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Data Analytics as an Enabler to Strengthen Supply Chain Resilience

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ABSTRACT:

This thesis examines the role of data analytics in building supply chain resilience. The aim of the study is to investigate how companies can use data analytics to identify potential supply chain disruptions, mitigate risks, and improve supply chain performance.

To achieve this aim, case studies of a companies that has successfully implemented data analytics in its supply chain operations was conducted. The case study analytics included an examination of the specific tools and techniques used, the data sources and types of data analysed, and the insights gained from the analytics. The study also explored the challenges faced during the implementation of data analytics and analysed the effectiveness of these analytics in building supply chain resilience.

Case firms were selected based on business and product type. This study includes companies with electronic product and component supply chains. Interviewees were selected based on their data-driving experience and supply chain operations exposure. Seven supply chain specialists from six case firms were interviewed semi-structured.

The results show that data analytics provide valuable insights for supply chain management and help companies to proactively identify and mitigate risks. The study also highlights the importance of data quality, data integration, and the need for new skills and capabilities in implementing data analytics in the supply chain. The findings of

the study have practical implications for supply chain managers and provide a basis for future research in this area.

Overall, the thesis contributes to the growing body of literature on the role of data analytics in building supply chain resilience and provides insights into the challenges and opportunities associated with implementing these analytics in practice.

KEYWORDS: Data analytics, Supply Chain Resilience, disruption, risk management

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1 INTRODUCTION

The COVID-19 pandemic has highlighted the importance of supply chain resilience (Linton & Bindiya, 2021). The sudden and unexpected disruptions caused by the pandemic have exposed vulnerabilities in supply chains around the world, leading to shortages of critical supplies and materials (Kazancoglu et al., 2022). Supply chain resilience has become a critical capability for companies to maintain their competitive advantage in today's rapidly changing and uncertain business environment. To achieve this, companies need to have access to accurate, timely, and relevant information about their supply chain operations. As an effort to address these challenges, companies are increasingly turning to data as a tool to enable supply chain resilience.

Data analytics can help companies to collect, process, and analyse large amounts of data from a variety of sources to gain insights into their supply chain operations. By leveraging these insights, companies can proactively identify potential risks, forecast demand, optimize inventory levels, and enhance their supply chain resilience (Mathivathanan et al., 2018; Chams and García-Blandón, 2019). In addition, data analytics can help companies to improve collaboration and communication with their suppliers and customers, which can further enhance their supply chain resilience.

Big data refers to the large and complex datasets generated by businesses and other organizations. The growth of digital technologies and the Internet of Things has led to an explosion of data, providing companies with a wealth of information that can be used to improve their supply chain operations. By collecting and analysing large volumes of data, companies can gain valuable insights into their supply chain performance, identify potential risks, and take proactive measures to mitigate them (Gunasekaran et al., 2017).

In this context, the use of data analytics can help companies to build more resilient supply chains. Data analytics can provide real-time visibility into supply chain operations, enabling companies to monitor and manage disruptions more effectively Wamba et al. (2015). Furthermore, data can be used for predictive analytics, allowing companies to

anticipate potential disruptions and take proactive measures to mitigate them (Behdani et al., 2012; Kim & Zhao, 2021).

The need for implementing data analytics in building supply chain resilience has become even more critical in recent years due to the increasing complexity and globalization of supply chains. With supply chains spanning multiple countries, regions, and continents, companies need to be able to manage a wide range of risks, such as natural disasters, geopolitical instability, and cyber-attacks. Data analytics can help companies to develop a more comprehensive and integrated view of their supply chain operations, which can enable them to identify and mitigate risks more effectively.

In summary, this paper will demonstrate that big data analytics can be a powerful tool for building supply chain resilience. By leveraging data analytics, companies can better anticipate and manage disruptions in their supply chains, improving their ability to respond quickly and effectively to changing circumstances. Resilient supply chains are better equipped to address sustainability challenges such as climate change and resource scarcity. By anticipating and adapting to potential disruptions, resilient supply chains can continue to operate sustainably even in the face of unforeseen challenges.

The need for implementing data analytics in building supply chain resilience is essential for companies that want to remain competitive and successful in today's business environment (Olugu et al., 2011; Hazen et al., 2014). By leveraging data analytics, companies can gain valuable insights into their supply chain operations and develop more effective risk management strategies. This, in turn, can help companies to enhance their supply chain resilience and ensure the continuity of operations, even in the face of unexpected disruptions.

This paper will explore the role of data analytics in building supply chain resilience. The intention is to discuss the various ways in which big data can be used to improve supply chain resilience, including risk management, enhanced visibility, predictive analytics, faster decision-making, and improved collaboration. Additionally, the study will highlight some of the key success factors for implementing data analytics in supply chain

management and provide examples of companies that have successfully leveraged data analytics to build more resilient supply chains.

1.1 Research gap

Nguyen et al. (2017) assert that there is a small amount of research exploring the potential enhancements in supply chain resilience via the use of data analytics. According to Duan and Xiong (2015), the authors assert that the inclusion of descriptive and predictive analytics in prescriptive models is essential, as these analytics provide crucial parameters that significantly impact the performance of the models. Consequently, the quality and insights derived from these analytics play a significant role in determining the effectiveness of the models.

The study conducted by Lamba and Singh, 2016, titled "Data-Driven Decision-Making in Supply Chain Resilience" examines the current state of resilience research and identifies a lack of consistency across the various stages of resilience.

In their article titled "Supply Chain Resilience: Development of a Conceptual Framework, Current State of Research, and Future Research Directions," Nalchigar and Yu (2018) assert the significance of data analytics and resilience in modern supply chain management. However, they note a limited number of studies that have comprehensively investigated the whole loop chain. There is a scarcity of comprehensive research on the use of tactical data analytics at various stages of resilience. The literature does not provide a clear understanding of the benefits of data-driven decision-making across the supply chain resilience cycle. A comprehensive supply chain resilience data analytics approach is required for this problem.

The scholarly works titled "Data-Driven Supply Chain Resilience: A Comprehensive Review and Framework" authored by Gupta and Sharma (2022) and "Big data analytics in sustainable humanitarian supply chain: Barriers and their interactions" by Bag and Wood (2022) emphasize the realistic implementation of data analytics and provide empirical evidence supporting its effectiveness in enhancing supply chain operations. Regrettably, these articles demonstrate the presence of fragmented knowledge, hence

presenting challenges in the development of data-driven supply chain resilience frameworks.

Despite an evident link between data analytics and supply chain resilience, research on how to incorporate data analytics throughout all phases is limited. This comprehensive study fills this gap by expanding knowledge and offering practical advice to firms aiming to improve supply chain resilience through data-driven decision-making.

1.2 Research motivation and research question

This study aims to investigate empirical case studies that can contribute to filling the research gap in understanding the implementation and effectiveness of data analytics in building supply chain resilience. By analysing successful cases of companies that have incorporated data analytics for this purpose, we can gain valuable insights.

This study examines how companies have incorporated big data analytics into their supply chain operations. It explores the various tools and techniques utilized, as well as the types of data analysed and the sources from which it is obtained. Additionally, the study investigates the insights gained through analytics and how these insights have been used to enhance supply chain resilience. This includes identifying potential disruptions and taking proactive measures to address them.

Furthermore, the study clarifies the challenges that the company faced during the implementation of data analytics and how they overcame these challenges whether this could include challenges related to data quality, data integration, and the need for new skills and capabilities.

The study analyses the effectiveness of data analytics in building supply chain resilience, including the specific outcomes achieved such as reductions in supply chain disruptions, improvements in on-time delivery performance, and cost savings. One approach is to assess the company's supply chain performance before and after data analytics implementation.

The primary research question is: How can supply chain management be made more resilient using data analytics??

In connection with the main research question, the following sub-questions are defined:

(1) To what extent do case companies implement data analytics for decision-making and strategy optimization in their supply chain

(2) How do case companies integrate different types of analytics to form a holistic approach to supply chain resilience?

By conducting such an empirical case study, this paper gains a more in-depth understanding of the implementation and effectiveness of data analytics in building supply chain resilience. The author believes that this research can provide valuable insights for other companies looking to implement similar solutions and help to identify specific factors that contribute to success in building resilience in the supply chain.

1.3 Structure of the thesis

There are six main chapters in this research paper. The author will provide examples of the thesis induction in the first sector, which provides a summary of the research problem, the rationale for the investigation, and the research questions. It also outlines the study's objectives and constraints. The second chapter gives the theoretical context for the fundamental ideas and tenets that guide a research inquiry. It offers a structure for comprehending and analysing the research problem. The systematic process for gathering, analysing, and interpreting data for a research project is provided in the third section, which also introduces research methodology. It includes several steps, such as gathering data, analysing that data, and drawing conclusions. The case studies of companies that have improved supply chain resilience through data analytics are described in the next chapter. It covers the company's supply chain operations, data analytics' application, results, and challenges. It also looks at how successfully supply chain resiliency is achieved by data analytics. The following chapter then deals with the findings and discussion. In this section, the outcomes of the case study analytics are

presented together with a discussion of the results considering the objectives and research questions. It also evaluates the implications for practice, explores the limitations of the study, and contrasts the findings with the body of recent research. In the final chapter, conclusions regarding the role of data analytics in building supply chain resilience are made after a summary of the study's main findings. It also provides recommendations for further research as well as beneficial managerial implications.

2 LITERATURE REVIEW

This chapter will discuss the concepts that are relevant to the subject matter of this paper. To assess and contrast current ideas and notions with the empirical findings of this study, this chapter's theoretical foundation on the subject is presented. The literature process is first explained. Then, to create a shared understanding of the subject, relevant literature is chosen and presented on the subjects of (1) Supply Chain Risk Management, (2) Resilient Supply Chain, (3) Data analytics and Supply Chain Data Analytics, (4) Data analytics as an enabler to Resilient Supply Chain. Finally, a research model is presented to show how the current theory is understood.

2.1 Supply Chain Management

2.1.1 Supply Chain Management

The topic of supply chain management has received a lot of interest from academics in recent decades. Given the recent rise of supply chain literature, a clear definition of supply chain management is a subject of discussion.

Ganeshan and Harrison (1995) defined supply chain management as a network of facilities and distribution options that buy inputs, process them into intermediate and completed goods, and then distribute them to customers. According to Lee & Corey (1995), supply chain management is the coordination of establishments that acquire raw materials, convert them into transitional products, and then distribute finished goods to clients through a distribution network.

The web of companies that participates in both upstream and downstream operations to deliver goods and services for the final consumer is referred to as the supply chain by Christopher (1998).

2.1.2 Supply Chain Disruption

One essential aspect of business operations is the control of the movement of products and information from upstream to downstream of the supply chain (Christopher et al.,

2011). Supply chain networks have become more complex in the current dynamic market environment, leaving companies more vulnerable to unexpected disruptions (Pettit et al., 2010). Disruptions to the supply chain occur when there is a possibility of goods and services flowing from suppliers to consumers without interruption. These interruptions could have a big effect on businesses, leading to delays, shortages, and increased costs. Peck (2005) divides disruption risks into three categories: disruptions that occur inside a company and are related to internal procedures and controls; external disruptions that occur outside the supply chain; and disruptions that occur inside the supply chain and are related to supply and demand.

The most commonly reported supply disruptions, according to supply chain studies, include supplier delays, supplier bankruptcy, and raw material quality (Behdani et al., 2012). Numerous factors, such as product complexity, supplier operational inefficiencies, catastrophic events, delays in logistics, and inadequate supply chain coordination, can be linked to the risk of supply disruption (Abbasi et al., 2016, Chopra & Sodhi, 2014, Chen et al., 2013, Simchi- Levi et al., 2014, Abbasi et al., 2016). The risk of supply disruption can be greatly increased by reliance on suppliers and the degree of flexibility offered by different sourcing choices (Chopra & Sodhi, 2014). According to Gunessee and Subramanian's (2020) most recent study, a complex supply network with safety concerns and potential for human error increases the probability of a worldwide supply chain disruption.

The disruption cycle's eight stages, as described by Sheffi and Rice (2005) and linked to the degree of corporate success over time, are shown in Figure 1. The authors also emphasize that after the entire effect has been felt, performance drops dramatically and that it takes time for a company to recover. Certain negative consequences, such those on a business's reputation or customer connections, may persist for a very long time despite recovery efforts.

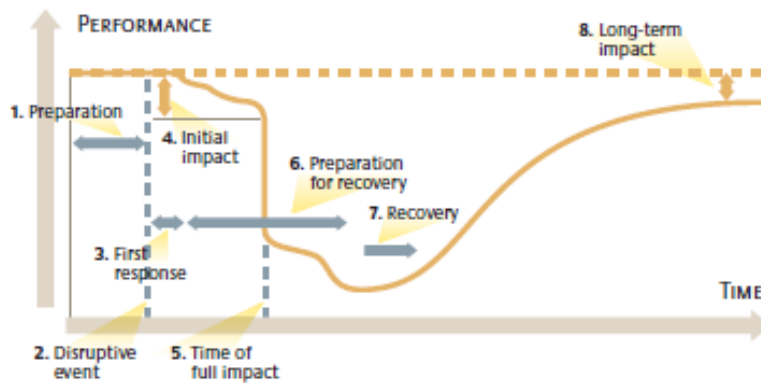


Figure 1: Stages of disruption (Sheffi & Rice, 2005)

2.1.3 Supply Chain Risk Management

According to Behdani et al. (2012), supply chain risk management is a systematic and ongoing process that analyzes the effects of disruptions throughout the supply chain on specific goals and addresses them throughout their whole lifecycle.

