DEGREE PROJECT IN INDUSTRIAL MANAGEMENT,
SECOND CYCLE, 30 CREDITS
STOCKHOLM, SWEDEN 2021

Data-Driven Decision-Making for Sustainable Manufacturing Operations

An empirical study of supply chain operations within the Swedish manufacturing industry

VIKTOR NILSSON

ARVID WESTBROEK

KTH ROYAL INSTITUTE OF TECHNOLOGY
SCHOOL OF INDUSTRIAL ENGINEERING AND MANAGEMENT

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Arvid Westbroek

Master of Science Thesis TRITA-ITM-EX 2021: 128
KTH Industrial Engineering and Management
Industrial Management
SE-100 44 STOCKHOLM

Datadriven beslutsfattning för hållbara tillverkningsprocesser

En empirisk studie om försörjningskedjor inom den svenska tillverkningsindustrin

av

Viktor Nilsson

Arvid Westbroek

Examensarbete TRITA-ITM-EX 2021:128
KTH Industriell teknik och management
Industriell ekonomi och organisation
SE-100 44 STOCKHOLM

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Arvid Westbroek</td></tr>
<tr><td>Approved
2021-05-27</td><td>Examiner
Jannis Angelis</td><td colspan="2">Supervisor
Luca Urciuoli</td></tr>
<tr><td></td><td>Commissioner
KTH Royal Institute of Technology</td><td colspan="2">Contact person
Mahesh Gopalakrishnan
Zuhara Chavez Lopez</td></tr>
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Abstract

A paradigm shift is taking place in the manufacturing industry, where companies strive for adopting digital tools to be able to compete against their competitors. The endeavor of becoming digitized is taking place simultaneously as the global awareness of sustainability increases. For the reasons that current literature is experiencing a knowledge gap that links data-driven processes, sustainability, and supply chain operations, there is a need for further exploration within this area. Therefore, the aim of this report is to investigate the business opportunities and challenges of data-driven decision-making, and how it relates to more sustainable supply chain operations within the manufacturing industry.

To investigate the area within data-driven decision-making and its impact on manufacturing supply chain operations, a literature review was initially conducted and was followed by interview sessions with case companies and experts. In total, 14 interviews were conducted within the area of sustainability, supply chain operations, and data-driven decision-making. The interviews were conducted to follow the designed framework and thus provide knowledge for the challenges, advantages, applications, and value capture in relation to data-driven decision-making and supply chain operations.

Comparing the empirical data with previous literature it was noted that data-driven decision-making entails both multiple challenges and advantages when it comes to improving manufacturers' sustainable performance. The main challenges include establishing efficient information sharing, standardized systems, and obtaining data that shows both reliability and validity. Consequently, by solving these challenges the sustainable benefits can be fulfilled, including a mitigated bullwhip-effect, improved planning, and reduced CO_2 emissions. These benefits are driven by the transparency, automatization, and optimization that is incorporated with data-driven decision-making. In conclusion, realizing data-driven decision-making within the manufacturing industry entails several challenges, but if companies overcome the challenges the potential benefits will be unlimited.

Keywords: Data-Driven Decision-Making, Industry 4.0, Digital Supply Chain, Sustainable Manufacturing.

KTH Industriell teknik och management	**Examensarbete TRITA-ITM-EX 2021:128** **Datadriven beslutsfattning för hållbara tillverkningsprocesser** Viktor Nilsson Arvid Westbroek

Godkänt	Examinator	Handledare
2021-05-27	Jannis Angelis	Luca Urciuoli
	Uppdragsgivare	Kontaktperson
	Kungliga Tekniska Högskolan	Mahesh Gopalakrishnan Zuhara Chavez Lopez

Sammanfattning

Ett paradigmskifte pågår för närvarande i tillverkningsindustrin, där företag strävar efter att använda digitala verktyg för att kunna konkurrera mot sina konkurrenter. Strävan efter att bli digitaliserad sker samtidigt som den globala medvetenheten om hållbarhet ökar. Av anledningarna till att den aktuella litteraturen upplever ett tomrum av kunskap som länkar datadrivna processer, hållbarhet och leveranskedjedrift, så finns det ett behov av ytterligare forskning inom detta område. Målet med denna rapport är därför att undersöka affärsmöjligheterna och utmaningarna med datadrivet beslutsfattande, och hur det relaterar till mer hållbara försörjningskedjor inom tillverkningsindustrin.

För att undersöka området inom datadrivet beslutsfattande och dess inverkan på leveranskedjedriften och tillverkningsindustrin så genomfördes först en litteraturundersökning som följdes av intervjussessioner med utvalda företag och experter inom området. Sammanlagt intervjuades nio företag och sex experter som valdes ut efter deras kompetenser inom hållbarhet, leveranskedjedrift och datadrivet beslutsfattande. Intervjuerna genomfördes med hjälp av en intervjuguide och därmed ge kunskap om kopplingarna mellan data, aktuella affärsverksamheter och förbättrad ekonomisk, social och miljöprestanda. Detta inkluderar att utforska utmaningar, fördelar, applikationer och värdefångst i kontext till datadrivet beslutsfattande och leveranskedjedrift.

Vid analysen av EMPIRISK data och jämförelse med aktuell litteratur noterades det att datadrivet beslutsfattande medför flera olika utmaningar och fördelar när det gäller att förbättra tillverkningsföretagens hållbara prestanda. De viktigaste utmaningarna är att etablera effektiv informationsdelning, standardiserade system och att erhålla data som visar både tillförlitlighet och giltighet. Genom att hantera dessa utmaningar kan de hållbara fördelarna uppnås, vilket inkluderar en minskad bullwhip-effekt, koldioxidutsläpp och förbättrad planering. Dessa fördelar drivs vidare av transparens, automatisering och optimering som ett datadrivet beslutsfattande medför. Sammanfattningsvis innebär förverkligandet av att använda datadrivet beslutsfattande inom tillverkningsindustrin flera utmaningar, men om företag övervinner utmaningarna kommer de potentiella fördelarna att vara obegränsade.

Nyckelord: Datadriven beslutsfattning, Industri 4.0, digital försörjningskedja, hållbar tillverkning.

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Acronyms and Abbreviations

Acronym	Description
AI	Artificial Intelligence
APS	Advanced Planning and Scheduling
AR	Augmented Reality
CPPS	Cyber-Physical Production System
CPS	Cyber-Physical System
CRM	Customer Relationship Management
DSC	Digital Supply Chain
DSN	Digital Supply Network
DT	Digital Twin
ERP	Enterprise Resource Planning
GSCM	Green Supply Chain Management
IIoT	Industrial Internet of Things
IoT	Internet of things
MES	Manufacturing Execution System
MNE	Multinational Enterprises
PLM	Product Lifecycle Management
RFID	Radio Frequency Identification
ROI	Return on Investment
SCM	Supply Chain Management

SDG	Sustainable Development Goals
SM	Smart Manufacturing
SME	Small-Medium size Enterprise
SPS	Smart Production System
TBL	Triple Bottom Line
VR	Virtual Reality

Acknowledgment

First and foremost, we would like to present our sincere gratitude to our supervisor at KTH, Docent Luca Urciuoli for helping us throughout the project with helpful comments, discussions, and recommendations. We would also like to express our appreciation to our peers and our seminar leader and examiner at KTH, Docent Jannis Angelis, who through vivid discussions together with our peers have helped us progress during the research and finalizing our master thesis.

We would also like to express a special appreciation to both Mahesh Gopalakrishnan and Zuhara Lopez, who presented us with a challenging and flexible project as a part of their funded project from KTH Industrial Transformation Platform. Mahesh Gopalakrishnan and Zuhara Lopez have throughout the project helped us to stay on topic and challenged our ideas by providing a different kind of perspective. Without their contribution, this research would not have been possible.

Finally, a special thanks to all case companies and helpful experts who have participated in our study and provided us with insightful discussions- your contributions cannot be stressed enough.

Viktor Nilsson & Arvid Westbroek
Stockholm, 2021-05-27

1 Introduction

In this section, the development of digital solutions connected to supply chain management and manufacturing is laying the foundation of the background and problematization for this research. The foundation is further developed with a holistic perspective on both digitalization and sustainability, which leads to the purpose of this study. Furthermore, the guiding research question is presented in order to meet the aim of the study. Lastly, the delimitations of the study are outlined.

1.1 Background

The industrial society is currently undergoing a transformation towards digitalization, which has been rapidly increasing during the last decade. This is due to the pressure driven by globalization, technology advancements, society, and a competitive landscape, which forces companies to begin a digital transformation (Zangiacomi et al., 2020). As a result, these factors have increased the importance of enabling not only flexible and cost-efficient systems, but also autonomous production, connected business entities, and integrated business systems, which all depend on the industry's digital capabilities (Rashid & Tjahjono, 2016). Consequently, the dependency and evolution of smart connected devices have led to the novel paradigm shift labeled Industry 4.0 (Tao et al., 2018) (see Annex A for a further description on Industry 4.0).

Even though Industry 4.0 comes with different definitions, its essence is the transformation from traditional to smart factories with automated and digitized systems (Schlechtendahl et al., 2015). To further enable smart factories, several different technologies can be utilized. However, in common terms, technologies such as Artificial Intelligence (AI), Internet of Things (IoT), Augmented Reality (AR), Blockchain, Drones, Virtual Reality (VR), 3D Printing and Robotics are commonly discussed as essential technologies to enable smart factories and have thus been described in past literature as the essential eight (PWC, 2017). On the other hand, to enable smart factories additional aspects must also be considered, for instance, the means of implementation, connectivity, Big Data analytics, and Cyber Physical Systems (Zangiacomi et al., 2020; Fatorachian & Kazemi, 2018). Adopting such technologies have been shown successful in meeting the industrial challenges businesses are currently facing, such as the higher demand for customization, flexibility, and productivity (Zangiacomi et al., 2020; Fatorachian & Kazemi, 2018). On the other hand, the aforementioned technologies differ significantly in their usefulness depending on the industrial area they are implemented in and are therefore not always used in certain industries.

One area that has the potential to excel with digitalization is the manufacturing industry. Digital manufacturing could lead to various improvements, where the improved possibilities to decentralize and use local manufacturing are seen as some of them (Durach et al., 2017). Decentralized manufacturing would consequently also enable a more sustainable production system, leading to Triple Bottom Line (TBL) benefits, e.g. economic, social and environmental benefits (Rogetzer et al., 2019). Furthermore, manufacturing losses are often heavily linked with either idle or blocked machine states (Skoogh et al., 2011). In order to overcome these types of losses, one solution could be to utilize decision support systems (Ylipää et al., 2017; Ma et al., 2002), since maintenance and machines that cause bottlenecks are usually difficult to anticipate (Roser et al., 2002). In addition, a decision support system could be used in order to increase sales figures, sale prices, satisfaction ratings, assortment planning, and inventory control. This is because better predictions can be made based on patterns in previous fluctuations of prices and customer experiences (Lloyd, 2011; Zhao et al., 2019).

Based on previous reasonings, utilizing efficient prediction systems in an organization can have positive effects on multiple levels in the organization. Looking at the supply chain level, organizations are in a dire situation to develop digitalization strategies as it is one of the fundamental parts of businesses (Mentzer et al., 2001). According to Seyedghorban et al. (2020), there are numerous opportunities that can be achieved by a digitized supply chain, such as increased information availability, transparency, access, and control as well as operations efficiency, giving economic, social, and environmental benefits. Additionally, by having data on time of order and arrival, lead time, cost price, and number of units ordered, supply chain operations also have the potential to be optimized with the help of data-driven decision-making (Zhao et al., 2019).

However, as the need for a digital transformation within society and businesses increases, the challenge of a digital integration is intensifying. Likewise, becoming more digitized will also generate the challenge of building the required competence regarding digital solutions. These types of challenges hinder the progress in which companies can adopt digital technologies. This is due to the fact that a company integrated competence, connected to data-driven agility, digital platform management, and IT architecture transformation, is needed for an efficient digital transformation (Legner et al., 2017). In addition, even though there are clear benefits of implementing digital solutions, another concern is the financial performance effect (Kohtamäki et al., 2020). According to Hasselblatt et al. (2018) and Ehret & Wirtz (2017), manufacturing companies often have the ability to collect large amounts of data, but often fail to capitalize on the benefits of the data in its digital applications.

Likewise, even if a company has the right approach to implement a digital foundation, additional factors such as environmental regulations and external circumstances can also prohibit digital integration. Environmental regulations are highly connected to the irresponsible industrial progress during the last century, which partly has caused global climate change. This climate change had consequently led to the act of the Paris Agreement where 196 nations agreed to mitigate global warming (UNFCC, 2021). Hence, due to governmental regulations, an implementation of a digital solution might not be feasible if it is not sustainable enough. However, according to Dechezleprêtre & Sato (2017), environmental regulations have also had a positive effect on the development of cleaner and more efficient technologies. Nonetheless, there is an increasing need for sustainable value creation (Kiel et al., 2017), which ultimately can help meet the sustainable development goals (SDGs) set by the Paris Agreement.

Besides environmental regulations, external circumstances can also affect businesses and the society as a whole overnight. This can be exemplified with the coronavirus outbreak in 2019, the Great East Japanese Earthquake in 2011 or the financial crisis in 2008. Similar crises and pandemics cause a lot of economic damage to industries and nations as a whole, but also to globalization and social interactions. Looking at the coronavirus pandemic, it is also estimated that heavily affected industries such as manufacturing, accommodation, food services, and retail will need a lot of time to recover from the virus's resulting effects (Shrestha et al., 2020). Furthermore, the need for a digital change has become apparent because of the coronavirus outbreak, as many organizations have had the need to adapt to alternative business models (Ritter & Pedersen, 2020). Consequently, the pandemic might have both substantial short-term and long-term effects, transforming the business landscape towards digitalization more rapidly.

1.2 Problematization

In accordance with the SDGs, industries are impelled to act to meet the sustainable goals demanded by society. Digitalization can be utilized to the extent to not only benefit companies' economic progress but also to improve the sustainability aspects of their operations (Ejsmont et al., 2020). In addition, Ejsmont et al. (2020) further demonstrate that the utilization of digital technologies has the opportunity to greatly improve the usage of resources. However, digitalization also possesses a risk towards some aspects of the SDGs connected to environmental, economic, and social factors (Birkel et al., 2019). Besides, most scientific studies have only been able to provide the risks of digitalization in regard to the technical challenges it provokes and have failed to include a holistic understanding of the sustainable challenges of digitalization (Birkel et al., 2019; Ejsmont et al., 2020). Therefore, there is a need for a more comprehensive view of the risks caused by a digital transformation.

Based on the work of Birkel et al. (2019), which to some extent demonstrates the risks connected to Industry 4.0, it is necessary to develop a further understanding in the area of sustainable risks and benefits to more specific applications within digitalization. It is therefore relevant to investigate the TBL of sustainability within manufacturing supply chain management since it is an area that is greatly affected by digitalization (Kiel et al., 2017; Zhou & Yang, 2018). In addition, manufacturing operations are also an area of great importance to investigate, as a digital shift towards Industry 4.0 has great potential in the manufacturing industry and is not yet fully understood, neither when it comes to how it is integrated into a company or its outcomes (Zangiacomi et al., 2020; Fatorachian & Kazemi, 2018).

Furthermore, it is apparent that it is crucial for manufacturing companies to adopt digital capabilities such as systems that allow connectivity, Big Data analytics, and virtualization. However, the productivity of such investments has been questioned as organizations' skills are lagging behind when it comes to technology advancements (Brynjolfsson & McAfee, 2011), and manufacturing companies often fail to capitalize on the available data (Hasselblatt, 2018; Ehret & Wirtz, 2017). Therefore, there is a need to gain an insight into how manufacturers can utilize data appropriately to make faster and better decisions and ultimately improve financial performance. Additionally, there is further need for investigation regarding the adoption of a digital supply chain, as there currently is a gap in research providing frameworks and guidance in how to adopt a digital supply chain (Büyüközkan & Göçer, 2018). Furthermore, Büyüközkan & Göçer (2018) also states that there currently exists academic literature regarding limitations and advantages of different digital supply chain strategies, but is limited by its number of real-life cases for the application of digital supply chains.

According to a study conducted by McKinsey & Company (2018), a large number of digital transformations fail to improve performance because of implementation challenges. Furthermore, the greatest risk, identified by board members and executives, is related to digital transformations (Protiviti, 2018). According to Tabrizi et al. (2019), there was a total investment in digital transformation of $1.3 trillion in 2018, whereas an approximated $900 billions of these investments went to waste. It is therefore increasingly important to identify the underlying reasons why digitized systems sometimes fail to deliver satisfactory results, and further how to overcome these types of complications. Nonetheless within supply chain management and manufacturing as they are two core application areas in which data-driven decision-making can be applied. There is therefore a further need to research real cases within the manufacturing industry where digital supply chains can be explored (Fatorachian & Kazemi, 2018), especially as the outburst of Covid-19 has changed the business landscape drastically.

1.3 Research Aim & Research Question

Given the problematization, one area that can and should be explored, due to lack of current knowledge in the area, is the effect data-driven decision-making has on the supply chain within manufacturing operations. Thus, the aim of this study is to explore the benefits and challenges of data-driven decision-making, and how it relates to more sustainable supply chain operations within the manufacturing industry. The research aim will be explored by answering the following main research question (*MQ*):

> *MQ: How does data-driven decision-making enable sustainable supply chain operations within the manufacturing industry?*

With this MQ, the intention is to understand how the systems, structures, and processes to plan and execute the flow of goods at the manufacturer level can be improved by utilizing data-driven decisions, seen from a sustainable perspective. In order to answer this, a prior understanding of how digitalization impact supply chain operations in a sustainable way is necessary and therefore the following sub-question is needed:

> *SQ: How does digitization impact manufacturing supply chain operations in a sustainable way?*

1.4 Delimitations

The number of digital solutions is continuously increasing. However, this study's focus will lie on *data-driven decision-making systems* as part of the digital transformation phenomenon and with a focus on *sustainable supply chain operations*. Additionally, this report is delimited by only focusing on *different sectors within the Swedish manufacturing industry* and has a main focus on firms with *over 1000 documented employees*. This is for the reason that larger organizations usually are more experienced in digital transformations, and thus commonly more able to provide deeper insights into data-driven decision making (Mittal et al., 2019). Moreover, the empirical data will be gathered from *in-depth interviews, with experts, researchers, and company representatives within the field of study*.

In this study, data-driven decision-making is seen from a general level, which is why it is delimited from technical aspects such as specific algorithms that make automated decisions. Instead, the focus is on the holistic meaning of the concept, and how it affects companies' manufacturing operations. Thus, this study mainly focuses on what data-driven decision-making entails, in terms of business activities, digitization, performance and sustainability.

Furthermore, the research will primarily concentrate on the *functional and industrial levels* of the system perspective described by Blomkvist and Hallin (2015) and therefore have *less focus on the individual level*. This will bring an in-depth analysis of the examined companies to facilitate the investigation of organizational structures and supply chains. Here, the research of manufacturing firms and their respective entities will give structure to the discussion on a functional level, whereas the investigation of the manufacturing industry as a whole will give way for the industry perspective and strengthen the discussion on an industrial level. However, the individual perspective that covers the view of management and employees will be included as well, but not to the same extent.

1.5 Disposition

Chapter 1 – Introduction: The introduction chapter describes the necessary background to understand the fundamentals of the report. It does so by introducing common concepts and challenges in current research, which subsequently demonstrates the current research gap regarding data-driven decision-making, the manufacturing industry, and sustainability. Consequently, the presented gap provides the research with an aim, research questions, and delimitations.

Chapter 2 – Literature review: Introduces the relevant academic research in regard to the presented research questions. It presents a deepening understanding of the challenges with data-driven decision-making and how it can provide the manufacturing industry with sustainable benefits. The goal of the literature review is to help the research answering the research questions.

Chapter 3 – Theoretical Frame of Reference: Includes the foundation of the conceptual model and discusses how it is relevant and developed for the purpose to assist the research to fulfill its aim. The conceptual model is discussed in relevance to the current literature and provides the research with the forming of its interview guide.

Chapter 4 – Method: This chapter discusses the selected methods in the research. It demonstrates how the applied methods are supported by academic research and its relevance in the study to eventually provide the necessary support to ensure sufficient research quality. Ethical considerations are also discussed and demonstrates how the Swedish Research Council's four ethical principles and The Code of Honour Swedish Engineers were taken into consideration.

Chapter 5 – Findings and Analysis: Presents the empirical findings gathered from the interviews, which is derived from both the perspectives of practitioners and experts. This chapter further provides the main findings and an analysis of how the perspectives of the practitioners and experts correlate.

Chapter 6 – Discussion: Provides propositions to the research questions in accordance with the findings and previous literature. First, the subquestion is discussed in relation to the common and different views of the experts, practitioners, and previous literature. Then, the main question is discussed in a similar way. The conceptual model is subsequently discussed in relation to what sustainable data-driven decision-making entails.

Chapter 7 – Conclusion: Concludes the study by offering answers to the research questions as well as presenting recommendations related to managerial implications. In addition, this chapter outlines both the academic and sustainability implications of the study. Lastly, the limitations and suggestions for future research are brought to attention.

2 Literature Review

In this section, the literature review is outlined. Here, a better understanding of data-driven decision-making, smart manufacturing, and digital supply chains is given. Furthermore, this chapter introduces both practical and theoretical perspectives to the problem statement.

2.1 Data-Driven Decision-Making

In recent times, the amounts of data have been ever-increasing, and especially within the manufacturing industry (Zhong et al., 2016). Data has further been added to one of the key resources for an organization, as the potential it provides if used correctly is endless (Mitra & Munir, 2019). For instance, it allows the utilization of Big Data, which ultimately can increase financial performance, optimize business prioritization and promote better decision-making (Caesarius & Hohenthal, 2018; Davenport, 2014). According to Zhong et al. (2016), service and manufacturing supply chain management have been integrating digitalization for a long period of time. In addition, SCM together with Big Data enables better decision-making systems, which can provide faster responsiveness to disruptions and failures (Zhong et al., 2016; Fatorachian & Kazemi, 2018).

Thus, data-driven decision-making facilitates the solution for complex business problems (Arunachala, & Kumar, 2018). Here, data-driven decision-making refers to the process of making decisions based on the analysis of data, rather than on intuition. Additionally, data-driven decision-making is not strictly limited to the analysis of data, since organizations can use it to a lesser or greater extent and combine it with expertise and experience (Provost & Fawcett, 2013). Further, looking at the decisions that can be made based on data, Provost & Fawcett (2013) illustrate two different types of decisions, which are decisions connected to 'discoveries' and decisions that underline and strengthen an intuitive one. Data could for instance supply more knowledge to a given situation to facilitate better forecasting, in which discoveries can be recognized. Brynjolfsson et al. (2011) further argue that data-driven firms are more productive than those who are not, and that the productivity increases the more data-driven a firm is.

However, to benefit from all the data available, and subsequently use it to make better decisions, one must tackle the challenges that the large amounts of data impose. These challenges can be compiled to the 5Vs, which stands for *Volume*, *Velocity*, *Variety*, *Verification,* and *Value* (Zhong et al., 2016). Here, volume stands for overcoming the high amounts of data. For instance, Markopoulos (2012) explains that a manufacturer generates approximately 4 trillion data samples per year. Velocity is the challenge of efficient data management, where e.g., the reliability of data transferring and collection of data is fundamental. Furthermore, various data sources such as sensors can come in various formats, which leads to the challenge of variety and integrating diverse sets of data into a common format. In addition, much of the available data is not always sufficient enough to make complex decisions, which leads to the challenge of verifying the data from good to bad. Lastly, it is not always straightforward if the value of Big Data is satisfying, as it could be difficult to measure the overall impact Big Data has (Zhong et al, 2016; Brousell et al, 2014; Zhou & Yang, 2018).

With data-driven decision-making, firms enable more data-driven manufacturing, where Tao et al. (2018) argue that the big data-driven manufacturing era is coming. However, when considering the lifecycle of a product and the sustainability aspects, the value Big Data provides to these areas is still unclear. In addition, it remains a challenge to fully become data-driven, hence a challenge to sufficiently implement Big Data (Tao et al., 2016). Therefore, it becomes essential to understand data-driven smart manufacturing (SM) and how to enable it, what type of manufacturing data there is, the connection from SM to a digital supply chain, and the obstacles for an optimized data-driven supply chain. These areas are thus presented below.

2.2 Data-Driven Manufacturing

For an organization to become fully data-driven, the entities within the organization are required to be both data-driven and smart, nonetheless within the manufacturing operations. To understand what is meant with data-driven SM, the definitions of data-driven manufacturing and SM are required. The former can be defined by the aforementioned section as a method to make decisions based on data analysis and interpretation (Provost & Fawcett, 2013), whereas the latter is the usage of data to build manufacturing intelligence and ultimately improve manufacturing operations (O'Donovan et al., 2015; Zhou & Yang, 2018). However, no truly accepted definition regarding SM currently exists (Kusiak, 2018; Ghobakhloo, 2020). It can therefore be argued that SM is highly dependent on a data-driven manufacturing process, whereas the full potential of data-driven manufacturing is dependent on SM (Tao et al., 2018). Consequently, data-driven SM can be explained by a physical-to-digital-to-physical loop (see Figure 1), where physical data can be analyzed and captured by machines to subsequently enhance the manufacturing process (Deloitte, 2018).

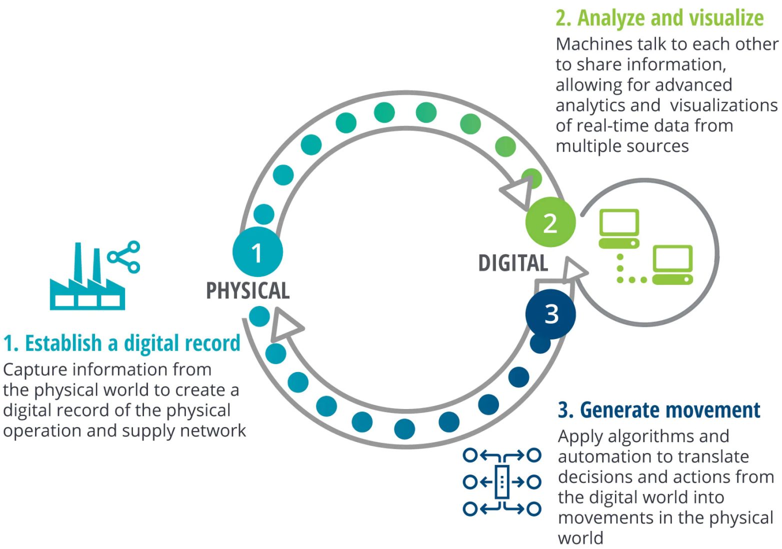

Figure 1. The physical-digital-physical loop (Deloitte, 2018).

