveness. Therefore, AI must be designed to provide clear, timely and relevant insights that match human cognitive capabilities (Steyvers and Kumar, 2022). Another critical challenge with AI and decision-making on the same theme is trust and transparency, which is explored by Meske and Bunde (2020). They highlight the so-called “black box” problem, which refers to when AI provides recommendations without clearly explaining their reasoning. The result of this is a lack of transparency which can lead to hesitation in trusting AI-driven decisions. Additionally, for AI to be effective the users need to understand how it works. This means knowing its strengths, weaknesses and limitations.

However, many decision-makers misinterpret the outputs which results in bad reliance strategies (Steyvers and Kumar, 2022).

It is evident that there are many potential advantages with AI and its usage within decision-making. However, despite this, AI also introduces potential risks and challenges. If AI is not used properly with consideration to this, AI-driven decisions can become a liability rather than an asset. According to Cui and Yasseri (2024), some suggest that AI can replace human intelligence in addressing complex societal challenges. However, this perspective has been widely challenged and Cui and Yasseri (2024) argue that AI should be viewed as a decision-support tool rather than a replacement for human intelligence. AI offers vast computational power and quick data processing and can serve as a tool for handling routine data-driven decisions. Whereas, humans can focus on strategic, ethical and qualitative decisions. By combining the strengths from both AI and human intelligence, a system with a greater collective intelligence can be achieved to help improve decision-making (Cui and Yasseri, 2024). However, understanding the human to AI relationship can be a complex task. Previous literature on how AI impacts decision-making have shown that if the AI is supplied with data that generates wrongful conclusions, the decisions made by humans using the AI are negatively impacted. This could be developed upon as a limitation of AI and it showcases the potential downside that AI has on decision-making (Kim et al. 2025).

2.4 Technology-Task Fit Theory

Technology-Task Fit theory (TTF) is built on the premise that "outcomes depend upon the degree of fit or alignment between an information system and the tasks that must be performed (Furneaux et al. 2011). Using this explanation, the effectiveness of the company in performing a certain task or process is dependent on the level of fit with the information systems and technology that it employs (Furneaux et al. 2011). Building on this, TTF theory indicates that the tasks performed and the technologies employed are interacting with each other and could produce a greater output than the "sum of their parts" (Howard and Rose, 2019). Performance can mean a great deal of many things, but previous literature on the topic of TTF has described it as increased efficiency, improved quality of the outcome and a higher level of satisfaction with the final product of the process, activity or task (Zigurs and Buckland, 1998). In previous research TTF theory has been applied as a way to understand how different tasks and the fit of the technology used in those tasks impacted the performance and results of those tasks, but also in order to understand factors that impact the adoption of new technology in organisations (Yu and Yu, 2010). Continuing on the topic of tasks, there are many different types of tasks and classification often referred to in TTF. There are 4 dimensions through which a task is characterized, (1) *Outcome multiplicity,* which covers if there are more than one desired outcome of the task. (2) *Solution scheme multiplicity,* which refers to whether there is more than one possible way to achieve the goal of the group. (3) *Conflicting interdependence*, which is about if the solution to solve one task, prevents or makes it more difficult to adopt a solution for another task. (4) *Solution scheme-outcome uncertainty*, which has been described as the extent there is uncertainty about the outcome that the proposed solution will have (Zigurs and Buckland, 1998).

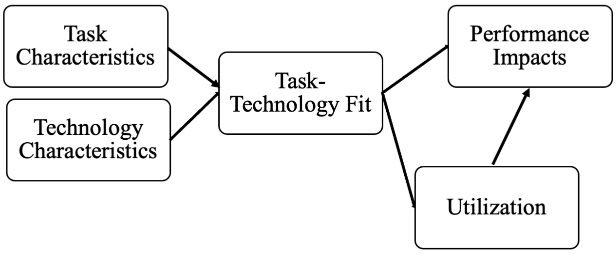

Figure 5: Model showing the flow of impact for TTF, copied from Goodhue, D L. & Thompson, R.L. (1995)

TTF consists of five different areas, shown in figure 5. Four of the five different areas are *Task Characteristics, Technology Characteristics, Utilization* and *Performance Impacts* (Goodhue and Thompson, 1995). Looking more closely at each area, starting with *Task Characteristics* it has in previous literature been described as the level of non-routines and interdependence of other organizational units. The greater the non-routines of the task, the more difficult it will be to fit the technology to it. In terms of interdependence, a greater level of it has a negative impact on the compatibility with the technology as it results in people feeling unsure about the reliability of the results and systems (Goodhue and Thompson, 1995). Continuing with the next, which is *Technology Characteristics.* Technology in this case is seen as the tool used by the individuals that are performing an activity or a process (Goodhue and Thompson, 1995). If the technology is aligned with the task and is reliable then that has a positive effect on the compatibility between the task and the technology. This was evaluated using eight factors *(1) data quality, (2) locatability of data, (3) authorization to access data, (4) data compatibility, (5) training and ease of use, (6) production timeliness, (7) systems reliability, (8) Relationship with users* (Goodhue and Thompson, 1995). *Utilization* in the model above, refers and is conceptualized as the *"the extent to which the information systems have been integrated into each individual's work routine"*(Goodhue and Thompson, 1995:223). *Performance impact* can be described as the final product of the technology-task fit, where a good fit between the task and the technology and good level of utilization will generate a positive performance impact. This positive impact could come in the form of improved efficiency or effectiveness as well as a higher quality of output. (Goodhue and Thompson, 1995; Spies et al. 2020).

2.4.1 Different perspectives on fit

Fit is an important aspect of ensuring that the technology supports the tasks that are being carried out since it impacts whether the company experience benefits from the technology or not (Cane and McCarthy, 2009). One way that fit has been looked at, dubbed *cognitive fit*, is described as *"that problem solving works best when the problem representation and any tools or aids all support the processes required to perform that task"* (Dishaw and Strong, 1999:12). Within SCRM and strategy fit has previously been described as the " *fit between the level of importance of different business objectives and the degree to which risk management achieves them"*(González-Zapatero et al. 2021:5276). Building on this and combining it with that of cognitive fit, the authors propose and adopt in the theoretical framework for this thesis that in the context of AI and SCRM, fit is seen as *the fit between the type of AI and the degree to which it helps in managing the type of supply chain risk.* Within SCRM there are several different types of risks and categories that companies and supply chains are exposed to and by using this definition, the different nature of each task is captured.

2.5 Theoretical Framework

Technology-Task Fit has been applied in research that has looked at many different areas and a large range of different types of technology, it is as such tried and tested (Spies et al. 2020). The theory has allowed researchers to understand how well a technology is suited for the needs of the practitioners (Cane and McCarthy 2009). The theoretical framework, made by the authors for this thesis is shown in Figure 6.

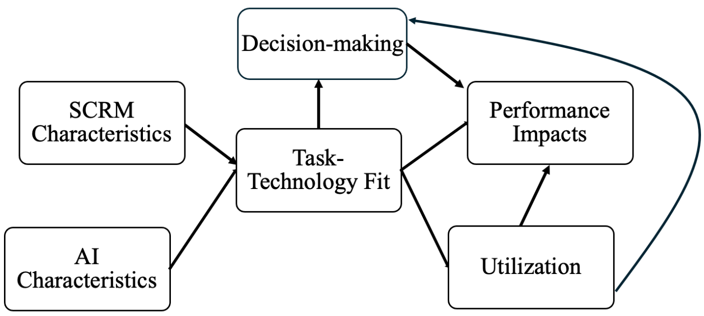

Figure 6. Theoretical framework developed by the authors.

The SCRM characteristics relate to that of the task characteristics in the Technology-Task Fit that were described as the level of non-routines and interdependence (Goodhue and Thompson, 1995). The greater the non-routine nature and variability of the SCRM task will have an impact on the fit with the chosen AI. The AI characteristics in the framework relate to the Technology Characteristics in the Technology-Task Fit theory framework. Recalling the first research question of how AI can be applied in SCRM, the AI is seen as the tool that would either aid the individual performing an SCRM task or complete the SCRM task itself. Furthermore, and with the second research question of what the effects on AI usage in SCRM are on the decision-making process, the authors have included decision-making in the developed framework. As was noted earlier in, AI has the potential to improve the decisions that are made (Steyvers and Kumar, 2022). However, depending on the task and the AI type being used, the degree of added value is not always the same (Tejeda et al. 2022). A good fit would result in the AI being able to improve the decision-making process (Steyvers and Kumar, 2022; Kaggwa et al. 2024) and a poor fit could risk negatively impacting the decision-making process (Kim et al. 2025). With the fit earlier being defined as *the fit between the type of AI and the degree to which it helps in managing the type of supply chain risk.*

3. Method

This chapter presents the methodology for the thesis. First the authors describe the research approach and design, followed by data collection and data analysis. Finally, the research quality and ethical considerations are critically discussed by the authors.

3.1 Research approach

The research paradigm most similar to the one the authors adopted is referred to as an interpretivist paradigm. This paradigm is characterised by detailed and nuanced qualitative data, relatively smaller sample sizes and a shorter distance between the object of research and the researchers themselves. Reality is regarded as subjective to the researchers perception (Collis and Hussey, 2021b). Which the authors argued improved their understanding of the results about SCRM and decision-making processes since they do not behave in a single way. Had the authors performed the research through a positivist paradigm, the belief would instead have been that there is only one absolute truth (Collis and Hussey, 2021b).

The authors argued that a qualitative research approach was the best choice, rather than using a quantitative approach due to several reasons. First of all, a qualitative approach allows researchers to capture complex and multifaceted problems (Eriksson and Kovalainen, 2015a), which the authors argue was necessary to answer the research questions and fill the identified research gap. Second of all, the authors wanted to understand how AI would affect the decision making process in SCRM. A qualitative research approach involves the use of qualitative data and analysis methods, that is to say data and analysis that is non-numerical (Collis and Hussey, 2021a), which the authors argue allows for better understanding of decision-making processes. As mentioned in the introduction, the authors had found that there was a research gap on the subject of AI impact on SCRM decision-making and that much of the existing research on AI and SCRM applicability had been done using quantitative approaches, warranting the need for more qualitative research.

3.2 Research design

This thesis started with the two authors researching SCRM and finding that the previously done research and written literature had gaps in terms of applicability of AI as well as the effects that AI had on decision-making in SCRM. These gaps generated the two research questions of the thesis, The first being *"How can AI be applied in supply chain risk management and what impacts its utilization?"* and the second *"How does AI's utilization* *impact supply chain risk management decision-making?".* Much of the research that the authors found on SCRM and AI was as aforementioned quantitative. The authors draw the conclusion that there was a need for more qualitative analysis and that it would fill a gap in the existing research. Furthermore, while previous research had been done on specific tasks that could be found in SCRM, it was then lacking the context of SCRM, its goals and phases. Figure 7 outlines the research design and the process by which the authors performed the research.

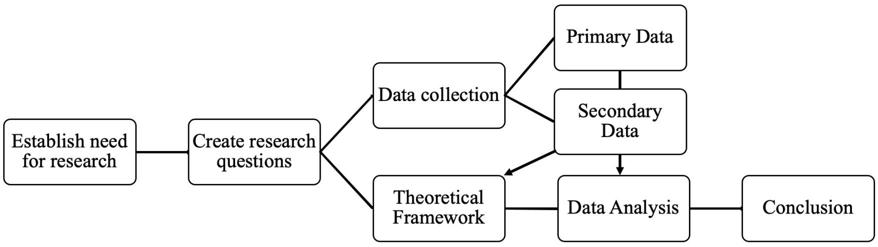

Figure 7: Overview of the authors research design

Theoretical frameworks and scientific theories are often found in research that utilises the case study method (Eriksson and Kovalainen, 2015). A theory is described as a *"set of interrelated variables, definitions and propositions that specifies relationships among the variables, and a variable is a characteristic of a phenomenon that can be observed or measured"* (Collis and Hussey, 2021d:40). Theories play an important role since they provide explanations to what the authors observe during the course of the research (Collis and Hussey, 2021d). The authors developed a theoretical framework based on TTF and the framework presented by Goodhue & Thompson (1995). This was then combined with the results and conclusions of other previous literature on AI, SCRM and Decision-Making. The authors argued that this adjusted framework was necessary due to the fact that TTF does not specifically look at AI and SCRM in specific, but more so task characteristics and information systems in general. The theoretical framework provided the thesis with structure, greater opportunities for a more structured analysis and was also used in explaining the observations that were made from the primary data collection.

3.3 Case Company

Case studies as a methodology for research is often used to explore phenomena taking place in a natural setting, allowing researchers to obtain in-depth knowledge (Collis and Hussey, 2021c). Furthermore, the case study method serves as a good option when a quantitative method is not the most appropriate (Eriksson and Kovalainen, 2015b). However, researchers also have to be aware of the fact that the necessary access to a case company can be difficult at times to negotiate (Collis and Hussey, 2021c). Since one of the authors worked at the case company, the authors were able to overcome this issue more easily and it did not make the authors experience any limitations.

Since the purpose of the thesis was to better understand how AI could be applied within SCRM and how the use of AI affects the decision-making process of SCRM, the authors argued that a case methodology was a good choice since it allowed for the authors to collect data in a practical and natural setting of SCRM. Furthermore, in order to answer the two research questions, the authors needed to gain access to data that explained how decisions were made in practice and also to how activities and operations related to SCRM were conducted in a business setting. Secondly, the data that was obtained from the case company would have been difficult to find for the authors elsewhere. The case company this thesis used was headquartered in Scandinavia. At the time it had an annual turnover between 10-20 billion EUR in annual turnover and more than 10 000 employees globally. The company described itself as having a market presence in more than 100 countries. The company had suppliers located across the world and a supply chain that the authors perceived as global. The case company had launched a digital transformation project some years earlier and had a technology infrastructure that was comparatively modern to other companies the same size. The authors wanted the case company to be one with global supply chains which the case company in question is. The underlying reason behind this was that global supply chains are exposed to greater risks and as a result of that, there would be more data to retrieve as for the SCRM practices and decision-making processes.

3.4 Data Collection

The authors collected and used both *primary data* and *secondary* data. With primary data, the authors refer to what previous literature has defined as data generated for the specific research that was undertaken (Collis and Hussey, 2021e). The different sources for primary data are summarized in Table 3. Secondary data, which is data that already exists and is collected (Collis and Hussey, 2021e) is discussed further in section *3.4.2 Secondary Data*. The authors wanted to use several different types of data since previous literature had found that it allowed for better means of evaluating and validating qualitative findings (Farquhar, Michels and Robson, 2020). As can be seen in tables 3 and 4, the authors collected data from a range of different sources. The process of using multiple sources of data collection is often referred to as triangulation, which makes it possible for researchers to view the research and data from different perspectives. It also allows the authors to improve their understanding of the subject (Denscombe, 2017).

Data source	*Name*	*Title*	*Theme*	*Date(s)*	*Number of Interviews*	*Length of Interview(s)*
Update meeting	*Anonymous 2* *Anonymous 8*	*AI Director* *Supply Chain Strategy Director*	*Update on progress and discuss current findings*	*29 Jan 2025* *12 Feb 2025* *26 Feb 2025* *12 Mar 2025* *26 Mar 2025* *9 April 2025* *23 April 2025* *30 April 2025*	*8*	*20 minutes* *20 minutes* *20 minutes* *30 minutes* *25 minutes* *20 minutes* *25 minutes* *20 minutes*
Interview	*Anonymous 1*	*Demand Manager*	*Demand Risk*	*28 Feb 2025*	*1*	*57 minutes*
Interview	*Anonymous 2*	*AI Director*	*AI*	*5 Mar 2025* *28 Mar 2025*	*2*	*53 minutes* *40 minutes*
Interview	*Anonymous 3*	*Transport Manager*	*Environmental Risk*	*7 Mar 2025,* *10 Mar 2025*	*2*	*50 minutes,* *43 minutes*
Interview	*Anonymous 4*	*Logistics Director*	*Process Risk*	*4 Mar 2025*	*1*	*54 minutes*
Interview	*Anonymous 5*	*Logistics Director*	*Supply Risk*	*19 Mar 2025*	*1*	*47 minutes*
Interview	*Anonymous 6*	*Data Manager*	*Information Risk*	*11 Mar 2025*	*1*	*50 minutes*
Interview	*Anonymous 7*	*Supply Manager*	*Control Risk*	*31 Mar 2025*	*1*	*56 minutes*
Document	*N/A*	*N/A*	*AI and SCM decision-making*	*N/A*	*N/A*	*33 Pages*

Table 3: List of data sources and interviewees.

3.4.1 Primary Data Collection

As summarized in Table 3, the primary data consisted in this case of semi-constructed interviews as well as regular meetings with contact persons at the case company, who were executives within the areas of SCM and AI respectively. The authors used two different interview themes, one for the interviews focusing on risks and one focusing on AI. Both of these interview themes are available in Appendix I: Interview Themes - Risk Interviews and II: Interview Themes - AI Interview. The authors consider the interviews as semi-structured since the characteristics of such an interview is that the researchers prepare questions in advance and the interviewee is free to talk about the main topics brought up in the interview which allows the authors to develop questions that were not thought of beforehand. (Collis and Hussey, 2021f) This has the added advantage of greater flexibility and allows the authors to explore areas not thought of prior (Adeoye-Olatunde and Olenik, 2021).

Apart from the interviews, update meetings with the case company were held to discuss the progress and current findings. Additionally, the authors were provided by the case company with industry-related documents. These documents were not used in the report. Instead they served as inspiration for the authors thought-process and helped them to view the research area from different perspectives. The documents and their impact are further discussed and detailed in Appendix V: Subject Reports. It could also be argued that with one of the authors being employed by the company, additional primary data that complemented the other data was gathered. This is discussed in greater detail in Appendix VI: Experience from the case company. The impacts and how the authors worked towards removing any unconscious bias is further described in section *3.6.4 Reflexivity*.

3.4.1.1 Sampling Process

Interviewing and retrieving the whole population of people working and making decisions within SCRM was not possible due to resource constraints. This resulted in the authors choosing to use samples. One method, referred to as "purposive sampling" involves selecting samples based on the strength of their experience and knowledge of the area that is being researched (Collis And Hussey, 2021f). The purposive sampling method is well aligned with the method the authors employed for the thesis. The literature review identified six types of risk that were prevalent in SCRM, reviewed under section *2.1.3.1.1 Classification of Risks.* Using purposive sampling, the authors used the knowledge they had of the company's supply chain organization, as well as information given by the main contact persons, and selected interviewees based on work-experience and SCRM risks they were likely to have been confronted with. The final sample consisted of seven interviewees. Six of these were experienced within SCRM and had worked in several positions and functions within SCM. The seventh was experienced within AI, analytics and digital transformation. Furthermore, all seven interviewees that were included in the sample were experienced decision-makers and had held managerial responsibilities.

3.4.1.2 Semi-structured Interviews

Table 3 summarized the semi-structured interviews that provided the thesis with primary data. The interviews were conducted in the time frame of 26 of February and 31st of March 2025 and were conducted in a digital setting using Microsoft Teams version. Each interview was conducted with a single interviewee at a time and started by the authors asking for consent to record the interview and later transcribe it. If any interviewee had not given consent to record and transcribe the interview, the interview would have been terminated.

However, all interviewees gave their consent to the authors. The interviews focusing on risks all followed the same theme, with minor adjustments to make sure the type of risks the authors were interested in were highlighted and referred to. The interview with Anonymous 2 followed a separate theme, focusing on AI strategy and organizational readiness (Appendix I; Appendix II). Both authors were present during all interviews and update meetings.

3.4.2 Secondary Data Collection

The secondary data collected for the thesis came in the form of a literature review. However, statistical databases such as Statista and white-papers from consultancy firms such as Accenture have also been analyzed by the authors. Furthermore, while not included in the thesis, the main contact persons at the company also shared documents and white-papers with the authors. However, since those were proprietary they were not included in the thesis. Greater detail about these documents are available under Appendix V: Subject Reports.

3.4.2.1 Literature Review

A literature review can be described as an critical evaluation of what previous research and literature have found relating to the topics of this study (Collis and Hussey, 2021X). The databases and platforms that were used by the authors in order to search and access previously written literature were a combination of three different. “Primo Super-Search”, a search platform and database owned and operated by the University of Gothenburg, Google Scholar and Business Source Premier. When selecting articles to include in the literature review the authors excluded previously written bachelor- and master's theses and retracted articles. “Primo Super-Search” has a function to clearly display if an article is peer-reviewed. Using this function all articles found using databases other than “Primo Super-Search” were scanned using the function manually by the authors to ensure that they were peer-reviewed. In terms of publication date the authors used two different approaches. For articles that related to the field of SCRM, decision-making and TTF-theory the timeframe for publication was more relaxed compared to the articles that were connected to the field of AI. The reason behind this was that since AI is quickly evolving, the articles included in AI had a greater need of being published in a time frame much more closely to the undertaking of this thesis. This was to ensure that the results did not rest on previous conclusions and contributions that were outdated. In table 4 the keywords and phrases that the authors used in order to find the literature are presented, as well as the number of articles that were later included from each set of keywords and phrases.

Search Words used	Amount of articles cited
Supply Chain Risk Management	7
Supply Chain Risk Management + Objectives	6
Supply Chain Risk Management + Characteristics	5
Supply Chain Risk Management + Uncertainty	4
Artificial Intelligence	6
Artificial Intelligence + Development	1
Artificial Intelligence + Characteristics	5
Artificial Intelligence + Supply Chain Risk Management	8

Table 4: List of key words and phrases used for searching previously written literature.

The authors used what can be described as a funnel approach to finding literature, at the start using keywords and phrases that were more open-ended and then narrowing down depending on the topics that were brought up by the previous literature. The reason behind this was due to the fact that SCRM is an area that is difficult to define and to narrow down without a solid foundation. Similarly, there are many different types of AI and the authors had to tackle the challenge of the thesis becoming too broad and lacking the necessary depth to answer the research questions.