The two main common approaches that have been discussed in the literature for handling supply chain disruptions are the anticipating approach, which focuses on assessing the vulnerabilities to disruptions and taking preventative measures to reduce negative impacts, and the resisting approach, which refers to reacting and adjusting processes once the disruption has occurred.

Mitigation in the context of managing disruptions refers to the application of strategies intended to minimize any potential negative consequences. Businesses should identify and understand any interruption risks that may arise, and then select the most appropriate mitigation strategies (Chopra & Sodhi, 2004). The majority of academic literature's approaches to reducing supply disruption have focused on cooperative strategies, flexibility, redundancy, and control (Behdani et al., 2012).

Along with resource allocation and organization, short-term proactive measures are a component of the preparation phase (Behdani et al., 2012; Kim & Zhao, 2021). Businesses need end-to-end visibility at this stage to identify anomalous events in the supply chain. This can be achieved by information sharing, performance monitoring, and

warning systems (Stecke and Kumar, 2009). Agrawal et al. (2021) state that in addition to identifying and planning for disruption, there should be real-time access to reliable data, analytics of the disruption profile to predict its impacts, and assistance with initial decision-making. All efforts conducted during the mitigation and preparedness phases are crucial to ensuring that the appropriate responses are made when a disruption occurs.

A successful response to a disruption when it happens requires real-time, quick resource allocation, active information exchange, and teamwork (Behdani et al., 2012; Kim & Zhao, 2021). It is possible to employ the mitigation phase's techniques, which include ordering from backup suppliers, using buffer stocks of goods, or leveraging flexible transportation (Stecke and Kumar, 2009).

Getting things back to normal is the goal of the recovery phase of the disruption management cycle. Supply chain recovery capability is defined as "interactions of supply chain entities and corresponding coordination of supply chain resources to return the supply chain to a normal and planned level of product flow" by Braunscheidel & Suresh (2009). Recovery strategies that focus on stabilizing and modifying supply chain operations should be implemented as soon as feasible to reduce long-term consequences and maintain business continuity (Ivanov et al., 2017). To guarantee the creation of original items in the event of temporary outages, Chen et al. (2021) recommended making emergency purchases from the unaltered supplier in bigger quantities. According to Chen et al. (2021), prolonged disruptions might call for a partial product type change that allows raw material substitution and supplier selection without affecting the main product design or manufacturing procedures. Furthermore, encouraging active learning from the disruptions is crucial since it will serve as the basis for future mitigation strategy design.

2.1.4 Supply Chain Resilience

According to Starr et al. (2003), enterprise resilience is the capacity to withstand systemic disruptions and adapt to new risk environments. They argue that a resilient organization can align various systems and create a competitive advantage by efficiently responding to changing risks. The concept of "resilience engineering," as defined by Erol et al. (2010), emphasizes the importance of identifying resilience and developing procedures to analyze and improve enterprise resilience.

As per Carvalho et al. (2012), resilience in supply chain management refers to the capability of supply chains to handle unexpected disruptions. Resilience is the opposite of sensitive, and it is the ability of the supply chain to mitigate the impact of unforeseen disruptive events. Resilience is associated with the effectiveness of the actions or plans taken before the crisis occurs, as opposed to being reactive during the crisis itself. According to Belhadi et al. (2023), Kamble (2020), and Fosso Wamba et al. (2019), resilience in supply chain systems refers to the system's adaptive ability to handle disruptions and promptly resume prior performance within certain defined bounds. More formally, resilience is the supply chain's capacity to anticipate unforeseen events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of interaction and control over structures and function (Ponomarov & Holcomb, 2009). This view is supported by several authors.

Table 1. Definitions of Supply Chain Resilience

Definitions of Supply Chain Resilience	
Gaonkar & Viswanadham (2007)	SCR stands for the capacity to continue, pick up, and restart operations following a disruption.
Fiksel, (2003,2006), Pettit et al. (2007)	SCR is the ability of complex industrial systems to withstand, expand, and adapt in the face of adversity.
Datta et al. (2007)	SCR is a proactive, organized, and integrated investigation of supply chain capabilities to handle unforeseen occurrences, not merely the capacity to recover from accidents.
Falasca et al. (2008)	SCR refers to a system's capacity to lower the likelihood of a disruption, lessen the effects of disruptions once they happen, and shorten the time it takes for operations to return to normal.
Ponomarov & Holcomb (2009)	SCR refers to the supply chain's adaptive ability to anticipate unforeseen occurrences, react to interruptions, and recover from them by preserving operations at the ideal degree of connectivity and function control.
Barroso et al. (2011)	SCR is the capacity to respond to the adverse consequences of disruptions that arise at any given time to uphold the goals of the supply chain.

Supply chains confront increased competition and uncertainty in the current economic climate, and disruptions can have a significant impact on how well a company performs (Azadegan et al., 2020). Several factors can lead to these disruptions, including catastrophes (Stecke & Kumar, 2009), man-made or natural disasters (Elluru et al., 2019), and occasions such as the 2008 global financial crisis, Brexit, the loss of important suppliers (Ponomarov & Holcomb, 2009), and other comparable occurrences.

In today's complex and linked business environment, supply chain resilience is crucial because it protects against disruptions that can stop the flow of goods and services. It can be viewed as a multi-stage process that mainly consists of two crucial phases: resistance and recovery, each of which has a unique set of tactics and procedures.

As the supply chain enters the Resistance stage, the main objective is to proactively prevent or reduce possible interruptions. The Avoidance strategy, which emphasizes the value of risk analytics and preventative measures, kicks off this phase. Companies can take proactive steps to lessen their exposure to risks by recognizing vulnerabilities and comprehending potential threats. The importance of avoidance methods is emphasized by Christopher and Peck (2004) because they enable companies to protect their supply chains against potential interruptions.

Containment is a tactic that complements avoidance. Containment strategies are essential for preventing the spread of disturbances when they do occur as well as minimizing their effects. Rapid detection, isolation, and damage control are all part of this phase. According to Gurtu and Jonny (2021), containment plays a crucial part in supply chain risk management. It enables businesses to take prompt, decisive action to reduce the negative effects of interruptions, protecting not just their operations but also their reputation and client relationships.

The next step, Recovery, becomes essential for restoring normalcy and optimizing operations while the Resistance phase prepares supply chains to withstand and minimize disruptions. Stabilization is the initial stage of this phase. Restoring functionality and ensuring that supply chain activities regain their footing are the main goals of

stabilization initiatives. According to Fiksel (2003), flexibility and adaptability become crucial during this phase. These characteristics make it possible for supply networks to recover from shocks and move through unpredictable situations.

Return is the next stage in the resilience process after stability. At this point, maximizing operations and fulfilling any ground lost are the main priorities. In this phase, Zhao et al. (2023) stress the need of efficient data analytics and the use of technology. Companies can quickly return to full operational capability by utilizing data-driven insights and technical capabilities. To improve overall resilience, this entails evaluating performance, identifying problem areas, and putting the disruption's lessons into practice.

Supply chain resilience is a dynamic and diverse process that includes both the Resistance and Recovery phases, each of which has its own set of tactics and methods. To strengthen supply chain resilience, academic research emphasizes the value of a proactive approach to risk reduction through avoidance and containment, quick detection and damage management, flexibility and adaptation, data-driven decision-making, and technology use. A comprehensive strategy that covers all these phases is necessary to ensure the ongoing flow of goods and services and preserve market competitiveness in an environment where business operations are becoming more complicated and unpredictable.

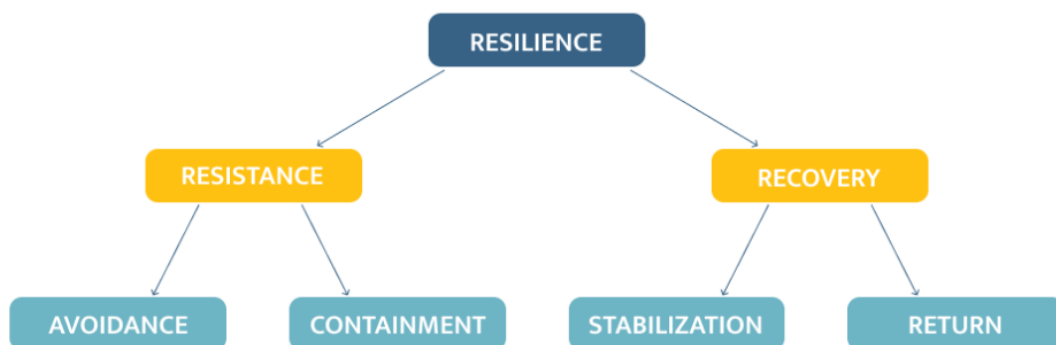


Figure 2. Tree of Supply Chain Resilience (Melnik et al., 2014)

Given the significant impact of disruptions on revenue, costs, and reputational damage, the literature has emphasized the importance of overcoming disruptions, and resilience has been integrated into preparedness strategies adopted by businesses to address them (Pettit et al., 2019).

Mandal (2014) argues that low capacity for resilience can have a negative impact on both operations and financial outcomes, reducing service quality, inventory yield, and gross margin. This can lead to higher capital consumption and financial chaos as a company's capacity to manage interruptions and keep operations running smoothly can be severely and negatively impacted by a low level of supply chain resilience. First off, it makes people more vulnerable to a variety of hazards, such as natural disasters, geopolitical tensions, and unanticipated market fluctuations. According to Tang and Musa (2011), supply chains are ill-equipped to endure such shocks when they lack resilience. A weak supply chain can also result in more operational hiccups and downtime, which has a detrimental effect on customer service and overall business performance (Kovács and Spens, 2007).

In addition, higher prices may be the result of a deficient supply chain resilience. According to Christopher and Peck (2004), organizations with low resilience frequently use pricey expedited delivery, alternative suppliers, and ad-hoc solutions to lessen the effects of disruptions. The profit margins and competitiveness may be harmed by these increased costs.

A lower level of resilience can also be detrimental to relationships with suppliers and clients. The availability of essential components may suffer if suppliers lose faith in a company's capacity to sustain stable demand (Tang, 2006). Customers may look for alternatives because of bad service and delayed deliveries caused by disruptions (Blackhurst et al., 2008).

2.2 Data analytics and Supply Chain Data Analytics

2.2.1 Data analytics

"Data analytics" refers to the process of collecting, processing, and analysing large and complex datasets to extract valuable insights and information. This involves the use of advanced analytical tools and techniques, such as machine learning, data mining, and predictive modelling, to identify patterns, trends, and relationships within the data.

2.2.2 Supply Chain Data Analytics

Supply Chain Data Analytics refers to the use of data analytics to improve supply chain operations and decision-making. This involves collecting and analysing data from various sources, such as suppliers, customers, logistics providers, and internal systems, to gain insights into supply chain performance, identify potential risks and opportunities, and optimize supply chain processes. By leveraging big data analytics, companies can improve supply chain visibility, agility, and resilience, which can help them to respond more effectively to unexpected disruptions and changing market conditions.

Based on its primary functions, data analytics can be divided into four groups: descriptive, diagnostic, predictive, and prescriptive.

According to Hans and Mnkandla (2017), descriptive analytics helps people make inferences about past occurrences so they can learn important lessons. It seeks to pinpoint issues and openings in both old and new processes (Arya et al., 2017). Using descriptive analytics, people can make inferences about past occurrences in the context of project management to learn important lessons. The process of extracting information from massive volumes of data to determine "what is happening?" can also be used to describe this kind of analytics. (Hans & Mnkandla, 2017).

Predictive analytics provides an answer to the question "what will happen" by forecasting demand based on historical data. (Hans & Mnkandla, 2017). It makes precise predictions about potential future events, projects them, and offers a justification for

why they might occur using mathematical methods and programming techniques (McKinsey & Company, 2022).

Based on models for descriptive, predictive, and mathematical optimization, prescriptive analytics generates decision recommendations. It responds to the query, "What ought to be occurring?" (Roy et al., 2022). It evaluates potential alternative decisions based on large and complicated datasets using mathematical models and cutting-edge statistical techniques (Arya et al., 2017).

Diagnostic analytics provides an answer to the question " why did it happen" (Roy et al., 2022). Diagnostic analytics is concerned with discovering the underlying factors behind problems or patterns in historical and present-day data. By providing information on historical performance that may be utilized to inform future decisions, it is used to explore why supply chain shipments have been delayed or sales goals have not been fulfilled.