Implementing well-functioning data-driven SM operations within organizations requires a substantial change, however, the benefits derived from such transformation can be significant (Cheng et al., 2000; Zangiacomi et al., 2020). The benefits are fundamentally driven by the capabilities to improve the manufacturing TBL of sustainability (Mittal et al., 2019; Khan & Turowski 2016; Fatorachian & Kazemi, 2018; Zhou & Yang, 2018), which in turn are driven by the flexibility, connectivity, and responsiveness of data-driven SM. Consequently, the realization of these benefits has led to global investments in digitalization enabling technologies. In addition, even though the investments needed for a transformation of such scale are extensive, they are still seen as economically sustainable as the Return on Investment (ROI) is expected between two to five years (Fatorachian & Kazemi, 2018).

Data-driven SM can further enable the increasing demand for customer-centric production (Kagermann et al., 2013). This becomes possible as big data analytics can generate the necessary data regarding customer demands, making it possible for interconnected and automated devices to adjust to the specific demands (Fatorachian & Kazemi, 2018). The interconnected systems' communication also allows further adjustments based on additional external and internal data. For instance, the communicating systems could derive additional information from other production sites or internal material flow, which makes it possible to shorten the lead time by enabling a highly self-regulated and self-organized production system (Tao et al., 2018). In addition, Tao et al. (2018) indicate that historical data also should be exploited as it is a keystone to create automated and self-learning systems. Consequently, 30% of the total industrial energy consumption which is spent on machine repairs and idling could be decreased by self-learned systems predicting machinery failure (Ylipää et al., 2017).

Tao et al. (2018) further imply that the presented systems above; self-learning, self-organized, self-regulated, self-executing, and customer-centric systems are the five most distinguishable positive characteristics of data-driven SM. However, agile manufacturing systems and interconnected systems are also seen as essential characteristics and benefits of data-driven SM (Kagermann et al., 2013; Öberg & Graham, 2016; Hu & Kostamis, 2015). Likewise, with the multiple positive features, an equal number of issues and challenges can be associated with becoming and remaining data-driven.

The issues connected to data-driven SM are multi-folded. However, a few fundamental concerns exist, where one is connected to social sustainability at the industrial, functional, and individual level (Kache & Seuring, 2017). Looking at the industrial level, Kache & Seuring (2017) show that two severe issues industries face are the major transformation regarding machines making current employees redundant and acquiring the right technological competence. This means that multiple organizations will experience concerned employees fearing layoffs (Fatorachian & Kazemi, 2018). This is also applicable at the managerial levels as data-driven and automated management could make management teams' work redundant (Sahlin & Angelis, 2019). For the reason that this topic also relates to the individual and functional level of the industry, the importance to ethically handle this must be stressed. Studies have shown that to have highly digitalized operations, support from employees and customers increases the success rate of digitized transformation by up to 30% (Ewenstein et al., 2015). Likewise, profits, productivity, and shareholder return are also likely to be improved (Schroeder & Modaff, 2018).

Moreover, Kache & Seuring (2017) observed that the most prominent challenges relate to the implementation process and more precisely, gaining the right IT capabilities. Implementing the right technologies is both a functional and an industrial issue because it requires large financial investments and collaborations from all parties connected in the industrial network (Ghobakhloo, 2020). This is due to the fact that data-driven manufacturing entails a digital supply network (DSN), meaning that the various systems must be able to generate a constant information flow throughout the entire industrial network (Ghobakhloo, 2020; Deloitte, 2018). In addition, DSN often requires that the parties in the network must invest heavily in Cyber-Physical Systems (CPS) because they enable the communication between humans, machines, and industrial parties (Mittal et al., 2019; Zangiacomi et al., 2020). Nevertheless, capturing and sharing the data is commonly not the main IT concern, instead, it is the ability to make sense of the vast amount of data that becomes an issue (Khan & Turoskwi, 2016). The reason for this according to Khan & Turoskwi (2016) is that the usage of Big Data analysis requires special technologies and usually lacks a clear purpose in the corporate strategy, making it both costly and time-consuming.

Lastly, several researchers also discuss the issue of having a secure data flow since the amount of data is increasing simultaneously as businesses are becoming more connected than before (Fatorachian &

Kazemi, 2018). The security issues are often linked to the industrial need to be transparent, because transparency enables both a company's internal operations and external organizations to quickly respond to different events, such as machinery failures or stock shortages (Sinha et al., 2020). However, transparency relies on that all information flowing through the DSN is secure, and if the security is breached the connected parties in the network will become reluctant to share information (Kache & Seuring, 2017). The challenge is therefore to both build systems that can monitor all data and create procedures that can restrict potential cyber-threats (Khan & Turoskwi, 2016). This becomes a challenge since the number of data-generating devices is increasing and thus more data and industrial nodes must be monitored as they face a potential risk of a cyber-attack (Khan & Turoskwi, 2016). It is consequently important to have a deep understanding of how data is generated to put in preventive procedures to secure the flow of data.

2.3 Lifecycle of Data within the Manufacturing Industry

As manufacturers are starting to value the strategic importance of data (Tao et al., 2018), it is increasingly critical to be able to interpret the knowledge that lies within the data. By doing so, manufacturers can enable SM, but also start leveraging digital solutions such as IoT and AI (Zhong et al., 2016; Tao et al., 2018). Here, IoT solutions can provide real-time data with the help of sensors (Mourtiz et al., 2016), and AI can facilitate the process of decision-making with no human interaction (Wuest et al., 2016). However, to utilize these solutions, one must be able to control the data generated by different manufacturing processes. The types of data that can be collected are *User data, Equipment data*, *Product data, Management data,* and *Public data* (Tao et al., 2018).

The collection of data may also vary depending on which type of data that is collected. For instance, management data can be collected from manufacturing information systems, such as ERP, CRM, and MES (Tao et al., 2018) (see Annex B for further description regarding information systems). Conclusively, data-driven decisions can be made on design schemes, orders, material distribution, product planning, marketing, and sales as well as service management (Tao et al., 2019). Furthermore, equipment data cover operating conditions and performance, while user data include data on customer-specific preferences on offerings and user behavior. Lastly, product data and public data are collected from IoT technologies (e.g. RFID sensors) and governmental databases respectively. Here, IoT technologies can provide data on product performance and environmental measurements such as temperature and air quality (Tao et al., 2018).

However, all of the data are not relevant if it is not translated, which is the process of standardizing all data in a common format. Translating data is also one of the main challenges practitioners currently experience (Zhong et al., 2016), especially if the excessive amount of data originates from both internal and external sources (Kumar Singh & El-Kassar, 2019). This entails formatting all data in a clear format so that it can be interpreted appropriately and support manufacturers to make better decisions. However, translating data to get detailed information requires that it passes through various steps (see Figure 2), which further explains why practitioners see the translation of data as a challenge (Tao et al., 2018). These steps are, as illustrated in *Figure 2*, consisting of data sources, collection, storage, processing, visualization, and applications.

Figure 2. The process of translating data, adapted from Tao et al. (2018).

The data sources can be collected from various sources, such as manufacturing information systems or from IoT technologies, which were previously presented in this section. All the collected data must further be stored both securely and effectively, which in later years has seen improvements through cloud computing (Agrawal et al., 2010). Subsequently, the data can be processed, meaning that the data are reduced from misleading, redundant, and inconsistent data. Hence, the data become clean and structuralized, which makes it possible to analyze the data for new information. This leads to data visualization, where the information is presented in a more accessible way, for instance with the help of graphs or diagrams. Lastly comes the step of data application, where the data are distributed and used appropriately, e.g., for making better decisions (Tao et al., 2018).

However, to get a consistent view of the business entities within an organization, one must recognize the underlying information objectives. This is commonly referred to as Master Data, which resides in the most fundamental information that drives the business operations (Zhao et al., 2020). For instance, Master Data includes customers, employees, suppliers, products, locations, contracts, and policies (Loshin, 2010). Thus, it is fundamental that firms have high-quality Master Data to make accurate business decisions (Vilminko-Heikkinen & Pekkola, 2017). Establishing high-quality Master Data has further become a vital challenge for organizations to overcome (Haug et al., 2013), as the data need to be coherent and unified (Loshin, 2010). Consequently, an organization's Master Data management needs to be sufficient enough to implement data-driven decision-making.

2.4 Enablers of Data-Driven Manufacturing

To enable fully data-driven manufacturing operations both data-driven and smart processes are needed, thus the barriers described in section 2.2 must be managed to enable data-driven manufacturing. However, the enabling factors for well-functioning data-driven SM cannot be fully described by the previously mentioned challenges. Therefore, several additional aspects must also be described. It should further be considered that the enablers must be managed differently depending on the company since small-medium size enterprises (SME) are generally behind multinational enterprises (MNE) when it comes to developing SM (Mittal et al., 2019).

Managerial Readiness

When pursuing a larger organizational transformation, the management has several aspects to consider making the transformation successful, which include both economic and social sustainability considerations (Ghobakhloo, 2020). In section 2.2, issues regarding social sustainability were presented, but additional social considerations must also be declared to enable data-driven SM. The social dilemma of providing a purpose for the digitalized machines must be given attention, as the machines should not replace existing employees but rather enhance their current tasks (Kagermann et al., 2013; Sinha et al., 2020). Otherwise, the likelihood of failure will increase as employees will not trust nor support the new systems (Ewenstein et al., 2015). Organizational actions toward human cyber-physical operation instead of fully automated systems have therefore become important. This has led to the development of the concept of Operator 4.0, which is a strategy that puts focus on human-in-the-loop processes instead of fully automated systems (Sinha et al., 2020).

Operator 4.0 has the ability to enhance employees' work processes and show that the management is investing in the employees and not for their replacement (Sinha et al., 2020). However, this also requires that the management is willing to offer the necessary training to enable the employees to utilize the digitized machines. This type of support and engagement from the higher management is essential for a digital transformation, due to the fact that it enables employees to accept changes in the operation procedures (O'Donovan et al., 2015). The openness for change is critical because individuals in the organization must be willing to participate in the process for the intra or inter-organizational change to take place, which applies to individuals at all levels within the organization (Ghobakhloo, 2020). A high level of support from the management is indispensable to increase the willingness for change, but also a key to enable the necessary resources needed for the whole adoption of SM (Ghobakhloo, 2020).

According to O'Donovan et al. (2015), managerial engagement is also crucial for evaluating the performance of data-driven SM and to consequently optimize the TBL of sustainability and overall equipment efficiency (OEE). However, to be able to evaluate the performance, a roadmap for the adoption process is necessary to compare the actual outcomes with the original plan (Zangiacomi et al., 2020). Roadmapping is also a powerful tool of framing the investments and thus gives an understanding of the resources required for the utilization of SM and if any legal actions such as GDPR must be considered (Zangiacomi et al., 2020; Kagermann et al., 2013). Consequently, given a structured roadmap, an organization can efficiently analyze if the investments will become economically sustainable. Otherwise, the transformation for digitized manufacturing operations can become troublesome for the reason that it is heavily reliant on the organization's financial abilities even though the costs for a digitized implementation have decreased in recent years (Fatorachian & Kazemi, 2018).

Virtualization

A second core principle to enable data-driven SM is virtualization, meaning that the company adopting data-driven and smart abilities must be able to create digital copies of the physical world (Mittal et al., 2019). However, to enable virtualization it is necessary that the organization shows both operational and digitalization maturity (Ghobakhloo, 2020; Kusiak, 2018). The reason for this is that data-driven SM requires a special standard to function properly. Hence, old types of machinery that no longer meet the requirements for SM must be upgraded to eventually progress and gain the benefits of SM (Schlechtendahl et al., 2015). To become operational and digital ready, manufacturers must initially set up investment principles to evaluate the existing technologies to understand if an upgrade is needed (Ghobakhloo, 2020). Subsequently, an upgrade of the required equipment must be pursued while also having an overall managerial readiness for SM to enable virtualization (Sjödin et al., 2018). Nevertheless, it is necessary to understand that this is a time-consuming process, which cannot be done overnight.

When the necessary equipment is acquired, the progress of enabling virtualization can be initiated. Installing BI systems have the ability to convert complex data sets to meaningful and useful information that ultimately serves as a tool to improve the decision-making process (Hoelscher, 2002). BI systems entail a combination of both virtualization and analytics, which paves the way to enable data-driven decisions, making BI systems a top software investment for companies in general (Hou, 2016). However, BI systems need a data warehouse built on structured master data, where it can extract both internal and external data to later analyze and visualize the information (Popovič et al., 2019). Consequently, as the analysis and visualization can be made in real-time, it can create substantial value for the organization as it facilitates faster and more accurate decisions (Popovič et al., 2019).

One of the most promising BI systems for virtualization is to enable a digital twin (DT). A DT does almost exactly what it says, it mirrors the life cycle of a physical product in a corresponding digital twin (Tao et al., 2017). In this way, the organization can track a product's digital footprint and consequently make decisions from detected problems, to further optimize TBL performance (Tao et al., 2019a). However, DT is merely a subset of CPS. It is therefore necessary to initially implement CPS before a DT because CPS is the key enabler for the communication between the physical and digital world (Tao et al., 2019b). In addition, DTs have not yet reached their full potential as they have to be developed further to be fully adopted (Tao et al., 2019b).

Moreover, when the manufacturing operations become virtualized, the operations become transparent, which is an important trait of virtualization (Sinha et al., 2020). The transparency makes it possible for both the internal organization and external partners to receive valuable inputs in real-time if systems such as CPS and DT are utilized (Mittal et al., 2019). However, as more data becomes available, both internally and externally, the risk of a security breach increases. Security must be ensured from the outset when implementing new digitized systems and become a central part of the company strategy, both to secure confidential data and to ensure the transmitted data have not been altered (Kagermann et al., 2013; Mittal et al., 2019). Likewise, secure systems must be integrated throughout the value chain as all parties are cyber-connected in the DSN and thus pose a risk of cyber-attacks (Ghobakhloo, 2020). Security systems such as Blockchain, Semantic technologies, vulnerability assessment, machine learning, data leakage technologies, risk detection, and integrity monitoring are according to Ghobakhloo (2020) fundamentals for a secure data-driven SM.

Connectivity

Connectivity is also a central factor for data-driven SM because being truly data-driven and smart, the systems must be able to connect and make decisions on the multiple variables they provide (Kusiak, 2018; Sinha et al., 2020). The connected devices are dependent on interoperability, in the sense that they must be able to exchange information (Mittal et al., 2019). However, to enable interoperability several technical steps must be executed. First of all, devices with interoperability capabilities must be integrated within the manufacturing operations (see Figure 3) and throughout the organizations' value chain, both horizontally and vertically (Ghobakhloo, 2020). This also highlights the need for managerial readiness as an implementation of interconnected systems between the value chain entities requires a high level of collaboration across the value chain (Kusiak, 2018).

A seamless integration further addresses the capability of machines to connect to devices of different brands by creating uniform communication and storage systems (Ghobakhloo, 2020). Based on a recent study, only 4% of manufacturing devices are able to connect to a network due to the lack of uniform communication systems (Fatorachian & Kazemi, 2018). Therefore, the importance of standardized networks must be highlighted to enable horizontal and vertical communication (Fatorachian & Kazemi, 2018). In addition, standardized communication and storage systems also stress the need for effective collaboration between the value chain entities (Kusiak, 2018).

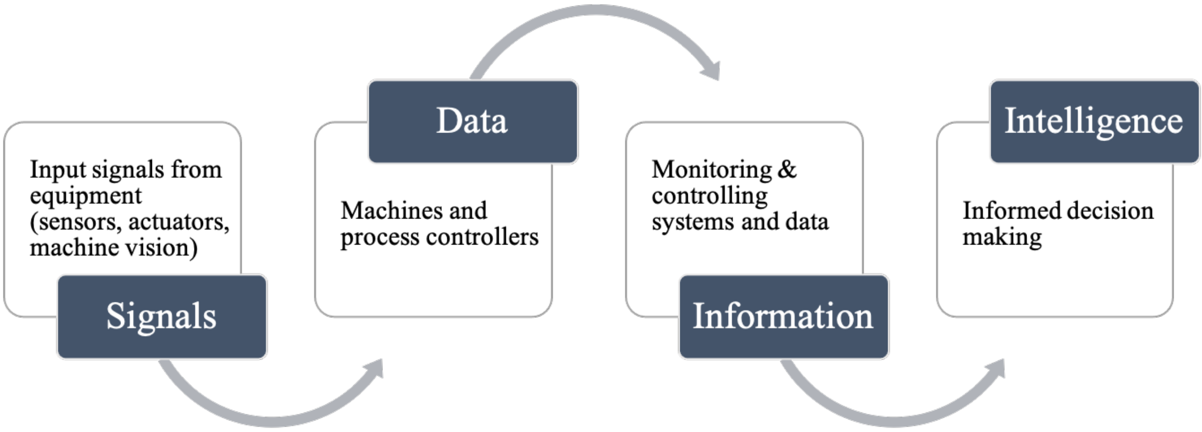

Figure 3. Communication process within manufacturing operations, adopted from Ghobakhloo (2020).

The integration and communication of devices create an embedded information network, where data flows through the organization as illustrated in *Figure 3*. Currently, different information systems are used by manufacturers including PLM, ERP, and SCM (see Annex B), for the purpose to enhance production planning, coordination, and management of resources (Tao et al., 2018). However, according to Koh et al. (2008), current systems do not provide complete connectivity, and thus new systems have been developed with the progress of Industry 4.0 (Tao et al., 2018). Consequently, to enable full connectivity, the existing systems must be updated or replaced with systems that are capable of capturing all product data and provide real-time and secure communication (Fatorachian & Kazemi, 2018). However, modern information communication systems are further dependent on a variety of technologies to function properly (see Figure 4), which also requires a substantial amount of energy (Ejsmont et al., 2020).

The Industrial Internet of Things (IIoT) is one of such enablers for connected information systems and can be seen, based on Ashton's (1999) definition of (IoT) describing it as the center of all connected devices in the industrial setting. Thus, IIoT enables a network where products, information, and people can connect (Kagermann et al., 2013). On the one hand, IIoT is a means to enable connectivity, but on the other hand not accountable for the communication itself. Instead, it is the CPS that allows the communication between humans and machines (Brettel et al., 2014), or Cyber-Physical Production Systems (CPPS) in a manufacturing context (Sinha et al., 2020). Nevertheless, IIoT connects CPS and CPPS to the Internet and therefore becomes a prerequisite for both systems as it provides a system to communicate through (Sinha et al., 2020; Fatorachian & Kazemi, 2018).

In addition, CPS and CPPS also rely on the embedded systems in manufacturing and that they are able to generate data. According to Brettel et al. (2014), one of the most important sources of data is in regard to commodity flow. Hence, it becomes essential that devices such as Radio Frequency Identification Devices (RFID) or similar technologies are embedded in the manufacturing systems and generate data that can be communicated through CPS and CPPS (Brettel et al., 2014). However, as several different CPPSs are available, a CPPS information server that can enable the communication between different CPPSs is also needed (Fatorachian & Kazemi, 2018).

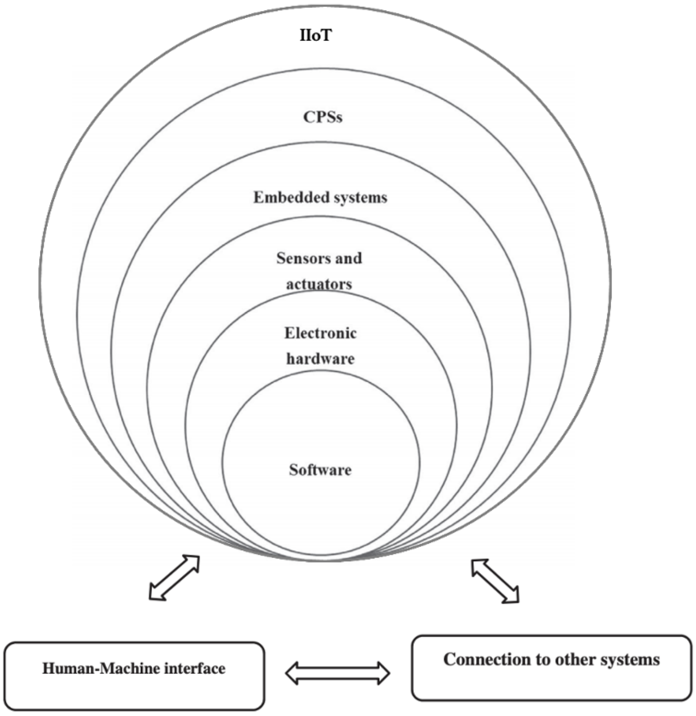

Figure 4. Enablers for humans-machines interaction, adopted from Brettel et al. (2014) and Fatorachian & Kazemi (2018).

Big Data Capabilities

Data-driven decisions are based on making sense of a vast amount of data generated internally or externally by CPSs and stand-alone devices (Kache & Seuring, 2017). Making sense of data is challenging and as of today, manufacturing companies often fail to effectively use the generated data, which leads to a slow transition towards becoming data-driven (Zhou & Yang, 2018). As mentioned earlier, BI systems have the ability to make sense of data and virtualize the industry operations to subsequently enable data-driven decisions. However, for BI systems to function appropriately, the vast amount of generated data must be sorted to become accessible for the BI systems, which becomes troublesome when the amount of data is increasing and becoming more complex (Debortoli et al., 2014). Therefore, it is essential for manufacturers to be prepared to handle Big Data to manage the larger and more unstructured datasets, which further build the foundation for a data-driven SM (Mitra & Munir, 2019; Tao et al., 2018).

In order to achieve Big Data readiness, manufacturers must obtain competences in data analytics, which means that manufactures are required to have capabilities to turn the 5Vs (*Volume*, *Velocity*, *Variety*, *Verification,* and *Value*) (see Section 2.1) of Big Data into useful information in the manufacturing operations (Mittal et al., 2019). Big Data analytics can, in general, be explained as the successor of BI systems and can through the analysis of a wider set of unstructured and semi-structured data answer new types of questions and through that create value for the organization (Debortoli et al., 2014; Popovič et al., 2019). While BI systems only answer known questions, Big Data analytical tools can explore unknown questions and thus discover and predict new industry trends, which helps the company to become more data-driven (Debortoli et al., 2014). However, as the analysis of data is of great importance, the methods to capture the data also become crucial. Therefore, cloud networks also become necessary as it allows the high-speed and real-time communication of data to be stored and accessible for analysis in a data warehouse (Fatorachian & Kazemi, 2018; Mittal et al., 2019).

To further benefit from Big Data in the manufacturing industry, Big Data and the analytic tools should be integrated within the organization's information systems (Elragal, 2014). Elragal (2014) demonstrates that applying Big Data analytics to CRM can provide a comprehensive view of customer data. Likewise, Kache & Seuring, (2017) and Li et al. (2015) present potential benefits and challenges with the integration of Big Data and SCM, where improved transparency and efficiency are stated as the core opportunities. In addition, marrying Big Data with PLM also has enormous application areas such as improved equipment, transport, and demand management (Li et al., 2015). Consequently, ERP systems have the potential to improve significantly if integrated with Big Data analytics technologies, as it is reliable on the data generated from the CRM, SCM and PLM systems (see Annex B) (Elragal, 2014; Ouiddad et al., 2020). However, these information systems must be ready to be integrated with Big Data to function properly, for example, by having IT and security capabilities (Mittal et al., 2019). Consequently, by obtaining Big Data readiness, organizations can exploit and apply the benefits associated with Big Data and thus enable data-driven SM.

More specifically, looking into ERP and how it coordinates the supply chain processes, the ability to handle Big Data within SCM could, as mentioned above, lead to meaningful improvements for ERP, nonetheless, within sustainability (Li et al., 2015). The reason to highlight the ability to handle Big Data within SCM is because Big Data can be extremely fruitful in an SCM context and thus a data-driven SM (Kache & Seuring, 2017). To gain the right abilities to handle Big Data within SCM, systems to manage and analyze the data flow must be enabled (Leveling et al., 2014). Consequently, by accessing IIoT, data can be derived from sources internally e.g. ERP systems and RFID tags, and externally from other supply chain entities (McKinsey & Company, 2016). However, the vast amount of generated data from these types of information systems occurs with a variety of quality and structure (McKinsey & Company, 2016). This becomes troublesome as the master data becomes difficult to sort out, which further makes it hard to gain the benefits of the generated data (Zhao et al., 2020).

One way to assort the master data is through master data management, however, today's databases for master data management such as SQL must be updated to manage the new types of data (Leveling et al., 2014; Zhao et al., 2020). This is because the data must be analyzed to different extents as explicit information such as RFID readings of inventory becomes structured and can be used fairly unprocessed whereas implicit network information requires a more profound analysis (Kache & Seuring, 2017; McKinsey & Company, 2016). Consequently, Leveling et al. (2014) indicate that new databases known as NoSQL databases must be utilized to manage and store the different kinds of data. Databases such as NoSQL have the ability to manage the volume, velocity, variety, and value of Big Data (Mitra & Munir, 2019). It, therefore, becomes possible for manufacturers to capture and use real-time information (Mitra & Munir, 2019), which SCM systems are heavily dependent on e.g. minimizing waste and increasing efficiency (Kache & Seuring, 2017). Moreover, this also requires that the manufacturers are able to obtain Big Data from the external supply chain entities, putting pressure on establishing a well-functioning DSN.

2.5 Adopting a Digital Supply Chain

With SM comes advantageous benefits such as dynamic visibility, optimized operations, and factory automation (Sinha et al., 2020), which subsequently supports the digitalization of the supply chain network (Ghobakhloo, 2020). Scholars further argue that the traditional supply chain will change because of demanding decision-making procedures, the increasing demand for sustainable products and services, as well as the change in customer behavior (Bernardes et al., 2020; Garay-Rondero et al., 2019). Here, new digital technologies and the value of data have further changed the business landscape (Deloitte, 2016), which also are the drivers for SM (Sinha et al., 2020). As a result, scholars argue that the traditional supply chain will shift into a DSN (Sinha et al., 2020; Deloitte, 2016; Bernardes et al., 2020; Büyüközkan & Göçer, 2018; Garay-Rondero, 2019), which is an integrated flow of information powered by multiple supply chain sources, see *Figure 5* (Deloitte, 2016).