Furthermore, the authors also used snowballing, meaning that from some of the articles, the authors looked at articles referred to when it was of interest and as such new research was looked at and evaluated. There are many different types of AI and there is, as previously mentioned in the literature review, a very broad definition of computer models and techniques fit into how AI is defined. In order to ensure that the study did not become too broad, or too shallow or even misdirected, the authors searched and analysed previous written literature on AI models that were connected to SCM and the previously identified areas of SCRM and types of risks. The authors made the delimitation to only look at the types of AI that previous literature had identified as useful in both an SCM and SCRM context. The types of AI and the sources that included the respective AI type are displayed in table 5.

AI Type	Citations
Machine learning	Baryannis et al. (2019), Baryannis et al. (2019b), Deiva Ganesh and Kalpana (2022), Baghalzadeh Shishehgarkhaneh et al. (2024), Meng and An, (2024)
Fuzzy programming	Baryannis et al. (2019), Deiva Ganesh and Kalpana (2022), Baghalzadeh Shishehgarkhaneh et al. (2024), Wu et al. (2010).

Deep Learning	Janiesch, Zschech and Henrich (2021), Hosseinnia Shavaki and Ebrahimi Ghahnavieh (2023)
Generative AI	Richey et al. (2023), Anantrasirichai and Bull (2021), Samuel Fosso Wamba et al. (2023), Shen et al. (2023), Vinay Yandrapalli (2023)
Multi-Agent Systems	Baryannis, G. et al. (2019b), Deiva Ganesh and Kalpana (2022), Giannakis and Louis (2011)

Table 5: List of AI types that previous research has looked at in the context of SCRM and their respective potential area of usage.

3.5 Data Analysis

Both primary data and secondary data was collected by the authors for this thesis. The authors started with transcribing the interviews ad verbatim in order to access all of the data. This was done shortly after each interview. The transcriptions were then imported to the analysis software Nvivo 14.24.3. The analysis method employed by the authors draws heavily from the method often referred to as the "Gioia methodology" (Gioia, Corley and Hamilton, 2013). The authors analyzed and coded the transcripts into first-order codes that described the observed phenomena. These first order codes were then grouped into second-order codes. The second-order serves to connect the observed phenomena with any theory to understand what has been observed. Once the second order themes had been created the authors combined them into aggregated dimensions that explained the different themes observed by the authors from the raw data (Gioia, Corley and Hamilton, 2013).

All the coding was done using the Nvivo analysis software. The first-order, second-order codes and aggregated dimensions, as well as the supports for each of these codes, summarized by Gioia, Corley and Hamilton (2013) as the *"data structure",* is available in Appendix III Data Analysis Framework. During the coding and analysis of the data, the authors read each other's codes and jointly agreed on the different order themes that followed. The choice of reading and evaluating each other's coding was made due to several reasons. For one, it ensured transparency which was important considering one of the authors being employed at the case company. This is further discussed under 3.6.4 Reflexivity. It was also made to lower the probability of valuable insights being left out due to human mistakes.

3.6 Research Quality

The quality of the research is an important aspect in any type of research. Three common concepts that can act as criteria for good quality research are reliability, validity and generalizability (Eriksson and Kovalainen, 2015c). Reliability refers to the accuracy of the measures that the authors use, whereas the validity of a study is related to the extent a test measures what the researcher wants to measure (Collis and Hussey, 2021h). Generalizability refers to whether the results of the research can be transferred to a wider context (Eriksson and Kovalainen, 2015c). Another established concept is reflexivity, which is used to describe the relationship between what is to be studied and the authors themselves (Dodgson, 2019). Researchers should discuss both the strengths and weaknesses in the research to improve the quality (Denscombe, 2017).

3.6.1 Reliability

Reliability is a term within research that describes the accuracy of the measures that the authors use, where a study with high reliability should not render any large differences if it is repeated. As such, the reliability of a study is closely linked to the credibility of the study's findings (Collis and Hussey, 2021). While high reliability is more connected to that of a positivist research paradigm, reliability is still important to research that is characteristized by that of an interpretivist paradigm which this thesis came to be categorized as by the authors (Collis and Hussey, 2021). Measuring the reliability of qualitative research is more difficult than in the case of quantitative research, resulting in the fact that qualitative research focuses on creating protocols to establish the authenticity of the research findings (Collis and Hussey, 2021).

On its own semi-structured interviews cause some level of subjectivity, but with a structured interview guide these effects are mitigated. This ensures that all participants are asked a similar set of questions, while also allowing them to further discuss the subject. Continuing with the selection of respondents, this study uses multiple respondents from different levels within the organization. This improves the reliability by looking at different perspectives and making sure that the results are not based on one single perspective (Denscombe, 2017). The reliability of a study is also improved by having transparency in the methodology.

The research of the study follows a clear and replicable methodology, covering how the respondents have been selected, how the data is collected and how the analysis is performed. In terms of analysis this study uses coding and the previously mentioned "Gioia method" to analyse the interview data. This strengthens the reliability of the study by minimizing subjective interpretation and also helps the consistency across the research (Denscombe, 2017). Additionally the methodology has been reviewed by both the university supervisor, which has helped to improve the consistency of the research. Despite these efforts, the human interpretation in qualitative research can cause a degree of variability. This means that it is almost impossible to achieve absolute reliability. Referring back to Collis and Hussey (2021), it is evident that there is a need for protocols and procedures that ensure authenticity of the results. This study aimed at achieving this by using systematic data collection and the "Gioia method" as analysis technique in order to ensure that the results can be replicated in a similar context.

3.6.2 Validity

The validity of a study is related to the extent a test measures what the researcher wants to measure and the results that are created as a result (Collis and Hussey, 2021). As such, research with a high level of validity will normally have findings that more accurately depict what took place in reality. There are a number of different ways that the validity of research can be evaluated against. For this thesis, the authors applied triangulation. A process where multiple sources of data are used to verify the findings (Denscombe, 2017). Meaning that both the primary data of the interview results and secondary literature is being used. While triangulation serves as a good tool for improving the trustworthiness and the research quality of the thesis (Collis and Hussey, 2021j), it has also the impact that it makes it more difficult to replicate (Collis and Hussey, 2021k). However, the authors of this thesis argue that these effects are mitigated through the use of "Gioia method" and Technology-Task Fit Theory in combination with a clear research design and methodology. Regarding the findings from the interviews both researchers of this study reviewed and confirmed the responses. Additionally, member checking was applied to reduce misinterpretations which strengthened the validity. Member checking is when results are returned to respondents to check for accuracy and alignment with their experiences during the interview (Birt et al. 2016).

Furthermore, the use of Technology-Task Fit Theory ensures that the results are theoretically grounded. This essentially improves the credibility of the interpretations since this theory provides a structured framework. This also makes sure that the results are systematically analysed. Continuing, this study will be using direct quotations from the respondents to support different conclusions. This helped ensure that the results of the thesis came from the gathered data rather than pre-existing assumptions. To ensure that any potential bias is avoided during the interviews, the respondents will be kept completely anonymous as this will help to keep the answers fully transparent. Additionally, the collected data from the interviews has been compared to the literature to verify both accuracy and consistency (Denscombe, 2017). Lastly, AI is still evolving which means that results may change over time. To mitigate this as much as possible the authors tried to use current literature, making the results applicable at the time of research.

3.6.3 Generalizability

Generalizability refers to whether the results of the research can be transferred to a wider context (Eriksson and Kovalainen, 2015c). Since the thesis was conducted with a case study, the findings may be specific for this context and not fully generalizable to all industries. However, in this case the nature of this case study reflects common themes of AI adoption making this study transferable to similar organizations (Denscombe, 2017). This study is based on data collected from a single company that allowed for an in-depth exploration of the case. The authors justified this design choice as the data gathered supports the validity of the findings. Additionally, interpretivists are able to generalise their findings if the analysis manages to capture the *"interactions and characteristics"* which it aims to study (Collis and Hussey, 2021h). Nonetheless, incorporating additional case companies could improve the generalizability of the findings and give a broader perspective.

Furthermore, the authors used TTF-theory as the basis for the thesis theoretical framework, translating the different parts with the characteristics of AI and SCRM. By using a theoretical framework, to both analyse and answer the research questions the authors would argue that the thesis not only becomes replicable but also more generalizable. TTF-theory has been applied and could be used for several industries and technologies, although originally developed for information systems. With this said, the generalizability can be somewhat limited when applying a case study approach. However, in this thesis those effects were mitigated by grounding the theoretical framework in the widely applicable TTF-theory and selecting a case that reflects common themes in application of AI.

3.6.4 Reflexivity

While the authors of this study have designed the research with objectivity in mind, it is difficult to remain completely objective when conducting qualitative research. In order for the reader of this thesis to be able to critically judge and understand the results and conclusions that the authors made in this thesis, there is a need to understand who is doing the research (Dodgson, 2019). Building on this, discussing the reflexivity of the research is important in order to achieve a good level of transparency and understanding. As previous literature has put it, discussing reflexivity is a minimum requirement for quality in qualitative research (Dodgson, 2019). As such, including reflexivity entails discussing and explaining the relationship between the researcher and what is being researched (Palaganas et al. 2017).

One of the authors of this study was employed by the case company that the thesis used. As such, the objectivity of one of the authors should be scrutinized as this could have introduced bias or preconceptions about certain data for the author employed by the case company. However, there were still benefits to choosing the case company. First of all, it allowed the authors to perform the purposive sampling based on the authors network and deep understanding of the organisation. Secondly, it allowed the authors to understand certain aspects of the data in a better way, since the authors understood much more of the context. To make sure that the author employed by the case company did not introduce bias to the results or steer the interviews, the authors made sure that they were both present in the interviews and that all data analysis was checked and verified by not one single author. Another form of reflexivity is that the authors had both studied logistics and SCM at an undergraduate level for 3 years and at a graduate level for almost 2 years, which could be argued has impacted their perception and interpretation when analysing the data positively.

3.7 Ethical considerations

When performing research, ethical questions and dilemmas are not unusual. The authors of this paper share the ambition to not use any methods that can be deemed as unethical or immoral. Not only due to personal beliefs but also because there is value to be gained from maintaining a high level of ethics and transparency. By consistently following ethical and moral guidelines, the research and the findings from this thesis stand stronger in the face of critical review, ultimately adding greater and valid understanding of the subject which the researchers have spent their effort on explaining (Remenyi, 1998). As such, the authors abided by several principles during the writing of this thesis that had been referred to as "important ethical principles" by other and more experienced researchers (Collis and Hussey, 2021i).

The first principle is referred to as *Voluntary Participation* and refers to the fact that if humans participate, it should be voluntary and not coerced in any way. They should not be offered any financial or other gifts as part of their participation as this could result in biased data (Collis and Hussey, 2021i). The authors upheld this principle by clearly stating the purpose of the thesis, that all data could be used and that the results would be published. The interviewees were then given the option to not participate and the interview would have been cancelled.

Another principle is that of *Anonymity and confidentiality.* Which refers to the fact that interviewees should be offered the option of remaining anonymous (Collis and Hussey, 2021X). To uphold this principle, all interviewees were given the option to remain anonymous in the data collected and in the presentation of interviewees. This question was posed to them both at the start of the interview and at the end of each interview. As such, the authors have obtained the explicit consent from all individuals that were included in this study.

4. Empirical Findings

In this fourth section the reader will be presented with the results of the empirical data that the authors have collected. Beginning with findings regarding AI and its current stage in the company. Furthermore, the identified obstacles to AI adoption will be presented. Next, focus is on the different types of SCRM risks and tasks being done. Finally, the findings related to the decision-making process in SCRM are presented.

4.1 Technology and State of Organization

The results showed that within the company there is a focus on innovating and improving the business and its processes. Closely linked to this was AI, which was regarded as a tool with the potential to be applied in the business to a greater extent (Support 124 to 130 in Appendix III). However, with AI being a relatively new tool there existed misconceptions about its capabilities and requirements amongst end-users. As such there was a need to improve AI literacy and data management processes in order to start utilizing AI more extensively (S. 167 App. III). Reacting to the challenges of implementing AI into the business, the company has created an organization responsible for creating an AI strategy and driving AI implementation. This organization is also responsible for improving the AI literacy (S. 168 App. III).

Amongst the employees, the overall perception is that AI enables for new business- and process opportunities. While excited, they perceived some risks of using AI and had as such decided to take a balanced and strategic approach (S. 147 and 154 and 158 in App. III). This involved identifying and beginning with the "low hanging fruit" where the company could get the most added value within the shortest possible time span. It is also seen as important that AI implementation is in line with the overall AI strategy, which itself is linked to the business strategy (S. 155 in App. III). Since there is an intention to use AI to solve business challenges, rather than just implementing AI for the sake of it, the criteria used was the added value, feasibility and strategic impact that implementing an AI solution would have (S. 155 in App III). While SCRM has not been a primary area for AI implementation at this point, it is regarded as an area that has a lot of potential. SCM in general is regarded as an area where AI can improve the business but there is a need to first upskill the SCM organization and to gradually transition to a state where AI is used with greater confidence and understanding (S. 156 and 157 App. III). Building on this, the success and added-value of AI was perceived differently depending on the area. Forecasting and supply chain optimization was seen as good AI areas, as they require large amounts of data to be analyzed (S. 170 and 172 in App. III). But there is a need for human judgement as it adds value, which was more apparent for areas such as human resources (S. 151 and 159 in App. III). Furthermore, the company had recognised the importance and challenge of data management. As a prerequisite to greater AI usage, they had started focusing on improving their data management processes. This in the form of improved master data and data governance with the aim of improving data quality (S. 138 and 139 in App. III). The ultimate intention of using this improved stage as a foundation for enabling more advanced analytics processes and AI initiatives (S. 137 in App. III).

4.1.1 Obstacles to AI Adoption

The interviews highlighted several obstacles to AI adoption. As aforementioned, *data* was seen as a challenge and a current obstacle for greater AI implementation. This came both in terms of data quality but also the availability of data inhibited quicker implementation. The company had seen in earlier tests that the AI would start generating faulty or outdated input when the data was not organized in a proper way (S. 131 to 133 and 140 in App. III). Furthermore, since several projects well before the advent of AI had been done, the data structure had changed which proved to be a challenge when training AI models (S. 136 in App III). Another obstacle that was mentioned was *data privacy and security.* As a result of AI models using a large amount of data there were concerns regarding what would happen with the data when it is used by an AI. There is a perceived risk that confidential data could leak to competitors and as such protective measures need to be taken, which takes time (S. 143 and 144 in App. III). A third obstacle to AI implementation was *ethical concerns*. Ethical challenges could appear in the form of the AI forming biases which lead to faulty outputs but also ethical concerns. Another form of ethical concern came with content creation and intellectual property that had to be taken into consideration (S. 142 and 146 in App. III). *Organizational change* was also an obstacle that often came in the form of a need for change management. AI was perceived as changing the roles and responsibilities amongst employees, which required people to accept and prepare for the change (S. 134 and 153 in App. III). *Compliance and regulatory impacts* also had an impact on AI adoption, since the case company had to comply with new AI regulations (S. 145 in App. III). Finally, *quickly evolving technology* was a challenge that resulted in AI implementations requiring a large amount of resources dedicated to them for it to be successful (S. 152 in App. III).

4.2 Supply Chain Risks

Table 6 summarizes the defined risk categories within SCRM, highlighting the environment of each risk category, providing examples of risks identified and the corresponding SCRM tasks. An in-depth description for each risk category is written in the proceding subsections.

Risk Category	Environment	Examples of risks	SCRM Tasks
Demand	Unpredictable	Overselling, volatile demand, incorrect forecast	Demand forecasting, Categorizing risks, S&OP, Forecast evaluation.
Supply	Unpredictable	Supply disruptions, incorrect forecasting, poor supplier performance	Scorecarding, supplier evaluation, S&OP, Root cause analysis, Countermeasure evaluation, Supply Chain Redesign.
Process	Predictable / Unpredictable	Limited capacity in production, inflexible processes	Customer collaboration, Ad-hoc solutioning, Data monitoring.
Environmental	Unpredictable	Natural disasters, labour market issues, geopolitical events, regulatory changes	Hauler evaluation, Identify critical transport flows, Diversify transport partners, Rerouting, Adjust stock levels
Information	Predictable	Missing or wrong data, blocking production and deliveries, false information	Data maintenance, Data creation.
Control	Predictable	Lack of end-to-end planning, poor visibility, bullwhip effects	S&OP, Capacity planning, Risk analysis, Risk assessment.

Table 6: Summary of high level results for each risk category. Compiled by the authors.

4.2.1 Demand Risk

Disruptions caused by demand risks had an impact felt through the full supply chain and could be impacted by several factors such as political events, natural disasters and changing customer behaviour. This became apparent during the COVID-19 pandemic for example. The factors resulted in more volatility, in what was otherwise described as a quite predictable environment (S. 22 to 23 in App. III). The consequence of wrong forecasting had previously resulted in bad investments, higher costs and lowered service levels and since the forecasted demand triggers much of the supply chain, demand risks pose a large risk of disruptions (S. 24 to 26 in App. III).

Several tasks were found to be done with demand risks in mind. First of all, different disruptions were categorized based on the assessed impact on profitability and business KPIs such as customer satisfaction. Which improved prioritization when focusing on mitigating risks (S.27 and 38 in App. III). The customer demand was also forecasted using both human-made forecasts, but also using a forecast generated by ML. These two forecasts complemented each other and were used for long-term predictions and short-term predictions.

The choice of using one or the other, was based on their performance according to different KPI's (S. 30 to 33 and 35 in App. III). The forecast, both manual and statistical, was evaluated continuously using different KPIs and assessment methods to ensure that it accurately predicted demand. This also made it possible to highlight the risk of under-forecasting or over-forecasting. When the KPIs indicated over or under forecasting, it was then adjusted to better predict the demand and lower the demand risks (S. 36 in App. III). As aforementioned, the volatility of the demand increased during large unexpected events such as the COVID-19 pandemic and during such times, there was a shift in the otherwise stable process of managing demand risks and forecasting, namely the process and tasks changed to involve a greater number of partners and a perceived greater need for alignment due to the volatility (S. 29 and 34 in App. III). The tasks that were carried out in order to manage demand risks were found to have an impact on other processes and areas. This since the forecast served as a trigger for other functions such as distribution, production and sourcing. Hence, producing a good forecast serves not only as a way to mitigate demand risks such as overselling or underselling, but it also serves as the ground for investment decisions into production capacity, procured volumes as well as distribution (S. 24 to 26 in App III).

4.2.2 Supply Risk

Supply risks and disruptions were found to have the possibility to impact not only service levels but also costs and project deadlines. Many tasks aimed at ensuring that no disruptions resulted in poorer service levels (S. 43 to 45 App. III). The environment around supply risks was also described as increasingly complex due to harsher customer demands and a growing network of global suppliers, resulting in greater complexity and uncertainty (S. 37 and 41 App. III). Supply risks could also come from within the company. For example, inaccurate demand forecasting had resulted in several supply disruptions and faulty investments in capacity that were not needed (S. 40 and 42 App III). To manage supply risks several and different tasks were being carried out. One task involved performing root cause analysis on past disruptions with the aim of making the necessary changes. This task was described as a very much routine and occured on a daily basis and was conducted as part of a supply evaluation (S. 49 to 51 App. III). The countermeasures and their effects that had been put in place were also evaluated to improve further future risk mitigation actions (S. 56 App. III). Another task that was done to manage or mitigate supply risks was described as scorecarding. Scorecarding involved monitoring certain KPI's, that included supplier performance and internal performance. Natural disasters were also included in these scorecards, for example the risk of disruptions such as the Suez Canal block. However, due to the large amount of suppliers and manual work that were put into the scorecard process, it was only possible to include key suppliers (S. 61 to 64 App. III). Furthermore, it allowed them to enforce contractual obligations when the suppliers were not performing as per their agreement (S. 55 App. III). Tasks involving collaborating with other parts of the supply chain were also found, and focused on managing risk that no single department could solve. The S&OP process was an example of this, where issues and supply chain predictions were jointly created and agreed on (S. 59 and 60 App. III). Collaborative tasks were also taking place with the suppliers. For example, a yearly review aimed at evaluating supplier performance as well as negotiating about changing the logistics set-up to minimise risk through smaller MOQs and shorter lead-times, was one task that was performed. On a more frequent basis, the company also collected information from their suppliers, as to the suppliers outlook and risk assessment, to be better informed themselves. When necessary and evaluated, supply chains could also be redesigned to improve costs and lower risks. Often this was the case due to increased volume (S. 52 to 54 and 66 App. III).

Furthermore, on an annual basis a long term prediction on demand and supply was being made, aiming to assess the capacity and if there are any risks to the growth expectations in the coming 2-3 years (S. 57 and 58 in App. III). When a risk had not been managed enough and there was a disruption to the supply chain, the tasks and actions performed become more ad-hoc and focusing on what the best possible solution for the moment is (S. 65 in App. III). There were also challenges that the company and the individuals performing all of the tasks were confronted with. The challenges related mainly to data availability, which prevented more detailed analysis. Quality of data on long-term prediction was also an issue and required fixing (S. 46 to 48 App. III). Another challenge was also the high dependency on the demand forecasts being of a high quality, as it would otherwise risk portraying the wrong outlook to suppliers which would increase the risk of disruptions (S. 40 in App. III).

4.2.3 Process Risk

Process risks were found to be both predictable and unpredictable, depending on the type of situation and risk. Process risks that the case company was exposed to came in the form of accidents and sudden manufacturing breakdowns, regulations, limited manufacturing capacity as well as issues with components and raw materials. Furthermore, the results also showed that process risks in many cases were related due to issues with demand, most often being too high for the available production capacity (S. 1 to 8 in App. III).

