Simulating Resilience in the Milk Supply Chain:

The role of Big Data

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December, 2023

Abstract

Purpose: Supply chains provide a way for organisations to partake in cost advantages and leverage on relationships within the network to provide quality goods and services. However, these supply chains face risks which can hamper their performance and one of such risks is the risk of disruption. In order to mitigate the risk of disruption in supply chains, literature suggests building resilience. With technological advancements, organisations are of the opinion that these technologies potentially carry specific advantages that have previously been difficult to access. One of those technologies is Big Data. This research, therefore, seeks to explore ways in which Big Data can be adopted by organisations in order to build resilience, with a focus on the milk supply chain.

Design/Methodology/Approach: The research adopts a mixed method: Interviews and Simulation. The interviews allowed the research to gather information on the challenges faced by supply chains that have encountered recent disruptions such as the COVID-19 pandemic and the simulation allows the research to examine different disruption types objectively.

Findings: The results suggest that Big Data can be adopted to build resilience by supporting collaboration, flexibility, supply chain design and data management. The research also found that demand disruption had the least impact on this milk supply chain and the associated cost. Additionally, the research found that inventory planning prevents stockout situations, keeps customer service levels high and improves resilience within the supply chain. The research also found that while Big Data offers several advantages, supply chains often encounter several challenges when trying to adopt Big Data

Originality/Value: The originality of this thesis stems from the fact that this research is one of the few empirical studies that identify how Big Data can be applied in a milk supply chain context. This research not only develops a resilience measurement tool, but also carries out simulated experiments leveraging real-world data to measure the effects of three disruption types on resilience. Through objective data analysis and documentation of the results, this study contributes to the literature on supply chain resilience by highlighting parameters that can aid an evidence-based assessment of resilience within milk supply chains leveraging big data analytics.

Keywords: Supply Chain, Disruption, Resilience, Milk, Big Data, Simulation

Intellectual Property and Publication Statements

The research work presented in this thesis is the result of original and independent research conducted by Edidiong Udo. The ideas, concepts, data, methodologies, and findings presented in this thesis are my original contributions, except where otherwise indicated. Any external sources, including but not limited to published works, research articles, or intellectual property belonging to others, have been appropriately cited and referenced.

This thesis is submitted with the understanding that it is for the purpose of contributing to the body of knowledge in Big Data Analytics and Supply Chain Management. While the findings and conclusions presented in this thesis are based on rigorous research and analysis, they are subject to further scrutiny, verification, and refinement by the academic and scientific community.

I acknowledge that the dissemination and publication of research findings are vital for the advancement of knowledge and scientific progress. Therefore, I intend to share the results of this research through appropriate scholarly channels, including but not limited to publication in peer-reviewed journals, presentation at conferences, and sharing with fellow researchers in the field.

By submitting this thesis, I affirm that I have adhered to the ethical standards and guidelines for research integrity, including obtaining necessary permissions, maintaining confidentiality, and conducting research with integrity and transparency.

I further acknowledge the contributions of all individuals, organisations, and funding agencies that have supported and facilitated this research, and I will duly acknowledge them in any publications or presentations arising from this thesis.

Acknowledgement

I am deeply grateful to the following individuals and funding body who have supported and encouraged me throughout my doctoral journey, enabling me to complete this thesis.

First and foremost, I would like to express my heartfelt appreciation to my loving husband Dr Ikpe Ibanga. Your constant encouragement, patience, and unwavering support have been the foundation of my success. Your belief in my abilities and sacrifices made during this journey are immeasurable, and I am truly grateful to have you by my side.

I would like to extend my gratitude to my father, Mr I.S. Udo your wisdom, strength, and belief in my abilities have been a constant source of motivation. Your unwavering support throughout my academic journey has played a pivotal role in my accomplishments. I am also thankful to my dear siblings for their love, encouragement, and understanding.

I extend my heartfelt gratitude to my esteemed PhD supervisors Dr Luisa Huaccho Huatuco and Prof. Peter Ball. Your guidance, expertise, and insightful feedback have been invaluable throughout this research endeavour. I also appreciate Mr. Tony Waller at Lanner Group for the commitment to modelling and simulation excellence which has significantly contributed to the quality and depth of this thesis.

I would also like to express my sincere appreciation to my friends, who have been a constant source of encouragement and inspiration. Your presence and friendship have made this journey not only academically rewarding but also immensely enjoyable.

I am deeply grateful to the Niger Delta Development Commission (NDDC) for providing the funding and resources that made this research possible.

Lastly, I would like to acknowledge the grace and guidance of a higher power. To all those who believe in God and have offered prayers, I am deeply grateful for your spiritual support. To everyone mentioned above and countless others who have touched my life in various ways, thank you from the bottom of my heart. Your support, love, and belief in my abilities have been instrumental in the successful completion of this PhD thesis.

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List of Acronyms

ADM	Agent based Modelling
AHDB	Agriculture and Horticulture Development Board
AI	Artificial Intelligence
BDA	Big Data Analytics
COVID-19	Coronavirus disease 2019
DC	Dynamic Capabilities
DES	Discrete event simulations
FAO	Food and Agriculture Organisation
GDPR	General Data Protection Regulation
HIPAA	Health Insurance Portability and Accountability Act
IoT	Internet of Things
IT	Information technology
KFC	Kentucky Fried Chicken
RBV	Resource Based View
RDBMS	Relational Database Management System
SCR	Supply Chain Resilience
SD	Systems Dynamics
SAP	System Analysis Program

Chapter 1
INTRODUCTION

1.1 Supply Chain

Organisations are increasingly having a difficult time surviving and competing as independent businesses possibly due to uncertainties, increased costs and competitive advantages (Wu et al., 2013; Ben-Daya et al., 2019; Ali et al., 2023). However, businesses operating as a part of a wider supply chain, which involves a network of multiple relationships across several businesses provides, benefit from better competitive advantages (Lambert and Cooper, 2000; Ireland and Webb, 2007; Fawcett et al., 2008; Tang and Nurmaya Musa, 2011; Ben-Daya et al., 2019). Specifically, food supply chains are essential for global food security with enhanced traceability and reduction in food poverty (Hendry et al., 2019a; Alabi and Ngwenyama, 2023; Perdana et al., 2023). They also offer competitive advantages to its participants which include increased individual business performance, environmental sustainability, social sustainability and employment opportunities, and as such, the effective performance and sustainability of food supply chains should be promoted (Hendry et al., 2019b).

Food supply chains are confronted by unique challenges which are not experienced by other supply chains; these challenges include infectious diseases caused by bacteria, fungi, viruses, parasites, etc. (Perrin and Martin, 2021; Perdana et al., 2023), a short shelf-life (Shanker et al., 2022; Perdana et al., 2023), a minimal margin (Thamaraiselvan et al., 2019), all of which which implies that members of the supply chain have restricted financial flexibility to target these issues when they arise. In the UK, the competitive pressure on members of food supply chains (e.g. small local farmers) caused by disruptions stemming from political upheaval such as the recent UK's exit from the European Union (Brexit) and the COVID-19 pandemic, makes the resilience of local food supply chains both an opportunity and a potentially critical challenge (Hendry et al., 2019b).

One typical example of a food supply chain is the milk supply chain which constitutes a staple in daily diet and any challenges that arise must be handled with unique measures to ensure customer satisfaction and competitive advantage.

Therefore, the optimal performance of the milk supply chain is essential, and any exposure to risks can be potentially detrimental both for the supply chain participants and the end users. A disruption in the milk supply chain can have far-reaching consequences. Beyond the immediate shortages of goods, disruptions can trigger operational and financial challenges, cascading impacts on multiple stakeholders, and potentially risking the health and nutrition of a significant portion of the population. Hence, tackling a disruption in this type of supply chain can lead to an improvement in the supply chain (Perdana et al., 2023)

Operationally, a milk supply chain disruption can lead to delays in the delivery of milk products which can affect the functioning of dairies and processing facilities, potentially resulting in product wastage, inventory shortfalls etc. Financially, the consequences include the additional costs incurred to mitigate the disruptions but also extend beyond individual companies, impacting the livelihoods of farmers, trucking companies, and other members in the supply chain. The economic stability and food security of communities can also be at stake. Scholars propose developing resilience within the supply chain as a way to mitigate these risks, especially the risk of disruption (Rice and Caniato, 2003; Christopher and Peck, 2004; Pettit et al., 2010; Melnyk et al., 2014; Mari et al., 2014; Matsuo, 2015; Schmidt, 2015; Macdonald et al., 2018; Ben-Daya et al., 2019). This thesis takes a critical look at the intricate web of milk supply chains, where the need for resilience is paramount, exploring ways to improve and sustain resilience within the milk supply chain.

1.2 Disruption Risks in Food Supply Chains

According to Ivanov et al. (2014), while several other risks exist, disruption contributes a significant risk within the supply chain. This is evidenced in the last two decades with several examples across various industries, including the food supply chain. These disruptions, either internally or externally triggered, impacted the supply chain in different ways (Table 1.1). One of the typical examples available in literature include the disruption of supply and demand caused by an unprecedented global disease outbreak which led to the COVID-19 pandemic (Chowdhury et al., 2021a). This affected the food industry as people were not allowed to congregate in public places such as restaurants.

Prior to the COVID-19 pandemic, the British Exit (Brexit) from the European Union (EU) took place. This was political and disrupted the availability of goods and services previously enjoyed from businesses around the EU (Hendry et al., 2019b) including imported food items and other services frequently utilised by the food industry. Another example of a politically motivated occurrence which led to a disruption is the United States vs China Trade war which resulted in a supply disruption. Towards the end of 2018, the Trump administration imposed trade tariffs on China (Tankersley and Bradsher, 2018) and China retaliated by imposing corresponding tariffs on the United States (Thornton, 2020). This resulted in an uncertainty that led to a disruption in supplies to businesses in both countries (Yu et al., 2019).

Externally caused disruptions can result from extreme climate events such as storms and earthquakes; examples of which include storms and earthquakes. Winter storms in the United States in February 2021 caused significant disruptions to the milk supply chain in Texas. Many dairy farmers were unable to milk their cows due to power outages. This also meant that production in production facilities were being shut down and this led to milk worth over $1 million being dumped daily and shortages in local stores were experienced (Counter, 2021; Lakhani, 2021). Additionally, the earthquake in Taiwan in 2006 disrupted activities at the Shanghai Sea port in China which led to both demand and supply disruptions.

Other disruptions in the supply chain may be caused by activities which are internal to the organisation and supply chain. In the past decade, examples abound where the food supply chain specifically was disrupted due to decisions made internally. In 2013, Tesco found itself in the middle of a horsemeat scandal (Madichie and Yamoah, 2017) where several of the beef burgers they carried contained horsemeat portions. While it was determined that the horsemeat in itself posed no significant harm to health and that Tesco itself was only a victim of fraudulent practices by members of its supply chain (Madichie and Yamoah, 2017), Tesco customers had already had their confidence shaken and this led to a decrease in demand for meat products in Tesco (Neate and Moulds, 2013). Another example of disruption caused internally is the supply chain disruption in KFC chicken delivery and logistics; a change in partnerships which was expected to save cost ended up costing the organisation millions as more than half of their stores had to be shut down for a while (O'Marah, 2018; Henderson, 2018).

Ericsson’s supply was also disrupted in 2000 due to a supplier’s fire accident. This disrupted Ericsson’s supply and the organisation lost about $400million and at the end was forced to merge with another company-Sony (Norrman and Jansson, 2004; Tang and Nurmaya Musa, 2011; Macdonald et al., 2018).

Other examples include the terrorist attack at the world Trade Centre in 2001, the blackout in North-eastern United States in 2003 (Tang and Nurmaya Musa, 2011; Colicchia and Strozzi, 2012). These examples (Table 1.1) led either to a major disruption within the supply chain or at the very least, a delay. This draws attention to how vulnerable a supply chain can be with any hiccups and could create problems.

Table 1. 1: Examples of Disruption Cases

Disruption type	Example	Effect	References
Externally triggered disruptions			
Global Disease Outbreak	COVID-19 Pandemic: Unprecedented disease outbreak	Demand and Supply Disruption	(Chowdhury et al., 2021b; Modgil et al., 2022)
Political	Brexit: Constitutional and Policy changes	Supply Disruption	(Hendry et al., 2019b; Roscoe et al., 2020)
	United States vs China Trade war: Government Policy	Supply Disruption	(Yu et al., 2019)
Extreme climate events	Earthquakes: Shanghai Seaport	Demand and supply disruption	(Tang and Nurmaya Musa, 2011; Colicchia and Strozzi, 2012)
	Storms: Winter Storm with Power outages preventing dairy farmers from milking cows and delivering milk	Supply Disruption	(Counter, 2021; Lakhani, 2021)
Internally triggered disruptions			
Partnerships	KFC Lack of Chicken: Change of Partner	Supply Disruption	(O'Marah, 2018; Henderson, 2018)
	Tesco Horse Meat Scandal: Lack of partner visibility	Demand Disruption	(Neate and Moulds, 2013)
Negligence of safety standards	Ericsson: Fire accident	Supply Disruption	(Norrman and Jansson, 2004; Tang and Nurmaya Musa, 2011; Macdonald et al., 2018)

1.3 Resilient Supply Chains

The disruptions discussed in section 1.2 do not only create a pause in the operations of the supply chain, without adequate preparation, a supply chain that has been affected could take a very long time to recover (Sheffi and Rice, 2005; Hendricks and Singhal, 2005; Tang and Nurmaya Musa, 2011). However, a resilient supply chain has the ability to recover quickly after a disruption to the same state of performance or an even better state; organisations within a supply chain and indeed the supply chain itself need to develop operational capabilities such as resilience in order to survive and possibly thrive in such events (Rice and Caniato, 2003; Christopher and Peck, 2004; Pettit et al., 2010; Melnyk et al., 2014; Mari et al., 2014; Matsuo, 2015; Schmidt, 2015; Brusset and Teller, 2017; Macdonald et al., 2018; Ben-Daya et al., 2019). This also implies that resilient supply chains are able to maintain functionalities and service customer needs even in disruption scenarios, thereby limiting the risks within the supply chain.

The impacts, and particularly, strong negative effects of supply chain disruption have generated interest with both practitioners and researchers seeking to address these risks and design supply chains that are resilient to either demand or supply disruptions (Kamalahmadi and Parast, 2016). However, traditional risk management strategies have been difficult and ineffective at best because they relied primarily on risk identification and statistical information (Fiksel et al., 2015; Kamalahmadi and Parast, 2016) which is helpful when the risks are foreseeable. However, in several cases, the risks which affected the supply chains were either unpredictable as the events were unprecedented or the statistical information seemed inaccurate for intended use (Kamalahmadi and Parast, 2016). One of the ways suggested in literature to build resilience to disruption in supply chains is the application of technologies like Big Data Analytics (Ben-Daya et al., 2019; Ivanov and Dolgui, 2019; Xu et al., 2023).

1.4 The Role of Big Data

The availability of accurate and timely information however can aid in the in the acquisition and transmission of data which allows for effective decision making within the supply chain (Ben-Daya et al., 2019; Xu et al., 2023). According to Gupta and Rani (2019), capturing, analysis and visualisation of data is the function of Big Data Analytics.