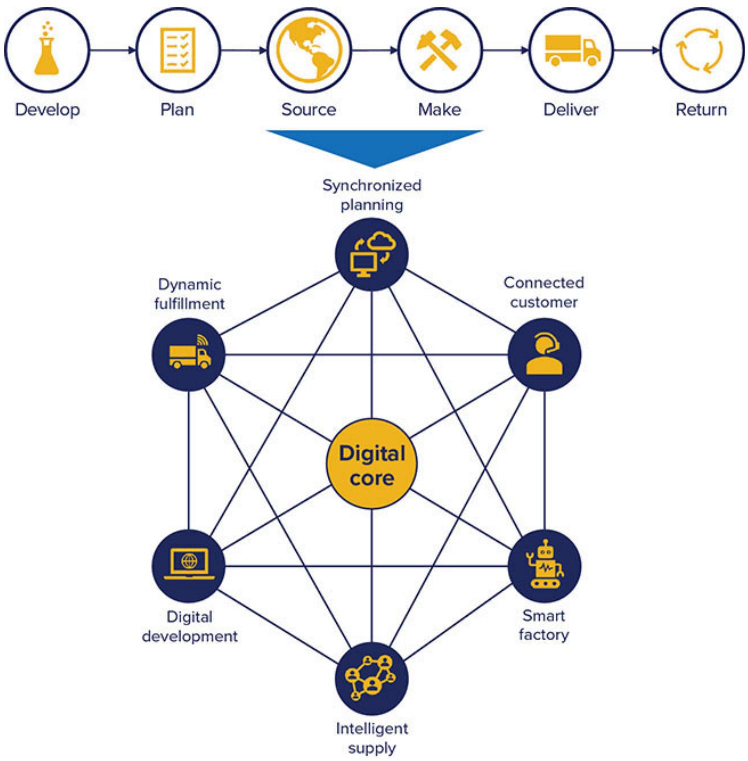

Figure 5. The shift from a traditional supply chain towards a digital supply network (Sinha et al., 2020).

The traditional supply chain often consists of a variant of *plan-source-make-deliver* (see Figure 5), whereas DSNs rather contain a digital core that simultaneously covers six various supply chain capabilities (Sinha et al., 2020). Furthermore, the differentiation between a DSN and a traditional supply chain is that DSNs allow (1) end-to-end transparency, (2) high levels of agility, (3) a connected environment, (4) resource optimization, and (5) holistic decision making (Sinha et al., 2020). Consequently, a DSN both support and enable full visibility within the whole supply network, facilitate more flexible responses between actors and processes, enhance communication and collaboration between all actors and functions, promote the collaboration between humans and machines, as well as enable better decision-making to ultimately improve the financial performance (Sinha et al., 2020). Additionally, organizations are more likely to adopt multiple DSNs to leverage real-time data from all parts of the supply chain (Deloitte, 2016). This allows companies to minimize the latency of processes, making DSNs more able to provide flexibility and customization, as well as fulfilling the strategic goals of the organization (Deloitte, 2016).

Rather than being dependent on a variation of *planning-sourcing-making-delivering*, the key capabilities of a DSN can instead move towards operating more dynamically, which are fundamentally driven by the factors in *Figure 5*; digital development, synchronized planning, intelligent supply, smart factory, dynamic fulfillment, and connected customers, (Sinha et al., 2020). For instance, digital development helps develop high-quality products and reduce R&D expenses, and as a consequence, increase the manufacturing flexibility. Synchronized planning further enables just-in-time processes and effective predictions on customer demand, as it can utilize historical and real-time data. Moreover, intelligent supply has the ability to improve the collaboration between actors by an integration of advanced platforms for certain needs and invoices. Another DSN capability is smart factory, which facilitates increased business performance and a safer working environment by the utilization of production and demand data. Dynamic fulfillment can further enhance customer experiences by delivering the right product to the right customer at the right time. Lastly, connected customers enable the enrichment of customer experience by better predictions of customer needs (Bernardes et al., 2020; Sinha et al., 2020; Deloitte, 2016).

However, in order to adopt a DSN, it is critical that a digital core is implemented, which in this case can be enabled by SM (Sinha et al., 2020). Consequently, it has to rely on various technologies and data to operate appropriately. As SM relies on e.g., CPPS and IIoT, so does a DSN. A digital core could for instance be fulfilled by the integration of a supply chain Control Tower, which has the ability to facilitate visibility among the entire supply chain (Trzuskawska-Grzesińska, 2017). Trzuskawska-Grzesińska (2017) further defines a Control Tower as a "planning and execution system that effectively deals with resource constraint and/or contention as well as process deviation to execute corrective and preventive actions in real-time". A Control Tower can gather and analyze multiple sources of data, thus allowing for process improvements and enhanced decision making that is aligned with the strategic business objectives of firms (Sinha et al., 2020; Trzuskawska-Grzesińska, 2017).

Further technologies that promote the operational ability of DSNs are digital technologies that are also driving the digital transformation, such as AI, additive manufacturing (3D printing), robotics, drones, and blockchain technology (Sinha et al., 2020; Deloitte, 2016). With the support of such interconnected technology solutions, a free flow of information can be obtained, which is the most fundamental part of a DSN (Deloitte, 2016). However, as the adoption of DSNs could be a daunting task (Bernardes et al., 2020), it is further important to acknowledge the benefits and challenges related to an integration of a digital supply chain. The benefits and challenges of adopting a DSN are therefore outlined below.

Obstacles for a DSN Adoption

As a DSN is interlinked with SM, so are the challenges that arise when implementing more digitized production processes. Therefore, the challenges presented in section 3.4 are further applicable when considering the adoption of a DSN. However, as a transition from a traditional supply chain is necessary, new challenges are thus presenting themselves (Deloitte, 2016). For instance, an implementation of new technology such as IoT in a work area is not sufficient to establish a DSN, instead, it is of greater importance to incorporate a culture of change linked to digitalization (Garay-Rondero et al., 2019). In addition, Büyüközkan & Göçer (2018) argue that some of the challenges for a digital supply chain consist of lack of information sharing, high volatility, and overconfidence in suppliers.

The development of a DSN can further be described by the integration framework by Büyüközkan & Göçer (2018), which is illustrated in *Figure 6*. Digitalization entails that companies who strive for a

DSC need to have a digital strategy, thus it is crucial to implement digital solutions (e.g., Big Data analysis, virtualization, and connectivity) that enable a digital work environment (Mittal et al., 2019). Additionally, it is important to have the necessary enablers for various technological implementations, which includes having sufficient financial resources, time, and an organizational strategy that aligns with the technological implementation (Büyüközkan & Göçer, 2018). When a secure and efficient flow of information is established, organizations can utilize real-time data and advanced analysis of the information. The improved data analysis can further be used to establish automated supply chain processes in order to manage supply chain fluctuations more efficiently (Büyüközkan & Göçer, 2018). Moreover, Büyüközkan & Göçer (2018) argue that an organizational reconfiguration is necessary to develop a DSC, as the advancements in technology entail an organizational change.

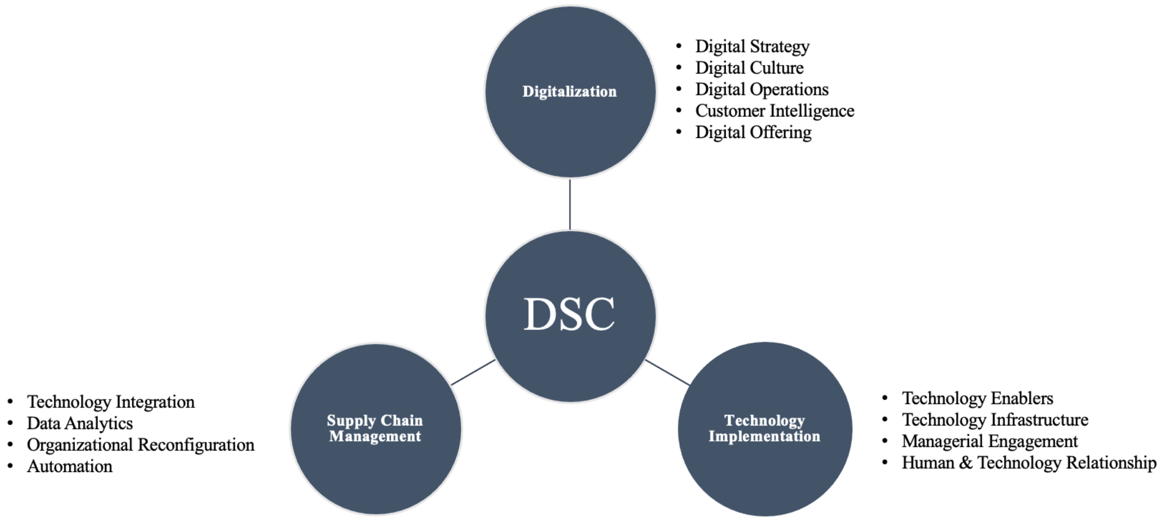

Figure 6. Integration framework for the development of DSC, adopted from Büyüközkan & Göçer (2018).

However, the most notable obstacles for a DSN integration are presented by Sinha et al. (2020), which can be derived in four main challenges that overlap with the implementation of SM. The first challenge is related to the benefit of connectivity, where the challenge of overcoming a behavioral shift among skilled workers is needed. For instance, workers within a DSN must embrace AR to improve the maintenance process, and AI to consolidate better forecasts and planning. Furthermore, with a more interlinked chain of operations, manufacturers need a more holistic consideration of consequences, and more importantly, be ready to manage huge amounts of data. Consequently, effective management of data simplifies the process of obtaining high-quality master data, which is needed for data-driven decisions (Vilminko-Heikkinen & Pekkola, 2017). Additionally, employees might also reject the idea of a DSN, as explained for the SM case in section 3.2, as a robot counterpart will impact process changes, which consequently change employees' work environment.

Furthermore, Garay-Rondero et al. (2019) suggest three steps to overcome the obstacles for successful integration of an interconnected DSC, which consists of (1) focus on the digital experience with the client in the initial digital adoption, (2) make an extensive investment in the virtual value chain, which reside in the "gathering, organizing, selecting, synthesizing, and distributing of information" (Rayport and Sviokla, 1995), and (3) perform the transformation to SM. However, Deloitte (2016) argues that it is important to think big, start small and act fast when adopting a DSN. Hence, manufacturers should first immerse themselves in innovation and acquire the necessary technological capabilities for a DSN. Subsequently, companies can make way for an implementation at the 'edges' of the organization, where there are no substantial consequences if failure. Lastly, by acting quickly the benefits of DSN can be proven and lead to greater readiness and beneficial exposure (Deloitte, 2016).

2.6 The Triple Bottom Line of Digital Supply Networks

By adopting a DSN, the benefits of end-to-end transparency, agility, connectivity, resource optimization, and holistic decision making can be utilized (Sinha et al., 2020), which further can lead to better sustainable performance (Hasan et al., 2019). For instance, with technology advancements within the supply chain, a green supply chain management (GSCM) that covers the TBL of sustainability can be realized together with increased operational performance (Yang et al., 2020). Here, the internal performance is linked with the economic aspect, whereas the external performance is linked with the environmental and social aspects (Hasan et al., 2019). Moreover, the efficiency gained by DSN processes can be translated to a positive impact on the environment, as the usage of raw materials can be optimized, and process waste reduced. In addition, sensors and tracking technologies could further improve waste management, thus reducing the environmental footprint (Sinha et al., 2020). However, it must be stressed that the technologies required to establish a DSN, and similar business processes linked to Industry 4.0 consume a significant amount of energy and thereby impacts the environment negatively (Ejsmont et al., 2020).

Furthermore, a GSCM considers the environmental performance of the complete value chain (Darnal et al., 2008). Consequently, a GSCM includes sustainable procurement, manufacturing, distribution, and logistics (Chin et al., 2015). In addition, Hasan et al., (2019) argue that a sustainable design is critical to achieving green business processes. For instance, it includes the design of the entire supply chain process, which ultimately affects material procurement, planning, and the logistics process. Therefore, Diwekar (2005) indicates that a sustainable design process helps to achieve enterprise sustainability. Moreover, a DSN allows for more sustainable strategies for transport, warehousing, office management, inventory control, and material handling systems, which all help achieving sustainable logistics systems (Hasan et al., 2019).

In addition, a DSN could further be utilized for beneficial marketing purposes, the manufacturing of more sustainable products, and influence pricing to affect consumers' willingness to pay for green products. Hence, by adopting a DSN, companies can benefit from multiple sustainability advancements, and ultimately achieve a sustainable value chain, which is presented in *Figure 7* (Hasan et al., 2019). Here, Aiello et al. (2020) argue that new business models are needed to further strengthen the more sustainable value chain.

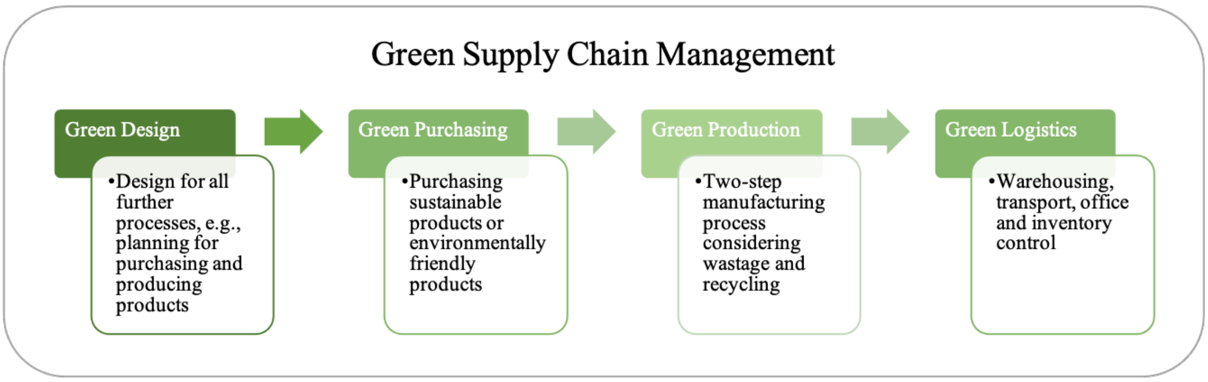

Figure 7. Green SCM value chain, adopted from Hasan et al. (2019).

3 Theoretical Frame of References

In this section, the theoretical frame is outlined, where a guiding model lays the foundation for the analysis and discussion. This is as a consequence of the subsequent need of a DSC, as it enables the utilization of data-driven decision-making.

3.1 Defining the Main Parameters Behind Data-Driven Decision-Making

Based on the literature review, three main parameters that are connected to data-driven decision-making can be identified. These include the enablers for data-driven decisions in the manufacturing industry, the current business activities and operations towards more data-driven processes, and what the companies end goal commonly is with data-driven processes. Moreover, these are found to be the main parameters in current literature in the field of data-driven decision-making in the manufacturing industry, which helps to generate an understanding of the current knowledge in this area. To provide further information on the parameters they are described below.

Enablers

In accordance with the reviewed literature, one must first build a digital foundation that can be driven by new technology (such as AI, Big Data analytics, and Blockchain) in order to utilize data-driven decision-making. Therefore, as presented in Section 2.5 a digital core is needed, which can be enabled by an integration of a supply chain Control Tower and SM (Trzuskawska-Grzesińska, 2017; Sinha et al., 2020). Consequently, manufacturers are bound to work more effectively with data, which is needed when making decisions based on data (Vilminko-Heikkinen & Pekkola, 2017). Mittal et al. (2019) further argue (see Section 2.5) that a digital strategy is crucial when developing a DSC. In addition, for a firm to become digitized it must be able to share and exchange information in real-time (Mittal et al., 2019), which subsequently entails that connectivity is a central factor when being data-driven (Kusiak, 2018; Sinha et al., 2018).

Furthermore, by having a solid IT infrastructure, firms can utilize data in an unlimited potential (Mitra & Munir, 2019). For instance, as presented in Section 2.1, data could facilitate better forecasting and mitigate the bullwhip-effect (Provost & Fawcett, 2013). However, to create value and make faster and better decisions, one must be able to analyze and visualize data in real-time (Popovič et al., 2019), which further requires data warehouses and structured master data (see Section 2.4). Thus, to enable data-driven decision-making a DSC is needed, which in itself is reliant on a sufficient IT infrastructure and data. The aspects of data and IT infrastructure thus facilitates one of the three main cornerstones of a DSC in the manufacturing industry.

Business activities

As described in the reviewed literature, manufacturers are currently pressured by globalization, technology advancements, society, and competitors to enhance their current operations (Zangiacomi et al., 2020). Therefore, manufacturers' business activities towards more data-driven and smarter operations are apparent, which has led to a paradigm shift in the industry (Schlechtendahl et al., 2015; Tao et al., 2018). However, the manufacturing industry's progress towards becoming digitized is slow as manufacturers' current business activities often fail to benefit from their digital systems (Hasselblatt et al., 2018; Ehret & Wirtz, 2017). This is driven by the challenges of companies' data lifecycle, which commonly shows weaknesses in transferring data between different systems and making sense of the data (Fatorachian & Kazemi, 2018). In addition, due to the extensive resources needed for digital transformation, it is common that MNEs usually are ahead of SMEs as they are more capable to invest in these types of business activities (Mittal et al., 2019).

Consequently, due to the challenges of becoming digitized, it can be seen that manufacturers' current business activities are behind other industries in the transition towards Industry 4.0. It can be seen in the literature that most companies still use older information systems for their business activities that are not capable of providing the right tools to enable fully data-driven operations as they lack in connectivity and analyzing the data (Koh et al. 2008; Zhou & Yang, 2018). Thus, as the quantity of data increases together with its complexity, companies' current business activities are undergoing a slow transition towards becoming data-driven (Zhou & Yang, 2018; Zhong et al., 2016).

End goal

In the manufacturing industry, digitalization can have limitless benefits, however, what has been seen in the literature the main goal for organizations is to become more sustainable in regard to the TBL performance (Mittal et al., 2019; Khan & Turowski 2016; Fatorachian & Kazemi, 2018; Zhou & Yang, 2018). Even though less focus has been observed regarding social sustainability compared to both the economic and environmental aspects, the end goal to improve social sustainability is still visible. By becoming more digitized there is a strive for the human-in-the-loop process, which means that companies desire to improve the work environment for the employees by utilizing machines to enhance and ease their tasks (Sinha et al., 2020). However, these improvements in the work environment also have the agenda to not only enhance the social aspects but also to improve the financial performance of the company by making the processes more efficient (Seyedghorban et al., 2020).

Consequently, the end goal by incorporating digital tools is also to improve the financial performance by minimizing machinery idle and bottlenecks (Ylipää et al., 2017; Ma et al., 2002), and to enable agile manufacturing (Kagermann et al., 2013; Öberg & Graham, 2016; Hu & Kostamis, 2015). In addition, the data-driven tools are also desired to support the decision-making processes to maximize profits and minimize waste experiences (Lloyd, 2011; Zhao et al., 2019). The improved decision systems would further help create more accurate decisions for the purpose to optimize the companies' supply chain and manufacturing operations.

In turn, it can also be seen in the literature that the economic benefits of optimized supply chain and manufacturing operations are the main drivers for data-driven operations, but the end goal to minimize the environmental impact of the company also exists. Companies strive to reduce the energy consumption for machinery operations, to minimize waste and usage of raw materials in the production process (Ylipää et al., 2017; Sinha et al., 2020). In addition, the financial optimization of the supply chain management often goes hand in hand with minimizing the environmental footprint of the supply chain (Hasan et al., 2019), which means that an improved inventory, transport, and warehouse management often leads to reduced environmental impact. This makes it possible to realize both end goals of improved financial and environmental performance by optimizing the production and supply chain processes.

3.2 Guiding Model for Sustainable Data-Driven Decision-Making

The theories regarding how to enable a DSC are not specified to Swedish manufacturer's supply chain operations, nor how a DSC relates to the TBL. Therefore, a guiding model (see Figure 8) is needed to understand the applications to fully understand the sustainable value creation from data-driven processes. It is further unclear how the enablers for data-driven operations relate to the condition Swedish manufacturers currently are in and their TBL goals, which is why benefits, challenges, and the value of incorporating a DSC is also needed to be understood. Furthermore, to cover the focus on data-driven decisions, the model examines data-driven decision-making in the supply chain to understand the sustainable value creation it can facilitate within the manufacturing industry. Here, the main parameters behind data-driven decision-making that were described in the previous section become important, as they lay the foundation for the guiding model.

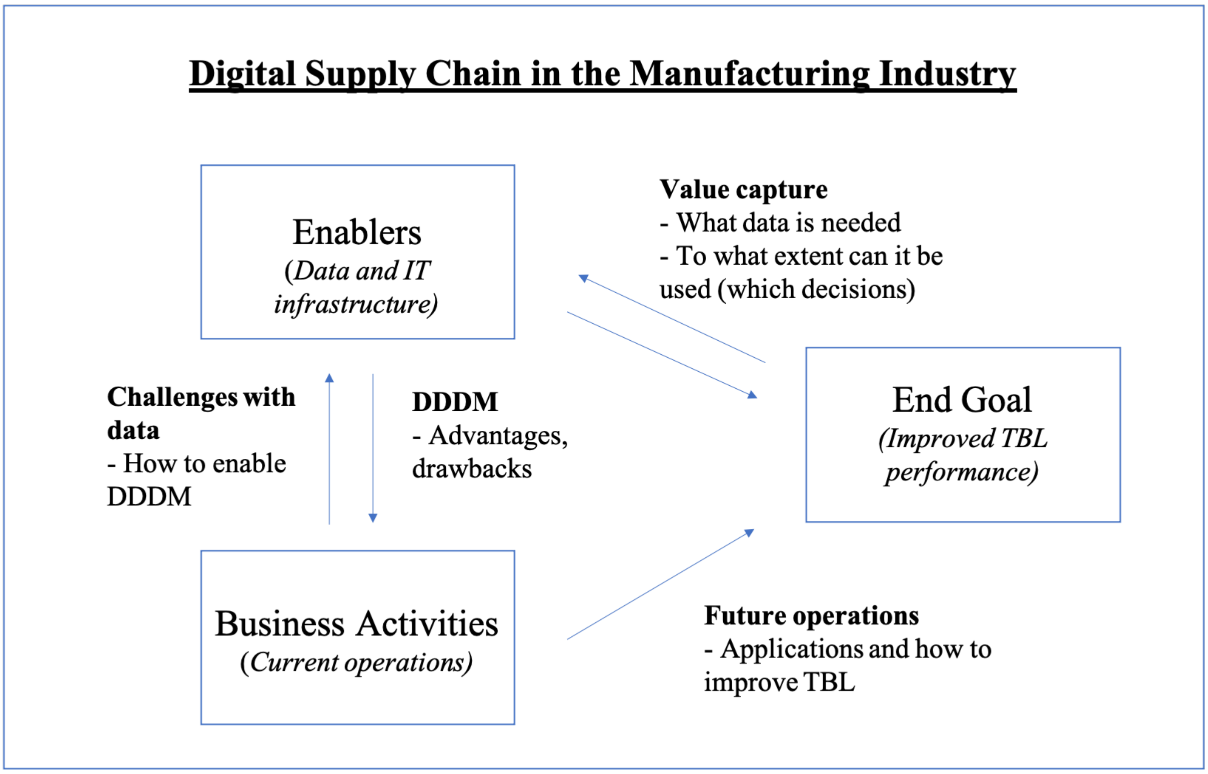

Figure 8. Guiding model for sustainable data-driven decision-making.

The linkages between 'Enablers' and 'Business Activities' consists of 'Challenges with data' and 'DDDM', as the linkages induce the understanding of how to further enable data-driven decision-making and what the main advantages and drawbacks are respectively. The link between 'Business Activities' and 'End Goal' consists of 'Future operations', which investigate the current business activities and the associated challenges with the current operations within the supply chain. Therefore, an understanding of how data-driven decision-making can transform the manufacturing industry towards a more smart and connected supply chain can be gained. Lastly, the linkages between 'End Goal' and 'Enablers' consist of 'Value capture', which can help get an insight of the value that is captured by improved sustainable performance. Ultimately, one can receive an understanding of how data-driven decision-making can enable a sustainable supply chain.

The linkages between the three parameters of 'Enablers', 'Business Activities' and 'End Goal' are not fully explored by current literature and further facilitates the understanding of how data-driven decision-making can enable a sustainable supply chain. Thus, by investigating the linkages between the three parameters, the aim of the study can consequently be fulfilled. Moreover, the sustainable performance is measured from the three aspects of the TBL and is evaluated through the captured value data-driven decision-making generates. This model is therefore acting as a guiding framework for the rest of the study and is laying the foundation for the analysis and discussion.

4 Method

This section addresses the methodology for the research, where the research design, research setting, data collection and data analysis is outlined. Here, the multiple case study approach is described and motivated concerning meeting the purpose of the study. In addition, the quality of research is detailed and presented with a subsequent discussion on the ethical considerations adopted within the research process. Figure 9 illustrates the research process, in which data was collected in two separate phases by semi-structured interviews. The data collection was subsequently followed by an analysis, where the results and conclusions from the interviews were compiled.

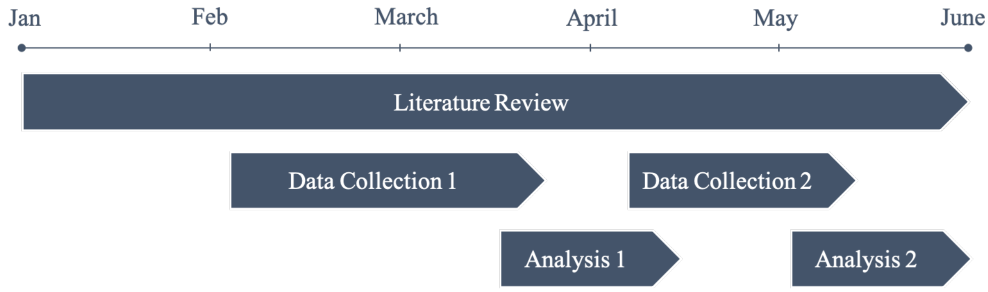

Figure 9. Schematic illustration of the research process.

4.1 Research Design

The research design of this study was established by a qualitative approach, meaning that the data analysis utilized non-numerical data (Saunders et al., 2015). This is mostly due to the limitations to access numerical financial and environmental data from external companies because of confidentiality and knowledge. Furthermore, qualitative research often commences in an inductive or deductive approach, which implies that the reasonings are based on particular observations or identified premises respectively (Gregory & Muntermann, 2011). However, a combination of an inductive and deductive approach can also be utilized, which was the case in this study. This concept is called an abductive approach, where inductive conjectures are refined and deductive ones are tested iteratively during the research (Saunders et al., 2015).

Additionally, the abductive approach was evaluated as appropriate in this study since the alternation between inductive and deductive principles allowed for flexibility and freedom, which further is a key feature in theory-building (Eisenhardt, 1989). This flexibility also initiated the systematic breakdown of the complexity of the researched phenomenon, as the literature could continuously be revisited to strengthen the empirical findings and is one of the reasons why an abductive approach was utilized. The process of the abductive approach can visualized in *Figure 9* and shows that after each data collection and analysis the literature has been revised, where redundant data have been removed and necessary information has been added in correlation to what have been found in the interviews. Consequently, the literature review has been a continuous process from January to June.

Moreover, Baxter and Jack (2008) argue that qualitative case studies are appropriate when exploring or describing specific phenomena in context, specifically when the focus of the study is to answer “how” questions. An exploratory case study further can generate sufficient insights in its real-life context, which subsequently can lead to rich empirical descriptions and development of theory (Saunders et al., 2015; Eisenhardt, 1989). In addition, case studies allow gathering data from multiple sources, which enables researchers to elucidate the case (Baxter & Jack, 2008). Drawing on previous reasonings, a case study approach was argued to be an appropriate strategy for this research. However, Yin (2003) expresses concern when it comes to unknowingly making subjective judgements within case studies. Hence, to avoid falling into the risk of biased conclusions, the study followed the guidelines regarding validity, which are further described in Section 5.5.1.