The different risks required different types of tasks to be carried out. For more unpredictable disruptions, and risks, tasks became much more ad-hoc and collaborative. Examples of this could be ad-hoc decisions and analysis due to machine breakdowns causing the company to find alternative production lines. However, the ad-hoc solutions did follow business prioritizations. In the case of disruptions, there were also tasks that involved manually allocating goods and resources (S. 9 to 16 in App. III). When risks were predictable, the tasks became routine and structured. One example being manual monitoring that data was correct to avoid disruptions related to data management (S. 17 in App. III).

Tasks could also involve collaborating with customers. This was the case when trying to mitigate the impact of poor service levels. Customers were proactively informed of the situation and the potential impact. However it required there to be a reliable outlook. By informing customers proactively, some of the negative effects of poor service levels were removed. Another task also involved cancelling or moving marketing activities that increased sales temporarily when the risk of disruptions became too high (S. 18 to 21 in App. III).

4.2.4 Environmental Risk

Environmental risks, and the surrounding environment, were described as very complex and at times unpredictable as there are many factors impacting the risks and disruptions. Factors such as global economic trends, geopolitical events and regulatory changes can all cause disruptions to the supply chain. For example, the Russian invasion of Ukraine caused sudden disruptions such as driver shortages despite there being trucks standing in the parking lots (S. 87 and 89 to 90 App. III).

There were several tasks being performed to manage environmental risks. Haulers and suppliers were often reviewed and their performance evaluated using different KPI's. There was also a framework of partner standards that had been set up with the aim of ensuring that there were clear requirements on the company's supply chain partners from the beginning and that by having stable partners the risk would be reduced (S. 92 and 93 App. III). All the potential supply chain partners were also evaluated before signing any agreements. Another task that was being performed with the aim of ensuring back-up solutions was to analyse potential risks and how they could be solved if turned into disruptions. Diversification of supply chain partners to avoid over-reliance was also a task performed (S. 97 to 98 App. III). Furthermore, the transport modality was continually evaluated to ensure flexibility (S. 94 App. III). Some of these tasks and their outcome had an impact on other parts of the SC, resulting in collaboration becoming important when making larger decisions. As such the impacts of some tasks were predictable but for others, it was perceived as very difficult to understand the impact beforehand (S. 95 and 99 to 100 App. III).

One of the greatest challenges when handling environmental risks is ensuring the needed coverage before a disruption occurs. It is first when a disruption occurs that the result of previous assessment and mitigation strategies becomes clear. The difficulty is as such in predicting likelihood of risks and deciding the right actions in advance. Another challenging aspect is making assessments of alternative solutions. A case mentioned was a railway transport from Germany, where one transport provider was not fully transparent about having an intermodal solution. This first became evident when the disruption occurred. Many risks are difficult to predict like the COVID-19 pandemic and the invasion of Ukraine. These risks impact transport capacity and costs due to the imbalances caused in import and export flows, which ultimately makes this tremendously hard to work with (S. 86 to 88 and 94 App. III)

4.2.5 Information Risk

The results showed the importance of good data management and low information risks. Today there is a heavy reliance on IT that turns data management into either an enabler or an inhibitor for much of the company's business processes, not to mention SCM. The risk of improper data was described as defined and relatively predictable, much to the benefit of industry rules and guidelines that need to be complied by (S. 102 to 103 and 108 App III). However, when a disruption did occur it had consequences such as prohibiting the company from delivering the right product to the right location, loss of sales and worsened customer relationships (S. 105 to 107 App. III)

The predictability of data risks, allowed the tasks to be much more structured and of a routine nature (S. 119 to 123 App. III). However, it was found to exist conflicting interests as to how certain risks should be approached by the different stakeholders (S. 104 App. III). Looking at the tasks performed the aim was to ensure correct and updated data both internally and externally at different business partners. Where the latter is also a challenge and requires a lot of coordination, internal and external (S. 101, 102 and 109 in App. III). Since the case company was also operating in a regulated industry, there were several regulations and industry-standards in terms of data that needed to be maintained and kept, resulting in the task of keeping up to date with guidelines and rules (S. 113 to 114 in App. III). In order to ensure that the data was updated and correct, several tasks focused on measuring the performance as well as the number of errors that existed in the data (S. 115 to 116 App. III). For certain parts of data management, there were also preventative actions made in order to lower the risk of errors. For example the amount of data that had to be filled in was continually minimized and processes were automated to automatically populate the data without human intervention, and the risk of human error (S. 117 and 118 in App. III). Furthermore, there had been steps taken to educate other departments and key stakeholders about the importance of data management as it was felt at times to be down-prioritized (S. 112 App. III). Within data management there were several challenges in managing the risks and also impacting the risks themselves. One challenge came from internal stakeholders who did not always understand the impact of information risks and the trouble that they could cause. There was also a negative sentiment towards changing certain data from important stakeholders like customers, since it resulted in extra work on their side (S. 109 to 111 App. III).

4.2.6 Control Risk

The company had faced several control risks such as a lack of end-to-end planning, poor supply chain visibility and at times bullwhip effects. However these risks were perceived as relatively predictable, something that made it possible to proactively plan for them (S. 69 App. III). However, control risks were still complex, and at times difficult, due to the poor visibility, their dependence on other tasks and at times conflicting business goals (S. 67 and 70 to 71 App. III). Important in order to manage control risks, flexibility and visibility were seen as important as changes, especially short term, and volatility were closely linked to them (S. 66 App. III). Similar to other disruptions, those stemming from control risks had an impact on the ability to deliver to customers (S. 68 App. III).

The tasks that were performed to manage control risks could be described as very analytical. Often the action involved some type of analysis, at times by themselves but also in collaboration with other departments when greater visibility and information was needed (S. 72 to 73 and 78 App. III). Risk analysis and risk assessments are examples of the latter, where the aim was to understand the size of risk and the potential impact. S&OP was also a collaborative task carried out, and one where focus was on predicting future states and the outcomes that followed. Collaboration when performing tasks was described as a consequence of a greater information need, where the data was not accessible by a single SCRM practitioner. There were also tasks that involved analysing historical performance using KPIs such as service levels (S. 74 to 80 App. III). Almost all of these tasks showed a heavy reliance on data and information to improve the visibility and make better decisions (S. 81 App. III).

When conducting the tasks there were several challenges present. First of all, the success of the tasks and the effects of them are dependent on many other tasks and departments performing well on their side. For example, working with the wrong demand predictions makes for a much more difficult time in managing control risks. Furthermore, control risks were also seen as difficult to mitigate due to the large amount of coordination amongst different stakeholders that were required (S. 82 to 83 App. III).

4.3 Decision-making

Decision-making in SCRM was described as very dependent on the type of risk or disruption that the company was facing. For certain types of SCRM tasks, decisions needed to be made in collaboration with other departments, while other SCRM tasks and their related decisions could be made by the decision-maker alone. As can be seen in figure 8 the process of making SCRM decisions was found to be impacted by the environment and by the access to data, information and facts. Decisions that were based on data, information and facts were perceived as better compared with decisions that were not. The effects of decisions that were not based on data were also characterized by less certainty about the effects of the decision (S. 240 to 242 App. III).

Figure 8: Displaying that environment, data, information and facts have an impact on the decision-making towards the goal of high service levels, quality and efficiency.

4.3.1 Environment around SCRM

The results showed that the environment of SCRM was quickly evolving and that increased collaboration and greater focus on problem solving was important. Yet at the same time with the evolution towards a more complex and demanding supply chain, the tools and structures used had not evolved quickly enough with it, and that there was now a gap (S. 178 and 179 App. III). Furthermore, the environment in which decisions are made was characterised by uncertainty in many cases. This uncertainty was dependent on many different factors, from supplier performance, to legislation and regulations that impacted the way operations were carried out. Global- events and disruptions also made for a much more uncertain environment and made for less predictability of risks and effects of decision-making. At the same time, demands from supply chain partners and level complexity increased which also resulted in a greater number of factors that needed to be taken into consideration (S. 380 to 385 App. III). However some areas were still predictable. This was the case for decision-making for data management where the environment was still changing but where there were opportunities to keep updated and to more easily understand the effects of the decisions. Similarly, some risks such as seasonal demand fluctuations were also regarded as predictable (S. 186 to 187 App. III).

4.3.2 Decision-making in SCRM

When making decisions in SCRM the overarching aim is to ensure that service levels, both internal and external, remain high. However there were some factors that could impact that goal, for example customer satisfaction, costs and the overall feasibility of the decision-outcome. The only area that did not see service level as the overarching goal of their decisions was data management, which had effectiveness and quality as the two overarching goals when making decisions (S. 188 to 192 App. III).

When making decisions, the format and the process of decision-making was found to vary depending on the type of risk (S. 193 App. III). Certain decisions, when the outcome has an impact on several parts of the supply chain, are done in collaboration between SCM functions. Alignment is then sought in an attempt to ensure that the decision and its outcome is feasible and not harmful to other parts of the supply chain that are important (S. 194 and 196 App. III). By grounding the decisions with the stakeholders, it was possible to achieve greater “buy-in” and responsibility for the decisions being made (Support 198 in Appendix III). If other stakeholders disagreed with the proposals, the decision would be changed (S. 199 App III). However, it was also noted that decisions with a cross-departmental impact, and thus requiring more stakeholders to participate were more difficult to make, as similar to decisions with a lot of uncertainty. It was then not always clear who should be a part of the decisions. Vice versa, when the decisions only affect the single departments control, they are easier to make and the problems easier to solve (S. 200 and 201 App. III). Decisions that were aimed at managing or mitigating larger risks and events, such as the COVID-19 pandemic, were described as more difficult to solve and required the decisions to be made at a quick pace, often with the support from senior management. However, this quick pace often came at the cost of not having all of the information normally needed available (S. 202 and 203 App. III). Decisions could also be made alone but were then dependent on that the decision-maker had good predictability of the effects and a low level of complexity (S. 204 App. III).

When making the decisions, the decisions or proposals, in SCRM, the decision-making process was described as involving both data and human experience, where quality of the decisions were also aided by accessing facts and data. The human aspect covered previous experiences and the individuals knowledge about the area and its risks (S. 205 to 207 in App. III). Before a risk was managed, some preferred to first analyse the situation in order to then make an assessment and to make their decision based on that assessment. In order to do this, having reliable facts and data to analyse was important to feel confident in making the decision but also to understand the effects of the decision. When there was a lack of data or visibility in terms of SCRM, the decision-making got impaired (S. 208 to 214 App. III).

4.3.3 Data and Information

When making decisions there were several aspects that were perceived as impairing the decision-making. As aforementioned, the uncertainty of SCRM and the effects of decisions, made it more difficult to make a decision and prepare for risks (S. 215 and 216 App. III). Furthermore, the process of making decisions was also found to be lacking, where the decision needed to be made within too short of a time-frame (S. 217 App. III). Still, too many people were in some cases involved and needed to make decisions, which made for issues in terms of time to make decisions (S. 218 App. III). A lack of trust between the people involved, unclear mandates and not sufficiently distinguished areas of responsibilities also resulted in decision-making becoming more difficult (S. 219 and 220 App. III). The findings also showed that when the mandates and ownership is unclear, necessary information was often missing and no good decisions could be made (S. 221 App. III). Another inhibitor to decision-making was that it was at times difficult to get accurate information from all stakeholders, since it was not brought to the meeting (S. 222 App III).

Data and access to information was a factor that was described as important to decision-making, acting both as an enabler or an inhibitor when making decisions. By not having access to reliable information and data when faced with a decision, the effects became increasingly uncertain (S. 223 App. III). Access to data and information was also a challenge that many of the interviewees had when making decisions on how to manage the different risks and achieve their goals. Some of the information that they had was not seen as reliable enough and getting access to reliable data quickly enough was a challenge. When not having the necessary data, the decision-makers had to do the best with what they had (S. 224 to 225 App. III). Having access to reliable data and information, allowed the decision-makers to improve the decisions and the outcome of those (S. 226 App. III).

4.3.4 Perceived impact of AI on decision-making processes in SCRM

AI is perceived as a transformative tool in SCRM and its decision-making processes and presents both opportunities as well as challenges. There is a risk of over-reliance in AI which could lead to worse decisions. Another aspect that could lead to wrong decisions could be due to AI lacking the full data scope. However, AI also brings the advantage of identifying risks that might go unnoticed (S. 227 App. III). Continuing, AI is expected to help provide insights from historical data and also predict future trends (S. 231 App. III). By doing this, repetitive tasks can be automated which helps to free up human expertise for more high-quality decision-making (S. 233 App. III). Important to note is that AI is seen as a support tool that augments people rather than a replacement, which helps professionals make better decisions (S. 233 App. III). Furthermore, AI is perceived as helpful in the operational decision-making process. It could help to predict and manage peaks in demand, which then clarifies how many haulers to use in certain situations. AI can therefore transition businesses from being reactive to proactive in risk management (S. 228 in App. III). Many activities are also believed to be simplified with AI and some decisions could be outright removed with better predictability (S. 229 in App. III). Additionally, AI is described as having the potential to analyse large amounts of data more objectively and faster than a human being which can aid the predictability (S. 230 App. III). Besides this, AI is seen as having potential in scenario planning, where it can offer recommendations that help organizations optimize their supply chain and their decision-making process (S. 234 and 235 App. III). Also noted is that AI can reveal hidden interdependencies between datasets that a human could easily overlook, which also strengthens the decision-making. However, human involvement is still needed as the AI-recommendations need to be properly interpreted (S. 236 to 237 App. III). In addition to this AI is viewed as a potential assistant that could be integrated with existing tools to provide consultation and support decision-making (S. 238 App. III). Lastly, AI is probably going to help with visibility and transparency which will help to predict forecasts. This will in the end provide better material for the decision-making process (S. 239 App. III). As seen in Table 7, AI presents both opportunities and challenges. The overall perception from the findings is that AI is viewed as a powerful enabler in SCRM and its decision-making processes. However, the challenges presented in data quality and the need for human judgement must also be managed to ensure fulfillment of the opportunities.

Interviewee	Key points on AI's perceived impact on decision-making in SCRM
Anonymous 1	AI can improve risk identification but could lead to over-reliance and limited data scope, leading to worse decision-making.
Anonymous 2	AI can improve insights, predictions and automation. Augmenting professionals decision-making as a support tool rather than replacement.
Anonymous 3	AI can help to predict and manage peaks in demand. Enables proactive risk management, as well as simplifying activities and decision-making.
Anonymous 4	AI can analyse large datasets faster and more objectively than humans, improving the predictability.
Anonymous 5	AI can improve scenario planning by identifying interdependencies between datasets, optimizing supply chain and providing recommendations.
Anonymous 6	AI can function as an assistant, integrating with tools and offering consultation support for decision-making.
Anonymous 7	AI can improve visibility and transparency, enhancing forecasting for better decision-making.

Table 7: Summary of the perceived impact of AI on decision-making in SCM. Compiled by the authors.

It is not only the accuracy and value that is important but also the interpretability of the AI (S. 171 in App. III), so that the reasoning behind each decision in the AI model can be followed. An example mentioned are the trending reasoning models, which allows the user to follow the decision-making process (S. 176 and 177 in App. III). Another trending type of AI is autonomous AI agents, which actually have the ability to make decisions for humans (S. 161 App. III). Despite this, there are still concerns regarding the variability of decisions as AI models provide different answers depending on the framing of problems (S. 162 App. III). Another concern mentioned is the nondeterminism that AI agents sometimes bring, due to being stuck in an infinite loop of reevaluating options without reaching a final action (S. 243 App. III). It is evident that AI is good at solving problems with historical data (S. 135 and 141 App. III). But struggles when met by unprecedented situations, where humans probably have an advantage compared to AI (S. 150 App. III). Therefore, a balanced approach is needed to determine where AI adds value and where humans add value. This is however quite tricky as there is no clear boundary (S. 149 App. III). AI should help human decision-making by providing all information and options with pros and cons allowing humans to make the final decision (S. 160 App. III).

5. Analysis and Discussion

This chapter presents the analysis and discussion done by the authors before arriving at the conclusions. The analysis was done by analysing each part of the theoretical framework and the four phases of SCRM introduced in chapter 2, connecting the empirical findings with the theory and the literature review.

5.1 SCRM Tasks

The results showed that the six types of SCRM risks were managed using different tasks with varying goals. Some specific for each risk and some that aimed at managing several risks. Different tasks had different characteristics and purposes. Tasks such as supplier evaluation and hauler evaluation were performed in order to evaluate the company's current supply chain partners and to highlight those that misbehaved, which exposed the flow of products moving through the company's supply chain to risks. While tasks such as forecasting and S&OP aimed at predicting future customer demand and limited capacity situations. As pointed out by Yu and Yu (2010) there are several different types of tasks, which impacts the fit between task and technology. The results further strengthen this. The characteristics of SCRM tasks vary depending on the type of risk, process and aim of the task. This is important to consider since the task impacts the degree of fit through the level of complexity and non-routines, which can either make it easier or more difficult to fit the technology (Goodhue and Thompson, 1995; Zigurs and Buckland, 1998). Figure 8 shows the analysis of the different tasks that the company carried out in order to manage or mitigate risk using the four dimensions proposed by Zigurs and Buckland (1998) to evaluate the complexity of each task.

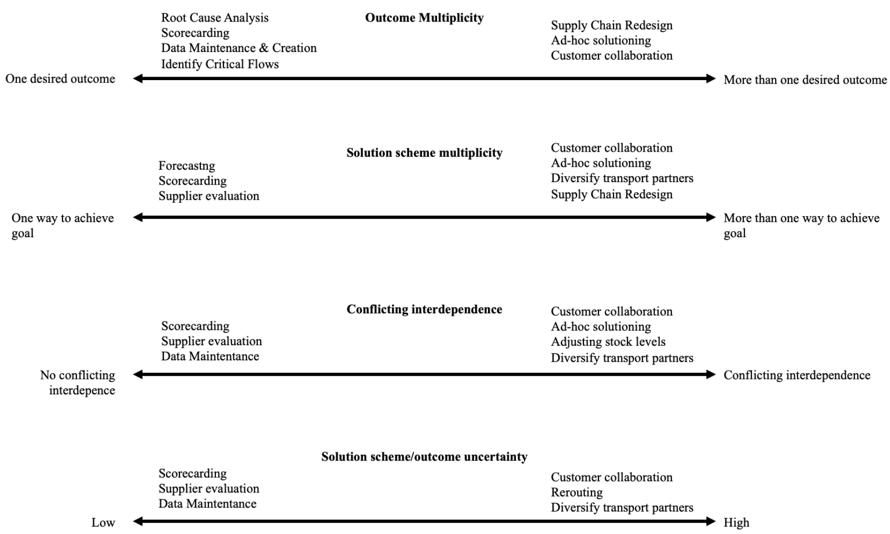

Figure 8: Excerpt from Appendix IV Table 1 - Analysis of complexity for each identified SCRM task.

It becomes clear that there is not a single way to define SCRM task characteristics. Tasks such as *root cause analysis* or *scorecarding* are performed with one desired outcome in mind, albeit that they are a part of a larger process. There is a clear and standardized logic that they follow and no conflicting interdependence. Furthermore, the outcome uncertainty of performing the tasks is low. Using Zigurs and Buckland (1998) parameters it can be said that they have a low level of complexity. In contrast, SCRM tasks such as *diversifying supply chain partners* could be done in more than one way, has conflicting interdependence since any changes to the existing transport partners will be difficult to revert to the same state they were before any decisions or tasks were done. The results also showed that it was difficult to know how changing transport partners would aid in managing or mitigating risks, until a disruption took place. Thus, indicating a higher level of solution scheme uncertainty and higher levels of complexity. The different SCRM tasks are categorized in Table 8. Displaying the different aims of the different task categories as well as their level of complexity, and showing the differences between the categories. The full analysis of task complexity is shown in Appendix IV: Table 1.

SCRM Task Categorization	SCRM Tasks	Complexity / Non-routine	Aim	SCRM Phase
Prediction Tasks	Demand forecasting Capacity planning Supply planning Risk analysis Risk Assessment S&OP	Higher levels of complexity	Predicting future states that impacts SC	Identification
Evaluatory Tasks	Supplier evaluation Hauler evaluation Countermeasure evaluation Scorecarding Critical transport flows Root Cause Analysis Forecast evaluation Risk Categorization Adjust stock levels	Lower levels of complexity.	Evaluate past and current SCM performance	Identification Assessment Mitigation Monitoring
Data tasks	Data maintenance Data creation	Low level of complexity	Manage and create data for SC	Mitigation
Disruption Management Tasks	Ad-hoc solutioning Rerouting Customer collaboration	High level of complexity	Managing disruptions already taking place	Mitigation
Change Tasks	Supply chain redesign Diversify transport partners	High level of complexity	Changing the supply chain set-up	Mitigation

Table 8: Displaying the categorization of SCRM tasks done by the authors.

Data tasks generally could be characterized by a low level of complexity, while prediction and disruption management tasks were characterized by a higher level of complexity. The six different types of SCRM risk are managed in more than six ways by several smaller tasks, while the overarching goal of them put together in an SCRM context is to ensure high service levels, as was noted from the interviews. Furthermore, these tasks spread across the four different phases of SCRM proposed by Deiva, Ganesh and Kalpana (2022). Demand forecasting or hauler evaluations could be imagined to give an indication of whether there is a high or low risk of disruptions and would then be included in the risk identification phase. While, supplier evaluations and diversifying transport partners are more closely connected to the risk mitigation phase. As such, there is not one way of defining or characterizing SCRM tasks, instead they have their own characteristics that are dependent on the task itself.

The environment which SCRM tasks are performed in, seem to differ due to the fact that the risks are either more predictable or unpredictable (van der Vorst and Beulens, 2002). For demand, supply, process and environmental risks the environment was perceived as more uncertain. Previous literature found that SCRM is characterized by uncertainty which also results in the tasks, and decisions, are performed with greater lack of information and visibility (Colocchia, Strozzi and Wilding, R. 2012; van der Vorst and Beulens, 2002).