One of the latest developments in information technology that has revolutionised supply chain management is Big Data Analytics (Ben-Daya et al., 2019; Ivanov and Dolgui, 2019; Park and Singh, 2022; Pratap et al., 2023). Big Data Analytics is the process of capturing, analysing, and visualising large and complex data sets that traditional data management tools cannot handle effectively (Lamba and Singh, 2017). The use of various technologies such as radio frequency identification (RFID), sensors, barcodes, and loyalty cards in recent years has facilitated the collection and coordination of different parts of the supply chain, making Big Data Analytics a valuable tool in supply chain management (Nguyen et al., 2018).

Scholars have used different definitions to describe Big Data, but a commonly accepted definition is based on its 3Vs: Volume, Variety and Velocity (Lamba and Singh, 2017; Selmy et al., 2024). However, other scholars have proposed additional characteristics such as Variability, Veracity, Value and Validity to further differentiate Big Data from traditional data (Gupta and Rani, 2019). Hu et al. (2014) also identified several key differences between traditional data and Big Data, including the volume, rate of data generation, structure, data source, data integration, data storage, and access to data (see Table 1.2).

Table 1. 2: Traditional Data vs Big Data, adapted from Hu et al. (2014)

	Traditional Data	**Big Data**
Volume	Gigabytes	Constantly updated (Terabytes or Petabyte currently)
Generated Rate	per hour, day, …	more rapid
Structure	structured	semi-structured or unstructured
Data Source	centralised	fully distributed
Data Integration	Easy	difficult
Data Store	Relational Database Management System (RDBMS)	Hadoop Distributed File System, Non-Structured Query Language
Access	interactive	batch or near real-time

The amount of data generated by business transactions on the internet is estimated to be around 450 billion per day, with the volume of data generated globally doubling every 1.2 years (Hu et al., 2014). This implies that organisations are continually generating data sets that can be qualified as Big Data. To make the most of this data, organisations need to leverage Big Data Analytics to mitigate risks and identify opportunities in their supply chains. By analysing data in real-time, organisations can identify critical data and make informed decisions to improve their supply chain performance (Hu et al., 2014).

Big Data Analytics involves the use of advanced digital and analytical techniques to extract valuable insights from large data sets (Tsai and Huang, 2015; Nguyen et al., 2018). By harnessing the descriptive and predictive capacity of Big Data Analytics, organisations can enhance critical data visibility, accurately forecast risks, and activate contingency plans in a timely manner to mitigate disruptions in their supply chain (Ivanov and Dolgui, 2019).

In conclusion, Big Data Analytics may be considered a game-changer in supply chain management, providing organisations with the ability to harness the power of data to make informed decisions, mitigate risks and identify opportunities for improvement. By leveraging the descriptive and predictive capacity of Big Data Analytics, organisations can achieve critical data visibility, enhance supply chain performance, and stay ahead of the competition in a rapidly evolving business environment. However, research into big data have been largely conceptual (Wang et al., 2016; Witkowski, 2017; Brinch, 2018; Ivanov et al., 2019) and are yet to quantify the expected performance improvements. This creates a gap for a scientific study to demonstrate objectively performance improvement as a result of Big Data.

1.5 Problem statement

The global food supply chain and in particular, the milk supply chain, can potentially be impacted by a number of factors. These can include environmental uncertainties, geopolitical risks, and resource constraints, all of which have been implicated in the milk supply chain disruption. These disruptions can result in significant economic losses, lower product quality, and damage to the reputation of companies involved, ultimately affecting consumer service and loyalty; especially in a low-switching cost environment (Sahagun and Vasquez-Parraga, 2014), typical in the food industry.

More recent disruptions in the milk supply chain have been caused by factors such as extreme weather events (storms), pandemics/epidemics, earthquakes, transportation issues, contamination, and trade policy changes (Colicchia and

Strozzi, 2012; Macdonald et al., 2018; Yu et al., 2019; Roscoe et al., 2020; Lakhani, 2021; Modgil et al., 2022). These disruptions highlight the need for resilience measures to minimise the impact of disruptions and ensure uninterrupted supply of milk and dairy products to consumers.

The resilience of a supply chain is its ability to cope with unexpected disruptions, recover quickly from disruptions, and maintain a consistent level of performance despite the disruptions (Ponomarov and Holcomb, 2009). Developing resilience measures requires a deep understanding of the supply chain, its vulnerabilities, and the impact of disruptions. However, measuring the resilience of a typical supply chain, may be challenging due to the complexity and diversity of factors involved and as such, while tools exist to measure resilience in other supply chains (Vieira et al., 2020; Park and Singh, 2022), no tools currently exist within the milk supply chain for this purpose. Therefore, there is a need to develop a scientific tool to accurately measure the resilience of the milk supply chain.

Big Data has emerged as a potential solution to improving the understanding of the resilience of supply chains. Big Data refers to large and complex data sets that can be analysed to uncover patterns, trends, and insights to support decision-making (Wang et al., 2016). Research shows that Big Data can support organisations to make informed decisions, mitigate risks, identify opportunities for improvement, create contingency plans etc. (Ivanov and Dolgui, 2019). By leveraging the capabilities of Big Data, supply chains can monitor and respond to disruptions in real-time, predict future disruptions, and develop resilience measures to mitigate the impact of disruptions.

Therefore, this research seeks to understand the challenges faced by the milk supply chain, identify potential disruption scenarios, measure its resilience, and ways of instituting mitigation measures by deploying the advantages and capabilities of Big Data. The research attempts to fill the gap in knowledge with regards to the development of a disruption-resilient milk supply chain, and by extension provide insights that can be generalised to other food supply chains, including meat, poultry and fruits and vegetables with similar characteristics with the milk supply chain. This study is critical and vital for the effective operation of today’s supply chain. This is especially so as existing studies assessing the interaction of Big Data with supply chain management are mainly conceptual in nature (Wang et al., 2016;

Witkowski, 2017; Brinch, 2018; Ivanov et al., 2019; Kamble and Gunasekaran, 2020) and therefore, provide limited empirical evidence. Where empirical evidence exists, it lacks the simulation of real-world situations and depends solely on feedback from supply chain participants (Singh and Singh, 2019a). Additional studies focus on other capabilities of Information Technology (IT) such as Artificial Intelligence (AI) (Baryannis et al., 2019) or the Internet of Things (IoT) (Ben-Daya et al., 2019). Overall, there is a scarcity of research in this domain and few empirical studies provide a basis for the application of Big Data in a supply chain to improve its resilience, using computer simulations to consider real-world scenarios. This thesis presents a critical assessment of food supply chains with the milk industry as the supply chain system of interest. This is with a view to unravelling the potential of deploying Big Data Analytics in driving performance and ensuring disruption events are effectively mitigated and normal operations restored in a timely fashion without detrimental impacts to both the supply chain participants and the end users.

1.6 Aim and Objectives

The aim of this research project was to explore the potentials and opportunities of Big Data in improving resilience by mitigating the risk of disruption in a milk supply chain. The study objectives were defined as follows:

- To explore the challenges faced by food supply chains and review their resilience to recent disruptions.
- To develop a resilience measuring tool to capture impact of supply chain disruptions experienced within the milk supply chain.
- To measure the resilience of the milk supply chain through data driven analysis of disruption scenarios.
- To assess Big Data in milk supply chains and propose its effective application in the development of a disruption resilient supply chain.
- To provide evidence-based recommendations to the operators within milk supply chains to enhance big data adoption for resilience.

1.7 Research Questions

The literature reviewed helped in shaping the following research questions:

1) How can Big Data be effectively applied in the development of a disruption-resilient milk supply chain? This question stems from the appreciation within literature of the potential for Big Data to improve the resilience of supply chains; hence, needing an investigation into the approach for its effective application.
2) What are the challenges faced by the milk supply chain and how resilient is it to recent disruptions? This question acknowledges that an understanding of the challenges faced by the milk supply chain forms a basis for evaluating its resilience to disruptions.
3) How can a resilience measuring tool be developed to capture the impact of disruptions within the milk supply chain? This question emerges from the recognition of a gap in resilience measuring tools to capture the impact of disruptions in the milk supply chain. It guides the research into resilience measuring tools that consider factors specific to the milk supply chain.
4) How can data-driven analysis be used to measure the resilience of the milk supply chain and assess the impact of potential disruptions? This question originates from an observation of limited empirical research for measuring resilience in the milk supply chain, leading to the development of simulation models to evaluate disruption scenarios.

1.8 Outline of the Thesis

This thesis is outlined in chapters, sections and subsections in order to provide clear guidance and to aid comprehension of thoughts. Figure 1.1 shows the structure of the thesis, including chapters, the research objective supported by the chapters and the research questions answered within the thesis chapters.

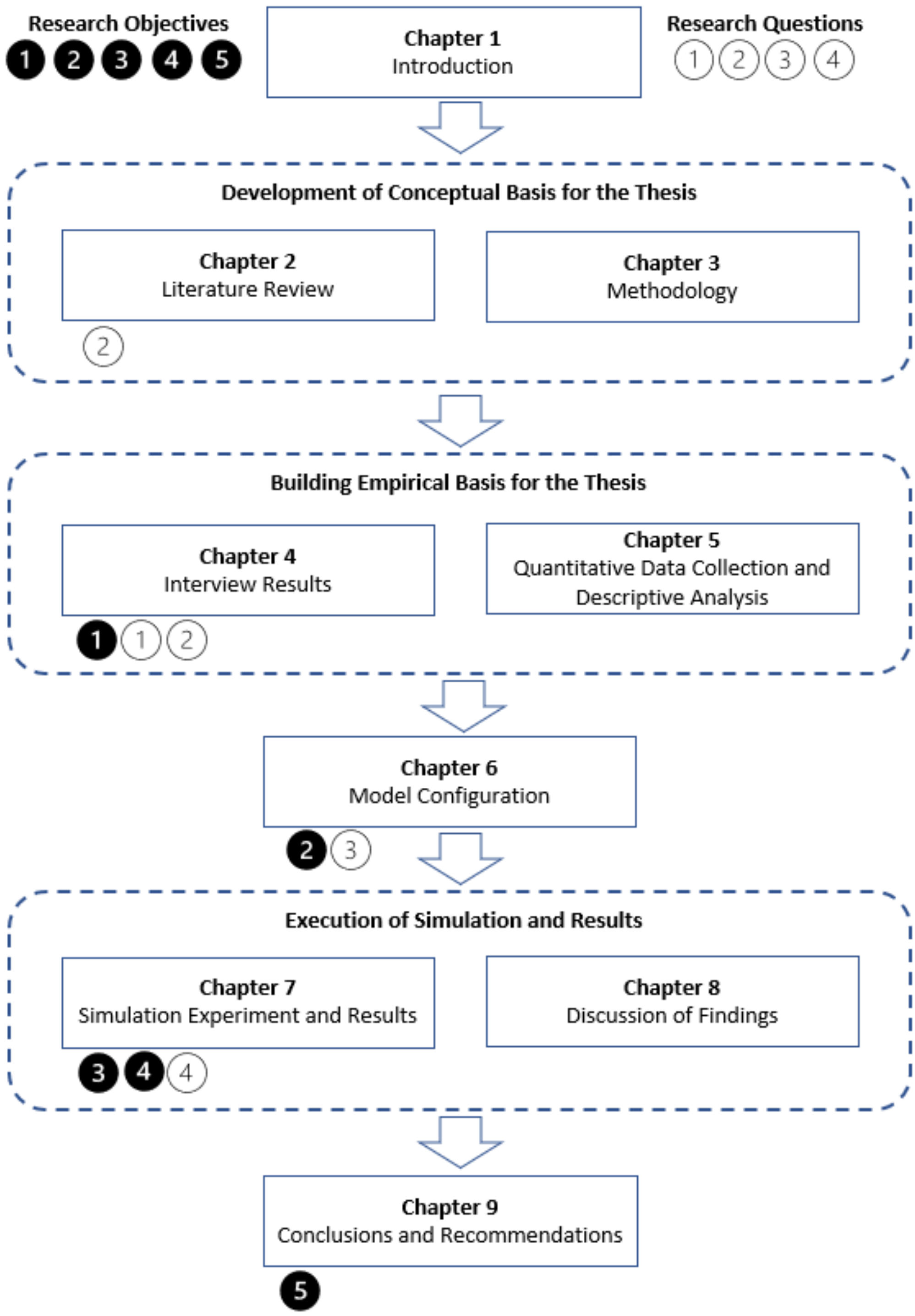


Figure 1. 1: Thesis Structure

Chapter 1 which is the introductory section provides the background to the research and gives the research context to aid understanding. The chapter then goes further to provide a problem statement, highlighting the research aim and objectives and concludes by outlining the structure for the rest of the research.

Chapter 2 provides a detailed literature review of the work that has been carried out by researchers in the field. This section analyses literature on Supply Chain Risks, Supply Chain resilience, and Big Data Analytics. The section also provides the theoretical framework to be for this research.

Chapter 3 focuses on the research methodology for this research. It discusses the research philosophy of the researcher, the research approach to be adopted for the study, as well as the research methods for the current study.

Chapter 4 analyses the qualitative data gathered during the interview process and presents the results. This chapter also goes ahead to discuss the key themes that emerge from the interviews.

Chapter 5 presents a descriptive analysis of the quantitative data collected. This chapter also discusses the initial insights that can be derived from the quantitative data in its raw form prior to simulation.

Chapter 6 discusses how the model was built using computer simulations. It also provides a step-by-step guide on how data was collected for each supply chain element relevant in the simulation.

Chapter 7 provides the results of the computer simulation; discussing the different parameters used to measure resilience and the different types of disruption simulated as part of this study.

Chapter 8 discusses the findings of this research in light of literature and provides a clear framework for addressing the research questions posed in this study.

Chapter 9 being the final chapter of this research provides conclusions and makes recommendations for further studies. It also highlights the research contributions both to practice and to knowledge.

Chapter 2
LITERATURE REVIEW

2.1 Introduction

This chapter provides a detailed review of existing literature surrounding this study. The research supports the proposition that the milk supply chain is a subset of the food supply chain and may face several risks including the risk of a disruption. In order for the milk supply chain to mitigate this risk of disruption, it is essential to build resilience. Big Data and analytical capabilities are then suggested as key to building resilience.

Hence, this chapter presents literature on the milk supply chain and its key members, supply chain disruptions and the various types of disruption. The chapter reviews the effects that a disruption could have on the milk supply chain and how that can be managed. The chapter then goes on to discuss supply chain resilience in the face of disruption, its indicators and quantitative methods for calculating resilience. This chapter also discusses the role of big data in the food supply chain and narrows in more specifically on the application of Big Data to the milk supply chain. Barriers to Big Data application is also discussed and finally, the chapter provides the theoretical background to this research and identifies the knowledge gap this research is attempting to fill.

2.2 The Milk Supply Chain and Key Members

The milk supply chain is a critical component of the global food industry, with milk being a vital source of nutrition for human beings. According to the Food and Agriculture Organisation (FAO), global milk production has been steadily increasing, from 609 million tonnes in 2000 to 930 million tonnes in 2022 (FAO, 2022). More specifically, the milk supply chain in the United Kingdom is a complex system involving various stakeholders who play critical roles in ensuring the efficient and sustainable production, processing, and distribution of milk. According to the Agriculture and Horticulture Development Board (AHDB, 2023), there were around 7,850 dairy farms in the UK in 2022, with an estimated 1.09 million dairy cows producing approximately 12.4 billion litres of milk. Dairy farming is an essential part of the UK agricultural sector, providing jobs for thousands of people and contributing significantly to the UK economy.