Case studies can further involve single or multiple cases (Yin, 2003; Eisenhardt, 1989), where a single case often is used to describe a critical or unique case and multiple cases when replicating findings across cases (Saunders et al., 2015). In this study, a multiple-case approach was concluded to be suitable to properly fulfil the purpose of the research, as several manufacturers were studied and cross-compared allowing for conclusions over the Swedish manufacturing industry to be made with limited bias (Yin, 2003). Additionally, by conducting a case study, analytical generalization could be applied (Blomkvist & Hallin, 2015; Patton, 2014), thus also allowing for transferability of the findings and making the study more rigorous (Patton, 2014). However, as stated earlier, the premises for unintended subjectivity are often illuminated when conducting case studies, which might be a poor basis for generalization (Yin, 2003).

4.2 Research Setting

To address the aim of the study and the described research questions, the selected cases were to include companies within the manufacturing industry. It was further chosen to cover the Swedish manufacturing industry and thus a focus on Swedish manufacturing companies were selected. To gather a holistic understanding of the Swedish manufacturing industry regarding data-driven decision-making and TBL of sustainability, companies at different stages of their digital transformation were studied. Likewise, for the purpose to generate a broad perspective on the impact of data-driven manufacturing and its effect on supply chain operations MNEs with different offerings were included. This was to establish an understanding if there are factors that must be considered depending on the companies' offerings. Consequently, by including multiple cases in the research, a chain of evidence can be generated, which can improve the validity and mitigate the bias of the study (Yin, 1994).

To cover the different stages of the case companies' digital transformation an internal evaluation of the companies was conducted, which included a comparison of the companies' level of digital integration based on a grading system. This was established through the respondents' answers and discussions in the interviews, where a positive point was given to each linkage of a current digital integration or plans to do so in the short-term future. Negative points were also included to further cover the level of digital integration among the current operations. For instance, points were deducted if they still used legacy systems, had a fragmented IT structure or were highly dependent on manual processes that could have already been automated (see Appendix A). Based on the different points given to each case company, a certain level of digital integration could be identified. Here, companies that were given zero to two points were evaluated to have a low level of digital integration, whereas the ones given three to five points a medium level and six to seven points a high level of digital integration (see Figure 10 below). These evaluations of companies' digital experience were made after each interview to ensure that before ending the interview process the study had gathered data from companies with high, medium and low digital integration.

Company	A	B	C	D	E	F	G	H	I
Level of digital integration	◑	●	○	○	●	◑	◑	●	◑

● - High ◑ - Medium ○ - Low

Figure 10. Level of digital integration as a comparison of the studied case companies.

Moreover, the importance of including both SMEs and MNEs can be highlighted as current research has shown that MNEs often are ahead of SMEs in their development towards SM (Mittal et al., 2019). This indicates that contributing factors affecting SMEs and MNEs development should be analyzed to gain a broader perspective of data-driven manufacturing. Therefore, academics in the field have been interviewed to give a better understanding of SMEs. However, the focus will be drawn towards MNEs as they commonly have more experience in the field of SM and thus capable of giving profound insights in a digital context (Mittal et al., 2019). Therefore, companies with over 1000 employees have been selected for interviews. The interviewees further occupied respondents with management positions in the organization as these respondents were more capable of reporting profound insights into the connection between TBL and data-driven decision-making.

In addition, the sectors including machinery manufacturing, metal manufacturing, furniture manufacturing, automotive manufacturing, hygiene & health, clothing & textile and petroleum & biofuel production have been in focus in this research to provide the research with a holistic perspective to the manufacturing industry. A holistic approach also increases the generalization of the study (Flyvbjerg, 2006), and thus also improves the research's validity and bias (Eisenhardt, 1989). To further reduce the bias in the selection process of the selected sectors, the interviewed companies were selected randomly but with some requirements to be met. These requirements included that the companies should have over 1000 employees and that at least five different manufacturing sectors should be interviewed.

By following these criteria, a search for Swedish based companies in the manufacturing sector was conducted on the site Allabolag, which is a private Swedish based webpage that provides information regarding Swedish companies (Allabolag, 2021). The search was consequently filtered for Swedish manufacturers with over 1000 employees and this resulted in a total of 83 companies (see Figure 11). These companies were subsequently emailed and contacted via their HR department or by direct interactions with suitable respondents for the interviews, finally leading to 9 company representatives from 7 out of a total of 24 sectors within the manufacturing industry (Swedish Standard Industrial Classification, 2007). These candidates were selected after recommendations or their LinkedIn profile, where a search was made for employees working in management positions in the area of supply chain operations, production or sustainability. By consequently pursuing interviews with companies who responded first to the emails, a random selection process could be established for the purpose to reduce the bias and improve the generalization of the report.

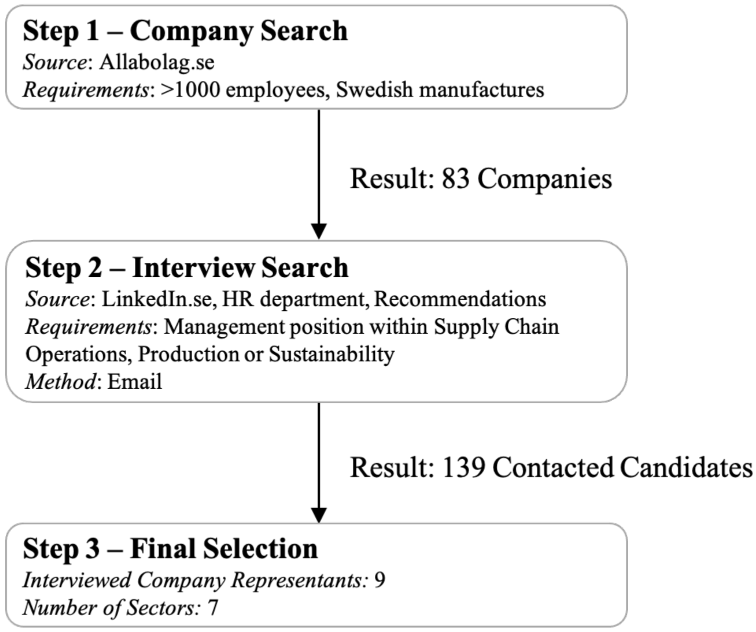

Figure 11. The search process for case company interviews.

Lastly, outside of the multiple case study, academics & experts in the field of digital supply chain and manufacturing were also included in the research's setting to get an academic insight. These include academics & experts from Swedish Universities and companies for the reason to gain specific details in the Swedish context. However, to separate the cross-comparison of the multiple case studies, the academics and industrial experts were compared separately from case companies. The academics & experts were contacted based on recommendations to get as suitable respondents as possible. In total, seven academics & experts were contacted, where six of them were willing to be interviewed within a short notice.

4.3 Data Collection

Due to the exploratory nature of the study, the research's data collection has progressed through literature reviews and semi-structured interviews. The reason for taking a semi-structured approach is based on Saunders' et al. (2015) research, which described semi-structured interviews as appropriate when conducting exploratory research. Likewise, the purpose of using interviews as a source of data is because it is a beneficial method when there is a need to explore new dimensions of an already explored research area (Blomkvist & Hallin, 2015). By utilizing semi-structured interviews, it was possible to direct the respondents towards the research topic while still allowing the respondents to talk freely around the topic. This allows the study to capture new phenomenon based on the respondents' answers (Saunder et al., 2015). To encourage this sort of behavior, the semi-structured interviews were based on open-ended questions with a flexible approach, making room for discussions rather than direct answers and a strictly followed manuscript (see Appendix B). The usage of open-ended questions is further beneficial as it helps to prevent bias in the research (Saunder et al., 2015).

For this research, 14 interviews have been conducted between the 23rd of February and 23rd of April (see Table 1). By conducting the interviews during a longer period, an abductive approach could be utilized where the literature was revised between the conducted interviews while also altering the interview questions based on previous interviews. The interviews were selected to involve two criteria, either academics & experts or industrial practitioners in the field of digital supply chains and/or manufacturing. In addition, the industrial practitioners have further been selected after their seniority to allow knowledge from different managerial perspectives to be obtained. The reason for including industrial practitioners was for the purpose to cover the research gap in current literature that explores real case situations as mentioned in the problematization section (Fatorachian & Kazemi, 2018). Furthermore, by also including academics & experts in the field, a holistic understanding of the current situation and the future could be covered.

Moreover, the 14 interviews included 15 respondents from approximately 40-60 minutes long in-depth interviews (see Table 1). The number of interviews was chosen after Saunders' et al. (2015) recommendations, who identified that twelve interviews for homogenous groups are adequate to draw commonalities from interviews and reduce the bias. For the reason that the interviews have been selected to only involve digital supply chain and/or manufacturers experts and practitioners, the respondents were identified as homogenous. In addition, to find suitable respondents a snowball sampling technique was also used by allowing respondents to recommend additional interviewees who they believed could contribute to the research even further.

It is, on the other hand, still possible that the interviews included some bias, even though a snowballing sampling technique was used and a random selection for suitable candidates and companies. This is due to the fact that some respondents' expertise did not correspond completely with the interview questions leading to misinterpreted answers. In addition, due to the age and seniority of the respondents, further bias and deceptive conclusions might be made as the interviewee could have a lack of insights into the company processes and understanding of different operations. However, it is believed that these consequences could be mitigated by including two people from the same companies in some of the interviews, and by having a broad variety of candidates in the area of supply chain operations, production and sustainability. Furthermore, by also choosing respondents after recommendations also can reduce the bias.

Table 1. Interview list.

	Title	Description of Role	Interview Date	Length	Sector
Company A	*Executive Vice President Supply & Trading*	Executive Vice President Supply & Trading with a focus on electricity, oil and fuel. 15 years of experience in the energy sector.	2021-02-23	Email Correspondence	Petroleum & Biofuel
Company B	*Operations Development Director Crushing & Screening*	Managing the operation development of the company's global supply chain operations. 20 years of experience in the area.	2021-02-26	55 min	Metal
Company C	*Supply Chain Project Manager*	Project manager with a focus on European housing and distributions. 5 years of experience in the area.	2021-03-02	51 min	Machinery
Company D	*Director of Supply Chain*	Previous CEO and 14 years of experience at a machinery company with various managerial positions.	2021-03-09	45 min	Machinery
Company E	*Global Supply Chain Operation Leader*	Works within the company's sustainability innovations section and is reliable for supply chain operations. 26 years of supply chain experience.	2021-03-10	57 min	Furniture

Company F	*VP Technology Global Manufacturing*	Responsible for technology engineering with a focus on personal care products.	2021-03-11	44 min	Hygiene & Health
Company G	*Head of Footprint design in Service Market Logistics*	Working with service market logistics and oversees the aftermarket logistics for the whole concern.	2021-03-15	59 min	Automotive
Company H	*VP Supply Chain Management Sweden*	Responsible for order placements and planning of the company's facilities in Sweden. 13 years of experience in the area.	2021-03-25	42 min	Metal
Company I	*Supply Chain Developer Manager*	Working with the development of the company's supply chain. 25 years of experience in supply chain management.	2021-03-25	40 min	Clothing
Expert A1 Expert A2	*Business policy expert* *Sustainability manager*	Working within the industry and trade policy sector and is responsible for questions regarding digitalization. 15 years of experience in the area. A leading expert in sustainable supply chains concerning environmental sustainability. 22 years of experience in the area.	2021-03-08	61 min	Industry Experts
Expert B	*PhD; Supply Chain Visibility*	Investigating the supply chain operations with a focus on visibility. 6 years of experience in production, sourcing, maintenance at the IT department.	2021-03-25	58 min	Academic in Automotive Sector
Expert C	*PhD; Global Industrial Development*	Investigating the building of factories and production investments. 15 years of experience in the manufacturing industry.	2021-03-29	59 min	Academic in Automotive Sector
Expert D	*Professor within Supply Chain & Operations*	Professor since 2012 with over 35 publications at the current University	2021-04-14	Email Correspondence	Academic
Expert E	*Professor within Logistics*	Professor since 2020 and previous 8 years as an associate professor at the current University with focus on sustainable logistics.	2021-04-23	51 min	Academic

The interviews were further conducted through either the digital meetings tools Zoom Meetings and Microsoft Teams or via email correspondence. Using digital meetings could lead to some bias in the study as the lack of physical interactions and/or connection errors could impair the interview environment leading to less detailed answers. However, during the interviews notes were taken in parallel with recordings of the interviews to help build follow-up questions to the respondent's answers to mitigate this sort of bias. The follow-up questions and the main questions (see Appendix B) were further created to guide the interviewees in the same direction as the research's aim and thus correspond to the guiding model for sustainable data-driven decision-making (see Figure 8).

Figure 8 was also shown and explained to the respondents and therefore used to direct the interviews to find answers to challenges, opportunities and advantages related to TBL and data-driven systems. In addition, by introducing the interviewees to the study's aim and *Figure 8*, valuable recommendations could be derived from the respondents by asking them if they believe the interview missed any aspects and allowing them to give inputs to the questionnaire. The interviews were subsequently digitally stored and transcribed, which enabled the ability to revisit and analyze the interviews and reduce misinterpretations and bias (Blomkvist & Hallin, 2015).

Secondary Data
The study is, besides the interviews, based on a literature review, which entails a data collection of secondary sources. These secondary sources have been used to review the current state of existing literature in the context of the research's purpose, which helps the research to be put in an academic context (Saunders et al., 2015). The search for relevant literature has primarily been made through the database Web of Science and the KTH Royal Institute of Technology's database Primo. To find literature that could be used in the research, the following set of keywords were adopted; Supply Chain, Digital Supply Chain, Data-Driven Supply Chain, Sustainable Supply Chain, Digital Supply Networks, Smart Manufacturing, Sustainable Manufacturing, Digitalization, Industry 4.0, Data-Driven Manufacturing, Data-Driven-Decision-Making, and Big Data. For the reason that the primary search for literature would not find all suitable and relevant sources, additional literature has also been found by exploring the sources that are referenced in the articles found in either Web of Science or Primo.

In addition, due to the increasing speed, new technologies in the research's context are being developed, the existing literature is quickly outdated. Therefore, the search was set to only include articles during 2014 and after. However, in the selected literature additional sources were found and that were used in the report if they seemed relevant even though they were conducted earlier than 2014. The literature was subsequently selected by their heading's relevance to this study's purpose. Consequently, the secondary sources comprised academic journals, reports, books, e-books, magazines and newspapers. The secondary sources have functioned to build the background needed to understand the analysis and further also functioned as complementary to the primary sources. Using both primary and secondary sources have made it possible to triangulate the analysis, meaning that the findings are based on comparative data analysis of both primary and secondary sources (Yin, 2003). Triangulation facilitates both increasing credibility and validity and is one of the main benefits of case studies (Yin, 2003). However, as the area of digital-decision making is limited in previous literature it can be expected that the literature can become biased as not sufficient information can be found in the area.

4.4 Data Analysis and Interpretation

Flexibility has been essential for the report as it is a key feature in theory-building according to Eisenhardt (1989), and hence a flexible approach has been needed in the data analysis. In addition, due to the research's qualitative approach, it has been evaluated as appropriate to employ a thematic analysis for the collected data, a method favored by Braun & Clarke (2006) for flexible and qualitative data analysis. Consequently, this study followed the six phases for a thematic analysis designed by Braun & Clarke (2006);

1. Familiarize with data
2. Generate initial codes
3. Search for themes
4. Review themes
5. Define themes
6. Write report

Following phase one and to familiarize ourselves with the data from the interviews, all interviews were initially transcribed into text. By re-listening the interviews and transcribing the information into text also helped to find certain patterns in the respondents' answers. In addition, to reduce the bias when reading the transcription non-verbal communication was included. Including aspects such as pauses and non-verbal reactions in the transcription allows the reader to capture more aspects of the answers, giving a profound understanding of the answers (Saunders et al., 2015; Braun & Clarke, 2006). The reason for utilizing this method even though it is time-consuming is because it is vital for the whole research, and according to Braun & Clarke (2006) transcription is an appropriate tool for phase one.

When the interviews' transcriptions were established and when the researchers were familiarized with the data, initial codes were generated. This process included deriving both the main latent and semantic content from each interview, which were further compared against each other to finally generate common codes for all interviews. The data were consequently color-coded to visualize the codes in the transcription and separate them from each other. However, to include all information from the transcriptions, irrelevant data were also coded since they could become useful later in the research. This is an important step according to Braun & Clarke (2006), as it can prevent information from getting lost or forgotten.

Phase three includes searching for themes, which is grounded in the literature review because the literature review gave the initial understanding of the content in the interviews. However, as new patterns and information were found in the interviews the literature was revised to generate a better linkage between the literature and the interviews, resulting in an abductive approach. In addition, the review of more recent interviews allowed the research to find new themes and codes that could be adopted in older transcriptions, giving an abductive approach in the data analysis as well. The abductive approach further helped to decrease the bias of the initial codes, as they were constantly reviewed after each new interview.

For the reason that the interviews' foundation lies in the guiding model (see Figure 8), the themes could be generated faster as the answers from the interviews were based to facilitate an understanding of the linkage between the categories 'Enablers', 'End Goal' and 'Business Activities'. However, to develop a broader perspective regarding the link between these categories, additional themes were developed by analyzing the codes, which resulted in additional and more profound categories than what the initial guiding model provided. Consequently, the categories were revised and refined to only include factors that provide information on the linkage between these categories. Thus, the themes were generated to both be connected to the codes and the categories that can be seen in the taxonomic tree in *Figure 12*.

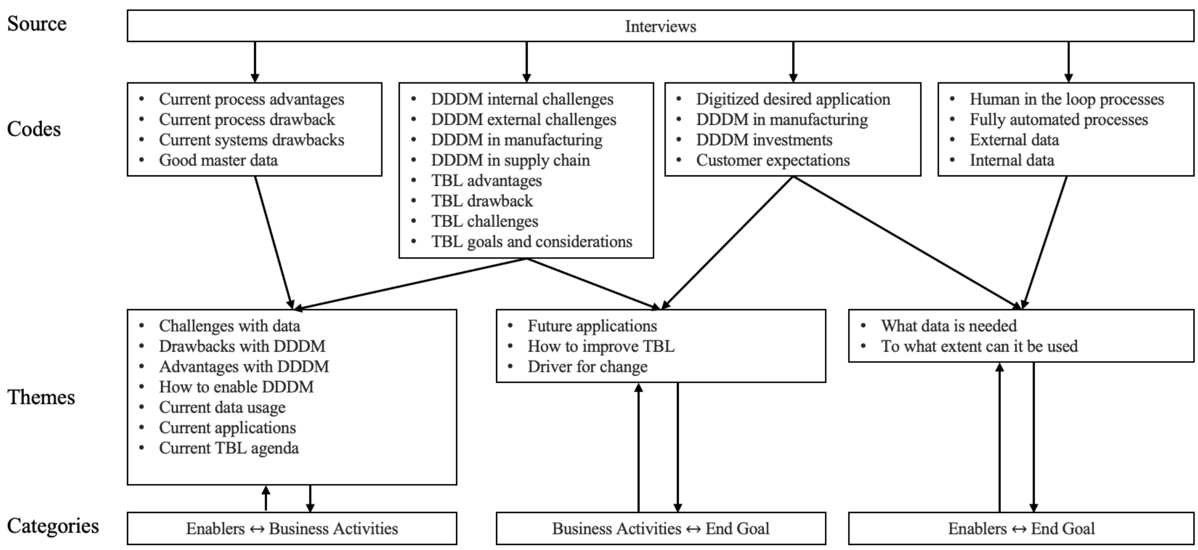

Figure 12. Taxonomic tree of the development from initial codes to final themes.

The themes were further reviewed and revised after both internal homogeneity and external heterogeneity, where themes with similarities were merged or were developed into more specific themes. This way themes could be merged meaningfully and distinct differences between the themes could be identified (Braun & Clarke, 2006). The final revision and analysis of the themes concluded if they could accurately provide information for the categories, which was done by providing each theme with a short summary. Consequently, the final themes could be derived (see Figure 12).

Moreover, finalizing the thematic analysis resulted in writing the findings and analysis section. Here, the separation of the categories was used to structure the section and give the section a logical order. Likewise, the themes were also used to build a logical order for each sub-section describing the categories. It should, however, be mentioned that the findings from practitioners have been separated from the findings from academics & experts to provide a clear understanding of the case companies' view contrary to the view of academics & experts. In addition, the taxonomic tree in *Figure 12* gives the structure for the empirics and discussion in the report. The taxonomic tree also set the structure for how the data analysis was made where the initial interviews and guiding framework gave the foundation in how the codes and themes were derived.

4.5 Quality of Research

To ensure a sufficient research quality, the "scientific holy trinity" of validity, generalization, and reliability was incorporated throughout the study (Kvale, 1995). To further strengthen the quality of research, the emergent theory was conducted by a parsimonious approach and the thematic analysis was based on substantiated data (Eisenhardt et al., 2016). By doing so, an integrated theoretical framework could be developed, which followed a minimum number of parameters to explain the researched phenomenon (Tenenbaum, 2016). Thus, by establishing an adequate quality of research, the risk of examining incorrect results was reduced (Saunders et al., 2015).

Validity

Gibbert et al. (2008) argue that three types of validity exist, which are construct validity, internal validity, and external validity. These criteria further strengthen the rigor of a study and are often suitable when conducting case studies (Yin, 1994), which is why they were considered in this research. Construct validity is typically linked to the data collection, as it indicates how well the results depict the reality of the investigation (Gibbert et al., 2008). In this case, the construct validity was maintained by triangulating the data and explaining the data analysis. This means that various perspectives were applied, for instance by the inclusion of different data sources such as semi-structured interviews, reports, and academic journals (Yin, 1994). In addition, the data analysis was clarified to further preserve construct validity (see Section 4.4).

Internal validity rather refers to the data analysis phase, in which it is fundamental to establish a clear link between the collected data and results (Gibbert et al., 2008). To increase the internal validity, a research framework was constructed by adopting a parsimonious approach. Consequently, the results were supported by a clear chain of evidence, which also enhanced the conclusions of the report. In addition, the internal validity was further strengthened by triangulation and by comparing results with previous studies (Eisenhardt, 1989; Yin, 1994). Furthermore, external validity is often referred to as generalization, which is discussed below.

Generalization

Generalization refers to which extent the added theory from a study can be used in another setting (Gibbert et al., 2008), which in this case means how well the theoretical contributions from this research can be applied to e.g., the service industry rather than the manufacturing industry. Scholars further argue that generalization can be divided into either statistical or analytical generalizations. Here, statistical generalization could relate to concluding remarks of a population, which cannot be applied in case studies (Yin, 1994). When conducting a case study, such as in this research, analytical generalization is more appropriate as it relates to building theory from the empirical data (Flyvbjerg, 2006; Gibbert et al., 2008). Thus, to ensure analytical generalization, a multiple case study approach was incorporated, as it allowed for a cross-case analysis and holistic theoretical contributions (Eisenhardt, 1989).

In addition, by including a clear background and motivation for the case study (see Section 1.2), the reader is given a more distinct understanding of this study's sampling choices, which further enhances the analytical generalization. However, even though the research aims at achieving generalization, the study's results are focused on the Swedish manufacturing industry and thus will not become fully adaptable in other settings. In addition, the generalization in the Swedish manufacturing industry cannot be fully met, since all the case companies are Swedish MNEs working on a global scale and are only representing 7 out of the 24 sectors within the industry. It is on the other hand believed that due to the random selection process and the usage of both multiple case studies and interviewed academics & experts, the study has the ability to provide a general understanding of the Swedish manufacturing industry.

Reliability

Reliability is heavily linked with both transparency and replication and is often described as to which extent the study is absent of random errors (Gibbert et al., 2008). Thus, a study is reliable if other researchers can come to the same conclusions as in the original study when using the same method of data collection and analysis. In this case, a database was used to store all notes, documents and audio files, which induce the reliability of the study as it is easy to access and revisit (Baxter & Jack, 2008). In this way, the reliability of the study was enhanced, as all important documents and transcriptions are accessible at any time. Furthermore, to ensure consistency during the project, which is often called internal reliability, the analysis of data and evaluations were discussed both internally and externally with the help of the supervisor of the project (Saunders et al., 2015). Thus, no conclusions have been formulated with only one person's opinions, which in itself reduced bias and researcher error.

Moreover, all participants within the study were contributing willfully and were given the choice of speaking freely about the subject. Consequently, the bias of the interviewed respondents was reduced, which further was strengthened by anonymity and an interview setting in a closed environment (Saunders et al., 2015). The interviews were also held in a semi-structured manner, where no specific time limit was pressuring the participants. In addition, the interview questions were open-ended to ensure transparency and exclude bias. Therefore, the reliability of the study was increased and the threats to reliability (i.e., participant error and bias as well as researcher error and bias) were reduced (Saunders et al., 2015). The respondents were further asked if they believed we missed any topics that should be taken into account for the reason to reduce our own bias in our questionnaire.

In addition, even though full reliability has not been achieved from the interviews, it is believed that the reliability from the interviews has been increased by utilizing a random selection strategy when selecting the case companies. The analysis of the interviews is on the other hand more prone to contain bias due to the researchers' interpretations, however, to reduce the bias the researchers have built up the codes, categories, and themes together, and built the findings and analysis from a joint consent. By having two persons instead of one, a wider perspective on the interviews could be built, but full reliability has not been achieved. Moreover, by further utilizing the guiding model during the interviews (see Figure 8), the reliability of the respondents' answers and our interpretations of their answers is believed to have increased as the interviews have been grounded from the model. On the other hand, some misinterpretations can still appear due to the researchers' own beliefs.

4.6 Ethical Considerations

This study has been carried out by carefully considering the ethicality during the progress of the research. The ethics of the report are mainly based on recommendations from The Code of Honour Swedish Engineers (Sveriges Ingenjörer, 2019) and The Four Principles by the Swedish Research Council (Vetenskapsrådet, 2002). The primary, The Code of Honour Swedish Engineers, is followed by considering the Ten Principles of the Code of Honour (Sveriges Ingenjörer, 2019) (see Appendix C), whereas the latter includes the principles to 1) inform the involved participants of the purpose of the study, 2) give consent to participate in the study, 3) be confidential regarding vulnerable data and not reveal personal information, and 4) manage the collected data solely for research purposes (Vetenskapsrådet, 2002). Consequently, by following these principles by Sveriges Ingenjörer (2019) and Vetenskapsrådet (2002), the ethics of this research can be supported.

The first recommendation by Vetenskapsrådet (2002), to ensure that every participant is informed about the study, requires carefully planned correspondence with the respondents. As a result, at the first point of contact, the respondents received information regarding the study's authors and purpose, and information about how they could be helpful in the research and what the interview would include. They were also informed of the ethical considerations of the research, thus assuring their anonymity and ability to review the transcript and remove any sensitive organizational data. After the first point of contact, an email with the questionnaire was sent to the respondents and answers to questions they asked. To further give them the ability to revise the content and prepare answers for the interview, the questionnaires were sent at a minimum of four days before the planned interview.

