Supply Chain Analytics implications for designing Supply Chain Networks

Linking Descriptive Analytics to operational Supply Chain Analytics applications to derive strategic Supply Chain Network Decisions

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Abstract

Today’s dynamic and increasingly competitive market had expanded complexities for global businesses pressuring companies to start leveraging on Big Data solutions in order to sustain the global competitions by becoming more data-driven in managing their supply chains.

The main purpose of this study is twofold, 1) to explore the implications of applying analytics designing supply chain networks, 2) to investigate the link between operational and strategic management levels when making strategic decisions using Analytics.

Qualitative methods have been applied for this study to gain a greater understanding of the Supply Chain Analytics phenomenon. An inductive approach in form of interviews, was performed in order to gain new empirical data. Fifteen semi-structured interviews were conducted with professional individuals who hold managerial roles such as project managers, consultants, and end-users within the fields of Supply Chain Management and Big Data Analytics. The received empirical information was later analyzed using the thematic analysis method.

The main findings in this thesis relatively contradicts with previous studies and existing literature in terms of connotations, definitions and applications of the three main types of Analytics. Furthermore, the findings present new approaches and perspectives that advanced analytics apply on both strategic and operational management levels that are shaping supply chain network designs.
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Jönköping, May 2019
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<td>SCM</td>
<td>Supply Chain Management</td>
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<td>LSCM</td>
<td>Logistics and Supply Chain Management</td>
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<td>IoT</td>
<td>Internet of Things</td>
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<td>Artificial Intelligence</td>
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<td>Machine Learning</td>
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<td>SCND</td>
<td>Supply Chain Network Design</td>
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<tr>
<td>KPI</td>
<td>Key Performance Indicator</td>
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<td>CSF</td>
<td>Critical Success Factor</td>
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1 Introduction

The first chapter contains introductory information about the framing of the research in order to establish a common ground for the reader. In the background, the importance of Business Analytics is thoroughly presented and then linked to strategic and operational supply chain activities in the field of Logistics and Supply Chain Management. The next section deals with the problem discussion and the importance to contribute new insights to research in the aforementioned fields. Thereafter, the purpose of this study is discussed and the research questions presented.

1.1 Background

There is a lot of discussion and research arguing about the predicted growth in the use of Internet of Things (IoT) technologies, coupled with cloud computing, data analytics, Machine Learning (ML), and Artificial Intelligence (AI) within our modern-day business practices (Tuptuk & Hailes, 2018). As a matter of fact, the importance of analytics has been historically recognized and played a significant role in Supply Chain Management (SCM) all the way back to deploying military operations during and after the second World War (Souza, 2014). In general terms, there are different types of resources that an organization depends on, such as technological resources, technical, managerial skills, and IT-based resources. In order to efficiently manage these resources at best, organizations need to be able to effectively manage their supply chains considering the dynamic competition environment in today’s global business landscapes. This emphasizes the need for having a successful integration and collaboration among supply chain partners, which is viable through latest developments in technology and results in interchangeably connected organizations through Information Systems (IS) (Barbosa, Vicente, Ladeira & Oliveira, 2018). These systems tend to produce tremendous amounts of information, approximately 1.6 billion new data segments monthly, which are originated from SCM and its interorganizational flow of goods and services accompanied by its attached information and monetary streams (Barbosa, Vicente, Ladeira & Oliveira, 2018; Nurmilaakso, 2008).

1.1.1 Big Data, Business Analytics, and Big Data Analytics

Acknowledging the increasing amounts of data, both practitioners and scholars around the world highlight the importance of Big Data and its potential ability to add value and enhance competitive advantage to firms. Big Data is defined as huge or complex sets of data, which has a range of exabytes and more. It exceeds the space of technical ability of storage system, processing, managing, interpreting, and visualizing of a traditional system (Tiwari, Wee & Daryanto, 2018). In collaboration with Business Analytics (BA), which the industry outlines as analytical techniques, methods, and data-driven analytic methodologies (Sabitha Malli, Viyayalakshmi & Balaji, 2018), the term Big Data
Analytics (BDA) and its equivalent Big Data Business Analytics (BDBA) was formed (Chae, Olson & Sheu, 2014; Wang, Gunasekaran, Ngai & Papadopoulos, 2016). Data characteristics described by volume, variety, and velocity are considered and processed by applying aforementioned concepts to make better decisions in organizations, in particular in Logistics and Supply Chain Management (LSCM) (Wang et al., 2016). These organizations have been applying any kind of analytical concept, namely in this field Supply Chain Analytics (SCA), for a long time to enhance information processing capabilities and supply chain operations (Zhu, Song, Hazen, Lee & Cegielski, 2018). This enables facilitating the decision-making process within organization’s supply chain.

1.1.2 Decisions-making levels and examples

SCA and its business equivalent BDA, touch upon all three decision-making levels, i.e. strategic, tactical, and operational. Within operational planning, BDA supports managers to crunch huge amount of data originating from demand planning, procurement, production, inventory, and logistics (Wang et al., 2016), and drive decisions to fulfill an organization’s customer demand (Lin & Wang, 2011). In the next decision-making level, the tactical level, middle managers make decisions dealing with inventory of raw materials as well as semi-finished and finished products (Lin & Wang, 2011). Aforementioned decision levels are strongly depending on holistic considerations and the derived strategic organizational objectives defined by an organization’s top-level management. Since the degree of information details is of lower accuracy in regard of strategic planning decisions, top-level decision makers aim to translate complexity and uncertainty of the organization’s external environment into more comprehensive and assimilable concepts for lower management levels (Townsend, Le Quoc, Kapoor, Hu, Zhou & Piramuthru, 2018; Wang et al., 2016). Applicable fields in strategic planning within SCM includes strategic sourcing, product design and development, and supply chain network design (SCND) (Wang et al., 2016). SCND deals with the configuration, shape, and planning of the strategic supply chain structure, which implicates the number, location, capacity, and technologies of an organization’s facilities, but also strategic alternatives regarding the entire SCND including buy-make and sell-decisions on local and global level (Santoso, Ahmed, Goetschalckx & Shapiro, 2005; Song & Sun, 2017). In short, the optimal SCND encompasses an organization’s plants, distribution centers, and retailers in terms of location and capacity (Souza, 2014), which have been recognized by every successful company through the design of their Supply Chain Network (SCN) (Song & Sun, 2017).

1.1.3 Supply Chain Network Design

Substantiating highly impactful decisions regarding the design or configuration of a SCN requires capital resources and decision support systems (Santoso et al., 2005). Therefore, a multitude of decision support systems have been developed by using e.g. a genetic algorithm (Biswas & Samanta, 2016), or optimization models (Sadic, de Sousa & Crispim, 2018) to enable the processing and extracting of knowledge with Business
Analytics tools (Sadic et al., 2018). However, previous models are challenged by an ever-increasing amount of Big Data, i.e. structured and unstructured, to make use of more and more variables and scenarios, and constantly changing SCNs (Wang, Gunasekaran & Ngai, 2018). Various scholars have studied mixed-integer linear models to for instance answer production and distribution planning related variables (Arntzen, Brown, Harrison & Trafton, 1995), the numbers of facilities in an optimal SCN (Badri, Bashiri & Hejazi, 2013; Amiri, 2006), the SCND with certain demand (Jindal & Sangwan, 2014), or uncertain demand (Benyoucef, Xie & Tanonkou, 2013). Other scholars (Owen & Daskin, 1998) researched facility or location models regarding the number of plants, DCs and retailers.

After thoroughly reviewing the literature, it came to our attention that a lot of quantitative studies have been conducted mainly on the tactical and operational management levels of organizations, nevertheless, the strategic level was somewhat neglected. Furthermore, there is lack of qualitative studies that research other key factors on the strategic level that may be significant. In this thesis, we want to shed a light on the strategic level and how BDA can be applied to produce valuable information that can be used for the SCND decision-making process, either by using a theory-based model or deriving the quantitative findings from the previous operations studies and link it to the upper-strategic level of the organization’s hierarchy.

1.2 Problem Discussion
There is no doubt that Supply Chain Analytics (SCA) entails major important implications for accomplishing effective supply chains. Since companies compete through their supply chains (Deloitte Consulting, 1999), it is undisputed to realize the importance of implementing an effective strategy based on empirical data from both strategic and operational levels by means of BDA techniques in order to reap the full potential benefits in the long run. Therefore, there is a need for conducting more empirical studies that deals with the accuracy of the outcomes from applying SCA for top-level supply chain managers (Tramarico, Mizuno, Salomon & Marins, 2015).

Demirkan and Delen (2013) discussed that both predictive and prescriptive analytics play a pivotal role in aiding companies making effective decisions on the strategic direction of the company. These two types of analytics can be applied to tackle complex problems concerning strategic sourcing decisions, supply chain design, and development of products and services. According to Wang et al. (2016), the two types of SCA (predictive and prescriptive) have been extensively used in previous Logistics and Supply Chain Management (LSCM) studies on strategic level. However, the third type of SCA, namely descriptive analytics, which answers questions related to “what happened and/or what is happening?” has not been researched much to underpin strategic LSCM decisions such as sourcing, supply chain network design, as well as product design and development, to name a few.
Moreover, Fosso Wamba, Gunasekaran, Papadopoulos and Ngai (2018) recognized the lack of theory-based explanations in the existing literature that might provide profound insights derived from big data. Operational supply chain areas, such as inventory or logistics, have been vigorously researched quantitatively. In addition, decisions within the SCND which concern all three management levels (strategic, tactical, operational), and whereby strategic decisions have the greatest impact on the return on investment (ROI) of a supply chain (Simchi-Levi, Kaminsky & Simchi-Levi, 2004), have also exclusively been answered through the application of numerous mathematical methods and models (Amiri, 2006; Prasad, Zakaria & Altay, 2018).

1.3 Purpose
Two main gaps in literature have been detected. Firstly, descriptive analytics implication on Logistics and Supply Chain Management’s strategy and operations are limited and yet to be further researched. Secondly, the lack of theory-based models which deals with supply chain operations and the strategic decision of designing supply chain networks by means of qualitative methods to derive insightful findings, as Figure 1-1 illustrates.

Therefore, the purpose of this study is to provide a comprehensive understanding of Supply Chain Analytics by

- exploring the implications of applying descriptive analytics, and its relation to predictive and prescriptive, in regard of making strategic decisions for designing supply chain networks; and
- investigating the linkage between operational applications and how it contributes to making strategic decisions for designing Supply Chain Networks.

\[\text{Figure 1-1: Research gap, adapted from Wang et al. (2016)}\]
In order to fulfill our thesis purpose, we decided to classify the research questions into two parts. The first step in fulfilling the purpose is to explore the effects of applying descriptive analytics in formulating Logistics and Supply Chain Management’s strategy and operations regarding designing Supply Chain Networks. Thus, the first research question (RQ) of this study is:

**RQ1: What are the implications of applying descriptive analytics on Logistics and Supply Chain Management’s strategy & operations, and how it relates to the predictive and prescriptive analytics?**

After identifying the implications of Supply Chain Analytics, the second step in fulfilling the purpose is to investigate the link between business strategy and operations within Logistics and Supply Chain Management by considering the three types of Big Data Analytics.

Thus, the second research question of this study is:

**RQ2: How strategic and operational management levels are connected when applying Supply Chain Analytics for designing Supply Chain Networks?**

### 1.4 Outline

This section provides the reader an overview to the study as illustrated in Figure 1-2. The introduction consists of the study’s background and problem discussion which leads to the study’s purpose and the corresponding research questions.

*Figure 1-2: Outline of the research study*
The next chapter will discuss the theoretical frame of reference in which a systematic literature review was conducted in order to examine the theoretical body of this study topic. In the third chapter, the study’s research methods will be thoroughly described, providing insights about the research philosophy, research approach, research design, research quality, data collection, data analysis, and ethical considerations of this study. Afterwards the empirical findings section will follow, in which the collected data will be presented to the readers. The empirical data will be then analyzed in the next chapter by comparing it with the extant theoretical findings. After accomplishing this step, chapter six will present the conclusion, which is followed by the discussion chapter. The discussion concludes this study by presenting managerial implications, limitations, suggestions for further research, and the study’s ethical implications.
2 Theoretical Frame of Reference

The purpose of this chapter is to provide the theoretical background to the topic in order to analyze and compare existing theories and concepts with the empirical findings of this study. First, the literature process is described. Subsequently, relevant literature concerning the topics of (1) Supply Chain Management and Analytical Models, (2) Big Data, (3) Business Intelligence and Big Data Analytics, (4) Information Value in Supply Chain Decisions, (5) Strategy and Operations in Supply Chain Management, and (6) Supply Chain Network Design are selected and exposed in order to establish a common ground for the topic. Finally, a research model is introduced to visualize the understanding of the existing theory.

The existing literature search process was initiated by determining keywords, which encompass the research topic and its relevant articles within academia. Keywords used in the search involved ‘supply chain analytics’, ‘business analytics’, ‘supply chain network’, ‘supply chain network design’, ‘supply chain strategy’, ‘supply chain operations’, ‘logistics and supply chain management’, and ‘supply chain management’. In order to include all relevant articles, the keywords’ abbreviations, synonyms, and alternative terms were also considered to refine the research topic (see Appendix 1 and 2).

The databases Scopus, Web of Science, and Informs revealed a multitude of possibilities to refine our research topic by using Boolean operators, combining keywords with their synonyms and abbreviations as well as their alternative terminologies. In Appendix 1 and 2 the keyword queries are listed. By not particularly excluding articles of other categories than business or management, which did not primarily fulfill the purpose of our study, we also reviewed the abstracts of slightly diverse categories to gain a bigger picture of analytics and Supply Chain Networks and its adjacent and related domains.

After reviewing the abstracts and deriving themes, which the articles entailed, the articles were selected according to their relevance for the study. An Excel spreadsheet compiled all selected articles and the corresponding themes, which enabled us to then emerge new themes and refine existing themes after reading the selected articles. Emerging and interesting topics related to Supply Chain Analytics (SCA) and Supply Chain Network Design (SCND) complemented the selected articles and provided new and appealing angles to our thesis topic. Furthermore, using a snowballing approach facilitated our literature search which enabled us to track the references of articles, which also contained valuable information. Thereby, it supported the greater understanding of SCA and SCND in early stages of our research to finally, analyze the literature in order to derive themes, which are listed in the remaining sections of this chapter. The theoretical frame of reference encompassing the themes derived from the conducted systematic literature
review serves as a backbone and fundamental source for the research model presented in 2.7 Research Model.

2.1 Supply Chain Management and Analytical Models

Today's organizations are struggling with increasingly intricate business processes and facing some serious problems when striving for standardizing their processes. This has resulted in the need for creating new methodologies and novel approaches to tackle this problem, particularly the issue of how to integrate business processes in supply chains for improving the flexibility and resilience of the entire supply chain (Trkman, Budler & Groznik, 2015). Due to today's dynamic and ever-changing business environment, supply chains need to be able to envision futuristic scenarios and design options to handle those scenarios by implementing the ‘dynamic capabilities’ approach. This approach enables firms to react responsively and in a timely manner to external changes by integrating the firm’s in-house competences to address those external changes effectively (Teece, Pisano & Shuen, 1997).

A hybrid approach is suggested to combine both analytical and simulation modeling to handle clients’ order processes, since basic analytical approaches failed to handle uncertain factors such as unexpected delays, queuing, breakdowns, and operation time. Therefore, there is a need for novel business models entailing advanced analytical approaches to effectively and efficiently handle the massive amounts of data generated within supply chains is uncalled-for in order to sustain and maintain the firm’s strategic position in the dynamic global marketplace (Tunali, Ozfirat & Ay, 2011).

2.2 Big Data

Recent academic studies started discussing and arguing about various definitions of Big Data. Some scholars say that it is merely a large set of data, others argue that it is incorrect to define Big Data without considering ‘analytics’ (Arya, Sharma, Singh & De Silva, 2017). Thereby, they identify three main characteristics that formulate Big Data as “the data itself, the analytics of the data and the presentation of the results of analytics that allows business value creation in terms of new products or services” (p. 1,572).

Fosso Wamba, Akter, Edwards, Chopin and Gnanzou (2015) define Big Data as a “holistic approach to manage, process and analyze five V’s (volume, variety, velocity, veracity and value) in order to create actionable insights for sustainable value delivery, measuring performance and establishing competitive advantages” (p.6).

Three characteristics, called the 3Vs, are first used to define Big Data by Laney (2001) - Volume, Variety, and Velocity. Volume describes the vastness of data. Variety refers to the numerous different types of files and challenges of utilizing them. Velocity directly affects the value of data, more specifically, the more time that passes, the more obsolete the data becomes (Hofmann & Rutschmann, 2018).
Analytics, then comes into the Big Data picture to formulate the so-called Big Data Analytics (BDA), which can be decomposed to Big Data and Business Analytics (Lai, Sun & Ren, 2018) as Figure 2-1 illustrates.

![Figure 2-1: Analytics evolution including terminology delimitation, adapted from Gorman and Klimberg (2014)](image)

BDA has been used and implemented in wide arrays of industries, some deemed it as novice rather firmly-established, while others embedded it into their software platforms, such as Apache Hadoop. It entails a collection of open source software modules that facilitate business processes by using a massive network of multiple connected computers to solve intricate problems involving massive amounts of data and computation (Tambe, 2014). In marketing, BDA proved to be useful in terms of providing invaluable tools to gain accurate and deep understanding of consumers and predicting their behaviors (Lai et al., 2018).

As a product, Big Data also has a lifecycle. This lifecycle of big data presents a framework that provide theoretical and practical infrastructure for manufacturing enterprises to optimize the decision-making process of their product lifecycle management. In addition, techniques like BDA and Data Mining can be used to make deep analysis on historical big datasets, discover hidden knowledge and then optimize the business process (Zhang, Ren, Liu, Sakao & Huisingsh, 2017). Big Data systems have a great contribution in risk management as it helps in understanding how people and organizations respond to disruptions in order to take the right counter risk policy. Furthermore, it provided good predictions to act proactively (Chehabi-Gamoura, Derrouiche, Malhotra & Koruca, 2018). Fosso Wamba et al. (2018) argued that “[…] operations and supply chain professionals are yet to exploit the true potential of the BDA capabilities in order to improve the supply chain operational decision-making skills” (p. 478).
2.3 Business Intelligence and Big Data Analytics

Data plays an integral role in shaping up different decisions related to supply chain and logistics operations for any given business. Our supply chains nowadays are constantly producing huge volumes of data that are versatile, rapid as well as sensitive (Ghosh, 2015).

2.3.1 Business Intelligence & Business Analytics definitions

Business Intelligence (BI) and Business Analytics (BA) are often confused and used synonymously and interchangeably. It is important to note that BI is a key analytical component of BA. The latter is not a technology rather than a set of approaches, procedures, and tools that organizations can use to gain information, predict outcomes, or provide problem solutions (Barbosa, Ladeira & Vicente, 2017). BDA refers to the thorough process of applying advanced analytical skills, such as Data Mining, statistical analysis to identify patterns, correlations, trends, and other valuable information that can be exploited strategically to increase the operational efficiency and business profits (Jin & Kim, 2018). Waller and Fawcett (2013) highlight the growing value of advanced analytics over many industries for improving performance. Inadequate perceptions about the correct data types for every matter is as crucial as utilizing analytics tools, which focus on organizations’ goals. Across SCM professionals, predictive analytics has been adopted most, and hence, underpin the value of analytics (Schoenherr & Speier-Pero, 2015).