5.2 AI Technology

The technology characteristics, or in this case the AI technology characteristics are as equal of a part as the SCRM characteristics in the fit. As Goodhue and Thompson (1995) put it, technology is seen in the context of a tool used by the individuals performing the task and if the technology is well aligned with the characteristics of the task it will have a positive effect on the fit. As was described in chapter 2, previous literature has pointed to several potential areas where AI as a technology can be applied. For example, fuzzy programming has been suggested to be suitable for identifying risks, evaluating suppliers and forecasting (Baryannis et al. 2019; Devia, Ganesh and Kalpana. 2022; Baghalzadeh Shishehgarkhaneh et al. 2024; Wu et al. 2010). The different types of AI are different also in terms of their characteristics. ML methods such as ANNs being composed of several linkages between nodes and neurons, and assigning weights to the neurons and adjusting them as it gets more and more information, can anticipate outcomes and events (Janiesch, Zshech and Henrick, 2021; Soori, Arezoo and Dastres, 2023). While decision-trees are characterised by the fact that they follow the outcome of pre-defined functions or events and as such are easy for a human observer to follow (Blockheel et al. 2023). The literature review shone light on the fact that the different types of AI, also have different strengths and weaknesses as seen in table 9.

AI Type	Characteristics	Strength	Weakness	SCRM Application	Sources
Machine Learning	Prediction or actions taken based on learnings from historical data sets, seeking to understand how different factors interact with each other	Range of methods Wide range of application Improving as times goes	Dependent on large amounts of quality data Stricter guidelines	Risk assessment, supplier selections, fleet management, forecasting,	Baryannis, G. et al. (2019); Baryannis G. et al. (2019b); Deiva Ganesh and Kalpana (2022); Baghalzadeh Shishehgarkhaneh. M et al. (2024); Meng, X. and An, N (2024)
Deep Learning	Machine learning developed further using neural networks that allow for more advanced operations, with the ability to learn itself	Able to carry out more advanced operations Relatively less strict guidelines	Large amount of training data required. Can also fail to generalize on unseen data. Complex and lack of transparency on output.	Risk identification, Forecasting, Supplier evaluation,	Talaei Khoei, T., Ould Slimane, H. and Kaabouch, N. (2023); Janiesch, C., Zschech, P. and Henrich, K. (2021); Hosseinnia Shavaki, F. and Ebrahimi Ghahnavieh, A. (2023);
Generative AI	Analyzing real examples and identifying patterns to understand the data. Can generate new content	Can generate new outcomes based on other data.	Large amount of data required Large investment and resource requirements Risk of bias	Forecasting, Inventory management, Sourcing assessment	Samuel Fosso Wamba et al., 2023; Richey, R.G. et al. (2023); Vinay Yandrapalli, (2023); Bandi, A., Adapa, P.V.S.R. and Kuchi, Y.E.V.P.K (2023)
Multi-Agent-Systems	Several computer systems grouped together, capable of autonomous actions to meet objectives	Can handle complex problems Could be applied proactively Can quickly adjust to changes	Slow computational times or high requirements for computational resources Requires monitoring	Supplier evaluation, inventory management	Nitsche, B. et al. (2023); Giannakis, M. and Louis, M. (2011); Nitsche, B. et al. (2023)
Fuzzy Programming	Mathematical programming approach to AI, allowing for decision-making with unknown variables.	Allow for greater flexibility Can manage uncertainty in data	Large amounts of data required Lack of transparency, difficult to understand Expertise needed	Inventory management, order management, risk identification, decision support	Baryannis, G. et al. (2019), Deiva Ganesh and Kalpana (2022); Wang, H., Xu, Z. and Pedryc (2017)

Table 9: AI types, characteristics, strengths, weaknesses and potential usage identified by previous literature.

The choice of technology, which in this case would be the choice of AI is important. As Goodhue and Thompson (1995) described, if the technology is aligned with the task and is reliable, there will be positive effects as for the compatibility between task and technology. Logically, the opposite could also be derived from that. If an AI model that is not compatible with the task is chosen, it will have a negative impact on the compatibility. AI types such as fuzzy programming, seem to have a greater tolerance for uncertainty and unknown variables, which allows for greater flexibility, while ML can predict or take action based on previous learnings and instructions. As a result, it could be said that different types of AI are differently suited for different tasks. This is made further complex depending on if you are applying AI to remove human judgement or act as a complement. As stated, AI can be utilized to generate insights from large datasets, which enables detection of hidden patterns that would be difficult for humans to identify (Helm et al., 2020). In the literature, AI also includes techniques that can mimic human behavior and therefore be able to even surpass human decision-making by solving complex tasks with minimal intervention (Janiesch, Zschech, & Henrich, 2021).

The abilities of AI models allows for new advantages in SCRM, but the effectiveness is much dependent on the availability of structured high-quality data. A concern linked with this is that AI lacks true understanding of the data it processes and can therefore misinterpret complex situations, which could lead to new risks (Mitchell, 2019). The success of AI decision-making is dependent on how well it can deliver clear, relevant and timely insight that aligns with human cognitive capabilities (Steyvers & Kumar, 2022). This means that human decision-makers play a crucial role in evaluating recommendations from AI, which leads us on to the interpretability of the various AI types being applied.

The findings from the interviews indicate that the interpretability of the different AI types decide to what degree the task and decision-making can be automated or augmented. For example, Fuzzy programming offers flexibility in handling uncertainty, however it lacks transparency and is difficult to understand (Baryannis et al., 2019; Baryannis et al. 2019b). This impacts the interpretability as expertise was described as necessary to fully understand the results. Comparatively, ML and decision trees are easy to understand as an observer as the transparent decision rules can be followed to see the reasoning behind each action (Blockeel, et al. 2023). Consequently, this positively impacts the interpretability, making it easier to understand the outputs. As a result, it seems that high requirements on interpretability is no insurmountable obstacle to AI adoption. The differences in AI models also illustrate the relationship between the AI type characteristics and the interpretability which decides the degree of human judgement needed.

Summarizing, the technology characteristics are dependent on whether AI should completely replace the SCRM practitioner or act as a complement. If the latter is the case, the goal should be to create a system where AI and humans work together to achieve improved SCRM performance (Cui and Yasseri, 2024). This is also underscored by the results which indicated that AI can help to automate repetitive tasks and free up human thinking for more high-quality decision-making. But human involvement is still needed as the recommendations from AI need to be interpreted. However, to what degree is then depending on the task at hand, the AI type, characteristics and interpretability.

5.3 SCRM and AI Fit

Earlier, the fit between task and AI was defined by the authors as *the fit between the type of AI and the degree to which it helps in managing the type of supply chain risk.* The fit between is important as the outcome of the task is dependent on the degree of fit (Furneaux et al. 2011) and it is a key factor in determining whether there will be added value from the technology and from the task (Howard and Rose, 2019). The technology should aim to aid in achieving greater efficiency and quality in the output from the task (Zigurs and Buckland, 1998). The fact that there are multiple characteristics of SCRM tasks indicates that for there to be a good fit, the AI model needs to be adjusted to the specific task characteristics. To illustrate, data management tasks that are characterised by a low level of complexity and clear routines will have different requirements compared to prediction tasks that are characterised by higher levels of complexity and a different aim.

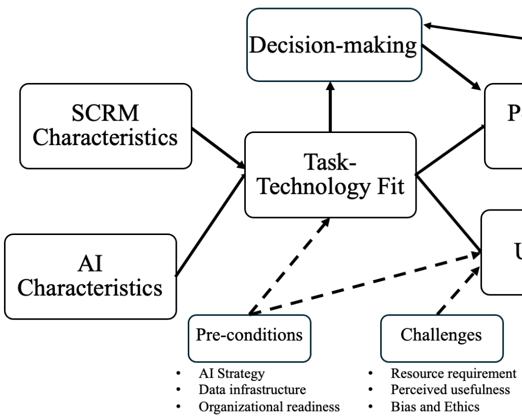

Figure 9. The theoretical framework with the, by the authors proposed, pre-conditions and challenges impacting the fit and the utilization.

Previous literature had divided SCRM into four phases, with different purposes (Deiva Ganesh and Kalpana. 2022). Reasonably each phase has its own tasks and characteristics, resulting in there being different requirements for what constitutes a good fit depending on the SCRM phase. Applying AI to SCRM would more reasonably involve applying AI to a specific SCRM phase. Risk identification focused on finding risks, which involves one set of task characteristics, while the risk mitigation phase of SCRM was focused on mitigating the effects of disruptions. As seen in table 8, this is further strengthened by the fact that the tasks carried out by the case company also have varying degrees of complexity associated with them. The framework in figure 9 illustrates the consequences connected to viewing SCRM as one task with one set of task characteristics.

5.3.1 SCRM - Risk Identification

The risk identification phase of SCRM involved identifying potential disruptions to the supply chain to allow for proactivity (Kleindorfer and Saad, (2005). Bandaly et al. (2012) pointed to different types of risks, each having their own characteristics and nature. For demand-, process-, control- and supply risks, the results showed that they were identified based on evaluated impact on service levels, internal as well as external.

Evaluatory- and *Prediction tasks* arguably play a role when it comes to risk identification. The task of forecasting demand was not only used to predict future customer demand, but it was also used in other SCRM tasks, such as capacity planning and supply planning. These tasks used the projected demand in order to analyse and plan SCM operations, but also to identify risks such as limited capacity. Prediction tasks were overall characterised by a higher level of complexity, where demand forecasting specifically was characterised by conflicting interdependence and outcome uncertainty (App. IV - Table 1). The case company had applied ML to generate a statistical forecast, which suggests that a good fit between SCRM task and AI can be achieved and is in line with what previous literature has suggested as a potential use for AI (Table 4). Furthermore, in the case of demand forecasting and if the AI does a better job, companies could identify more risk categories than just demand risks, since many other risk identification tasks were dependent on the demand forecast. Previous literature has also pointed to the fact that as long as there is enough data, AI's such as ML and DL has the ability to find patterns between different variables (Baryannis et al. 2019b; Panch, Szolovits, and Atun, 2018; Janiesch, Zschech and Henrich, 2021) which could be valuable when forecasting future customer demand or performing capacity planning and supply planning, as applying AI could lead to better insights and improved predictions.

Continuing with *evaluatory tasks,* which were also used to identify risks. Hauler evaluation, being an example of this, where future potential partners were evaluated before being accepted as haulers. Hauler evaluation had a low level of complexity as it followed a structured and routine analysis that was used for all potential haulers. Applying AI to such a task would require that the AI model is applicable for a task with a lower level of complexity, making it easier to achieve a good degree of fit. Provided that the organisation has the data infrastructure required, ML, DL and MAS all have been suggested to perform supplier evaluations (Table 9). Depending on how the organisation views the need for interpretability, decision-trees could also be applied due to the low level of complexity. The aforementioned AI types could improve the risk identification phase in the form of evaluating haulers also by identifying and learning what factors are more important, learning from the cases that went wrong and from the cases which did not cause any disruptions.

5.3.2 SCRM - Risk Assessment

The risk assessment phase of SCRM aimed at determining the potential impact of risks (Deiva Ganesh and Kalpana 2022). Bandalay et al. (2012) pointed to two important variables for this step, which was the likelihood of disruption and the potential impact on supply chain performance. The results showed that the company categorized risks, to some extent, by their impact on service level, financial results and which customers would be affected. This was carried out by the task of risk categorization, which was overall characterized as a task with relatively low complexity (Table 1 - App. IV). However, this task did not involve the first variable that Bandalay et al. (2012) pointed to. Previous research has established that there are many different techniques to assess risks (Choudhary et al. 2022). The results showed that the SCM environment had become more complex and unpredictable due to changing customer demands and more complex SC-networks, which is in line with previous literature (Blome and Schoenherr, 2011; Kumar Sharma and Sharma, 2015). This added complexity impacts the choice of AI technology to achieve a good level of fit. Fuzzy programming has been suggested as an AI that could manage greater unpredictability (Wu et al. 2010; Baryannis et al. 2019). Previous research had pointed to five characteristics of assessing risks which were uncertainty, hierarchy, propagation, expected impact and cause-effect relationships (Choudhary et al. 2022). AI types such as ML, DL, Generative AI can all learn how different factors interact with one another (Table 9). This could be used to find patterns and connections previously unknown to SCRM practitioners when assessing the risk using the two standardized variables of likelihood and impact. In line with what previous research stated, ML is an AI type that is well suited to find patterns through analysing and learning from large amounts of data (Men and An, 2024). Becoming better as it learns more about the association between variables in the data (Baryannis et al. 2019b; Panch, Szolovits and Atun, 2018).

However, AI does not necessarily have to be automating the whole risk assessment phase. It could be used to augment it as well, helping to assess impacts of risks. The results showed the task of risk categorization where using risks were categorized using standardized measures such as financial impact, customer importance and impact on customer satisfaction. Standardization and routines were described as aspects that make for easier data management and less task complexity (Sun and Medaglia, 2019; Goodhue and Thompson, 1995). Using standardized measures, applying AI would be less difficult. ML could be one tool that is used since it could then learn which measures to calculate and approach. Similarly Generative AI could be used to analyze historical examples and then when requested generate updated measurements for the SCRM practitioner to review.

5.3.3 SCRM - Risk Mitigation

The risk mitigating phase involved managing and reducing the impact that disruptions will have (Deiva Ganesh and Kalpana 2022). Several task categories with varying levels of complexity would be suitable for this SCRM phase. Starting with *data tasks* related to information risks such as data management there were industry rules and a logic that was to be followed. The *data tasks* that followed had a low level of complexity, where data was both managed and measured, as well as created when needed. Achieving a good degree of fit would in this case necessitate that the AI is suited for a lower level of complexity. Since the tasks followed guidelines, the SCRM practitioner could translate this into a logic from which ML types such as decision-trees could be applied to the task, both to automate and to augment (Blockeel et al. 2023). Tang (2020) found that by process standardization and multi-location sourcing risks could be applied in what the authors would argue is the risk mitigation phase of SCRM. By standardizing and automating tasks such as data management AI could help in mitigating risks.

Change tasks such as *supply chain redesign or diversifying transport partners* that aim to change the supply chain set-up would also fall within mitigation since they are done in order to improve the supply chain flow and lower the risk of disruptions. *Change tasks* and *Disruption management tasks* were characterised by a higher level of complexity (Table 8)

These tasks have a high level of complexity, disruption management tasks being similar in this regard.

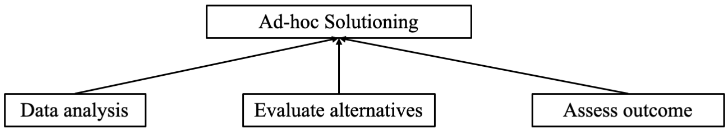

Figure 10: Figure illustrating complex tasks being broken down into smaller tasks.

However, it would be much more dependent on how AI is applied for these tasks and the requirements for a good fit would be different depending on this. Using *ad-hoc solutioning* as an example, the task itself was described as involving several smaller tasks that were less complex, such as analysing data, evaluating different alternatives and assess outcomes. This is illustrated in Figure 10. AI could be applied on these "subtasks" where the complexity is arguably lower. In this regard, previous literature has pointed to for example generative AI, DL and ML as options for evaluations (Table 4). However, despite becoming a more complex task and as such increasing the requirements to achieve a good degree of fit, AI could also be applied on tasks such as ad-hoc solutioning itself. MAS, where several agents break down complex problems into smaller problems (Nitsche et al. 2023) could potentially be an AI type that is suitable. MAS are able to handle complex problems and quickly adjust to changes which fits well with the task characteristics. The decision and outcomes of the assessment phase are important, since it was earlier established that an action that decreases one risk could also turn into a risk itself (Bandaly et al. 2012). These trade-offs were also found in the data surrounding ad-hoc solutioning with the added difficulty of poor visibility of the effects of the outcome. Hence if applying AI could generate better insight into those effects, the decision-making and the mitigation of risks could be improved further.

Some *evaluatory tasks* could also be connected to the risk mitigation phase. For example, critical transport flows was a task being done to mitigate the impact disruptions would have. Using different KPIs and metrics, critical transport flows were identified and haulers were being evaluated based on their performance. The different transport modes were evaluated for these critical flows. By identifying critical transport flows, the company was able to focus on adding resources to the place where they would make the greatest difference in case of disruptions. As can be seen in Appendix IV: Table 1, the complexity of evaluatory tasks often have lower levels of complexity, making them easier to apply AI to. As aforementioned AI models such as ML, DL and MAS have all been suggested as having the right capabilities to perform evaluations and since the critical transport flows were identifiable based on KPIs, AI could be applied to follow these KPIs to identify and then evaluate the different transport flows. Since AI could enable for a greater number of potential partners to be evaluated, it could be argued that AI allowed for improved visibility, which Diabat, Govindan and Panicker (2012) found improving the process of mitigating risks.

5.3.4 SCRM - Risk Monitoring

The risk monitoring phase involved monitoring risks and checking how well risk mitigation strategies were working (Deiva Ganesh and Kalpana 2022). Previous literature proposed several methods to do this. Examples range from using IoT to monitoring KPIs and checking how the supply chain is doing (Zhang et al., 2011; Tsang et al., 2018). From the results, it seems that mainly *evaluatory tasks*, as per the authors definitions, are prevalent in this phase. In general, evaluatory tasks were found to have a lower degree of complexity which would make applying AI, generally easier compared to tasks with greater levels of complexity.

Countermeasure evaluation was one evaluatory task being done that aimed at understanding how well previous actions had impacted risks. This task was analysed to have a low level of complexity (Appendix IV: Table 1). The aforementioned tasks of scorecarding and supplier evaluation could also be applied to the risk monitoring phase since they involved monitoring certain KPIs that followed performance and risk of natural disaster, as well as focusing on how well the suppliers and the supply chain was performing. For these two tasks, achieving a good fit with AI would be possible. Scorecarding followed, as aforementioned, specific KPIs that had been selected and supplier evaluation was also described as following a structure that allowed for yearly supplier reviews. A challenge for both tasks was that they were too time consuming to perform for all suppliers on a more regular basis. Applying AI to present and calculate the scorecards was mentioned earlier, and could be done in this phase as well. This would arguably allow for greater predictability in the supply chain, which is an important aspect of the risk monitoring phase (Tummala and Schoenherr, 2011). Furthermore, AI types such as MAS and DL had been proposed by earlier literature as fitting to perform tasks such as supplier evaluation (Table 9). By being able to handle more data and analyze a wider scope, which was described as an inhibitor by some interviewees, applying AI could improve the overall risk monitoring phase. This is in line with what previous literature has suggested, that by enabling larger amounts of data more intelligent insights could be generated (Zekhnini et al. 2020).

5.3.5 Pre-conditions and challenges that impact fit and utilization

With AI in mind, the authors identified several pre-conditions that have an impact on the fit between SCRM task and technology, as shown in figure 9. The results showed that the case company had realised many of the challenges and complexities of implementing AI, necessitating an *AI strategy* to guide AI adoption. Through the AI strategy, the company could ensure that AI is utilized to add immediate and long-term value, and avoid falling into the risk of adopting new technologies for its own sake. This result is in line with what Enholm et al. (2022) proposed, that by developing an AI strategy the company will be able to align AI usage with their strategic goals and KPIs. Having an AI strategy could act as a determinant of the fit, since it would describe how the AI is going to be used.

Another pre-condition that the authors found was *data infrastructure.* As had been noted by the company and previous literature, the quality of AI output is dependent on the amount and the quality of the data. This also means that a company interested in AI needs to have ways to produce data, manage data and store data for the AI to train and learn. Data and the access to data was an important factor in the original TTF-theory (Goodhue and Thompson, 1995) and AI seems to be no different where data and the access by the model to it acts as either an inhibitor or enabler to apply AI (Sun and Medaglia, 2019; Riad, Naimi and Okar, 2024). The case company had noticed this and had launched data management initiatives to better prepare for AI. Despite the AI type being a good fit to the SCRM task characteristics, if there is not enough accessible and quality data the output of the AI will be lacking (Samuel Fosso Wamba et al., 2023; Sun and Medaglia, 2019). As Richey et al., (2023) pointed to, data is an integral part of AI. A majority of the AI types require there to be a sufficiently large amount of data, of good quality and preferably in a standardised format (Samuel Fosso Wamba et al., 2023; Sun and Medaglia, 2019). Furthermore, as Enholm et al. (2022) pointed to, the infrastructure in the form of computing power and storage also needs to exist in some form for the AI to be applied in SCRM.

A third pre-condition identified is *organizational readiness*. It was noted that there were mixed feelings about AI being implemented in SCRM. The results also showed that the perception amongst SCRM practitioners was that AI will change the roles and responsibilities amongst employees, which warranted the need for change management. This is in line with what Shrivastav (2022) and Hangl, Behrens and Krause (2022) proposed, that any company applying AI into SCRM also needs to ensure that the organization is ready for it. Enholm et al. (2022) used organizational readiness as a term to refer to human, technical and financial resources available for implementing AI, which the authors would also argue applies here and is in line with the results. If there is no willingness from the practitioners to apply AI in SCRM, then that could have a negative impact on the utilization.

Using the definition of utilization by Goodhue and Thompson (1995), since the AI is dependent on there being data, and the organization is dependent on being ready themselves for AI, the ability to utilise the AI becomes dependent on the pre-conditions. As stated earlier, despite the fit between SCRM task and AI type being good, it does not mean that the AI will make much use if there is no data for the model to train on and apply its algorithm on.