The dairy farmers, who are the primary producers of milk, play a critical role in maintaining the health and welfare of their dairy herds to ensure that the milk produced is of high quality and meet safety standards. They also work to minimize the environmental impact of their farming practices and adhere to animal welfare regulations. In recent years, there has been a significant focus on improving the sustainability of dairy farming practices, with farmers adopting various measures such as reducing greenhouse gas emissions and improving soil health (Brito et al., 2021; Timlin et al., 2021)

Milk manufacturers, who are responsible for processing the raw milk into various dairy products, also play a critical role in the milk supply chain. They produce a range of dairy products such as cheese, butter, yogurt, and milk powders. Milk manufacturers have to ensure that the milk is processed and packaged in hygienic conditions to maintain its quality and safety. They also work to reduce the environmental impact of their operations by minimizing waste and energy use.

Wholesalers and distributors are responsible for the distribution of dairy products from the processors to the retailers, supermarkets, and other outlets. They play a crucial role in ensuring that the products are transported efficiently and safely to minimise waste and spoilage. Retailers and supermarkets, on the other hand, are responsible for selling the dairy products to the end consumers. They have to ensure that the products are stored and displayed correctly and that they adhere to food safety and quality regulations. Consumers are the final users of the dairy products and are essential to the milk supply chain. Milk and dairy products are a vital source of nutrition for many people, providing essential nutrients such as calcium, vitamins, and protein.

While it is clear that the milk and dairy industry has been growing in the last two decades (Rosati and Aumaitre, 2004; Huang et al., 2014; Ong et al., 2014), this industry faces several challenges and can be affected by various factors such as changing dietary habits, health concerns, and price increases. These challenges could disrupt its operations and affect its sustainability. One of the significant challenges facing the milk supply chain is the variability in milk production caused by climatic changes, diseases, and other natural factors (Perrin and Martin, 2021).

For instance, droughts or floods can affect the quality and quantity of milk produced, leading to a shortage in supply. In addition, the seasonal nature of milk production can also lead to supply fluctuations, with dairy farmers having to manage the cyclical nature of lactation and milk production in their herds (Timlin et al., 2021). Another challenge facing the milk supply chain is the issue of milk quality and safety. The quality and safety of milk depend on various factors, such as the health of cows, the cleanliness of milking equipment, and the hygienic conditions of the processing plants. Failure to maintain high-quality standards can result in the contamination of milk with harmful bacteria, which can pose a health risk to consumers (Martin et al., 2018). For instance, outbreaks of bovine tuberculosis and brucellosis have been reported in various countries, leading to the culling of infected cows and the implementation of strict measures to prevent the spread of the diseases (Azami et al., 2018).

Another challenge the milk supply chain faces is that it could be subject to disruptions such as those caused by geopolitical factors or trade policies. For instance, if a country were to impose trade restrictions or tariffs on dairy products, it could affect the supply and demand for milk globally (Stevens, 2020). Similarly, conflicts or political instability in regions where milk is produced could disrupt the entire supply chain, leading to shortages or increased prices for consumers (Stevens, 2020). The milk supply chain can also be subject to other types of disruption which range from production disruption, logistics disruption and demand disruption which are discussed extensively in section 2.4. Given the centrality of the milk supply chain to the health, nutrition, and wellbeing of consumers, as well as the economic benefits provided by this supply chain, disruptions experienced can have a wide spreading effect.

Hence, it is clear that dairy farming is essential to the agricultural sector which makes the milk supply chain critical to ensuring that milk products are transported efficiently and arrives to the customer, ensuring demand meets supply and spoilage/waste is reduced. However, the milk supply chain faces challenges that could reduce its effectiveness and one these challenges include the risk of a disruption. It then becomes imperative to understand supply chain disruptions that could affect the milk supply chain.

2.3 Supply Chain Disruption

Supply chains are crucial and provide a competitive advantage (Vlajic et al., 2013). According to Ponomarov and Holcomb (2009), every activity within the supply chain is a potential source of risk (Dolgui et al., 2018) and could lead to an unexpected disruption (Namdar et al., 2018). A disruption in demand or a disruption in supply could constitute a supply chain disruption risk.

This disruption could be caused by natural disasters, such as hurricanes, earthquakes, tsunamis, floods etc. or other man-made causes such as negligence, terrorism or cyberattacks; more recently, the exit of Britain from the European Union and the inception of the unprecedented COVID-19 pandemic. Any of these causes of disruption could have a devastating effect on organisational revenue and cost (Ivanov et al., 2014) which is why supply chain disruption management remains a topical issue discussed both by academics and practitioners (Dubey et al., 2019; Modgil et al., 2022; Wieland et al., 2023).

The rise in supply chain disruption has been attributed to an increase in natural disasters (Dubey et al., 2019), however, a number of the more recent cases of supply chain disruption (Table 1.1) were not due to natural disasters but decisions made by one or more members of the supply chain and other external factors beyond the control of supply chain members. In either case, the organisations suffer significant consequences, which explains scholarly interest in the topic of supply chain resilience and how it affects competitive advantage (Brandon-Jones et al., 2014; Chowdhury and Quaddus, 2016). Hence, several organisations including Nike, Levi and Lafarge are working actively with their supply chain partners to build resilience within the supply chains (Dubey et al., 2019).

While there has been previous studies that discussed supply chain disruption (Wagner and Bode, 2006; Ivanov et al., 2017), its causes (Craighead et al., 2007), its effects on organisational performance (Hendricks and Singhal, 2005) and how to manage supply chain risks (Tang, 2006; Ivanov and Dolgui, 2018), limited research has gone into the utilisation of Big Data and how Big Data analytics capabilities can be best utilised by organisations that seek to improve resilience (Fan et al., 2016). The research by Brandon-Jones et al. (2014) stipulates that information sharing and visibility within the supply chain can have potential effects on supply chain resilience. However, does not provide a clear pathway to applying the available data in order to obtain expected benefits.

This study provides an objective approach to engaging big data analytics to increase collaboration and information sharing, and also develop resilience within the supply chain against potential disruption.

2.4 Types of Disruptions

Disruptions to the supply chain can be caused by various factors, such as natural disasters, political unrest, and economic shocks. Understanding the different types of disruptions is critical to developing effective risk mitigation strategies and ensuring the resilience of the supply chain. In this section, we will review the three main types of disruptions to the supply chain: production, logistics, and demand (Hishamuddiin et al., 2015; Sreedevi and Saranga, 2017; Shanker et al., 2022).

Production disruptions occur when there is a breakdown in the manufacturing or processing of goods. This can be caused by various factors, such as equipment failures, power outages, labour strikes, or natural disasters. For example, a study by (Ramani et al., 2022) found that a shortage of semi-conductors due to the COVID-19 pandemic led to production disruptions in the global automotive industry. Similarly, a study by Haraguchi and Lall (2015) found that the 2011 floods in Thailand led to production disruptions in the electronics and automotive industries, as several manufacturing facilities were damaged or shut down.

Logistics disruptions occur when there are disruptions in the transportation or distribution of goods. This can be caused by various factors, such as accidents, port closures, customs delays, or labour strikes. For example, a study by Wassenberg (2020) found that the strikes by French truck drivers led to significant disruptions in the transportation of goods across Europe, leading to a ripple effect in other European Union member states.

Demand disruptions occur when there is a sudden change in consumer behaviour or preferences. This can be caused by various factors such as changes in economic conditions, new product innovations, or changes in social trends. For example, studies have found that the COVID-19 pandemic led to significant changes in consumer behaviour, with many consumers shifting towards online shopping and home delivery (Varade, 2020; Cavallo et al., 2020). This led to significant disruptions in the supply chain, as many retailers and logistics companies struggled to adapt to the new demand patterns.

It is clear that disruptions to the supply chain can come in various forms, including production disruptions, logistics disruptions, and demand disruptions. Understanding the effect of different types of disruptions is critical to developing effective risk mitigation strategies and ensuring the resilience of the supply chain. Supply chains must be proactive in identifying and mitigating potential risks to ensure the continuity of their operations. By adopting a proactive and collaborative approach, supply chains can ensure that disruptions are minimised, and their operations remain resilient in the face of unexpected events. This research proposes Big Data analytics as the right medium for implementing proactive (section 7.5) and collaborative (section 4.4.1) approaches in maintaining resilience.

2.5 Effect of Disruption on the Milk Supply Chain

As discussed in section 2.4, understanding the effect of disruptions on a supply chain is central to developing proactive strategies in combating supply chain disruptions. However, based on the focus of this research, this section will focus on the effect of disruption on the milk supply chain. This is significant as milk is a perishable product that requires timely processing and distribution to maintain its freshness and quality. Any delay or interruption in the supply chain can result in spoilage or waste of milk, leading to economic losses for farmers and manufacturers (Odeyemi et al., 2020; Liu et al., 2022).

Disruptions in the milk supply chain can occur at various stages, such as production, transportation, and distribution. For instance, a disease outbreak in dairy herds could reduce the supply of milk, leading to shortages or increased prices for consumers. Similarly, breakdowns in processing equipment or transportation vehicles can lead to delays in the supply chain, affecting the freshness and quality of the milk. Moreover, disruptions in one part of the milk supply chain can have a ripple effect (Ivanov, 2017) on other parts, leading to a more extensive impact on the industry. For example, if a manufacturing plant experiences a significant disruption, it can affect the milk supply for multiple retailers, leading to shortages or price increases for consumers.

The impact of disruption on the milk supply chain can be further exacerbated by consumer behaviour. Panic buying or hoarding by consumers in response to a disruption can lead to a sudden surge in demand, putting additional pressure on an already fragile supply chain. This was experienced during the disruption caused by the COVID-19 pandemic which influenced consumer buying behaviour and led to panic buying and stockpiling (Shanker et al., 2022), leading to a significant shortage of essential items such as milk.

In conclusion, the milk supply chain is vulnerable to various disruptions that can have severe consequences for the industry and consumers. It is crucial to adopt proactive risk management strategies that can help mitigate the impact of disruptions and ensure the continuity of the milk supply chain.

2.6 Managing Supply Chain Disruption Risk

The management of supply chain disruption risks has been documented in various ways in literature. Suggestions such as maintaining resilience within the supply chain, considering the role of insurance, sharing revenue, the peculiarity of individual supply chains and the needs of the supply chain has been made. Ivanov et al. (2014) considers the implication of one disruption event to the whole process of supply chain management. Existing research holds that when one part of the supply chain is disrupted, the effect of this disruption will be faced throughout the supply chain. This implies that if the effect of a disruption in one part of the supply chain can be experienced in other parts of the supply chain, potentially, a mitigation of the disruption in one part of the supply chain will trickle down to the subsequent links. This effect is discussed by scholars as holding true for both large and small supply chains regardless of the supply chain structure adopted (Ivanov et al., 2014).

It is therefore logical to expect that a clear understanding of the mitigation strategies and the application of the right strategies can help managers mitigate disruption risks across the supply chain (Ivanov et al., 2014). However, there is little research with a clear structure on how to minimise disruption risk. Hence the need for research on how exactly organisation can mitigate disruption risks, ensure business continuity and potentially increase their profitability (Ivanov et al., 2014). Such research will provide adequate information to aid organisations in developing flexibility, resilience and avoiding disruption (Ivanov et al., 2014). This research will meet some of these requirements in part and focus on aiding organisations build resilience.

2.7 Supply Chain Resilience

Resilience is a multidimensional and multidisciplinary concept (Ponomarov and Holcomb, 2009; Castillo, 2022), which has been generating interest from social scientists and natural scientists alike. Within the physics and engineering research communities, resilience is considered as the ability of a material to withstand the pressure of being compressed stretched or bent (Castillo, 2022), and to be able to return to its original form. It is described as displaying a “similar to elastic” behaviour (Spiegler et al., 2012). The idea of resilience has also captured the attention of the operations management community (Ponomarov and Holcomb, 2009; Spiegler et al., 2012), and from literature within the supply chain and operations management research group, resilience is defined as a the property within the supply chain system’s ability to retain its original state after a disturbance or advance to a new and more desirable state (Christopher and Peck, 2004; Peters et al., 2023). A resilient supply chain has the capacity to return to its standard operating performance in an acceptable timeline, given that the disrupting forces have withdrawn (Spiegler et al., 2012). In recent times resilience is used to particularly measure how organisations respond to image and disruption in supply chains and disaster relief effort (Tomlin, 2006; Lodree and Taskin, 2008; Ratick et al., 2008; Falasca et al., 2008; Boin et al., 2010). This implies that parties within the supply chain have to be positioned strategically and be adequately planned for. However, due to the complexity of supply chain procedures and the dynamic nature of the marketplace, it is also important to handle risks that arise at the operational level. With the rise of globalisation and the resulting global supply chain, the longer transportation distance and additional resources used means an increase in operational disruption (Spiegler et al., 2012). This connotes that developing a resilient supply chain needs to incorporate strategies for dealing with risks at operational level as well as risks at supply chain level.

2.7.1 Resilience Strategies

Achieving resilience in supply chains is a complex and ongoing challenge for researchers and industry professionals alike. The inherent complexity of supply chains necessitates the use of multiple approaches and strategies to achieve resilience (Christopher and Peck, 2004). In the literature, there are several different strategies that have been suggested to increase supply chain resilience. While some authors argue for increased visibility to achieve resilience (Brandon-Jones et al., 2014; Michel-Villarreal et al., 2021), others emphasize the importance of supply chain collaboration (Rice and Caniato, 2003; Christopher and Peck, 2004) or building supply chain security (Rice and Caniato, 2003; Christopher and Peck, 2004) protect against cyberterrorism and theft. Most of the strategies employed to improve resilience can be categorised into proactive and reactive strategies (Kırılmaz and Erol, 2017).

Proactive strategies aim to prevent disruptions and their impact before they take place. Kırılmaz and Erol (2017) propose a proactive strategy through increased numbers of potential suppliers and building a more resilient product using different components, thus minimizing the impact on producers. One widely studied approach is the need for increased visibility within the supply chain (Michel-Villarreal et al., 2021). Improved visibility enables better tracking and management of the supply chain and can help to identify and mitigate risks before they become disruptive. Additionally, enhanced visibility can improve coordination and collaboration within the supply chain, leading to better decision-making and a more efficient response to disruptions.

Another key approach is the need for collaboration between different entities within the supply chain (Rice and Caniato, 2003; Pettit et al., 2010). Collaboration can enable better sharing of resources and knowledge, leading to improved forecasting, risk sharing, and postponement strategies. This approach often involves information exchange and cost-sharing between different supply chain partners, working together for mutual benefit.

Furthermore, risk management has also been highlighted as an essential factor for achieving supply chain resilience (Schmitt and Singh, 2012; Soni et al., 2014). The use of risk management techniques, such as scenario planning and risk assessments, can help companies identify and mitigate risks before they occur. This approach can improve supply chain decision-making and enable companies to respond more effectively to disruptions. However, proactive strategies may require significant investment in resources and may not be cost-effective for all organizations.