BA can be classified into three main categories based on their core functionalities: descriptive, predictive, and prescriptive.

Descriptive analytics depicts past events and enables individuals to draw conclusions about those events to gain valuable insights (Hans & Mnkandla, 2017). It aims to identify problems and opportunities within both historical and existing processes (Arya et al., 2017). In the domain of project management, descriptive analytics depicts past events and enables individuals to draw conclusions about those events to gain valuable insights. This type of analytics can also be described by deriving information from large amounts of data to find answers to “what is happening?” (Hans & Mnkandla, 2017).

Predictive analytics derives demand forecasts from past data and answers the question of “what will be happening?” (Souza, 2014). It uses mathematical algorithms and programming techniques to accurately predict and then project what might happen in the future and provide a reason to why it may happen (Arya et al., 2017).

Prescriptive analytics derives decision recommendations based on descriptive and predictive analytics models and mathematical optimization models. It answers the question of “what should be happening?” (Souza, 2014). It uses mathematical models and advanced statistical methods to assess prospective alternative decisions based on high volume and complexed datasets (Arya et al., 2017).
2.3.2 Examples

The extant literature provides numerous examples on how IT-systems using BDA techniques, most prominently in manufacturing and retail industries, which are commonly using RFID (Radio-frequency identification) techniques to discover valuable information or hidden knowledge that could be used for supporting applications in LSCM (Zhong, Xu, Chen & Huang, 2017). Many firms reported greater productivity and profitability and delivery time reductions when applying BDA (Akter, Wamba, Gunasekaran, Dubey & Childe, 2016; Leveling, Edelbrock & Otto, 2014). However, companies are encouraged to process large data amounts in order to extract insights for their decision-making processes (LaValle, Lesser, Shockley, Hopkins & Kruschwitz, 2011).

2.3.3 Benefits

BDA can overcome several functional challenges and operational hurdles that firms can encounter by providing models, sophisticated algorithms and techniques at different stages of the supply chain like storage, processing, pattern recognition, visualization, standardization, and interpretation (Yu, Wang, Zhong & Huang, 2017). Achieving greater end-to-end demand and supply chain visibility, cost trends and fluctuations, inventory management, production optimization, predicting volatile demand patterns, and enhancing overall supply chain performance (Nguyen et al., 2018; Pereira, de Oliveira, Santos & Frazzon, 2018).

Top performing firms, which embraced advanced analytics and data-driven decision-making achieved an undeniable competitive advantage and regarded it as technological innovation and strategic resource (Hazen, Skipper, Boone & Hill, 2018; Lai et al., 2018). Aside from supporting the sustainability initiatives in SCM, BDA enhances financial measures, social and environmental performance measures (Tiwari, Wee & Daryanto, 2018). BDA is becoming more prevalent causing a paradigm shift by including all information sources regardless if they stem from inside or outside the organization (Kache & Seuring, 2017). Applying these advanced technologies can lead to more contextual ‘intelligence’ shared across all supply chains (Hofmann & Rutschmann, 2018).

Wang et al., (2016) explained the hierarchical advantage of applying BDA. In the strategic phase of supply chain planning, BDA plays a pivotal role in aiding companies to make effective strategic decisions on sourcing, supply chain network design (SCND), as well as on product design and development. In contrast, the operational planning phase has been used to assist management in making supply chain operations decisions, which often include demand planning, procurement, production, inventory, and logistics.

2.3.4 Supply Chain Analytics

Thus far, we thoroughly discussed the significant importance of BDA in general terms. To be more specific, we would like to briefly highlight one of the major types of data analytics, which is termed as Supply Chain Analytics (SCA). This particular type of
analytics has the capability to influence the entire supply chain both in long- and short
terms. According to Arya et al. (2017) SCA encompasses tools and techniques that
harness data from a wide range of internal and external sources to produce breakthrough
insights that can help supply chains reduce costs and risk whilst improving operational
agility and service quality. It can even benefit the military logistics and result in massive
savings to the governments. If it is leveraged strategically, it can facilitate transparency
and increase sustainability across the supply chain (Zhu et al., 2018). As the term suggest,
SCA focus on logistics and supply chains. At a strategic level, it is applied on business
areas such as insourcing, supply chain network design (SCND), and product design and
development. At tactical and operational levels, it is used for implementing strategies to
improve operations efficiency and measure supply chain performance (Wang et al.,
2016).

2.4 Information Value in Supply Chain Decisions
Organizational decisions require profound and reasonable information to rely on. At
strategic level, which deals among others with the supply chain network design,
conventional decision-making practices have limitations. They are based on historical
data and the decision maker’s experience, which increases the probability of having
inaccurate decisions especially in a Supply Chain Network (SCN) (Arya et al., 2017;
Hofmann & Rutschmann, 2018). Moreover, Big Data and its strategic value have been
recognized by businesses enabling them driving timely and effective decisions in order
to improve operational performance and reduce costs and risks (Ghosh, 2015).
Additionally, a literature review investigating the value of information in supply chain
decisions confirms that decisions are made data-driven and highlights the value of
information associated with Big Data (Viet, Behdani & Bloemhof, 2018). Accurate and
valuable information increases the importance of strategic decision-making practices for
a developed decision tool. It determines the most efficient knowledge management
combination out of e.g. performance criteria, or supply chain drivers for developing an
agile supply chain (Raisinghani & Meade, 2005). In the case study of a pharmaceutical
firm in India, a new cross-functional supply chain approach is used to increase reliability
and responsiveness of carriers along with, inter alia sales forecast, which is highly
important for the firm’s strategic goals. Thereby, an Analytic Network Process (ANP)
was used to improve the integrated cross-functional decision-making process with the
established Supply Chain Cell (SCC), and finally, decrease supply chain related costs
(Choudhury, Tiwari & Mukhopadhyay, 2004).

2.5 Strategy and Operations in Supply Chain Management
A long-sustained definition of strategy Porter (1996, p. 68) provides: “Strategy is the
creation of a unique and valuable position, involving a different set of activities.”
Translating this business definition into the context of Supply Chain Management (SCM),
a supply chain strategy should bridge high-level strategy and its operations (Qi, Huo,
Wang & Yeung, 2017). Hereby, the supply chain strategy “[…] should correspond to
competitive and operations strategy” (p. 74) in order to create value to products and to equip it with greater value using operations (Ivanov, Tsioulcanidis & Schöneberger, 2017). Determining supply chain strategy and consequently, deriving its operations play an important role for businesses from their launch. When commercializing products in new markets, an emergent-oriented supply chain strategy is required, since legitimacy and ongoing experimentation needs to be achieved. Therefore, strategic goals and the supply chain’s distinctive structure and relationships are prerequisites for identifying the most appropriate supply chain strategy (Golicic & Sebastiao, 2011). By utilizing agile or lean/agile strategies cost savings are the result depending on the target market and product characteristics (Qi, Boyer & Zhao, 2009). In turn, supply chain operations performance can statistically be expressed in SCM strategy (Brun, Castelli & Karaosman, 2017), which is exemplarily presented in a strategic distribution optimization problem of a process industry provider (Blackburn, Kallrath & Klosterhalfen, 2015). In order to compete in different dimensions of performance, an organizations strategy needs to incorporate lean principles (Jajja, Kannan, Brah & Hassan, 2016), which captures the strategic shift of moving towards a collaborative strategy benefiting also the suppliers (Blackman, Holland & Westcott, 2013). For this purpose, the match of business strategy and supply chain strategy is required but not at every instance within the supply chain domain given (Mckone-Sweet & Lee, 2009; Harrison & New, 2002).

2.6 Supply Chain Network Design

Today’s Supply Chain Networks (SCN) constantly face challenges such as uncertain demand, which is inter alia caused by global competition or lacking adaptability of organizations’ supply chain (Manavalan & Jayakrishna, 2019). Other challenges deal with decisions about single-sourcing, which decreases operational complexity among facilities, or multi-sourcing, which might result in cost savings due to advancements in Information Technology (IT) (Easwaran & Üster, 2009). Limiting uncertainties and improving Big Data results’ quality has shifted many research papers towards quantitative or mathematical modelling approaches to solve large-scale discrete problems regarding a company’s Supply Chain Network Design (SCND) (Hofmann & Rutschmann, 2018; Shi & Ólafsson, 2009). Since Big Data requires analytical processing, the extracted knowledge afterwards is used in optimization models (Sadic et al., 2018). These optimization models are widely used in the literature and have the benefit of providing the optimal solution, whereas other modelling techniques use approximation, which provides a certain scope next to the optimum (Shi & Ólafsson, 2009). In this regard, Big data and its potential enhancements for decision-making in organizations increases the value of organizations’ SCNs in becoming the most powerful and robust one.

2.6.1 Distribution and Manufacturing Networks

In a fictive case of a distribution network design with over 2,000 stores a simulation showed that demand variability, outbound transportation costs and the size of the customer base is of importance in designing such large-scale network (Wang et al., 2018).
HP, one of the largest IT component producers, undertook a similar mathematical model-based analysis for investigating various scenarios with a single or multiple manufacturing location partnered with one of the outbound hubs. Results showed *inter alia* the business implications of adding another hub to operations (Business Optimization Lab, 2010). Big Data and its strategic value have also been recognized by developing a software tool that combines customer and manufacturing information for a more efficient dynamic manufacturing network. It was derived from historical data stored on a data platform and resulted in a multi-objective mixed-integer linear programming (MILP) model, which benefits decision makers by revising ‘what if’ scenarios and simultaneously providing a multitude of possible manufacturing network configurations (Sadic et al., 2018). Another manufacturing network design example incorporates smart apps, which generate alternative manufacturing network configurations for the focal firm and support the customer involvement in the product design on the go for any mobile device. Thereby, information is provided to customers as well as to Original Equipment Manufacturers (OEMs) to embed first requests or orders in real-time to provide up-to-date information to manufacturing related functions (Mourtzis, Doukas & Vandra, 2017).

### 2.6.2 Partner/Supplier Selection

Many performance evaluation decisions are based on developed analytical or simulation models for not only predicting single performance, but also system or network performance (Srivathsan & Kamath, 2012). Partner selection decisions using an Analytic Network Process (ANP) to evaluate their performance throughout a multi-echelon supply chain enables the focal firm choosing quickly the most suitable partners and deciding on the optimal production and/or distribution quantity (Che, Chiang & Che, 2012). The ANP also helps to make strategic supplier selection in regard of sustainability. Issues such as brand image or corporate responsibility are considered using the Analytic Hierarchy Process (AHP), which prioritizes user experts’ opinions upon various criteria levels. The AHP is especially of importance for strategic partnerships (Faisal, Al-Esmail & Sharif, 2017).

### 2.6.3 Disruptions in Supply Chain Networks

Designing a SCN considering disruption risks requires applying a multi-criteria programming model. Thus, the goal programming technique enables incorporating the decision maker’s preferences to question facilities and transportation links’ cost. The model evaluates each disruption, such as facilities and transportation, separately (Rienkhemaniyom & Ravindran, 2014). However, the dynamic programming technique uses a different approach. It divides each problem into subproblems, which are solved sequentially. In the exemplary case of a Chinese bus and coach manufacturer the mathematical solution helps decision makers by providing more clarity and reliability. A strategic trade-off between the number of partners and their reliability was substantially calculated, which determines the optimal supply chain configuration (Wu & Barnes, 2018). The example Kolon Sport, a leading South Korean outdoor brand, showcases once
more the important value of Business Analytics (BA). By modeling the demand forecast using a standard multiple linear regression in combination with an optimization model for packing and distribution decisions, Kolon Sport increased sales by 8-10 percent (Woong Sung, Jang, Hoon Kim & Lee, 2017).

2.6.4 Global and Closed-loop Supply Chain Networks

Some papers used also other approaches solving complex Supply Chain Network (SCN) problems. In the case of a global SCN, a scenario-based approach was applied for capturing a capital-constrained global supply chain. Hereby, operational and financial strategies, such as exchange rate uncertainties, are incorporated in a mixed-integer linear programming (MILP) model. Findings show that inter alia in case of an extreme demand increase, new facilities might be leased to decrease uncertainty issues (Wang & Huang, 2018). Further, an example using uncertainty as an incentive to apply mathematical modeling belongs to the settings of a closed-loop supply chain. Value can be captured by e.g. remanufacturing or refurbishing, which requires the multi-layered design decisions dealing with facility locations, the amount of facilities, and their capacities. These variables and demand/return uncertainties are composited in a two-stage stochastic model following the Bender decomposition approach. The optimal solution covers all potential scenarios well on average, which is crucial to run an effective SCN (Üster & Hwang, 2017).

2.6.5 Other Supply Chain Network Examples

Western Digital, a memory and electronics component producer, identifies a mixed-integer stochastic programming model to improve the qualification process for each product to a certain facility (site). Site qualifications are important to control capacities and advanced technological capabilities in Western Digital’s network. The resulting optimization model serves as a decision support tool and avoids ‘spreadsheets’ activities around the SCN. Furthermore, former qualification practices with human approximations, such as ‘rules of thumb’, are replaced by this decision tool (Liao, Yano & Esturi, 2017). Similarly, a Bender decomposition algorithm is used for investigating the bioenergy SCN in the U.S. state Texas. This included biomass and biofuel logistics and its strategic decisions regarding location, production, inventory, etc. Findings show inter alia a link between biorefineries’ locations and the bioenergy demand (Memişoğlu & Üster, 2016). Another paper investigates a model to quantitatively assessing the inventory level and service level trade-offs. Regardless of the fact that order sizes were not considered, the developed model in terms of a software tool provides base-stock levels for the facilities embedded in the SCN. This is achieved by analyzing performance relevant data, such as Bill of Materials (BOM) lead-times, and generating performance measures, such as total inventory capital, throughout the SCN (Ettl, Feigin, Lin & Yao, 2000). In the context of omni-channel retailing, a conceptual model characterized through a predictive and adaptive management approach gathers demand forecast information from Big Data in combination with Machine-Learning (ML) techniques. This is established by the
application of simulation-based optimization methods, which analyzes material, financial, and information flows to answer customer needs at best (Pereira et al., 2018).

2.7 Research Model
The conducted systematic literature review revealed different themes, in which the literature can be classified. Figure 2.2 illustrates those themes in relation to their context and dependency. Hereby, data analytics and its corresponding techniques used in the context of Logistics and Supply Chain Management (LSCM) create the term of Supply Chain Analytics (SCA). It uses data originated from Big Data sources outside the focal company and supply chain relevant data stemming from inside the company. SCA generates actionable insights from a multitude of data sources in order to provide strategic and operational levels decision-relevant information concerning Supply Chain Management’s (SCM) efficiency and performance. One of the benefited areas, which belongs to the strategic decision level of organizations, is the Supply Chain Network Design (SCND). This SCM field is heavily reliant on analytically processed data, which can be consequently extensive and challenging to consider in every large-scale decision (Wang et al., 2018). In this regard, information has to be transformed into business terms to drive decisions related to SCND decisions, which are reflected in strategic and operational management levels of an organization. The research model (Figure 2.2) presents the current findings stemmed from the literature.

*Figure 2.2: Research model*
3 Methods

The following chapter will explain the methods/tools used by the authors of this study and discuss the philosophical assumptions on which the research is based upon as well as the implications of these for the methods adopted. The first step is to define the research philosophy which is then followed by explanation of the research approach. Thereafter, the research design of the study is described. Subsequently, the data collection and analysis methods are presented. Finally, the quality of the study’s findings is presented.

3.1 Research Philosophy

In order to describe the philosophical assumptions that constitute this thesis, two main positions need to be discussed. Scholars have debate on the understanding of various philosophical issues that underpin the development of social research in general. The different positions are divided into two areas: Ontology is concerned with the nature of the social world and what is there to know about it, while epistemology is more concerned with the ways of knowing and learning about the world and how we can learn about reality and what forms the basis of our knowledge (Easterby-Smith, Thorpe & Jackson, 2015).

According to Easterby-Smith et al. (2015), one person's truth may or may not be shared by other individuals, and the facts presented are not independent on the individual viewpoint of the observer. Thus, the collected and presented empirical findings within this study are dependent on the individual's own perception of the phenomenon, which is relative; i.e. there can be multiple truths.

Relativism argues that there is no single objective truth which is universal. Rather, each point of view has its own truth (Easterby-Smith et al. 2015). This study assumes that the phenomenon in study is the result of occurring events and interactions between people involved with it. In order to increase the understanding to the implications of this phenomenon, the study has further investigated into these events to get deeper understanding. Hence, the authors hold relativism as an ontological view of this thesis, as the views aimed to gather throughout the interviews are going to be relatively different in terms of perception and consideration by each one of the interviewees.

From the constructionist position Easterby-Smith et al., 2015, “the assumption is that there may be many different realities, and hence the researcher needs to gather multiple perspectives thought a mixed of qualitative and quantitative methods, and to collect the views and experiences of diverse individuals (triangulation)” (p. 54). The authors believe that the events of interest between SCA and the process of designing Supply Chain Networks (SCNs) have occurred because it is being socially constructed. Social construction, also known as constructivism, stems from the belief that individuals build and their social reality among those who share that same belief and personal perceptions.
Since there is no single truth about the strategic implications of SCA, adopting an epistemological view of social constructivism will enable the authors to gain deeper understanding of the social interactions between the phenomenon and actors involved by detecting meaningful and constructed interpretations based on the selected interviewees (Easterby-Smith et al., 2015).

3.2 Research Approach

According to Ritchie, Lewis, McNaughton Nicholls and Ormston (2014), the research approach is a plan and procedure that consists of the steps of broad assumptions of detailed methods of data collection, analysis, and interpretation. Three main research approaches can be distinguished within this context, namely deduction, induction, and abduction.

On the one hand, inductive reasoning involves building knowledge from the bottom-up through observations of the world, while deductive reasoning follows a top-down approach to excavate knowledge by deriving a hypothesis from a theory and test it against empirical observations to gain insights about the world, which will either validate or refute it. The former is a useful approach to investigate the perspective of individuals and their interpretation of the social world. Abduction in turn, can be considered as a third alternative that combines elements from both deductive and inductive reasonings (Ritchie et al., 2014).

Concerning the study’s purpose, inductive reasoning has been identified and chosen as the most suitable research approach. Looking at the gaps identified in section 1.3 Purpose, applying deductive approach is rather unrealistic, since the aim of this study is to develop theoretical understanding based on collecting empirical data. The adoption of abductive approach would have been possible as well. However, this option has not been chosen since the study’s specific purpose requires a simultaneous collection of theories and empirical data (Ritchie et al., 2014). The conducted qualitative study requires flexibility to either develop new theories or refine the ones existing in the literature based on the findings derived from empirical data.