To address the second recommendation, to receive full consent of the respondents' participation in the study, several precautions have been considered. Initially, the respondents were asked if they would find it interesting to participate in an interview in which their answers would be used and published in this research. Additionally, the same question is asked during the start-up of the interviews as well as consent for recording the interview. Lastly, when the transcription of an interview is finished, it was sent to the interviewee who could revise it and subsequently give their approval of using the material in this research. Moreover, by providing the interviewees with the transcriptions and allowing them to remove any confidential information, the third recommendation by Vetenskapsrådet (2002) is processed. Likewise, the third recommendation is also processed by the anonymity of the report, meaning that all aspects that risk the respondents' identity are removed such as names, company names, and specific products.

Due to the open access of the report, the fourth recommendation cannot be fully managed as external partners' use of the report will not be controlled. However, by following the previous recommendations and by informing the reader regarding how the information in the research has been used and collected, it is supposed that the reader will possess a sufficient understanding of the report and thus use the research respectfully.

Besides Vetenskapsrådet (2002) recommendations, the study also follows the Ten Principles of the Code of Honour (Sveriges Ingenjörer, 2019). It does so by describing and discussing a technological shift in the supply chain, which ultimately has the ability to improve the TBL in both public and private contexts. In addition, the research has also had a focus on a loyal collaboration with the research' commissioner and a focus on using appropriate methods and consequently not leak confidential information, use exaggerated conclusions nor be biased in our statements.

5 Findings & Analysis

In this chapter, the findings and analysis from the interviewed case companies and experts in the field are presented. To separate the two fields of respondents we primarily present the view of the case companies, followed by the experts' view, which is subsequently linked together in the last subsection. The structure of this chapter is based to answer the links in the guiding model (see Figure 8) that consequently help to provide answers for the developed research questions. Each section is initially presented with key findings (marked C for case companies and E for experts) that is followed by an analysis to support the evidence.

5.1 Current Digital Operations - The Linkage Between Enablers and Business Activities

Cross-Comparison of case companies

Challenges

Informants have during the interviews stressed several concerns regarding data-driven processes, which can be categorized into two categories, internal and external challenges. Even though the challenges to some extent vary between the nine interviewed case companies, some similarities can be found. In terms of internal challenges, three main issues could be derived. Eight out of nine companies stressed that they struggle with standardization and integrations of systems, meaning that companies struggle to share data between company entities as they are run by different systems or because they do not have a digital infrastructure. In addition, four out of nine companies showed concerns regarding change management and how to incorporate change from both a managerial and production level. Lastly, data management also becomes a challenge for companies as four out of the five interviewed manufacturing companies tend to struggle with excessive data, which further led to making the data analysis more difficult.

The external challenges can also be divided to some extent. Transparency, reliability, and validity issues were the main challenges where seven out of nine companies showed concerns in either of these issues. Transparency issues could be linked to either the third party's refusal to share data or the technical inability to collect data further down the supply chain. The denial to share data could further be linked to either security issues, where supply chain entities do not want to share sensitive data, or that laws and regulations can prohibit full customer transparency. Reliability and validity on the other hand become a struggle as the interviewed companies find it hard to secure the source of data and to further validate that the data have not been altered and can be trusted.

> **Finding C1:** *Standardization and integrations of IT systems, change management and excessive data are three main internal challenges derived from the interviews, whereas transparency, reliability, and validity issues can be seen as the main external challenges.*

From the interviews, it is further important to analyze the findings depending on the case company, because the challenges varied between the companies due to how developed they are in their digital transformation, their supply chain, and their size. As explained above, eight out of nine case companies found standardization and integrations of IT systems challenging, however, some companies did not have it as a top challenge. Looking at Company E, which did not put standardization and integrations of IT systems as the main challenge, it could be seen that Company E has come further in becoming digitized and can put more pressure on external partners to use the same type of systems. Likewise, Company B and H also had other more severe challenges and they had further been noticed to have larger ownership of their supply chain and thus been able to have better control of the systems in use. On the other hand, Company C, D, and I who put standardization and integrations of IT systems as the main challenge had less power to decide their suppliers' systems and also had less control over the supply chain compared to Company, B, E, and H.

> *"One of the challenges is how important you are to your suppliers because if you want data-driven processes you need efficient data flow between the suppliers and to make this worth it for the supplier you have to be an important factor to them."* (Company D).

Moreover, looking into change management, competence and cost, the case companies found these as both external and internal challenges. High costs, which according to the interviews always is an issue, but not always the main issue, becomes the starting challenge to become data-driven. Here, Company C explained that the journey to becoming data-driven starts with the prioritization of resources. However, Company C is at the starting point of a digital transformation of their supply chain. Other companies such as Company E and I who have come further in their digital journey (see Figure 10) have on the other hand put change management as a more difficult challenge to overcome compared to cost. Likewise, Company F who also is at the forefront in digital processes among the interviewed companies found competence as a top challenge in their digital journey. It should further also be mentioned that the Covid-19 pandemic has affected the challenge to overcome cost issues, which was indicated by Company G whose resources for becoming digitized were reduced due to the pandemic and that therefore made costs their toughest challenge to overcome.

Likewise, experiencing challenges with excessive data are drawn to companies' digital process, since the majority of case companies with the most digital developed culture (see Figure 10) found excessive data challenging. The reasons for Company B, E, F, and H's struggle with excessive data were because of various reasons, where it could be seen from Company F and H's perspective that one of the reasons for their excessive data generation was because of their usage of multiple systems. Company H is built on multiple mergers of different companies, which has affected their ability to effectively separate the unnecessary and necessary data from each company segment. For Company F, the challenges were derived from their usage of different internal IT systems that consequently lead to communication errors and an overflow of data. However, even though these exact correlations cannot be drawn to Company B and E, they still expressed challenges with excessive data. In addition, Company B, E, F, and H have the similarity of more extensive operations compared to the average case company.

> *"Generating excessive data creates massive confusion in the use of the data. Every time I get to a new team, I always ask what it is that you are generating for decision-making and challenge them to answer what type of data is actually needed."* (Company B).

In comparison, the external challenges were less correlated to the case companies' digital transformation, instead, it was the control level and bargaining power in the case companies' supply chain that had the largest impact. To demand transparency for larger companies such as Company A, E, F, G, and H was therefore not as challenging as these companies usually are vital for their suppliers and thus could demand transparency. However, other challenges to obtaining high-quality transparency such as secure, reliable, and validated data remain. Company G has for instance stressed security concerns as dealers do not trust the systems and therefore do not want to be fully transparent, whereas Company A, E, and F had more issues regarding the reliability and validation of the shared supplier data. However, for Company H who has a more internally controlled supply chain, fewer issues concerning security, validation, and transmission of sensitive information were derived.

Advantages

Even though it can be seen that the challenges to become data-driven are multiple, the investigated case companies have also experienced several advantages. The experienced advantages with data-driven processes were highly dependent on the companies' digital progress (see Figure 10) and their operations, however, some similarities between the companies also existed. Currently, the majority of the case companies experienced a positive impact from data-driven processes regarding gaining an overview of the company processes. This means that the case companies have with the help of their data-driven processes been able to both gather, share and analyze data more efficiently than before, helping them to observe and evaluate the whole supply chain and production processes.

Furthermore, with the help of data-driven decision processes, five case companies have found the planning and optimization of the supply chain less complicated, where the most visible aspects included where to locate distributors, how to drive down cost in the supply chain and reduce lead time. In addition, three companies had also seen benefits in a reduction of the bullwhip-effect, which also helps to drive down cost and lead time, by decreasing overproduction. Consequently, these findings can be concluded as the following:

> **Finding C2:** *The current main advantages the case companies have experienced from data-driven processes include a reduced bullwhip-effect, improved planning, and more efficient troubleshooting processes of the supply chain. The most mentioned advantage is the improved visualization and overview of the company processes.*

What could be derived from the advantage of improved visualization and overview is that the companies who have seen these advantages have a relatively established digital structure (see Figure 10), meaning that Company C for instance has so far been unable to fully obtain this benefit. Contrary, Company E and B who have integrated digital systems are more able to share and gather data both internally and externally. However, companies have been seen to not be able to fully exploit their visualized data and only use it as support for further decisions. Company G and H explain this by mentioning that they do not take decisions from the data-driven processes, but they use it to know where to look for mistakes by for instance comparing production and order data.

Analyzing the improvements in the supply chain, companies have different views for the bullwhip-effect, planning, and troubleshooting aspects. Decreased costs are commonly the main driver, but companies also stressed concerns regarding a need to satisfy customer expectations. By reducing the bullwhip-effect and obtaining a more efficient supply chain, therefore, help to achieve better customer rating, as explained by Company I. However, Company B stressed that the systems across the supply chain entities must be able to provide a full supply chain overview to minimize the bullwhip-effect, something that is challenging with current systems.

Moreover, for companies with less environmental impact, the focus on ecological aspects of sustainability became less of a concern. For instance, Company D mentioned that they only stand for 5% of their supply chain emissions and were, therefore, more prone to focus on improvements concerning either lead time or to drive down costs. Contrary, Company H saw both the economic and ecological benefits with their data-driven processes, as they had more aspects to improve in terms of ecological sustainability. Furthermore, the majority of the case companies also described that the benefits are found end-to-end in the supply chain, but companies tend to be able to make the most extensive improvements at the beginning, where the raw material is produced and where the digital capacity is or previously has been limited.

Drawbacks

However, as companies are still undergoing their digital transformation, the data-driven processes are currently generating several drawbacks as well. For the companies who participated in the interviews, one drawback was specially put in focus, that fully automated systems lead to a reduced understanding and insights of the data generation. Companies, therefore, stressed their concern over if their data can be trusted or not as they lose control over the data generation. Human-in-the-loop processes were therefore put as essential for the case companies to complement the data with human assessment and to increase the trust and understanding over the data-driven systems. In addition, the case companies also stressed that their current systems are difficult to use and commonly contain faulty information, which requires resources to both validate the data and to keep the digital systems running appropriately. The drawbacks with the data-driven systems could also be drawn to the economic cost to update old legacy systems, resources that otherwise could help the companies to improve current products.

> **Finding C3:** *Decreased understanding of certain company processes due to automatization combined with the resources required to run and update current digital systems efficiently are the main drawbacks with data-driven systems perceived from the case interviews.*

The drawbacks with decreased understanding are something that seven of the nine case companies stressed upon. Company A and E identified this drawback with the explanation that data-driven systems are mainly driven by data, a process that is not always understood and therefore leads to misinterpretations. People should, according to Company A and E, integrate personnel in the data-driven processes to reduce the likelihood of misinterpretations. In addition, Company B, D, and F saw that the need for human-in-the-loop processes was instead correlated to the drawback with the required system updates since their current systems are too expensive to use and update or are not standardized enough for automated communication.

The drawback with system updates was seen in most companies but to a variating extent. Company C for instance, which has barely started their digital journey (see Figure 10), identified the update of their current systems as the biggest drawback since it will require resources to be taken from other projects, which is something they cannot afford. However, for Company D and I who already have updated most internal digital systems, the drawback with update requirements still arose. Company D mentioned that since their systems are made by an external party, it becomes too resource-demanding to make it run efficiently as the external party demands heavy fees. Likewise, for Company I, who instead has internally made data systems, it becomes a drawback that their systems are too time-consuming to update and run efficiently since they are dependent on their internal resources. Nevertheless, it could further be seen that the case companies with larger resources did not experience these drawbacks to the same extent in their Swedish-based operations.

> *"I think SAP is a great system, but it is very expensive to make changes, which is why we often work around the problems instead of making updates in the system. I simply believe*

we are too small to manage SAP, we cannot have 10-12 people who work with SAP full-time." (Company D).

At the same time, larger companies also saw that their data-driven systems usually do not work as desired. Small errors in the systems can, according to Company F, lead to extensive errors, which further become both an environmental and an economic drawback. In addition, according to Company E digital systems are usually extremely specific in what they can do, which makes it easy to overlook certain factors that the systems do not include. Consequently, the need for human integration in the digital processes has been stressed as essential according to the case companies.

Academics' & Experts' View

Challenges

According to the academics & experts, the main internal challenges can be derived from data management, competence, and information not always being available. Currently, most companies do not have the structure to manage data efficiently, as explained by Experts A1 and A2. The same respondents argued that it can be a challenge to clarify who owns and verifies the data. Expert B further argued that integrating systems internally is difficult, which harms data management. Expert C further stressed the importance of knowing what and where to implement data, which was found to be one of the main internal challenges. The academics & experts further argued that there is a need to have sufficient security and standards when investing in a digital supply chain. A challenge that often occurs among such circumstances is to find the right time to invest, as waiting too long could make the opportunity disappear, as stressed by Experts A1 and A2.

A further challenge that was found to be both internal and external was the availability of information. Here, Expert C explained that if a company possesses information in which they do not understand, they might not want to share it with other companies or actors within a supply chain. The same respondent further argued that there currently does not exist a standardization of systems nor how data should be formatted. In addition, the systems must be secure, as it often requires large volumes of data, which also can affect the willingness to share information, as explained by Expert B, C, D, and E. The external challenges can further be derived from the importance of regulations (such as GDPR), to transfer competence to subcontractors, the difficulty of making customers buy or use the same system, and that no technology suits all.

> **Finding E1**: *Data management, competence, and information not always being available were found to be the main internal challenges according to the academics & experts, whereas lack of regulations, transfer competence to subcontractors, information sharing, and usage of the same system among all actors in the supply chain was seen as the main external challenges.*

Drawbacks & Advantages

The academics & experts further acknowledged the main drawbacks of data-driven decision-making and digital supply chains. Experts A1 and A2 argued that the main issue with digital supply chains is located in the beginning, as people tend to enter wrong data from the start. The same respondents added that SMEs often do not have the same access to data as MNEs, consequently, the smaller the customer, the lesser amount of accessible information. The academics & experts also stressed the importance of regulations and standards, which currently are not set in place in which digital supply chains can operate. Here, Experts A1 and A2 discussed the significance of all actors within a supply chain that needs to be in interplay and that there currently exist different standards all around the globe and not a common one. Furthermore, Expert C and E argued that the costs are still central, and not sustainable gain, which makes implementation of a digital supply chain difficult as long as it is expensive.

On the other hand, the main advantages were found to be linked to real-time information, opportunities, enhanced life span of products, more efficient management of unexpected events, and improved competitiveness and service. For instance, with real-time information, there are opportunities for optimized surveillance of emissions, water usage, etc. Here, Expert B also stressed that unexpected events, such as demonstrations from suppliers or deviations in the delivery of products, could be managed more effectively with real-time information. Experts A1 and A2 further explained that the more you aggregate, the more opportunities for AI models to find new patterns for example, which leads to an unlimited number of opportunities with data. In addition, with better data and more information comes the advantage of better operational decisions, as explained by Expert B and D. Moreover, Expert B further argued that the bullwhip-effect can be mitigated with fewer disturbances as well as the advantage of improved trust among all actors within the supply chain. Consequently, a digital supply chain has the advantage of improving competitiveness and providing better service.

> **Finding E2**: *The main drawbacks with data-driven systems are that people tend to enter incorrect data, the need for established regulations and standards as well as high costs. The main advantages were found to be linked with real-time information, unlimited opportunities, an enhanced life span of products as well as improved competitiveness and service.*

Experts A1, A2, and C argued that there currently is a superstition that digitalization will be able to solve all problems, which is not the case. Just as competence and data management are internal challenges when it comes to digital supply chains, they are vital when trying to implement digital solutions. To enable digital supply chains, Experts A1 and A2 further explained the need for certain standards and formats that can help when sharing information. However, Expert E further stressed the importance of standards and regulations, but that it can be a major challenge to realize and establish. Experts A1 and A2 further added that politics can bring visions, regulate or threaten industries, which can affect the business becoming more digitized. According to Expert B, the integration of digital supply chains can be summarized with the push-pull effect. For instance, companies push because they sense a value capture, whereas a pull-effect is the continuous societal development towards digitalization outside of the manufacturing industry. The same respondent further explained that there for example might come requirements that make you give an account for where products originate from.

Generally, there are fragments of the manufacturing industry that are digital according to the academics & experts. For instance, Experts A1 and A2 explained that there is no full integration of digital solutions within an entire supply chain. In addition, those who are developed digitally often have difficulties collecting data, as explained by the same respondents. This is also connected to the drawback of incorrect insertion of data by people at the start of the supply chain. Expert B further argued that current systems are inefficient when it comes to sharing information and are not adapted to the globalized environment that currently exists. The same respondent also explained that companies often turn to ERP systems when collecting data, as well as mail conversations and meetings, which are the dominant sources of information. Furthermore, the automotive industry is generally seen as more digitized than other industries, since it has merged with its side organizations and standardized the exchange of information, as explained by Experts A1 and A2.

> ”*You need to have the systems and that they are connected to each other. There is often a type of legacy, which brings problems. In the best of worlds, there is a consistency and a common standard, which is not the case. Especially if there are dimensions such as sustainability that are added.*” (Expert A2).

When it comes to the current TBL agenda within the manufacturing industry, the academics & experts stressed several issues the industry is facing and are trying to overcome. For instance, there currently exist different perspectives on what sustainability entails around the globe. Experts A1 and A2 argued that this might inflict complications when collecting data to achieve a sustainable business. Furthermore, companies often focus on the product’s environmental impact during the user phase, which for instance involves improving product design to reduce the users’ emissions. The same respondents thus stressed the need of evaluating suppliers to identify the most impactful stages. In addition, Expert E stressed the importance of collaboration, as the companies that are at the forefront and are driving the development of sustainability are doing so by strong cooperation and open communication. However, it was further found that it takes a lot to terminate a contract with a supplier who does not meet the set requirements, even with continuous investment requirements and laws.

Experts A1, A2, and E further explained that companies should start implementing change where the biggest challenges are located. For instance, processes that are accomplished with child labor or processes that are high energy-intensive should be improved first and foremost. However, the most energy-intensive stages often occur in countries with poor electricity production, and generally have a bigger negative impact on the environment than transports, as explained by Experts A1 and A2. The same respondents further argued that it therefore would be most advantageous to exclude countries with unsustainable electricity utilization, which also can be economically unfavorable. Thus, as explained by Expert B and E, it is more common trying to reach carbon neutral factories. Furthermore, Expert C argued that there often is an internal initiative to become more sustainable, which can affect the external communication for more sustainable products. The same respondent also explained the importance of encouragement from management to drive digitalization. However, it generally comes down to costs, quality, delivery, and sustainability, which are the areas where data is used, as explained by Expert B and E.

5.2 Future Operations - The Linkage Between Business Activities and End Goal

Cross-Comparison of case companies

As the digital transformation is taking place, new potential operations are starting to be developed. Looking at data-driven decision-making and a digital supply chain, the empirical findings are mainly pointing towards future applications that allow for transparency, automated planning, and optimized transportations. These applications are further driven by the challenges that companies currently experience both internally and externally. For instance, one of the main external challenges derived from the empirical findings was transparency and the need for visibility. Here, five of the respondents argued that by adding visibility within the supply chain, customers can be able to follow transports from start to finish, and companies can have access to real-time information, transport more goods on time, ensure the quality of decisions, and have less human interaction in a faster decision-making process.

The respondents further stressed the advantages of automatizing planning, since a prioritization of transports can be made accessible, the bullwhip-effect can be mitigated and faster decisions on volume purchases with delivery at an optimal time can be utilized. By digitizing the supply chain, the respondents also argued for optimized transportations, as future demands can be analyzed and processed into supplier orders without any delays and plans can be changed accordingly from real-time information. Such applications can be heavily linked to an improved TBL performance as well since applications such as better planning can reduce the need for flight transportation that has a great negative sustainable impact both financially and environmentally. This is due to the reason that flight transportation is often a consequence related to errors in the planning and forecasting or unoptimized locations of warehouses, resulting in flight transportation. By having automated and improved analysis systems, Company G and I stressed that they can ensure that the right products are always in stock, as they can plan their processes better. The improved analysis systems are further stressed to provide optimized locations of warehouses and thus reducing the need for flights. However, Company G still stressed that the need for flight transportation will persist to some extent but can be dramatically reduced with improved planning systems.

Three of the respondents further argued for the development of TBL performance with future operations that are driven by a digital supply chain, such as an optimization of the production process. Here, a demand-driven supply chain can help mitigate the bullwhip-effect even further and by having a more planned process, less time is spilled on unnecessary work.

> **Finding C4**: *Future applications are mainly driven by transparency, automated planning, and optimized transportation, which can enhance the TBL performance by primarily decreasing the need for flights and optimizing the production process.*

However, as some of the case companies experienced various challenges that were specific to their business, further linkages between current operations and an improved TBL performance were found. For instance, Company B was found to be more digitized in comparison to some of the other case companies (see Figure 10) and has developed their business according to their digital transformation. An additional future application that Company B has already implemented are service contracts, which are based on connected machines that are operating at customers' facilities. In that way, customers are bound to the company when requesting new parts and the company can supply better service because of better information and better planning on the connected machines. Company H was also found to be more digitized concerning the other case companies (see Figure 10) and was found to have implemented forecasting models that are not only based on historical data but also real-time macroeconomic factors. Better forecasting models were also a future application that Company A, B, E and I were arguing for, as they can provide information for automated analyses, optimize warehousing and drive better pricing.

> *"If the gold price goes up, we would sell more because then the gold mines run harder. There are more things like that where you look at the history of how customers have bought in the past, but also that you look at macroeconomic factors going forward to create a good forecast."* (Company B).

With more data and connectivity among operations, the TBL performance can be even further enhanced. Company K argued for better packaging, as more precise measurement data can be obtained to reduce the amount of free space in each packaging. The same respondent also explained that customers' addresses can be verified and that orders arrive at the exact location, which would imply fewer returns and delays. Company I, H, and B further explained the possibilities of better recycling, as it becomes easier to clarify the specific material of components in a product, as well as getting more information on what products the customers will return for recycling and how to reuse energy to heat buildings, offices, etc. Company C further indicated that with more transparency and visibility along the supply chain, there are fewer rooms for mistakes. For instance, unnecessary shipments across certain warehouses should be avoided in favor of shipping directly to customers. More visibility would also open up for increased collaboration among suppliers and manufacturers, which could have a positive effect on each actor in the supply chain regarding sustainability. Here, Company B explained that manufacturers often rely on suppliers, to tell the truth, and deliver reliable data.

> *"If you have good data, it will allow you to make faster decisions for production, inventory, cost, quality, waste and all those sorts of things. So, having proper data is a fundamental help for that."* (Company F).

By sharing information among all actors within the supply chain, Company D argued that it would be advantageous because of the possibilities to calculate and minimize harmful sustainable effects, such as the environmental footprint of transports. In that way, losses to the sustainability factors could be mitigated, which often is the case when data are not sufficient as it typically generates rework, as explained by Company F. Company D further argued that the TBL performance could also be enhanced as seen from the social aspects, as data-driven processes can entail less personnel and less physical labor. By having more product data and appropriate tools to analyze such data, the same respondent explained that the environmental footprint on a product level could be improved. For instance, by having more sufficient information on a specific material, more sustainability aspects can be covered. Additionally, Company A further argued that an automated simulation of the performance of raw materials can lead to increased efficiency concerning the given conditions in the production facilities and reduced emissions in both production facilities and at the customer level when using the product.

> *"We want to maximize profits and we do this by producing the right things and taking them to the right place immediately, and as a result, we reduce our footprint. Here there is no opposition to economics and the environment, they go hand in hand."* (Company B).

One of the main drivers for change was according to the respondents to become more customer centric. In a supply chain context, what generally matters the most is to better serve your customers and consumers. Becoming more digitized allows for improved customer satisfaction, as future operations can enable transparency, automated planning, and optimized transportation. Consequently, the TBL performance will improve because of more precise, timely, and sustainable transportations that subsequently enhance customer satisfaction. The empirical findings further revealed that most companies currently invest in a digital supply chain as a consequence of economic benefits and to meet growing customer demands. As stated by one of the respondents, everything also becomes cheaper, which increases the possibilities of collecting more data and becoming more digitized.

> **Finding C5**: *Becoming more customer-centric, economic benefits and meeting growing customer demands were found to be the main drivers for change when implementing a digital supply chain.*

The investigated case companies further argued for specific drivers for change in relation to their current businesses. For instance, Company C, E, and I have all noticed significant pressure from customers to become more environmentally friendly, which has driven them to become more digitized. Company D also shed light on new customer behaviors, as there is a greater demand to be able to deliver faster and more accurately. Other companies, such as Company E, stated that it is a question of survival and that you have to become more digitized to compete in the current business landscape. It has further been more accessible to implement digital improvements as everything becomes cheaper, which has driven the possibilities to collect more data, as explained by Company B. Lastly, Company I stressed the affection of the recent Covid-19 outbreak, which has affected how companies interact with customers and suppliers more digitally and virtually.

> *"If you were to think about any supply chain, at the end of the day you measure it through the satisfaction that you receive, the quantity they wanted, the quality they wanted. […] What matters in the supply chain context is how to better serve your customers and consumers"* (Company G).

Academics' & Experts' view

The interviews with academics & experts indicated that data-driven processes will create better decision support systems that further will help to improve the TBL performance. The majority of the interviews also indicated future improvements for making proactive decisions and through that reduce the number of machinery failures and errors in the supply chain. However, it is further seen that future applications regarding data-driven systems are driven by technologies that can improve transparency and how governments and industries position themselves regarding standardized systems and sustainability. If a de facto standard is realized, the future digital applications in a supply chain context will increase, as they will become easier to use according to the interviews. Moreover, with the help of AI-technologies, it is also believed that data and systems can become more connected, which further would improve companies' analysis of trends and scenarios. Combining the future improvements in transparency and intelligent data-driven systems, four respondents stated that environmental improvements could be realized by having real-time information and analysis of company emissions and their supply chain.

> **Finding E3:** *Future applications are driven by companies' interests, but also how governments and significant actors in the industry work towards sustainability and standardization of data systems. With new intelligent technologies and better transparency, companies will have a better chance to apply effective data-driven systems for improved TBL performance by enabling real-time analysis over the supply chain and emissions, which further can be used to create proactive means in the supply chain.*

The overall application for data-driven systems described by the academics & experts is to simply implement it to generate better decisions. Moreover, it can also be seen from the interviews, that it is the companies' interests to improve their resource efficiency and economic sustainability in both the production and supply chain that is the main driver for where data-driven systems should be applied. On the other hand, Expert E stressed that it is mainly the Covid-19 pandemic that has led to the most recent drastic changes towards digitalization. The same respondent further argued that it would be beneficial if companies implemented certain supply routes based on a classification of products to improve the circular economy. For example, a classification of products ranging from 'A' to 'E', where a product classified as 'B' would need to undergo adjustments within the internal factory or a product classified as 'E' would need to be sent to subcontractors based on various measurements.