The overarching goal of SCRM was to identify, manage and lower the risk exposure in the supply chain (Gurtu and Johny, 2021) which would allow for less uncertainty and vulnerability (Chowdhury and Quaddus, 2016). Where a requirement for this was a satisfactory level of visibility in the supply chain (Nooraie and Mellat Parast, 2020). The results were in line with this, but went further in showing that it was becoming increasingly difficult. AI, being described as a source of greater visibility by allowing the company to increase efficiency and productivity, find previously unknown dependencies, and offer greater insight (Meng and An, 2024; Chang, El-Rayes and Shi, 2022) aligns well in theory with the purpose and goal of SCRM.

Beyond these pre-conditions, the authors found several general challenges that can impact AI utilization. A common theme mentioned both in the interviews and in the literature was the importance of understanding the challenges to fully understand the potential benefits of AI implementation (Richey et al. 2023), both for implementing AI and its utilisation in SCRM. Something that was mentioned was the large amounts of resources and costs needed to keep up with the quickly evolving landscape of AI. This had also been identified by previous literature and recognised as a challenge (Sun and Medaglia, 2019). Another significant challenge is the issues of ethics and bias. The interviewed SCRM practitioners pointed to concerns such as the risk of biased AI outputs and questions of intellectual property. These concerns are consistent with those mentioned by Dogru and Keskin (2020), who warn that without oversight, AI can lead to harmful bias. Closely linked with this is regulations and compliance, which the results show that organizations are facing in the form of the European Union AI act. All of these challenges can limit the utilization of AI, even if the technical fit and data availability is there. Looking at this, it is evident that AI adoption is not just a technical challenge. Instead, it is a transformation that also requires strategic, ethical and regulatory considerations. Therefore these more general challenges can directly impact whether AI can be utilized to its full potential or whether the AI adoption is constrained despite a seemingly good fit. Organizations must therefore approach AI with an understanding of its challenges to ensure that the potential benefits are reached and utilized in a responsible manner.

The goal of SCRM was earlier described as to identify, manage and lower the risk exposure to a company's supply chain, which Chopra and Sodhi (2004) pointed out can be done in several different ways. Previous literature has proposed several different SCRM areas where AI could be applied in SCRM, performing forecasting, SC-partner evaluations and selections and inventory management (Table 4). But as Baryannis et al. (2019) pointed out, the successful application is dependent on that both the data is there and the model is suited for the task that it is going to perform. In order for AI to be applied in SCRM, the company or organization trying to implement AI needs to ensure that the pre-conditions are met and that the AI can manage the SCRM task characteristics. The company would also improve the challenges in ensuring that they are able to overcome the identified challenges, which otherwise risk impacting the utilization and as a result the performance impacts. In the case that the fit between SCRM task and AI, the goal of managing and lowering risk exposure will not be aided by the AI. As Goodhue and Thompson (1995), the performance impact and utilization is dependent on the technology-task fit. A good fit results in a positive impact and a poor fit results in a negative impact. The results also showed that SCRM risks are interlinked. This would mean that by applying AI successfully it is possible to achieve positive benefits for several areas.

5.4 Decision-making in SCRM

The results showed that when making SCRM decisions, the decision-making was both collaborative and individual depending on the type of decision and risk that the decision aimed at managing. Furthermore, the environment in which decisions were made was described as an environment changing rapidly and uncertainty. The uncertainty and unpredictability stemmed from different factors such an increasingly complex supply chain, regulations and global political events. These findings correspond well with how previous literature have described SCRM decision-making, as characteristically uncertain and complex, resulting in a bigger challenge when it comes to making decisions and lost efficiency (Colocchia, Strozzi and Wilding, 2012; Bode and Wagner, 2015). The results showed that the SCRM practitioners perceived themselves to be heavily reliant on their access to data and information. In order to make decisions related to SCRM many decision-makers relied on their access to data and information. The access had the potential to act either as an inhibitor or enabler. Having access to data and information improved the ability to make decisions and the perceived quality of those decisions through reduced uncertainty and better assurance of the effects of the decisions. However, the results also pointed to finding and accessing reliable data in time to make the decision, leaving decision-makers in a less than optimal position.

5.4.1 AI Impact on decision-making

AI could as such have a very positive impact on SCRM decision-making. As Sharma et al. (2022) and Ma and Chang (2024) proposed, by utilizing AI decision-makers can gain improved visibility and access to a larger amount of information much quicker, which was also the perception amongst the SCRM practitioners and decision-makers. However, there are still risks and challenges. As was noted in the results, there is a fear of receiving the wrong conclusions or information from the results, and that while AI could be helpful there is a fear of becoming overly reliant on AI with the risk of it producing false positives. This is in line with one limitation of AI in decision-making brought up by Kim et al. (2025) where the amount of data and data quality is lacking, would risk generating the wrong information and make wrong conclusions that could have a negative impact on the decisions that are being made in the organisation.

AI will not universally add value to decision-making as Tejeda et al. (2022) pointed to, instead being dependent on how well the choice of AI type and model fits with the task and the organizational readiness for AI to aid decision-makers (Steyvers and Kumar, 2022; Kaggwa et al. 2024). Being dependent on both the AI characteristics and the task characteristics, it could be argued that the positive or negative impact that AI will have on decision-making is directly linked with the technology-task fit. A poor fit where an AI type and model would not be suited for SCRM or producing information for decision-makers would have a higher risk of making the wrong conclusions or not providing enough information to the decision-maker. Whereas a good fit, would make for improved information access to the decision-maker. The fit is also impacting the utilization as described by Goodhue and Thompson (1995), which as shown in figure 9 is itself impacting the decision-making. If utilization of the AI is hindered or made increasingly difficult, determined partly by the fit, the decision-maker would not be able to enjoy the benefits that

AI could bring. The uncertainty and complexity in SCRM decision-making was found to vary, suggesting that different AI types are differently suited for the task, which would impact the utilization through the fit. If the fit is poor, utilization is likely to suffer resulting in a situation where the decision-maker does not have access to the insights and information provided by the AI.

Human decision-making could both be found in SCRM tasks and be considered as an SCRM-task in itself. As was shown in the results, SCRM practitioners performed scorecarding, supplier- and forecast evaluations using standardized KPIs as information in order to make SCRM-related decisions. Some of which took a considerable amount of time and resources. It could be argued that an AI that can quickly calculate these KPIs would improve the decision-making process conducted by a human. Such a scenario would generate one specific set of task characteristics for the AI, while if the AI was entrusted to perform the entire supplier or forecasting evaluation and make decisions on its own it would require a different set of task characteristics. However, as noted by the findings AI should be seen as a support tool that augments professionals in their decision-making, rather than acting as a replacement for the decision-making. In the end, human oversight is always going to be needed as someone has to interpret the outputs generated by the AI.
Pointed to by Miller and Lee (2001) well-motivated and well-informed decisions make for improved decision making, but it requires good visibility and efficiency (Moshood, Rotimi and Shahzad, 2025). The decision-maker needs to understand the information and what it is based on, which can prove to be a challenge for AI's such as fuzzy programming, DL and generative AI that have been characterized as lacking transparency and understanding (Table 9). For decisions where the AI is completely entrusted with the task of making decisions, the requirement of transparency and ease of understanding, could be argued to not be a requirement. However, with the risk of bias or making the wrong decisions, the SCRM practitioners would need to be able to manage the risk of the AI making the decisions. As had been noted by Baryannis, Dani and Antoniou (2019) AI's such as decision-trees could be applied in SCRM scenarios where transparency and interpretability requirements of AI reasoning are high, further strengthening the importance of a good fit profile between AI and SCRM task and the impact that it has on decision-making.

6. Conclusion

This thesis delves into AI applicability with regards to SCRM and how its utilization could impact decision-making within SCRM. This is done by integrating previous literature on AI and SCRM with a theoretical framework that was based on Technology-Task Fit theory, as well as data from a case company. The thesis explored AI and its potential application and effects on SCRM and decision-making, finding several pre-conditions and challenges that had an impact on the applicability as well as the possible benefits that AI could bring.

The thesis had two research questions that it aimed to answer. The first being *"How can AI be applied in supply chain risk management and what impacts its utilization?".* This research question aimed at filling the research gap of exploring how AI can be applied in an SCRM context that Toorajipour et al. (2021) mentioned. The results show that AI can be applied to several SCRM tasks in all phases of SCRM as defined by Deiva Ganesh and Kalpana (2022). AI could be applied to what the authors categorized as prediction tasks, evaluatory tasks, data tasks, disruption management tasks and change tasks. However, when applying AI, it is important to take into consideration the complexity of the tasks and choose an AI type that has a good fit to the task. The degree of fit is important in determining if applying AI will have a positive or negative outcome. Furthermore, the success of applying and utilizing AI is also dependent on pre-conditions that the authors identified as *AI strategy, data infrastructure* and *organizational readiness.* While the fit between AI model and task could be good, the performance impact of applying and utilizing AI in SCRM will be sub-optimal. The authors also found that there were several challenges that had an impact on the utilization, which needs to be taken into consideration in order to fully leverage the benefits that AI can offer.

The second research question was *"How does AI's utilization impact supply chain risk management decision-making?".* The findings reveal that the utilization of AI has a notable impact and effect on the decision-making environment in SCRM. By utilizing AI, decision-makers could enjoy benefits such as improved visibility, response times and access to larger amounts of information. With growing complexity and data access being perceived as issues to SCRM practitioners, this could result in higher quality insights being available to decision-makers. However, the effectiveness depends on the type of AI and how well it fits the specific task. A poor fit increases the risk of inaccurate conclusions, while a good fit improves the insight gained from AI and supports better decisions. Whether the decision-making should be automated or supported is dependent on the requirements of interpretability of the AI. Ultimately, it should be viewed as a support tool to assist rather than replace human decision-makers, as human oversight remains essential to interpret the outputs of AI.

6.1 Theoretical and practical contributions

This thesis contributes both to academia and business practice by expanding on the application of TTF theory in the context of AI and SCRM. By integrating established theory with empirical findings, this thesis provides a framework that guides how specific AI types can be applied on certain SCRM tasks and how its utilization impacts the decision-making process. Additionally, the existing TTF theory is also extended by illustrating that the fit alone is not sufficient for success, as there are several pre-conditions and challenges that have to be managed to fully utilize AI in SCRM. Furthermore, the gap in qualitative AI-SCRM literature is addressed. Having a qualitative research approach proved to be valuable as it furthered greater understanding of the relationship between AI and SCRM, as well as its impact in decision-making.

There are also practical contributions made by the thesis. The conclusions from the authors underscore the importance of achieving a good fit between SCRM task characteristics and AI type. Furthermore, practitioners interested in applying AI to SCRM should not view SCRM as a single set of characteristics. Practitioners should instead look at each phase of SCRM and the different tasks associated with said phase to determine the requirements of a good fit. The conclusions and results from this thesis show that AI can be applied in SCRM in numerous ways and that there certainly are benefits that can be achieved from it. However this is dependent on the fit as well as the pre-conditions and challenges that the authors identified.

6.2 Limitations and suggestions for future research

The authors acknowledge that there are some limitations to the results of the thesis that have the potential to impact its findings. First of all the thesis is limited to exploring the applicability of the specific types of AI in ML, DL, generative AI, MAS and fuzzy programming. There exists several other types of AI that could have added further depth and width to the conclusions made by the authors.

Secondly, with regards to sample size and case company. While the authors argued that using a case company allowed for more depth and access to data which filled a gap in the research on AI and SCRM, using a case company and qualitative approach does limit the amount of interviewees. As a result, there could be data that would have been interesting considering the two research questions. However, the authors did continue until they perceived data saturation to answer the two research questions and with the research design in mind, the data collected was enough.

The conclusions and limitations of the study results in several potential avenues that future research could take, and which the authors would suggest:

- *Longitudinal studies;* Given the rapid evolution of AI, longitudinal studies are also recommended to track how the application of AI develops in SCRM over a longer time and how organizations adapt to this. Furthermore, as AI gets more widely adopted the amount of data will likely increase which makes this area interesting to research further in the future.
- *Quantitative research;* This thesis has expanded on technology-task fit theory and quantitative research presents an exciting opportunity to build on the contributions of this thesis. Quantitative research approaches often allow for greater sample sizes and could be used to validate the findings that the authors managed to make with the in-depth qualitative data.
- *Comparative analysis:* Future research could therefore address these limitations by including multiple companies from different industries to provide broader insights. This would also allow the assumptions and findings from this study to be further validated and strengthen the generalizability of the findings.
- *Extending the AI methods:* Another suggestion would be to explore the application of a wider range of AI types beyond those covered in this study. Different AI types have evidently different characteristics, which could open up for more ways to apply AI to SCRM.

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8. Appendix

Appendix I: Interview Themes - Risk Interviews

<u>Formal Questions</u>

Q: Are we, the authors of the thesis, allowed to record and later on transcribe this interview?
Q: Do you wish to be anonymous in the thesis?

<u>Introductory Questions</u>

Q: Can you describe your role at [Company Name]?
Q: Can you briefly describe your role within supply chain management?
Q: What is your experience with Supply chain risk management?
Q: What do you think is the future role of AI in SCRM?

<u>Task Characteristics</u>

Q: Could you describe today how you are working and managing risks that relate to [Risk Category][Examples of risk category risks]?
Q: What are the main challenges in managing the risks?
Q: How do you know that it is a risk?
Q: Depending on the risk, what would a successful outcome be according to you?
Q: Is the successful outcome the same as the goal or are they different?
Q: How are you working to reach that goal or outcome?
Q: How do the activities you perform affect other processes?
Q: Are you certain about the effects of your activities when you perform them?

Q: Do you use AI today in any way?
Q: When performing risk management related activities do you always do them the same way or what type of factors impact the way you perform the activity?
Q: What type of technology do you use today?
Q: Do you think that the technology you use is sufficient or is it lacking in some aspect?
Q: What makes a technology good do you think?

Q: How do you make any decisions related to activities that are done to manage risks?
Q: Are the problems you face easy or are they difficult?
Q: What makes the problems you face easy or difficult?
Q: How would you characterise the environment of demand management and its risks?
Q: What do you feel that you need before you make a risk related decision?
Q: What are you aiming to achieve with the decision? Is there just one aim or several?
Q: Do you feel that you are lacking anything to make decisions today?

Q: What is your view of AI usage in supply chain management in the future?
Q: We are beginning to wrap-up, but do you have any final comments that you would like to make?

Appendix II: Interview Theme - AI Interview

Formal Questions:

Q: Are we, the authors of the thesis, allowed to record and later on transcribe this interview?
Q: Do you wish to be anonymous in the thesis?

General Questions:
Q: Can you describe your role at [Company Name]?

Questions regarding AI applicability factors
Q: How do you view AI?
Q: Could you describe the culture at [Company Name]?
Q: How would you describe the sentiment towards innovation?
Q: Do you think there is an interest in AI amongst top management?
Q: Do you think your organisation is ready for AI?
Q: What would the reaction be to AI being implemented?
Q: In terms of organisational readiness, do you think there is an adequate amount of resources to implement AI?
Q: Do you see any negative impacts of AI?
Q: Do you feel any pressure to implement and start using AI?
Q: Do you see that your company is committed long-term to AI?

AI applicability in SCRM:
Q: Have you implemented any AI solutions?
Q: What do you think are the biggest obstacles to AI adoption?
Q: In what ways do you think AI can improve SCRM?

Decision-making and AI
Q: In your experience, how do you believe AI can influence the decision-making process in SCRM?
Q: What do you believe are the pros and cons of applying AI into decision-making processes within SCRM?

Appendix III: Data Analysis Framework: First order, second order, third order and aggregated themes

Aggregated Dimensions, Second Order, *First Order,* Support	
SCRM Characteristics	
Process Risk	
Predictable	Support 1: I would say if it's. It is kind of predictable. So if you look, we didn't talk about yet, but if you look about distribution transport, so we know when the peaks will come. So we prepare for that. So that's also more like a standard process that every before Christmas, six weeks before Christmas six weeks before Easter, we know that we have peaks in transport, so we need to secure extra capacity or if we know

	that there is a promotion, we need to secure extra transport capacity. So I think there is quite quite OK predictability and also quite standard way of working if we talk about. **** <u>Support 2:</u> Where we have supply and demand outlook for the coming at least 12 months, but most time, of course two years or something. So I think, yeah, we we are. That is something you could predict. When do we expect to have a shortage in capacity.
Limited capacity situations	<u>Support 3:</u> Yeah. So if you talk about limited capacity situations, we have unfortunately experienced that quite a lot recently or at least last year and also this year.
Unpredictable	<u>Support 4:</u> Yeah, if a recall is necessary, if there is a quality thing that is that that is not something you can predict, this is something that just happens. Totally unexpected *** <u>Support 5:</u> But if we talk about quality problems, breakdown in the line, those kinds of things that of course you can't plan for except that you do pre maintenance or what is it, the preventive maintenance and you have spare Parts.
Components and raw material impacting production poses a process risk	<u>Support 6:</u> But you have your restrictions, so simple things like if if the problem is in the [product category], then you have to width of the mother reel which can't come from every factory. So there's a restriction.
Demand issues linked with and impacting process risk	<u>Support 7:</u> And and then of course the baseline demands. Yeah, that is difficult to influence, but it could be that we choose to say OK, to maximise our production outcome we decide to stop with a a few articles so that we have less different articles to produce and use the production. Yeah. To the Max, let's say so.
Accidents or breakdowns	<u>Support 8:</u> Ehhm If you talk about processes, it's OK when you have risk like a fire, which we had last year but also in the warehouse or in the factory.
<u>Process Risk Task</u>	
Non-routine	<u>Support 9:</u> So it's not that we have on paper immediately, a process that says OK if there is a fire in [Manufacturing Site], we will then next time get it produced from from [Manufacturing Site] or something. It always needs to be seen at that moment, so that is what we see often that is ad-hoc management. *** <u>Support 10:</u> When there is an capacity issue, then we see that we will get crisis teams. So we set up meetings, daily meetings. Weekly meetings to set up a crisis team and and that they deal with with the issue because like I said, it's those. There's never. That's maybe not correct, but it's difficult to find a standard way of working. The process probably is finding out where alternative capacity. What do we need to say to the customer? Everything but it's very. Yeah, specific at that moment, I would say, yeah.
Ad-hoc solutioning	<u>Support 11:</u> So if the first you need to find out what products can we still deliver, can another production facility produce those products. If so, then we need to set up all the lanes and say OK, if we normally get delivered from Finland to Sweden, can we maybe get it then delivered from our factory in France or in Belgium or whatsoever? This is definitely let's say it's ad hoc management. So it's not that we have on paper immediately, a process that says OK if there is a fire in [Factory Name], we will then next time get it produced from from [Factory Name 2] or something. *** <u>Support 12:</u> So practically, that means that we create an overview together with the factories. *** <u>Support 13:</u> So the first thing is try to to map where will be the issues, then OK what is the impact on our customers and how can we reduce that impact. And reducing the impact is of course want to see if we can have alternative supply alternative products that we can do short term. If we can cancel promotions or delay or postpone the promotions.

Dividing stocks amongst markets	Support 15: What we do is also using tools for that, so put things on allocation as we call it, so that we really because otherwise you need to manage it all manual. What we try to do now to do is to use tools in our systems that say, OK you can only send this amount to this customer, so that we are in control of what we're sending out. So this is what we're using.
Limited capacity situations - finding out potential impact	Support 16: So what we're doing then is of course within the organization is finding out. Some kind of outlook to get some kind of supply outlook. So when and where do we expect the issue?
Data monitoring	Support 17: Ehm if you talk about Master Data and everything you said that was about risk management and that one Yeah, I think that is more that if that's why you're aiming for. But that's more in the processes. So how do you steer that you have the right data within your total supply chain? I think we have processes that have what we call the four eyes principle or or checking in different stages. So somebody's the requester. Somebody is in the in the system and somebody's checking if that has been done correctly. So I think those processes most of the time are quite well arranged and it is not, this is not an ad-hoc procedure, but this is a standard procedure. So those kind of things are standard procedure to make sure that no mistakes are made and that the information is correct.
Customer collaboration	Support 18: In which months we receive, we expect to have an a shortage in which product areas and with that information we try to steer at least our customer demand. Which we have of course not fully in control, but at least the promotions which we agree upon with customers, those we try to limit or try to re-plan. So that is one of the first things we do. *** Support 19: And so if you talk about what to do when there is an issue, then it's all about proactively informing and giving them as openly as possible information. *** Support 20: So the first thing is try to to map where will be the issues, then OK what is the impact on our customers and how can we reduce that impact. And reducing the impact is of course want to see if we can have alternative supply alternative products that we can do short term. If we can cancel promotions or delay or postpone the promotions. *** Support 21: Yeah, cancelling promotions, prioritization within customers is also very sensitive topic
Demand Risk	
certainty	Support 22: Yes I could say so, I am pretty high on that. I feel more secure at what I need to do in order to get the expected result or outcome. Both when it comes to out of stocks or if we are over forecasting. In both cases. *** Support 23: Yes, we are a bit spared with our flows because we have products that are needed everyday and will most likely always be needed. Except when there are no more babies born, then we will not need to sell [product name] but [product name 2] is something that will always be needed. So if you say that the demand is always pretty stable. Pretty expected.
Demand serves as a trigger for the entire supply chain	Support 24: Ehm, it affects other processes to a high degree, and if I could say something negative about AI, if you say so, forecast and demand affects and triggers the entire supply chain. The forecast is the trigger, from master data to production to replenishment to warehousing to transport, until it ends up being delivered to the customer. It all starts with the forecast, so I see that it is vital to have in place. *** Support 25: So taking a CapEx decision is is a risky one based because it's based on demand and how reliable is that demand? So that is a big thing I would say. And that's the same with investment in warehousing and everything. If you say we need more space because we are having a very increased demand, yeah, how secure are we about that demand?
wrong forecasting causing leftovers or lower service level	Support 26: The experience is that the greatest risk management within demand management is if we have a forecast that is too high or too low because you have an inherent risk that we will not be able to supply the customers or that we have too much in leftovers that turns into a cost for the company to decrease.