Due to the different organizations and industries involved with the phenomenon of SCA, as well as the specific purpose that the study is aiming to fulfill, this study is not delimited by a context to ensure a greater understanding of the phenomenon under study. Thus, no single or multiple case studies are chosen as methodological approaches other than qualitative study using interviews. Qualitative methods have been implemented in order to gain a greater understating of the strategic implications of SCA. Previous qualitative research studies on this phenomenon are quite scarce and mostly implementing quantitative methods. There is a lack of theory-based models to interpret and understand the phenomenon from a managerial perspective. Therefore, qualitative methods have been chosen for this study to facilitate the understanding of different views and perceptions received from the interviewees about the phenomenon. The qualitative
approach will aid the authors in generating new insights on the phenomenon or help in developing new potential theories by uncovering trends in thought and opinion.

### 3.3 Research Design

Ritchie et al. (2014) emphasize the importance of defining a clear design for the research study, which should be coherent between the objectives, research questions, and methods proposed. In order to describe the research design, the authors ought to present what philosophical assumptions are made beforehand, the adapted research method, data collection techniques, data analysis approach, and finally how the material will be presented and how the findings are planned to be published (Myers, 2013).

An adopted research design is illustrated (Figure 3.1) and representing the progress of this study, according to the research design model presented by Myers (2013). Considering Figure 3.1 it starts with the philosophical assumptions that were made and discussed in 3.1 Research Philosophy. Thereafter, it is followed by the chosen research techniques, which will be presented in this section, along with the adopted data collection and analysis that are further discussed in 3.4 Data Collection and 3.5 Data Analysis.

![Figure 3-1: Research design model, adapted from Myers (2013)](image)

In order to follow a consistent research design, Ritchie et al. (2014) suggest systematic steps to follow after developing the research questions. The researcher must choose the appropriate method to pursue for collecting the data and then systematically analyzing it. The most common research designs are experiment, survey, case study, action research, grounded theory, ethnography, and archival research.

One strategy that aids in-depth exploration and provide insights into the research phenomenon more generally, is the case study design. However, as previously argued in sub-section 3.2 Research Approach, case study methodology was not chosen. For this study, a qualitative study using interviews was chosen in order to gain deeper insights from various perspectives and contexts about the phenomenon of SCA. Further, it will enable
effective gathering of the data from a variety of sources, and eventually assimilate it to illuminate the topic of the thesis.

Since the purpose of this study is to investigate the phenomenon of SCA in a real-life context, the qualitative interview study approach is therefore deemed to be the most suitable approach for this study. Not to mention that an interview study will be a good match to the exploratory nature of this study as it will allow the authors to answer both research questions presented in 1.3 Purpose, namely the “what?” and “how?” ones.

3.4 Data Collection

Researchers can make use of secondary data or collect new data (primary data) specifically collected for the purpose of a study (Saunders, Lewis & Thornhill, 2016). In order to answer the study’s research questions, primary data was gathered. As earlier mentioned in chapter 3.2 Research Approach, a deeper and insightful understanding is of importance to the quality of this study.

Generally, data collection techniques vary in length and scope. Yin (2018) lists six sources of evidence, which namely are documentation, archival records, direct observation, participant-observation, physical artefacts, and interviews. The latter was chosen, because of its ‘richness’ of information and communication and the reflecting respondents’ insights receiving from a relativist perspective (Gillham, 2005; Yin, 2018). Additionally, in order to gain the respondents’ views and interpretations, and respond to his or her answers, the authors interfered, pondered, probed and prompted various statements throughout the interviews, which characterizes a subjective interview approach (Saunders et al., 2016).

In this context, there are existing different types of interviews. ‘Structured’ interviews are mainly classified by simplicity, specificity, and closed questions, whereas ‘unstructured’ interviews are characterized by listening to other people in a verbally observational manner. ‘Semi-structured’ interviews are a combination of both, more specifically open-ended and closed questions, which is balanced with naturalness and structure (Gillham, 2005). In this study, the authors chose to conduct ‘semi-structured’ interviews, since firstly, it gives a pre-defined structure, which serves as guideline, and secondly, it can be used to gain other directions and perspectives within/ surrounding the research topic. Finally, it will contribute to the research quality and adhere to the chosen interview study design by expanding on existing knowledge.

As semi-structured interviews are used to gather empirical data and finally, answer the research questions, the interview questions are key to the interview procedure as well as to following the exploratory study. Thereby, the authors used semi-structured interviews to understand relationships between variables (Saunders et al., 2016). Open-ended questions are favorably chosen to get deeper insights, and background information regarding particular events of interest. This more open questioning technique serves also
in favor of collecting various angles and perspectives enabling to achieve a multi-faceted analysis of the collected data.

Fifteen interviews were conducted via Skype or an alternative web communication platform, which enabled the authors not to have high travel expenditures, while gaining expert insights from abroad. Furthermore, it was more convenient for the respondents not having organizational effort for the interview. Three interviews were face-to-face, which were in proximate venues in Sweden. During those interviews, we perceived lots of facial expressions and gestures, which contributed our understanding of their responses. One respondent was just able to share his knowledge via Email due to time constraints at work, whose results were received in a narrative manner.

3.4.1 Selecting Interview Respondents

Due to the complexity and to some extent novelty of this research topic, answering the developed research questions by the entire population would increase the impracticability of the study, which consequently leads to sampling from a previously defined target group (Saunders et al., 2016). Sample criteria were defined formerly, which started by targeting experts who are currently working or have worked in the past within the domain of Business Analytics (BA). The second criterion was searching for any experience within the field of Supply Chain Management (SCM) or its adjacent areas such as logistics or production management. The final criteria consisted of the linkage of criteria one and two, which defines a respondent, who has both knowledge in the domain of analytics as well as in SCM.

Keeping these sampling selection criteria in mind and considering the research design, a non-probability sampling technique was chosen as it provides the researchers subjective judgments regarding selection of the sample (Saunders et al., 2016). This can be substantiated by the relatively poor researched topic of this study, where the sample is rather purposively chosen to ensure an information-rich study, and finally, answer the research questions. Thereby, the authors were fully centered in defining the strategy for selecting cases according to the research questions (Saunders et al., 2016), which enabled the authors to get profound insights from best-suited respondents.

Following a purposively heterogeneous sampling technique throughout all selection initiatives, the researchers made the effort to get valuable and practical information about the multiple perspectives of analytics and its surrounding sub-domains by flying to London for the purpose of getting first-hand touchpoint with both professional practitioners and executives working within the fields of Big Data and analytics. Therefore, the authors visited the annual international fair outside of Sweden; entitled ‘Big Data World’ which took place between 11th to 12th of March 2018 in ExCeL, London. A multitude of experts were approached in the fair to obtain numerous perspectives from different managerial levels, which some of them were subsequently interviewed for the purpose of this study. This approach represents the diverse
characteristics in the contacted experts as well as the maximum variation in the work field they were in, which results in a purposively heterogeneous sample (Saunders et al., 2016).

Further efforts led to a comprehensive internet search on various websites and web platforms dealing with analytics or its related functional areas, which turned out to be as successful as the initial efforts. The authors managed to contact the relevant organizations’ workers to participate in interviews, which were also critical to the success of this study. They held respectively different perspectives which gave the authors the opportunity to deliberate about those distinct views, and test the genuineness of the research (Yin, 2018).

In addition to the precious endeavors, final efforts were made simultaneously by leveraging the authors’ own private networks of professional contacts to conclude the data collection process. Those contacts turned out to be key to this study, since they gave the authors access to other interviewees, who met all selection criteria and supported the research by providing both contradicting and corroborating insights (Yin, 2018). The resulting interview respondents are shown in Table 3-1. Company O’s respondent declined an interview but shared his views via an ongoing Email discussion. The interview questions served as starting point, from which further information were prompted enabling a more open-ended discussion.

*Table 3-1: Interview respondents.*

<table>
<thead>
<tr>
<th>Date</th>
<th>Interview type</th>
<th>Duration (min)</th>
<th>Respondent’s position</th>
<th>Organization name</th>
</tr>
</thead>
<tbody>
<tr>
<td>2019/03/21</td>
<td>Skype video call</td>
<td>55</td>
<td>Director of Architecture</td>
<td>Company A</td>
</tr>
<tr>
<td>2019/03/22</td>
<td>Face-to-face</td>
<td>55</td>
<td>Supply Chain Manager</td>
<td>Deloitte AB</td>
</tr>
<tr>
<td>2019/03/25</td>
<td>WebEx audio call</td>
<td>40</td>
<td>Strategic Account Manager</td>
<td>Company C</td>
</tr>
<tr>
<td>2019/03/29</td>
<td>Skype audio call</td>
<td>55</td>
<td>Supply Chain Manager</td>
<td>Stora Enso AB</td>
</tr>
<tr>
<td>2019/04/01</td>
<td>Skype audio call</td>
<td>75</td>
<td>Co-Founder &amp; CEO</td>
<td>Galileo Analytics</td>
</tr>
<tr>
<td>2019/04/02</td>
<td>Skype audio call</td>
<td>60</td>
<td>Advisory Industry Consultant</td>
<td>SAS Institute AB/ SAS Analytics</td>
</tr>
<tr>
<td>2019/04/03</td>
<td>Skype video call</td>
<td>55</td>
<td>Academic lecturer</td>
<td>Noroff School of Technology &amp; Digital Media</td>
</tr>
<tr>
<td>2019/04/08</td>
<td>Face-to-face</td>
<td>70</td>
<td>CEO</td>
<td>Company H</td>
</tr>
<tr>
<td>2019/04/08</td>
<td>Face-to-face</td>
<td>50</td>
<td>COO</td>
<td>Company I</td>
</tr>
<tr>
<td>Date</td>
<td>Type</td>
<td>Duration</td>
<td>Role</td>
<td>Company</td>
</tr>
<tr>
<td>------------</td>
<td>---------------</td>
<td>----------</td>
<td>---------------------------</td>
<td>--------------</td>
</tr>
<tr>
<td>2019/04/10</td>
<td>Skype audio</td>
<td>45</td>
<td>BI Solutions Specialist</td>
<td>Company J</td>
</tr>
<tr>
<td>2019/04/12</td>
<td>Skype audio</td>
<td>50</td>
<td>Business Consultant</td>
<td>Company K</td>
</tr>
<tr>
<td>2019/04/16</td>
<td>Skype video</td>
<td>37</td>
<td>Researcher</td>
<td>Company L</td>
</tr>
<tr>
<td>2019/04/19</td>
<td>Skype audio</td>
<td>30</td>
<td>VP of Global Data Operations</td>
<td>Company M</td>
</tr>
<tr>
<td>2019/04/24</td>
<td>Skype audio</td>
<td>55</td>
<td>Senior Manager</td>
<td>Company N</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Global Business Services</td>
<td></td>
</tr>
<tr>
<td>2019/05/09</td>
<td>Skype audio</td>
<td>60</td>
<td>Co-Founder &amp; Head of Application Board</td>
<td>Optilon AB</td>
</tr>
<tr>
<td>2019/04/10</td>
<td>Email</td>
<td></td>
<td>Consultant Manager</td>
<td>Company O</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>Analytics</td>
<td></td>
</tr>
</tbody>
</table>

3.4.2 Development of interview guide

The interview guide was crafted to keep discussions during interviews vibrant and informative. It includes a set of 17 questions, which were organized in different themes/categories. Those created themes enabled to list some key questions, which vary from interview to interview depending on the organization and the respondent’s work domain (Saunders et al., 2016). The classification/categorization enabled the authors to refer to the questions and the resulting findings to fully answering the research questions. The sequence and scope of questions has changed over time due to saturation of empirical findings. The interview guide was sent to the respondents in advance on request, which is stated in Appendix 3. The authors used the interview guide to probe and prompt the respondents during the interviews, which is also presented in Appendix 4. Within the interview guide and the actual interviews, the term ‘Business Analytics’ in the context of Supply Chain Management (SCM) was used instead of ‘Supply Chain Analytics’, because the latter can almost exclusively be found in the literature and was rarely known or used by the respondents in the approached organizations.

3.5 Data Analysis

After collecting the empirical data, the analysis of the data was performed to answer the research questions accordingly. Following the inductive study approach, the authors analyzed the data as it is collected, and aimed to understand the social context of the interviewed people, in this study the application of Supply Chain Analytics (SCA) in strategic Supply Chain Network (SCN) decisions, and the interview respondents’ views and perceptions. In this regard, the procedure of the thematic analysis was followed
subsequently, which provide an easily replicable and organized analysis method that is accessible and flexible (Saunders et al., 2016).

The empirical data is collected through semi-structured interviews, which produce a multitude of different datasets composed of different levels of accuracy and scope. During transcribing and re-reading the data at a later point in time, the authors started to get familiar with the data collected to immerse into the underlying meanings behind it (Saunders et al., 2016). Afterwards, every single finding was coded/labeled according to its meaning and then compiled in the themes derived from the literature. These themes had to be adapted while assigning the codes, since new themes emerged from the codes, which were non-assignable to an existing theme (e.g. ‘4.7.3 Data vs Human Intuition’). Similar findings with a similar meaning were attached to the same code, whereas findings with different meanings were coded discretely (e.g. ‘relationship 3 AnTypes’) (Saunders et al., 2016). ‘Searching for themes and recognizing relationships’ is the next step of thematic analysis according Saunders et al. (2016), which involves making judgements about the collected data, linking sub-themes to main themes or vice versa, and investigating the relationships among the themes. These activities were already done for the most part during the ‘coding’ phase and were also considered in an accurate and diligent fashion during the coding process (e.g. ‘4.5.1 Key Elements for Designing Supply Chain Networks’ and ‘4.5.2 Digital Supply Chain Network Design’). Lastly, the themes and sub-themes were re-organized, which helped to devise the coded themes to assign them to the research questions (Saunders et al., 2016). This was done by re-considering the codes in the developed themes to decide whether they are of an interest to the research question (e.g. ‘4.4.2 In Supporting strategic Supply Chain Decisions’), or they can be discarded (e.g. ‘Data Problem Examples). Through perceiving a potential linkage between the themes, the researchers were able to develop propositions, and test them to derive valid conclusions (Saunders et al., 2016), to finally answer the research questions.

3.6 Research Quality

Authors are arguing about what types of contexts are transferred to which findings but are certain about the case when findings include the wider population originated by the sample, or settings outside the proposed study design (Ritchie et al., 2014). Considering the authors´ agreement from another perspective, findings of a particular study might also be generalized to different contexts or settings, which are excluded in the sample (inferential generalization) (Ritchie et al., 2014). In this regard, the quality throughout all parts of the study has to be ensured. This is achieved by four different test objects, namely validity, internal validity, external validity, and reliability, and research ethics, which ensures the latter object (Yin, 2018).

3.6.1 Validity

Validity refers traditionally “to the ‘correctness’ or ‘precision’ of a research reading” (p. 356) and “to the extent to which a finding is well-founded and accurately reflecting the
phenomenon being studied” (p. 354) (Ritchie et al., 2014). The latter part of the definition represents an operational set of measures for data collection the researcher needs to develop. Furthermore, the study needs to be preventive against ‘subjective’ judgements (Yin, 2018). This threat was diminished by the fact that the respondents had no relation to us before the start of the research and during the study conducted. A professional and research-oriented focus has been maintained throughout the study. Additionally, due to fact of writing the master thesis together, the level of subjectivity during the data collection process and the analysis enabled us constantly to discuss findings and all steps of the data and analysis process together in a more objective manner.

Multiple sources have been used in this study. We collected primary data through semi-structured interviews and secondary data through complementing company-relevant information to amplify our understanding about the investigated phenomenon. Exemplary demonstrations of different analytics and visualization tools by the vendors/providers at the Big Data World fair, expanded our general understanding as well as added them up in chapter 5 Analysis. Using multiple sources for data collection increased the clarity of the phenomenon studied as well as made the findings more precise (Ritchie et al., 2014). Another aspect of validity refers to member validation, which enables researchers to send the research data back to the respondents to check on accuracy (Saunders et al., 2016). At the end of every interview, we offered the respondents to provide them a transcribed interview document and engaged in further discussions via Email to prove meanings and gain more clarification. Furthermore, discrepancies in the transcription files were discussed immediately and before starting the coding.

Internal validity refers to “the extent to which causal statements are supported by the study” (Ritchie et al., 2014, p. 356). Ensuring receiving accurate and precise data during the data collection, a clear and proper formulated interview guide was prepared, which also includes probes and prompts to gain rich and fruitful insights. Those findings were gleaned by an open-ended interview type, which enabled us to ask for further elaboration of the interviewee on some key notes. The generic meanings of the interview findings were occasionally doublechecked with the interviewees to capture the most explorative statements. The theoretical relationship of Supply Chain Analytics (SCA) and Supply Chain Network (SCN) design was examined through gaining rich data through the data collection processes, which confirms internal validity of the study (Saunders et al., 2016). Exemplary interview questions were sent out in advance on request to respondents in order to resolve any concern they had before moving on within the study.

External validity can be described as the degree a study’s findings can be generalized (Yin, 2018). This is impacted by the actual number of accessed interview respondents, the quality of findings, the connection to given theory, and the characteristics of the sample itself. The underlying study comprises a sufficient amount of empirical data to be able to make generalizations about the phenomenon of SCA in the context of designing SCNs. The quality of the findings is given by, firstly, the professional interviewees and
secondly, by some high-profile (C-suite) respondents, which enriched the study with deep knowledge from numerous management levels. Further, the chosen research design (qualitative study) drives unprejudiced and explorative research to capture various angles and their relations. This fact decreases the applicability of the study to similar studies, which is reasoned by the variety of angles considered in this study. Another scenario when trying to replicate this study to others is the circumstance that SCA has complex techniques and technologies involved which change constantly due to technological innovation. Therefore, undertaking a similar study within this research topic might result in different conclusions than presented in the underlying study. Nevertheless, the findings obtained during the study, may reveal new approaches SCA can be used more efficiently, which favors generalization possibilities of the study (Saunders et al., 2016).

3.6.2 Reliability
Reliability or ‘replicability’ of findings is whether findings are repeated by using same or similar methods originally undertaken (Ritchie et al., 2014). In this regard, transparency is of utmost importance. During conducting the study any information was accessible for revision for the respondents. The design, approach, and methodology are stated and describe clearly how the study could be replicated. The outline and purpose of our study was communicated while approaching respondents and was also repeated before conducting the interviews. The interview guide as well as data collection and analysis techniques are also described in a granular manner. Ensuring total objectivity in interpreting empirical results, the raw data was considered separately and one for one, and later discussed among the authors to guarantee a transparent and reasonable coding process. All information presented from other authors than us are cited using APA style. Nevertheless, there might be the threat to be not fully replicable since a qualitative study’s intention is to convey the respondents’ (social) settings they are in at that time (Saunders et al., 2016). The underlying study examines the phenomenon, namely SCA and SCN designs, and the respondents’ perceptions in dealing with it. Due to the fast-growing innovation of technologies, SCNs might grow and change with the same speed, and therefore their factors, requirements, and goals.