2.2.3 Lifecycle of Data within Supply Chain

Understanding how to evaluate the knowledge found in data is becoming more and more crucial as businesses start to realize the strategic value of data (Tao et al., 2018). In this way, manufacturers can use digital technologies like artificial intelligence and the Internet of Things to support supply chain management (Zhong et al., 2016; Tao et al., 2018). Without involving humans, artificial intelligence can assist in decision-making (Sakib et al., 2018). The ability to manage the data generated by different industrial processes is necessary in order to apply these solutions. It is possible to collect information about users, products, equipment, management, and the general public (Tao et al., 2018).

Depending on the type of data that is collected, the data gathering process may also change. For instance, factory information systems like Enterprise Resource Planning (ERP), Customer Relationship Management (CRM), and Manufacturing Execution System (MES) can be used to gather management data (Tao et al., 2018)

Tao et al. (2019) found that decisions concerning design strategies, purchasing, material distribution, product planning, marketing, and sales, as well as service management, may be made using data. Additionally, data on operating conditions and performance pertains to equipment, but information on customer preferences for available options and user behaviour pertains to user data. IoT technology (such as RFID sensors) and government databases, respectively, are used to gather product data and public data. IoT technology can offer information on product performance as well as measurements of the environment, such as temperature and air quality (Tao et al., 2018).

All the data, nevertheless, are meaningless if they are not translated—that is, if every data set is standardized into a single format. Data translation is currently one of the largest challenges facing practitioners (Zhong et al., 2016). This is especially true when there is a large amount of data coming from both internal and external sources (Kumar Singh & El-Kassar, 2019). To be adequately reviewed and support manufacturers' decision-making, all data must be structured clearly. However, there are several steps that need to be followed to translate data accurately, which further clarifies why practitioners consider data translation to be challenging (Tao et al., 2018). As seen in Figure 3, these procedures comprise data sources, collection, processing, storage, visualization, and applications.



Figure 3. The process of translating data (Tao et al. ,2018).

The data sources can be gathered from a variety of places, including IoT technologies that were previously discussed in this section and factory information systems. Additionally, all the data must be kept efficiently and securely. Cloud computing has made this task easier in recent years (Agrawal et al., 2010). The data can then be processed, which means that inaccurate, redundant, and inconsistent data are removed from the data. As a result, data is organized and cleaned up, allowing for data analytics to uncover new information. This results in data visualization, which is the more approachable presentation of information, for example with the use of graphs or diagrams. The next step is data application, in which the data is shared and used effectively, for example, to help make better decisions (Tao et al., 2018).

The underlying information objectives must be understood, nevertheless, in order to obtain a consistent picture of the business units inside a company. The most fundamental data that powers corporate operations is referred to as master data and is where it may be found (Zhao et al., 2020). For instance, Master Data consists of clients,

workers, suppliers, goods, places, contracts, and regulations (Loshin, 2010). Therefore, having high-quality master data is essential for businesses to have in order to make informed business decisions (Vilminko-Heikkinen & Pekkola, 2017). The demand for coherent and unified data has made establishing high-quality master data an even more important task for businesses to accomplish (Haug et al., 2013). Consequently, data-driven decision-making requires an organization's master data management to be adequate.

A strategic method called "data-driven decision-making" uses data analytics to inform and direct organizational decisions. The systematic gathering of both internal and external data is the first step in this process, which includes other elements as well (Provost and Fawcett (2013). Data is collected, cleaned, reprocessed, and then thoroughly analysed using techniques including descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. Understanding is improved by using charts and dashboards to visualize data. Decision-makers may set goals, manage risks, and optimize processes with the help of these insights. Iterative data collection and analytics are required for data-driven decision-making to evaluate outcomes, compare performance to goals, and adjust methods. The key to bridging data and decision-making is data analytics, which turns raw data into useful knowledge and factual proof to support choices. It spots chances for improvement, enabling effective operations and cost savings. As a cornerstone of agile, competitive, and modern businesses, the process' feedback loop assures continuing alignment with organizational goals, boosting their resilience and responsiveness to changing business environments (Zhong et al., 2016; Brousell et al., 2014; Zhou & Yang, 2018).

2.3 Data Analytics as an enabler to Supply Chain Resilience

Data analytics and supply chain management coming together is a transformative force in today's corporate environment. At its root, risk management has been a long-standing concern in supply chain management. Global supply chains have always been complicated and uncertain, necessitating sophisticated risk mitigation techniques. Building trust in supply networks has traditionally been a focus, as highlighted in

Christopher and Lee's (2004). In this context, confidence refers to a company's capacity to anticipate, deal with, and recover from supply chain interruptions. The relationship between Data analytics and supply chain resilience is created based on this idea.

A key component of creating resilience, as noted in Tang and Zhou's research (2012), is improved supply chain visibility. Big Data analytics becomes essential in this situation. Organizations can monitor, evaluate, and foresee any disruptions because of their ability to handle massive amounts of data in real-time. One of the crucial stages of supply chain resilience is anticipation, and thus real-time monitoring is a crucial component of anticipation.

But the effects of data on supply chain resilience go beyond predictions. According to Naim and Wikner, 2012, scenario planning is an effective risk management technique. It involves creating a range of possible situations and examining the potential operations of supply networks in each. Data analytics improves this process by providing more accurate, timely, and comprehensive data. Businesses may now imitate a greater variety of interruptions, strengthening their resistance throughout the resistance phase.

Resilience of the supply chain and sustainability are linked in today's world. The study by Li et al. (2006) emphasizes how crucial it is to incorporate sustainability factors into supply chain decision-making. Data analytics is crucial in this situation since it makes it possible to track and improve supply chain operations with a focus on sustainability goals (Liu et al., 2023). It enables businesses to gather and evaluate social and environmental data, enabling them to choose actions that are sustainable and meet the demands of many stakeholders.

The conceptual model developed by Trkman and McCormack (2009) for managing supply chain network risk is particularly pertinent to comprehending the function of data analytics. Their concept emphasizes how important risk management is for the entire supply chain network. This is an area where data analytics excels in the modern environment, with its global and networked supply chains. It gives businesses the ability

to continuously assess data from numerous sources, revealing potential weak points and facilitating efficient risk mitigation.

Collectively, these research findings highlight the rising importance of data analytics as a crucial facilitator of supply chain resilience. Organizations are better positioned to succeed in an increasingly unstable world if they can make data-driven decisions, predict disruptions, and effectively respond to them. Transparency, enabling experimentation to uncover needs, expose variability, and improve performance, segmenting populations to customize actions, replacing and/or assisting human decision-making with automated algorithms, and innovation of new business models, products, and services are all examples of value creation through big data (Manyika et al. 2011). The interpretation of significant business data adds value to the analytics (Sahay et al. 2008), therefore analyzed data must be presented to key decision makers in a timely, effective, and efficient manner (Giunipero et al., 2006). Big data's potential worth can only be achieved when it is used to start making decisions (Gandomi et al. 2015). Data analytics can be utilized to maximize value generation at the level of individual companies, industries, and entire economies (Manyika et al. 2011). Furthermore, core abilities should be used to convert short-term competitive circumstances into long-term competitive advantage, according to the dynamic capacities theory. This presumption also pertains to data analytics since, prior to data management and analytics, raw data may be seen as an unstructured resource that hasn't been turned into a powerful tool. According to Richey et al. (2016), analyzing a wider range of forecasts and making well-informed decisions are two ways that big data might enhance forecasting and decision-making. Data from several internal and external sources must be integrated in order to extract information from the data, apply analytics tools and techniques to it, and make decisions and conduct actions based on the insights (Sahay et al. 2008). To develop short-term demand forecasting forecasts that account for patterns and seasonality, predictive analytics is required (Wang et al. 2016). Since better forecasting improves the organization's ability to handle risks associated with decision-making, supply risk management has a great deal of potential to benefit from data collection, analysis, and use to identify risks (Richey et al. 2016). Predictive and prescriptive analytics can help businesses make strategic

decisions more successfully (Demirkan et al. 2013). According to Wang et al. (2016), data analytics can be utilized to solve issues with supplier chain structure, organizational culture shifts, sourcing decisions, and the design and development of products and services.

Employing data analytics improves the ability to find insights, which improves risk management and corporate performance. Data analytics helps in the assessment of the best sourcing strategy and makes capacity management and product delivery from producers to consumers easier. Data analytics delivers data scalability through the collection of highly detailed information with a limitless number of possible combinations, division of suppliers based on critical attributes, support for the sourcing strategy, and risk and cost balancing. The possibility for applying data analysis for diversification increases as a company's suppliers and consumers increase, according to Manyika et al. (2016) and Brown et al. (2011).

2.4 Conceptual framework: Data Analytics in Supply Chain Resilience

Prior research has emphasized the crucial importance of data analytics in enhancing supply chain resilience, as explained in the parts that came before. Although the importance of resilience has been highlighted in the literature (Calvo et al., 2020), it mostly focuses on the use of resilience in the recovery phase. This study suggests a conceptual framework called "Data-Driven Supply Chain Resilience" (see figure 4) to fill up these research gaps and combine key findings from the literature review. This paradigm combines ideas from the existing literature, such as the disruption management cycle, important aspects of resilience, and supply chain facilitators of resilience.

The phases of supply chain resilience—resistance, and recovery—along with the analytical tools of supply chain analytics—descriptive, diagnostic, prescriptive, and prescriptive. These stages make up the process of building resilience: resistance, which is characterized by diagnostic analytics that identifies vulnerabilities, and recovery, which is aided by prescriptive analytics. Organizations can efficiently predict, resist, and

recover from disruptions with the help of this comprehensive framework, which also strengthens supply chains so they can endure the complexities of the contemporary business environment.

In the next subsections, we will continue our discussion of the framework parts and comment on each of them in relation to supply chain resilience.

2.4.1 Descriptive Analytics for Proactive Resistance in Supply Chain Resilience

The Resistance Phase, which is a key component of a resilient supply chain, is characterized by its primary aim of maintaining uninterrupted company operations in the event of interruptions or disturbances. The prevention, mitigation, and effective management of risks and vulnerabilities are the main goals of this proactive phase. The significance of descriptive analytics becomes evident in the complex context of supply chain resilience, namely in enhancing tactics for mitigating risks.

Descriptive analytics plays a crucial role in enhancing the proactive resilience of companies by using real-time and historical data insights. The use of data allows firms to make informed decisions that greatly enhance their capacity to manage the obstacles encountered during the Resistance Phase. The deliberate use of this analytical instrument enables organizations to get a more thorough understanding of and adjust to interruptions, hence facilitating the continuous provision of goods and services.

Risk assessment is an essential part of descriptive analytics in the Resistance Phase. The tight association between supply chain disruptions and historical data patterns and trends has been underscored by Gartner, 2018. Through this process, organizations can enhance their comprehension of the supply chain ecosystem, facilitating the identification of potential weaknesses and the acknowledgement of the wide range of risks associated with the supply chain. Equipped with this information, corporations are more prepared to proactively address these risks and mitigate their implications.

Descriptive analytics is a crucial component in the field of resource allocation. According to Ivanov et al., 2019, this analytical tool facilitates informed resource allocation

alternatives. Organizations possess the ability to strategically allocate resources to mitigate disruptions by conducting a thorough analysis of previous performance data. Through the strategic optimization of resource allocation, businesses may effectively mitigate possible concerns, so assuring seamless operational continuity in the face of supply chain disruptions.

In summary, within the Resistance Phase, descriptive analytics serves a crucial role exceeding being used as an analytical instrument. It assumes a pivotal role in the identification of effective avoidance techniques. By using knowledge obtained from both past and present performance data, organizations may proficiently mitigate risks and enhance the resilience of their supply chains. In turn, this guarantees a steady flow of goods and services, boosting the market's overall competitiveness. In an era characterized by persistent supply chain interruptions, the use of descriptive analytics emerges as a fundamental element of proactive resilience. This capability enables firms to successfully manage obstacles and sustainably fulfil consumer requirements.

2.4.2 Descriptive and Diagnostic Analytics for Effective Response to Supply Chain Disruptions

A robust supply chain's Containment stage in the Resistance Phase controls and mitigates interruptions. It includes several crucial features to prevent disruptions from escalating and minimizing their effects. Descriptive Analytics offers the foundation for containment techniques by analysing previous and present data to illuminate the supply chain. Descriptive Analytics helps companies identify supply chain interruptions and threats (Lee and Mangalaraj, 2022) in providing historical perspective to detect vulnerabilities and disruptive trends.

The vulnerabilities that are detected via the use of Descriptive Analytics are then examined and analysed through the utilization of Diagnostic Analytics. The analysis seeks to identify the underlying factors contributing to the occurrence of disruptions. Through the examination of historical and current data, diagnostic analytics have the capability to identify the fundamental factors responsible for disturbances. The analysis of

diagnostic data indicates that the delays in the delivery of components in the previous scenario were caused by limitations in supplier capacity. Based on this understanding, firms possess the ability to develop containment strategies aimed at directly addressing the capacity challenge. These strategies may include engaging in collaborative efforts with suppliers to augment production or diversifying their supply sources (Lee and Mangalaraj, 2022).

Diagnostic and Descriptive Analytics provide a complete picture of supply chain vulnerabilities and causes. This understanding allows for proactive, accurate, and effective targeted containment methods to mitigate Resistance Phase disturbances.