Demand Risk Task	
Classifying risks	Support 27: We need to define all the risk depending on what the effect is on profits and customer satisfaction. So a product that we sell larger volumes of, a golden customer if you say so, is a greater risk if we don’t have our demand or forecast as correct as possible. So ehm, this is evaluated using several different classifications *** Support 28: How do I know if it is a risk, well that is through my experience in working with logistics of course. I know our business drivers, I know what classification both from what our customers and our portfolio and I know where to focus in order to minimize the risk that something goes wrong. While the tails, gets lets attention so to say. So that is a classification in my mind.
COVID-19 required more departments to be aligned	Support 29: For us it meant that we had to rearrange and with that I am saying that we had to make quick decisions at a high management level and that we really had to cut the tails, cut our product portfolio in order to maximise capacity in production in very short time and really just push it out.
Forecasting	Support 30: The challenge with managing risk is that we use and we have a forecast, a statistical forecast and for that we use machine learning *** Support 31: long term it could be used even more so ehh that it will predict ups and downs in our demand in order for us to become more efficient, save costs and be more effective. So that is the way I see it connected to demand. We are not there yet, but we are on our way. *** Support 32: This partly because we need to cover in case anyone quits but also because we see cases where it does a better job predicting our forecast than what we do ourselves, in those cases we should use that forecast instead. *** Support 33: Of course if an employee disappears or quits we have secured that we have a statistical forecast rolling. Ehh, so that ensures that we manage it long term since we have a statistical forecast that goes on. But of course, long term it could be used even more so ehh that it will predict ups and downs in our demand in order for us to become more efficient, save costs and be more effective. So that is the way I see it connected to demand. We are not there yet, but we are on our way.
risks with higher impact receive more attention	Support 34: Yes it really depends on the character of the issue. You almost always have to grade and classify and then it is important to have a classification across our entire mission. What is the most important, what is the least important before you end up in one of these risk-situations. I think that it is invaluable in all risk management to have it clear So that you can focus and prioritize when you things such as this take place.
Using KPI’s to track risks related to demand	Support 35: There are numbers of different KPIs that can be used to measure this and since we have done a classification we can see weekly if there are any trends, and we can assess if there is a risk. We have very many different alarm systems like our KPIs, and our service level which is our most important one when it comes to volumes and time, what the customers expect. *** Support 36: Within demand planning we have one KPI, BIAS, that allow us to monitor these trends. Have we sold more than expected and in our forecast? Our could we se lower, and then using this you can start to explain. Those are two examples on how we so to say capture if there is a risk eller if we can meet the requirements that are placed on us.
Supply Risk	
Greater complexity in supply chains	Support 37: Well, I think supply chains have become more and more complicated. And and we certainly see that they, I mean we're in the global team. So we really see that things have become a lot more global.
Impacted and dependent on other processes and departments	Support 38: We don't actually have any specific targets and our objectives, for example about project hits and I believe that the reason for that is that there are so many things that are not in our control. When it *** Support 39: comes to that, for example, we have a lot of issues around artwork being ready on time. If the artwork's not ready, we can't prepare for the corrugates or the poly and therefore we can't produce. But

	there's nothing our team can do to to enable that so everything is around the service level as opposed to project launches, but that doesn't mean I don't have expectations of my team that they are working towards delivering what's expected of them within the project.
Inaccurate forecasting a risk to supply	Support 40: the bigger risk we have that the forecast is not so accurate or that something could go wrong in between, so we're constantly trying to tighten up the lead times and when we also have big minimum order quantities where we have to take massive batches all in one go what tends to happen is we're over stocked for a very, very long time.
Increased pressure from customers	Support 41: I also see that customer expectations are really increasing. They demand not even ask. They demand to have better service, to have faster launches, to have more promotions, to have smaller drop sizes, to have quicker delivery times
overambitious and human-gut feeling leads to faulty investments	Support 42: That in itself is a bit problematic because we can have several suppliers who are producing from the same product category. So we have to just put some general growth assumptions in there, but at least we get a bit ahead of the curve by doing that. I mean the risk associated with that is that potentially we make an investment that's not needed. That has happened in the past where we had, let's say, overambitious growth assumptions by the market in the 1st place
risk is defined as something that impacts the service level	Support 431: I mean, for us it's something that will impact our targets. I mean, I guess it could be bolder than that, but I would say that's the key one. If we are not going to deliver something that we said we would and our target for service level is of course not 100%. *** Support 44: I mean, our key KPI is service level, right? So for for us, the avoidance of impact to our service level and managing the risks associated with that is is how I'm mostly involved. *** Support 45: Yeah. So as I said, our our main KP is around service level. So this is where we are working on risk mitigation and we have lots of different levels of routines.
Supply risk challenge	
Missing data and information	Support 46: So typically we can't look at this article level which would be ideal for us because we plan on article level. *** Support 47: So we tend to take the base data for the next year as year one and then it's manual beyond that we we ask people to overlay growth assumptions. I mean, we can see trends from history, of course, but what we cannot see are the anticipated growth or even new launches if they are they are not yet set up in SAP, so there's a lot of things that we know as a business, but for which there is no data from either history or from the settings in our systems that enable us to see that far ahead. *** Support 48: No. I mean SAP only is going out to two years and in all honesty the quality beyond year one is pretty poor.
Supply risk tasks	
Root Cause Analysis	Support 49: So we look backwards and we look at the things that have failed in the last few days and this is where we take the opportunity to do problem solving on the key element that arise there. To to make sure they're not going to repeat again in the future that we have true countermeasures in place to at least offset and hopefully prevent those things from reoccurring. *** Support 50: We are looking at the manufacturing bucket, if you like, from our team's perspective. But there are other buckets that we can choose to dive into and partner and collaborate with other functions. *** Support 51: So you know, for example, if we look at one area where the service is very low and we see most of it is relating to demand planning for example, we can partner with demand planning and say, hey guys, you haven't completed your root causing for this and we can see that it's impacting our service level quite substantially.

Supply Chain Redesign	Support 52: So for example, I mean we mostly supply the smaller regions via the [Company Name] network rather than direct from suppliers, which means the lead times are longer and it also costs us more money to do it that way. But the volume is not at the critical point where we can switch the supply to go direct. So we do check in on that once per year. And just see if anyone has. Kind of reached that tipping point from a cost perspective where we can switch the supply chain instead of going A to B to C, go straight from A to C and then of course when the lead time is shorter. It helps support the service level. It also removes congestion from our European warehouses and it has other benefits as well, *** Support 53: So continuously shrinking the minimum order quantities, reducing the lead times and that helps us a lot to manage the risk.
collecting manual input and data from suppliers on their capacity and what risks that they see	Support 54: And we also ask them to to look at the forecast that we've given them for the future to make sure that they have secured the capacity that we need, that they have secured the raw materials in order to provide and that they can't see any risks within their own supply chain for the future.
Enforcing contractual obligations when suppliers are not performing as agreed	Support 55: but we also review with procurement when we see.That there is a particular vendor that is not performing in line with expectations. We start to enforce contractual obligations. You know, we start to impose maybe penalties on our suppliers in order to get them to perform to the level that we expect.
Contermeasure evaluation	Support 56: Then, on a weekly basis, we look backwards at the quality of the root causing that we did. And the countermeasures that have been put in place, we have tools for looking at what the team have entered. They record all of the problem solving they have done and they record the countermeasures that they have done and we can also see.
Long Term Supply Planning	Support 57: I didn't go to the annual bucket actually on an annual basis, we do a three-year outlook. And we gather information from all of the markets. This is completely a manual process. It's not perfect, but it's giving an indication of the growth that is going to hit us in the next few years because you can imagine for buying a new production machine, it takes a long time. So this is how we kind of get ahead of this long term view as well, with the three-year plan on an annual basis. *** Support 58: I mean the reason why this activity is only annual because ideally it would be quarterly is because it's a huge investment and a manual workload for everybody.
Predictive analysis	Support 59: And we look forward for the next three weeks. We have PowerBI's that assist us with the data for that, where we can look forward for the next three weeks and we can see both things that will go out of stock but also things that drop below the safety stock and here we discuss what kind of activities.
S&OP process	Support 60: Then we have our S&OP process also on a monthly basis, which is where we can ask for help or decisions that are needed in order to mitigate those risks.
Scorecards	Support 61: And then on a, on a monthly basis, we have a scorecard for all of our key suppliers. I can't do it for all of them because there's about 150, but for our key suppliers and by key, we define those as either strategic supply, they have a large amount of volume or value or that we have had issues with those suppliers, so it. *** Support 62: For example, you know when we had the Suez Canal issues or we have strikes in harbours and things like that so all of those things are included in the scorecard, and we review those and we again. We record all of the actions that need to be taken in order to to mitigate or to solve, *** Support 63: I can't do it for all of them because there's about 150, but for our key suppliers and by key, we define those as either strategic supply, they have a large amount of volume or value or that we have had issues with those suppliers, so it. *** Support 64: So we, we monitor them and we have a scorecard where we look at several different things,

	service level from them to ask our service level within the network, the forecast accuracy that we have given them because very often we find it's not them, that's a problem, it's actually been us.
Ad-hoc solutioning	Support 65: You know, maybe we need to do some air freights and we need some money for that. Maybe we need to buy an additional machine in our suppliers or support them with that, maybe. Maybe we've got a big launch coming and we risk to hit the launch timeline.
Supplier reviews and evaluations	Support 66: And we have these business review meetings once per year with our suppliers where we really look overall at performance and and give them some feedback on whether we are happy with them or not. So happy with them and the areas that they need to work on.
Control Risk	
Changes in the short term make for a challenge when managing control risks	Support 66: Well I mean depending a bit on the horizon, but let's say if most of the things. That we see where a lot of attention or changes are happening is in the coming six weeks.
Conflicting goals	Support 67: But the point is that we do not have a, let's say between brackets a backup of availability of raw materials. Company has chosen to to supply from far away countries like we, for instance, we get the bags for for our [product name], partly from from Turkey. Which is rather unstable when it comes down to reliability on availability in our factory. And we see that they for some suppliers, they bet on one, of course. Yeah. For one. For some material, they're bet on one supplier which is cheap and you can really get the lowest price, but then it's a matter of not wanting to have certain materials as a safety stock in our in our raw material warehouse.
Control risks are seen as risks when they risk preventing deliveries to customers	Support 68: Yeah. I mean when when you look at at planning, your first objective is to serve your customers. So if you see there is a risk that you're going to be out of stock for a for a certain periods. That already requires attention in order to see OK what's what can we do to either avoid it or make it as short as possible.
predictable risks	Support 69: I would say predefine, but you can look at each launch. You know upfront already. What kind of risks do you see coming and how are you going to deal with those risks?
the goal is to be able to serve the rest of the supply chain at lowest cost possible	Support 70: Have the prerequisites available, or make the right decisions on your prerequisites because everybody says oh,
unclarity on what the future brings	Support 70: So the the bigger the supply chain, the bigger the risk. Because if we look at. The data or let's say the forecast quality throughout the supply chain is that if you look, if I look at total inco pants, I would say at the end of the week what what data markets forecast and what did they sell, it's not that far away, but if you would take it one step deeper and go into sales organization it's already a lot worse. If you then go deeper and look at SKU level, it's even more bad.
volatility and conflicting goals	Support 71: And let's say the company as such is always saying that we want to have as low working capital as possible. So no finished goods, no raw materials. But still demands a kind of a flexibility from from operation to meet the market demands. So for me the volatility in in the markets is not covered all the time with your raw materials because I think. What. What. The reaction that I get from markets is most of the time you are not flexible. You need to rebuild. Why can you not do a rebuild right now?
Control Risk Tasks	
Analysing situation and forecasts	Support 72: And you do quite a lot of validation, and of course the thing is that you. Start high over and then you go deeper when necessary.

Analysis as a task	Support 73: I mean, for me it's really the. The. The education on the people doing. The analysis or making the the decisions finally.
Analysis using KPI's and outlooks	Support 74: we have the the queries from the from the coming out of the system. But it is just in excel. So we work with with macros to to compare data with each other. You see the tendency of more and more working with Power BI as we have lots of data and a background and then showing results of of like let's say service level or other KPIs that you that you follow through PowerBI.
Assessing the situation	Support 75: the big fish is try to to take out. And make, let's say an assessment whether you say, OK, we wait until we have it corrected the system the week after or we have to do. Make a a decision right now and then I need to go through the all the data that I have available and make an assessment and then tell the hub OK we do it like this. So it's. It's also a bit about the severity of things. How big mistakes or changes there are, but also the horizon.
Consequence analysis	Support 76: Every time you get data you need to make a relation to. What does it mean now and what does it mean? In a bit further away, and how can you manage those things together and that is what I also try to to get through in into the hub, that's whatever you do. There's a a consequence of what you say now versus something in the near future. And if you if you do something on this article, you have to look maybe it's a consequence of something else, either materials or from from your capacity that you have available to to make certain decisions.
Non standardised way of working as of today	Support 77: So yes, I really would applaud to get more standardized way of working, standardized reports, because that makes it only a lot more easy, because then we all all talk about the same things. But that is unfortunately not in many cases, the situation right now. So you're still working in in your own way in certain ways. To just make sure you can, yeah, do your daily work and but it's not the definition that we have the best idea of how things should be.
Risk analysis using several departments	Support 78: It is first of all, it's not seen everywhere because that's why I mean when when you do as an example, when you do a project in a factory. Then you bring all the the people together that can say something about the impact of a project and you do a risk analysis. And what I have been
risk assessments	Support 79: A risk assessment, for instance, when you talk about phase in phase out because phase in phase out is the bread and butter we do both in the markets and in in in factories and it is not always seen as, something you can really. I would say predefine, but you can look at each launch. You know upfront already. What kind of risks do you see coming and how are you going to deal with those risks?
S&OP is a task	Support 80: Because now I mean take an example for. Volumes, I mean we make an S&OP every month. There are different timings of different needs in the month of having data available. This Help us to explain and align on the last Wednesday in a month. Because the controllers need to have input before the end of the month to make the new outlook for the coming months as of the first day of the of the new month.
Using systems to gather information	Support 81: The base is that's what you see in the system is seen as the truth unless, you come up with something else. So it's. Throughout the years working for two unit units.
Control Risk Challenges	
Control risks are difficult to mitigate and to manage due to the large amount of coordination	Support 82: And you can also argue about that We see that most of the time the stocks are there globally, but all spread out in a wrong way. And then you have the the way that the system is is calculating, saying OK, the replenishment for instance to [warehouse name] is five days earlier than when you have direct deliveries. So if you are in a shortage or you are in a low stock situation, then most of the time the stocks are already sent to a DC in another country while the orders for your direct deliveries are not not able to to be handled. So it's it's it's a combination of of lots of different items.
dependencies on many factors	Support 83: Are we flexible? And what is flexible in the markets? All those kind of things. That you need to define because the the point is that. With the current. Yeah, let's say reliability in both production or in the markets when it comes to forecast quality, you will never get it completely right. So you need to say, OK, this is the this will be the process. This is the risk and when in time, do you need to take certain

	decisions in order to have the last glance on what you have as data and then together make the last decisions either it's.
dependent on how well others are performing	<u>Support 84:</u> And that means that, let's say the supply chain with safety stocks and and and and. A pool strategy. It is is is very much reliant on on forecast quality.
tasks are dependent on the outcome and performance of other tasks	<u>Support 85:</u> But if you want to avoid, of course, a perfect forecast would of course help. But I know that that is not not going to be realistic.
<u>Environmental risk</u>	
difficult changing factors impacting degree of difficulty	<u>Support 86:</u> No I can't change or affect what is going on in the world. What you can do to mitigate and affect within the EU a bit, is by looking at what other companies you working with? Again, in order to mitigate the risk a bit. We spoke briefly about that last time, how many, how many forwarding companies we are working with? Those who only use subcontractors, those with their own fleet. But finally it is the market with all its problems. There are very many Eastern European drivers involved in this, no matter what type of actor you choose. You can do some good by broadening your portfolio, to not only confine to those that work with sbucontractors or those that have their own fleet. If you have a good mi there you are abl to mitigate some risk. But in the end, nine out of ten it is an Eastern European driving the truck.
geopolitical factors	<u>Support 87:</u> The geopolitical aspects are of course much more difficult and they can have an impact that is comparatively larger as well. Look at when covid hit, what imbalances did we see on the market all of a sudden? Or the invasion of Ukraine again when drivers just disappeared and there is so much going on the world. It is impossible then to really prepare for everything if I am being completely honest.
global economic shifts affecting transport flow predictability	<u>Support 88:</u> The predictability, there are these balances depending on how the international trade looks like with import and export flows. This has a direct impact on how the trucks are moving or how many trucks there are. Which are the attractive flows and which are not, so if there is some type of change in the global economy, that hits immediately within the transport industry.
global factors impacting transport risk	<u>Support 89:</u> No it is not calm because it is affected by so many factors. In this moment the transport industry is very much affected about what goes on in the world.
invasion of Ukraine disrupting transport capacity	<u>Support 90:</u> The same geopolitically speaking, lets take the invasion of Ukraine again. All of a sudden a large share of the drivers just disappeared and what happens then? Yes well then there is less capacity on the market. The trucks are there, but there is no one to drive them or wanting to drive them.
risk of new strikes	<u>Support 91:</u> Because there was a large risk that there would be a strike now again and now we had just finished this years tender process so it was really like this if there was going to be another strike this year again. What can you offer? How can you handle it?
unable to get facts	<u>Support 92:</u> Precisely because you, you don't have the possibility to get exactly all the facts you want on the table during a tender process. Of course you make your best effort and we have these general checks on both the financial health, that they are are compliant with our global supplier standards, checks of the technical functionalities and so on.
<u>Environmental risk solution</u>	
diversification of transport partners	<u>Support 93:</u> No I can't change or affect what is going on in the world. What you can do to mitigate and affect within the EU a bit, is by looking at what other companies you working with? Again, in order to mitigate the risk a bit. We spoke briefly about that last time, how many, how many forwarding companies we are working with? Those who only use subcontractors, those with their own fleet.
having several	<u>Support 94:</u> So a lot of this is about securing this. Look at what the critical flows are. Where do we have a

options	greater risk that this sort of thing could happen and then have an alternative back-up solution. One example is railroad. There has been a lot of talking abut using rail. We are fortunate and have a railway-connection to [warehouse name] for example. Even a few sites or warehouses in Germany.
increase stock and gather stakeholders	Support 95: try increasing stock levels and then you need to assemble all the impacted stakeholders.
market driven flexibility	Support 96: Plus that we can then use what we call spot-buy. That is to say that we post the offering on the market. But that is definitely a part of the decision-process. And what actors am I referring to? I of course do not fall for partners that make a dream offer you know they can never keep in the end.
not relying on a single partner for critical operations	Support 97: No but precisely, but it is also a lot about the fact that we are trying to not put all the eggs in the same basket. So for large and critical flows we aim to have at least two different partners that we are working with.
risk mitigation through diversification of partners	Support 98: That bit is pretty easy to mitigate through contracting more haulers and partners, which allows you to limit the risk.
Impact on others	Support 99: Yes but it does. It could have an impact on costs. Then it also impacts the stock levels, if we take the railway example again, it could be used to explain a lot. There is a different process both at the loading by the warehouse, loading a truck instead of a train-carriage and it is just the same over at the inbound in [warehouse name]. It is different processes, and they are handled differently. So that could also be that we would have mega issues with the trains and we need to send lots and lots of trucks. Then we need to align this with [warehouse name] because they can't receive 20 trucks from Germany all of a sudden, there is a capacity limitation. That could impact in some cases that the cost would increase, it could turn into longer lead-times in other words that the transport takes longer time. That happened when we had to transport via the Baltics up to Finland, so it impacts and it can also impact stock levels then as well. In the worst case we won't receive the goods on itme and then we go out of stock and then we are not delivering in full to the customer as an effect of a transport and not a supplier related issue or production related issue.
Alignment need with others	Support 100: Now that issue has repeated itself several times so there is always a forum. I am not the one to take the decision, most often it is a joint decision because as I said, if I send 20 trucks and then people might say "Hey guys, I can't handle this" and then Sladjana will come and say "But [interviewee name], what are you doing?" So there is always an alignment surrounding this.
Information risk	
data is not always aligned between the different supply chain partners	Support 101: And then there are different points. Because as soon as it goes outside [company name]'s premises, exactly then we can't control it, then it is just EAN that applies internally
data management today is an enabler for sales and manufacturing	Support 102: But sure it could be so that you do some type of error it could also be reports so you get completely wrong figures on results that should have gone to one division and not to a completely different one, so yes the product master data is extremely sensitive and important and can. It should be a production enabler, a sales enabler.
environment of information risks is relatively predictable	Support 103: No but I think that our environment in sort of ways. We know our environment and keep us pretty updated, there are many. Yes, but I probably think that it is quite predictable I would say, our working environment. We know our manufacturing sites. We have at the very least talented people who knows it, they have been through alot and can often predict what might go wrong pretty well and also work with risk management. Not to say the least about our RnD colleagues and so. SO I would probably say that its pretty, yes relatively at the very least.
grey areas of	Support 104: Yes there goals for the years, but there are some where there is a grey zone. I mean we are