3.6.3 Ethical Considerations
Ethical issues are omnipresent when conducting a research. Hence, researchers need to ask regularly difficult questions about ethics and politics of their own research in order to be as thinking and reflective as possible (Easterby-Smith et al., 2015). From research practice, it is known that data collection involves an ongoing tension between gathered information and its derivation of knowledge, and ethical subjects (Yin, 2018). However, the tension does not stop because research ethics needs to be taken into consideration even for further research actions. Ensuring rich information, the respondent was also willing and authorized to share, which deals with the interviewee’s consent (Yin, 2018). Following the key principles provided by Bell and Bryman (2007), the informant consent by the respondents was achieved through asking them during the sampling phase whether
they are willing to share their insights and contributing to our study. Thereby, the relationship between the participant and his/ her organization and us as researchers was framed by introducing our role as well as their role for the underlying study (Easterby-Smith et al., 2015). Further, the timeline and purpose of this study has been communicated, and the interview guide was sent out in advance if required by them. This represents transparency and honesty provided by the authors (Bell & Bryman, 2007). Before starting the interview, we always asked for the interviewee’s permission to record the interview to ensure our full attention on the interviewee and his/ her responses. Additionally, it enabled us to re-listen and transcribe the gained data in a precise and rigid fashion. The questions were always asked without the intention to harm the privacy of the respondents or the companies and were respecting the companies´ politics or potential conflicts of interests (Easterby-Smith et al., 2015). If respondents could not expose certain information, we accepted that and continued with other questions. A consent form was provided to the interviewees after the interview for further consideration and clarity of the research and its goals and terms.

Completing the data collection process, the gathered information was transcribed and sent to the respondents in case they wanted to reflect on the given information. Their corrections and changes were incorporated in the final transcribed version. Hereby, further investigations on the collected data were done in order to not reveal the respondents´ identity and privacy (Bell & Bryman, 2007). Different considerations of the analyzed data were possible due to new insights gained from the interviews. These new consideration angles and the presentation of those as empirical data were discussed among the authors to decrease the threat of misinterpretation of the data during coding and the analysis of the study (Bell & Bryman, 2007). In respect of confidentiality (Bell & Bryman, 2007), the findings were treated with utmost confidentiality and stored on a locked personal computer. Only the two authors were given permission for access. Most of the company names are kept undisclosed and were anonymized upon the respondent’s own request. The anonymized names and descriptions were aligned with the respondents to provide their full consent. Any information which might relate to the respondents´ organizations was also kept confidentially and is not revealed in the study. After completing this study, a copy version is offered to the respondents to review.
4 Empirical Findings

The following section of this work represents the empirical findings and results. Firstly, the different companies are introduced followed by the presentation of the findings. The findings have been separated into seven themes: (1) Supply Chain Management Drivers; (2) Big Data and Data Analytics; (3) Supply Chain Analytics Applications and Decisions; (4) Supply Chain Analytics in Designing Supply Chain Networks; (5) Emerging Datasets on Operational and Strategic levels; (6) Supply Chain Analytics Value in Organizations; (7) and Data-driven Technologies in Supply Chains.

4.1 Overview of Companies

The underlying qualitative study of Supply Chain Analytics (SCA) in supporting designing Supply Chain Network (SCN) decisions made use of a great number of respondents, which vary by industry/ role within Logistics and Supply Chain Management (LSCM) and/ or analytics domain, and by management levels. An overview of all respondents participated is illustrated in Table 4.1.

Table 4-1: Overview of companies participated.

<table>
<thead>
<tr>
<th>Organization</th>
<th>Industry/ Role</th>
<th>Respondent’s position</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Company A</td>
<td>Data analytics/ solution integrator</td>
<td>Director of Architecture</td>
<td>Software consultancy company specialized in cloud, data warehousing, business intelligence, and data science (Company A, 2019).</td>
</tr>
<tr>
<td>Deloitte AB</td>
<td>Consulting/ Consultancy firm</td>
<td>Supply Chain Manager</td>
<td>Management consulting that provides professional services. One of the &quot;Big Four&quot; accounting organizations (Wikipedia, 2019).</td>
</tr>
<tr>
<td>Company C</td>
<td>Data integration/ Platform provider</td>
<td>Strategic Account Manager</td>
<td>Online platform provider that is specialized in Data Integration, Data Migration, Data Quality, Data Cleansing, Data Warehousing, BI, and Analytics (Company C, 2019).</td>
</tr>
<tr>
<td>Stora Enso AB</td>
<td>Pulp &amp; paper manufacturer/ User</td>
<td>Supply Chain Manager</td>
<td>A manufacturer of pulp, paper, and forest products, which provides renewable solutions in packaging, biomaterials, wooden constructions, and paper (Storaenso, 2019).</td>
</tr>
<tr>
<td>Galileo Analytics</td>
<td>Data analytics/ Solutions provider</td>
<td>Co-Founder &amp; CEO</td>
<td>A visual data exploration and advanced analytics company focused on democratizing the process of accessing and analyzing clinical health data (Galileo Analytics, 2019).</td>
</tr>
<tr>
<td>SAS Institute AB/ SAS Analytics</td>
<td>Business analytics/ software provider</td>
<td>Advisory Industry Consultant</td>
<td>The market leader in Analytics with 40+ years of Analytics innovation (SAS, 2019).</td>
</tr>
<tr>
<td>Noroff School of Technology &amp; Digital Media</td>
<td>Higher education</td>
<td>Academic lecturer</td>
<td>A privately owned and operated university college and vocational school offering a variety of different study programmes, based in Oslo (Noroff, 2019).</td>
</tr>
<tr>
<td>Company H</td>
<td>IT services/ Cloud and technology solutions provider</td>
<td>CEO</td>
<td>Software-as-a-Service platform provider that offers creative solutions and designs logistics management software (Company H, 2019).</td>
</tr>
<tr>
<td>Company I</td>
<td>IT services/ Cloud and technology solutions provider</td>
<td>COO</td>
<td>Software-as-a-Service platform provider that offers creative solutions and designs logistics management software (Company H, 2019).</td>
</tr>
<tr>
<td>Company J</td>
<td>Business analytics/ platform provider</td>
<td>BI Solutions Specialist</td>
<td>Analytics platform, which provides self-service reporting and visualization across various application (Company J, 2019).</td>
</tr>
<tr>
<td>Company K</td>
<td>IT services/ Digital business service provider and consultancy</td>
<td>Business Consultant</td>
<td>A digital transformation company providing strategic consulting to service design, digital development, data, AI &amp; Analytics, and managed cloud services (Company K, 2019).</td>
</tr>
<tr>
<td>Company L</td>
<td>Science/ Research institution</td>
<td>Researcher</td>
<td>A non-profit research organization focused on advanced research in strategic areas of computer science, in close collaboration with international industries and academia (Company L, 2019).</td>
</tr>
<tr>
<td>Company M</td>
<td>Data science/ Data science platform provider</td>
<td>VP of Global Data Operations</td>
<td>IT-platform provider specialized in Predictive Analytics, Business Modelling &amp; Business Intelligence services (Company M, 2019).</td>
</tr>
<tr>
<td>Company N</td>
<td>Biotechnology/ User</td>
<td>Senior Manager Global Business Services</td>
<td>Multinational biotechnology company, using Analytics to discover and develop therapies for the treatment of neurodegenerative diseases to patients worldwide (Company N, 2019).</td>
</tr>
<tr>
<td>Company O</td>
<td>IT service company</td>
<td>Consultant Manager Analytics</td>
<td>IT service company that provides data-driven business transformation services (Company O, 2019).</td>
</tr>
<tr>
<td>Optilon AB</td>
<td>Supply chain optimization/ consultancy firm</td>
<td>Co-Founder &amp; Head of Application Board</td>
<td>Consulting company leading in managing and optimizing supply chains and specialized in business analytics, supply chain design &amp; planning, and service optimization (Optilon, 2019).</td>
</tr>
</tbody>
</table>

The empirical findings gained during the data collection process were classified, firstly, in themes derived from the 2 Theoretical Frame of Reference. Secondly, those themes were expanded and edited according to the empirical findings. Lastly, in case the empirical findings could not be assigned to any given themes, new themes, and eventually their corresponding sub-themes, emerged and complemented contextually the existing themes.
In following eight sub-sections the empirical results themed by their contexts are presented.

4.2 Supply Chain Management Drivers
This theme lists the interviewed respondents’ views on current supply chain drivers. The responses vary in their perspective and what they focus in. In this regard, overall technologies and its correlated data, emerging supply chain concepts as well as existing general approaches in the context of supply chain management are discussed.

From the point of view of the Supply Chain Manager at Deloitte, the customer focus from the very beginning is vital for driving supply chains. Starting from the product development, he underpins the importance to really understand the customer experience, more precisely, how customers expect a product to be.

Similar views shared by the BI Solutions specialist from Company J by describing customers’ needs since they concentrate on the whole ‘journey of the prospect’ or the product. He emphasizes the importance of demand throughout the supply chain and considers analytical aspects as driver for an entirely demand based supply chain because all actors involved thrive towards a demand-driven approach to facilitate reduce stock and shortages.

The Consultant Manager Analytics of Company O confirms the trend of a demand-driven supply chain but attributes lean-thinking also as a driver. Nevertheless, companies practice looks different, in which they rely heavily on stock, and only few companies can maintain a fully applied ‘pull’ strategy, which relies exclusively on customer demand.

Lean-thinking supported by closely related concepts, such as Just-In-Time (JIT) or lean manufacturing, drives the supply chain within the supply chain perspective of an Industry Advisory Consultant of SAS Analytics. In the technology perspective, real-time data is a predominant driver for supply chains.

The Senior Manager Global Business Services of Company N lists several core tools in terms of supply chain drivers. In his eyes, digitalization is driven by more digital mindsets of humans, since

“[…] everyone wants to have you know, immediate access to data, everyone wants to have access to live data, and ensure that we can we can support our decisions with digitalization.”

Besides Blockchain and IoT, he underlines the value of analytics and dashboards tools in his organization by dedicating departments focusing on operational analytics.

One important aspect from his standpoint, where the characteristics of ‘true’ data is likewise important, is creating measurable Key Performance Indicators (KPI) throughout the organization. These KPIs are influencing the supply chain in many ways that is why
they need to deliver ‘true’ information and need to be understandable the same way within the organization.

The researcher of Company L mentioned that increased availability of sensors and actuators, in addition to the data storage and retrieval, enabled the manufacturing and transportation sectors to use previously developed methods in optimization and statistics to increase the efficiency of their operations.

4.3 Big Data and Data Analytics

The following themes introduces the terminologies of Business Intelligence (BI) and Business Analytics (BA). Further, various analytics types are discussion and their mutual relationship investigated. Lastly, data processing practices are given in the domain of Supply Chain Management.

4.3.1 Differentiation between Business Intelligence and Business Analytics

Sub-theme number one provides an understanding and differentiation between Business Intelligence (BI) and Business Analytics (BA). The answers we obtained here vary slightly between different professions and industries. The perception of these terms is quite different as well as its applications. Furthermore, the interviewees associate adjacent areas with BI and BA, such as analytics types, data types, or decision-making, to their understanding of both BI and BA.

From the perspective of a Supply Chain Manager at Deloitte, the scope of BI might start by plain financial calculations, such as spend analysis, and include both the world of machine-learning and human-learning interchangeably. Furthermore, the interviewee links BA to the field of procurement as a single analytics field separated from Supply Chain Analytics (SCA). Other consultancy insights he provides deal with the technique of ‘digital twinning’, which makes a digital copy of physical assets within the ‘Industry 4.0’ concept available and the necessary data for getting actionable insights through BA.

The Supply Chain Analyst of Stora Enso only argues BI as a part of BA. As an exemplary tool for a BA tool he named ‘SAS Mining’, which the company is using to predict demand underlying historical demand data.

The Business Consultant of Company K shares similar views by referring BA to a broad term, which entails BI and data science practices in order to enable forward-looking analysis of certain business cases. BI practices are oriented towards backward-looking by considering historical data until present to e.g. assess a trend over time.

Prior to the differentiation of BI and BA, the Advisory Industry Consultant from SAS Analytics claims that the term ‘intelligence’ means “different things to different places”. Subsequently, he explains BI as more descriptive analytics or descriptive statistics in plain words “this is what happened” and “what’s going to happen next?”.
A slightly different approach in distinguishing between BI and BA provided by the lecturer at the Norwegian University Noroff using a digital marketing perspective with support of the Google Analytics tool. According to her, BA puts data a company holds into practice to improve results for the company’s bottom line. In contrast, “BI entails BA and incorporates smart technical solutions”, which are numerously available in the online marketing area.

The CEO of Company H refers BI to “what happened” and to “later” data compared to real-time data. In this regard, he underpins the common trend which is present in our consumer-intense world that companies try to affect actions when they are being operated rather than the data becomes outdated:

“The user needs to be able to impact when he can actually also do something about it.”

From the CEO’s standpoint, BI tools are designated for tactical decisions, day-to-day and operational decisions with a considerably shorter planning scope, whereas tactical decisions are mainly supported by BA.

The CEO and Co-Founder of Company M describes BI as in a way a business’s details and facts, whereas BA, or generally analytics, as the facts and extracted intelligence in order to make data actionable for facilitating business options. In short, the CEO classifies “how would you use the data or reaching for it?” into the analytics domain versus to know “what you need then to do the analytics?” into the BI domain.

A contrary perspective provides the BI Solutions Specialist of Company J in claiming that there is no “very specific line of difference”, and consequently, “both terms go hand in hand”. Therefore, the perception decides on the consideration of both terminologies. In his continuing explanation stating examples, he signposts that focusing on a specific business domain, where the task is to make a process more cost-effective deals with BA. In contrast, by considering the entire supply chain and its processes and not targeting a particular area, he pins down to BI. In his perception, it is a ‘crossover’ between the different domain and depending on the scenarios they are used (BI strategy or analytical strategy).

The Director of Architecture of Company A reveals another angle by pointing at the drivers of future performance and the drivers of “why we were there?” and “what will be in the future?” towards BA. In contrary, he refers the current performance and the driving questions of “what did we sell yesterday?” and “what did we sell today?” to BI.

The Senior Manager Global Business Services of Company N only approaches an example where BI tools are used. He states that these tools are heavily used in various reconciliation processes, such as in finance or inventory. In this regard the biotechnology producer is collecting data and presenting it in standardized reports.
The Consultant Manager Analytics of Company O supports a contradictory standpoint and considers both terms in reality as semantics and only see “little value in distinguishing between them. “

Company L had a different response when it comes to distinguishing BA from BI:

“[…] we didn’t change or create a new discipline for analytics or artificial intelligence. It’s just a repackaging of what we used to do […]”

The Co-Founder and Head of Application Board of Optilon links BA to descriptive analytics and not to BI, explaining that the main purpose of descriptive analytics is to visualize what previously happened:

“[…] the descriptive analytics visualize what has happened, nothing more than that. So here we put business intelligence, the word intelligence suggests something else, but it’s truly not intelligence. It’s just visualizing what has happened […]”

4.3.2 Contextual Relationship between main Types of Business Analytics

Sub-theme number two deals with the contextual relationship between the three main types of Business Analytics. The interviewees’ responses vary depending on their domain and industry focus. Hence, the characteristics of data in usage of each typology as well as application fields and functions in companies are brought out. Both the used tools and academic perspective of all three types are also discussed.

The Supply Chain Manager of Deloitte sees the application of descriptive analytics in production/manufacturing where it might pace up production time and predict production downtime by spotting gaps within the production cycle.

The Supply Chain Analyst of Stora Enso considers descriptive analytics as ‘customer optimization’ technique, which is being used for distinguishing low and high profitable customers. In the context of inventory management, he associates the working capital of the company with descriptive analytics in order to manage inventory. For the purpose of ad-hoc or monthly reporting jobs descriptive analytics is also being used, whereas predictive analytics is used for demand planning. Additionally, he describes predictive tools as semi-automated, since human intervention is required to prescribe actions of unexpected outcomes in the first place.

The Co-Founder and CEO of Galileo Analytics defines descriptive analytics as processing historical data, but exclusively includes forecasting and trends. Such activities are manageable by using BI dashboard tools, such as Tableau, Click View, or Spotfire, and can be associated with predictive and prescriptive analytics as well. He is also concerning about the theoretical conception, which separates these terminologies, whereas his argumentation includes all three types jointly to run good quality analytics. He goes into the analyst’s mindset, which is merely descriptive and favors building
dashboards to assess the current state of data. However, it is in the capability scope of each analyst using descriptive, predictive, or prescriptive analytics techniques.

As characteristics of descriptive analytics, an Industry Advisory Consultant of SAS Analytics thinks of “what happened?” or “why did it happen?”, which can provide information like the average lead time or the delivered items overtime. Predictive characteristics take historical data and intend to find patterns by using e.g. time series analysis to for instance, predict sales volume. Within the exploration of the data, an analyst compares and scrutinizes values and discovers correlations. Only then, the industry expert brings predictive analytics into action by modeling the earlier analyzed data. In this regard, predictive analytics tries to explain the underlying causes and tracks them if they happen again to uncover patterns. “What will happen, and what is the best action to take?” he classifies as prescriptive analytics in his work context.

The VP of Global Data Operations of Company M views prescriptive analytics as the part where his organization advises their customers on strategy, which is based on intelligence taken from analytical results. Predictive analytics is about predicting a trend what is going to happen. Descriptive analytics comes into play when the data science platform provider creates a model and the algorithms behind it to forecast the future. Hereby, the VP explains that historical data is analyzed by its changes over time, and the current and future expenditures of an industry added and projected.

Company A’s Director of Architecture summarizes descriptive analytics as “what happened?”, predictive as “what will happen?”, and prescriptive as “what if …?”. By drilling down the historical data (to see “what happened?”), building a model is possible like a time series prediction for the future, and asking hypothetical questions containing “what if …?”. He supports his classification by piggybacking on a different view on data analysis, which is provided by Teradata, and adding two more steps for analyzing data, namely

“[...] ‘operationalizing’ which is ‘what is happening?’ and ‘what is happening now?’; and ‘activating’ which is ‘making things happen.’”

The main motive behind this data view is that the three common analytics types miss out the chance to make changes in behavior.

This has an increased need for real-time data as a result because changing someone’s current behavior involves having most current data. He doubts the opportunity to do so by calling it as a ‘quantum leap’.

In contrast to previous definitions of analytics types, the BI Solutions Specialist of Company J agrees fully with the three main types of analytics. Descriptive he classifies as specific area talking about “why” and “why we’re seeing that particular program?”, whereas predictive analytics provides answers to “why that program is going to appear up again in the upcoming six months?”. The third, prescriptive analytics he describes as
the reason and “why it’s actually happening?”. From his working domain he adds another type of analytics to the list, the ‘diagnostic’ one. According to the BI Solutions Specialist, people are nowadays aware of the reason and “what can go wrong”, but they also need a recommendation or suggestion how to solve an issue or task. With a retail example he illustrates in more detail that the diagnostic analytics type is going to give the ability to understand how to decrease customer retention to learn from their behaviors.

The COO of Company I matches descriptive analytics with the human-being who actually needs to make decisions relying on historical data. Prescriptive analytics he labels as “different ballgame”, because a solution and its underlying system needs to decide on the actual task. But if some data piece is missing, he explains, add it and the system starts again to generate results and give insights. Encountering the quality of historical data, a check in the system needs to be initiated from the beginning to make use of both descriptive and predictive and draw conclusions.

The Business Consultant of Company K draws more hierarchically upon the three questioned types of analytics. Starting with descriptive and depending on how much data you have, and moving then to the other types, predictive, and prescriptive, he shares from his work context.

In the work domain of a Senior Manager Global Business Services of Company N, the questioned classification is not used in his daily vocabulary, however the originating data of those types is being used in the organization.