2.4.3 Diagnostic and Predictive Analytics in the Response and Recovery Phases: Creating Stabilization

The Stabilization step in the Recovery Phase of a resilient supply chain is of vital importance as it represents the resumption of normality and organizational stability after a disruption. The phase in which diagnostic analytics demonstrates its true efficiency in the presence of disturbances is during this period. Through a detailed examination of both historical and real-time data, this research undertakes comprehensive retrospective investigations in order to reveal the fundamental factors contributing to disruptions. These insights provide companies with the ability to make informed decisions that are focused on swiftly resolving and mitigating long-term risks. As a result, the resilience of the supply chain is enhanced, hence reducing the possibility for future disruptions.

When used in combination with diagnostic analytics, predictive analytics becomes a beneficial companion as it directs its attention towards future outcomes and occurrences. The use of this analytical instrument utilizes both historical and real-time data to forecast disturbances and their possible consequences. People and organizations may take proactive steps to either avoid or lessen possible disruptions when they have the capacity to predict future occurrences.

The intersection of diagnostic and predictive analytics is where the true power is. Diagnostic analytics focuses on identifying and analyzing the underlying causes of problems, whereas predictive analytics looks forward to foresee and forecast potential future difficulties. According to insights from Wu et al. (2012) and Sheffi and Rice (2005), this peaceful cohabitation considerably supports supply chain recovery and protection. The combination of diagnostic and predictive analytics forms a crucial partnership that plays a vital role in ensuring supply chain stability throughout the Response and Recovery stages. Predictive analytics, according to Brandtner (2022), gives the insight required for proactive decision-making whereas diagnostic analytics acts as a retrospective lens, examining previous disruptions for improvement. The alliance acts as a guiding compass for firms in navigating the ever-evolving area of supply chain management, promoting stability and facilitating development in the presence of disruptions.

2.4.4 Prescriptive Analytics: Enhancing Supply Chain Resilience through Data-Driven Approaches

The Return stage, situated inside the Recovery Phase of a resilient supply chain, signifies the ultimate phase in surmounting a disruption and transitioning towards regular operations once again.

Prescriptive analytics is the highest level of supply chain resilience powered by data, enabling firms to strategically plan and enhance their supply chain operations. This approach extends beyond the scope of descriptive and diagnostic analytics by offering valuable insights and recommendations for enhancing supply chain resilience. Prescriptive analytics facilitates data-informed decision-making for businesses via the use of historical and real-time data to analyse many variables, constraints, and optimization objectives. The use of data-driven decision-making facilitates a proactive reaction to supply chain disruptions, hence enhancing resilience.

The significance of prescriptive analytics lies primarily in its capacity to enable speedy reactions to disturbances. The process assesses a range of situations and prospective courses of action, ultimately determining the most efficacious techniques for achieving

recovery. Prescriptive analytics plays a crucial role in reducing the effects of interruptions by facilitating actions such as rerouting shipments, modifying manufacturing schedules, and reevaluating supplier relationships. In addition to its immediate advantages, prescriptive analytics develops a culture of ongoing improvement inside the supply chain, constantly modifying plans, improving processes, and gaining insights from previous disruptions. Prescriptive analytics plays a crucial role in a dynamic supply chain setting characterized by unforeseen disruptions. It offers real-time decision support, allowing firms to make flexible and data-driven choices as conditions continue to develop. In summary, prescriptive analytics signifies an important advance in the development of stable supply chains that demonstrate resilience in the presence of unpredictability and challenges.

During the Recovery Phase, the organization's utilization of Prescriptive Analytics is enhanced through the integration of data-driven methodologies. This approach demonstrates notable efficacy in the examination of extensive datasets and the formulation of suggestions for further actions. Prescriptive analytics aims to optimize resource allocation, leverage technology, and provide adaptive solutions to enable enterprises to restore their full operating capabilities efficiently and effectively (Brandtner, 2022; Deepa et al., 2023). Continuous monitoring of performance is an additional approach to enhance resilience.

2.4.5 Data Analytics in Supply Chain Resilience

In the following sections, the author will undertake a comprehensive examination of the 'Data-Driven Supply Chain Resilience' concept and its use for the purpose of augmenting supply chain resilience. Prior to moving further, there is a graphic representation that is prepared to shed light on the complex relationship between data analytics methodologies and the crucial stages of a robust supply chain. At each step of the resilience-building process, this image acts as a road map, directing us via the strategic use of descriptive, diagnostic, prescriptive, and predictive analytics. This analysis will examine the ways in which analytics technologies enable firms to successfully handle

disruptions and strengthen their supply chains during the complexity of the modern business environment.

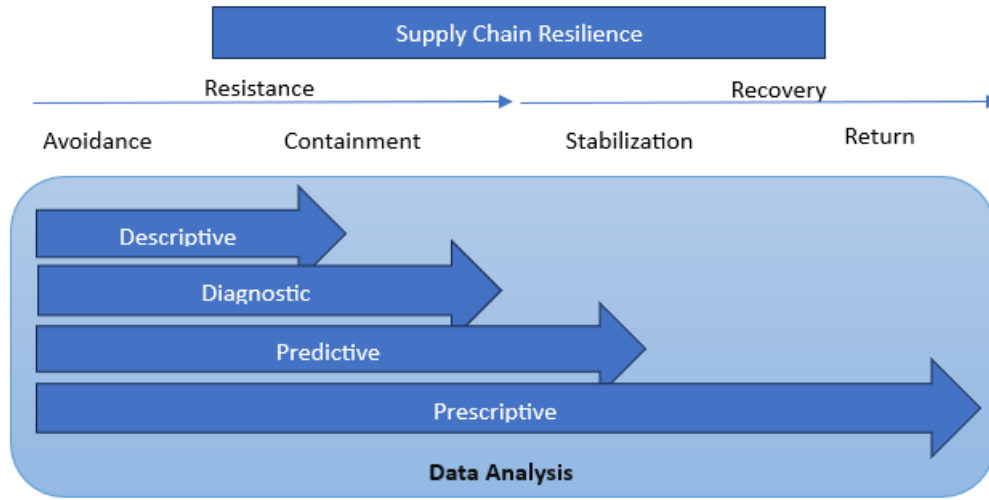


Figure 4. Conceptual framework: Data-driven Supply Chain Management

This conceptual framework will serve as a foundation for the empirical data analysis that will be conducted as part of this study. It is a synthesis of the important theoretical ideas gained from the research that was conducted before. The process of study continues with the following phases consisting of data collecting and data analysis. Consequently, the interview process will be developed using this framework to collect empirical data through semi-structured interviews with case firms. The framework can also be used to create thematic data groupings, which will improve the quality of the data analysis and result discussions.

3 RESEARCH METHODOLOGY

3.1 Research approach

A qualitative multi-case study was the chosen methodology for this thesis. Understanding and analyzing prevailing views and how they are used in everyday activities is how a social topic is explored in qualitative research. Qualitative research is more adaptable and permits the study and reinterpretation of existing phenomena than quantitative research, which is concentrated on collecting data in a strict, controlled manner. Several components, connections, interpretations, and processes can be investigated through qualitative research. A case study is a type of qualitative research technique that seeks to provide a realistic, vibrant, approachable, and personal explanation of difficult business problems. Eriksson and Kovalainen (2008) state that case studies can be used to generate hypotheses and can be carried out once or more times. Case studies look at the phenomenon from the perspective of the individuals involved.

3.2 Data collection

The selection of the sample, the creation of the interview protocol, and the interview procedure related to the gathering of empirical data are covered in this part.

The empirical study's goal is to examine how businesses have integrated data analytics in different phases of their supply chain resilience. In qualitative case-study research, choosing the case company and interview subjects is crucial. Purposive sampling principles were utilized to choose the study's sample. According to predetermined criteria, interview samples are chosen using this technique to allow for the knowledge and investigation of the research themes while maintaining the necessary level of diversity for comparative analytics (Ritchie et al., 2013). Purposive sampling selection criteria are influenced by a variety of factors, including the main goals of the study, existing knowledge, or theories about the field of study, potential research hypotheses, or knowledge gaps regarding the study population, according to Ritchie et al. (2013). The

selection criteria in this study are primarily centred on the exploration of data analytics as a tool for creating resilient supply chain.

The selection of case companies was based on their product offers and business model. Electronic products and components should be involved in the supply chain operations of the organizations selected for this study. The interview applicants were selected based on their experience with data-driving processes and their work status, which should be directly related to supply chain operations.

A total of six cases companies with seven supply chain experts were the subjects of semi-structured interviews. Purposive sampling principles were used to guide the purposeful selection of the six organizations for the empirical study on data analytics integration in supply chain resilience. These businesses were picked because they show different degrees of data-driven execution and represent a variety of industries. The study's author thinks it can capture a wide range of experiences and practices because it chose organizations from various industries and with varying degrees of maturity in data-driven techniques. The chosen firms differ in industry and size, as shown in table 2, to provide a range of perspectives.

Table 2. Overview of case interviews

Number	Industry	Size	Interview's position	Experience	Interview date
1	Telecommunication	500-1000	Delivery Manager	6 years	21.9.2023 52 min 32 sec
2	Automobile factory	500-1000	Logistics director	12 years	19.9.2023 46 min 20 sec
3	Electronics manufacturing	100-200	Manager in Operational and supply chain	8 years	02.10.2023 53 min 17 sec
4	Health care devices and applications	50-100	Procurement manager	8 years	10.10.2023 57 min 25 sec
5			Planning manager	6 years	10.10.2023 51 min 47 sec
6	Retails in spare part and accessories to home and leisure product	200-500	Commodity manager	11 years	20.9.2023 49 min 20 sec
7	Digital appliance device manufacturer	200-500	Head of Procurement	20 years	26.9.2023 35 min 21 sec

3.3 Questionnaire development

Precisely defining the data required to answer the research question is the first stage in creating a questionnaire. This entails identifying the precise features of supply chain resilience and data analytics that are being evaluation. In the present study, the four stages of supply chain resilience - avoidance, containment, stabilization, and recovery - are the main emphasis of the research topic.

The purpose of the questionnaire is to learn more about the target respondents' experiences with supply chain management using data analytics. The following topics are the focus of these questions:

- 1) The types of data analytics techniques that have been used in the supply chain.
- 2) The effectiveness of data analytics in different stages of supply chain resilience.
- 3) The challenges and opportunities associated with using data analytics in the supply chain.
- 4) The future of data analytics in supply chain management.

Thirdly, in terms of constructing the question wording, the question is designed to be easy to understand, clear, and concise, enable respondents to offer more in-depth responses by using selected questions that are open-ended.

Following the questionnaire's flow, the questions are then arranged logically. This order involves identifying the aspects of supply chain resilience and data analytics that are being examined. In this instance, avoidance, containment, stabilization, and recovery are the four stages of supply chain resilience that are the subject of the study topic. The purpose of the questionnaire is to get the relevant data in the shortest amount of time. To find any issues with the questionnaire, a pre-test is carried out with two responders. To provide the study with more accurate data input, two specific respondents in this study agreed to a second interview after the final form was completed. Clarity, length, and understandability are all checked during this process. Based on the feedback from the pre-test, the final survey form is revised and finalized. The final aims to be clear, concise, and easy to complete.

3.4 Data analysis

This research uses Thematic Analysis and Yin's five-step qualitative data analysis to analyse empirical data rigorously. This methodological approach uncovers and highlights essential themes in a large qualitative dataset to effectively communicate important research findings to a wider audience. The fundamental technique for locating and comprehending important dataset components is thematic analysis, according to King and Brooks (2018).

This qualitative data analysis procedure begins with data arrangement in a structured 'database'. To simplify access and organization, notes and recorded material are carefully organized before analysis. In this research, interview audio was thoroughly transcribed and categorized in Excel. Excel uses the matrix concept, where each column represents a firm case, and each row classifies data by developing themes or codes developed in later phases.

Disassembling the gathered material into smaller, more manageable chunks is the second stage. In this step, new labels or "codes" for these portions are explored. Thematic analysis relies on coding to index data using abbreviations to find important topics to answer research questions. King and Brooks (2018) recommend template analysis for coding, which this research uses. This method creates a customizable coding template from a portion of data. The coding template may be improved to reflect the dataset's numerous subtleties.

Inductive coding identifies themes from data, whereas deductive coding pulls motifs from theoretical or practical considerations. This method keeps analysis current and advances theory. This study examines the topics from the conceptual framework that shaped the interview questions. Eriksson and Kovalainen (2008) propose that codes derived from empirical data improve objectivity, thus it's important to agree. King and Brooks (2018) advise employing priori themes sparingly and reevaluating or removing them as appropriate.

The next step is rearranging and recombining the data to reveal patterns and connections after identifying common themes and codes. This technique compares disruption management strategies across firms. Excel is ideal for this work since it organizes interview quotes by theme. Yin (2011) suggests using two-dimensional matrices, which fits this analytical method.