uncertainty	not allowed to change the number of products, that is black and white. That is scamming custpe,rs. It could also borderline, absolutely not. But if it is a case that it can't differ 20% in weight, if it then differs 21% in weight. Of course you can't there is a fixed metric on it, but then you have made the assessment that with this customer we shouldn't do any changes. They want stability for one or the other of reasons. Yes, well then perhaps you can think that it is in some light grey zone and you start looking what happens here, why does this rule exist at all? Yes because you can, can tolerate 20% and it should still work that you are getting what you can tolerate. Then maybe you can tolerate 1% as well if it avoids business interruptions. So we try to have an open dialogue. We encourage also those that orders the products, talk to us so we can help assess what the effects are.
if data is not maintained, customers and consumers will be impacted	<u>Support 105:</u> Because EAN codes are the unique identifier that is out on the market. What the end customer ses, both consumers and also our customers. So that is very important if you go in and for example order via the internet instead of going into a store. This time you get a picture and you get some information and you say "I want that one, and then you order it to your home". Then it is very important that it is what you have seen and what you have read when it is delivered to your home.
poor data management impacting sales performance as it disrupts the flow of goods.	<u>Support 106:</u> If you change the EAN code, then it is a manual task changing from the one to the other. There are always cases when this is missed, so you know you will see a drop in sales for at least two weeks.
poor data management negatively impacts other options	<u>Support 107:</u> Yes. If we do really, so if it is not only about the measure and quality we write something completely different we won't even be able to produce it in the right way. It might not be able to produce, such errors I hope not, so that is not really what I have been talking about so far. But sure it could be so that you do some type of error it could also be reports so you get completely wrong figures on results that should have gone to one division and not to a completely different one, so yes the product master data is extremely sensitive and important and can. It should be a production enabler, a sales enabler. But of course the backside to that is if you don't manage it well thats not good.
predictable environment	<u>Support 108:</u> No but I think that our environment in sort of ways. We know our environment and keep us pretty updated, there are many. Yes, but I probably think that it is quite predictable I would say, our working environment. We know our manufacturing sites. We have at the very least talented people who knows it, they have been through alot and can often predict what might go wrong pretty well and also work with risk management. Not to say the least about our RnD colleagues and so. SO I would probably say that its pretty, yes relatively at the very least.
<u>Challenges Information Risk</u>	
Changes to data can cause drops in sales due to manual maintenance needed	<u>Support 109:</u> Because the business will often want to be able to sell our products smoothly. That it should only be replenishment and replenishment. And if you have the same GTIN code the sales just keep going. When the product is empty on the shelves you just refill it. It is reordered. You might not even have to do any manual changes, at times it could be done automatically. If you change the EAN code, then it is a manual task changing from the one to the other. There are always cases when this is missed, so you know you will see a drop in sales for at least two weeks. But you could also drop mer because, this automatic it it atleast used to be that way before. Perhaps I shouldn't hold myself responsible for these two weeks, but before it was very clear that there was a drop in sales for two weeks. You need to account for that and it can make quite a big difference with global products. If you take something that is sold all over the world and you dip in sales for two weeks, no one really wants that to happen.
Other departments don't understand the big impact data management has	<u>Support 110:</u> We are trying to secure that we are educating the business because there is an opposition in having all of this correct, to always follow the GTIN rules because this is a rule that is quite important. This also impacts automated warehousing, for example if you way something different and so on. Then things can crash as well, so there are some effects. So we try to train and educate the business in understanding what could happen in case this goes wrong.
Resistance from customers to do	<u>Support 111:</u> The customers don't want this because they don't want to perform the manual task. So there

changes in data management	is an opposition to following the rules from this perspective. And it is probably that balance that is the greatest challenge and you really need to inform and explain these risks, what could actually take place if you don't abide by the rules.
<u>Information Risk Solution</u>	
educating other departments and key stakeholders about importance of data management	<u>Support 112:</u> We are trying to secure that we are educating the business because there is an opposition in having all of this correct, to always follow the GTIN rules because this is a rule that is quite important.
keeping up to date with rules and regulations about products	<u>Support 113:</u> So it is about keeping a jour regarding the existing rules and regulations and how they are updated. Within product master data it is a lot about what product it is. *** <u>Support 114:</u> If it is a medical device there are many regulations regarding things that we need to fulfill because we at [Company Name] have med-tech products in different classes and in that area there is very much going on and you therefore need to be conscious and updated about the rules and regulations. So that we actually maintain the data that is required, in order for us to be allowed to sell these articles and what data we need to offer.
measuring performance and data	<u>Support 115:</u> I am very much for measuring. Love working with KPI's, SLAs and putting it into the goals and make them as measurable as possibility, so that is my way of working generally. But I am also very thorough with that we are measuring things that matter.
measuring the amounts of errors	<u>Support 116:</u> In addition to our KPIs, we also have some things that go a bit deeper. It is monthly sales assessment or monthly assessment, everything that is created during this period. WHat, how are the doing? Have we made any errors before it hopefully shows up somewhere and as I mentioned we also try to work as much as possible with preventative methods.
prevenative actions - autopopulating data	<u>Support 117:</u> But we are also trying to build preventative measures so that it could be that it is we can change something in the system that you check beforehand, where there can't be any errors. Or that these fields should be auto populated and that it is based on this so that we only have one thing we need to look at.
process automation used to check data and ensure it is aligned with other partners	<u>Support 118:</u> Now we have an automated process that we can perform ad-hoc, which is also very good when you need to redo it if something is wrong and it needs to be made correct. Then it is much faster to see the results of it compared to waiting until the next quarter.
Routines	<u>Support 119:</u> Yes within product master data there are many different scenarios. Some components are the same. We need to have created an article number, we need to create numbers for all raw materials if they are not there. We need the specifications of them. We need to have a picture of each material that can be produced with the right quantities and to the right quality and so on. So some things are. There is like a basic package with components, but then there are many different scenarios, what you do to develop a product.
rules - information risk	<u>Support 120:</u> GTIN Allocation Rules is pretty old and has been in existence for a long time in order to make it easier with Supply Chain and Logistics and so on. But in pace with the rest of the world changing, this becomes increasingly important.
standardized	<u>Support 121:</u> Yes within product master data there are many different scenarios. Some components are the same. We need to have created an article number, we need to create numbers for all raw materials if they are not there. We need the specifications of them. We need to have a picture of each material that can be produced with the right quantities and to the right quality and so on. So some things are. There is like a basic package with components, but then there are many different scenarios, what you do to develop a product.
use universally accepted rules	<u>Support 122:</u> And even if it also applies to medical devices and B2B, it is primary to consumer and it is

	very very important att we follow something called GTIN Allocation Rules. That is barcodes which are eAN codes, and here in Europe they help identify products and then it is pre-decided what things need to be exactly the same between these and also what is allowed to have yes, tolerance you could say or a range where it needs to be this or that close. And this plays a very large role not the least for e-commerce. *** Support 123: GTIN Allocation Rules is pretty old and has been in existence for a long time in order to make it easier with Supply Chain and Logistics and so on. But in pace with the rest of the world changing, this becomes increasingly important.
Artificial Intelligence	
AI perception	
Perceived benefits of AI	Support 124: I understand the concept that it can handle complex scenarios, it can process large quantities of that that we people can't process as quickly. *** Support 125: I would like it to help us because if you look at the entire supply chain. There is a lot to this with demand, that is, being able to predict demand. So the right people here as possible help with both production planning, warehouse planning and transport planning. Everything is very, very tightly connected. This is how I want to believe that AI could do a lot and predict what will happen. Yes, the right products, in the right place, which the transporter can then also pick up and that we don't have these peaks in the transport flow either. So I feel that spontaneously. This is probably where you can find a lot. *** Support 126: We have to learn about AI or technology in general because this is a big thing. Something that is going to empower us. It's not about replacing us, we can upgrade ourselves and we can be more effective with our jobs and this is what we should be stressing. Rather than the common rhetoric that AI is going to take away jobs. *** Support 127: So there are probably quite many things that can be made simplified and maybe some decisions that can be outright removed if you get better predictability. *** Support 128: Going a bit iterative you learn and then you can become smarter and smarter and use the data in a better way, get better accuracy. *** Support 129: Yes you can probably use AI to understand how transport prices will evolve in the future. *** Support 130: AI brings a lot of opportunities. It has always had a lot of opportunities, now people are mostly looking at the generative AI part. We already have AI like machine learning, deep learning. So there are components of AI that are already there. We probably did not use them to our full potential in the past and that we are also looking at. But generative AI brings another layer of capabilities that we are very excited about.
Importance of data	
Data is a challenge to implement AI	Support 131: Data is very important for AI because if we don't have the right data quality or if we don't have the data available then AI wouldn't help us. *** Support 132: But every time we do this kind of use case, we end up in the same situation. If the document where we have all those policies is not well organized, then the chatbot kind of struggles. Because, for example, if we have many versions of the same policy document, then the chatbot would pick the wrong version and base the answer on that. *** Support 133: Or for example, if there are lots of other documents, unrelated documents, there might be cases of hallucinations as well. So the way we structure the document base is also important. It's a very simple use case, but in other use cases I think we'll have the same issue because most of the time AI is going to use our data to help us, and if the data is not of the right quality then we will struggle

Data privacy and change management	<u>Support 134:</u> For example, there are data privacy issues that we should be careful of when we use AI tools available on the internet. There is a big challenge in terms of change management because we have to be very transparent and we have to be very open about how AI is going to evolve all of our roles and how we make ourselves ready for this change.
AI excels when having historical data	<u>Support 135:</u> Something that is pretty well known is AI is only good at solving a problem if historically, that problem has been already seen and solved. OK, because it learns from all the historical information.
Challenges in data quality	<u>Support 136:</u> If we want to use historical information to predict the future, then there is a big break somewhere like in 2022, they started with [Name of digital transformation project] when suddenly things have changed. The information that you had before is a bit different from what we have now, so we need to see how to use all that information,
Transforming the company to produce and manage data	<u>Support 137:</u> When we started this advanced analytics and AI initiatives because this is a step further. The thing is, in many areas we are still going through this journey. We already know that this is important, that we need to have the right data. You have heard about [Name of digital transformation project] and [Name], you are a part of it, all this digital transformation is about data and how we can have the right governance around the data.
Importance of data management	<u>Support 138:</u> That was the first step. We started with the master data, then we started building this ecosystem of reporting around the master data, for financial reporting or for standard reporting in general and to provide insights.
Importance of data quality	<u>Support 139:</u> It started quite some time ago when we started to fix the governance around master data. We know that data is important and we need to have reliable reports and insights from our data, we need to have the right data, in the right quality.
Data quality issues related to AI adoption	<u>Support 140:</u> But every time we do this kind of use case, we end up in the same situation. If the document where we have all those policies is not well organized, then the chatbot kind of struggles. Because, for example, if we have many versions of the same policy document, then the chatbot would pick the wrong version and base the answer on that. Or for example, if there are lots of other documents, unrelated documents, there might be cases of hallucinations as well. So the way we structure the document base is also important. It's a very simple use case, but in other use cases I think we'll have the same issue because most of the time AI is going to use our data to help us, and if the data is not of the right quality then we will struggle.
Experienced data being crucial for the value added by AI	<u>Support 141:</u> We are exploring the challenges and most of the time we see that we face the same challenges very much around data like how for example, we have this HR services, chatbot, a chatbot can help us. Most of the time our HR people get asked questions where people can actually go and read the policy and provide answers themselves. So hey, if we have a chatbot based on all those policy documents, people can just interact with the chatbot and get the answers rather than looking for a policy document or HR person to answer those questions.
<u>Ethical concerns related to AI</u>	
Proprietary information	<u>Support 142:</u> For example, when we use AI for let's say image generation for marketing campaigns. So AI has been trained using data publicly available on the Internet, and sometimes it can copy the style of an artist and then it's a bit of an ethical choice that we have, if we go forward and publish or use that marketing campaigns. Are we being fair with the artist who actually made their art available publicly? The AI learned from it and reproduced some part of it. Those are some ethical questions that all companies today have.
Data privacy	<u>Support 143 :</u> For example, related to data privacy, people come to know about new tools and like the other day, I was having a conversation with a colleague who is very excited about a tool that can visualize an idea. For example if you have a big copy of text you will just input it into the tool and it can visualize with diagrams and with some pictures, it is very friendly. But then of course when, you use such a tool which is in beta version. You know that when you upload any confidential information, that tool will use

	that information for the next version of that tool, and that information kind of makes it public, so that this is like a very small example *** Support 144:But what I want to say is data privacy is a risk because if we are not aware of that when we use a tool. How are they going to manage our data? Are they going to keep the data on the system? Are they going to use the data to retrain their models?
Corporate Social Sustainability	Support 145: So that's something that we have to do. This is our obligation and I think I'm pretty sure that we as a very ethical company like [Company Name], we are pretty committed to doing that and actually in some cases we are even taking a further step. We know that we have to use AI in a responsible manner, and even though, like in certain countries, we can actually cut corners because the regulatory measures don't really demand it. But we are pretty ethical about it and we know that we shouldn't be misusing or maybe I wouldn't say misusing, but we can't cut corners. So, that's the approach. ***
AI usage	Support 146: So this is kind of a challenge that we have. There are issues with ethical aspects like for example, if we use AI, let's say for CV screening. One of the biggest problems that we have in all companies is that whenever we're looking for candidates, we have to go through thousands of CVs. Sometimes humans can get tired, or sometimes they cannot evaluate and rank all those CVS efficiently, but AI can. But the problem is AI comes with bias. If we are not aware of that part, then it can be a disaster. For example, in one of the recent researches by University of Washington, they used one of the off the shelf large language models like llama by meta and it kind of preferred white male candidates most of the time. So that's the risk that we are talking about. If we're not aware that AI has a lot of bias built in, because it has been trained on data provided by data available on the Internet, then it's a bit of a problem.
Approach to AI adoption	
Important to balance value and risk when implementing AI	Support 147: So at [Company Name] we have this balanced approach. We want to harness the potential of AI to its max, balancing value creation, risk management and challenges. So that's what we are very much excited about and every time new cases are coming up or new ways of using AI I am really excited. I was already excited about it about a year ago, trying to figure out how to set this up, which is called agentic AI. Using AI agents can be a game changer in many of our process engineering efforts as well.
The challenge of finding applicable areas of AI in decision-making	Support 149: It's actually tricky, I mean, we need to find out exactly,, where AI can really add value and where humans are really good. Because there is no clear boundary there.
human value	Support 150: But we humans are good at problems that we have never faced in our lives because we learn from other experiences and we cross our learnings. So when there is a problem that has never been faced, we are intelligent enough to tackle that and find a possible route out and here AI most probably would fail.
when to automate process	Support 151: Now when we come to the other part, which is very much about automation. So now things get a little bit tricky. Why? Because we need to think about what are the different processes that we have and what areas in those processes, which are mostly human driven processes where there is clear human added value.
obstacles to AI adoption	Support 152: AI in general is a little bit tricky because it is evolving so quickly and staying up to date with that is already an issue and that we have to probably add a lot of resources to stay up to date, look at the capabilities and how we can empower ourselves. Data quality is going to be one of the biggest obstacles, because usually people think of short term gains and when you go for AI in many cases you won't see short term gains, because you will have to work on your data infrastructure and data quality to actually get the gains, so that kind of pushes AI games to more like a mid term gains. Many times people are not willing to invest whenever the payback is more than two years or three years, then people think we should probably focus on somewhere

	else. Prioritize something else that can give me some short term gains. *** Support 153: Also basic skills or know-how around AI is an obstacle as well. Because many people don't know very well what AI can do, what it cannot do and how to go about it. Change Management is a big thing, because I know that people love to use ChatGPT because it can create some cool articles that I can share or something like a song that I can sing and share with my friends. But if it's used in your work, then you are concerned you have other questions in your mind, that's a big change for me, I am used to working in a certain way and now I need to adapt. That's kind of an obstacle as well. Those are like some major ones I can highlight at the moment.
Prioritizing areas for AI adoption	Support 154: All right. I think the biggest obstacles in general for any large organization like us. Is like a very structured approach, for example, you know that most of the time we kind of tend to try it out and we don't really think in a very structured way how we should evolve and what should be the right priorities. So priorities in place are going to be key. Because if we don't prioritize well, then we will lose all our attention and our you know resources will be in different areas and we kind of may lose out a bit
starting with low hanging furit	Support 155: One is a traditional idea funnel where you have the use cases rolling in and then you pick based on prioritization from different governing bodies. Usually they use a framework like the value feasibility framework and you find out, this is probably a low hanging fruit, this is high value and high visibility, so it's a no brainer, you go and implement it. if it's medium value but high visibility, yeah we should go for it. And those are the questions.
AI not applied in SCRM yet	Support 156: We haven't really used AI there. I know that we are in discussion about using AI more in optimization of certain processes maybe. But not necessarily in the risk management part. *** Support 157: And at the moment, supply chain risk management isn't one of those areas where we are actively driving this conversation. So most probably yes, that's why we haven't really taken a look at it. But supply chain is a big area that we are very focused on and I think supply chain is an area where we will see a lot of AI adoption.
Top Management Support	Support 158: So this is the difference that I'm talking about and the good thing about [company name], today we have already started this journey. There is a lot of interest from the top management. There's a lot of interest among my peers, among the whole organization to drive this agenda further, and this is what I think is important.
Avoid using AI where human value can be added	Support 159: On the other hand, if we are talking about if the Impact is high, let's say HR processes, we are very much focused on building a talent plan. If we are using AI there it gets tricky because we believe that it's very much human value. Value added by humans is important there, so we need to be careful about that.
AI and Decision-making	
AI as an assistant	Support 160: Like having this AI assistance to see how AI can augment us by providing all the right information and the different options, like when we talk about making a decision it's great if AI can give us all the options available with the pros and cons so that we can decide.
Using AI when human judgement is low	Support 161: So there are a lot of AI agents. It can be autonomous agents, so these agents actually make a decision for us. We need to see what's the scope we are talking about and what are the guard rails that we need to put in place to actually make decisions for us. Because in some areas where the impact is quite low and we can have a lot of benefits because of automation, we should go ahead and think about using AI.
Concerns for variability	Support 162: I mean you always don't get the same answer. Because it depends a lot on how you frame the problem, and depending on how you frame the problem that rises to this new discipline, right?
Removing need for decision-making	Support 163: on a daily level. So there are probably quite many things that can be made simplified and maybe some decisions that can be outright removed if you get better predictability

AI impact decision-making	<u>Support 164:</u> Then we are talking about prediction, predicting the future and being future ready and then we are talking about automation. If we automate the boring task or manual tasks then we have more mental space towards high quality decision making. AI would enable that and frankly with generative AI, and agentic AI in general, I think new opportunities will arrive with decision-making. Because, if you have all the possible scenarios in front of you and possible pros and cons where you can add more from your human expertise, that is the ideal thing. Today, most of the decisions are made on the fly with minimum data available or minimum insights available and here AI can provide a lot. OK, so this is what I think is going to be the game changer.
<u>Organizational readiness</u>	
Employee-ai trust	<u>Support 165:</u> because for many of the AI related initiatives, you have to trust the data that you have from the past.
Organizing to implement AI	<u>Support 166:</u> It's been a journey, I would say, you might have heard about [Company Name]'s Analytics journey. It started quite some time ago when we started to fix the governance around master data. We know that data is important and we need to have reliable reports and insights from our data, we need to have the right data, in the right quality. That was the first step. We started with the master data, then we started building this ecosystem of reporting around the master data, for financial reporting or for standard reporting in general and to provide insights.
AI literacy	<u>Support 167:</u> I mean, sometimes I say technology in general, but of course most of the time, those conversations that I have are focused on AI, people are really excited about it. Some of that excitement may be based on very high expectations from AI, so that's probably something that we have to look into. We have to educate all our people on the capabilities that AI has today and what it can do, and also the importance of data. Data is very important for AI because if we don't have the right data quality or if we don't have the data available then AI wouldn't help us.
AI organization	<u>Support 168:</u> The AI center of Excellence was created to lead that part, because what we have to do is we are the owners of all the different AI related tools and projects, the whole portfolio of projects at [company name]. We are also in charge of drafting the AI guidelines and guiding the whole company and coordinating all our AI related efforts in a very strategic manner. Of course we are in charge of building AI literacy within the organization because we have to upscale the whole organization in terms of AI skills, to make people aware of the capabilities that AI brings and of course the challenges that come with those capabilities and opportunities as well. So that's our part. And of course we are also in charge of AI compliance because we need to comply with the European and AI act and the other legislations and the regulatory measures. Also as a very ethical company like [company name], we have our own commitments towards the ethical use of AI and we are the guardians of that. So that's a very quick way to describe the AI center of excellence model. So we are very much about best practices, sharing, coordinating the efforts if there are similar projects running in different departments, bringing them together and bringing new opportunities to light.
positive perception in organisation but any issues are really impacting the perception	<u>Support 169:</u> It's very much like it's a journey together, people are very excited about AI. Of course, we encounter certain challenges like we need to fix our data and it's a big investment. Then most probably you know you can see some people taking a step back and rethinking it.
<u>AI Application and SCRM</u>	
When to Apply AI in SRCM	<u>Support 170:</u> So there's different kinds of AI there, different kinds of AI tools that need to be applied there. It can be a rule-based system or it could be like an optimization problem where you already have a few constraints and the algorithm finds the right way to do so. These cases are a no brainer. We humans shouldn't really be doing that and it should be, of course, the AI algorithms that should be doing that.
AI is well suited for forecasting	<u>Support 171:</u> we talk about accuracy but also Interpretability which is also very important for us humans to act. So that's something pretty clear that we need to consider which models can be interpreted well.