The Consultant Manager Analytics of Company O does not support this classification in practice either. He rather refers to the common business language, which is captured in every business differently:

“The kind of analytics the company requires is specified in your own word using the language of the business.”

Nevertheless, he carefully classifies predictive as prognosis and budgets, prescriptive as decision-making support for automated processes, and descriptive as just analytics. Further, regardless of optimization or AI techniques, companies need to consider all aspects of a problem to achieve their goals.

A researcher at company L stress the importance of using all available tools to find a solution regardless of which discipline they may be categorized under.

When asked about the three main analytics types, the Co-Founder and Head of Application Board of Optilon describes both prescriptive and predictive analytics as the ‘holy grail’ to design supply chain networks relying on historical data as a baseline to enable the system to learn from experience and drive Supply Chain Network (SCN) decisions:
“[...] the models are data driven, so we need to feed the model with some sort of a historical data [...], we need to tell the system something about what happened before, it needs ‘experience’[...] in order to make decisions on designing supply chains [...]”

### 4.3.3 Historical Data Processing

Sub-theme number three deals with the processing of historical data and how it is included in forecasts or trends to support decision-making. The responses vary significantly depending on their work domain and what function data has to fulfil in the respondents’ organizations. Functions, application, and characteristics of historical data but also real-time data are discussed and presented in this section.

The VP of Global Data Operations of Company M considers historical data as important because it enables creating model in order to predict the future, validate it with historical data, and looking back and align the model with the actual results. In that sense, he refers to the term of ‘triangulation’ which underpins the importance not just for his organization as a mean of growth, but also for other organizations, who are not into predictive analytics. It can guide them in tailoring their business strategy how to succeed in the marketplace.

Beginning with the amount of data, which is generated along the supply chain, the BI Solutions Specialist of Company J describes examples of different algorithms dealing with the most efficient delivery route or providing a product recommendation. Further, he gives an example how trends extensively affect the manufacturing domain, more specifically manufacturing scheduling processes.

The Director of Architecture of Company A speaks generally about the operational domain, which is very data-intense and real-time demanding. He emphasizes the importance of the location of a shipment within retail. Furthermore, he deferred to the characteristics of real-time data, which he classifies as more ‘dashboardy’ reflecting the current status, whereas relational solutions or dashboards include historical data to drill around. He compares real-time to relational solutions by the fact that real-time is just about “slicing and dicing” without ‘drill ability’, because it is only about the company status.

The Strategic Account Manager of Company C lists characteristics of real-time data, since it is very distinct from other data types. He considers real-time data as “streaming”, which has been collected couple of “seconds” ago. This data is not “sitting” in a database for days, and is lost if not processed or stored immediately, according to him.

Similar characteristics Company H’s CEO shares his perception of real-time by referring business real-time to three groups, *inter alia* milliseconds, up to ten seconds, and up to fifteen minutes.

The Business Consultant of Company K sees companies using historical data for marginal looking, planning or forward-looking analytics. In his eyes historical data is a good start,
but needs be added by market trends, which also influences planning process to make it more intelligent. In that sense, historical data is always part of the forecast and final decision-making, however market data needs to be added, too.

A S&OP (Sales and Operations Planning) process perspective the Senior Manager Global Business Services of Company K provides in his description how current market data is used in this regard to quantify and derive the demand plan on a local level. For this demand plan, the S&OP representatives understand the customers’ needs in order to, finally, develop forecasts based on this market data. As basis for these forecasts, the biotechnology producer uses the most commercial data with the support of internal intelligence. To sum it up, he generates projections by looking at past/ historical forecast combined with current market data and the competitors’ market share.

The Consultant Manager Analytics of Company O shares another perspective of data processing in an organization. In his argument, leading and lagging indicators mirror the requirements of each business area, which he exemplifies by breaking down lagging indicators into components, such as the performance of the customer order team, a leading indicators has been established for each buyable purchasing unit. As result of data processing he advocates for visualization tools which provide decision-makers a clear and coherent idea and recommendations, but in the end, a person will interpret the numbers and make the decisions, he argues.

The Head of Application Board of Optilon explains how processing historical data is included when designing SCNs. Historical data together with a solid amount of customer and product data and the design of a SCN can be initiated.

### 4.4 Supply Chain Analytics Applications and Decisions

In order to have a clear understanding of how analytics are providing technological tools and comprehensive solutions across various industries, this section provides an overview based on the practical insights we obtained from the interviewees within the SCA sphere.

#### 4.4.1 In Operational Supply Chain Processes

This theme deals with application fields of analytics within operational process settings. Hereby, the responses provided by the interviewees vary by application areas, viewpoints of the supply chain, and data principles in an organization.

First practical examples given by the Supply Chain Manager of Deloitte dealing with predictive demand planning using Artificial Intelligence (AI). In this regard, Deloitte worked with companies, such as Tesco in the UK and H&M in Sweden, to implement analytics with AI technology to manage demand planning activities in order to maximize their sales revenue. In the example of Tesco, there is an ongoing analytics project to automate their stores and make them completely predictive and without human intervention. Further, he underlines the shift of companies being more aware of analytics with e.g. Tesco as first-mover.
In the field of procurement, Deloitte is running RFPs (Request for Proposal) with AI. Other processes such as source-to-pay, purchase-to-pay and order-to-cash are integrated, analyzed, and managed by analytical techniques.

The CEO and Co-Founder of Galileo Analytics shares also an inventory example, in which analytics is utilized to predict the quantity needed for raw materials based on real-time information from an end-to-end connected supply chain, which requires total supply chain visibility among all levels and supply chain partners.

In the eyes of the Advisory Industry Consultant of SAS Analytics, he had a rather different view on analytics applications in manufacturing companies. Predicting failures and monitoring ‘fault frequencies’ exposed invisible errors that might result in big problems. In this case, he advocates time series analysis to realize that there is actually a problem, which he exemplifies by showcasing the impact of production breakdowns:

“Let’s say we have 8% of our production processes are breaking down, it may take a while before it actually shows up in the top report or you can detect that shift with analytics by monitoring the trends automatically [...].”

Analytical solutions support exemplary Volvo Trucks and its subsidiary Mack Trucks, two of the business analytics software provider's clients, to reduce the unplanned downtime. Volvo is currently optimizing their downtimes by implementing remote diagnostic and preventative maintenance services based on Internet of Things (IoT) technology combined with analytics and AI. In the domain of retail, analytics is used for demand-driven planning and optimization activities according to the Advisory Industry Consultant.

The Director of Architecture of Company A provides a buying and merchandizing example. It showcases the usage of analytical techniques in determining the tradeoff between the demand of buyers and the cost of transportation companies.

A different viewpoint the BI Solutions Specialist of Company J reveals in considering operational processes spanned over the entire supply chain. Most basic areas, such as transportation performance or order fulfilment, are making use of analytics by “predicting the most cost-effective way to reach the customer.”

A principle perspective, the Consultant Manager Analytics of Company O discusses, since the use of data for operational purposes has to be communicated holistically throughout the organization.

### 4.4.2 In Supporting Strategic Supply Chain Decisions

The second sub-theme deals with the decision bases for strategic processes in an organization. Hereof, the interviewees’ responses vary in respect of their work domain, the industry, and the perception of important aspects for strategic decisions. Applications
fields, requirements as well as the effects of data analytics in regard of strategic decisions are provided in the following paragraphs.

The Business Advisory Consultant of SAS Analytics emphasizes the strategic importance of analytics if companies take data analytics seriously:

“[…] putting together an enterprise data strategy should be a fundamental responsibility of any organization that is serious about using data analytics to provide insights and direction […]”

If leveraged strategically, Supply Chain Analytics (SCA) can be immensely useful for developing long-term strategic plans such as market development, supplier’s expansion, and designing supply chain networks, he elaborates.

Stora Enso’s Supply Chain Manager mentions that they have been using SCA for almost two years now to enact their strategic five years long planning cycle for business growth and market expansion. SCA is also prescribing the demand supply balancing element of the S&OP (=Sales and Operations Planning) process. They call it decision support system. By using analytics, the role of the decision support system is allowing the senior management to look at the market through different lenses and see the impact of any of the scenarios occurring. Business Analytics tools are aiding the decision-making process by prescribing the decisions and tie it to potential solutions. In the following statement he underpins the importance of SCA in terms of strategic scenario planning, which enables to get an outlook for the market.

The CEO and Co-Founder of Galileo Analytics thoroughly explains how data analytics follows a strategic flow by identifying the primary customer of the product. It is often the case that they find themselves working with two or three levels below the strategy board level in a bottom-up approach, because data results are presented on different levels:

“[…] so, operational data is analyzed then the results are presented to the operations management. Henceforth, the results will move up to the tactical management team, and then ultimately reach out to the strategic board management level […]”

He further emphasizes that company has enough capacity before producing and launching the product. The strategic importance of analytics in forward-thinking and giving indications that everyone in the company can benefit of analytics and work on the “same level of granularity in decision-making processes” to incorporate forward-thinking and develop “forecasts and discover trends based on historical data.” However, for the long-term strategic decisions that are years in advance, there is still not enough data to enable the usage of analytics in day-to-day operations according to the CEO and Co-Founder.

Yet, one must understand the limitations of decision support systems, as they are based on models and historical data, while the real-life application is constantly changing. As the name suggests, these systems support decision making, they do not replace humans. Further, he examines that for making strategic decision a fundamental amount of data
needs to be in place. Additionally, he hints that there is a common misconception about what companies can do with Big Data through analytics. Even though a company might have roughly 20 years old sets of data, in most cases this data is no longer representative. Therefore, he pledges for a balance between enough data and representative data.

Deloitte’s Supply Chain Manager considers a functional ERP system as the most important base for strategic decisions. Besides the software area, the people (e.g. data scientists) working with it are “key CSFs” in order to adopt digital technologies into the supply chain as an example, he lists Walmart, which is going to implement a drone system in their warehouses in order to increase traceability and decrease risks as well as to decrease selling and administrative costs, which is part of their overall strategy.

In contrast, a comprehensive understanding of the process structures the person in charge need to have because at each manufacturing stage the particular product is associated to a lifetime risk assessment, according to the BI Solutions Specialist of Company J. From his viewpoint, all these stages within e.g. the manufacturing process are linked to certain data points, which in turn are evaluated to assess how effective the supply chain performance is going to be. That in mind, the demand of a particular product as well the design of it, play besides the knowledge about the process structure and the evaluated data points a vital role in making strategic decisions.

As one of the bases of strategic supply chain decisions the Senior Manager Global Business Services of Company N considers a constant and clear communication between senior leadership and commercial organization. If not, supply issues, such as over-, under- or not-supplying, develop, which in turn affect the customer side:

“[...] they're not synchronized in the way of working, then you potentially will be on the supply chain side, supplying ‘over-supplying’, ‘under supplying’, or ‘not-supplying’ at the optimum, whereas the commercial organization makes deals, that the supply chain will not be able to translate into tangible products or will not be able to serve them as a customer.”

The desirable close link of both the senior leadership and the commercial organization will not only positively influence the previously mentioned supply chain dynamics, it will also reduce financial risk, and in the worst case, save the potential loss of reputation “in case you are unable to meet the market demand.” In the same way, the Senior Manager demonstrates the importance of data for strategic supply chain decisions. In his eyes, companies need to look “at the same data, with the same understanding.”

The tons of datasets and KPIs he sees sometimes confusing for making supply chain strategy related decisions. Therefore, he pleads for the same understanding of KPIs and lead-time because it ensures meeting the demand and a common understanding.
Further, the Co-Founder and Head of Application Board of Optilon emphasizes the value of operational data as starting point for strategic directions, such as being cost-efficient as an organization or not.

4.5 Supply Chain Analytics in Designing Supply Chain Networks

Analytics is aiding the decision maker to plan, forecast and design Supply Chain Network (SCNs). The significance of analytics in not only designing but also redesigning SCNs as part of the following sections. Firstly, key elements of SCNs are introduced. Secondly and thirdly, virtual and physical designs of SCNs are discussed.

4.5.1 Key Elements for Designing Supply Chain Networks

This theme deals with key elements considered in the design of SCNs. Since establishing and coining extensive supply chain networks has lots of factors, the interviewees´ answers stagger according to their work area, business experience, and industry. In the following paragraphs, tools, technologies, datasets, capabilities, and the evolution of SCNs are exemplified.

From the perspective of the Supply Chain Manager of Deloitte, reports and simulations based on historical data are tooled to shape SCNs.

Smart algorithms in combination with Machine Learning (ML) and cloud computing are two key elements the Advisory Industry Consultant of SAS Analytics lists. Further, realizing that investing in big data sets can render valuable insights as well the common understanding of the value of communication supported by education, which is crucial within SCNs. The importance of analytics for an organization needs also to be understood by the top-level management, he advocates.

The CEO of Company H argues in favor of visibility throughout the supply chain. Questions like “where is something?” and “where is it going?” were raised by insurance companies in the past and benefit e.g. customer service and transportation. As an example, he also mentions spare parts visibility for manufacturing purposes, which involves all partners of the SCN.

After visibility, the BI Solutions Specialist Company J names planning and sourcing as other capabilities to shape SCNs. By referring to decision-making he argues that those areas are decided first, and that the SCN is planned on top of it. In his work space, planning is first priority, because if planned improperly, it will be challenging to change things at later stages. However, the risk exposed, such as lead-time delays, in such extensive SCNs plays a significant role. In this regard, quality assurance needs to be in place to secure the output. But the degree of exposure is depending on the product category and its value. By reflecting on the key capabilities, he warns against having a “loophole in the supply chain network.”
From the perspective of a distribution network, the Senior Manager Global Business Services of Company N makes clear that trends within an industry influence internal and external capabilities. In this regard, there are two options, firstly, contract manufacturing, or secondly, deciding to run it internally. Substantiating the influence of trends in supply chain network decisions, he exemplifies a decision that Company N had to make in order to be prepared for lower and higher demand in the same point in time in their distribution network. The solution was to produce per demand in the main manufacturing facility, and on demand in a supplementary smaller facility to exploit synergies of both demand characteristics.

Therefore, he underpins the mission and vision to always supply as one of the key aspects of acting in a SCN. Additionally, the most appropriate number of partnerships, where cost and historical data were decision indicators, he considers key in a SCN. However, he dissociates from the perception where cost is the most important criteria in respect of the Supply Chain Network Design (SCND):

“So, throughout the network design, we had scenarios where we looked at the lowest-cost-possible model, we had the optimum model, and then we had the best-in-class model, and then we ended up merging these three into a cocktail, [...]”

The Consultant Manager Analytics of Company O considers the organic and continuous development of SCNs besides money as key factors of SCND. From his experience, companies start establishing their network where the company was founded. The surrounding infrastructure, such as logistics hubs, are key and shape the SCN.

In the digital marketing sphere of Noroff University, the biggest aspect in terms of SCNs is having a “clear objective” and “hands-on” mentality to drive decisions in a business.

4.5.2 Digital Supply Chain Network Design

Digital Supply Chain Networks (SCN) are reluctantly mentioned but widely used, which the following section showcases.

When interviewing Deloitte’s Supply Chain Manager, a new innovative concept Deloitte predefined entitled ‘Digital Supply Chain’ is discussed. This new concept breaks down the silos between different departments within and in-between organizations in the supply chain, so they understand the different trade-offs, and consequently, benefit the whole Supply Chain Network (SCN). Deloitte is using both predictive and reactive analytics modellings in order to successfully implement this concept and design virtual SCNs.

Digitalization is a key driver the Supply Chain Manager of Stora Enso names. Analytics for decision-making and Artificial Intelligence (AI) for supply chain processes he lists as main elements.

The CEO of Company H also mentioned that their clients´ supply chains are becoming more digital and less physical. This digitalization phenomena of SCNs initially came from
the Japanese manufacturing industry due to their scarcity of money and space. It enables them to run supply chains with lot less capital binding and managing it in a whole different way. In this regard, the CEO of Company H recognizes a shift from a physical to a virtual SCN, which he explains as following:

“[…] is a digital representation of your supply chain. In theory, it’s unthinkable from an asset-based optimization view, but in practice, it is already happening.”

The researcher at Company L mentioned that the difficulty of designing a supply chain depends on the size of the network, some logistics companies have a limited number of hubs to route their packages, while others have millions of hubs and routes to choose from. Amazon is one example.

4.5.3 Physical Supply Chain Network Design

Network design projects are quite extensive and are always made on a strategic level. Analytics strategically contribute in identifying the number, location, size, and capacity of the facilities (e.g. warehouses, plants, distribution centers).

The CEO of Galileo Analytics emphasizes the strategic need for analytics in planning and designing SCNs highlighting the impact of the location of a facility and its strategic importance:

“[…] approximately, 80% of the cost of running a supply chain lies in the location of facilities and product flows between them. An analytical approach is therefore needed to strategically plan and design such extensive network.”

According to Company L’s researcher, there are major considerations to be reckoned with when assessing and designing SCNs. Firstly, the location of the facility is one of the major considerations to which accounts for almost one-third of the decision. Secondly, the depots in the countries surrounding the facility. Analytics can aid in providing sheer insights for conducting feasibility studies before deciding on designing potential SCNs and conducting cost-benefit analysis within five or ten years after making the decision of designing those substantial networks. Decisions cannot be made at the same time, rather they have to be made in a sequential manner, he elaborates. Hence, solving various problems, such as the location-, routing-, and inventory problem simultaneously by using analytics is still quite tricky and somewhat cumbersome, that’s why it is still undergoing extensive research.

The Co-Founder and Head of Application Board of Optilon piggybacks on optimization methods in advocating sensitivity analysis in order to diminish uncertainty:

“[…] sensitivity analysis of scenario handling or management is the way around the uncertainty in data that you don’t have today.”

Furthermore, he considers the division of risk critical to cost, which are both key factors in SCNs models. Budget and forecast as well as potential demand information about
products he underpins in his argumentation for optimization models. From a data point of view, some sort of basic data about the customers and products grounded in historical data is required for facing different kind of scenarios (e.g. uncertain/ new transportation lines due to a change). The quality of data used for modeling is crucial because errors will cause a wrong model. However, baseline or ‘as is’ models do not need to be perfectly aligned with reality, rather a quite near picture is sufficient. Additionally, models are often depending on the time-horizon, especially important when running greenfield analysis, but also existent agreements may hinder changes in the SCN.

Further, Company N’s Senior Manager stated that ‘clean’ master data is a prerequisite for the success of analytical processes and their results in designing SCNs. Reliability of data is another element highlighted by the Senior Manager by arguing also for its significance for swinging between the management levels:

“[…] all sub-functions of the supply chain we would be looking at, to a great extent, reliable data and then we would make decisions together on how we move forward, be very vertical, or even in certain instances strategical.”

4.6 Emerging Datasets on Operational and Strategic Levels

Supply Chain Analytics (SCA) is heavily relying on high quality operational datasets and its context to market data as Deloitte’s Supply Chain Manager mentions.

According to the CEO of Galileo Analytics, analytics is using both top-down and bottom-up approaches. Bottom-up when one gathers all the information from operational level and pushes it up. Within the top-down approach, decision-makers base their decisions on information won from those operational levels and push the resulting decisions back to the bottom:

“[…] top-down based on the bottoms of information, the ‘decision maker power’. They decide based on the information that is coming bottom-up, so they agree on that information, and then push it down into the operations organizer.”