In contrast, reactive strategies aim to reduce the impact after a disruption has taken place (Kırılmaz and Erol, 2017). Reactive strategies, such as contingency planning and creating inventory space, have also been studied as means of enhancing supply chain resilience (Colicchia et al., 2010; Pavlov et al., 2019). These strategies attempt to forecast possible disruptions and minimize their effects and financial damage. However, their effectiveness is limited by the ability to predict disruptions accurately. It is therefore important to note that the principles and strategies developed in other industries, such as the automotive industry, can also be applied to food supply chains. However, the specific context of the food supply chain necessitates unique considerations and approaches.

The adoption of Big Data Analytics can be used as a proactive strategy to improve visibility (Kamble and Gunasekaran, 2020), collaboration and enhanced tracking across the supply chain or can also be applied as a reactive strategy to support decision making for the optimal inventory levels that support customer satisfaction across the supply chain (Vieira et al., 2020). This research proposes that resilience strategy for the milk supply chain incorporates insights into the vulnerabilities and capabilities of the milk supply chain and highlights the need for both proactive and reactive strategies to enhance resilience.

Overall, while both proactive and reactive strategies are important for achieving supply chain resilience, organizations must carefully consider the costs and benefits of each approach and align their strategies with available resources to ensure effective coordination. The development of decision support tools could aid organizations in assessing the impact and effectiveness of resilience strategies in real-time, helping to optimize decision-making and enhance supply chain resilience.

2.7.2 Qualitative Indicators of Supply Chain Resilience

Regardless of the resilience strategy adopted or being adopted by a supply chain, it is essential that the decision makers within that supply chain are able to deduce if the supply chain resilience strategy employed is effective. This necessitates a clear multi-dimensional and measurable indicator for resilience. This section attempts to highlight the qualitative indicators and drivers of Supply Chain Resilience (SCR) evidenced in literature which have the capacity to portray the resilience within the supply chain. Key indicators considered include flexibility, visibility, agility, collaboration, supply chain risk management culture, sustainability, information sharing, robustness, sensitiveness, security, velocity and adaptability (Hosseini et al., 2019; Singh et al., 2019).

A resilient supply chain is expected to display the characteristic of flexibility (Singh et al., 2019) which is portrayed as the capacity of the supply chain to adjust to changes within its environment and the requirements of its stakeholders, using very minimal time and effort (Hosseini et al., 2019). Literature presents that flexibility in transportation, sourcing strategy, postponement, labour arrangements and order fulfilment could improve the resiliency of the supply chain (Hosseini et al., 2019; Singh et al., 2019) by supporting versatility amidst turbulence. Chopra and Sodhi (2004) hold that flexibility can be demonstrated at organisation level or at the supply chain level. However, the best form of flexibility contains hybrid elements (Rice and Caniato, 2003) as this leads to a faster reaction and recovery from disruption (Sheffi and Rice, 2005). Hence, when attempting to identify a resilient supply chain, it is imperative to assess the flexibility of the organisations within that supply chain as well as the flexibility of the entire supply chain.

Another indicator worth examining to determine the resiliency of a supply chain is the visibility of the entire supply chain. Visibility here gives the supply chain manager the ability to view the supply chain from end to end in order to accurately identify the exact point of disruption (Christopher and Peck, 2004). This allows the supply chain manager to makes faster decisions and respond rapidly and intercede while continuing to evaluate changing scenarios.

Agility refers to the ability of supply chain firms to respond quickly, smoothly, and cost-efficiently to sudden changes in supply or demand. Collaboration refers to the capability of two or more autonomous firms to work effectively together, planning and executing supply chain operations toward common goals (Singh et al., 2019). Finally, information sharing is the exchange of information and sharing between supply chain entities prior to and after a disruption, necessary for the resiliency of the supply chain (Christopher and Peck, 2004). Overall, in determining the resilience of a supply chain, literature suggests that specific factors be taken into consideration. These factors include collaboration, flexibility, visibility and agility of the supply chain as these can provide an indication of how resilient a supply chain is or will be when faced with a disruption.

2.7.3 Quantitative Measures of Supply Chain Resilience

When a disruption occurs, it is usually an unplanned and unanticipated event; as a result, these disruptions will normally disrupt the typical flow of goods and materials in a supply chain (Macdonald et al., 2018). Once a supply chain has been disrupted, the performance of that supply chain will be jeopardised (Carvalho et al., 2012) and researchers are exploring the relationships between supply chain disruptions and resilience (Macdonald et al., 2018). Resilience is a critical component in supply chain management as it helps organisations to mitigate the impact of disruptions and uncertainties that may arise. In the case of milk supply chain, disruptions can occur due to various reasons such as a production problem at the milk manufacturer, transportation challenges affecting milk delivery, and a spike or reduction in demand. The ability of the supply chain to withstand these disruptions and maintain its operations is crucial for the sustainability of the entire system (Carvalho et al., 2012; Hishamuddiin et al., 2015).

To measure the resilience of milk supply chain, some quantitative parameters have been explored by researchers. For example, the time it takes for the supply chain to recover is considered to be a critical factor (Christopher and Peck, 2004; Sheffi and Rice, 2005; Ponomarov and Holcomb, 2009). This parameter is influenced by the level of preparedness of the supply chain to respond to disruptions. A resilient supply chain should be able to recover quickly and resume normal operations (Pavlov et al., 2018; Dubey et al., 2019). The total cost incurred due to the disruption is another parameter considered in literature (Jabbarzadeh et al., 2018). This cost includes both direct and indirect costs such as transportation, storage, and production costs. A resilient supply chain should be able to minimise the cost of disruption and mitigate the impact on the entire system. Thirdly, the ability of the supply chain to maintain consistent and reliable service levels is also considered (Sokolov et al., 2016). This is determined by the level of flexibility and agility of the supply chain. A resilient supply chain should be able to adapt to changing conditions and maintain its service levels.

However, before attempting to measure the resilience of a supply chain, Carpenter et al. (2001) suggested that two questions need to be considered very critically: The first one is what type of supply chain is intended for resilience and the second one is what type of threats should be prepared for in that specific supply chain. This research will be measuring resilience in the milk supply chain with particular attention to its performance (ability to make products available to consumers at the right time). Threats to the milk supply chain's performance could be the availability of quality inventory or the ability to get the inventory to the customers location (logistics) (Van Der Vorst et al., 2009; Navickas and Gružauskas, 2016). With that in mind, relevant studies that have measured resiliency in supply chains based on several individual factors were examined for this research.

It appears that researchers investigating supply chain resiliency do not have a unified view on the index with which to measure resilience (Pourhejazy et al., 2017). For instance, Priya Datta et al. (2007) considered a multi-product supply chain on a multi country basis quantified resiliency on four basis: the customer service level, the average inventory at a given distribution centre, the production change over time, and the total average network inventory across all the distribution centres. However, Spiegler et al. (2012) who adopted a systems dynamic simulation model devised a measure which they called "the integral of time multiplied by the absolute error" (ITAE), with which they measured how much the system strayed from the target customer service in a period of response and recovery to disruption. Schmitt and Singh (2012) in their study of consumer package goods company show that buffer stock becomes more important when a supply chain operation has been disrupted.

Research by Wu et al. (2013) used downstream market share as a measure of performance where products are heterogeneous. Their research concluded that market share, customer time and stock out duration can be used to determine resiliency. Zobel and Khansa (2012) quantitatively measure the resilience of a system by calculating the time series between the disruption starting and the system recovery, using the equation 3.1:

$$\boldsymbol{R(X,T) = \frac{T - XT}{T^*} = 1 - \frac{XT}{T^*};\ X \in [0,1], T \in [0, T^*]} \qquad \textbf{Eq. 3. 1}$$

Where: R = Resilience, $\overline{X}$ = average loss experienced per unit time, T = time until system recovers and T^* = maximum recovery time.

Resilience according to this equation is representative of the relative functionality retained in the supply chain over a period of disrupted activities. It takes into consideration the average amount of loss experienced by the system at a given time, the time it takes the system to recover, and the maximum time allowed for the system to recover (provided by a selected decision maker). According to this equation, the value of resilience must be between zero and one where zero is total system loss and one is no impact from the disruption. The values and exact application however will be adapted to suit the objectives of this research and the methodology utilised.

Measuring the area under the curve (Figure 2.1) in order to better understand system response has been adopted in several academic disciplines including information security and inventory control theory (Macdonald et al., 2018). The research by Bruneau et al. (2003) was the first work to apply this technique in measuring seismic resilience to disruption, where they hold that a resilient system is one with a reduced probability of failure, reduced consequence from failure and reduced time to recovery. This method of measuring resilience has since been extended to supply chain design, uncertainty, multiple-related disruptions and trade-offs between loss and recovery time (Macdonald et al., 2018). Several other studies consider additional measures to resiliency. This research however would pay particular attention to the time it takes for the supply chain to recover, the customer service levels a supply chain is able to maintain and the total cost incurred by the supply chain during a disruption.

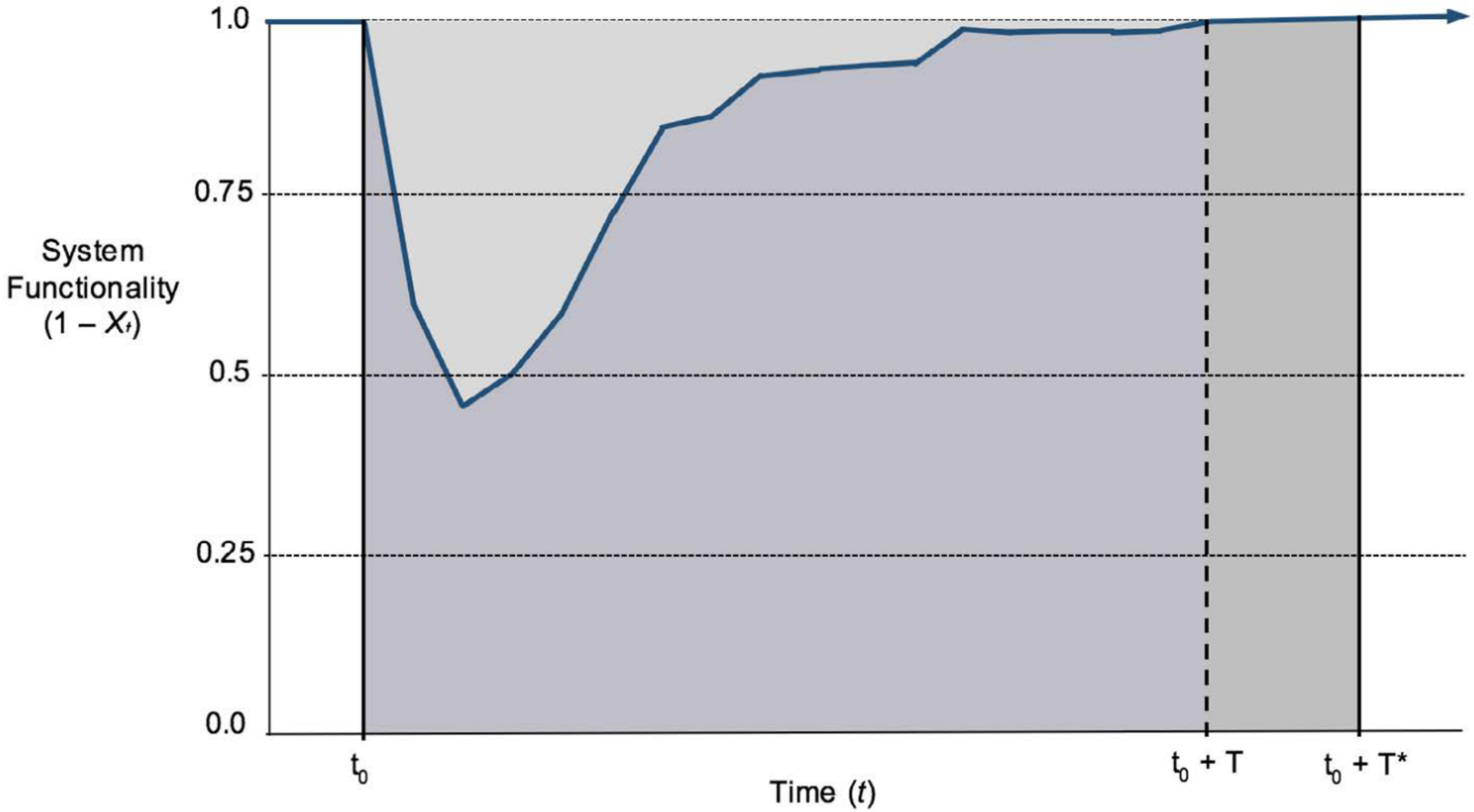


Figure 2. 1: Calculating resilience as the area under a differenced response curve (Macdonald et al., 2018)

2.8 Big Data in the Food Supply Chain

The food supply chain in general expects a significant impact from the application of technology (reference). One of the more prominent impacts is that customers are now able to purchase food items online, with the expectation of a well organised distribution system. Additionally, with regulations in the food industry, food items have to be tracked and delivered on time and in high-quality (Navickas and Gružauskas, 2016); when combined with the complications of food perishability, the food supply chain presents a very unique type of supply chain. This also means that the distribution system in a food supply chain will be uniquely complicated. Hence, it becomes imperative to understand the workings of the food supply chain (Navickas and Gružauskas, 2016). The food supply chain will normally begin with suppliers who provide the raw material; raw material in the food supply chain includes items such as raw meat, grains, vegetables etc., each having unique characteristics and guiding regulations. Next, the raw materials supplied need to be transported to a warehouse and each item may have a different storage requirement; for example, they may require a specific truck type or temperature during transportation. After this, comes the challenge of warehousing. While just in time production is ideal for the food supply chain, partial warehousing is required for items that may not have been used up straight away (Navickas and Gružauskas, 2016), and this raises the concern of temperature control and humidity based on the product type and manufacturer. After all these have been taken care of, the next challenge will be that of distribution to customers. This would be different depending on the quantity to be distributed, the type of markets to be distributed in, durability of the item to be distributed, and the consistency in demand. Regardless of these peculiarities, the supply chain is still expected to deliver the right product to the right people at the right cost. This implies that the cost and the time is especially important in all supply chains and especially so in the food supply chain.