The last steps of analysis include data interpretation and conclusions. Evaluate the data to find the most important analytical points. The results may need to be checked again to guarantee completeness and correctness. In this research, facts are carefully compared to theories to determine their practicality. This step's findings are organized into important topics in the thesis's succeeding chapters. The synthesis of ideas, empirical facts, and replies to research questions yields conclusions that summarise the study and provide significant insights. This thorough methodology assures the study's reliability and validity and helps supply chain disruption management practitioners understand their procedures.

3.5 Limitation of research method

A key constraint associated with qualitative case studies is to the difficulty in achieving generalizability. Due to the limited scope of these research, which often concentrate on a restricted number of cases or participants within circumstances, the generalizability of their results to larger populations or various settings may be limited. The limited number of observations and the unique circumstances under which they were conducted give rise to reservations about the applicability of the findings to a broader population or setting. The possibility of subjectivity and prejudice that are part of qualitative research is another significant drawback. The subjective character of data analysis implies that researchers' own opinions and biases might impact the study's design, data gathering, and interpretation, thus weakening the objectivity of the results. Furthermore, the considerable amount of time and resources required for conducting qualitative case studies may provide practical limitations. The comprehensive examination of instances requires substantial time and resources, thus limiting the viability of investigating a greater quantity of cases or performing studies with more extensive parameters. The

previously mentioned constraints highlight the need of thorough discussion and open disclosure in qualitative case study research, with the aim of reinforcing the reliability and significance of the results within the boundaries established.

4 EMPIRICAL FINDINGS

The use of data analytics in supply chain management has been explored extensively via the analysis of many case firms, enabling a comprehensive assessment of the extent to which these organizations can implement such practices.

The outcomes of the interviews with each specific case firm are collected in the next section. There are three subsections within this chapter. First, a brief synopsis of every example company is given, along with a detailed depiction of each one's supply chains. These subsections define the themes that developed from the process of data analysis, clarifying the impact of diverse supply chain analytics on the resilience of the supply chain. The second subchapter provides insightful information on how supply chain data analytics can be used to inform data-driven choices that will improve supply chain resilience by promoting proactive resistance. Finally, by including a brief outline of the empirical findings, the final sub-chapter functions as a summary of the entire chapter that came before it.

4.1 Background of case companies

A total of six firms have consented to participate in this investigation. These entities function across several sectors, showing a variety of organizational sizes that span from medium to huge. Gaining a comprehensive understanding of the supply chain operations of each case firm is crucial to effectively examine the various ways used in using data analytics to enhance supply chain resilience. To maintain the confidentiality of the organizations involved, identities will be assigned to each company in the thesis, selected to reflect their respective areas of specialty or industries.

The first company, known to as "**Telecommunications**" has an important role as a multinational entity within the telecommunications sector. Their company's main area of focus is the creation and delivery of communications solutions, which include software, hardware, and services. The organization now has a workforce of 1000 individuals. Furthermore, they engage in close collaboration with several international

offices to facilitate the provision of goods and services to both distributors and end consumers. Given the substantial size of its workforce and worldwide scope, the business manages a considerable volume of data related to many elements of its supply chain.

The second company, known as "**Automobile**", operating within the industrial machinery manufacturing sector, has shown substantial development and an increasing market presence, employing almost 700 individuals, focus on the production of essential systems for technical research areas. The company's intentions to expand its impact internationally within the industrial equipment manufacturing business are shown by the apparent quick expansion, which is suggested by the planned factory's completion by the end of 2023. Based on its size, development pattern, and the complexity of its activities, the company has a remarkable degree of data analytics capability. Data analytics is believed to have a significant impact on enhancing the efficiency of the supply chain, aiding in research and development efforts, and helping the growth of industrial equipment manufacturing companies into international markets.

The third company, known as "**Electronic Manufacturing**", is a significant business engaged in the provision of electronic manufacturing services. It claims an employee base of more than one hundred individuals. The company operates as a contract manufacturer, offering various services such as producing printed circuit boards, cables, and other electronic mechanism assemblies. Case "Electronic manufacturing" asserts that their competitive edge and performance in supply chain operations rest in their emphasis on flexibility and delivery accuracy, which is facilitated by their relatively small organizational structure. Their supply chain is reportedly quite stable, with robust supply paths and buffer supplies. The organization has a rather moderate amount of data analytics. The emphasis placed on stability, adaptability, and delivery accuracy implies a potential prioritization of operational effectiveness and dependability rather than complex data analytics. Nevertheless, there is still enough opportunity for the implementation of data in the organization.

The fourth company, known as "**Healthcare**", specializes in the development and production of electronic healthcare products and applications. More than fifty people are employed by the company's headquarters and its international locations combined. The company's main concentration is on product design and prototype, and Electronics Manufacturing Services (EMS) companies handle a sizable amount of the production process. These EMS providers take care of the manufacturing of completed goods and the acquisition of components. The firm purchases components, manages supply chain activities, and optimizes production processes by relying on the data analytics capabilities of its EMS partners. For the administration of a global presence, advanced data analytics solutions are necessary to estimate demand, monitor in real-time, and adjust to local market dynamics.

The fifth company, case "**Retails**" is a retail organization that specializes in the sale of automotive accessories and spare parts. In the mid-2000s, following its acquisition by a larger group, the company expanded its operations and logistics to meet rising demand. The company has demonstrated exceptional growth and resilience, surpassing competitors among disruptions in the industry. Predictions suggest that the company's annual revenue will continue to rise, which demonstrates its success and ability to adjust to the changing retail environment. In light of the dynamic and competitive character of the retail sector, the organization has implemented data analytics as a means to improve its operational processes. This involves comprehending customer preferences, inventory management, and demand forecasting, among other things. The reference to enhancing expansion via strategic acquisitions implies that the organization requires effective analytics to incorporate and optimize these recently procured elements into their operational framework and supply chain.

The sixth company, a business produces "**Digital appliance**" products, such as sensor, camera, and thermostats, among other things. It is dependent on a sophisticated international supply chain, which procures components from several different nations and assembles the devices in a number of different locales. Due to the complex of global operations and the presence of numerous assembly locations, they acknowledge that

the utilization of efficient data analytics becomes crucial to optimize the supply chain, guarantee punctual production, and effectively address fluctuations in component availability and market dynamics.

4.2 Data analytics to enable Supply Chain Resilience

4.2.1 Resistance

In this part, the results relating to the avoidance and containment elements of supply chain resilience during the resistance phase are discussed.

4.2.1.1 Avoidance

Supply chain analytics are utilized in a methodical manner throughout the Avoidance stage, which is part of the process of building a resilient supply chain. In most cases, the process starts with descriptive analytics, which is looking at historical data to get an understanding of prior patterns and disruptions. Early shortage detection is essential for timely, proactive response to preparedness for disasters.

We use data analysis to investigate the main reasons and patterns that keep happening with certain problems. These problems often occur because of difficulties with transportation routes or customs and national procedures. (Case "Automobile")

It's valuable to sync up the data from our past inventory and shortage records. It helps us figure out why certain products always seem to be unavailable. Understanding this situation gives us the ability to confidently tackle and find a solution to the problem. (Case "Healthcare")

The identification and mitigation of shortages are reliant upon the involvement of many supply chain stakeholders, including suppliers and subcontractors. Most of the firms under examination receive regular updates regarding the availability of components and the status of purchase orders from their manufacturing partners and suppliers, frequently on a weekly basis. Keeping up to date with current events and devising alternate strategies is especially important. Then a comparison analysis was conducted to compare the findings with the real needs and priorities.

We have a weekly review with our supplier to make sure our needs and their supply are aligned. These updates are instantaneous, which allows us to respond quickly and minimize any potential disruptions. Case “Electronics manufacturing”

Table 3 presents a comprehensive overview of the typical benefits that firms get via the use of data analytics to mitigate disruptions. The table includes just a limited number of quotations as samples, since other firms have seen some benefits.

Table 3: Empirical findings: Data-driven benefits in Avoidance Stage

Advantage	Illustrative quotes
Alignment	<p><i>Keeping our information up to date is important for both us and the supplier. It allows us to ensure that we are aligned with each other's needs and abilities. (Case “Retails”)</i></p> <p><i>Making sure that everyone understands the same information is important because it reduces the chances of miscommunication or misunderstandings. (Case “Digital appliance”)</i></p>
Responsiveness	<p><i>Having instant updates allows us to promptly respond to any changes or unexpected events that may occur in the supply chain. (Case “Automobile”)</i></p> <p><i>Being flexible is really important when it comes to dealing with disruptions quickly. (Case “Electronics manufacturing”)</i></p>
Disruption Mitigation	<p><i>Visualizing vendor capacity and scheduling helps us anticipate and minimize interruptions, lowering their effect on operations. (Case “Retails”)</i></p>
Prioritization	<p><i>Supplier's capacity and schedule in their coverage table allows us to alter our priorities depending on, ensuring most important demands are covered even with limits. (Case “Automobile”)</i></p>
Efficiency	<p><i>Current information helps us to improve decision-making. Based on current data, we may allocate resources and change production plans. (Case “Electronics manufacturing”)</i></p>

	<i>We use data analytics tools to analyse historical sales data and customer demand patterns. Based on this analysis, it appears that certain products tend to be more popular during times of the year. (Case “Automobile”)</i>
Relationship Building	<i>Maintaining open and honest communication, as well as sharing data regularly, can help foster a stronger relationship between your company and the supplier. Fostering trust and collaboration is important because it can greatly benefit long-term partnerships. (Case “Healthcare”)</i>

Data analytics serves as both an investigative tool and an anticipatory instrument for the optimization of supply chain operations. This tool facilitates the identification and proactive analysis of possible disruptions, offers valuable insights into the performance of suppliers during times of crisis, and enables decision-makers to make informed decisions about the allocation of resources and the development of emergency measures. By using data analytics, companies can effectively oversee external risks and develop a supply chain that is both robust and adaptive, so enabling it to resist unforeseen obstacles. Firm may be proactive in reducing the disruption, planning for it, and being proactive thanks to data-informed strategy. The achievement of these outcomes is facilitated by maintaining the coherence and coordination of various supply chain activities and stakeholders.

4.2.1.2 Containment

The strategy of containment serves as an alternate strategy to avoidance. The use of containment measures is crucial to effectively mitigate the spread of disruptions in the event of their occurrence and to minimize the resulting impacts. This capability allows companies to respond to disruptions promptly and decisively, therefore mitigating their adverse impacts on both operational efficiency and the organization's reputation and customer connections.

Most of the time, data pipeline and data reporting provide visibility to real-time information for companies, allowing them to rapidly adjust their strategy to address an issue.

One thing we're currently working on is using technology to enhance visibility and transparency throughout supply chains. It's all about finding ways to make things clearer and easier to understand. This can really help you out by allowing us to identify and address risks in a faster and more effective manner. (Case "Automobile")

During the disruption, we kept a close eye on real-time data, which included online sales, customer inquiries, and social media sentiment. We also keep tabs on the progress of component shipments from the supplier. (Case "Electronics manufacturing")

We have developed a system that automatically sends alerts whenever the inventory levels of important components or finished products fall below a specific threshold. These alerts are designed to notify inventory managers and procurement teams so that they can take necessary actions to avoid running out of stock or experiencing interruptions in production. (Case "Healthcare")

During a period of containment, the process of data interpretation plays a crucial role as an essential component within the framework of scenario planning. By conducting an examination of historical data, companies get significant contextual information, which facilitates their ability to identify trends, patterns, and previous occurrences that may have an impact on future situations.

Historical and instantaneous shipping data helps us analyse shipping trends and risks. Routes, logistics vendors, and transportation methods were accessed. This might include establishing alternate shipment paths and modes, backup logistics partners, and stockpiling finished goods in crucial locations. (Case "Electronics manufacturing")

Due to trade tensions between two important suppliers, semiconductor supply chains are disrupted. We record their component supply chain, discovering alternate vendors and storage sorts. Our team of analysts uses data analytics models to study the impact of a component supply interruption. This includes looking at

manufacturing delays and how they can lead to higher prices. (Case “Telecommunication”)

We have been exploring hypothetical situations for our business, which we refer to as scenario analysis. This tool assists us in preparing for unexpected circumstances by examining various scenarios and how they could affect our supply chain. (Case “Digital appliance”)

Table 4 presents a comprehensive analysis of the benefits associated with the use of data analytics within the supply chain, with a specific focus on enhancing supply chain resilience during the containment phase. The presented table defines several benefits and offers illustrative examples that demonstrate the contribution of data analytics to each advantage.