The Business Analytics Consultant of Company K divided datasets according to their source. That are internal datasets created within the organization and external datasets stemming from benchmarking from another organization and market research. The latter tends to be more forward-looking and is characterized as deep and broad. In addition, he further indicates data characteristics in general, which is associated with the quality of the data and its granularity as metrics for the performance of analytics:

“[…] it’s more about the quality of the data and if it’s granular or not. The depth of the data will make the analytics works properly, but it’s not always good.”

According to Company N, it remains a tricky question to see which datasets might be more impactful than others as analytics can help to populate for strategic decision-
making. Examples are given such as ‘Continuous Analysis’ of KPIs, metrics, operational cost efficiency, which are mostly used to roll out for strategic decision making.

Historical datasets are sometimes more important and used for both predictive and prescriptive analytics. These datasets are becoming more broken according to Company H’s CEO, who alluded that quality and timeliness is becoming evidently problematic in a data-driven world. The quality of the data itself is more important than the dataset type, which is often underestimated. Datasets that are available, accurate, and consumable are more important than any other datasets. Big datasets can be quite informative, but it is not always the case that it has to be your own dataset. Considering the Amazon example, analyzing huge amounts simultaneously to understand customers’ behaviors is highly important in online retailing.

Another rather intriguing point made by Company M’s CEO, who claims that there is no single dataset that is more important than the others in order to analytics functions properly. Without descriptive analytics, prescriptive analytics would not be possible, despite everything the focus is on prescriptive analytics, because from that type actionable insights can be won.

BI Solution Specialist of Company J gives another perspective stating that it is not possible to classify datasets to be more useful or not for analytics, rather than they are collectively and mutually important.

“[…] once you have the history of that descriptive one, then only you can decide to predict the further ones, and then go forward with the prescriptive ones.”

### 4.7 Supply Chain Analytics Value in Organizations

Supply Chain Analytics (SCA) is shaping up the future of nowadays supply chains by enabling decision-makers to make data-driven decisions. SCA is helping companies to get more granular view over their supply chains. The following two sub-themes further highlight our findings in terms of the future of supply chains and the organizational perception of analytics.

#### 4.7.1 Analytics and the Future of Supply Chains

In this sub-theme respondents share various tools enabling them driving future supply chains in a more efficient and streamlined way. Data analytics and its strategic value also support the future orientation of supply chains.

Analytics, along with some artificial intelligence (AI) technologies, most notably Blockchain, RPA (Robotic Process Automation), and Machine Learning (ML) are disrupting the IT business marketplace nowadays and re-shaping the future of today’s supply chains, according to SAS Analytics’ Business Advisory Consultant. He believes in the opportunities that analytics can convert “sub-optimal supply chain processes to optimal ones” under the prerequisite to leverage on analytics strategically.
The COO of Company I also support the view that analytics is being strategically leveraged by many companies to establish new facilities in their Supply Chain Networks. However, some of the companies still base their decisions on historical data, which can be critical, he argues. As an example, the COO claims Zalando and Amazon as companies that screen their data with the ‘analytical lens’ to conclude whether a new warehouse needs to be built, or an existing network needs to be utilized.

Besides ML and AI, a bigger role is also being played by Internet of Things (IoT) according to the BI Solution Integrator of Company J in terms of making supply chain more efficient and less dependent on external factors or human errors.

### 4.7.2 Perception of Analytics in Organizations

Despite the increasing popularity of analytics among many companies worldwide, there is still a great deal of companies who tend to be skeptical and hesitant to invest in such advanced technologies. Throughout the interviews, we noticed that some of the respondents have reported diverse reasons behind this tendency and why analytics is not fully adopted yet by most companies to effectively manage their supply chains.

The CEO and Co-Founder of Galileo Analytics clarifies the interlink between analytics and human skills by fundamentally sharing:

“[…] the question of “what is the question?” is always going to be predominantly human. Yes, analytics can help us to identify the specifics of the question, but the concept of the question is something that I think is still going to be human even after we’ve got some advanced analytics and AI capabilities […]”

In general, one of the questions, which is frequently asked, and its reason for asking it, the CEO highlights:

“[…] how good are the data? There’s a tendency to accept data even if it has some flaws.”

Generally, analytical thinking in many cases is way more important and critical to avoid making incorrect conclusions from what are extremely good datasets when using analytics in decision-making processes.

The Business Advisory Consultant of SAS Analytics stresses upon identifying the primary goal of using analytics from the get-go. According to him, the company that is interested in vesting analytics into its business, it should try to identify what does the company really try to achieve in the first place and then see how analytics can support them achieving these goals effectively. Besides, companies also need to understand certain analytical concepts in order to make the most out of analytics, such as “what is time series analysis?”, “what is A/B testing?”, “what is the predictive model?”, or “what is the neural network?”. According to him, the challenge should not be to understand them.
According to the Business Advisory Consultant of SAS Analytics, there is a desperate need to pitch to the senior management in order to get them engaged, and involved from the get-go, because having a clear vision about the company’s objectives is essential to align analytics to them.

There is a general misconception from customers who thinks that by using BDA, they can extract as much valuable data as possible, while it is the other way around. Clients need to define themselves their own goals and objectives or what they want to do or change and then see how analytics can help them achieve that.

Company I’s COO states that sometimes organizations hesitate to adopt analytics in fear of losing or changing some human jobs. Furthermore, in order to sell analytics solutions in the market, the COO suggests adopting it internally first, which is “slowly already happening.”

According to the Business Consultant of Company K, many companies previously used manual tools to analyze their data such as Microsoft Excel. However nowadays, they start to understand the importance of analytics to leverage on the Big Data they have in order to get a little bit deeper into the parameters underlying those big datasets. He further shares his insights on how analytics is shifting the job market by either hiring data scientists or re-skilling the company’s employees.

4.7.3 Data vs Human Instinct

When it comes to analyzing Big Data, the amount of information can rather be overwhelming to the human mind. The respondents share their inputs on where does the human gut feeling (or instinct) fit amidst this massive clusters of data.

Deloitte’s Supply Chain Manager favors human instinct over data analytics:

“[…] If a person has a good track record, say 10-20 years of experience, then most likely gut-feeling overrules the concert data from analytics.”

While the Supply Chain Manager of Stora Enso thinks that big data drives most of the decisions nowadays with little reliance on one’s own instinct.

The CEO and Co-Founder of Galileo Analytics has a more profound view on balancing the data and one’s own instinct because data’s strategic implications are increasing. Furthermore, the foundation of qualitative models will be increasing, data is constantly being generated:

“[…] nowadays companies started to realize the strategic implications of business analytics. So, if they have a large-scale database, it will be ideal to collect really good samples of data in order to build good quality models. Data is and will continue driving the decisions on both micro and macro strategic levels.”
The Advisory Industry Consultant of SAS Analytics has an interesting point on this tricky balance as he indicates that the human mind is extremely weak when it comes to comprehending big data sets, machines are better at those tasks. Further he doubts the human intuition on making rational decisions:

“Opinions based on facts are the most reliable ones. There’s still a lot of intuition, we tend to overestimate the human’s capability to make rational decisions.”

The CEO of Company H shares almost an identical viewpoint by correlating instincts with historical data, and doubting humans’ gut feeling:

“[…] instincts are based on historical data. I think that’s the biggest or one of the biggest weaknesses we have as humans, it’s our gut feeling. It’s not always good, it’s not the best thing to rely on […]”

The Business Consultant of Company K has a slightly different answer. According to him data is still not fully reliable yet, so the human gut feeling will overrule in many cases. Certain skills which machines not have, or data volume they cannot process, the Business Consultant substantiates in his statements against data a single decision-making source.

4.8 Data-Driven Technologies in Supply Chains

The type, number, and volume of the data generated by supply chains is tremendously huge and unstructured. By integrating and automating these massive amounts of data from various sources across the supply chain, it leads to a much leaner productivity and higher operational efficiency, which is discussed in this theme.

Deloitte’s Supply Chain Manager confirms that analytics provide insights on new patterns or trends emerging from the customer's big datasets,

“[…] when analyzing the client’s huge data sets, analytics are spotting some business trends, though not always new ones. They might be already existing there without the company being aware of them, and then analytics exposed them to the naked eye.”

He also highlights ‘servitization’, which involves firms (often manufacturing firms) developing the capabilities they need to provide services and solutions that supplement their traditional product offerings by using analytics through different models:

“[…] servitization change your business model fundamentally, to come up with a parallel business model. ‘Commoditization’ of data and ‘servitization’ are currently driven by different technologies available in the market that are enabling companies to look at their own business and come up with different models.”

However, not every company that claims to be data-driven necessarily means that they are using analytics in their business model. In order for a company to be truly data-driven, it has to use results from analytics for making major decisions, as the COO of Company I shares:
“[...] at the end of the day, a human is sitting there making all the decisions and decide what numbers and data to look at and what to trust and what not to trust.”

The idea of an ‘autonomous supply chain’ is brought up by the CEO of Company H as it is recently launched to autonomize parts of the supply chain. This novel idea is implemented because planning and optimization is something computers are much better at. He emphasizes its importance by sharing:

“[...] if you're not automating and optimizing your supply chain, you are not playing tomorrow.”

The idea of the ‘customer journey’, more specifically data-driven decisions resulting in demand generation, is introduced by the BI Solutions Specialist of Company J. He further elaborates that:

“[...] if you are able to emulate the customer demand based on the data driven decisions, it will impact your whole supply chain networks furthermore [...]”
5 Analysis

Chapter 5 presents the interpreted analysis of the collected empirical data for this study. The identified themes and sub-themes shown in this chapter are based on 16 interview responses. At the end of this chapter an updated research model is shown.

The interviews within this study have revealed various patterns and similarities but also opposing answers. Those answers and insights were merged and classified into three themes with respect to the research questions, namely 5.1 Analytics Connotations and its Implications on Supply Chain Management, 5.2 Supply Chain Analytics in operational and strategic levels, and 5.3 Supply Chain Analytics in designing Supply Chain Networks. The subsequent sub-sections combine 4 Empirical Findings with the findings from the 2 Theoretical Frame of Reference.

One important note: During the data collection process, the term Supply Chain Analytics (SCA) was poorly perceived in practice, therefore we stuck to the more general term of Business Analytics (BA) within the context of Supply Chain Management (SCM).

5.1 Analytics Connotations and its Implications on Supply Chain Management

This theme deals with the different concepts and connotations that analytics entails in both the literature and among practitioners. It also discusses the various implications that analytics has on Logistics and Supply Chain Management (LSCM) strategy and operations and how the quality of the data in use for analytics is deemed to be crucial for an optimal analytical performance.

5.1.1 Business Intelligence and Business Analytics

The definitions of both Business Intelligence (BI) and Business Analytics (BA) were further discussed and invoked with the interviewees who had disparate views on their perceptions of these two terms. The empirical findings distinguish between both definitions in practice and in terms of their applicability. For instance, many respondents stated that BI is more of a forward-looking technique, while BA is backward-looking dealing more with historical data, figures and trends that happened in the past. Further, most of the interviewees stated that BI incorporates smart technical solutions which entails BA. In theory, the latter is seen as not a technology, but rather a group of approaches, organizational procedures and tools (Barbosa et al., 2017; Gorman & Klimberg, 2014). Nevertheless, other respondents disconfirmed the literature findings in terms of distinguishing between BI and BA. For instance, respondents like Galileo Analytics and Company H argued that both terms go hand in hand and there is not a specific line of difference between them in practice, rather it is more about the perception,
while Company O stated that it is just a matter of semantics and jargons depending on the usage of each industry.

Among all the different types of BA, we found that Supply Chain Analytics (SCA) in particular, is being widely used by practitioners to primarily evaluate, plan, and optimize the whole value chain of their organizations starting from strategic sourcing and manufacturing all the way down to inventory management, distribution, and logistics, which goes hand in hand with the theoretical findings. These findings see potentials in improving visibility, flexibility, and integration throughout supply chain processes to counter volatility and fluctuations (Wang et al., 2016).

The majority of the respondents had a consensus about the main purpose of using SCA nowadays, which is to improve efficiency for various operational processes by enabling data-driven decisions to be taken at both strategic (long-term) and operational (short-term) levels. The application fields of SCA turned out to be quite far-reaching and span over many supply chain related areas. For instance, predictive demand planning, order fulfillment, market development, supplier’s expansion and designing supply chain networks are few given examples that are leveraging on SCA in application fields.

### 5.1.2 Analytics Types

The analytics main types, namely descriptive, predictive, and prescriptive, are delimited in theory (Arya et al., 2017). For instance, prescriptive analytics is theoretically considered as advanced methods to assess prospective alternate decisions (Souza, 2014), whereas in practice it is mainly about “what will happen?” and “what actions to take?”. Further, the literature distinguishes and separates between the three types of analytics (Hazen et al., 2018), and exposes their sole and autonomous benefits respectively for each analytics type in various supply chain relevant applications, whereas practitioners see that there are some clear overlaps or interdependency between the analytics types with each other. The interviewees demonstrated extensively the importance of all three main types of analytics and its benefits by considering all types interchangeably when applying them in practice. In fact, by reviewing some of the interviewees’ analytical solutions, there is no real separation of the analytics types, except from predictive solutions. One type cannot fully operate solely on its own and function standalone. This finding contradicts with the classical theoretical classification of analytics in the existing literature. In theory, analytics is separated and classified merely based on their types, purpose and what key questions analytics can answer. Further, a differentiation of application fields between different management levels is also described in theory (Souza, 2014). However, in practice, they are serving the same objective and are interlinked in many functional and application areas. For instance, Company A and K relate techniques like BI and Data Mining for identifying correlated data to descriptive analytics, while Deloitte and SAS Analytics relate demands, trends, and forecasts to predictive analytics, which provides answers to questions that cannot be answered by BI, such as “what will happen next?”
and “what if the existing trends continue?” Optilon on the other hand, linked both simulation and optimization techniques to prescriptive analytics.

5.1.3 Predictive, Prescriptive, and Descriptive Analytics

With respect to predictive and prescriptive analytics, many respondents shared a similar understanding and perception of these types of analytics. However, some did not view them differently and dubbed them as buzzwords. For predictive analytics, they described it as ‘semi-automated’ since human intervention is still required to predict actions of unexpected outcomes and potential trends about what is going to happen such as prognosis and budgets, while prescriptive analytics strives to describe the reason and answer questions of “why it is actually happening?” or “what if ...?”. According to the views of many respondents, prescriptive analytics is still a rather new idea dealing with automated processes where decision-making can be based on analytics.

When it comes to descriptive analytics in particular, some of the respondents had different perceptions on historical data and how it relates to descriptive analytics. The empirical findings show that questions like “what happened?” or “why did it happened?” are found to be directly answered by descriptive analytics not just in theory (Hans & Mnkandla, 2017; Arya et al., 2017), but also in practice as well. However, the application fields of descriptive analytics vary immensely among practitioners and are not necessarily used to fulfill the same purpose as the existing literature states that it is merely an analytical technique that provides information about “what happens?” based on the knowledge of previous events (Irzavika & Supangkat, 2018). For instance, some respondents are using descriptive analytics in their production and manufacturing processes to pace up the production time and predict production downtimes. Others are using descriptive analytics as customer optimization technique to distinguish high and low profitable customers. It is also being used for managing inventory stock for many organizations according to the empirical findings.

5.1.4 Datasets and Data Quality

The historical data sets are deemed to be quite important for many of the respondents to enable both predictive and prescriptive analytics to function properly. For instance, we found that when companies create a predictive model, they opt to validate their model by using historical data and see if the model performance aligns with the actual results. Furthermore, the majority of interview cases, historical data found to be essential for providing a baseline to build up both predictive and prescriptive modeling for the future. In particular, when designing Supply Chain Networks (SCNs), the respondents explained how prescriptive analytics is largely used to optimize SCNs based on visualizing historical data by use of descriptive analytics. Generally, for optimization models big datasets are essential (Sadie et al., 2018), which are often provided by historical datasets depending on the purpose. Hereby, descriptive analytics appeared to serve as a baseline when designing SCNs from scratch. Respondents like Optilon, Stora Enso, and Company
N, explicitly explained how they usually start with processing historical data sets by means of descriptive analytics and then depending on how much data organizations have, they move forward to the other analytics types, namely predictive and prescriptive. Therefore, there is a strong need to descriptive analytics as a base, otherwise performing predictive and prescriptive analytics is going to be sub-optimal even if the company’s sheer focus is merely on prescriptive analytics to get the actionable insights from it. The empirical findings show that there is an interdependency between all three types of analytics starting from descriptive analytics as a baseline and integral part of the analytical process, whereas authors separate them as autonomous terms (Hans & Mnkandla, 2017; Souza, 2014; Arya et al., 2017).

Data quality is not thoroughly mentioned in theory, while researching and reviewing the existing literature about analytics. Accurate and valuable information increases the importance of strategic decision-making practices (Raisinghani & Meade, 2005). However, supply chain managers need to have the correct understanding of the data they are dealing with (Waller & Fawcett, 2013), which was not debated among the interviewees, rather, several respondents demonstrated the critical importance of data quality for further and reliable analytical processing and mentioned that the quality of the data itself is more important than the data type, which is often underestimated. Having complete and clean data is key when working with data-driven technologies such as analytics.

5.1.5 Summary and Interpretation

In a nutshell, this theme provides an overview on how different types of analytics have different connotations based on the industry they serve in and the professional user’s own perception in their work-contexts. Moreover, the different analytics types are found to be separated in theory, however interlinked in practice. The descriptive analytics serves as a fundamental baseline to establish and facilitate the subsequent analytical performance of predictive and prescriptive analytics in order to provide a holistic, fully-integrated analytical solution. Further, the implications of analytics are found to be far-reaching and spanning over many industries nowadays. Analytics is mainly adopted by big companies who have the required financial and human resources to adopt and integrate it into their business models.

After thoroughly synthesizing the empirical findings, we found that professional users start analyzing and crunching their historical data sets by means of descriptive analytics before moving onwards for further analysis with predictive and prescriptive analytics. Therefore, descriptive analytics indirectly establishes the companies’ strategic supply chain decisions by providing a thorough analytical picture based on the past and current business events, which in turn, is complementing and enabling effective strategic decision-making processes. Consequently, descriptive analytics provides an analytical baseline and holistic overview on how previous situations have been handled, how they may correlate to other situations, and by learning and having this historical analytical
picture in mind, how one can leverage of this picture to predict futuristic trends and demand patterns to further optimize the entire supply chain.

While many of the respondents argued that their companies managed to effectively run their businesses relying on descriptive analytics and having a high-quality data to make their strategic decisions, they also pinpointed on intangible factors for a successful implementation of analytics, namely the gut feeling. Deloitte, for instance, believes that having a good professional track record of ca 10-20 years will most likely lead professional users to rely on their own gut feeling or instinct. Conversely, other respondents (Company H, SAS Analytics, Company K) argued that strategic decisions are becoming more data-driven nowadays with human instinct integrated to make the best final decision as instincts are based on acquired historical data, which cannot necessarily guarantee a plausible decision-making process. The question of whether to fully trust the results derived from analytics or rely more on one’s own instincts remains indecisive and up for discussion, since analytics is still developing and there are a lot of scholars’ and practitioners’ high-fly utterance surrounding it that needs to be further researched and investigated.