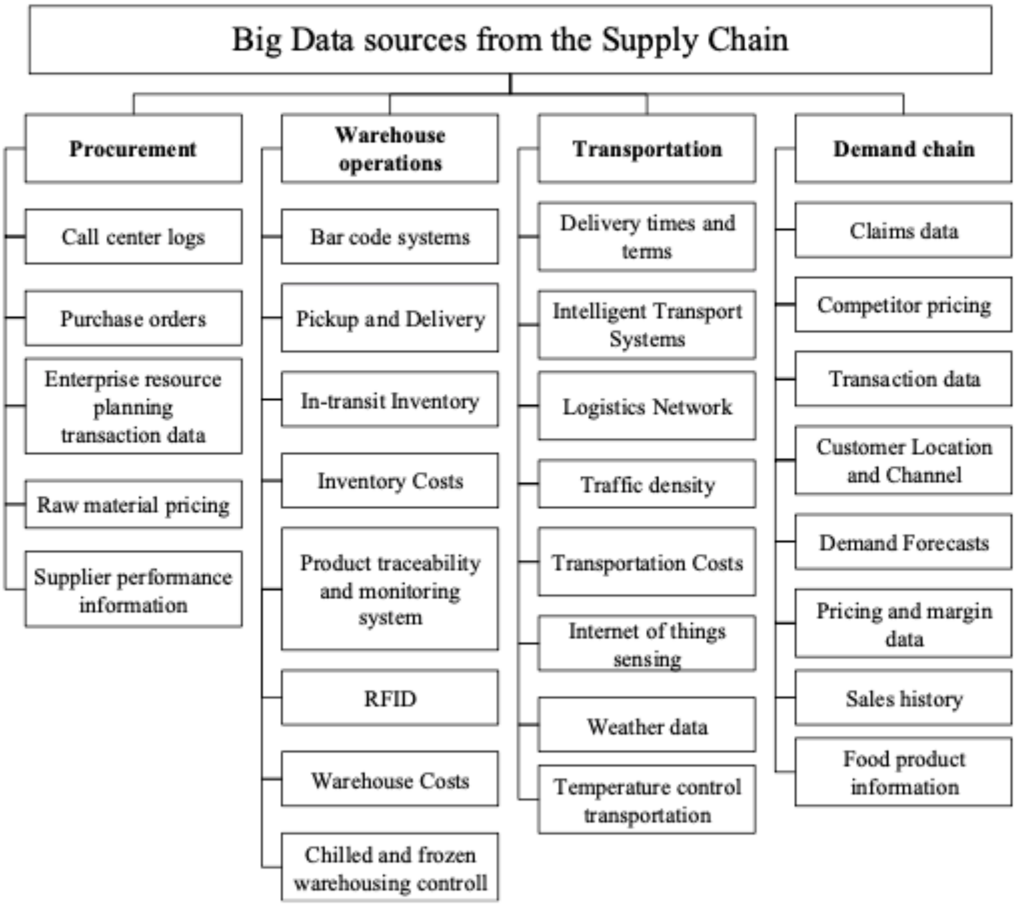


Figure 2. 2: Big data sources from the supply chain (Navickas and Gružauskas, 2016)

To ensure that regulations are met, and food reaches customers in the right condition, data is consistently being generated and analysed. There are four main points of information gathering in the supply chain and these are procurement, demand, transportation, and warehousing (Figure 2.2). Data is generated from these sources, using a variety of devices, and analysed systematically to aid decision making. Tracked and analysed data also helps supply chain participants understand the customer's perception of the food received and this information is then fed back into the food design and delivery process (Ji et al., 2017). These data can be captured by organisation, government, third party logistics providers, or data generating companies or individuals. Once analysed, insights can be gained to optimise every process within the supply chain.

In conclusion, big data plays a critical role in the supply chain by enabling stakeholders to collect, analyse, and share data in real-time. This data can be used to optimise production and logistics, improve quality control, manage risk, and improve sustainability. As the milk supply chain becomes increasingly digitalised, the importance of big data is only set to increase in the future. This research takes advantage of data made available by big data capabilities to simulate the milk supply chain and conduct experiments to support resilience to disruptions.

2.9 Big Data in the Milk Supply Chain

Big data is becoming increasingly important in the milk supply chain as it enables stakeholders to make informed decisions based on accurate, real-time data (Papadopoulos et al., 2017a; Ivanov et al., 2019; Belaud et al., 2019; Nestlé, 2023). In the past, the milk supply chain was largely manual and paper-based, making it difficult to collect, analyse, and share data effectively. However, with the increasing use of digital technology, big data can become a critical tool for managing the milk supply chain efficiently.

One of the main roles of big data in the milk supply chain is to provide insights into milk production, transportation, and storage. By collecting data on milk production from dairy farms, transportation routes, and storage facilities, stakeholders can optimise the entire supply chain. For example, data on milk production can be used to forecast supply and demand, enabling milk processors to plan their production schedules accordingly (Navickas and Gružauskas, 2016; Lamba and Singh, 2017). Similarly, data on transportation routes and storage facilities can be used to optimise logistics and minimise waste. Big data also plays a crucial role in quality control in the milk supply chain. By monitoring the quality of milk at every stage of the supply chain, from the farm to the processing plant, stakeholders can ensure that milk meets the required quality standards. This is especially important for milk products that are consumed raw, such as drinking milk, as they can pose health risks if they are not properly monitored for quality and safety (Martin et al., 2018).

Furthermore, big data can help stakeholders in the milk supply chain to manage risk. For example, data on weather patterns can be used to predict the likelihood of disease outbreaks or other issues that could impact milk production. This can enable stakeholders to take preventive measures to minimise the impact of these risks. Big data can help to improve sustainability in the milk supply chain. By collecting data on energy consumption, water usage, and greenhouse gas emissions, stakeholders can identify areas where they can reduce their environmental footprint. This can include optimising transportation routes, using renewable energy sources, and implementing more efficient production processes.

Big Data technology has the potential to revolutionise the milk supply chain by providing valuable insights and enabling more efficient and effective collaboration between the different players in the chain (Kache and Seuring, 2017). The ability to collect, store, and analyse large amounts of data from various sources can provide supply chain actors with a more comprehensive and accurate view of the supply chain (Kache and Seuring, 2017), which can help to improve forecasting, increase transparency, optimize logistics, and improve customer service in the milk supply chain (Kamal *et al*., 2018). By analysing data on customer behaviour and preferences, retailers can improve the customer experience and build stronger relationships with their customers. One of the main benefits of big data technology in supply chain management is the ability to gain a more detailed and accurate understanding of consumer demand (Navickas and Gružauskas, 2016). This can enable milk suppliers and manufacturers to better anticipate changes in demand and adjust their production and logistics accordingly. For example, by using data from social media, online sales platforms, and other sources, suppliers can gain a better understanding of consumer preferences and trends and adjust their production and distribution accordingly.

Another implication for big data technology in the milk supply chain is increased transparency, visibility and traceability (Ji et al., 2017). Big data technology can be used to monitor inventory levels and logistics in real-time, enabling suppliers to quickly respond to changes in demand and avoid stockouts or overstocking (Ji et al., 2017). This can be achieved through the use of sensors and other digital technologies that can collect data on various aspects of the supply chain such as production, transportation, and distribution (Gupta and Rani, 2019). This data can then be analysed to identify patterns and trends that can provide insights into potential risks and vulnerabilities. For example, data on temperature and humidity during transportation can be used to identify conditions that may lead to spoilage, and data on truck location and speed can be used to identify potential bottlenecks in the supply chain (Gupta and Rani, 2019). By identifying these issues, organisations can take steps to address them and improve supply chain resilience.

In addition to improving visibility and traceability, big data technology can also help organisations make more informed decisions. For example, data on consumer preferences and demand can be used to optimize production and distribution operations (Ji et al., 2017; Gupta and Rani, 2019). This can help organizations avoid overproduction and reduce waste, which can save costs and improve efficiency. Additionally, data on consumer sentiment can be used to identify potential issues before they become a problem, allowing organisations to take proactive measures to address them (Yang et al., 2017). For example, if social media data suggests that consumers are becoming concerned about the use of antibiotics in milk production, an organization can take steps to address this issue before it becomes a major problem.

Predictive maintenance is another area where big data technology can have a significant impact in the milk supply chain (Lee et al., 2014). By analysing sensor data and other operational data, processors and retailers can identify potential issues and take preventative measures to avoid disruptions. For example, data from sensors can be used to predict when equipment need maintenance, which can help to minimise downtime. This can help to improve the efficiency and effectiveness of supply chain operations (Lee et al., 2014) and ultimately lead to greater resilience and adaptability in the face of unexpected disruptions.

Big data technology can also help to optimise logistics in the milk supply chain (Lamba and Singh, 2017). By analysing data on transportation, inventory, and other logistics, retailers and processors can optimize their supply chain operations and reduce waste. They can also use the data to identify opportunities for collaboration with other businesses in the supply chain (Kache and Seuring, 2017; Lamba and Singh, 2017). For instance, data on truck availability and capacity for transportation across logistics providers in the supply chain can be used to optimise truckload, supporting decisions for a full truckload (FTL) transportation or a less than truckload (LTL) transportation option. This can help to improve the efficiency of supply chain operations and reduce costs, which can ultimately lead to greater resilience and adaptability in the face of unexpected disruptions.

The application of Big Data to the milk supply chain is evidence in literature as having the potential to improve the resilience of the milk supply chain to disruptions optimise performance. This research is interested in understanding specifically how

Big Data can be applied effectively, given that, while Big Data technology can offer specific advantages and improve resilience in milk supply chains, there are potential risks, challenges and barriers to the application of Big Data in any supply chain and more specifically, the milk supply chain as documented in section 2.10.

2.10 Barriers to Applying Big Data in the Milk Supply Chain

The use of big data technology in supply chain management as discussed in section 2.9 has the potential to improve resilience in milk supply chains by providing more accurate and real-time information about demand, alternative suppliers, their product availability and their location, alternate delivery routes etc. This can enable better planning and decision making and help to reduce the risks associated with over-reliance on a limited number of suppliers. However, as with any technology, there are also potential challenges and barriers associated with the use of big data in milk supply chains.

An important challenge to consider when applying Big Data to the supply chain is the implication of big data technology on data management in the milk supply chain. The milk supply chain is a complex system, and the data collected from it can be equally complex. Managing large volumes of data presents a challenging task (Sivarajah et al., 2017); as the volume of data being collected and stored increases, organisations need to ensure that they have the necessary infrastructure and systems in place to manage and process this data effectively. This includes data storage, data management, data analysis, and data visualisation tools. Organisations need to have the capability to process and analyse this data, which may require specialised software and personnel with specialised skills (Ivanov et al., 2018). Organisations then need to ensure that the necessary personnel and expertise to process and analyse the data are available and that have a clear understanding of the data quality and accuracy. A lack of the personnel or staff with expertise in handling Big Data infrastructure and the analytical skills required can pose a challenge (Sivarajah et al., 2017). Additionally, organisations need to ensure that they are collecting and analysing data from all relevant sources, including internal data, external data, and social media data. By collecting and analysing data from all relevant sources, organisations can gain a more comprehensive and detailed understanding of their supply chain operations and identify potential risks and vulnerabilities more effectively.

Moreover, organisations need to consider the importance of data governance in the milk supply chain. Data governance refers to the management and control of data, including data quality, data security, data privacy, and data compliance. Organisations need to ensure that they have a clear data governance framework in place to ensure that data is being collected, stored, and used in an ethical and responsible manner. Additionally, organisations need to ensure that the data is accurate and reliable, and that it is being used appropriately. Organisations need to ensure that they are in compliance with relevant regulations and standards (Kache and Seuring, 2017), such as the General Data Protection Regulation (GDPR) in Europe and the Health Insurance Portability and Accountability Act (HIPAA) in the United States. For example, if data is collected and shared without proper consent, it can lead to privacy concerns and regulatory fines. Additionally, if data is not properly secured, it can be vulnerable to cyber-attacks, which can also lead to regulatory challenges (Gupta and Rani, 2019). The data management implication of Big Data application includes consideration for data storage, the staff or personnel with the required skill to support big data technology, data sources, data governance and compliance. Ensuring standardisation across all these can present financial considerations to organisations.

Technological and cultural factors in collaborating organisations can also impact the application of big data in milk supply chains; for example, a lack of infrastructure or connectivity in rural areas can make it difficult to collect and share data, which can limit the ability of suppliers to respond to changes in demand. Additionally, a lack of skilled workers in collaborating organisations with the knowledge and expertise to collect, analyse, and act on big data can also limit the application of big data throughout the supply chain (Gupta and Rani, 2019). Where a supply chain seeks to incorporate big data technology across its network, it is imperative that this technology is implemented across all organisations participating in that supply chain. however, the technological capabilities and willingness of other organisations within that supply chain provide a barrier to a network wide application. It is also important to note that big data technology alone is not a panacea for improving supply chain resilience. While it can provide valuable insights and improve decision-making, organisations also need to consider other factors such as risk management, supply chain design, and collaboration with suppliers and other stakeholders (Ivanov et al., 2018). It is also important to consider the cultural and organisational changes that may be necessary to effectively implement big data technology across the supply chain to realise its full potential and also, consider the ethical implications of big data technology in the milk supply chain (Ogbuke et al., 2020). For example, organisations may collect data on farmers and suppliers, which could be used to exploit or discriminate against them. Furthermore, organisations may collect data on consumers, which could be used for targeted advertising or other purposes that may not align with consumer preferences or values. Organisations should ensure that they are collecting, storing and using data in an ethical and responsible manner, as well as being transparent with their customers and suppliers. Big data technology has the potential to improve supply chain resilience in the milk industry by providing more accurate and detailed information on various aspects of the supply chain, and by helping organisations make more informed decisions. However, for a supply chain wide application to be effective, the supply chain must consider the technological capabilities and willingness of each member of the supply chain as well as organisational culture and if they align with the wider cultural preference of the supply chain.

In conclusion, given that Big Data is proposed to offer extensive advantages, it is important for this research to not only review how Big Data is being applied in participating organisations that apply it, but to also consider if there are additional barriers that could lead to other organisations that participate in this research lacking the ability to take full advantage of Big Data opportunities. Organisations may need to consider the costs and challenges of implementing big data technology, including data infrastructure, data processing, and investment in specialised personnel. Other barriers and challenges to consider may include system failures, technological factors and cultural factors. Taking this into consideration allows the research to make better recommendations as highlighted in research objective 5.

2.11 Simulating Supply Chains and Disruptions

Supply chain simulation is an important tool for understanding and mitigating the impact of supply chain disruptions (Ivanov, 2017; Ivanov and Rozhkov, 2020). It involves creating virtual models of the supply chain to test different scenarios and identify potential risks and vulnerabilities (António A.C. Vieira et al., 2019). Researchers have explored different methods for simulating supply chains and disruptions in literature. In this section, we will review some of the existing literature on this topic.

One approach to simulating supply chains is using system dynamics models. System dynamics is a modelling technique that focuses on understanding complex systems and feedback loops. In a supply chain context, system dynamics models can be used to simulate the flow of goods, information, and funds between different members of the supply chain. For example, Alzubi et al. (2023) developed a system dynamics model to simulate the citrus supply chain in Jordan Valley. The model helped to identify obstacles and challenges that hinder the supply chain and develop strategies to improve sustainable performance.

Another approach to simulating supply chains is using agent-based models. Agent-based modelling involves creating virtual agents that represent different actors in the supply chain, such as suppliers, manufacturers, and retailers. These agents interact with each other based on predefined rules, such as supply and demand dynamics or pricing strategies. For example, in the study by Wu et al. (2013) an agent-based simulation model is developed that considers how consumers respond to stockouts for different products. The resilience of both the retailer and manufacturer is measured by examining changes in their market share. The study provides insights for manufacturers and retailers on how to respond to stockout disruptions.

Finally, network-based models are another approach to simulating supply chains. Network-based models focus on the structure of the supply chain and the relationships between different actors. These models can help to identify potential bottlenecks or vulnerabilities in the supply chain and develop strategies to mitigate them. For example, the research by Ghaithan et al. (2022) developed a network-based model for predicting the delivery time of oxygen gas cylinders in Saudi Arabia during the COVID-19 pandemic. The model helped to identify potential supply chain failures.