Furthermore, improving customer service and thus improving companies' competitive power is also a driver for digital advancements. However, Expert C and E stated that the applications will further become more based on environmental factors in the near future and that the data-driven systems will have a more environmental focus due to customer expectations or governmental pressure. Likewise, Expert B described the increased possibility to establish a circular economy with a digital supply chain, where transportations and production can become more environmentally neutral as products will be recycled more frequently and better control over emissions will be established through the data-driven systems.

Transparency is however essential for data generation and to establish data-driven systems. Therefore, Experts A believed that through blockchain technologies, companies can reduce their transparency issues and get access to real-time data. Blockchain technologies are also under constant development and thus will be able to generate and share data more efficiently and safely. With safer and more accessible real-time data both Experts A and B stated that AI technologies are likely to become integrated with the data-driven systems and consequently produce better simulations and forecastings. Combining AI technologies with data-driven systems the analysis, visualization, and automatization of company processes will further become more accessible according to Expert B. Furthermore, Experts A1, A2, B, and E believed that with efficient data generation and analysis it becomes easier to detect and foresee errors in the supply chain that otherwise could lead to expensive production stops or failures. Expert E stressed that the future systems would be likely to be applied for making faster reactive responses to external events such as natural disasters. Therefore, there is a significant application area for data-driven systems within maintenance and finding proactive means within the production and the supply chain.

> *"Many people believe AI is successfully adopted, but it is not. My opinion is that AI has not been put in use in the manufacturing industry nor the supply chain in terms of digitalization. The next step is therefore to integrate AI."* (Expert B).

Even though it is mainly the internal economic and competitive winnings that are the drivers to develop data-driven systems and where to apply them, the external factors must not be overlooked. According to Experts A1, A2, B, and E, it is commonly a push effect that decides the application areas for companies, meaning that wherever companies see a potential in the supply chain is where the likelihood for data-driven application is the highest. It can also be seen from the respondents that these internal drivers are commonly driven by economic factors. Moreover, external aspects also have an impact where governments, customers or the industry pressurize companies towards environmental and social sustainability. If the government or the industry finds standardized systems for data-driven processes, the technologies will become more accessible for SMEs and lead to faster data adoption according to Experts A1 and A2. In addition, governments and customers are more likely to pressurize or collaborate with companies in the near future to improve their digital progress, but also their environmental and social sustainability according to Experts A1, A2, B, C, and E. On the other hand, Experts A1 and A2 also mentioned that the government can hinder the adoption rate of data-driven systems if regulations are put against it.

> *"Companies commonly do not work for environmental or social sustainability to be nice, they do it for the economic winnings."* (Expert E)

5.3 Value Capture - The Linkage Between End Goal and Enablers

Cross-Comparison of case companies

In regard to the linkage between data and TBL performance, the value capture was investigated in relation to what data is needed and to what extent data can be used. The case interviews revealed that there are many different types of data that can be valuable when developing sustainable strategies and that there often is no limit to what data actually can do. Most companies were found to continuously explore what type of data that can be helpful for environmental improvements, and here transparency will become important as it will pave the way for more integration of customer data that can enhance the TBL performance. For instance, some of the interviewed companies argued that it would be beneficial to get weekly reports on what type of transports and how much CO_2 emission they have generated from external actors as well as have more access to customer orders, which could be fulfilled by better collaboration and information sharing.

> **Finding C6**: *The data that are mainly needed to increase the TBL performance and to capture value can be derived from customer data. Simultaneously, the case-interviews revealed that most companies are continuously learning what kind of data they need to become more environmentally friendly.*

As the level of digital development varied among the interviewed case companies (see Figure 10), so did their challenges and views of what type of data that can be necessary to develop the TBL performance. For instance, Company F elaborated that there is no specific type of data that can help financially, as it depends on the company itself. The respondent further discussed that if a company wants to optimize costs, then they need to produce a lot of data regarding costs. Thus, it will be increasingly important to collect and own data, as explained by Company G. Company C further argued that master data such as the volume of articles can be highly valuable, as it would help optimize the transportation of products by better packaging. Furthermore, Company H, which was found to have a high level of digital integration (see Figure 10), explained that all product data, customer data, capacity data and demand is needed to not only make better decisions but also to improve the TBL performance. However, the same respondent also argued that it is important to be able to combine the different sources of data and to use it on various detailed levels. For instance, in the short-term it is important to have specific and detailed data, but in long-term it is better to be less detailed because of flexibility, as explained by Company H.

> "*If our customers could inform and integrate us earlier, we would have done a better job. Would our customers also have better forward planning it would lead to us having better forward planning, which eventually would make us more environmentally friendly.*" (Company D).

As sustainability further has become a major topic among companies, many of the interviewed case companies have developed internal sustainable strategies. However, with data and a digital supply chain, some of the respondents argued for the allowance of now helping external actors within the supply chain as a way to reach sustainability collectively, not only internally. Thus, the case interviews revealed that there is a potential to integrate data along the end-to-end supply chain within the manufacturing industry. For instance, by choosing the right raw material in the beginning of the supply chain to eventually recycle the finished and used product in the end of the supply chain. There are further specific areas within both the upstream and downstream supply chain that can be automated with the help of data and digital tools, such as order placements, as explained by Company I.

> **Finding C7**: *There is no end to what extent data can be used, and that the integration of data can be utilized from end-to-end in a manufacturing supply chain. Hence, the main pursuit when developing the TBL performance was found to be helping external actors with sustainability and not only improving such aspects internally.*

When speaking of the extent digital applications can be used within a supply chain context, other challenges and opportunities further arrive. For instance, Company D explained that in certain areas within their supply chain where there is no ERP system, work needs to be carried out manually. Currently, data is often not available and there is a need to combine data from different sources, which can lead to conflicts when evaluating investments according to the same respondent. Furthermore, even though future systems might be able to make fully automated decisions, there are currently such systems existing already. However, Company A, B, E, and H stressed the importance of including a human-in-the-loop process, as there is a need to find a balance between what you can let a system do automatically and when a human needs to intervene. Consequently, the data will be traceable, and the connections made for decision-making will be easier to understand, as explained by Company H.

> "*The share of humans involved will decrease. It will never become 100% automated, I don't think it is needed. I think that someone would like a human to be responsible for making decisions instead of the programmer of the system.*" (Company B)

Company G further argued that data can reduce effort and allow faster decision-making, which would ensure better time management and planning. For instance, Company D explained that they currently have a planner that is making sure all orders are in line and that they are not buying an excessive or insufficient amount of material, which has the potential to be automated with digital tools. In addition, Company B and I argued for better simulation and analysis of data, which would further make the decision-making process more efficient. Nonetheless, Company D elaborated on the difficulties when trying to implement new digital tools and the integration of data, which are mostly derived from costs. For instance, when making a small change in an ERP system, consultants are needed to carry out this type of change, which is very expensive and is making it difficult to fully drive digitalization.

> "*All these things with digitalization look easy on paper, but it is often other factors and costs that play the bigger part.*" (Company D).

Currently, communication between actors within the supply chain is mostly by email and phone, as explained by Company I. For instance, the same respondent argued that they have a purchasing office operating in Asia, which is helping them with monitoring and communicating by phone. As this is a manual process, Company C explained the risks this might infer, for example, a disturbance in a current sales process such as a backlog, which would not be notified by the customer automatically and could lead to delays. However, in many cases, humans are operating more efficiently than machines, especially in marketing communications to customers, which was discussed by Company F. The respondent further elaborated by explaining that a human currently is better at capturing the interest of the customer and is better at building emotional relationships.

> "*The digital transformation is a huge step forward when it comes to ensuring the quality of decisions. At the same time, you have to understand the flow and data, so there should always be a form of assessment that humans need to be involved in.*" (Company E).

Company J further argued that a demand-driven supply chain would mitigate the bullwhip-effect, as it would entail reduced lead times and a more accurate inventory. The same respondent further explained that this would subsequently lead to a more efficient supply chain, however, you would also need to connect the demand from all actors, which requires large amounts of data. On the contrary, Company C argued that a digital supply chain might only help with a small percentage when reaching their internal CO_2-emission target. For instance, shipping things directly and not across certain warehouses will only have a limited positive effect when considering the sustainability aspects, as explained by the same respondent. Scholars usually tend to dramatize the effect to an overblown proportion, as further explained by Company C, where for example overstocks are not as big of a problem as people often may think, compared to other more severe problems.

Academics' & Experts' view

Looking into the linkage between data and TBL performance, the conducted interviews with academics & experts revealed that there is no real limit in what data can do, especially when it becomes connected to AI technologies. In today's environment, the usage of data has not reached its full potential and is therefore mainly limited to capture the value from low-hanging fruits, such as being used as a supporting tool for smaller economic benefits and local problems. For these low-hanging fruits where data is currently used, clean and structured data are required according to the respondents, meaning all unnecessary data must be eliminated, which currently often requires manual processes. It is therefore important to only collect data where a concrete problem is visible to avoid getting overrun by data. The continuous development of data-driven systems will however lead to improved data capacity as the systems will become more efficient to sort, structure, and analyze the information. The respondents consequently stressed that data regarding the whole supply chain should be gathered, including external events such as weather and pandemics, to generate accurate analysis and forecasts.

> **Finding E4:** *Current systems are limited to capture value from low-hanging fruits and are reliant on structured data and human integration. Future data-driven systems are likely to handle complex and an extensive amount of both internal and external information and thus be prone to improve TBL performance through the whole supply chain.*

All participants stressed the importance of having validated data to subsequently establish accurate analysis over the TBL aspects. However, as the current information flow usually contains faulty data humans are required to inspect and clean the data. In terms of environmental and social sustainability, Expert E stressed that the cause of bad data in these areas is because they are reliant on multiple unstandardized factors and measurement methods. According to Experts A1 and A2, human integration could also be valuable to include even though the data is accurate because it is not always the result that is of interest, but the data analysis could be of value as well. Moreover, as current systems are reliant on human integration, it is important to solely collect valuable data since the resources to clean the data otherwise will not become economically sustainable (Expert C). Likewise, due to the current limitations, Expert C discussed that today's systems are only efficient in solving local and uncomplex problems, which is why it is essential to derive concrete problem formulations as it contributes to a precise and structured data collection. In addition, Experts A1, A2, and E stressed that companies can be legally limited in their data collection and usage, and must therefore have the right authority before using the information for company interest.

Following the current limitations for data-driven systems, Expert B and E believed that it is not the systems that are the problem, instead, it was believed that the in-data is the major problem. Receiving correct internal or external data would thus be able to increase the TBL value. In addition, Expert B also believed that more value could be captured if data from the whole supply chain could be gathered, including customers' forecasts, product information, and external global events. This is however problematized by Expert C who believed that too much data can have a contradicting effect as today's systems are not advanced enough to effectively handle this amount of data. Hence, combining AI tools and the data flow would help to analyze and create value from the data as it then would become possible to make improved forecasts, scenario analysis, decision-making processes from complex and extensive amounts of data according to Experts A1, A2, and B. With the development of data-driven systems, Expert A concluded that there is no real limit to what data can generate, as long as you have adequate resources.

> *"The more data you generate the possibilities to create better AI tools increases. So the sky's the limit for the potential and possibilities with data, but you have to start somewhere and today that would be the lower hanging fruits."* (Expert A1).

5.4 Connecting the Fields of Experts and Practitioners

When looking into the findings and the analysis from both the practitioner's perspective and from the view of academics & experts, similarities and differences can be found. Therefore, to present their common thoughts and differences regarding the research questions, a concluding table (see Table 2) and a connection between the two fields is presented which are derived from the previously described findings and analysis. As the sub-research question is formulated in a way to help answer the main research question, the similar and indifferent views of practitioners and experts are thus initially concluded by the sub-research question.

Table 2. A summary of the findings in terms of practitioners and academics & experts.

Main Findings	Practitioners	Academics & Experts
Internal & external challenges	Main internal challenges ● *Standardization & Integration of IT systems* ● *Change management* ● *Excessive data* Main external challenges ● *Transparency* ● *Reliability* ● *Validity*	Main internal challenges ● *Data management* ● *Competence* ● *Data availability* Main external challenges ● *Regulations* ● *Competence* ● *Information sharing* ● *Standardization of systems*
Main Advantages	● *Reduced bullwhip-effect* ● *Improved planning and troubleshooting process in the supply chain* ● *Improved visualization and overview over company processes*	● *Real-time information access* ● *Unlimited opportunities* ● *Improved competitive power* ● *Proactive maintenance of machines*
Main Disadvantages	● *Decreased understanding* ● *Required resources to run and update current systems*	● *Faulty in-data* ● *High costs* ● *Uncertain future development.*

Future applications & improved TBL performance	Consists of ● *End-to-end transparency* ● *Automated planning* ● *Optimized transportation*	Consists of ● *Integration of intelligent technologies* ● *End-to-end transparency* ● *Real-time analysis and reactions*
What data is needed	● *Customer data* ● *Uncertainty of what data is needed*	● *Specific data for specific problems* ● *Clean & structured data*
Value of data	● *Unlimited potential* ● *Utilization from end-to-end in the supply chain* ● *Collaborating effort for TBL improvements*	Current value capture ● *Current limitations to low hanging fruits* Potential value capture ● *TBL decisions based on a complex and extensive amount of data*

How Does Digitized Supply Chains Impact Manufacturing Operations in a Sustainable Way?

According to the case companies, a more digital environment can help establish a more sustainable supply chain in many different ways. For instance, the company representatives argued that with data-driven systems one could reduce the bullwhip-effect, improve planning, have a more efficient troubleshooting process, decrease the need for flights, optimize the production process, become more customer-centric, gain financial profits and meet growing demands. The academics & experts rather argued for an enhanced life span of products and improved competitiveness, forecasting, and service. However, it was further found that the transformation towards digitalization comes with some sustainable disadvantages. Here, both the case companies and academics & experts argued that it comes with high costs, as a lot of parameters need to be interlinked. The case companies also stressed the importance of a reduced understanding of processes when implementing new digital technology, which also can be seen as a sustainable loss socially. In addition, the academics & experts further argued that there is a need for regulations for a digital and sustainable supply chain to fully operate, which is very difficult to establish. This also comes with sustainable complications, as it affects the social aspects within the TBL. The cause of insufficient data is often related to the difficulties of measuring social and environmental sustainability, as further explained by the academics & experts.

The improved TBL performance can be summarized by *Table 3*, where each aspect is covered by advantages that are driven by future operations realized with a digital supply chain. For instance, the economic aspects of sustainability can be improved by a reduced need for flights, which is currently expensive and simultaneously affecting the environmental impact with high CO_2 emissions. With digital tools, it was found that the packaging of products can be optimized, which would entail better utilization of space, thus fewer transports per product and financial benefits. In addition, with accurate and real-time information, companies can avoid producing an excess of material and know when, where and what to transport instantly. Thus, better utilization of material and reduced number of unnecessary transports, which would further bring financial benefits. The respondents further argued that better planning can be realized with improved forecasts, which can lead to more profits with accurate pricing and less time wasted.

Table 3. TBL value of digital supply chains according to the empirical findings.

Economic	Social	Environmental
• Reduced transport costs • Increased utilization of packaging • Avoid producing excess material • Accurate pricing • Better planning and less time waste • Less personnel	• Reduced physical labor • Decreased level of rework • Enhanced trust among all actors • Improved competitiveness & service	• Lower transportation and production emissions • More efficient recycling process • Reusage of energy • Enhanced life span of products • Decreased wastages

Some of the respondents further argued that less personnel are needed with an implementation of a digital supply chain, which would further entail reduced physical labor and social benefits. With better planning and access to real-time information, the amount of rework can also be mitigated, which can lead to less stress and frustration among employees. One of the main advantages with a digital supply chain was found to be visibility, which can also have the effect of enhanced trust among all actors within the supply chain. Moreover, looking at the environmental benefits of digital supply chains, there is potential to reduce CO_2 emissions, take advantage of more efficient recycling processes, reuse energy and enhance the life span of products.

How Does Data-Driven Decision-Making Enable Sustainable Supply Chain Operations Within the Manufacturing Industry?

To fully reach the sustainable value that digital supply chains can entail according to the empirical findings, the academics & experts argued that data-driven decision-making can provide real-time analysis over emissions in the supply chain. In addition, data-driven systems have the ability to handle complex and extensive amounts of information simultaneously, as further explained by the academics & experts. Furthermore, both the company representatives and academics & experts argued that data-driven decision-making has unlimited possibilities when developing the TBL performance of manufacturing companies. For instance, it was found that data-driven decision-making entails visualization and subsequently the possibility to help external actors within the supply chain improve their sustainability. As data-driven decision-making is fulfilled by a digital supply chain, the benefits of both areas are connected. From the case interviews, it was found that future applications are mainly linked to transparency, automated planning and optimized transportation. This is mainly due to the fact of easier access of real-time information and an end-to-end integration within the supply chain, as explained by both the case companies and academics & experts. However, academics & experts argued that it is the companies' own economic interest combined with governmental and significant industrial players that drives the progress of both digital and sustainable progress.

Data-driven decision-making brings certain challenges, which further has to be overcome in order to enable a sustainable supply chain. For instance, the case companies argued that there currently are issues standardizing and integrating IT systems, having managers drive a digital transformation, issues with information sharing and challenges regarding cost, reliability and validity of data. It should, however, be highlighted that the case companies' challenges varied in accordance to their current digital integration, where companies with a high level of digital integration experienced different challenges and advantages compared to companies with low digital integration (see Figure 10). Moreover, the academics & experts stressed the importance of competence, setting up regulations both globally and nationally, effective management of data, transfer competence to external actors within the supply chain, have customers use the same systems for connectivity and that people tend to enter incorrect data from the start. However, the academics & experts further argued that current systems are limited to low hanging fruits and are reliant on structured data and human interaction.

6 Discussion

In this section, the research questions are discussed concerning the empirical findings and previous literature. Additionally, the guiding model is evaluated in terms of how it relates to understanding and enabling sustainable data-driven decision-making.

6.1 The Sustainable Impact of Digitization on Manufacturing Supply Chain Operations

To realize the purpose of the study a prior understanding of how digitalization impacts manufacturing supply chain operations in a sustainable way is needed. Thus, considering the following question:

> *SQ: How does digitization impact manufacturing supply chain operations in a sustainable way?*

The empirical findings were divided among practitioners and experts, where it was found that the practitioners saw the most sustainability advantages. For instance, the practitioners argued that with digital supply chains, manufacturers can fulfill sustainable benefits such as a mitigated bullwhip-effect, a decreased need for flights, reduced emissions, and becoming more customer-centric. Even though the bullwhip-effect, flights, and emissions will persist according to the findings they can be dramatically reduced with the power of intelligent decision support systems. These factors can further be linked to planning operations, which is why we stress the importance of planning processes as it leads to improved inventory control, forecasts, and transportations. Both the practitioners and experts further stressed the importance of satisfying customer expectations and providing better service, which further can be realized with digital supply chains. Such sustainable benefits indicate that the manufacturing industry can improve according to the TBL performance in all three aspects. For example, a mitigated bullwhip-effect will affect the financial, environmental, and social performance by less wastage, reduced risk of overproduction, and less confusion among suppliers respectively.

The practitioners further argued that the planning can be improved, which consequently can lead to lower lead times, fewer time wastages, and optimized transportation. Previous research supports these findings, as better planning is often tied to more efficient and sustainable logistic processes (Lloyd, 2011; Zhao et al., 2019; Tao et al., 2018; Sinha et al., 2020; Hasan et al., 2019). Lloyd (2011) & Zhao et al. (2019) further mention that the improved planning and inventory control is directly correlated to the decision support systems' ability to provide better predictions based on patterns in historical and real-time fluctuations. However, the empirical findings simultaneously expressed skepticism towards the extent and impact of such sustainable benefits. Currently, many deliveries are on time and resource wastages are generally not devastating in terms of financial and environmental effects, as expressed by the empirical findings. Nonetheless, both the empirical findings and previous research emphasize the effect digital supply chains can have on products' environmental footprint. For instance, digital supply chains come with the benefits of optimized surveillance on e.g. water usage and emissions as well as optimized usage of raw materials (Tao et al., 2018; Sinha et al., 2020), which can lead to a more efficient troubleshooting process and improved product performance.

In contrast to the empirical findings, previous research has proposed positive sustainability impacts such as improved agility (Sinha et al., 2020), enhanced marketing (Tao et al., 2019; Hasan et al., 2019), better allowance of purchasing sustainable products (Hasan et al., 2019), improve quality (Tao et al., 2018;

Sinha et al., 2020), reduce R&D expenses (Sinha et al., 2020) and a safer working environment (Bernardes et al., 2020; Sinha et al., 2020; Deloitte, 2016). Regarding the negative sustainability aspects, previous research has rather focused more on high energy consumption (Ejsmont et al., 2020), a need for time and organizational strategy (Büyüközkan & Göçer, 2018), the need for a behavioral shift among workers (Sinha et al., 2020) and data management readiness (Zhong et al, 2016; Brousell et al, 2014; Zhou & Yang, 2018; Leveling et al., 2014; Zhao et al., 2020).

This indicates that we truly are experiencing a digital transformation, as most sustainability disadvantages are tied with organizational change and a behavioral shift among both customers and workers. In addition, the empirics further highlighted the worry of reduced understanding of processes, risk of misinterpretations, and the need for set regulations. Consequently, digitizing supply chains come with high costs, which is the main negative sustainability impact, as it is supported by both the empirical findings and previous research (Büyüközkan & Göçer, 2018). However, worth noting is all the positive sustainability impact of digital supply chains, nonetheless in terms of financial performance, which might exceed the initial investment costs. Here, both the practitioners and previous research expressed the relationship of economic benefits and digital supply chains (Caesarius & Hohenthal, 2018; Davenport, 2014; Sinha et al., 2020; Seyedghorban et al., 2020; Ylipää et al., 2017; Ma et al., 2002), since it can be identified with effective predictions and just-in-time processes (Sinha et al., 2020), as well as the ability to meet growing demand, drive better pricing and have less personnel, as expressed by the practitioners.

It is further worth acknowledging the differences among companies when it comes to financial resources, ability to change, and the number of employees since it affects the digitization of supply chain operations. For instance, incumbent firms are currently driving digitalization, mainly because they have the financial resources to do so and have easier access to data, as stressed by the experts. The larger companies can thus affect future regulations and laws to a greater extent than smaller companies, which are needed for efficient digital supply chains. This can be derived from the benefit of better communication along the end-to-end supply chain (Tao et al., 2018; Sinha et al., 2020), and the disadvantage of the different standards and views of sustainability all around the globe, as further expressed by the experts. Consequently, this indicates that the larger companies should force a digital transformation not only internally, but also externally among suppliers and subcontractors. This is due to the fact that a digital supply chain is built on communication and could lead to more comprehensive standards and a more common view of sustainability globally.

The interviewed companies were all incumbent firms with large financial resources and a high number of employees, nonetheless, the level of digital integration varied among the different companies. This can be associated with many different factors such as customer expectations and organizational strategies, however, it indicates that a digital transformation is reliant on support from management and can be developed with collaboration with actors from different industries. Currently, there are many different parameters that are driving digitalization within supply chain operations, where the empirical findings point towards benefits such as improved competitiveness, less amount of rework, and improved resource efficiency. However, it can further be discussed that digitalization might be a question of survival and comes from the pressure from customers to deliver faster and more accurately, as was also stated by the practitioners. Nonetheless, as the digital transformation is continuously growing, digital supply chains will become more widespread, simply because they come with benefits that exceed the disadvantages and it is easier and more efficient to work that way.

Proposition 1: Digital supply chains come with a considerable sustainable impact, which can improve the TBL performance at companies to various extent. Incumbent firms currently drive digitalization and should force external actors to develop digital solutions as a way to realize digital supply networks, establish a circular economy and improve the TBL performance collaboratively.

6.2 How Data-Driven Decision-Making Enables Sustainable Supply Chain Operations within the Manufacturing Industry

As previously discussed, digitalization and data-driven decision-making are likely to have a significant impact on manufacturers' supply chain operations. However, how data-driven decision-making enables manufacturers to realize these advantages has still not been fully covered, which lead us to answer the main research question:

MQ: How does data-driven decision-making enable sustainable supply chain operations within the manufacturing industry?

It will consequently be discussed what data-driven related factors that pave the way for reaching sustainable benefits. Primarily to reach the benefits, there are several challenges to overcome. Therefore, it will initially be discussed how to meet these types of challenges that will enable data-driven decision-making to improve the supply chain operations' sustainability performance.

Overcoming challenges

Initially, to become data-driven companies need to generate and analyze data. This challenge requires companies to both have standardized and integrated IT systems, two challenges that can be derived from the findings and the literature review. Standardization becomes a challenge since without it the connectivity between the systems becomes inefficient (Fatorachian & Kazemi, 2018; Kusiak, 2018). According to Fatorachian & Kazemi (2018), only 4% of manufacturing devices can connect to a network due to the lack of uniform communication systems. Both the case companies and the academics & experts verified this issue by explaining real-life scenarios regarding standardization challenges. These scenarios showed that due to special standards their systems are unable to connect and share information to external or internal systems. In addition, the findings also demonstrated that it is not always the standardization of the systems that is challenging, but instead it is the formatting of data that requires standardization. Likewise, Zhong et al. (2016) also indicated that one of the main challenges is concerning the translation of data, which is the process of standardizing all data into a common format.

Overcoming the challenge with standardization can be seen from both an internal and external perspective. Internally, it becomes necessary to update current systems towards standardized communication networks where information can be efficiently transmitted (Fatorachian & Kazemi, 2018). This further requires both standardized IIoT and CPS systems, which are the enablers for communication networks between machines and communication between machines and humans (Kagermann et al., 2013; Brettel et al., 2014). Moreover, according to Kusiak (2018), Ghobakhloo (2020), and the empirics, collaborations can also pave the way for the generation of standardized systems. This is because the systems both require communication internally and to external collaborating partners, which consequently requires everyone connected to the supply chain to have common systems. Additionally, it is not only the systems that need to be standardized but the data format as well. This is especially important regarding environmental data, as the findings revealed that the reason for bad environmental communication is because of the lack of standards in how to measure and format environmental data, such as industrial emissions.

External factors that can help companies standardize their systems are related to government legislation and the major companies. According to the findings, regulations and other governmental initiatives have the power to pressure companies to work within a special framework and make it possible for both small and larger companies to have a standardized communication foundation. In addition, larger industries also have the power to establish de facto standards, as their systems are commonly used by smaller entities who are reliable in their collaboration, which is something that both the academics & experts and the case companies agreed upon. However, these external factors are not equally stressed within the literature, but due to their significance in the findings, we believe that they should not be overlooked. Therefore, we believe it is of great importance that governments and the head industrial companies agree upon standardization of systems and communication to benefit everyone in the supply chain. However, since governmental regulations can generate a backlash for companies' digital development according to the academics & experts, their push for standardization must be done with careful considerations.