5.2 Supply Chain Analytics in Operational and Strategic Levels

This theme deals with the application of Supply Chain Analytics (SCA) in organizations on both operational and strategic levels. This involves profound and reliable information and clear structure in order to affect both levels at best.

5.2.1 Operational and Strategic Levels

Applications areas of analytics range within several business areas, which was widely argued among the respondents. Inventory management, order fulfilment, demand planning, among others, are allocated to the operational level, whereas procurement and the Sales & Operations (S&OP) process related to the strategic decision level. This separation of operational and strategic levels besides similar application areas is also factored in theory (Wang et al., 2016).

In operational settings, the respondents emphasized how data-intense and real-time demanding the operational supply chain domain is. It stems from partially, end-to-end connected supply chains and the resulting emergence of big datasets. In this regard, data quality is of a significant importance, since it raises questions like “how good is the data?” or “is the data that we’re seeing reliable?”. Referring to the 3Vs, the ‘velocity’ dimension of data comes into play, since the more time passes by, the more obsolete the data gets (Hofmann & Rutschmann, 2018), which hints to the need for real-time data processing. In that matter, the consideration of real-time data was often discussed and differently defined, however it was referred to “streaming” or “seconds” old data, which is instantly processed. Predicting the most cost-effective solutions for companies many respondents highlighted regarding analytics applications.
In most of the responses, the value that historical data can bring was assessed as good basis, but not enough for strategic initiatives. This was reasoned by the circumstance that data might not be representative anymore or the data available is too little to substantiate decisions specified by the academic respondents (Noroff, Company L). Advanced analytics is not just about the right kind of data, since it is about analytical tools targeting business outcomes (Waller & Fawcett, 2013). However, in practice, several solutions of the respondents offer predictive analytics functionalities, which are exploiting historical demand datasets for predicting future customer demands (SAS Analytics, Company N). This mirrors the strong trend of demand-driven supply chains, where demand variability and cost are factors to overcome (Wang et al., 2018).

Shifting into the strategic space, most current and future market data needs also to be involved. Strategic long-term plans aiming for business growth, market expansion, or the Supply Chain Network Design (SCND) are examples where analytical techniques are used to gain from big datasets. However, as it was predominantly stated among the respondents, datasets from operations deliver the basis for upper management decision-making. Operational data is originated from BI tools, which capture the day-to-day decisions, whereas BA is used for strategic or more integral considerations. According to the literature, BA is analyzing big datasets applying tools (Lai et al., 2018), which make use of Big Data Analytics (BDA) in order to integrate all sources of information, internal as well as external ones (Kache & Seuring, 2017).

### 5.2.2 Linkage of Both Operational and Strategic Levels

Although the application areas are separate to certain extent, the datasets and the impact on each other are strongly related to both levels. Technologies, such as Blockchain, IoT, AI, and dashboards realize visibility, automatization, and more efficient processes along the supply chain. The literature extends those benefits by demand patterns, cost trends and fluctuations, and end-to-end demand visibility (Pereira et al., 2018). A lean-thinking approach, which results in overall resource efficiency across all business areas in companies and adopting a mindset for ‘digitalization’ contribute from a human-thinking perspective, to a streamlined supply chain. In this regard, hidden knowledge and business process optimization initiatives emerge also from BDA and data mining techniques (Zhang et al., 2017), and strengthen the coherent link of technologies and human interventions.

In principle, two respondents (SAS Analytics, Galileo Analytics) introduced their practical approaches for applying SCA in their organizations, namely bottom-up and top-down. Within the former, the professional user supported by analytical tools is making use of data originated from operational levels, which is then retrieved, allocated, and assessed on strategic level by top-managers. After checking the disseminated information for validity and accuracy (data quality), applying the top-down approach pushes the datasets back to the operational levels, where further analytical processing is continued.
Generally, in practice, critical success factors when using analytics in a strategic manner, are

- clear and continuous communication between top management and lower management levels, and
- the same understanding/ consideration of data and its derived Key Performance Indicators (KPI) on the lead-time of a product.

The importance of analytics in influencing strategic decisions was exemplified by practitioners in enabling companies to think proactively in order to discover trends and forecast demands. Furthermore, it aids organizations in creating certain scenarios and finally, evaluate the impact of those scenarios on the organization. Similar needs are also raised in academia where the ‘dynamic capabilities’ approach enables companies to react to external changes (Teece et al., 1997), and combining both analytical and simulation modeling (Tunali et al., 2011). However, the application of analytics implies having a profound and holistic process understanding of the focal company and its partners as well as about the data streams and its correlated KPIs.

5.2.3 Summary and Interpretation

By interpreting the practical insights together with theory, the separation of operational and strategic levels is important for dividing responsibilities and share work between the levels. Nevertheless, successful application using analytics in operational business areas has effects on the strategic level, since the operational benefits can be seen as for strategic ones, too. The benefits of those effects are rooted in the interlinked approaches, namely bottom-up and top-down, which intensify their interdependency and value not only for supply chains but also for the organizational structures. Most often, similar settings are in place in organizations, which ease the use of analytics to some extent.

Analytical techniques provide the tools for gaining insights from big datasets generated along the supply chain, which human-beings make use of for business decisions regardless of the management level. This involves using all data sources available to have a more sophisticated and information-rich picture, which will highly contribute to decision-making process for strategic matters. Therefore, the conducted research proposes an interchangeable link of both management levels (strategic and operational) to benefit from each other. In complex and nested supply chains this linkage is inevitable, since data is generated at every single step and thus, plays a crucial role. The data needs to be processed instantly, which creates considerable challenges for companies in terms of reliability and up-to-dateness. In this regard, as several respondents highlighted, the data quality needs to be ensured, since only valid and true data can drive high level and forward-looking decisions.

The vast amount of technologies surrounding analytical techniques adds value to the insights that analytics provides. A shared technology ecosystem, which is characterized by core components that are provided by a platform owner and complemented by other
technology products from other companies (Wareham, Fox & Cano Giner, 2014), is recommendable to make use of synergies of data-driven technologies and its interconnectivity. If analytics used standalone, overall communication and a shared and jointly agreed view on data and its performance indicators as well as on the processes involved needs to be considered. Making sophisticated decisions requires the involvement of all stakeholders as it is well-known from project management practice. Undoubtedly, the value of correct and trustable data is significant to enable companies to rely on their internal or external data, to shape their supply chains in the most desired and profitable way. However, especially external data has to fulfil certain criteria in order to make the most out of it. This prerequisite companies need to involve in their analytics approach used, since data quality is one of the key pillars of analytics within the supply chain domain.

5.3 Supply Chain Analytics in Designing Supply Chain Networks
Dealing within the scope of Supply Chain Network Design (SCND), Supply Chain Analytics (SCA) plays a key role in providing rich and derivable data to shape a Supply Chain Network’s (SCN) design in the desired way.

While the literature substantiates the Supply Chain Network Design (SCND) using one single perspective, the physical one (Song & Sun, 2017; Santoso et al., 2005), in practice SCND can be classified into twofold according to several respondents (Company B, L, H). Firstly, the digital presentation of a SCN, which encompasses a digital copy of a physical SCN. Through real-time communication and the use of predictive and reactive analytics modeling techniques as well as AI, supply chain processes become more streamlined and efficient. Digitalization-thinking and trend towards a fully digital representation of a SCN are present drivers. However, global e-retailers struggle with the product variety and the number of product categories they offer to the market. Additionally, the target market influences cost while utilizing agile or lean/ agile supply chain strategies (Qi et al., 2009). This has unpleasant effects on e.g. the choice of transportation modes, which leads to the second classification of SCNs found in the literature, the physical one.

5.3.1 Critical Success Factors
Critical success factors influencing physical SCNs consist of the facility location and their surrounding depots, clean master data, and overall reliable data generated by all kind of business functions. The success of the SCND is also significantly dependent on visibility among the involved supply chain partners, planning and sourcing decisions for strategic orientation, and the constant support and involvement of the top-level management among the partnered organizations. In addition, collaborative strategies with suppliers are considered as profitable for both (Blackman et al., 2013). More decision relevant success indicators involve

- the efficient use of historical data,
• the costs perspective,
• a prevalent and organization widely maintained mission and vision,
• the most appropriate number of partnerships, and finally,
• decisions made in a sequential manner,

since those decisions are significant in many dimensions. These metrics were fairly shared among the respondents (Company F, H, J, L), except from one, who exemplified the process of greenfield analysis. Data quality, existent historical data about customers and products, the critical relation of supplier risks and cost, and the budget and forecasts he underpins as key success factors when designing SCNs. Further empirical data did not include technical tools embedding previously listed factors. Potential methods to provide deeper information are, for instance, a software tool using a mixed-integer linear programming (MILP) model, which provides various scenarios regarding possible network configurations based on historical datasets (Sadic et al., 2018), or mathematical model-based analyses in order to decide on single or multiple manufacturing locations and the connected hubs (Business Optimization Lab, 2010). Dividing a problem into several sub-problems and solving them, consequently, helps to identify the optimal supply chain configuration and to expose the strategic trade-off between the number of partners and their reliability (Wu & Barnes, 2018).

While the literature pledges for the match of business strategy and supply chain strategy even if it is not entirely carried out through the supply chain domain (Mckone-Sweet & Lee, 2009; Harrison & New, 2002), one scholar emphasizes primarily a clear objective where the supply chain is heading to, and its steady communication within the organization when deciding on the design of those extensive networks. Investments in big datasets and education about how to render valuable insights from those data, emphasizes the value of analytics among industry experts. Others direct their argumentation towards clear goals and a supply chain´s distinctive structure to achieve the most successful supply chain strategy (Golicic & Sebastiao, 2011). Hereby, analytics initiators use reports and simulations based historical data and smart algorithms and its complementing technologies, such as ML and cloud computing, to shape SCNs across various management tiers in organizations. Exemplarily in the literature, a hybrid approach combined analytical and simulation modeling to decrease uncertainty factors (Tunali et al., 2011). By using an analytic network process (ANP) the performance of each tier and the engaged partnership can be assessed, and the optimal production/distribution quantity derived (Che et al., 2012).

5.3.2 Benefits and Challenges
Benefits of using analytics in the context of designing SCNs include massive cost reductions through optimization and efficiency in SCNs, and sheer insights through feasibility studies to reveal potentials and threats to then conclude with a cost/benefit analysis. This analysis has strategic value and contributes to a positive bottom-line (Jin
& Kim, 2018). An eventual challenge in extensive supply chains, which needs also to be considered when designing them, is the associated risk with the lead-time and quality assurance. Depending on the product’s value and its category, a loophole could cause substantial business losses. Goal programming techniques enable to facilitate the decision dealing with the decision-maker’s preferences about particular facilities and transportation links and the associated costs (Rienkhemaniyom & Ravindran, 2014), and how to work against these risks. In order to counter the general uncertainty and the risks at many data points of the supply chain, scenario planning tools in combination with sensitivity analysis methods are realized to counter them.

Nevertheless, industry and market trends are reflected in the SCND and making companies gearing up for uncertain and volatile demands by combining internal resources and capabilities with external ones. The literature points towards solutions using quantitative or mathematical modeling approaches for such large-scale problems (Hofmann & Rutschmann, 2018; Shi & Ölafsson, 2009). Exemplarily, a predictive and adaptive management approach combines huge demand forecast datasets with Machine Learning (ML), and draws conclusions on material, financial, and information flows for satisfying customer needs (Pereira et al., 2018).

Others change the viewing angle from considering historical data to a forward-looking approach using analytics to, for instance, deciding where to build warehouses in order to meet the demand. Through an ‘autonomous’ supply chain, which works fully automated using a mixture of intelligent technologies, human errors can be diminished, and planning and optimization improvements achieved. The extracted knowledge by exploiting analytical techniques is utilized to create optimization models (Sadick et al., 2018). However, only particular parts of the supply chain are currently making use of analytical techniques according to a few industry experts. Human errors can also be reduced by using decision tools, which avoid ‘spreadsheet’ activities, and which are framed in an optimization model (Liao et al., 2017).

5.3.3 Summary and Interpretation

Interpreting the practical insights along with academic literature, the existence of the digital representation of a physical SCN is as important as the actual/physical supply chain. New technologies and new thinking approaches capture the threats, such as the multitudinous of products and variety, and promote supply chains with more transparency and visibility among the partners involved. Referring to the physical SCND, many mathematical methods have been developed with example cases in the literature. However, in practice, the industry experts reported only superficially by neglecting technological or mathematical techniques, rather mentioning thoughtful aspects from their business practices. Acknowledging that, SCND decisions are perceived as high-level decisions, and originate from changes in the external environment of organizations. By monitoring the market, small shifts can instantly process in the SCN configuration and benefit organizations.
The mentioned key success factors span over many dimensions and touch upon adjacent domains such as procurement. This implies that versatile information and skills need to be present in order to make use of existent mathematical models and simulations to overcome the SCN’s constraints. Advanced analytics and its multifaceted data capabilities serve as facilitator for the optimal SCND, which can be proved by its many benefits regardless the business area. The value of data and its various origins is of high importance when providing models or simulations of numerous settings of future SCNs. Therefore, the strategic and operational tiers of a company are united and represent an intertwining body to reveal all potentials of analytics for sophisticated SCND decisions. Their reciprocal dependence can also be complemented by analytics since it derives actionable insights for businesses, and respects rethinking initiatives of data in organizations. In this regard, SCA needs to be more accepted in organizations, and investments in data science are seen as a consequence. The SCND will not stop reshaping and responding towards an ever-changing market, which makes SCA indispensable for all sizes of organizations.

An important note, which was also several times mentioned among the respondents, was the alignment of supply chain strategy and its analytical capabilities with the overall business strategy of the organization. This leads to a general top-down approach because strategic decisions are made by top-level managers. SCA in this regard, is mainly used at middle or lower management segments, which contradicts with upper management levels’ SCND decisions taken because both initiatives ground on different authority levels. A significant move towards data-driven technologies and SCA competencies positioned at the top management level, which favors managerial structure, but would lose the link to operational data sources.

5.4 Updated Research Model

Figure 5-1 illustrates the updated research model after analyzing the literature and empirical findings. The analysis has shown that a segregation of the different analytics types cannot be confirmed in practice, rather there is an interchangeable dependency on each other even though their terminologies are not consistent between theory and practice. Supply Chain Analytics (SCA) extracts knowledge and actionable insights from Big Data in order to deliver rich and reliable information to both strategic and operational levels favoring business decision support processes. Hereby, operational and strategic management levels merge together, and exchange granular information which is enriched between both levels. The interconnectivity of both levels increases also the value of SCA and its opportunities when applying them in Supply Chain Management (SCM). In this regard, hybrid approaches are predominately used, which include both top-down and bottom-up. This hybrid approach benefits not only the overall information content spanned throughout the management levels in an organization but also decisions regarding the Supply Chain Network Design (SCND). Hereby, SCA contributes to the
most efficient and profitable SCND through optimal and profound decision-making bases stemming from Big Data and the applied analytics techniques on top of it.

Figure 5-1: Updated research model
6 Conclusion

This chapter presents the conclusion of this study by summing up both the findings and the analysis. By doing so, the two research questions are answered, and the study's research purpose is fulfilled.

The purpose of the study was to provide a comprehensive understanding of Supply Chain Analytics (SCA) by exploring the implications of descriptive analytics on the strategy and operations of Logistics and Supply Chain Management (LSCM) and investigating the link between operational and strategic levels in making strategic decisions of designing Supply Chain Networks (SCN). The following two research questions enabled the authors of this study to fulfill the purpose by conducting a qualitative study and carrying out 15 semi-structured interviews.

RQ1: What are the implications of applying descriptive analytics on Logistics and Supply Chain Management’s strategy & operations, and how it relates to predictive and prescriptive analytics?

Interviews with various consulting firms, IT-vendors and professional end-users have been conducted to investigate the implications of SCA with a focal focus on descriptive analytics. In general, the following two implications were detected: 1) Descriptive analytics as integral part of Business Analytics (BA), which establishes the baseline for a further intact analysis process with both predictive and prescriptive analytics. Without considering descriptive, predictive delivers poor models to prescribe actual data and optimize the potential business outcomes. 2) Descriptive analytics is interlinked with both predictive and prescriptive analytics in a sequential manner, i.e. descriptive analytics starts by correlating historical and current data sets before further analyzing the processed data to predict potential outcomes (predictive) and then potentially, optimize these outcomes by means of prescriptive analytics.

However, not all of the findings can be generalized as some respondents claimed that they are using descriptive analytics along with their own instincts. The human gut-feeling is an intangible emerged theme that was highlighted by many respondents. Additionally, the analysis has shown that the various definitions and connotations of analytics based on its functionality could be matched with the existing literature to a certain extent. However, in practice, there was a mismatch between all definitions of the three types of Analytics, as they were perceived differently based on the respondents’ own industry jargons.

RQ2: How strategic and operational management levels are connected when applying Supply Chain Analytics for designing Supply Chain Networks?

In order to answer RQ2, the authors opted to separate the results into two parts, namely the connection between both strategic and operational management levels (5.2 Supply
Chain Analytics in Operational and Strategic Levels), and analytics’ contribution to designing SCNs (5.3 Supply Chain Analytics in Designing Supply Chain Networks). Generally, both the study’s findings and analysis revealed that operational data is serving as a key driver for making strategic decisions as there is a detected link between the data stemming from company’s operational level and the strategic level that manages and act upon this data. This link is characterized by strong interdependence, since operationally originated data is crucial for making strategic decisions. Therefore, both levels are equally important and are as successful in applying SCA as the data and its insights reveal. Moreover, due to the multitude of factors involved when designing SCNs, an integral business strategy has to be followed, and then, a business’s SCND re-organized according to the business strategy. SCA supports consistent data gathering and processing throughout the management levels. In this regard, SCA is decisive when dealing with SCN relevant decisions, which incorporates massive amounts of data and connects organizational levels in order to benefit from SCA application for the entire supply chain.

The authors believe that the most significant and relevant information that they have discovered within this study is connected to RQ2. When weighing the empirical data, it appeared that a hybrid approach encompassing both top-down and bottom-up approaches, is found to be pursued when making strategic decisions for designing SCNs. Since this study identified new practical insights within the context of SCA applications and implications, it can be concluded that the study enriches existing literature by adding new undetected insights of applying this technological phenomenon in SCM practice.
7 Discussion

Within the following chapter the discussion dealing with this study and managerial implications are given, limitations of the study, and propositions for further research are briefly discussed, and lastly the ethical considerations of this study are presented.

As previously mentioned in 1.2 Problem Discussion, Tramarico et al., (2015) suggest to conduct more empirical studies that deals with the accuracy of the outcomes of applying Supply Chain Analytics (SCA) to gain a greater understanding of how SCA is providing accurate processed information to enable effective decisions for designing Supply Chain Networks (SCN). Many authors, which were mentioned in this thesis have touched upon SCA-related topics and suggest adopting approaches, such as the ‘dynamic capabilities’ approach (Teece et al., 1997), or ‘analytical and simulation’ approach (Tunali et al., 2011). In turn, our findings of the frequently mentioned hybrid approach encompassing both top-down and bottom-up approaches, were empirically embraced by many of this study’s respondents, who are working at upper management levels with SCA. However, the examined literature did not showcase the same direction when referring SCA in using it at both management levels. It entails a rather segregated and more overarching view on the use of SCA in strategic and operational settings (Golicic & Sebastiao, 2011). Nevertheless, the theory confirms the strong and integrative alignment of business strategy with SCM strategy (Mckone-Swee & Lee, 2009; Harrison & New, 2002), which was mentioned among the respondents a fair amount.