Simulating supply chains and disruptions is an important tool for understanding and mitigating the impact of supply chain disruptions. Researchers have explored different methods for simulating supply chains, including system dynamics models, agent-based models, and network-based models. These models can help stakeholders to identify potential risks and vulnerabilities in the supply chain and develop strategies to improve its efficiency and resilience. This research will discuss in detail the simulation approach adopted by this research in section 3.7 alongside other simulation approaches.

2.12 Theoretical Background

This research considered several theories in the supply chain management literature in considering the theoretical lenses including Contingency Theory, Research Based View and Dynamic Capabilities which have been well adopted by previous researchers in reviewing capabilities and resources within firms (Kumar et al., 2024) and selected the Resource Based View and Dynamic Capabilities. This is because both Resource Based View and Dynamic Capabilities are more beneficial where the objective is address uncertainties such as disruptions. While Contingency Theory can support the review of organisational resources and capabilities, it is more beneficial when the resources and capabilities are rare (Kumar et al., 2024). These theories are selected based on the applicability and relevance to this research and extensive use and acceptance within the supply chain resilience field especially where technological capabilities are also being considered. Hence, this section details the Resource Based View (RBV) and Dynamic Capabilities (DC) as the main theoretical lenses for this research. It provides a background into the theories which support this research.

2.12.1 Resource Based View (RBV)

The Resource Based View provides the argument that organisations can generate competitive advantage by building strategic resources and capabilities (Barney, 1991; Barney et al., 2001; Sirmon et al., 2011). It argues that superior performance for an organisation depends on the extent to which the organisation possesses resources which are simultaneously valuable (V), imitable (I), rare (R), and properly organised (O) (Amit and Schoemaker, 1993; Barney et al., 2001). These resources could either be tangible (such as infrastructure, machine or equipment) or intangible (such as information or knowledge sharing) (Größler and Grübner, 2006). Organisational resources could also be physical, human, technological or reputational (Gunasekaran 2017). When put together, these resources have noteworthy value (Grant, 1991; Sirmon et al., 2008).

While resources refer to the tangible and intangible assets of an organisation, capabilities on the other hand are subsets of the organisation’s assets which are nontransferable and are targeted at improving the performance of other resources (Makadok, 1999). Thus, resources could be an essential need for an organisation (Hitt et al., 2011), and rely upon the environmental conditions in which an organisation works. In any case, RBV identifies that resources may be unable to provide the needed competitive advantage on their own. Sirmon et al. (2007) discussed the role played by top managers in building capability and organizing the resource portfolio, utilizing the specific processes (acquiring, accumulating, and divesting); previous researchers have explored the significance of managerial decisions in acquiring resources and deploying them (Gunasekaran et al., 2017), as well as coordinating them (Gunasekaran et al., 2017).

With the increased usage of big data in organisations, scholars have found that big data has the capacity to transform business processes (Mishra et al., 2018). Hence, the need for a better understanding as regards the applications of Big Data Analytics and how it can be harnessed as a valuable resource with which organisations can gain competitive advantage (Abbasi et al., 2016; Côrte-Real et al., 2017; Miah et al., 2017).

2.12.2 Dynamic Capabilities

The dynamic capabilities concept also allows for the development of a better understanding of how organisations can develop competitive advantages by adopting new technologies such as big data analytics (Côrte-Real et al., 2017). This concept was initially proposed by Teece and Pisano (1994) who defined the dynamic capabilities theory as the ability of an organisation to build, configure and integrate both internal and external competencies in order to address a rapidly changing environment. Eisenhardt and Martin (2000) further developed the theory to include capabilities that integrate and reconfigure resources available to an organisation in order to create new routines which allow managers build up newer resources. This basically implies that an organisation uses what it has in its possession as tools or arsenal to position itself better for competing in a dynamic market.

Dynamic capabilities also refer to an organisation's capacity to respond in an environment that is changing rapidly (Sher and Lee, 2004). This implies that an organisation which possesses Dynamic capabilities can react quickly to changes in its business environment. Hence, as disruption causes a change in the supply chain, Dynamic Capabilities can offer some capacity for the supply chain to respond in a favourable way both to the organisations as well as the supply chain. Another important feature of the Dynamic Capabilities theory is the availability of tools which promote integrative learning of internal knowledge (Singh and Singh, 2019a). This promotes the dynamic capabilities and allows an organisation to develop its competitive advantage (Eisenhardt and Martin, 2000; Ganguly and Rai, 2018). Scholars believe that while the possession of Dynamic Capabilities is not a direct guarantee for performance enhancement, they are necessary to enhance performance as they are of strategic importance especially for organisations that operate in a fast-changing environment where reaction time and adaptability is of utmost importance (Singh and Singh, 2019a).

Research also links dynamic capabilities theory to responsiveness, managerial cognition, innovative capability, adaptability, and knowledge in an organisation as they can change operational routines and competencies (Teece and Pisano, 1994; Zollo and Winter, 2002; Easterby-Smith et al., 2009). It can then be argued that possessing dynamic capabilities in an organisation, as the ability to gain insight from Big Data Analytics, can enable organisations anticipate and mitigate events which could potentially lead to a disruption, and possibly build a competitive advantage through resilience.

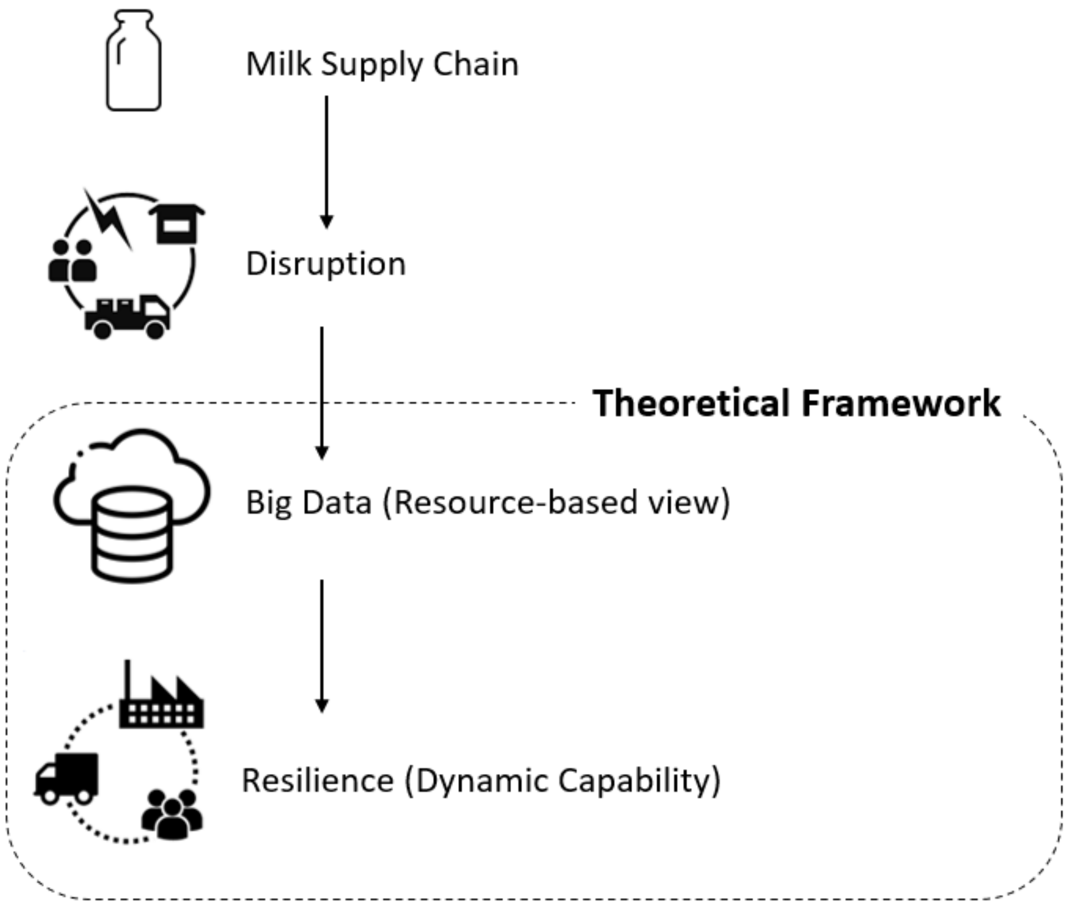


Figure 2. 3: Theoretical Background – Big Data Analytics and Supply Chain

Figure 2.3 proposes an initial theoretical framework for the study of the potential impact of Big Data Analytics on Supply Chain Disruption. This research attempts to explore the benefits of Big Data Analytics in building resilience for mitigating supply chain disruption. However, building a capability such as resilience takes deliberate effort and utilises organisational resources such as big data. Hence, the organisation must make a conscious plan to ensure that the supply chain is resilient in the case of a disruption – all of which is within the scope of this study. This plan needs to be carried out and reviewed for any strengths and/or weaknesses – all with a view to ensure that organisations as well as the supply chains are not only resilient to disruption but stay resilient. Hence, these underscore the need for the current research with a scope which would assess these opportunities, potentials and interdependencies to make organisations better plan and become proactively resilient to any future disruption events.

2.12.3 Theoretical Development and Limitations

Initially, RBV focused on tangible resources such as physical assets and financial capital. Over time, researchers expanded the concept to include intangible resources such as knowledge, reputation, and organisational culture (Kamasak, 2017). This broadening of resource types enhanced the theory's applicability to diverse industries.

Scholars such as Teece et al. (1997) introduced the concept of dynamic capabilities within the RBV framework. Dynamic capabilities refer to an organisation's ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing needs. This extension emphasised the importance of adaptability and learning in sustaining competitive advantage over time.

RBV has been integrated with other strategic management theories to provide a more comprehensive understanding of competitive advantage. For example, combining RBV with transaction cost economics helps explain how firms make strategic decisions regarding factors such as pricing, resource acquisition and deployment (McIvor, 2009; Gancarczyk, 2016; Lai et al., 2023). Subsequent researches on RBV have delved deeper into the attributes of valuable resources, particularly the rarity and inimitability of resources. Scholars have explored how firms can develop unique capabilities that competitors find difficult to replicate, thereby reinforcing the theory's emphasis on sustainable competitive advantage.

RBV has been extensively applied in empirical studies across various industries to examine real-world examples of resource-based competitive advantage (Teece and Pisano, 1994; Teece et al., 1997; Mentzer et al., 2001). Researchers have analysed how firms leverage specific resources to achieve superior performance and adapt to market changes. In this research, the focus is on leveraging Big Data to achieve resilience in a market where disruptions exist.

The Resource-Based View (RBV) and Dynamic Capabilities (DC) theories, while influential in strategic management, exhibit certain limitations that are particularly pertinent when applied to research on enhancing milk supply chain resilience through Big Data analytics (Barney, 1991; Teece et al., 1997).

One notable limitation of RBV is the challenge of resource identification and valuation within the context of supply chain management. Milk supply chains involve diverse and dynamic resources, including physical assets (e.g., processing plants, transportation infrastructure), knowledge assets (e.g., quality control expertise, supplier relationships), and intangible assets (e.g., brand reputation, customer loyalty) (Barney, 1991). The subjective nature of resource valuation, especially for intangible assets e.g., reputation or knowledge, can complicate the application of RBV principles to assess how these resources contribute to resilience.

Furthermore, RBV may oversimplify the role of external factors and industry dynamics in shaping supply chain resilience. External influences such as market demand fluctuations, regulatory changes, and environmental factors significantly impact supply chain performance and resilience (Mentzer et al., 2001). RBV's internal focus on resources may overlook the interconnectedness of supply chain actors and broader ecosystem influences that shape resilience outcomes.

In the context of Dynamic Capabilities, the theory's emphasis on organisational learning and adaptation may encounter challenges in rapidly evolving supply chain environments (Teece et al., 1997). Milk supply chains are subject to continuous technological advancements, market disruptions, and changing consumer preferences. The dynamic nature of these external forces requires supply chain actors to continuously evolve their capabilities to remain resilient, which may go beyond the scope of traditional DC frameworks.

When considering the research on Big Data analytics in milk supply chain resilience, the limitations of RBV and DC underscore the need for a more comprehensive and integrative approach. While RBV provides a foundational understanding of resource-based competitive advantage, it should be complemented by broader ecosystem perspectives that consider external influences and interdependencies within supply chains (Mentzer et al., 2001).

However, despite these challenges, the unique characteristics and complexities of milk supply chains make RBV and DC particularly suitable theoretical frameworks. The dynamic and multifaceted nature of milk supply chains necessitates a nuanced understanding of internal capabilities and external factors, aligning well with the principles of RBV and DC (Barney, 1991; Teece et al., 1997). Integrating these theories with empirical insights can enhance our understanding of how Big Data analytics can drive resilience in milk supply chains, taking into account the specific challenges and dynamics inherent in this industry.

In summary, while challenges exist in applying RBV and DC to supply chain resilience, these theories remain valuable foundations that can be adapted and extended to enhance the understanding of resilience in milk supply chains. By acknowledging the unique characteristics of this industry and integrating complementary perspectives, researchers can leverage RBV and DC to inform effective strategies for leveraging Big Data analytics and enhancing supply chain resilience.

2.13 Theoretical Framework and the Research Questions

The theoretical framework of the thesis, centres on the Resource Based View (RBV) and Dynamic Capabilities (DC), provides a lens through which the research questions are examined in the context of Big Data Analytics and supply chain resilience. RBV theory underpins Research Question 1 by focusing on the importance of strategic resources and capabilities in providing competitive advantage for organisations. Big Data is then explored as a valuable resource that allows organisations in milk supply chain to enhance their resilience.

Both RBV and DC theories inform Research Question 2 by emphasising the importance of organisational resources and capabilities in addressing challenges and building resilience. This research holds that understanding the value of resources, alongside the dynamic capabilities to respond to changes during a disruption, contributes to the resilience of milk supply chains.

RBV theory guides Research Question 3 by supporting the development of a resilience measuring tool as a strategic resource. This tool improves an organisation's capability to assess the impact of disruptions within milk supply chains, aligning with RBV's emphasis on valuable and properly organised resources.

DC theory informs RQ4 by highlighting the organisation's capacity to respond to changes rapidly, including disruptions within milk supply chains. Big Data Analytics is explored as a tool to enhance dynamic capabilities, enabling organisations to anticipate and mitigate disruptions, thereby enhancing supply chain resilience.

Figure 2.3 demonstrates the interconnectivity between Big Data Analytics, organisational resources and capabilities, and supply chain resilience. By integrating RBV and DC theories, the framework facilitates the exploration of how organisations can harness Big Data Analytics to build resilience and mitigate disruptions within milk supply chains. This framework serves as the theoretical basis for investigating the research questions and understanding the dynamics of supply chain resilience in the context of technological capabilities.

2.14 Chapter Summary and Knowledge Gaps

Big Data Analytics has the potential, when applied to the supply chain to help organisations and the supply chain build resilience as well as mitigate the impacts of disruption. However, some key areas remain unclear in the literature - these must be addressed especially if organisations must explore the potential advantages of big data in developing disruption resilience. These gaps in knowledge are summarised as follows:

- Limited research has been conducted on the application of Big Data in improving the resilience of milk supply chains. While there has been some research on the use of Big Data in the food industry, there are still gaps in knowledge as to its application in the milk supply chain context. Thus, it is imperative to understand how Big Data can be applied to support the workings of milk supply chain. Hence, research questions 1 and 2 focus on understanding the challenges within the milk supply chain including disruptions and how Big Data can be harnessed in its totality to improve a supply chain's resilience to disruption. For example, Nestlé has implemented a Big Data solution to track milk quality and improve supply chain efficiency (Nestlé, 2023). This shows that organisations within the dairy industry are considering the implications of more data-driven solutions within their supply chains. However, there are currently no research studies focused on understanding empirically, Big Data implications for the milk supply chain. Studies such as this one can provide insights into the specific challenges and opportunities of using Big Data in the milk supply chain context.