Moreover, establishing IT integration throughout companies' supply chains is also a fundamental challenge for companies to overcome to reach the benefits connected with data-driven decision-making. This issue is, however, more of an implementation challenge which is an issue that has previously been studied. Therefore, challenges related to implementation are mostly derived from the literature instead of from the interviews. These areas are mainly found in Büyüközkan & Göçer (2018) research, which concerns technology enablers, infrastructure, managerial engagement, and human-machine relations.

However, what has been observed in the interviews is mainly connected to change management. Investment costs and the actual integration of technologies did not seem to be the most difficult obstacles according to the findings, even though high expenses can be seen as the main sustainable drawback. Costs must thus still be given attention because the financial resources are a huge challenge to overcome since the digital transformation is heavily reliant on organizations' financial abilities (Fatorachian & Kazemi, 2018). Instead of costs as the main challenge, we believe the implementation difficulties can mainly be drawn towards the social aspects, which concerns the willingness for change, competence, and the managerial aspects. This is something stressed in the findings and the literature, especially according to Ghobakhloo (2020) who connects the willingness for change to the ability to enable the necessary resources needed for the whole adoption of SM. It is therefore essential for companies to establish conditions where the employees and management are willing to incorporate digital changes. Here, we believe that Operator 4.0 and other human-in-the-loop strategies can be essential to overcome the implementation challenge as it provides human-machine relations. Moreover, it should be given attention that financial resources are a huge challenge to overcome even though it is not seen as the most challenging aspect.

Furthermore, reliability and validity are two additional challenges that must be overcome to enable the benefits of data-driven decision-making to be met. However, to overcome this hurdle, we stress that companies must establish efficient data management. According to the respondents, excessive amounts of data and faulty in-data are the greatest data management challenges, which entails the challenges to manage the data volume and its reliability and validity. Likewise, Zhong et al. (2016) also demonstrated that data volume, reliability, and validity are crucial and common obstacles but also puts the data management challenges in correlation to the 5Vs; Volume, Velocity, Variety, Verification, and Value. The velocity, variety, and value are not equally highlighted by the respondents but become three additional data management challenges that must be given attention.

What can be connected to the challenge concerning the volume is that systems are becoming more developed and consequently more capable to handle a vast amount of data. The academics & experts did, however, believe that current systems are capable of handling the volume of data whereas the case companies did not. Per the case companies, it becomes essential to have both structured data and data from a concentrated problem, since their systems cannot handle unstructured data efficiently nor the vast amount of data. Therefore, we believe that in the manufacturing industry companies must have well-sorted and concentrated data for a specific problem to be able to provide real-time analysis and handle the velocity and variety of the data flow. In addition, we see human integration as an important factor to validate the data, because the in-data is commonly a problem as seen in the findings. Humans are further a necessary step to find the value of data since current systems are limited to answer specific questions and not create new conclusions as described in the findings and by Debortoli et al. (2014).

> **Proposition 2**: To fulfill the advantages the challenges must be overcome. Therefore, it is our belief, based on the findings and the literature, that companies should consider collaborations with other supply chain entities to establish unified systems. Companies should further investigate governmental actions and powerful players in the industry to understand what types of standards will become de facto standards. Lastly, to overcome the hurdle connected to data management, companies should establish human-in-the-loop processes.

The continuous enablers for sustainability

As the initial and ongoing challenges of data-driven processes have been addressed, the continuous evolvement of data-driven decision-making towards enabling sustainability must be discussed. Looking into the areas where data-driven decision-making currently improves the sustainability aspects, they are currently limited to low-hanging fruits as explained in the findings. However, Tao et al. (2018) demonstrated the continuous development of digital abilities during the progress of Industry 4.0, but where the existing systems are somewhat limited to their current abilities. It is, on the other hand, believed that the application area and abilities connected to data are limitless if they are managed correctly.

Examining the findings, it could be derived that transparency, automated planning, and optimized transportation are the main factors that drive the applications for data-driven decision-making. These are also factors given attention from Sinha et al. (2020) and Li et al. (2015), who especially stressed the importance of transparency to enable the full benefits of data-driven processes. Sinha et al. (2020) further emphasized the need for end-to-end transparency, which concurs with the findings and can improve both reliability and validity, but which is something quite difficult to obtain. This is because it requires the challenges connected to the technical abilities to be overcome as explained in the literature and also to overcome the willingness of external actors to be transparent and regulations as shown in the findings. Therefore, we see that the external aspects should be equally stressed as the technical aspects when discussing transparency.

Increasing the willingness of external actors to become transparent is a factor commonly overlooked in the literature, but which has shown to be of great importance in the findings. Therefore, we believe companies should give attention to building well-functioning relations with external actors, as a way of establishing the trust needed for continuous end-to-end transparency in the supply chain. Connected to this is also security, which the literature often described as an obstacle in the process of sharing information (Kagermann et al., 2013; Mittal et al., 2019). Security is, on the other hand, not equally highlighted in the findings as the case companies did not experience a significant challenge with transparency and security, which also is linked to the supply chain control of the case companies. Therefore, we see that companies with little control over their supply chain should give attention to security investment related to data transmission, whereas it can be questioned to what extent manufacturers with internally controlled supply chains should invest in cyber-security. This is because these companies will share most data internally and are not affected by external factors to the same extent. Moreover, since these sorts of investments such as Blockchain technologies are expensive (Ghobakhloo, 2020), companies should question if they are needed internally.

Transparency is furthermore important to establish visualization over companies' supply chains. Visualization has the power to present the massive amount of data in a more accessible way and has consequently become an essential factor for how data-driven decision-making can improve TBL performance (Tao et al., 2018). Likewise, the findings also link visualization with sustainability as it allows the management team to identify inefficient processes and improvement areas. We, therefore, see that visualization can be applied to find applications for where data-driven decisions can be beneficial. Consequently, by having visualization tools, the transportation in the supply chain can be optimized as every order is accessible and controlled. Moreover, Popovič et al. (2019) highlighted the importance of having real-time information to maximize the value creation in the transportation process, as this allows for real-time adjustments in the supply chain.

However, analyzing real-time information can be challenging as it requires efficient analysis systems. Connecting a flow of real-time data with automatization technologies such as AI, allows the systems to utilize real-time information, which more manual systems are too slow to manage as seen in the findings. Thus, the supply chain can be further optimized. The findings, therefore, stressed that the connection of AI and real-time information can make large improvements in the supply chain. Consequently, we see that the integration of intelligent systems and real-time data provides the ability to establish automated planning systems for the supply chain as the slow manual processes can be eliminated. Contrary, as seen by Sinha et al. (2020) and in the findings, human interaction should not be fully eliminated because of the social aspects and that the human understanding of analysis, planning, and decisions is core for companies. Therefore, we believe that even though the manual processes can be eliminated, human integration should only be reduced and not fully eliminated.

For the more automated processes to function, companies are further required to establish well-structured and high-quality master data. Master data is the foundation in building efficient automatization systems, which was stressed by both the case interviews and previous literature (Vilminko-Heikkinen & Pekkola, 2017; Popovič et al., 2019; Zhao et al., 2020). For the reasons that efficient analysis systems are core for visualization, we believe that master data should continuously be controlled to ensure the systems are basing their analysis on accurate company information.

The systems should, however, not only be controlled that they have the correct master data because having data available is also a fundamental aspect to consider. This is something especially considered in the findings, where it is found that the lack of availability for both internal and external information is a major problem for current systems. Contrary, the literature stated that the number of available data increases where data becomes accessible from new and modern data warehouses (Fatorachian & Kazemi, 2018; Mittal et al., 2019; Zhong et al., 2016). Consequently, investing in data warehouses could become a beneficial solution for manufacturers to enable the constant availability of data. From these sorts of systems, simulations of scenarios should constantly be created as shown in the findings. This is due to the reason to create improved forecasting models that further can be used for proactive means in the supply chain.

> **Proposition 3**: To obtain the sustainable benefits of data-driven decision processes several aspects should be taken into consideration. Manufacturers should establish relations and technical abilities that allow them to obtain end-to-end transparency, as it is key for generating visualization over the supply chain processes. Consequently, utilizing efficient analysis systems, real-time information should be analyzed in a human-in-the-loop approach to subsequently create automated planning and optimized transportation. The systems should further run simulations and have access to data warehouses to enable constant analysis and data-driven decisions to be made.

6.3 Development of a Conceptual Model

Based on previous literature, it was noted that there existed some gaps concerning how data-driven decision-making can enable a sustainable supply chain. Three different parameters that are connected to data-driven decision-making were identified, data and IT infrastructure, current operations, and an improved TBL performance. However, the linkages between these three parameters had not been investigated, leading to a lack of understanding regarding sustainable data-driven decision-making. Thus, by investigating the linkages between each parameter, we explored the business opportunities and challenges of data-driven decision-making, and how it relates to more sustainable supply chain operations within the manufacturing industry, consequently fulfilling the aim of the study. Each linkage has further been covered in the previous two subsections in which answered both the sub- and main research question. The conceptual model can consequently be derived from *Figure 13* below, which covers the main aspects within each linkage (see Appendix D for an extensive view of all aspects).

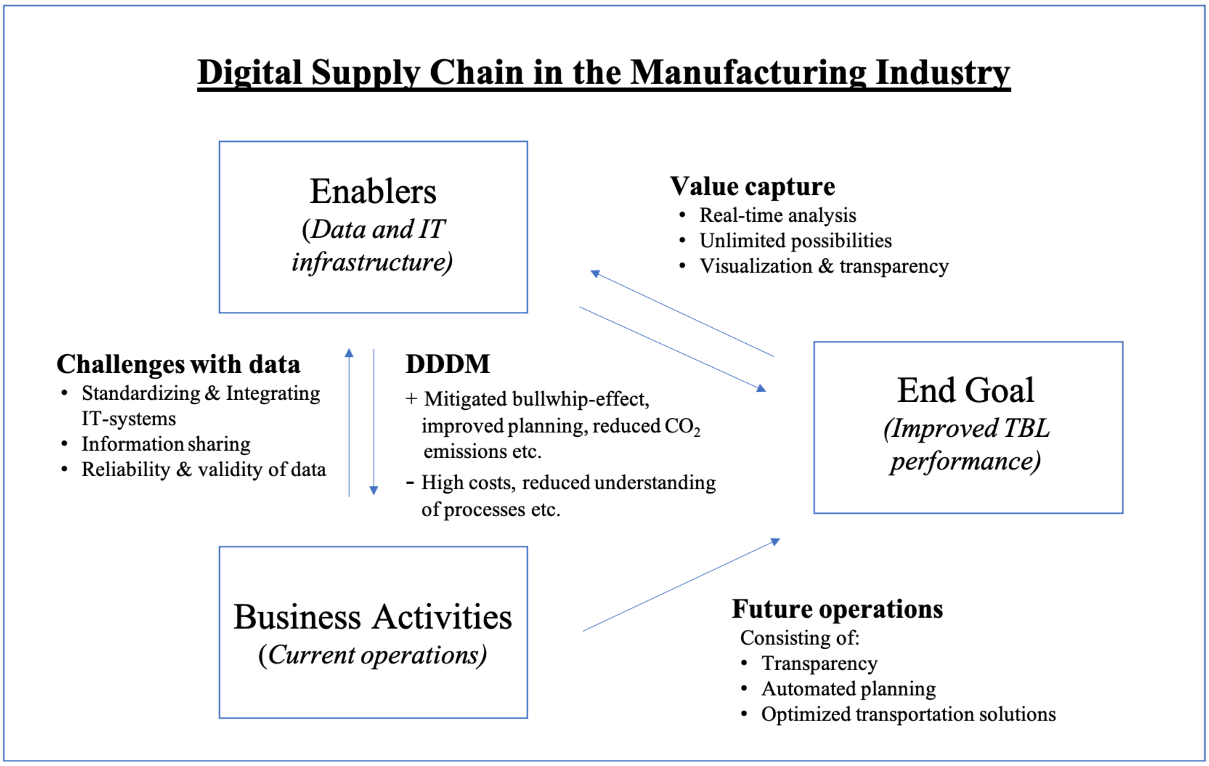

Figure 13. A Conceptual Model of Digital Supply Chains in the Manufacturing Industry.

Based on previous literature and the empirical findings, data-driven decision-making is heavily reliant on an organization structured on digital solutions and strategies. For instance, without sufficient communication and visibility, the value capture of real-time analyses as well as the advantage of improved planning and future operations driven by transparency cannot be fulfilled. As a consequence, companies need to undergo an organizational reconfiguration and embrace digitalization within their business models and operational strategies to fully reach the sustainable advantages data-driven decision-making can provide. In addition, it can be concluded that most incumbent firms are currently in the initial process of transforming towards a digital landscape, which subsequently leads to companies reaching for lower-hanging fruits. The empirics revealed that data more often than not comes with unlimited possibilities, and companies are currently experiencing a phase of exploration in relation to what data can be helpful when looking at improving the TBL performance and how data can help operationalize more optimized processes such as transportations. Therefore, it is challenging to come to terms with tangible future applications, which is why *Figure 13* and the findings merely describe future operations in an indefinite way (i.e. the future operations are *driven by* transparency, automated planning, and optimized transportation solutions).

A major point of discussion is also the importance of collaboration and the improved circular economy that can be realized with data-driven decision-making and digital supply chains. As data can be integrated with the end-to-end value chain, all actors within a manufacturing supply chain will be affected by the digital transformation. Thus, we want to stress the importance of collaboration and for incumbent firms to improve their ability to help external actors as a way to achieve the sustainable benefits that are entailed by digitizing the supply chain. Additionally, based on the empirical findings and as expressed by previous research, the traditional supply chain will shift into a DSN (Sinha et al., 2020; Deloitte, 2016; Bernardes et al., 2020; Büyüközkan & Göçer, 2018; Garay-Rondero, 2019), as the value capture and the future operations mainly are driven by transparency and visibility.

Subsequently, it is just a matter of time when all products are connected to cloud solutions or have a digital twin, which entails enhanced communication and collaboration between actors within the end-to-end supply chain, leading to a DSN and new business models. For instance, as products become more connected, it could entail more service-driven business models such as PaaS (Platform as a Service), IaaS (Infrastructure as a Service), and SaaS (Software as a Service).

It is further important to acknowledge the differences among the studied case companies, as they originate from various sectors within the manufacturing industry, are varying in size, and are working at a global scale in different ways. For instance, Company E was a furniture manufacturer that has seen rapid growth during the Covid-19 outbreak and was found to have integrated more digital strategies and omni channels within their business, consequently driving their digital transformation forward. When looking at Company G that was an automotive manufacturer, it was found that the pandemic had an opposite effect in comparison to Company E, as the financial investments driving their digital transformation had been frozen and located elsewhere. Consequently, even though the automotive sector is currently one of the leaders in the digitalization journey, as stated by the academics & experts, some opportunities will not present themselves as clearly in different sectors. This can further be derived into many different factors, but the importance of a digital strategy cannot be stressed enough.

As stated earlier and continuously throughout the report, MNEs are currently driving the digital transformation, mainly because they have the financial means to overcome the high costs associated with digital change and new technologies. However, MNEs are generally operating at a global scale, which can have an unfavorable effect when investing in a digital change because of the risk of a fragmented IT structure. In addition, as explained by Moore's law, new technology will constantly become cheaper. Both these factors are beneficial for SMEs, as the barriers to change can be overcome more effortlessly. For instance, a digital supply chain can operate efficiently at a global scale, but legislations and different business cultures in countries abroad could generate significant obstacles for a digital reconfiguration. Thus, it could be a more straightforward process for SMEs to implement data-driven decision-making when excluding the financial aspects, as it might be easier to do so locally or on a national level because of well-established relationships among different actors in the supply chain as well as common views of sustainability and same national regulations.

7 Conclusion

The conclusion presents the most important findings and discussions in regard to the study's research questions and aim. It does so by utilizing the conceptual model that brings the aim of the report forward by explaining the linkages between Enablers, Business Activities, and End Goal. This section will further conclude the research's theoretical contributions and its managerial and sustainability implications. Lastly, the limitations of the research are presented as well as suggestions for future research within the research area.

7.1 Revisiting the Research Questions

To answer the aim of the research the research questions must primarily be concluded since they provide the foundation for elaborating the aim. Therefore, the findings and discussions presented in sections 5 and 6 are unified to conclude the research questions. In regard to the sub-question:

> *SQ: How does digitization impact manufacturing supply chains operations in a sustainable way?*

It was found that digitalization impacts manufacturers' supply chains to various extents in terms of TBL performance. It was further seen that the visible impacts digitalization has on the supply chains is related to company size, sector, to what extent digital tools are being used, and what TBL aspect companies choose to put focus on. Incumbent firms, governmental regulations, and customer expectations are also factors that affect where and how digital systems should be used for both SMEs and MNEs. The TBL impact the utilization of digital systems have on supply chain operations are for the most part positive, but with some drawbacks including a reduced understanding of the analysis processes, initial resource requirements, high energy consumption of systems, and errors that can lead to faulty and inefficient decisions.

The positive aspects considering sustainability and digital supply chains are concluded to incorporate the economic, social, and environmental aspects. A digital supply chain further contributes to improved control over the whole supply chain making it possible for companies to enhance their inventory control, forecasts and transportations while mitigating the bullwhip-effect. This becomes possible as the digital supply chain's analysis systems can use real-time information to provide fast or automated reactive actions from fluctuating external and internal information. The improved control over the supply chain further makes it possible for manufacturers to identify unsafe work environments, by receiving constant data that can help predict system and machinery failures, and give information about inappropriate work environments such as child labor. Consequently, by optimizing the supply chain processes with the help of digital tools, the emissions will be reduced since last-minute transportations and inefficient transportation routes can be avoided, and where resource efficiency would be improved. Lastly, by incorporating digital supply chains and utilizing digital supply networks, a circular economy would become easier to achieve as transportations and production can become more environmentally neutral. Consequently, products will be recycled more frequently and better control over emissions will be established through the data-driven systems.

For the main research question:

MQ: How does data-driven decision-making enable sustainable supply chain operations within the manufacturing industry?

It was further found that the benefits given by the sub-question are only likely to be reachable if the challenges related to data-driven decision-making are met. Therefore, it is key to establish unified systems along with the supply chain entities and consider powerful industrial players, customer trends, and governmental actions to understand the standardization processes for data-driven systems. This way, companies can establish effective communication channels to transmit the necessary data needed for optimizing transportation and generating accurate forecasts. Additionally, companies should put a great focus on human integration in data-driven processes since this would enable companies to retain the company knowledge within its people, which is a necessary social aspect to consider. Implementation challenges must also be considered as well as the process to only generate structured and relevant data for current data-driven systems in use.

Data-driven decision-making enables sustainable supply chain operations as it increases companies' transparency, visualization, and efficient analysis systems. With improved transparency, visualization, and efficient analysis systems, companies can generate more sustainable decisions as they will receive an increased control, flexibility, and understanding over the supply chain. By utilizing data-driven processes, the amount of transparency is able to increase making it possible for companies in the supply chain to obtain necessary real-time information throughout the supply chain, which is needed for fast and responsive actions. Transparency is further a requirement for data-driven decision-making to function properly, and if a sufficient amount of transparency is achieved the digital systems are able to generate comprehensive visualizations over the supply chain. Visualization is the ability to convert complex data sets to meaningful and useful information that ultimately serves as a tool to improve the decision-making process to further enhance the TBL performance in the supply chain. However, to generate efficient visualization processes, companies also need efficient analysis systems. Therefore, by connecting the fast-flowing data with intelligent and automated systems, the processes to visualize real-time data become achievable. Additionally, intelligent and automated systems also have the potential to generate automated planning and decisions, which enable faster reactions to real-time fluctuations.

By combining the sub and main-question the foundation for answering the research's aim is laid. This is further used to establish a conceptual model that helps to visualize an understanding of digital supply chains (see Figure 13 and Appendix D). Consequently, by exploring the research questions and the value capture, challenges, benefits, drawbacks, and the future regarding digital supply chains provided by the conceptual model, the aim is fulfilled. This is because the research questions and the conceptual model provide answers to the business opportunities and challenges for data-driven decision-making, and its relation to sustainable supply chain operations within the manufacturing industry.

7.2 Theoretical Contributions

From the problematization section, several gaps in existing literature have been described and that has, to some extent, been explored in this research and contributing to the research's theoretical significance. First of all, this study presents a holistic perspective over risks related to digital transformations, something that has been limited in previous studies and therefore has been needed to be further explored. The holistic perspective in the manufacturing setting has been achieved by exploring different sectors and interviewing employees and experts within different kinds of fields, backgrounds in the industry and academic sectors. However, the study is limited by primary looking at incumbent firms in the Swedish manufacturing sector and thus, the theories cannot be fully adopted for SMEs nor companies outside of the Swedish context.

Moreover, as this study also dives deeply into data-driven decision-making in the supply chain and manufacturing processes, the research has been able to explore specific applications for data-driven systems in the supply chain and manufacturing sector. By exploring different types of applications in regard to sustainability, the research has established an understanding of both the risks and benefits related to data-driven systems and their applications. Based on the problematization, it is argued that a deeper understanding in the area of sustainable risks and benefits to more specific applications within digitalization is obtained, which is a research gap that the study, therefore, is believed to provide a theoretical contribution to.

Additionally, as Industry 4.0's potential in the manufacturing industry is not fully understood, this has also been an area of interest for the research and an area to which it is believed that the study contributes. This is for the reasons that this research explores data-driven decision-making, which is a segment within Industry 4.0, and further also explores its applications, value capture, benefits, and challenges, especially within the manufacturing sector. Consequently, this contributes to and somewhat fills the gap in current literature related to Industry 4.0's potential in the manufacturing industry. By discussing this area, the challenges related to data-driven decisions are addressed as well as how to overcome them and subsequently reach their benefits. For the reasons that this is discussed in a supply chain and manufacturing setting, the study further contributes to filling the gap in regard to the adoption process of digital supply chains.

One of the main strengths of this research is based on its exploration of real-life cases and combining them with academic theories. Academic literature regarding limitations and advantages of different supply chain strategies have been previously explored, however, due to the limited number of real-life cases for applications of digital supply chains this research contributes to the existing literature by delivering real-life knowledge to the area within digital supply chains. This is especially relevant to explore as the outburst of Covid-19 has drastically increased companies' digital development.

7.3 Managerial Implications

Currently, managers from all industries have been affected by the recent pandemic, which further has had an impact on companies' digital strategies. MNEs are driving the digital transformation with their financial resources, but it is nonetheless significant to acknowledge the importance of having a digital strategy to further drive digitalization. In addition, many of the studied case companies are currently organizing their internal IT structure, which is a necessity when investing in data-driven decision-making and digital supply chains. However, the findings revealed that it might become difficult to have external actors utilize the same systems within the supply chain to achieve full visibility and transparency. This further leads to the challenge of information sharing, as companies might experience complications when trying to obtain valuable information from external actors. The findings revealed that companies might be reluctant to share such data because of an unawareness of what the data can be used for and for what purposes.

Consequently, manufacturers need to overcome a behavioral shift among both customers and workers as well as the above-mentioned challenges associated with a transition towards a digital supply chain.

To do so, we suggest, based on the findings, that managers at incumbent firms need to establish clear digital strategies and incorporate digitalization within the entirety of the company. Here, we want to stress the importance of including the perspectives of the customers, production workers as well as the people working with incorporating new technologies such as AI and blockchain. We advocate that this is necessary since the older generations generally are less intuitive when it comes to new digital solutions and are used to work more traditionally. Thus, managers need to include both short-term and long-term solutions that include the behavioral shift among both workers and customers.

> **Recommendation**: Managers need to encourage a digital change, as well as establish a clear digital strategy both long-term and short-term to cover the behavioral shift among workers and customers.

Digital investments often come with high costs, leading to complications when motivating the necessity of the transition. This is rooted in the capitalistic structure in which companies currently are operating globally. However, with constant pressure for change and more demands for sustainable processes and offerings, a growing number of companies are starting to incorporate sustainability within their businesses, as derived from the findings. This could imply that future operations demand transparency as a way of accounting for the TBL performance at companies. Thus, a future transition towards a digital supply chain might not only be driven by its financial advantages but rather as a necessity to become more sustainable. This further implies that managers need to overcome the different views and regulations regarding sustainability globally. Currently, there is no single standard or no common formatting of data, which entails that managers need to focus on creating a sufficient organization for data management.

> **Recommendation**: Managers have to acknowledge the effects of the growing sustainability demands can have on the business landscape. Consequently, incorporate sustainable strategies that cover a common view of sustainability and different regulations globally, where a focus is on creating a desirable organization for data management.

Based on both previous literature and findings, the traditional supply chain will rather transition towards a digital supply network (Sinha et al., 2020; Deloitte, 2016; Bernardes et al., 2020; Büyüközkan & Göçer, 2018; Garay-Rondero, 2019), with enhanced communication and a free flow of information. Consequently, managers have to consider their current relationships along the supply chain as well as their technical abilities, since such factors will help obtain visualization over the supply chain operations. By doing so, companies can utilize real-time information, automate planning and optimize transportations, as expressed in the findings. In addition, this further entails new business opportunities, where managers have to acknowledge new possibilities related to financial constructs to generate profits and provide better service. Here, business models that allow servitization could have a major role in future manufacturing business activities where the improved communication and connection between machines and systems from digital supply chains would enhance the process to enable servitization.

> **Recommendation**: Managers must recognize the shift from traditional supply chains towards a digital supply network. This further entails the possibility of new business models that could generate enhanced profits, such as servitization.

7.4 Sustainability Implications

Exploring the research's implication for sustainability it can be seen that it can have a significant effect on several different SDGs. For data-driven decision-making in terms of supply chain management in the manufacturing industry, it has been concluded that the SDGs 8, 9, 10, 12, 13, 14, and 15 are especially affected. These include:

- Goal 8: Decent Work and Economic Growth
- Goal 9: Industry, Innovation, and Infrastructure
- Goal 10: Reduce Inequalities
- Goal 12: Responsible Consumption and Production
- Goal 13: Climate Action
- Goal 14: Life Below Water
- Goal 15: Life on Land

What can be seen regarding SDG 8 is that data-driven decisions require collaboration throughout the value chain to enable the required transparency and communication. This puts pressure on larger companies to assist supply chain entities in the early digital stages to develop sufficient communication tools, which is done by education, financial resources, or collaborative development of necessary technologies. Through education, financial assistance, and technology development, these companies can create conditions that allow them to obtain quality job conditions. Additionally, by improving transparency, it becomes more accessible for companies to evaluate and improve current work conditions in supply chain entities. However, automated and digital work environments can also have a negative effect since they can make employees redundant if not human-in-the-loop processes are used. Alternatively, by using automated systems as a substitute for human employees, companies can make threats for their substitutions if they do not agree to decreased salaries, which aggravates current work conditions.