The impact of AI is dependent on the area of SCRM	Support 172: I mean it depends on the different areas of supply chain risk management, for example, If it's a forecasting problem, you can do a lot with AI because we are not that good with analyzing a lot of information that we have, so it's a pretty clear problem.
By automating you are freeing up resources	Support 173: Then we are talking about prediction, predicting the future and being future ready and then we are talking about automation. If we automate the boring task or manual tasks then we have more mental space towards high quality decision making.
AI usage	Support 174: That's a good one. So at the moment AI is helping us with insights. So it is very much about, let's say, if you use demand forecasting. It already kind of helps us predict our demand and we can use it to be ready to make our supply chain lean and productive
AI seen as as a support tool rather than replacement	Support 175: Yeah totally. It's all about augmenting us, augmenting us as professionals with a lot of insights with a lot of supporting ideas and value related information so that we can decide better.
Interpretability AI	
The interpretability exists in reasoning models, however quite costly	Support 176: So this kind of interpretability is already kind of there, so we can use reasoning models. To solve that kind of problem in a very interpretable way. Of course it's more expensive because when this large language model generates all this text, it's consuming energy. So we have to be very careful exactly where we use the reasoning models and where it's just a simple model that can be used.
the interpretability of AI models and the examples of reasoning models	Support 177: I mean, it depends on how you engineer the AI models. So as you know that all the generative AI models are evolving really quickly. So now the more I will say the recent trend is about using reasoning models. So there you can already see how the model reasons about a certain decision. You know it is step by step. It shows that if I want to solve this problem A I need to think about problem B and subproblems C and for problem B need to look for this data. Does it sound good? What about C?
Decision-making	
Environment for decision-making	
Quick developments in the environment	Support 178: I'm not sure that our logistics network. Our tools. I think there are a lot of things that are not really equipped to be quite ready for that yet, and we see a lot more digitalization of course across the board. Lots of different ways, a lot more things moving
More Collaboration	Support 179: And and kind of traditional boundaries of roles are slowly decaying. I would say it's much more about collaboration and problem solving and working beyond the boundaries of your existing role, working more end to end in kind of. We have the process excellence because of the centralization, but it's more about huddles so that you know you have groups of people who are co-located working together on a common issue.
changes and events on the macro impact the environment and makes the environment more volatile	Support 180: The predictability, there are these balances depending on how the international trade looks like with import and export flows. This has a direct impact on how the trucks are moving or how many trucks there are. Which are the attractive flows and which are not, so if there is some type of change in the global economy, that hits immediately within the transport industry.
Environment becomes more volatile	Support 181: What is different is that the rest of the world is changing more quickly, which has an impact on the demand. I see that it is more volatile, the demand. This could be due to inflation, those elements affect more and more. It has evolved into becoming more volatile, which then brings a higher risk in case you don't capture it in time.
Environment has become more complicated and	Support 182: Well, I think supply chains have become more and more complicated. And and we certainly see that they, I mean we're in the global team. So we really see that things have become a lot more global. ***

there are more factors to take into consideration	Support 183: I also see that customer expectations are really increasing. They demand not even ask. They demand to have better service, to have faster launches, to have more promotions, to have smaller drop sizes, to have quicker delivery times.
Unpredictable	Support 184: Hey it will need to be realistic. I think some things you can't change, so customer impact you have no but but we're lacking as of course is more reliable data about supply Predictability, yeah.
Dependent on many factors	Support 185: No it is not calm because it is affected by so many factors. In this moment the transport industry is very much affected about what goes on in the world. Because harshly said it is a bit special industry right? There are a lot of subcontractors and suppliers. There are very many rows of stakeholders.
Information - environment is quite predictable	Support 186: No but I think that our environment in sort of ways. We know our environment and keep us pretty updated, there are many. Yes, but I probably think that it is quite predictable I would say, our working environment. We know our manufacturing sites. We have at the very least talented people who knows it, they have been through alot and can often predict what might go wrong pretty well and also work with risk management. Not to say the least about our RnD colleagues and so. SO I would probably say that its pretty, yes relatively at the very least.
Some parts of the environment are more predictable	Support 187: I would say if it's. It is kind of predictable. So if you look, we didn't talk about yet, but if you look about distribution transport, so we know when the peaks will come. So we prepare for that. So that's also more like a standard process that every before Christmas, six weeks before Christmas six weeks before Easter, we know that we have peaks in transport, so we need to secure extra capacity or if we know that there is a promotion, we need to secure extra transport capacity. So I think there is quite quite OK predictability and also quite standard way of working if we talk about
Aim with SCRM decision-making	
Service level is the ultimate goal of the decisions	Support 188: I mean the ultimate target, that is that there shouldn't be any impact on service levels. That means that we can really lower the amount of delays as much as we possibly could. Secure the capacity that is. We shouldn't work with any hauler that could go bankrupt all of a sudden. That is not so good. No so the ultimate target, that is being able to deliver on-time. Yes always, that is not possible, but so that is the ultimate goal and that is better than the cost.
service level is the aim of the decisions	Support 189: No, it's really balancing. Yeah. So from my perspective, again, it's about maximising deliveries to the customer.
Other important aims are customer satsifaction, costs and feasibility	Support 190: customer satisfaction and there we need to find the balance. So what does it mean for the plant? What does it mean for distribution? What does it mean for the costs? What is the long term impact on reputation on costs, on on competition? So I think there are all kind of things which you take into account to see if you. Yeah, it's a broad thing. You can't do it just with one, one few points. That's impossible.
service level is the primary aim with the decisions, but there are limitations as to cost or feasibility	Support 191: Yeah. I mean, from our perspective, it's always service level. I mean however, Sometimes that's not everybody's priority, right? So I would say it's it's the trade off between cost, service and inventory. I mean, we have to make that balance our preference is service level, but if it comes at significant on cost or it's going, we don't have the storage space to be able to do it. Then of course those other factors have to to come into play as well.
Information - process and effectivity are the two main goals	Support 192: Yes, generally seen there are most often several goals, but are there any goals within master data for me it is effectivity and quality.
Decision-making process	
the type of risks	Support 193: Yeah. So depending again, I think on the topic. You're doing it together, so if you talk about

decides the approach on how decisions are made	from our perspective from the sales and marketing perspective, if there was risk in distribution in transport, you do them together with distribution team. So you have a couple of meetings a year where you try to predict together or we have at least every month a meeting, by the way, obviously, OK, what is the expectation for the coming months and do we need to have extra capacity buying in extra capacity, I think like I said, for prediction planning we do that with the S&OP meetings and and the most other things like that are maybe more ad-hoc and then we have a crisis team and then we are making already from the start. If there's let's say a fire has been a fire or something, we say. OK. We meet each other every week in the crisis team and then we discuss. So it's again a bit different on what risk you're talking about, but. And if you talk about product allocation, for example, also that is something where you have regular meetings with demand planning and the and sales organization to set the right things, yeah.
Collaborating with others in decision-making	Support 194: I guess that it depends a bit on what it is, but most often it is in alignment with others. I might have spoken with colleagues to get some input here and there but I try to bring what we learnt during the years, and then making a broad and stable decision of whom we should work with. Can they offer altnerative solutions? Yes. It is about using the information that is available and try to think of all the aspects. But then you can, you can never protect yourself against everything, right? That can't be done
Collaborating with others when needed	Support 195: So nowadays I only do it when I feel a need. There are some tricky flows. When discussing those I can ask some colleagues for support to bounce ideas a bit and in order to get their view on certain topics. If you look at the full scope, there are only a few flows really. My team works ith it daily. I collect information from there as well. There we also get to know along with our KPIes, how does a hauler work? What is important? Do we want to continue working with them? Do we want to develop further on our partnership or should we scale it down? There is quite a bit of that going on regularly that I might not think about immediately.
Seeking alignment and understand with other departmetns in order to make decisions	Support 196: Yes I like to make decisions a bit in accordance with others. I want to look at both what opportunities there is. Some alternatives, what is is that we need to achieve? What are the different set-ups? We can't keep digging for how long, but would like to have more than one way to discuss. I want to align and anchor the decision with the people that are most affected.
Grounding the decisions with stakeholders	Support 198: That I like making decision in alignment with the people who are going to be affected by the decision, does not mean that I always do what the other person wants but I try to be transparent about that as well when I go against the input I have received. Because I think that they stick better, I mean have you made a decision where someone has been allowed to join in or you have explained why you made decision A or B. Then you already have managed to get a buy-in on it, you are you are already in on it. You need yo be kept responsible because you have been allowed into the dialogue.
If others disagree and have arguments for it the decision can be changed	Support 199: Sometimes it can be. I have two options. I prefer this one because it fits better with a different project that we will do. But I can consider that depending on your input, you take the other if you present a good argument that counters my arguments.
decisions that involve several stakeholders are more difficult to make	Support 200: The more difficult things are when we can see a problem but we don't necessarily know who can help us to fix it, or finding someone who will take accountability to fix it.
decisions that are only affecting supply are easier to make	Support 201: But I mean the things that are within our control are usually the easier ones to solve.
Larger risks requires mor thought and are more difficult to solve	Support 202: Yes often they are more complex, now always but yea the situation with the pandemic when everyone started hoarding toilet paper. That is a typical ehm we have max capacity in production, we can't produce what is demanded on time. So there we had to consider. It was a more difficult problem to sole, than if a product is out of stock for a couple of days.

Decision-making during crisis requires top management support and quick decisions, at the cost of a lack of facts	Support 203: Sometimes quick decisions are needed if it is a real crisis without having information that the decision would normally be based on. In those cases it is about there being a crisis team that gather with different senior managers from different departments, that just decide on how we are going to do. There were several of those decisions during the pandemic.
making decisions alone	Support 204: Nowadays I do actually, but it is also what type of product that you are talking about and how everything is working and perhaps also what kind of experience you have.
facts and data improve decision-making	Support 205 326: But I really need the facts on the table in order for me to make as good decisions as possible of course.
making decisions involves both data and human experience	Support 206: This is the complexity brought together that makes me make a decision to adjust the forecast.
inherent knowledge and experiences are used	Support 207: I might also by some experience know and through the fact that I know which customers it is, how the demand will evolve.
analysing situation, making an assessment and then making a decision	Support 208: I look at previous outcomes in order to predict a forecast going forward. I see a risk in that we have to low of a forecast in order to deliver to our customers. I make an assessment by looking at facts back in time in order to describe how it has looked. *** Support 209: So it is really about getting as good of an picture of the situation as possible. Be open with what you want, try to check the situation as well as you can and ensuring that all concerned stakeholders do their bit.
Acquire facts and data and analyse	Support 210: What can you offer? How can you handle it? It is about trying to get as clear of a picture as possible into what our partners can do. It is very dependent on the partners. And also to manage expectations internally.
learn from past year and be proactive	Support 211: Well I guess it was really about the learnings that we took from the year before. How can we handle it and also be proactive with our transports?
scenario-planning and making decisions of that, but data is necessary	Support 212: Something along those lines where we'll say, OK, this is what happens if we do it under scenario one under scenario two and under scenario three. And therefore we propose scenario one.
data is essential to understand effects of decision-making	Support 213: I think I need data. I mean we we take all of our decisions based on the best outcome, right? I mean, very often we we might offer several different scenarios, but we have a strong recommendation that we want to make behind. So in order to get to that point where we have scenarios, we need to have the data. So we need to understand what are the impacts usually for inventory, for cost and for service level.
decision-making is impaired due to a lack of data and visibility	Support 214: So yeah, just just having the data at my fingertips and and that is the tough part sometimes. As I mentioned, especially right now where we don't have scenario planning capability. To be able to do something in the system where I could say OK if I change the supply chain like this, what happens to my inventory? What happens to the cost to serve? What happens to the end to end lead time? This could be really, really interesting, and it's definitely we are quite far away from that right now.
The perceived impact of data and information	

global events impacts the decision-making and makes it more difficult	Support 215: The geopolitical aspects are of course much more difficult and they can have an impact that is comparatively larger as well. Look at when covid hit, what imbalances did we see on the market all of a sudden? Or the invasion of Ukraine again when drivers just disappeared and there is so much going on the world. It is impossible then to really prepare for everything if I am being completely honest.
understanding the effects of the decisions are difficult	Support 216: Yeah. So one is the cost impact in that sense that is not the most difficult part I think. Easy to calculated. It's more the commercial impacts. So how will? Yeah. I think from from my perspective, the commercial impact. So what will do with our customers and consumers? Because we can't. We are not able to deliver certain products and yeah, if your consumers are gone to competition, then it's difficult to win them back and of course reputation. So if you launch a product and they are not delivered in a good way, it can also ruin your reputation. So I think that is important and if you talk more from a factory point of view, if we now want to safeguard supply for the future and what happens in in our organization easily is that people say we need to increase forecast.
Time is often quite short	Support 217: Because what you can say is that there is quite a high pace when you are making a tender-process and a large part of it is pretty straight forward as well.
Too many people involved in making the same decisions slows down the process	Support 218: It requires a bit too many people to get involved in order to arrive a quick decision. I definitely think that we can do that part better, that we much more quickly group the key stakeholders that are going to make this decision and activate it straight away. Instead for it to become some form of long bench that only add to the problems during the situation.
unclear mandates proves to be a challenge	Support 219: Yes, but that could be in case there are unclear mandates. I dn't really like working that way most often. Nowadays I am not working in a line context, at this moment. But now I am working in a project like but in a line context like I worked in before. Then I was quite clear on that I wanted a pretty large autonomy. I am running this; I am running all master data operations. You. And of course informing my manager, but I, for that that could ve the largest challenge which is when you have unclear mandates or it is unclear who makes this decision or.
trust is an important factor in decision-making	Support 220: So I think it is pretty easy if you have faith in each other. And if you don't? Well then it doesn't work. Ja. Then it is almost unsolvable because you will be stuck in this loop. Then I think that it is an eternal challenge.
unclear ownership and missing inputs make the decisions more difficult to make	Support 221: And sometimes finding the right person is not always the easiest, so that can make decision making very hard because you don't know the full picture. You don't know who can take the ownership and that can slow us down as well.
people are not bringing what is required to make decisions	Support 222: Yes, it goes way to slow and another aspect is that perhaps not everyone brought what they should to the meeting. If we need to take a difficult decision, everyone needs to bring the right input in order to make the decision. The worst thing I know are these "work meetings" that end up "yes I will look at that".
getting accurate information and unpredictability of environment makes decision-making more difficult	Support 223: The challenge is that it is difficult and you don't really know what you get. It can sound excellent and that is a lesson learnt by us. Then it is also not sure that the operations will suffer terribly from it as we have to make actions quickly. But yes, I would probably say that it is the main challenge together with all of the macro-factors that we discussed last time as well.
not having access to the necessary data and insights is a challenge	Support 224: I would say the same thing again. I mean, just not always having all of the data that we need or or it taking too long to get all of the data that we need. I mean, sometimes the decision is actually made for us because it takes too long.
the necessary	Support 225: But it is not always that there are any information to get depending on the situation. In those

information does not always exist	cases you need to be more pragmatic and do best what you can to do in such a situation.
understanding the different options available more quickly would be better	Support 226: To to understand what we other options we had and and by that time actually we don't have another option. So yeah, having having data at our fingertips that enables us to take quick decisions.
AI impact on decision-making	
AI perceived as both risky and beneficial	Support 227: If we get a more positive picture of AI going forward and we see that it adds value, it could turn into a risk in too high expectations that it is the truth and that you make decisions for risk management for it, which might…. it just takes into consideration some of the problem or the risk but it lacks the total scope, which then results in us making the wrong decisions. That is something that could happen. But it could also happen that it spots something that we missed, which is great… we capture and minimise risk or mitigate it completely.
Predict peaks with AI	Support 228: But using AI to predict the peaks or maybe even evening out some of these peaks helps a lot in decision-making. How many haulers should you use? What can you prepare them for? So that helps a lot there. I would probably want to say that it helps a lot in the daily decision-making as well. How should you act when we might be informed that we are running a promotion or that we have a promotion in the works or a peak in volume, how do you act then? Can you predict that in a different way, you can also act differently. Today we are at times reactive, which makes it difficult and often leads to negative consequences. So there I think you can do a whole lot
Remove unnecessary decisions with AI	Support 229: I don't know, but there are many decisions. There are many decisions that go into that. I have been doing it for the past few weeks, but even on a daily level. So there are probably quite many things that can be made simplified and maybe some decisions that can be outright removed if you get better predictability.
AI can analyse more data	Support 230: analyzing the facts in objective way presented always in the same way. So I think that really helps to do so and taking in more data than a human being can be can do. It's faster. It's can do more so in that sense. I think and the prediction of course is.
Using AI for historical data analysis	Support 231: using it for decision making and you can talk about insights, for example insights from the historical information. That is one thing. Then we are talking about prediction, predicting the future
Automating repetitive tasks	Support 232: If we automate the boring task or manual tasks then we have more mental space towards high quality decision making. AI would enable that
Improving decision-making	Support 233: It's all about augmenting us, augmenting us as professionals with a lot of insights with a lot of supporting ideas and value related information so that we can decide better.
AI Assistance	Support 234: if we could have pre-prepared scenarios with recommendations and outputs of those scenarios at our fingertips, I think this would help decision making a lot *** Support 235: see how we can amend our supply chains, but it would be so much more effective if actually the system would tell us you need to update your supply chain, this is a much more effective route.
AI possibilities and limitations	Support 236: the interdependencies between different pieces of data are quite hard to bring together when there isn't a relationship between them in the systems. Whereas I think AI could really help us *** Support 237: You're going to need humans to understand what is a good or bad or an indifferent suggestion. So I think you're always going to need a human being to ultimately make the decisions and to to make the changes

AI as an assistant	Support 238: Like a consultation. That is something that should arrive in a pretty close future. But also like an assistant should also be able to use in many ways, most often integrated to different tools.
Improving visibility and decision-making	Support 239: So getting more visbility and transparency. Yeah, but. We. Because I've been looking at the statistical forecast in in markets can probably do a forecast in your prediction on your production as well. Which at the end will will provide you with probably better information to make your decisions better as well.
Data is important for decision-making in SCRM	Support 240: Yes well if you say in a shortage situation I first want to known how long this shortage will last, what it depends on, what the root cause is ehm. It is very difficult to start deploying countermeasures if you don't know what the root cause is, then there is a risk that you will being to counteract the purpose itself. *** Support 241: So yeah, just just having the data at my fingertips and and that is the tough part sometimes. As I mentioned, especially right now where we don't have scenario planning capability. To be able to do something in the system where I could say OK if I change the supply chain like this, what happens to my inventory? What happens to the cost to serve? What happens to the end to end lead time? This could be really, really interesting, and it's definitely we are quite far away from that right now. *** Support 242: I think I need data. I mean we we take all of our decisions based on the best outcome, right? I mean, very often we we might offer several different scenarios, but we have a strong recommendation that we want to make behind. So in order to get to that point where we have scenarios, we need to have the data. So we need to understand what are the impacts usually for inventory, for cost and for service level.
AI getting stuck in an infinite loop.	Support 243: Another thing that I have seen is using AI agents brings a little bit of nondeterminism in there, because when we are talking about different agents working together. Depending on the order of the information being phased and everything today, I mean we know that there are many cases that the agents can enter into an infinite loop

Appendix IV: Table 1 - Analysis of complexity for each identified SCRM task

Risk Category	SCRM Task	Outcome Multiplicity	Solution Scheme Multiplicity	Conflicting interdependence	Solution Scheme/outcome uncertainty
Demand	Demand forecasting	No	No	Yes	High
Demand	Risk categorization	No	Yes	No	Low
Demand & Supply	S&OP	No	Yes	Yes	High
Demand	Forecast evaluation	No	No	No	Low
Supply	Scorecarding	No	No	No	Low
Supply	Supplier evaluation	No	No	No	Low
Supply	Root cause analysis	No	No	No	Low
Supply	Countermeasure evaluation	No	No	No	Low
Supply	Supply chain redesign	Yes	Yes	Yes	No
Process	Customer collaboration	Yes	Yes	Yes	Yes

Process	Ad-hoc solutioning	Yes	Yes	Yes	High
Process	Data monitoring	No	No	No	Low
Environmental	Hauler evaluation	No	No	No	Low
Environmental	Identify critical transport flows	No	Yes	No	Low
Environmental	Diversify transport partners	Yes	Yes	Yes	High
Environmental	Rerouting	No	Yes	Yes	High
Environmental	Adjust stock levels	No	No	Yes	Low
Information	Data maintenance	No	No	No	Low
Information	Data creation	No	No	No	Low
Information	Stakeholder education	Yes	Yes	No	Low
Control	Capacity Planning	Yes	Yes	Yes	High
Control	Risk analysis	No	Yes	Yes	High
Control	Risk assessment	No	Yes	Yes	High

Appendix V: Subject Reports

Through the courtesy by one of the main contact persons that the authors had at the case company, the authors gained access to several reports on the subject of AI and decision-making made by Gartner, a research and advisory firm. While the reports were proprietary and shared with restrictions, preventing them from being quoted and widely used in the thesis, they added value to the thesis by opening up for greater perspectives in relation to the research questions. The reports were studied by the authors prior to the analysis as well as after the analysis. The authors also had discussions about the perspectives brought up in the analysis, complementing them with the perspectives from reports. It is important to mention that the authors maintained a distinction from the reports and the data, both primary and secondary, included in the report. The authors did not include any perspectives that they could not verify and back with the data that is available to the reader. However, the authors would still argue that gaining access to a greater amount of perspectives is beneficial when conducting qualitative research as it provides greater ability to interpret the data that has been collected.

Appendix VI: Experience from the case company

Prior to and during the time of writing the thesis one of the authors was employed by the case company used for this study. The author had worked with supply chain management which added greater understanding to the data that was collected from the interviews and the different tasks that were described to the authors. The author had himself performed many of the tasks that were described which offered valuable insights into the way the tasks were performed and what the characteristics of the tasks were. Since one of the authors had been employed for several years, much of the context surrounding the case company's data management processes and strategy was also made accessible by the authors. This allowed the thesis to form better perspectives and for the authors to discuss and incorporate viewpoints and information that would have otherwise been inaccessible. In the end this complemented the results and the analysis of the thesis by allowing for more accurate interpretation of the data collected. The fact that one of the authors was established within the case company arguably aided with the data collection process. This took form in two different ways. First of all there was a deep understanding of how the organisational structure looked like and worked in practice. Secondly, sending out interview requests and getting interviewee’s to accept the request for interviews was made easier.