- Few studies have focused on developing a resilience measuring tool that can capture the impact of disruptions within the milk supply chain. And those studies that have do not address Big Data applications. While there may be existing tools for measuring resilience in supply chains, they may not be suitable for the milk industry due to its unique characteristics. While these characteristics may be similar to the wider food supply chain, it is also important to note that widening to the food supply chain, little has also been done with regards to a resilience measuring tool with Big Data consideration. Research question 3 looks to develop a resilience measuring tool that is specific to the milk supply chain. This tool could take into account factors such as the perishability of milk, the importance of temperature control, and the reliance on local suppliers. It could also consider the impact of disruptions on key performance indicators such as lead times, costs, and customer satisfaction.
- There is scarcity of literature on data-driven simulation of disruption scenarios. While there are existing models for other industries, none has provided models in the milk supply chain. It is important to understand how these models can be adapted to the milk supply chain context. Hence, research question 4 investigates critically how data driven analysis can be applied in the measurement of resilience within the milk supply chain. One potential research approach is to develop a simulation model of the milk supply chain and use it to evaluate the impact of disruptions. It could also consider different disruption 'what-if' scenarios.

Chapter 3
METHODOLOGY

3.1 Introduction

This chapter provides insight and justification for the methodologies applied in conducting this study. In particular, it adapts sections of the research onion (Table 3.1), developed by Saunders et al. (2019), to guide the development of the current study through the stages of clearly defining the research philosophy, approaches, strategies, choices, time horizon, techniques and procedures applied throughout this study. Bryman (2016) argued that the adoption of the research onion for studies such as these offers the advantages of ease of adaptability to various research types and effective progression through which to efficiently design a research methodology. The chapter also presents a description of the computer simulation applied to model disruption scenarios that companies within the sector may potentially face and how they can build resilience.

The sources of data utilised in the study include primary qualitative data collected through semi-structured interviews with supply chain professionals, consultants, academics, and modelling experts and quantitative data collected from the focal milk supply chain. Qualitative data collection took place between November 2020 and September 2022, during which interviews were conducted, and simulation models were developed and tested. Quantitative data was collected in March 2022 with data spanning 3 years and 3 months from November 2018 to February 2022. This ensured that the study captured a timeline that could provide a comprehensive understanding of the milk supply chain and potential disruption scenarios. There is also a consideration of the ethics of conducting this study, and potential research limitations associated with this study.

Table 3. 1: Research methodology, adapted from Saunders et al. (2019)

	Layer of Research Onion	Choices Applied
1	Philosophy	Interpretivism
2	Approach	Abductive
3	Research Choices	Mixed Methods (quantitative and qualitative)
4	Research Methods	Interviews and Computer simulation

3.2 Research Philosophy

The research philosophy considers the source, nature and knowledge development in the research context (Saunders et al., 2019). The research philosophy constitutes the belief system on which data is then gathered, analysed, interpreted and used as part of the research phenomenon (Kivunja and Kuyini, 2017). This implies that the researcher's perception (or believe) of reality stimulates the way in which knowledge about the research concepts and phenomenon will be derived for the purpose of the research. Academic research considers four main types of research philosophy: Pragmatism, Positivism, Realism and Interpretivism.

Pragmatism considers the research questions to be the most important determinants for research (Kaushik and Walsh, 2019). However, pragmatism does not provide a philosophical rationale for the mixed methods approach (Kaushik and Walsh, 2019), implying that when investigating a research problem that has separate layers, it becomes challenging to measure and/or observe all the layers (Feilzer, 2010). Thompson (1997), another critic of pragmatism, also argued that pragmatism has a limitation on the ability to identify and analyse structural social problems, which typifies the current study.

Positivism as a research philosophy is arguably linked to the natural scientist who prefers working with and observing realities with the intention of producing generalisable results. Additionally, research carried out with a positivist philosophy is undertaken in a value-free manner as much as possible; and is highly likely to use a structured methodology for the purpose of replication (Gill and Johnson, 2002). The emphasis here is on making quantifiable observations that aid statistical analysis. Given the complex nature of supply chain, the aim of this research is not to generalise but to understand the complexity of supply chain elements. As positivism aims to generalise the result of research, there is the chance of neglecting potentially relevant insights from individuals whose understanding and interpretation of events, phenomena or issues may reveal significant truth about reality (Pham, 2018). Thus, positivism will not be adopted for the current study.

Realism on the other hand, proposes that what our senses show us as reality is indeed the truth; and proposes that objects exist in a space that is independent of the mind (Maxwell, 2012). The realist philosophy holds that entities exist independent of the theories about them (Maxwell, 2012). The key demerit with this philosophy is that realism claims that it is possible to build knowledge about parts of reality that is not open to observation (Øgland, 2017), and that negates the view for the current study which hopes to explore and develop knowledge from the insights from key players within supply chain.

Interpretivism as a Philosophy is adopted in this research because it seeks to explore and interpret the happenings within a supply chain such that meaning can be derived from the actions of each participant and the resulting effects (Woods and Trexler, 2001). The interpretivism philosophy will allow the researcher to immerse into the 'world' of the supply chain participants and help in understanding the decision-making process and how each participant builds resilience against disruption. Qualitative insights from interpretative approaches will aid the design of simulation models and support the validation of simulation results, enhancing the robustness of findings. By integrating qualitative depth with quantitative rigour, this research gains a more comprehensive understanding of supply chain dynamics and encourages informed decision-making. Klein and Myers (1999) opined that interpretivism is an ideographic research approach which studies individual cases or events and can offer the capacity to understand different people's voices, meanings and events; thus, the meanings of the different events constitute the source of knowledge (Richardson, 2012).

3.3 Research Approach, Design and Method

It has been argued that the research approach helps to provide guidance when developing the research outline and can be considered a crucial part of the research process. According to Cooper and Schindler (1998), and highlighted by Saunders et al. (2019) in the research onion, there are two approaches that can be adopted in a research - Inductive and Deductive. The main variance between these two approaches lies in the fact that the inductive researcher works from bottom up, considering data before theory and hypothesis; whereas the deductive researcher considers the theory before the data – the top to bottom approach (Creswell and Clark, 2007; Soiferman, 2010). The inductive approach allows for research conclusions based on a consideration of all gathered evidence and facts (Cooper and Schindler, 1998).

The use of the inductive approach particularly allows for the sequence in which activities occur to be taken into consideration; and this is particularly helpful when analysing supply chain disruption because it allows the researcher to capture the individual activities that comprise supply chain disruption (Ivanov et al., 2014). The inductive approach allows for research analysis and inferences to be made from observations rather than from a structured outline (Bryman and Bell, 2007). The deductive approach, on the other hand, is concerned with the exposure of a well-developed theory to severe testing, using a well-structured methodology (Gill and Johnson, 2002).

This research utilises a third research approach: abductive approach which is also utilised in studies such as Mackay et al. (2020) and combines the inductive and deductive approach allowing the research to draw new insights from traditional inductive and deductive approach. This implies that the theories or hypothesis developed using the inductive approach can be tested using deductive approach.

Research method can be qualitative or quantitative, and the choice of the method would directly affect the research instrument adopted (such as questionnaires, oral or written interviews, observation and focus groups) (Greener, 2008; Kothari, 2008). Qualitative research employs the use of narrative reporting to describe the context in which the research takes place. Qualitative research method allows the research to explore the meaning of the participants' experience (McCusker and Gunaydin, 2015), while the quantitative research method deals with the researcher's ability to adequately quantify the relationship between variables in numerical value (Nykiel, 2007).

Nevertheless, the current study has adopted the mixed method, combining both qualitative and quantitative methodologies to create the unique set of data required for this study (Figure 3.1). The mixed method is deemed ideal particularly because of the advantages it offers, including (i) comparing and understanding the contradictions between qualitative and quantitative data and findings, (ii) adequately reflecting participants' point of view and ensuring findings are grounded in their experiences, (iii) fostering multidisciplinary approach to research and scholarly interactions, (iv) affording methodological flexibility and adaptability to various research designs, and (v) allowing for the collection of a more robust and comprehensive data sets required for understanding supply chain disruption and resilience (Wisdom and Creswell, 2013). However, there may be downsides with regards to the increased complexity of data analysis/evaluation and the amount of resources required to employ this method.

The adoption of a mixed-method approach in this research involves integrating quantitative and qualitative methods to gain a comprehensive understanding of the milk supply chain. Quantitative methods, such as the computational simulation adopted in this study, provides numerical data and statistical analysis, while qualitative methods, such as interviews, offer the in-depth insight into the perspectives and experiences of this milk supply chain's members.

The process of quantitative/qualitative integration in this research will involve several steps. Firstly, qualitative data from interviews will be collected and analysed to identify key themes and insights regarding supply chain operations, challenges, and strategies. These qualitative findings will serve as a basis for developing the conceptual framework and building a representative model.

Subsequently, quantitative data will be gathered through computational simulation to test and validate the insights drawn from qualitative analysis. Simulation experiments will allow this research to observe how different scenarios and variables impact supply chain performance and resilience.

The role of the theoretical framework in choosing the research method is pivotal. Theoretical frameworks, such as the Resource-Based View (RBV) and Dynamic Capabilities theory, provide the conceptual basis for understanding supply chain dynamics and resilience. They inform the selection of variables and the design of simulation experiments.

By grounding the research method in established theoretical perspectives, the mixed-method approach ensures alignment between the research objectives, data collection methods, and theoretical frameworks. It enables the research to triangulate findings and offer a more nuanced understanding of supply chain phenomena. Ultimately, the integration of quantitative and qualitative methods enhances the robustness of research outcomes in exploring complex milk supply chains.

A range of methods including ethnographic method, case study, etc. were considered for their suitability in achieving the research objectives. Participant observations and ethnographic studies were considered not suitable due to their requirement for prolonged immersion in the field, which are feasible within the scope of this research project (Denzin and Lincoln, 2018). Unstructured interviews were also considered less suitable as they lack the necessary focus and direction to effectively explore specific research questions and may lead to data collection issues (Denzin and Lincoln, 2018). Additionally, focus groups were not selected due to their potential limitations in providing depth of insights into individual perspectives within the supply chain context, as well as the challenges in coordinating participants' schedules (Kitzinger, 1995), especially as interview data collection for this research was happening during the COVID-19 pandemic which was characterised by restrictions to movement and face to face gatherings. Overall, while these methods have their strengths in other contexts, they were deemed less suitable for addressing the research objectives and requirements of this study for the milk supply chain.

For this study, semi-structured interview has been selected as the qualitative method mainly because it allows for interviewees to be engaged in such a way as to provide the depth, breadth and saliency of data required for authentic analysis and reporting (Saunders and Townsend, 2016).

This implies that the research attempts to answer its research questions by interacting with participants who have experienced supply chain disruption based on the participant criteria in Table 3.2 or have substantial interaction with methods and strategies that could be used to mitigate a supply chain disruption (Given, 2008). This allows for the understanding and interpretation of interactions (Lichtman, 2006; Johnson and Christensen, 2008). The interviews will allow the researcher to explore the factors that cause supply chain disruptions and help put the research in context, while highlighting the key components in a supply chain that could potentially increase resilience.

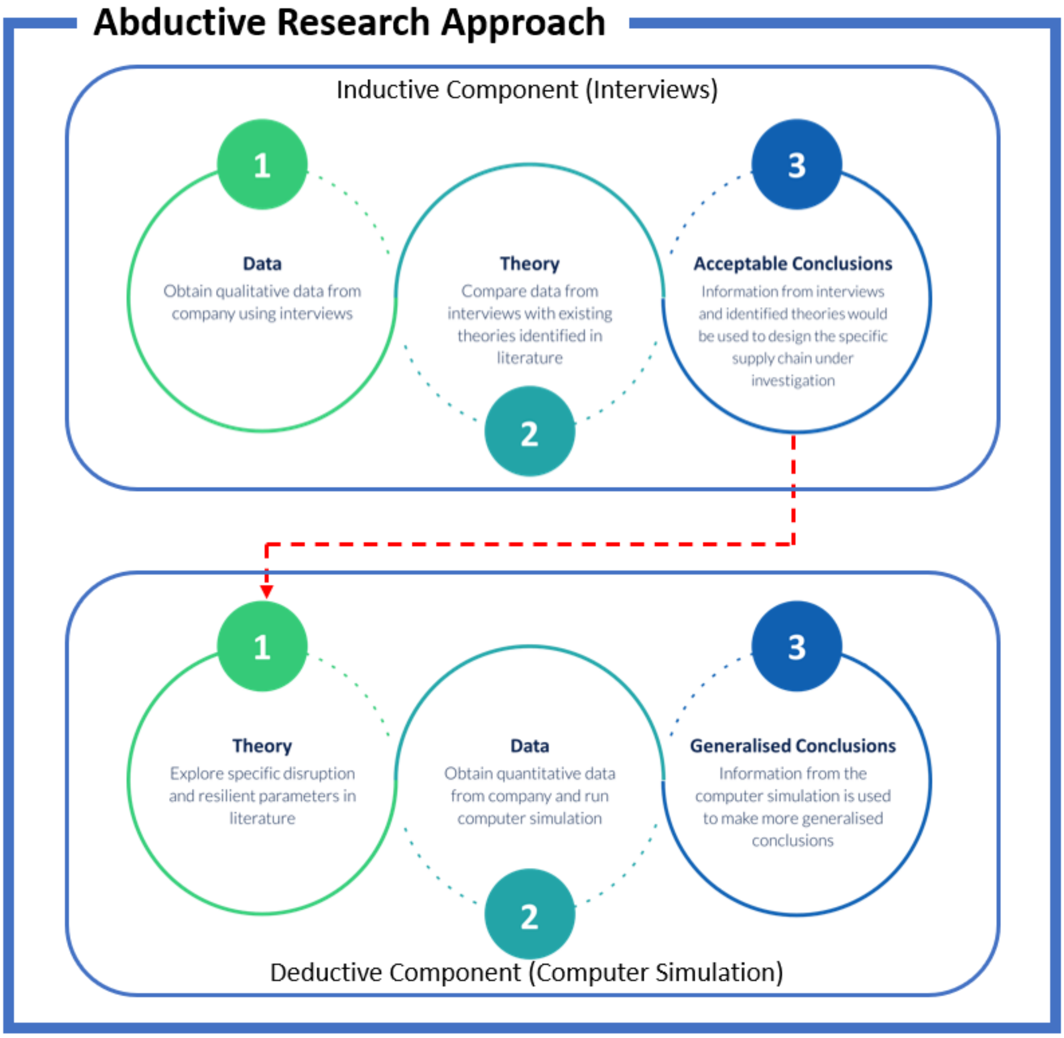


Figure 3. 1: Choice of Research Approach indicating the mixed methods adopted for the current study.