Table 4: Empirical findings: Data-driven benefits in Containment Stage

Advantage	Illustrative quotes
Rapid Detection	<i>As soon as the system notices a significant decrease in stock for a popular product, it promptly sends out alerts to restock the inventory. Rapid detection is beneficial because it helps prevent situations where there is a shortage of stock and customers are left unsatisfied. (Case “Digital appliance”)</i>
Precise Isolation	<i>We can isolate and recall a batch of items if a manufacturer's quality control data analytics find errors. This accuracy avoids mass recall, saving time and money. (Case “Digital appliance”)</i>
Visibility	<i>Delivery record such as delivery date and time helps identifying delays and route deviations early, enabling quick reaction to disturbances. (Case “Electronics manufacturing”)</i>
Robustness	<i>We use past data to identify providers with late delivery or quality concerns. Data analytics may help a corporation diversify its supplier base for a more dependable supply of goods. (Case “Retail”)</i>
Agility	<i>Data-driven demand forecasting methods can predict seasonal demand surges. With this knowledge, we can immediately alter production and</i>

	<i>inventories to suit client demands without delays or shortages. (Case “Digital appliance”)</i>
Velocity	<p><i>Integrating data analytics into inventory management systems enable real-time stock and order changes. (Case “Retails”)</i></p> <p><i>This information speeds up our order processing and delivery, ensuring things flow quickly through the supply chain. (Case “Automobile”)</i></p>

From suppliers to customers, supply chain analytics provides critical knowledge. Firstly, visibility helps track items, analyse component performance, and identify real-time disruptions. Data analytics helps supply chains identify gaps, increase inventories, and simplify procedures. By examining prior data and external factors, organizations may anticipate and prepare for disruptions, improving agility. To meet customer expectations, data analytics optimizes operations, reduces lead times, and speeds up disruptive response times in supply chains. Case firms use supply chain data analytics to build resilient supply networks that maintain product and service flow. Historical descriptive analytics performance insights boost visibility and robustness. Diagnostic analytics enhances resilience and agility by finding causes. Disruptions are predicted via predictive analytics, boosting agility and velocity. Data-driven prescriptive analytics boosts speed. These analytics provide visibility, diagnose issues, predict disruptions, and recommend solutions to build resilience. A multifaceted approach helps organizations develop resilient supply networks, enhance performance, and reduce disruptions.

4.2.2 Recovery

4.2.2.1 Stabilization

Stabilization is the preliminary phase within the Recovery Phase of supply chain resilience. Following a disturbance, the main objective is to establish stability within the supply chain and reinstate regular operational activities. The process of reconfiguration may play a crucial role in achieving stability which include modifications in supplier

relationships, transportation networks, or industrial infrastructure to efficiently restore operations and recuperate from the impact caused by the interruption.

In the Stabilization phase, it is advisable to address the impact of interruptions by including redundancy measures in key components of the supply chain, as shown in the case study of the firm under examination. The incorporation of redundancy functions as a preventive strategy in the case of primary system breakdown, hence enhancing the overall operational stability.

Predictive analytics assumes a crucial role in the context of supplier diversification, as it furnishes enterprises with valuable insights and projections. These analytical tools enable organizations to make well-informed choices about supplier selection and diversification strategies.

When it comes to situations where customized components are important and expensive to replicate, predictive analytics can be useful in evaluating the potential risks that come with relying on a single supplier. By anticipating possible disruptions and understanding how they could affect us, we can create backup plans and ensure we have enough essential components in reserve. (Case "Automobile")

The fundamental attributes of a resilient supply chain are flexibility and adaptability, which are especially crucial during the Stabilization phase. This phase aims to restore the supply chain to a level of normality after experiencing interruptions. The use of data analytics, in conjunction with a data-driven methodology, plays a significant role in enhancing these essential characteristics.

Flexibility and adaptability are considered essential characteristics of a resilient supply chain, particularly in the context of the Stabilization phase. The objective of this phase is to reinstate the supply chain to a state of normalcy after periods of disruption. The use of data analytics, in combination with a methodology centred on data-driven approaches, plays a substantial role in augmenting these fundamental attributes. Table 5 summarizes how data analytics may be used to improve supply chain stability.

Table 5: Empirical findings: Data-driven benefits in Stabilization Stage

Attribute	Description
Real-time Demand Forecasting	<p><i>Data analytics allows us to accurately predict and stay updated on demand, ensuring that supply chain activities align with changing consumer needs. (Case “Retail”)</i></p> <p><i>Having flexibility helps to reduce the chances of having too much inventory or not enough inventory. (Case “Automobile”)</i></p>
Inventory Optimization	<p><i>When it comes to predictive analytics, we have developed a Bayesian method that helps us determine the best inventory levels. We do this by analysing past data and current market trends. Being flexible in this way allows for the ability to maintain low inventory levels while still making sure that products are easily accessible. (Case “Automobile”)</i></p>
Supplier Performance Monitoring	<p><i>Using data analytics, we can constantly monitor the performance of our suppliers. When there are disruptions, being adaptable helps us find other sources or change our procurement strategies so that our supply chain keeps running smoothly. (Case “Healthcare”)</i></p>
Efficient Production	<p><i>Predictive analytics is a tool that allows us to make better production schedules by using up-to-date data and predictions of customer demand. The ability to adapt ensures that manufacturing processes can stay efficient, even when unexpected disruptions occur. (Case “Electronics distributor”)</i></p>
Scenario Analysis	<p><i>Data analytics helps us analyse different scenarios to understand the potential effects of various strategies. We can use this adaptability to assess and execute the most effective plan of action by utilizing real-time data. (Case “Automobile”)</i></p>
Customer Insights	<p><i>Using a data-driven approach allows us to gain a thorough understanding of what customers want and expect. We can enhance customer satisfaction by adjusting our products, services, and delivery methods to meet the changing needs of our customers. (Case “Digital appliance”)</i></p>
Risk Mitigation	<p><i>Predictive analytics helps to identify possible risks and disruptions in the supply chain, allowing companies to take proactive measures to mitigate</i></p>

	<i>these risks. Our ability to adapt allows us to respond swiftly to new threats and take proactive steps to prevent them. (Case "Healthcare")</i>
Resource Allocation	<i>Predictive analytics helps in making resource allocation more efficient by ensuring that resources are allocated effectively to meet the changing demand, while also minimizing any unnecessary waste. The ability to adapt helps to lower the costs of operations. (Case "Healthcare")</i>

4.2.2.2 Return

The "Return" phase within the supply chain resilience process has significant importance for enterprises since it prioritizes the prompt recovery of full operating capacity after an interruption. In this stage, the effective use of data analytics, particularly prescriptive analytics, assumes a crucial role in enhancing the robustness of the supply chain. The specifics of how prescriptive analytics improves the supply chain in this regard are provided in the following detail.

Analytics serves as a crucial guidance, using diverse techniques to navigate through the recovery stage. Particularly useful are diagnostic analytics, which enable businesses to do an in-depth of interruptions, identifying underlying causes and provide guidance on the steps required for recovery. This kind of study offers a framework for improved readiness and recovery from upcoming disruptions in addition to assist in understanding the past.

Next year's sales margin estimate is determined using prescriptive analytics. We do an analysis of market trends, competition intelligence, and historical sales data. Operational business units establish sales and profitability objectives that are particular to product groups. Monitoring the organization's progress toward objectives allows us to timely adjust our strategy. (Case "Healthcare")

Data-driven pricing models are beneficial because they assist us in determining the most effective prices for our products and services. This helps us to stay profitable

even when faced with difficult circumstances. When revenue streams increase, it helps to create a stable and resilient financial situation. (Case “Electronics distributor”)

Predictive analytics provides sensible recommendations for the purpose of decision-making and allocation of resources. It directs businesses toward the most effective recovery techniques by taking into consideration a variety of restrictions, goals, and historical data. These suggestions might help businesses speed up the recovery process and lessen the effects of interruptions.

During the supply chain resilience return phase, an effective learning and growth plan is essential for guiding the company toward recovery and strengthening it against potential disruptions.

When reaching the return phase, we use historical data to identify areas that can be strengthened to enhance resilience and then implement innovative measurement in those areas. (Case “Telecommunication”)

We plunge deep into what happened to identify any weaknesses. Set up classes or training events where people can share what they've learned from this study. This help create a mindset of always learning. (Case “Automobile”)

4.2.3 Risks in Data-Driven Supply Chain Resilience

Case companies in the study face numerous risks and complexities as they embark on the path towards building a data-driven supply chain resilience. There are several risks that can come up in relation to data quality, unexpected results, the complexity of the supply chain, and the need for accessibility. This section explores the risks involved and offers insights on how they can affect data-driven approaches to supply chain resilience.

Retailers gather a significant amount of data from different sources, including point-of-sale systems, customer loyalty programs, and social media. On the other hand, this data can be separated and not consistent, which makes it challenging to have a comprehensive understanding of the supply chain. (Case “Retail”)

In several cases, when companies conduct analyses, the outcomes are often regarded with a degree of suspicion. A common first response often expressed is, "This assertion lacks credibility." The presence of doubt may be attributed to uncertainties over the precision and reliability of the data. If the quality of the data is low, the validity of the conclusions drawn from it is also uncertain. The presence of inaccurate data has the potential to result in inefficient decision-making inside businesses, and in certain cases, it may potentially worsen vulnerabilities within the supply chain.

Retailers frequently work with numerous suppliers, which can make it challenging to gather all the necessary data for a complete understanding of the supply chain. (Case "Retailers")

Data was gathered from different sources, including sensors on machines and production lines, quality control systems, and customer feedback. However, the data we have can sometimes be filled with noise and may not be complete, which can make it challenging to spot trends and patterns (Case "Electronics distributor")

Healthcare device supply chains undergo extensive regulation and follow to demanding quality standards. Regulatory changes or product recalls can disrupt their operations and make them vulnerable. (Case "Healthcare")

The primary limitations in establishing a data-driven culture are the absence of data integration, heavy reliance on previous experiences, and resistance to change.

It's kind of frustrating how departments tend to work in their own little bubbles. They make decisions without really considering all the data from different areas of the organization. It's like they're missing out on the bigger picture. It would be so much better if they could see things from a broader viewpoint. (Case "Electronics manufacturing")

In many cases, decision-making power is granted to employees based on their experience. As a result, employees tend to rely on their past experiences and

knowledge when making decisions, rather than thoroughly analysing current trends. (Case "Automobile")

Employees often hesitate to adopt new technologies or methodologies because they feel at ease with the current processes, even when data indicates that making changes could result in improvements. (Case "Retail")

4.3 Conclusion of findings

The research issues presented in the thesis are addressed by the empirical results of this investigation. To begin, the utilization of analytics on vast quantities of data equips interviewed companies with the capacity to anticipate and prepare for disruptions in a proactive manner. Companies in the study use predictive analytics to assess the likelihood of operational disruptions, which allows them to proactively implement preventive measures. The use of data-driven decision-making in a strategic manner emphasizes the belief that supply chain resilience includes more than simply reactive responses to unexpected events but can also be achieved via proactive planning.

Furthermore, the integration of diagnostic analytics during the resistance phase assumes a crucial role in the identification of vulnerabilities within the supply chain. Case companies demonstrated their capacity to implement targeted measures to protect areas in danger and alleviate the negative effects of disruptions. By addressing potential vulnerabilities before they turn into major disruptions, companies increase their resilience and lower the risks they may face.

Additionally, the use of prescriptive analytics throughout the recovery phase contributes to the development of recovery techniques, resource allocation, and decision-making processes. By maximizing resource allocation throughout the recovery process and allowing for greater flexibility, it helps companies recover faster and more successfully. The research shows that data-driven recovery efforts may significantly boost supply chains' resilience, ensuring a minimal amount of downtime and a quick return to normal business as usual.

The results also emphasize the possible competitive advantage that a data-driven, inclusive resilience system may provide. A corporation is distinguished by its capacity to withstand disruptions and navigate complex business environments. Drawing from the previous research, one can infer that the implementation of data analytics to enhance the resilience of supply chains holds the capacity to provide a competitive advantage in today's global economic scenario.

5 DISCUSSION

This chapter presents the principal discoveries considering the theoretical framework that centres on Data Analytics as an enabler of supply chain resilience. In the discussions, empirical findings are analysed and contrasted with the theories that have been reviewed. The current chapter is structured into two primary subchapters. In the initial subchapter, the facilitator role of data analytics in establishing supply chain resilience is examined. The second section evaluates the ways in which the study contributes to the development of the conceptual model.

5.1 Data Analytics in Supply Chain Resilience

The result from case studies have proved earlier findings from previous articles that the use of all analytical tools has a big impact on supply chain resilience (Aker and Wamba, 2016; Gunasekaran et al., 2018; Jacobs & Chase, 2013). It helps organizations come up with a strategy based on data, which helps them predict, handle, and recover from disruptions more effectively.

Descriptive analytics with its capability to provide a comprehensive understanding of how the supply chain is currently operating plays a crucial role in improving supply chain resilience. It serves as a starting point to measure any improvements that can be made. When moving toward resilience, this step is critical in mapping out the complexities and inefficiencies of the supply chain. Consistent use of descriptive analytics will optimize its effects and provide a solid foundation for all following analytical steps.

During the resistance phase, diagnostic analytics plays a crucial role by identifying vulnerabilities within the supply chain. This analytical tool is designed to thoroughly analyze both historical and real-time data. It assists organizations in identifying potential weak points and sources of risk. By accurately identifying vulnerabilities, organizations can strategically allocate resources to strengthen these areas, thus reducing the impact of potential disruptions. When descriptive and diagnostic analytics are integrated, it

helps improve the identification process. The insights gained from the descriptive phase provide a solid foundation for recognizing vulnerabilities more accurately.