Through education, financial assistance, and technology development, smaller suppliers obtain tools to develop and improve their businesses to become more innovative and establish more sustainable business processes, which have an impact on SDG 9. Moreover, the standardization process required for efficient data-driven systems also affects SDG 9. From industrial collaborations and governmental regulations, standardization of digital systems becomes possible, which further builds the necessary foundation for companies to create their digital infrastructure and build innovative digital solutions. On the other hand, if bad standards or if the standards become too expensive for SME to utilize, it can instead kill the innovation and development of digital solutions.

Both SDGs 10 and 12 are greatly affected by data-driven decision-making, which is due to the reason that it enables visualization and an overview of the whole supply chain. This makes it possible for companies to detect inequalities and inefficient production, and subsequently provide proactive means to manage the issues. Moreover, the data-driven systems also enable faster and more responsive actions against real-time information from the production processes, which further decreases production errors, waste and improves efficiency. For instance, the findings conclude that the data-driven systems can establish shorter and more efficient transportation routes leading to a decrease in transport-related emissions. However, if digital solutions become a substitute for humans, SDG 10 would be negatively affected, since this would commonly make the standardized work procedures automated whereas more technically educated employees' tasks would persist. This could lead to higher unemployment for especially less-educated individuals.

From the improved efficiency that can be established through data-driven decision-making, the SDG 13 is likely to experience great positive implications. From the improved efficiency, manufacturers are more likely to reduce their overall impact on the environment by for instance reducing their emissions. In addition, from the data-driven systems, companies are also more likely to detect and manage areas with high emissions, and further also deliver more precise emission reports. Likewise, these benefits linked to data-driven decisions similarly affect SDGs 14 and 15. Through the data-driven systems, areas that pollute the water and land can be detected, which further can be managed with the data-driven decisions by finding alternative and improved supply chain processes with less land and sea impact. The systems would for instance help regulate and visualize how companies extract raw materials from land and sea, which consequently could lead to decisions to make raw material extraction more sustainable in both land and sea environments.

7.5 Limitations & Future Research

The holistic approach of this research has primarily been limited by the number of available respondents. By including additional sectors and several practitioners within the same case company the research would be able to capture additional perspectives, which could have changed the outcomes of the research to some extent and is why the number of available respondents is seen as a limitation. However, it is believed that the random selection of case companies increased the likelihood to capture an unbiased and holistic perspective from practitioners. Additionally, the practitioners have been limited with their answers due to confidentiality and knowledge related to certain aspects. Therefore, this study has been limited in generating exact information in terms of financial and environmental numerical data. This has led this research to discuss data-driven decision-making on a general level since numerical data were excluded.

Due to the limitations to access numerical data and precise figures regarding data-driven decision-making in this research, there is a future possibility to conduct a quantitative study of the subject and thus explore the advantages, challenges, and applications at a numerical level. Consequently, the benefits, challenges, and applications described in this research could be verified in a quantified study. It is further recommended that future research explore how data-driven processes change companies' business models. This is because it has been seen that data-driven processes require improved transparency and trust between companies, which consequently could open the door for service as a business since companies would allow external companies to access their data. Lastly, as technology is continuously getting less expensive and more prominent alternatives, future research could involve SMEs since this research was delimited to only include MNEs.

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Annex A: Industry 4.0

Annex A outlines the digital transformation and Industry 4.0 and how it affects information systems.

Industry 4.0 is the result of the digital transformation within the manufacturing industry, which is accelerated by technologies such as AI, 3D printing and IoT (PWC, 2017; Deloitte, 2015). These technologies have further the ability to be employed in current manufacturing information systems such as ERP and MES (Boiko et al., 2020). For instance, technologies such as cloud computing and wireless networks can facilitate the introduction of smart networks that can improve the production scheduling (Boiko et al., 2020). Industry 4.0 can also be derived into four main characteristics (Deloitte, 2015):

1. The *Vertical Networking* of SPS, which cover the communication between business operations such as production, supply chain and customer service
2. A *Horizontal Integration* that enhances cooperation between international business entities as well as integrate business partners and customers
3. *Through-Engineering*, which facilitate product lifecycle throughout the value chain
4. *Acceleration through Exponential Technologies* because of reducing prices of advanced technologies and increasing computing power.

Furthermore, Industry 4.0 is often described in literature as an industrial revolution that is based on large amounts of data, computing power and connectivity (Balog et al., 2019). For instance, with more connected networks facilitated by a supply chain Control Tower (see Section 2.5), companies could benefit by adding customer-specific modifications in all stages of the value chain. This would ensure transparency and flexibility that positively affect key performance indicators such as time, price, quality and environmental sustainability (Deloitte, 2015). In addition, Kiel et al., (2017) argue that Industry 4.0 can enhance a sustainable value by incorporating the TBL within all business objectives. For example, with more networked systems, more optimized sustainable and renewable energy planning can be utilized (Zarte et al., 2019).

However, in order to utilize the data that are produced by the various information systems, one must be able to integrate and analyze the data (Li et al., 2013). Here, business intelligence (BI) systems have become increasingly powerful with the advancement of new technology such as AI. These types of systems are mainly used as decision support systems, as they are able to coordinate data with analytical functions, which entails data-driven decision-making. Popovič et al. (2019) further argue that BI systems currently are not utilized to their fullest capabilities, thus allowing for the potential of enabling better and faster decision-making that are driven by data such as Big Data analytics. BI systems can also be utilized for data visualization.

According to Chu (2016) the main technologies of Industry 4.0 are Big Data and IoT, but other emerging technologies such as Machine Learning further help shaping the industry. For instance, new technology can extend current PLM systems with cyber-physical data to improve the entire lifecycle of products, thus enhancing product design, manufacturing and service (Tao et al., 2018). Moreover, the manufacturing industry is currently fragmented in the sense of its industry specific or proprietary data formats and networking hardware (Chu, 2016). Here, Big Data analytics can resolve these issues, and consequently new insights can be generated to support decision-making (Deloitte, 2015).

Annex B: Manufacturing Information Technology Systems

Annex B sets the stage by introducing the most common manufacturing information systems currently available, from both an academic and practical view.

In order to track and monitor the progress of different processes, organizations can utilize information systems that provide such information (Ganesh et al., 2014). Based on current research, the most common application of manufacturing information systems is Enterprise Resource Planning (ERP), which can integrate enterprise-wide functions into a single unified database (Crocker et al., 2012). In addition, based on the research by Olhager & Selldin (2003), 83.6% of Swedish manufacturing firms had either implemented ERP systems or were in the process of implementing such systems. ERP systems further allow for multiple advantages, such as connecting all functional areas, improved efficiency, increased tracking, enhanced customer service and improved decision-making process (Crocker et al., 2012; Ghobakhloo et al., 2018; Ouiddad et al., 2020). Moreover, ERP systems consist of numerous modules, which facilitate the integration of all business processes and functions (Ganesh et al., 2014). Here, the most prevalent modules cover Product Lifecycle Management (PLM), Customer Relationship Management (CRM) and Supply Chain Management (SCM) (Koh et al., 2011; Ganesh et al., 2014; Monk & Wagner, 2012; Singh & Misra, 2019; Boiko et al., 2020).

Product Lifecycle Management

Stark (2015) defines PLM as "the business activity of managing, in the most effective way, a company's products all the way across their lifecycles". In recent years, the need for more efficient production processes has increased as a result of technology advancements (Singh & Misra, 2019). Here, PLM has further been considered as the most appropriate management system to overcome this issue. This is mainly because of the many benefits PLM systems provide, for instance it has the ability to make product information cohesive, traceable and reflective (Grieves, 2006). PLM further manages the entire portfolio of products (Stark, 2015), which subsequently results in reduced time to market and production costs (Singh & Misra, 2019). Consequently, PLM can facilitate the optimization of the product portfolio, increase the value creation for both customers and shareholders, as well as enhancing the productivity and performance of the organization (Stark, 2015; Singh & Misra, 2019).

Customer Relationship Management

In order to establish long-term relationships with customers, CRM becomes beneficial as it allows for customer-focused management (Hendricks et al., 2007). According to Katz (2002) and Suresh (2004), some of the functionalities of CRM systems are data mining, sales force automation and support of decisions. In addition, CRM systems provide an integration of customer information in a centralized database, thus reducing maintenance and duplication in data entry (Hendricks et al., 2007). Ultimately, CRM can uncover profiles of key customers, purchasing patterns and customer profitability (Conlon, 1999), which lead to reduced cost of sales and services and integrated customer touch points (Chen, 2001). With a centralized database of customer information, CRM also provides the opportunity of increasing revenues since customers from various businesses often overlap (Hendricks et al., 2007).

Supply Chain Management

The main advantage of an integration of SCM systems is the benefit of enhanced operational and business planning (Hendricks et al., 2007). However, these benefits further constitute the primary challenge of SCM, which is the integration of information (Davenport & Brooks, 2004). By overcoming such an issue, an SCM system implementation could ease real-time planning capabilities and help manufacturers to respond quickly to changes in supply and demand (Hendricks et al., 2007). Thus, the "bullwhip effect" can be mitigated, which is the amplified variation of customer demands and inventory of raw material that causes problems with costs and time (Lee et al., 1997). SCM further has the ability to improve customer service quality, consequently leading to increased sales (Davenport & Brooks, 2004). Moreover, to fully get an understanding of SCM systems, they often fall into four different categories: (1) supply planning tools, (2) demand planning tools, (3) plant scheduling tools and (4) logistics systems for warehouse management support (Gormley et al., 1997).

Manufacturing Execution System

These modules help establish an efficient ERP system and can ultimately help making better decisions connected to the product portfolio, customer integration, as well as business and operational planning. However, ERP systems mainly cover the management of operation, but often fail to pay attention to the shop floor (Ugarte & Pellering, 2009). Here, an additional information system is Manufacturing Execution System (MES), which ensures effective business execution of e.g., quality management, process management and product tracking (Nnamdi & Telekdarie, 2020). Thus, MES functions are mainly linked to manufacturing activities and are utilized in most manufacturing industries (Ugarte & Pellering, 2009). Much like ERP systems, MES solutions are based on various modules that can be compiled in three different clusters of (1) client/server applications, (2) integration framework or (3) data storage/management (Ugarte & Pellering, 2009). Thus, by utilizing MES one can access shop floor data promptly, and consequently facilitate better decisions based on inventory availability, customer orders, production schedules, equipment utilization and supplier's status (Ugarte & Pellering, 2009; Helo et al., 2014).

According to the ANSI/ISA-95.00.01-2010 standardization of manufacturing information systems by the International Electrotechnical Commission, the functional operations and systems can be divided into four levels, categorized after their hierarchical order (International Electrotechnical Commission, 2003). Consequently, in accordance with ANSI/ISA-95.00.01-2010 standards, the previously described information systems ERP, MES, PLM, CRM and SCM can be categorized in hierarchical order as can be seen in *Figure A* (Chen, 2005).

Level 0 according to the ANSI/ISA-95.00.01-2010 standards puts focus on the actual physical processes that are subjected to be monitored, whereas Level 1 is the sensing of processes through sensors. Moreover, Level 2 in the standards relates to the monitoring and supervision activities, which provides data for level 3 and 4. In Level 3 there is a focus to preserve records and coordinate processes to ultimately optimize the manufacturing processes according to the standards. Consequently, MES is categorized in Level 3 and PLM, CRM and SCM in Level 2 (Chen, 2005). Lastly, in the ANSI/ISA-95.00.01-2010 standards, Level 4 includes systems that work in the interval of months and days, and that can be used for the purpose to improve the actual business operations, including the business planning and logistics activities.

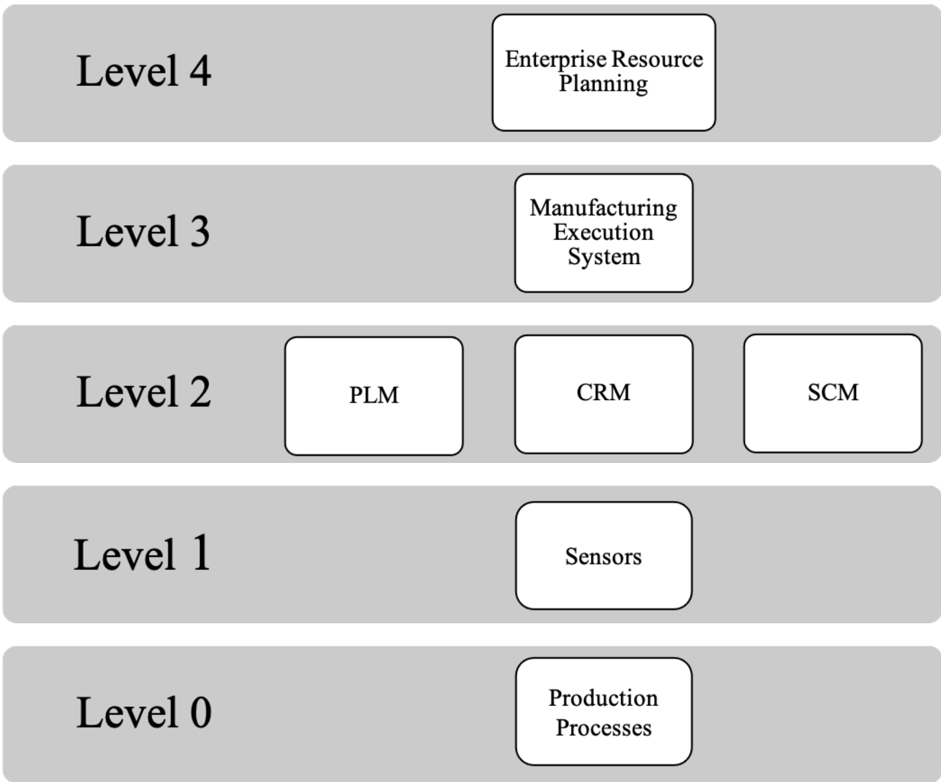

Figure A. Manufacturing Information Systems functional hierarchy

However, with current digital transformational needs and a globalized market (Helo et al., 2014), Akkermans et al. (2003) conclude four limitations of ERP: (1) lack of extended enterprise functionality, (2) lack of flexibility in adapting to changing supply chain needs, (3) lack of advanced decision support capabilities and (4) lack of open, modular system architecture. Furthermore, current MES solutions do not have the ability to cope with adaptability, reorganization and configuration (Helo et al., 2014). Moreover, emerging technologies are taking place that can further enhance these information systems, hence improve the decision-making and operational performance of manufacturing firms.These technologies also lay the foundation of Industry 4.0 and Smart Production Systems (SPS), which is transforming the manufacturing industry towards a new era (Alavia et al., 2019).

Appendix A: Level of Digital Integration

COMPANY	POSITIVE POINTS	NEGATIVE POINTS	TOTAL POINTS
A	• Use simulation tools • Analysis of optimal raw material • Include vast variety of regulations • Utilize real-time information	• Only utilize historical data in forecasts	3
B	• Visualize data in Power BI • Produce new KPIs related to data • Have a global data warehouse • Introduction of a new system • Develop automatization and alerts • Good at analyzing data • Have implemented connected machines • New segment focusing on digitalization	• Fragmented IT structure • Many manual processes	6
C	• Look at implementing a Control Tower • Plans at getting a global system • Conducting small local solutions • Digitized front-end	• Use legacy systems • Many manual processes • Fragmented IT structure	1
D	• Automated sales process • Utilize new ERP systems • Look at hiring a digitalization expert • In the process of computerization	• Many manual processes • Fragmented IT structure • Only utilize historical data in forecasts	1
E	• Demand transparency • Utilize new ERP systems • Can laborate with KPIs and data • Digital sales process • Value digital improvements • Look at introducing blockchain • Are standardizing the IT landscape	• Fragmented IT structure	6
F	• Utilize many different types of data • Currently a mix of digital solutions and manual work • Utilize new ERP systems • Digital sales process • Process control systems • In the process of becoming more digitized	• Fragmented IT structure	4
G	• Look at optimizing transports • Look at having a digital twin of the supply chain • Automated input process • In the process of utilizing cloud solutions • Look at improving alerts • In the process of optimizing the supply chain	• Fragmented IT structure • Trust the suppliers not to betray them	4

H	• Are standardizing the IT landscape • Utilize data in processes • Utilize cloud solutions • Have been developing digital solutions for a long time • Collaboration and contract with digitalization experts • At the forefront in the industry • Have forecasts looking at real-time information		7
I	• Digital internally • Look at standardizing the IT landscape • Utilize visualization technologies • Have been developing digital solutions for some time • Look at improve the recycling process • Look at automate processes	• Many manual processes	5

Interview Guide

The aim of this study is to explore the business opportunities and challenges of data-driven decision-making, and how it relates to more sustainable supply chain operations within the manufacturing industry.

> MQ: How does data-driven decision-making enable sustainable supply chain operations within the manufacturing industry?
>
> SQ1: How does digitized supply chains improve manufacturing in a sustainable way?

Framework

By understanding what managers within the manufacturing industry see as the main challenge with current supply chains, we hope to get an understanding of how data-driven decision-making could improve current supply chain operations from a sustainable perspective. By further asking in which ways to improve current systems, an idea on how to establish a sustainable and digital supply chain can be developed. Consequently, **SQ1** can be answered, thus helping us to meet the aim of the study.

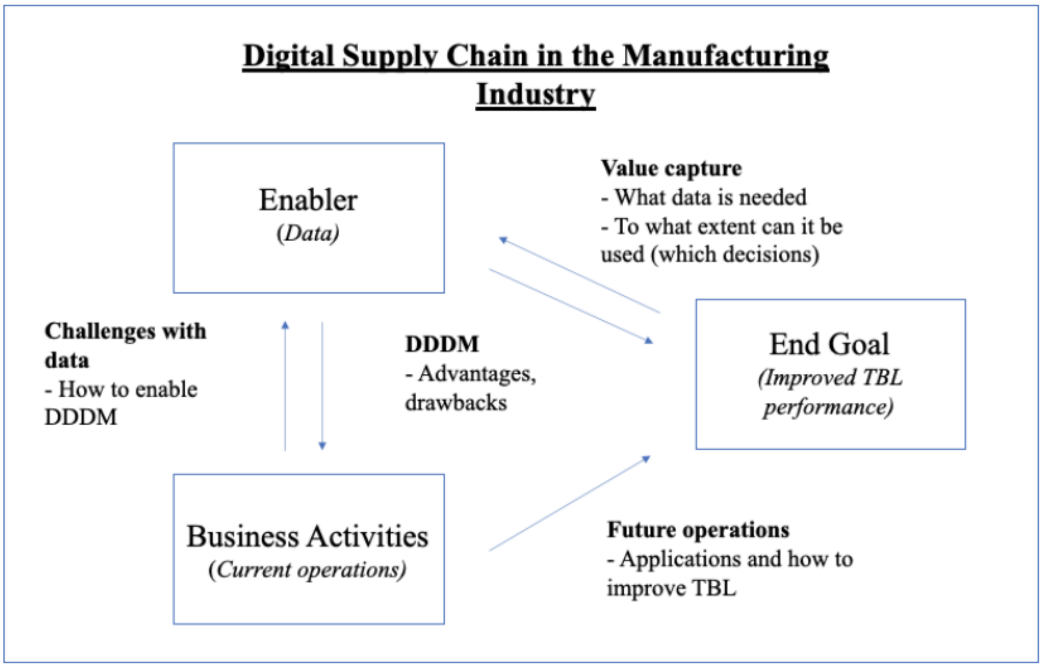

Figure 1. Conceptual model to meet the aim of the study.
TBL is the economic, social and environmental aspects of sustainability.
DDDM is the acronym for Data-Driven Decision-Making.

Introduction

1. Could you tell us a bit about yourself and your current role?

Data and Current operations

1. How does your supply chain currently incorporate data?
2. How do you currently collect and manage the data you use to make improved operational decisions?
3. What do you base your SCM decisions on today?
    a. What are the issues of the current decision-making process?
    b. There are different information systems within manufacturing that can give input on planning, inventory etc., (e.g., ERP, APS, MES). So in terms of making the manufacturing and supply chain operations more sustainable, what are the drawbacks with these current systems?
4. By incorporating data-driven decision-making one can make faster and more accurate decisions that are based on data. What are the main opportunities and challenges for data-driven decision-making in the supply chain and manufacturing operations?
    a. By implementing data-driven decision-making, one must first create data, then integrate the data and lastly analyze the data to make final decisions. Which of these steps is the biggest challenge and why?
        i. How is your organization working on overcoming that challenge?
5. In information sharing, what are the main issues?
6. Are there any technological developments that are necessary before the manufacturing industry can become fully connected with the supply chain operations (sensors, systems, security etc.)?

Current operations and improved TBL performance

1. How are you working to achieve sustainability within your supply chain today (economically, socially and environmentally)?
    a. How valued is it within your company?
2. Researchers and practitioners have recently developed the concept of Digital Supply Chains, meaning that the supply chain entities are interconnected and able to share real-time information of all processes in the supply chain. We have seen that this could help establish more flexible and efficient supply chain operations.
    a. How does your digital supply chain make the supply chain operations more sustainable (i.e. more economic, social and environmental)?
        i. Where in the supply chain can the biggest improvements be seen?
    b. What are the main challenges with a Digital Supply Chain (competence, security etc.)?
    c. How does this affect the progress of becoming more digitized?

3. Scholars argue that one of the main advantages with a Digital Supply Chains are resource efficiency because of better waste management and the possibility of more sustainable strategies. With such advantages, how does your Digital Supply Chain improve the manufacturing operations in a sustainable way?
    a. What are the challenges to reach these advantages?

Improved TBL performance and Data

1. What types of decisions can be optimized with data to improve the sustainable performance of supply chain operations?
    a. What data is needed for such decisions?
2. What type of sustainable value can be captured with the help of appropriate data (i.e. data to decrease excessive inventory, analyzing environmental impact and mitigate the bullwhip effect)?

Appendix C: Ten Principles of the Code of Honour

Engineers in their professional capacity ought to feel personally responsible for technology being used in a manner that benefits humanity, the environment and society.

Engineers ought to strive to improve technology and technological knowledge so as to achieve more efficient use of resources without harmful effects.

Engineers ought to offer their knowledge in both public and private contexts so as to ensure the best possible basis for decisions and to illuminate both the opportunities and the risks associated with technology.

Engineers ought not to work for or cooperate with companies and organizations of a questionable nature or with objectives that conflict with personal beliefs.

Engineers ought to show complete loyalty to employers and colleagues. Difficulties in this respect ought to be raised in open discussions, in the first instance at the workplace.

Engineers must not use inappropriate methods when competing for employment, assignments or orders, and nor should they attempt to damage the reputation of colleagues with unfounded allegations.

Engineers ought to respect entrusted information of a confidential nature and others' rights to ideas, inventions, studies, plans and blueprints.

Engineers must not favour vested interests and ought to openly report financial and other interests that could impair confidence in their impartiality and judgement.

Engineers ought to both publicly and privately, in writing and rhetoric, strive for factual presentations and avoid erroneous, misleading or exaggerated statements.

Engineers ought to actively support colleagues who encounter difficulties as a result of acting in accordance with these principles and, to the best of their belief, avert criminal actions against them.

Appendix D: Extensive Summary over Conceptual Model

Finding	Practitioners	Academics & Experts	Literature Review
Advantages	● Reduced bullwhip-effect ● Improved planning ● More efficient troubleshooting process ● Decrease the need of flights ● Optimized production process (JIT) ● More customer centric ● Economic benefits (financial performance) ● Meet growing demand ● Lower lead time ● Reduced risk of overproduction ● Satisfying customer expectations (service) ● Optimized transportations ● Less time wastages ● Optimized warehousing (inventory control) ● Drive better pricing and packaging ● Less returns and delays ● Better recycling ● Less rooms for mistakes and amount of rework ● Less personnel and physical labor ● Reduced emissions and environmental footprint on a product level	● Improved competitiveness ● Optimized surveillance (e.g., water usage, emissions) ● More efficient management of unexpected events ● Improved trust among all actors (communication) ● Better operational decisions ● Reduced number of machinery failure ● Better analysis of trends and scenarios (predictions) ● Improved resource efficiency ● Improved circular economy ● Reduced emissions and environmental footprint on a product level ● Satisfying customer expectations (service)	● Improved planning ● Optimized production process (JIT) ● Economic benefits (financial performance) ● Reduced risk of overproduction ● Optimized transportations ● Optimized warehousing (inventory control) ● Reduced emissions and environmental footprint on a product level ● Improved agility ● Improved marketing ● Allowance of purchasing sustainable products ● Improved quality ● Reduced R&D expenses ● Safer working environment
Disadvantages	● Reduced understanding of processes ● High costs ● Risk of misinterpretations ● Human-in-the-loop (communication errors) ● Risk of overlooking factors (niched products/systems) ● Pressure from customers to deliver faster and more accurately ● Question of survival	● High costs ● Need of set regulations ● Risk of investing too late	● High costs ● High energy consumption ● Need of time and organizational strategy ● An organizational reconfiguration is necessary ● Need to overcome a behavioral shift among workers ● Process changes that change employees' work environment ● Need of operational and digitalization maturity

Challenges	● Competence ● Human-machine relations ● Implementation challenges (e.g. costs, change management etc.) ● External regulations and standards ● Standardizing & integrating IT systems ● Reliability & validity of data ● Connectivity & transparency ● Generate & analyze data	● Availability of data ● Competence ● Data management ● Human-machine relations ● Implementation challenges (e.g. costs, change management etc.) ● External regulations and standards ● Collaboration ● Connectivity & transparency	● Implementation challenges (e.g., costs, change management, equipment installation etc.) ● Data management & the 5Vs ● Competence ● External regulations and standards ● Connectivity & transparency
Future Operations	● End-to-end transparency ● Automated planning ● Optimized transportations ● Service contracts ● Better forecasting models ● Better packaging ● Verification of orders ● Better recycling ● Identifying harmful sustainable effects ● Automated simulations	● Better decision support systems ● Identifying machinery failure and errors ● End-to-end transparency ● Improved analysis of trends and scenarios ● Improved resource efficiency ● Classification of products ● Possibility of circular economy ● Blockchain technology ● AI technology	● Big Data ● Decision-making systems ● Self-regulated and self-organized production systems ● End-to-end transparency ● IoT solutions (sensors) ● Operator 4.0 ● Digital twins ● BI systems ● Interconnected machines ● Control Tower ● Additive manufacturing (3D printing) ● Robotics ● Drones ● Virtualization
Value Capture	● Unlimited possibilities ● Production automatization ● End-to-end visualization and transparency ● Collaborating effort for TBL improvements ● Faster and accurate decision-making & responsiveness ● Real-time analysis of complex & extensive amounts of data	● Unlimited possibilities ● Production automatization ● Human-in-the-loop processes ● TBL decisions based on complex and extensive amounts of data ● Faster and accurate decision-making & responsiveness ● Real-time analysis of complex & extensive amounts of data ● Currently limited to low-hanging fruits	● Production automatization ● Enrich manual labor ● Human-in-the-loop processes ● Holistic & synchronized decision-making ● Faster and accurate decision-making & responsiveness ● Real-time analysis of complex & extensive amounts of data

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