A lot of statements made by authors mentioned in this study regarding the need for further studies on developing theoretical models that considers the link between SCA and LSCM strategy and operations for supply chain managers (Wang et al., 2016). We believe that the empirical results of this thesis have provided a reasonable contribution pertaining to top-management that are using analytics methods and techniques in their companies. The conclusion derived in this study have been based on the systematically gathered and analyzed information during the data collection process which makes it original and new.

The predictive and prescriptive analytics types mentioned in theory as well in practice reveal some distinctions in terms of applicability and functionality (Demirkan & Delen, 2013; Wang et al., 2016). While descriptive analytics was heavily used in quantitative mathematical models for operational application fields (Sadie et al., 2018; Owen & Daskin, 1998), its importance for the strategic levels was somewhat undermined. In practice, many respondents (Galileo Analytics, Optilon, Company J) pinpointed the impact and influence descriptive analytics has on strategic decisions, such as Supply Chain Network Design (SCND) as well as its value and contribution to the other analytics types.
7.1 Managerial Implications

The findings of this study emphasize the importance of having a holistic view of analytics within the context of Supply Chain Management (SCM). Combining different types of analytics and jointly consider them for gaining mutual benefits is deemed to be critical for an optimal outcome of analytics. As the theoretical concepts and connotations of analytics do not necessarily match in practice, it is highly advised to define first the objective that the company would like to achieve, or the problem to tackle before opting for investing in analytics. By doing so, analytics can then provide a potentially optimal solution to tackle the predefined problem and achieve the organization’s ultimate strategic goal in the long run.

Additionally, there is still lack of trust in Supply Chain Analytics (SCA) capabilities as key enablers for improving analytics-based decision-making processes on a strategic level, partially due to the need for more practical success stories that showcase how analytics is optimizing businesses by rendering an excellent analytical performance that is twice as good as the human’s capability of logical reasoning. Furthermore, top-management involvement is strongly advised to be considered from the get-go to ensure an effective adoption and smooth application process of analytics between the all organizational departments.

As analytics collapses the hierarchal levels and removes organizational silos, it might be useful to embrace a one-level organizational structure that combines first, middle and top-level managers all together when adopting analytics. Moreover, the quality of the data used in analytics is deemed to be crucial for ensuring an accurate and valid performance of analytics. Essential traits of a high-quality data are found to be clean, structured, representative and current datasets, which drives substantial strategic decisions. Lastly, there is a need to question the data in use, as the authors noticed that there is a general tendency among practitioners to trust the extant data without questioning both its quality and accuracy.

7.2 Limitations

This study was conducted on a small-scale throughout the course of five months, which makes it a small study. Thus, the findings are restricted to the given timeframe, which makes them representative only to the timeframe from the initiation until the completion of this study. A further limitation is related to the sampling process of this study equivalent to 15 semi-structured interviews. Although the information obtained from the interviews has been quite rich and granular, however the findings are not exhaustive. Therefore, additional interviews and views could have enriched the study with further information regarding the research topic. Therefore, there are still needed to interview more professional end-users in order to further obtain and incorporate the perspective of IT-platform providers to enrich the findings of this study furthermore. The majority of the interviews were conducted via Skype. Thus, the authors believe that more face-to-face interviews would have provided even more profound insights by encouraging the
interviewees to be more open and willing to share their knowledge about the topic in person. It would also enable the authors to read the responds to the interviewees’ body language and make it more personal and induce more elaborative conversations.

Lastly, the results of this study are based on the perspectives of some consultancy firms, IT-vendors, and few professional end-users. Thus, gaining more of professional users’ perspectives in different industries e.g. manufacturing, retailing, and healthcare might reveal new insightful findings since different industries have different actors involved in their supply chains that might use analytics differently. Therefore, studies within other industries might lead to different outcomes due to different approaches and usage of analytics.

7.3 Future Research

As the study aimed to investigate the implications of Supply Chain Analytics (SCA) on Logistics & Supply Chain Management’ (LSCM) strategy and operation by focusing on descriptive analytics, it is of a further interest for the authors to investigate the extent in which the other two types of analytics (predictive & prescriptive) are jointly and interchangeably used in designing Supply Chain Networks (SCN).

During the progress of this study, many interesting topics and themes have emerged, such as the dilemma between trusting and choosing data from analytics over one’s own instinct or gut feeling. As companies nowadays are becoming more data-driven, it would be interesting to add the ‘human instinct’ as a construct to investigate its significance when using analytics as key enablers for the decision-making process.

Moreover, in order to verify the findings of this study or discover different ones, it would be interesting to add more insights into the topic of SCA and descriptive analytics and its connection to other strategic applications, such as product development and design or strategic sourcing, which are still areas of research interest but have been fairly researched in the past (Wang et al., 2016).

The results regarding the implications of SCA and its connection to LSCM’s strategy and operations are not ranked in terms of significance in this study. Therefore, the authors implore to carry out a future quantitative study which aims to investigate the implications of applying mathematical problem-solving methods to provide a more universal understanding for professional users and establish a set of approaches for improving supply chain metrics. Furthermore, investigating the leadership (top management) involvement as Critical Success Factors (CSF) for effective adoption and application of analytics in organizations might also be of interest for future research.

Finally, since the study took a triadic perspective (consulting firms, IT-vendors and end-users) into account, the authors suggest adding a fourth perspective, namely industry comparison and investigate the connection between both strategic and operational management levels in contrast with industries’ best-practices for analytics. By doing so,
new findings might emerge with regards to the strategic decision of designing SCN by means of analytics. Thus, the triadic perspective of this study can be further extended to a quadratic one.

### 7.4 Ethical Considerations

Some of the ethical considerations were induced by this study in terms of ‘trust’ in the capabilities of Supply Chain Analytics (SCA). The question of trusting the information given by analytics and letting adjacent technologies like Machine Learning (ML) decide on behalf of the human-being, is ethically considered and needs more discussion.

Further, if Artificial Intelligence (AI) and ML deciding what the user is supposed to do, then what are the user responsible for? Many of this study’s respondents speculates that analytics and AI are going to replace human intelligence in the near future. This pose an ethical question of whether analytics are going to potentially cause loss of jobs due to surge in demands for hiring well-versed analytical experts.

Consequently, this might pressure futuristic employees to re-skill themselves to become Data Scientists in order to understand the advanced technique behind analytics and then convert it to comprehensible information.

This study disclosed some other ethical concerns in terms of privacy and confidentiality. For instance, one can ask where the limit ends when using analytics, since analytics platform providers might have access to confidential information about the organization’s customers databases and their best business practices.

Trustworthiness for both the data and analytics techniques, is another essential ethical consideration that have been detected after conducting this study. For instance, smart algorithms are getting more sophisticated and complex and cannot represent human behavior to 100%, which is raising some ethical questions here about how much we can put trust in the capabilities of analytics and not into our own human instincts.
References


Appendices

Appendix 1: Keywords and Results of Initial Literature Search

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<td>(TI=(supply chain analyt* OR business analyt* OR big data analyt* OR big data business analyt*) AND TI=(supply chain network* OR supply chain management OR LSCM OR Logistics and supply chain management OR scnd) AND TS=(supply chain*)) AND LANGUAGE: (English)</td>
<td>88</td>
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<td>27</td>
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<td>Informs</td>
<td>Publication Title: &quot;supply chain analytics&quot; OR &quot;big data analytics&quot; OR &quot;business analytics&quot; OR &quot;big data business analytics&quot; OR &quot;supply chain network*&quot; OR &quot;scn&quot; OR &quot;scnd&quot; OR &quot;supply network&quot; OR &quot;supply chain network&quot;</td>
<td>38</td>
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</table>

Appendix 2: Keywords and Results of Additional Literature Search

<table>
<thead>
<tr>
<th>Database</th>
<th>Key word query</th>
<th>No. of results shown</th>
<th>No. of results after reading abstract*</th>
<th>No. of results read</th>
</tr>
</thead>
<tbody>
<tr>
<td>Web of Science</td>
<td>TITLE: (&quot;supply chain operation*&quot;) OR TITLE: (&quot;supply chain strategy&quot;) AND TOPIC: (&quot;supply chain management&quot;)</td>
<td>32</td>
<td>8</td>
<td>8</td>
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</tbody>
</table>
Appendix 3: Interview Guide for Respondents (provided if requested beforehand)

Interview questions

**Thesis purpose**: Establishing a framework incorporating ‘Supply Chain Analytics’ to ‘Supply Chain Networks Design’ by

- exploring the managerial implications of applying descriptive analytics in regard of strategic decisions for designing supply chain networks;
- investigating the linkage between operational applications of ‘Supply Chain Analytics’ and how it contributes to strategic decisions of ‘Supply Chain Network Design’.

**Introduction**

1. Could you please give us a brief overview about yourself?
2. Can you describe your current position?
3. In your own opinion, what drives supply chains nowadays?

**Analytics concepts and data processing**

4. ‘Business Intelligence’ entails ‘Business Analytics’ practices in data analysis to optimize business decisions and performance. How do you differentiate ‘Business Analytics’ from ‘Business Intelligence’?
5. In the academic literature there are three main types of ‘Analytics’ (descriptive, predictive, prescriptive). Assuming you are familiar with them, do you agree with these classifications in your work-context?
6. How do you process historical data? How do you include forecasts/trends into supporting decision-making alternatives?
7. Assuming you are dealing with ‘Business Analytics’ in managing operations, what are the operational processes that are frequently making use of ‘Business Analytics’ practices?

**Supply chain decisions and networks**

8. What are the bases for the strategic supply chain decision processes in your organization?
9. Designing supply chain networks involves physical/virtual configuration to facilities in terms of number, location, capacity, transportation modes. What are the key elements considered in designing those extensive supply chain networks?
Business Analytics & Supply Chain Networks

10. How does big datasets contribute to the design of supply chain networks?
11. How analyzing operational processes can impact the design of supply chain networks?
12. Could you explain the importance of ‘Business Analytics’ regarding making strategic supply chain network decisions?
13. Are there any certain Analytics type/datasets deemed to be more important than others?
14. Do you see the application of ‘Analytics’ is significant for both operational and strategic supply chain management?

Value of Business Analytics in organizations

15. In what way ‘Business Analytics’ can shape supply chain networks?
16. How will data-driven technologies prove futuristic supply chains to be more popular?
17. How are you encouraging the use of ‘Business Analytics’ for gaining insights from ‘Big Data’ in your organization?
Appendix 4: Interview Guide Included Prompts and Probes

**Interview guide**

**Purpose:** Establishing a comprehensive understanding incorporating ‘Supply Chain Analytics’ to ‘Supply Chain Networks Design’ by

- exploring the implications of applying descriptive analytics, and its relation to predictive and prescriptive, in regard of making strategic decisions for designing supply chain networks; and
- investigating the linkage between operational applications and how it contributes to making strategic decisions for designing Supply Chain Networks.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Questions</th>
<th>Prompts/Probes</th>
<th>Theme/Category</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intro (5)</td>
<td>Could you please give us a brief overview about yourself?</td>
<td>• How long have you been working for XY?</td>
<td>Background</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• What is your background?</td>
<td></td>
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<td></td>
<td></td>
<td>• Previous positions?</td>
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<td></td>
<td></td>
<td>• Any supply chain/logistics work experiences?</td>
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<tr>
<td>Can you describe your current position?</td>
<td></td>
<td>• Major responsibilities?</td>
<td>Job Description</td>
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<td></td>
<td></td>
<td>• Team structure?</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>• Major clients (global/domestic)?</td>
<td></td>
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<td></td>
<td></td>
<td>• What type of industries are you serving the most?</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>• Major projects you were involved in (or managed)?</td>
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<tr>
<td>In your own opinion, what drives supply chains nowadays?</td>
<td></td>
<td>• Any disruptive techniques?</td>
<td>Expert opinion</td>
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<td></td>
<td></td>
<td>• In future?</td>
<td></td>
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<td></td>
<td></td>
<td>• Difference to conventional supply chains?</td>
<td></td>
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<td></td>
<td></td>
<td>• Data flow?</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>• Importance of data nowadays?</td>
<td></td>
</tr>
<tr>
<td>General/common understanding (20)</td>
<td>‘Business Intelligence’ entails ‘Business Analytics’ practices in data analysis to optimize business decisions and performance. How do you differentiate ‘Business Analytics’ from ‘Business Intelligence’?</td>
<td>• Which data is daily involved?</td>
<td>Definitions &amp; applications</td>
</tr>
<tr>
<td></td>
<td></td>
<td>• What role plays Big Data?</td>
<td></td>
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<td></td>
<td></td>
<td>• How do you apply data from BI application (⇒Benefits/Drawbacks)?</td>
<td></td>
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<tr>
<td></td>
<td></td>
<td>• How do you make use of BI findings in BA (⇒Benefits/Drawbacks)?</td>
<td></td>
</tr>
<tr>
<td>In the academic literature there are three main types of ‘Analytics’ (descriptive, predictive, prescriptive). Assuming you are familiar with them, do you agree with these classifications in your work-context?</td>
<td>• If yes, what are the differences? are they applied separately or collectively? • Otherwise, explanation is needed (or synonyms, examples) • If no, what are the classification you are using?</td>
<td>Analytics types</td>
<td></td>
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<td>---</td>
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<td></td>
</tr>
<tr>
<td>How do you process historical data? How do you include forecasts/trends into supporting decision-making alternatives?</td>
<td>• Do you further process these datasets analytically? • How do the processed results benefit present business practices? • Do you process big volumes of data? • What type of software and/or techniques are you using to process such datasets? • Organizational application fields? (operational/strategic levels) • Which role does data processing play in your organization? Which management levels are involved? • How can these results drive future practices (predictive, prescriptive)?</td>
<td>Connection to Analytics types and decision levels</td>
<td></td>
</tr>
<tr>
<td>Assuming you are dealing with ‘Business Analytics’ in managing operations, what are the operational processes that are frequently making use of ‘Business Analytics’ practices?</td>
<td>• How does an exemplary business process would look like in BA? • Is it used to drive decisions? On which level? • Are these processes seamlessly connected? • How are processes dependent on each other and on Analytics?</td>
<td>Analytics link to operations/strategy</td>
<td></td>
</tr>
<tr>
<td>Exploration/Context (10) What are the bases of the strategic supply chain decision processes?</td>
<td>• Factors? • People involved? • Time horizon? • Data? • Processes within strategic procurement, and product design &amp; development.</td>
<td>Supply chain decision elements</td>
<td></td>
</tr>
<tr>
<td>Core discussion (20)</td>
<td>How does big datasets contribute to the design of supply chain networks?</td>
<td>How analyzing operational processes can impact the design of supply chain networks?</td>
<td>Could you explain the importance to 'Business Analytics' regarding making strategic supply chain network decisions?</td>
</tr>
<tr>
<td>----------------------</td>
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</tr>
</tbody>
</table>
| Designing supply chain networks involves physical/virtual configuration to facilities in terms of: number, location, capacity, transportation modes. What are the key elements considered in designing those extensive supply chain networks? | • Relationships - supplier/custumers?  
• Competitors?  
• Market?  
• Economic metrics?  
• Products?  
• Industry-specifics?  
• Simulation/calculation tools? | | |
| • Are analyzed datasets part of the decision process? To what extent?  
• Do you consider analytical findings vital for designing supply chain networks?  
• Which datasets you deem essential for designing SC networks?  
• Which potentials do you see in using Big Data for supply chain network design? | | • Mass data from operations (IoT, etc.)?  
• Reflection on lead time?  
• Various analytics forms? Combined?  
• Operation results for operational decisions (=>Motives)  
• Linkage to strategic applications (=>Motives)?  
• Reasons/Motives for not making use of operational results on a strategic level? | |
| | | • Which value Analytics added to SCND? Economies of Scale? Optimization? Decision-making basis?  
• How analytical findings are specifically linked to strategic SCND?  
• Historical/current data or future trends? | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | |
| | | | | Supply chain networks elements  
Big data & supply chain networks  
Supply chain networks & operations  
Business Analytics importance in SCND |
| Are there any certain ‘Analytics’ type/datasets deemed to be more important than others? | • Which one? And why?  
• Are the other type(s) used for other strategic supply chain decisions (expt from SCND)?  
• Possibly, all three types connected together? | Conspicuousness |
| --- | --- | --- |
| Do you see the application of ‘Analytics’ is of significant importance for both operational and strategic supply chain management? | • How?  
• Any alternatives for ‘Analytics’? ERP?  
• Human gut feeling? Data vs instinct?  
• Maturity of Business Analytics? | Analytics futuristic implications |
| Closing (5) | In what way ‘Business Analytics’ can shape supply chain networks? | • Proved in operations, why not in strategic settings?  
• “Let the data speak to you...”  
• Potential for most successful supply chain network?  
• Replaces human decisions? | |
| How will data-driven technologies prove futuristic supply chains to be more popular? | • Data drives every single decision?  
• Machine-learning is ubiquitous, also Business Analytics?  
• Responsiveness?  
• Human resistance?  
• Data lakes – too much data? | Practical insights |
| How are you encouraging the use of ‘Business Analytics’ in gaining insights from ‘Big Data’ in your organization? | • Top management support?  
• Maturity of disruptive technologies?  
• Any initiatives in progress?  
• Disruption in any industries?  
• Customers/clients demand usage of BA? | |
Appendix 5: Consent Form

Consent Form for Research Participation

‘Supply Chain Analytics and its Strategic Implications on Designing Supply Chain Networks’

- I, ___________________________ voluntarily agree to participate in this research study.
- I understand that even if I agree to participate now, I can withdraw at any time or refuse to answer any question without any consequences of any kind.
- I understand that I can withdraw permission to use data from my interview any time after the interview, in which case the collected data will be deleted.
- I have had the purpose and nature of the study explained to me and I have had the opportunity to ask questions about the study.
- I understand that participation consists exclusively an interview.
- I understand that I will not benefit directly from participating in this research.
- I agree to my interview being audio-recorded (Yes / No).
- I understand that all information I provide for this study will be treated confidentially.
- I understand that in any report of the results of this research my identity and/or organization will remain anonymous. This will be done by changing my name and disguising any details of my interview which may reveal my identity or the identity of clients I may speak about. (Yes / No)
- I understand that disguised extracts from my interview may be quoted in the Master thesis.
- I understand that if I inform the researcher that myself or someone else is at risk of harm they may have to report this to the relevant authorities - they can discuss this with me first but may be required to report with or without my permission.
- I understand that the signed consent form and original audio recordings (if agreed upon) will be retained on the authors’ private computers for the duration of five years.
- I understand that a transcript of my interview in which all identifying information will be retained for five years.
- I understand that under freedom of information legalization I am entitled to access the information I have provided at any time while it is in storage as specified above.
- I understand that I am free to contact any of the people involved in the research to seek further clarification and information.

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Date _______________________________  
Signature of research participant