According to (Kylaheiko and Sandstrom, 2007), an organization must be proactive in scanning the environment and become more adaptable to handle both internal and external changes. Proactive resilience may be built with the use of predictive analytics, which focuses on forecasting future events and their potential impacts. The study's example companies have been able to prevent or lessen interruptions by taking proactive measures since they utilize both historical and real-time data to forecast them. Being able to predict and get ready for possible disruptions helps businesses keep things running smoothly and lowers the chances of problems happening (Pettit et al., 2013; Jüttner and Maklan, 2011; Christopher and Peck, 2004; Sokolov and Ivanov 2012). A proactive approach to supply chain resilience is created by combining predictive analytics with descriptive and diagnostic data to provide a thorough awareness of past, current, and possible future difficulties.

Jüttner and Maklan (2011) determined that the four essential characteristics of supply chain resilience are flexibility, rapidity, visibility, and cooperation. When it comes to these qualities, case companies in the study have proved that performance insights from historical descriptive analytics improve robustness and visibility. Diagnostic analytics helps to discover the underlying causes, which promotes resilience and agility. By predicting disruptions, predictive analytics helps increase velocity and agility. Prescriptive analytics' data-driven methodology improves overall speed and expedites decision-making. When taken as a whole, these insights provide a substantial contribution to visibility, problem diagnosis, disruption prediction, and solution suggestions, all of which help to build resilient supply chain networks. By using this multimodal strategy, studied companies review that result in maximizing efficiency and reducing supply chain interruptions.

The ability to respond quickly in emergency situations is a major factor in determining supply chain resilience (Sheffi and Rice, 2005; Wieland and Wallenburg, 2013). Potential disruptions are predicted through the utilization of predictive analytics, which analyses

both historical and real-time data. By means of this early warning system, organizations can respond proactively to issues before they escalate. Prescriptive analytics, in accordance with its inherent nature, not only forecasts disruptions but also suggests precise courses of action to alleviate their consequences. It provides concrete suggestions based on data to facilitate prompt responses. Companies and supply channels may incur substantial financial losses because of a postponed reaction to disasters (Pettit et al., 2013). The significance of response and recovery capabilities in the development of SCRE is underscored by Wang et al. (2010), Ponomarov and Holcomb (2009), and Sheffi and Rice (2005). It is argued that critical organizational capabilities include the ability to promptly respond to environmental forces, reconfigure resources, and recover from vulnerabilities. As an essential component of resilience assessment, recovery (Sheffi and Rice, 2005; Christopher and Peck, 2004; Ponomarov and Holcomb, 2009) is evaluated based on factors such as cost, time required to recover, absorption of disruptions, and power to mitigate adverse effects. Predictive analytics assists organizations in optimizing resource allocation through the implementation of suggested courses of action, thereby ensuring coordinated and effective response endeavours. Diverse data analytics techniques contribute to the improvement of supply chain resilience, particularly during the phase of recovery. Through the delivery of insights into past performance, descriptive analytics facilitates the comprehension and enhancement of recovery processes. Diagnostic analytics facilitates targeted recovery strategies by identifying the root causes of disruptions. By facilitating in the prediction of potential disruptions, predictive analytics enables proactive measures to reduce recovery time and expense. Prescriptive analytics utilizes real-time data to suggest optimal recovery strategies, thereby ensuring that recovery efforts are both efficient and effective.

Combining these technologies enables businesses to develop a thorough data-driven plan, improving their capacity to negotiate the complexities of the contemporary business environment. The integrated approach to supply chain resilience not only helps organizations better handle disruptions but also highlights the importance of data analytics in being proactive and maintaining resilience. This allows businesses to

redefine their approach to supply chain resilience in a dynamic and ever-evolving global environment. This leads to first proposition:

Proposition 1: By effectively integrating all analytical tools, a company may improve its ability to anticipate future events, mitigate risks efficiently, and maximize measures for recovery. These collective efforts significantly enhance the resilience of the supply chain.

According to Korhonen and Seager (2008), organizations may enhance their resilience and adaptability by gaining knowledge from previous disasters. Comfort (1994) asserts that the continuous acquisition of knowledge is of the highest priority in developing creativity, flexibility, and resilience. According to Giunipero and Eltantawy (2004), organizations have the potential to mitigate the risk of losses resulting from disruptions by collecting insights from previous experiences. The presence of unanticipated interruptions highlights the need of implementing a flexible supply chain resilience plan. In specific case companies in this study, the use of data analytics is of extreme significance. Interviewed companies accumulate substantial amounts of data and experiences throughout these stages to enhance their strategic approach. The comprehension of previous disruptions plays a crucial role in strengthening the resilience of supply chains via the use of effective risk mitigation methods. Case companies in this study have proved that they may become more proactive, flexible, and resilient via ongoing learning and adaptation. For case *Telecommunication* and *Machinery manufacturer*, the companies can streamline its recovery procedures by using the data on bottlenecks and recovery times as a reference that enable the companies to resume more quickly and developing supply chain architectures more flexible after a disruption. Each instance of interruption and subsequent recovery presents distinct possibilities for learning. Businesses may decide to implement technology development and training programs as a risk mitigation strategy (Khan & Burnes, 2007). Ritchie and Brindley (2007) assert that training and development programs, particularly those that concentrate on improving technical proficiency, assist supply chain professionals in reducing risks.

Kylaheiko and Sandstrom (2007) argue that the acquisition of information, experiencing learning, and drawing lessons from past experiences are essential factors in addressing

and mitigating vulnerabilities. When disruptions occur and subsequent recovery phases begin, data analytics are instrumental in significantly facilitating the process. In addition to facilitating the restoration of regular operations, these measures also provide valuable information that directly contributes to the development and improvement of avoidance tactics. This two-way sharing of information makes sure that the weak spots that led to problems are found and that the effectiveness of recovery steps is carefully studied. This leads to changes that keep these issues from happening again. By enhancing the avoidance phase, it seamlessly transfers the output of the recovery phase to a forward process. Case Retails has proved that the insights they gained from data analytics directly informed the development of avoidance tactics. Such learning is also critical to the supply chain's increased resilience, lower risk, and increased flexibility (Comfort, 1994; Manuj and Mentzer, 2008).

It takes a committed commitment to data-driven decision-making at each stage of the supply chain to incorporate this ongoing, cyclical resilience strategy. According to Pettit et al. (2013), benchmarking and experience-based learning are crucial components of supply chain resilience. Learning is a crucial component of crisis management, as was previously noted (Mitroff and Pearson, 1993). As a result, it could be claimed that learning and growth contribute to improved resilience inside a business and its supply chain. The whole of the process highlights the concept that resilience is not a fixed state, but rather an ongoing commitment to use proactive and evidence-based approaches. The information obtained from the first loop of the previous cycle was used as input for the subsequent cycle, hence contributing to the development of avoidance strategies for the subsequent cycle.

In conclusion, the idea of supply chain resilience as a continuous, data-driven process is crucial in a corporate environment that is rapidly evolving. This highlights the need for firms to have an agile and adaptable approach in response to unforeseen circumstances. The acquisition of useful information during each phase of disruption and subsequent recovery serves to enhance the resilience and effectiveness of the supply chain over time. This then gives rise to second proposition:

Proposition 2: The concept that supply chain resilience is not a singular effort but an ongoing commitment necessitating data-informed, adaptable policies at all stages of the supply chain.

Supply chain analytics have proven to be beneficial in improving the resilience of supply chains. However, like any tool or strategy, they also have their own set of drawbacks. The degree of success that a firm achieves is largely dependent on its level of proficiency in Data Analytics. According to Popovic et al. (2018), establishing proficiency in Data Analytics requires the involvement of senior management. Several other variables also affect how Business Data Analytics affects Supply Chain effectiveness. Akter et al. (2016) have mentioned the strategic alignment between data analytics and company as one of these elements. The stage of Data Analytics recognition is another element, as Zhang et al., (2018) pointed out. Additionally, Jeble et al. ,2018's analysis of the supplier base's complexity and Zhu et al. ,2018's investigation of the supply's degree of uncertainty both contribute to the moderating effect of Data Analytics on supply chain performance. The real results show difficulties in creating a data-driven culture in firms, which is consistent with the literature. The weaknesses that have been noted are resistance to change, a strong dependence on past experiences, and a lack of data integration. Examples of these issues in the actual world are shown by the cases of "Electronics manufacturing," "Automobile," and "Retail". These findings support the literature by illuminating how research-outlined challenges emerge in real-world organizational contexts. This highlights the urgent need to address these constraints to promote a more robust and efficient supply chain through data analytics. To advance their data analytics abilities, supply chain practitioners must prioritize finding solutions to these problems.

As a result, experts must make sure that their knowledge of data analytics aligns with their strategic objectives. Businesses must undergo an immense cultural transformation toward data-driven decision-making as they adopt data-driven approaches. This method entails optimizing the benefits provided by data analytics in strengthening the resilience of the supply chain, taking risk reduction strategies into account, and integrating analytics into the business's general culture.

Traditionally, decisions about the supply chain were made mostly based on intuition, experience, or established norms. As a result, it took a lot of leadership commitment to support and integrate data-driven methods. According to Lee et al., 2019 and Gani et al., 2023, organizations must promote a data-driven culture that enables all members of the organization—including executives, managers, and lower-level staff—to make informed decisions based on data (McAfee and Brynjolfsson, 2012; Ross et al., 2013). Comprehensive training programs should be created to close this knowledge gap since many staff may not have had previous exposure to data analytics. This includes the establishment of clear information ownership, the practice of conservation, and the responsibility for data quality. Educational programs of this kind should involve the whole of the business, including those in supply chain management, procurement teams, and logistics experts. These initiatives aim to educate these individuals with the necessary skills to understand data, analyse insights, and effectively use analytical tools. The possibility exists that staff members may demonstrate opposition against a change from traditional methods to analytics. To overcome this opposition, it is essential to implement change management techniques that are efficient and successful. These tactics should be led by leaders that advocate for the advantages of data-driven methodologies and foster a collaborative culture that fosters adaptability. To assist this transition, it is essential for leaders to effectively address issues, provide necessary resources, and promote a smooth and uninterrupted move towards decision-making based on data.

In a culture that prioritizes data-driven approaches, the significance of ongoing development and learning cannot be overstated. It is essential for organizations to include feedback loops as an inherent component of their decision-making process. This entails regularly assessing the results of choices made using data analysis and modifying plans, accordingly, using the knowledge acquired. In addition, the capacity to extract knowledge from previous disruptions and integrate these insights into subsequent decision-making procedures is crucial in the development of supply chain resilience. This leads to third proposition:

Proposition 3: Organizations are required to undergo a significant cultural transformation as they move toward data-driven decision-making, which entails embracing the potential of data analytics to mitigate risks and enhance resilience as well as addressing the associated challenges.

5.2 Framework for Data-Driven Supply Chain management

An important change in the traditional linear approach to supply chain analytics research is being brought about by the exploration of supply chain resilience and the broader insights that result from this exploration. Resilience is becoming more widely understood as an ongoing commitment rather than to a one-time event. The previously mentioned insight emphasizes the necessity of applying flexible and data-driven tactics at every phase of the supply chain. The recognition that every data analytics approach can be extremely useful and relevant at various stages of supply chain resilience is an important realization.

A comprehensive and continuous action, supply chain resilience is currently understood to involve intentional utilization of a variety of data analytics methods at different phases of the supply chain. The application of data analytics techniques, such as prescriptive, predictive, diagnostic, and descriptive methodologies, is becoming more and more important in improving supply chain resilience.

It is becoming more apparent that firms interviewed in the study who possess a strong ability to use data analytics are finding themselves in a more advantageous position to not only identify disruptions in the supply chain, but also to actively reduce risks and enhance the procedures involved in recovering from such disruptions. The use of analytics is not confined to a singular stage of resilience; rather, it serves as a comprehensive solution implemented throughout all phases to guarantee continuity and readiness.

By incorporating these data analytics techniques throughout the supply chain, organizations are enhancing their ability to effectively address disruptions. In addition to reactive responses, they are also engaging in proactive risk mitigation measures.

Moreover, the recognition that this is not a singular occurrence but rather a continuous dedication has had a significant impact. This statement underscores the significance of constantly adjusting to the evolving environment and being led by insights obtained through data analysis. Businesses that adopt these flexible tactics and use data analytics to make well-informed choices are clearly outperforming those that stick to more conventional, linear processes.

Unquestionably, prescriptive analytics, which is regarded as the most advanced kind of data analytics, offers significant advantages in building resilient supply chains. It is extraordinary in its ability to recommend the best path of action based on predictive models. Nevertheless, it is evident that the firms surveyed for this research have not widely adopted it. The low use of prescriptive analytics may be linked to the substantial requirements in terms of investment in IT capabilities, human resources, and the considerable time needed to develop knowledge in modelling and understanding its results.

Given the constraints shown during the interviews, the author is required to adjust the fundamental framework, recognizing the constraints and practical challenges posed by a broad application of prescriptive analytics. Based on a thorough assessment of the existing environment and the competencies of the investigated firms, the decision was made to either eliminate or restrict its role within the framework. This decision does not diminish the overall potential and utility of prescriptive analytics for enhancing the resilience of supply chains. Instead, it respects the existing constraints and prioritizes the optimization of alternative analytical methods that are more suitable and often used inside these organizations. The practical adaptation ensures that the modified framework is more suited to the actual challenges encountered by these businesses, hence enhancing the efficiency and viability of using data analytics in their supply chains.

The framework suggested in this paper offers a comprehensive direction for organizations to effectively use data analytics in supply chain management. The construction of the project was informed by academic research and supported by empirical evidence gathered from multiple case studies.

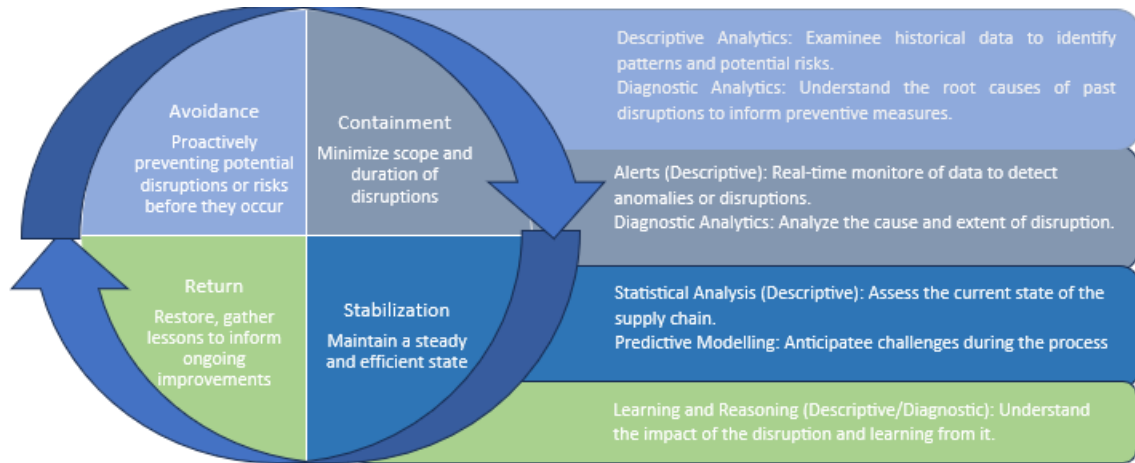


Figure 5. Modified and elaborated Conceptual framework: Data-Driven Supply Chain management.

6 CONCLUSION

The objective of this thesis was to explore the theories of supply chain data analytics and understand how they contribute to building supply chain resilience. The study focused on how different aspects of resilience can be applied to manage supply disruptions. It aimed to understand how having a resilient supply chain can assist firms in effectively dealing with disruptions. The purpose of the study was to address the following research questions:

How can we use data analytics to strengthen supply chain management and make it more resilient?

(1) To what extent do case companies implement data analytics for decision-making and strategy optimization in their supply chain

(2) How do case companies integrate different types of analytics to form a holistic approach to supply chain resilience?

The research offered thorough insights into the ways that supply chain management resilience is strengthened by data analytics. The study thoroughly examined how data analytics affects supply chain resilience. It looked at the various ways in which it impacts supply chain operations. The research demonstrated how data plays a crucial role in strengthening supply chains by using real-life examples from various industries. The study explored different areas like risk management, demand forecasting, and inventory optimization. It showed how data analytics helps in making the supply chain more adaptable and resilient against disruptions. The study effectively answered the sub-question about how data analytics affects supply chain resilience by exploring different avenues.

Additionally, the research explored the methods needed to effectively implement data analytics in the supply chain. The article provided a thorough examination of the most effective methods, obstacles, and approaches that companies need to consider when integrating data analytics into their supply chain management systems. The study used

both theoretical frameworks and actual case studies to answer the sub-question about the approaches required for successfully implementing data analytics in supply chain management.

This chapter goes on to provide further details on the thesis's primary theoretical and management contributions. In conclusion, the study concludes by discussing its limitations and providing recommendations for future research.

6.1 Theoretical contribution

This study critically addresses supply chain resilience deficits by connecting data analytics to all stages of resilience. A thorough review of academic papers strives to integrate the concept of data analytics across the supply chain resilience cycle. The study gives a holistic view of data analytics by consolidating and evaluating this information. It clearly outlines the advantages and disadvantages of data-driven supply chain resiliency.

This report also highlights the positive and negative aspects of incorporating data analytics throughout supply chain resilience stages. It explores the complex effects and consequences of data analytics and offers practical advice for companies seeking to improve supply chain resilience via data-driven decision-making. To sum up, this study fills in important gaps in the body of knowledge on data analytics and supply chain resilience. Nguyen et al. (2017), Duan and Xiong (2015), Lamba and Singh (2016), Nalchigar and Yu (2018), Gupta and Sharma (2022) have all pointed out the gaps in the literature, which indicate a lack of thorough studies investigating the possible improvements in supply chain resilience via the use of data analytics. Prior research has recognized the significance of integrating both descriptive and predictive analytics into prescriptive models, highlighting their significant influence on the performance of the models. Nevertheless, it is still difficult to fully comprehend the advantages of using data to inform decisions at every stage of the supply chain resilience cycle.

By filling up these gaps, my research advances the subject by offering a thorough analysis involving practical data analytics at different resilience stages in addition to exploring them. Through this approach, the study aims to address the current knowledge gap highlighted by studies by Gupta and Sharma (2022), providing an authoritative framework for the practical application of data analytics to improve supply chain operations. In addition, my research closes the gap Nalchigar and Yu (2018) pointed out in the few studies that investigated the entire loop chain. The research at the same time provides a framework for the creation of a comprehensive supply chain resilience data analytics methodology through empirical findings and insights. This study addresses separated knowledge and identified the challenges of implementing data analytics in supply chain resilience to provide clearer understanding and actionable recommendations for organizations seeking a resilient, data-informed approach to strengthen their supply chains.

6.2 Managerial implications

The analysis of data analytics applications in enhancing supply chain resilience from a qualitative perspective has management consequences. Above all, the research emphasizes how important it is to make data-driven decisions. With a better understanding of how data analytics affects decision-making, managers can more effectively negotiate uncertainty, allocate resources wisely, and create strategies that adapt to changing supply chain circumstances. As a result, companies are better equipped to make strategic choices that improve overall operational resilience.

Second, the results highlight the need of taking proactive steps to mitigate risk. To allocate resources more effectively and lessen the impact of any interruptions, managers might strategically employ data analytics to detect vulnerable points within the supply chain. In a turbulent business climate, this proactive strategy is essential because it enables firms to anticipate and address any issues before they become more serious.

Lastly, the research emphasizes how important organizational flexibility and learning are. Managers may encourage an organizational culture of continual learning by using

qualitative findings as direction. This guarantees that employees can use data analytics tools efficiently, keeping up with technology developments, and implementing industry best practices. Within a corporate world that is changing quickly, this dedication to learning and flexibility makes the firm more resilient and competitive overall.

In essence, this study adds considerable value to the body of literature by recognizing the connection between data analytics and supply chain resilience and by offering practical advice to businesses looking to use data-driven decision-making at every stage of the cycle. This research aims to aid practitioners and scholars in advancing the subject and building a more resilient and adaptable supply chain network by providing a thorough grasp of the role of data analytics in strengthening resilience.

6.3 Limitations and further research

This study has a few inherent limitations due to the specific nature of the subject issue and the methodology applied. There are specific limitations associated with examining its impact using a qualitative approach. The primary limitation of qualitative methods, including interviews and case studies, is that they frequently impede a comprehensive evaluation of advantages and disadvantages due to their reliance on the personal interpretations and opinions of a select group. Although these insights provide a comprehensive comprehension, they may be biased by the presumptions and perspectives of the interviewees, thus potentially negating the complete impact of data analytics. To acquire more substantial and concrete proof regarding the positive and negative aspects of data analytics in supply chains, it would be advantageous to employ quantitative analysis on a broader and more varied dataset.

Additionally, the study's generalizability is narrowed by constraints related to industry, location, and company position. The outcomes are influenced by the circumstances and complexities of a specific industry, geographical area, and the standing of the analysed firm in the marketplace. Such a limitation hinders the generalizability of the results to various sectors or geographic regions, thereby reducing their overall significance. The limitations and scope of the conclusions may be imposed by the fact that the

complexities unique to each industry and company may not reflect the broader landscape of supply chain scenarios.

Finally, most implications associated with the implementation of data-driven approaches in supply chain management are neglected in most cases studies, which is a critical oversight. When cost-effectiveness is of the highest priority in today's competitive business environment, the financial impact of such implementations should not be overlooked. The assessment of costs related to the implementation of technology, procurement of data, provision of training, and maintaining of the system is crucial. The potential negative consequences of these expenses may surpass the advantages, presenting a substantial obstacle for businesses, especially those of a smaller or medium scale, thus impacting the viability and long-term viability of these solutions.

To achieve a more comprehensive comprehension of data analytics in supply chains, it is advisable for future research to incorporate both quantitative and qualitative methods of analysis. The inclusion of a wide range of industries in research can improve the applicability of findings by providing a more comprehensive understanding of the diverse effects that exist across sectors. Furthermore, to evaluate the financial effects of adopting data-driven methodologies, it is imperative to perform a comprehensive cost-benefit analysis. This will furnish invaluable insights, particularly for smaller organizations. Continuous studies have the capacity to capture the dynamic impact of technology as it progresses over time. Conversely, comparative analyses among companies may reveal the most effective tactics and obstacles, thereby enhancing our comprehensive understanding of the role of data analytics in strengthening supply chain resilience.

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Appendix A: Interview Outline

Section 1: Demographics

1.1. Please provide your basic demographic information:

Name (optional):

Job Title:

Organization:

Years of Experience in Supply Chain Management:

Section 2: Data Analytics

2.1. How would you describe your understanding of data analytics in the context of supply chain management?

2.2. Have you personally used or overseen the use of data analytics tools in your organization's supply chain operations? Please describe your experience.

Section 3: Descriptive Analytics

Descriptive analytics entails the examination of historical and current data in order to gain insights into past and present conditions. It provides a comprehensive picture of what has occurred in the supply chain, assisting organizations in identifying strengths, weaknesses, and trends. In essence, it provides a response to the query, "What has happened?"

3.1. Can you share examples of how Descriptive Analytics has been used to identify vulnerabilities and risks in your supply chain during the resistance phase?

3.2. How has Descriptive Analytics helped your organization in understanding the historical performance and limitations of your supply chain?

3.3. Have you utilized Descriptive Analytics to conduct a comprehensive risk assessment during the? What insights did it provide?

Section 4: Diagnostic Analytics

Diagnostic Analytics: Diagnostic analytics looks deeper into data to determine why something occurred. Its goal is to analyze historical and real-time data to determine the core causes of supply chain disruptions or difficulties. It aids in the identification of the precise elements that contributed to a problem. Diagnostic analytics provides a solution to the query "Why did it happen?"

4.1. Could you provide instances where Diagnostic Analytics has been employed to investigate root causes of supply chain disruptions?

4.2. How has Diagnostic Analytics aided in formulating strategies to prevent similar disruptions in the future?

4.3. Can you share any experiences where Diagnostic Analytics was instrumental in identifying vulnerable areas in your supply chain?

Section 5: Predictive Analytics

Predictive Analytics: Predictive analytics forecasts future events or trends in the supply chain using statistical models and machine learning techniques. It uses past data and present situations to forecast probable disruptions or opportunities. Predictive analytics provides a solution to the question, "What is most likely to happen?"

5.1. Have you used Predictive Analytics to forecast potential supply chain disruptions? If so, please provide examples.

5.2. How has Predictive Analytics assisted in proactive planning and risk mitigation in your supply chain?

5.3. Can you describe any instances where Predictive Analytics successfully predicted disruptions, allowing your organization to take preventive measures?

Section 6: Prescriptive Analytics

Prescriptive analytics goes beyond prediction and provides recommendations for actions to improve supply chain operations. It makes recommendations based on complex optimization techniques, simulations, and data-driven insights. Prescriptive analytics provides a solution to the question, "What should we do to achieve the best possible outcome?"

6.1. In your experience, how has Prescriptive Analytics contributed to decision-making of supply chain disruptions?

6.2. Can you provide examples of how Prescriptive Analytics recommended specific actions to mitigate risks and enhance resilience in your supply chain?

6.3. How has Prescriptive Analytics improved the allocation of resources and response strategies during disruption?

Section 7: Overall Impact of Data Analytics

7.1. What roles has data analytics—descriptive, diagnostic, predictive, prescriptive, or a combination—played in resuming regular operations and improving supply chain efficiency during recovery?

7.1. In your opinion, how have the combined efforts of data analytics, especially Descriptive, Diagnostic, Predictive, and Prescriptive Analytics, along with other methods, contributed to the overall resilience of your supply chain?

7.2. Can you describe any challenges or limitations you have encountered in implementing these analytics methods for supply chain resilience?

Section 8: Additional Insights

8.1. Is there anything else you would like to share regarding the role of data analytics in creating supply chain resilience?