Likewise, there are several quantitative methods which can be applied to a management research such as this, including survey questionnaire (Pinsonneault and Kraemer, 1993), operational research method (Jones, 1993; Cooper, 1999), panel data studies (Castro and Ariño, 2016), econometrics (Thiel, 1992), etc. Nonetheless, this study adopts computer simulation as the quantitative method particularly because it allows for advancing theories and research on complex behaviours and systems (Harrison et al., 2007). The computer simulation allows for in-depth analysis, using deterministic experiments to examine the effect that different disruption scenarios could have on the supply chain. It is the intention of this research to simulate alternative optimised supply chain scenarios based on information derived from the participants (Gilbert and Troitzsch, 2005).

At this point it becomes imperative to restate the research objectives, which include:

- To explore the challenges faced by food supply chains and review their resilience to recent disruptions.
- To develop a resilience measuring tool to capture impact of supply chain disruptions experienced within the milk supply chain.
- To measure the resilience of the milk supply chain through data driven analysis of disruption scenarios.
- To assess Big Data in milk supply chains and propose its effective application in the development of a disruption resilient supply chain.
- To provide recommendations to milk supply chain producers.

Objective 1 is addressed with in-depth interviews with supply chain experts as highlighted in Table 3.2 and analysed in section 4.4. Figure 3.2 highlights that Computer Simulations will be used in addressing objectives 2 and 3. The output from both qualitative and quantitative studies will be used to inform the proposition of an optimal disruption resilient supply chain (Objective 4). Objective 5 is addressed by synthesising the research findings and insights gained from the mixed-method approach to offer tailored recommendations aimed at enhancing the resilience and efficiency of milk supply chains (see section 10.3)

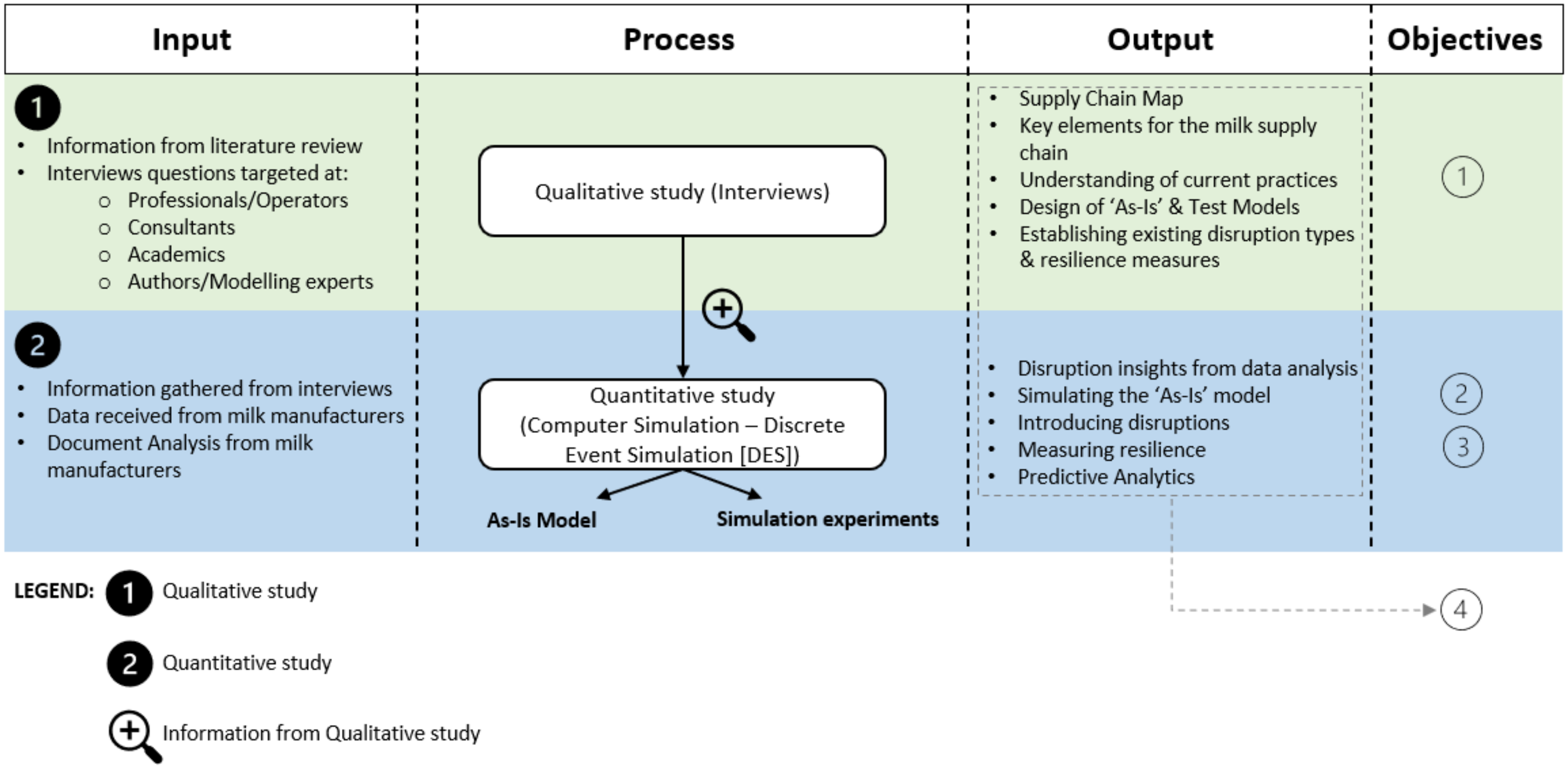


Figure 3. 2: Research Design and Method

3.4 Interviews

The adoption of qualitative methods for research in the field of social sciences is considered essential in investigating specific phenomenon and providing both social and cultural perspectives (Zhang and Wildemuth, 2009). The activities and decision making within a supply chain exist within a social and economic environment which necessitates the application of interviews as a qualitative method for initial primary data collection. This is a good way of providing clarity of research direction and gauging the additional data and time that will be required in the next phase of the study (Given, 2008; Yin, 2013). Data collected properly using interview as a qualitative method will provide substantial and holistic information, revealing the complexities of a supply chain (Arkhipov and Ivanov, 2011; Manavalan and Jayakrishna, 2019). These attributes allow the researcher to understand the dependent and independent aspects of the supply chain network instead of attempting to predict them (Alabdulkarim, 2013).

Additionally, the application of interview as a method for data collection is characterised by an in-depth contact with the supply chain being studied which makes it essential for analysing the processes within the network (Merriam, 1998). There are three categories of interviews which can be employed by qualitative researchers: structured, semi-structured and unstructured (Robson, 2002). Structured interviews comprise a predetermined set of questions to asked in a specified order. The semi-structured interviews utilised by this research comprises questions which are predetermined; however, the researcher had the liberty to rearrange the order of questioning as well as wording/text of the questions as perceived necessary and the interviews took an average of 30-45 minutes using online mediums such as skype or zoom. The unstructured interview on the other hand occurs when the researcher identifies the broad subject matter or area of interest and allows the conversation and interactions to occur naturally, setting the pace for the follow up questions. The unstructured interviews are generally informal and possesses the risk of the conversation veering towards an unplanned direction (Robson, 2002).

In early 2020, while this research project was ongoing, the COVID-19 pandemic hit the world (Davies et al., 2020); spreading from China (where it was alleged to have first appeared in Wuhan in December 2019) to other parts of the world including the UK (Şahin and Şahin, 2020). This led to a staggering but seemingly immediate cessation of all business activities world-wide, only allowing what was considered essential work to continue. As a result, the study was redesigned to be fully conducted with the available online capabilities. This helped to mitigate any challenges associated with data collection due to travel restrictions, physical distancing, and requirements for UK residents to stay within their homes aimed at reducing the transmission of the coronavirus (Davies et al., 2020). It was the intention of the study to conduct interviews with participants in the food supply chain industry, and supply chain academics who may provide vital information for the research to consider. Consultants, academics and computer simulation (modelling) experts as well as SC professionals were being considered in order to obtain unique insights that will aid a more robust and evidence-based understanding of the supply chain industry to advance this study. Qualified participants were identified through referrals and by carrying out a thorough online search for candidates matching the pre-defined participant inclusion criteria (Table 3.2).

Table 3. 2: Research Participant Inclusion Criteria

Participant Group	**Inclusion Criteria**	**Target Sample**	**Expected Data**
SC Professionals & Operators (6 participants)	≥ 3 years working experience in SC	9	In-depth perspective on the operation of the food and milk industry
SC Consultants (2 participants)	≥ 3 years of consulting experience for major operators within the SC industry	3	Broader perspective on the operation of the food industry
Academics (1 participant)	Significant publications in Food SC or SC disruptions	2	Perspective on relevant research component and insight to support current study
Authors/Modelling experts (1 participant)	Book publication in Computer Simulation or relevant/equivalent experience in SC Modelling	2	Perspective on SC Computer Simulation

Interview participants were selected using a purposeful sampling method in order to ensure that the research meets its aims and objectives. Purposeful sampling method is engaged by strategically identifying places, participants or situations that present the largest potential in providing advanced understanding (Given, 2008). This sampling type has been chosen particularly because it has been shown to help with the identification and selection of information-rich cases which relate to the phenomenon of interest (Palinkas et al., 2015). Participants working as senior professionals were most preferable for inclusion in this study, and especially those with relevant knowledge of the current disruption challenges faced by modern supply chains. Moreover, with the pandemic occurring at the time of this research, the participants were able to comment and provide insights based on their management of the disruption occasioned by the events of the pandemic.

The target sample sizes for each participant group were carefully chosen to ensure a comprehensive collection of insights for the study and was based on the work of Saunders and Townsend (2016) who argued 15 participants as being ideal. Nine supply chain professionals and operators were targeted to provide detailed operational perspectives on the milk supply chain, with six participants recruited successfully. Three supply chain consultants were targeted to offer a broader industry perspective, two of whom participated. Two academics with significant publications were targeted to integrate theoretical insights, and one academic was successfully recruited. Additionally, two authors or modelling expert was targeted to ensure accurate and realistic simulation models, one participated. This diverse and targeted sampling approach ensures the study captures a wide range of relevant insights, enhancing the validity and applicability of the findings.

The inclusion criteria for each participant group were carefully selected to ensure that diverse perspectives and expertise relevant to the study objectives are represented. For the SC Professionals & Operators group, individuals with a minimum of 3 years' experience within the food and milk industry were sought. This group includes expertise in the milk supply chain. This criterion ensures that participants have first-hand knowledge of the operational dynamics, challenges, and best practices specific to the food and milk supply chains.

SC Consultants were also required to have at least 3 years of consulting experience, preferably with a focus on supply chains. This criterion ensures that participants bring a broader understanding of supply chain operations across various industries, along with insights into strategic decision-making and industry trends. Academics were selected based on their significant publications in the field of Food Supply Chain or Supply Chain disruptions. This criterion ensures that participants have expertise in relevant research areas, providing theoretical perspectives to support the study objectives.

Authors/Modelling experts were chosen based on their authorship of a book in Computer Simulation or equivalent experience in Supply Chain Modelling. This criterion ensures that participants possess expertise in supply chain simulation techniques and methodologies, offering valuable insights into simulation design and ensuring that this research build a representative model.

With regards to the number of participants, these selected 10 participants for the semi structured interviews. Although Saunders and Townsend (2016) argued that the norm of between 15 and 60 interview participants is likely to be considered ideal, the actual number is dependent on the research purpose, saliency of data and the ontological and epistemological dispositions of the researchers. This study successfully recruited 10 participants and considers this sufficient based on the work of Malterud et al. (2016) who maintained that six to 10 participants with diverse experiences were ideal to provide sufficient power for descriptions of different self-care practices in their cross-case analysis; and this is the case with the current study noting that participants are drawn from the academia, consultants, operators and computer simulation experts.

Having fully informed participants and obtained consent, data from the interviews is collected using both handwritten notes and digital voice recording to capture inputs by participants which will later be transcribed and analysed accordingly.

3.5 Simulating the Supply Chain

The supply chain being an integrated system of several companies, comprises of organisations carrying out upstream and downstream activities to ensure items are received by the final customer (Behdani, 2012). However, despite being called a ‘chain’, the supply chain may not always be connected in a linear and sequential way (Behdani, 2012). This is because more than one member may be involved in a particular stage of the supply chain; for example, a manufacturer may have several suppliers, in several locations. In some instances, the manufacturer may be connected directly to retailers or to the final consumer or both. Hence, the appropriate modelling and simulation technique must be selected to reflect how decisions are made in this complex network of activities and actors.

To design the simulation of any system, the researcher must start by defining the problem based on real world situations (Robinson, 2004). Having derived a clear understanding of the real-world situation, an appropriate conceptual model can then be derived. This research obtained an in-depth understanding of the focal supply chain (see section 5.2) through multiples interviews with a key informant within the supply chain and analysing data and other supporting documents shared with this research. These are used to inform the activities and interactions within the simulation environment.

Several scholars have employed a wide range of research methodologies to evaluate supply chains as well as its resilience (Pettit et al., 2019). Taking advantage of modelling and computer simulations have allowed the complex network of supply chains and stochastic environment of businesses to be captured (Pettit et al., 2019). Table 3.3 shows the modelling and simulation approaches engaged in the last ten years.

Table 3. 3: Modelling and Simulation Approach

	Modelling and Simulation Approach	**Application Example(s)**
1	Weighted goal programming	(Mari et al., 2014)
2	Discrete event simulations (DES)	(Carvalho et al., 2012; Macdonald et al., 2018)
3	Systems dynamic simulations (SD)	(Spiegler et al., 2012)
4	Agent based Modelling (ABM)	(T. Wu et al., 2013)
5	Structural equations modelling	(Munoz and Dunbar, 2015a)
6	Petri-net modelling	(Blackhurst et al., 2018)

However, the current study favours the use of computer simulations to explore the opportunities offered by the application of Big Data Analytics (BDA) in supply chain management particularly because they are an ideal tool for measuring nonlinear, processual relationship, and thus, can help in evaluating the interactions of several supply chain and organisational processes (Davis et al., 2007; Macdonald et al., 2018).

3.6 Approach for Simulating the Milk Supply Chain

Three key approaches – Agent-Based modelling (ABM), Discrete Event Simulation (DES) and Systems Dynamic (SD) – have been greatly discussed in literature for simulating supply chains which are complex socio-technical systems (Behdani, 2012), such as the milk supply chain. These approaches present a unique set of assumptions about the world both explicitly and implicitly (Behdani, 2012). These assumptions are presented below (Table 3.4) as understanding them is key to selecting the simulation approach to engage and ultimately the tool to be utilised in representing the supply chain.

As seen on Table 3.4, SD takes a top-down approach to modelling; focusing of the aggregate state of variables (the average of the whole), ABM and DES take a bottom-up approach, seeking to represent the individual parts of the supply chain and how they interact.

Systems Dynamics (SD) has been used in literature to explore cause and effect relationships between system quantities (Cagliano and Rafele, 2008). For instance, Spiegler et al. (2012) explored the application of a Systems Dynamic simulation to determine the relationship between supply chain design and its impact supply chain resilience and robustness, finding that lead time and transportation in the supply chain design can affect the robustness of the supply chain.

System Dynamics is a feedback-based simulation approach (Behdani, 2012), applied at strategic points in a system where the required operational details are minimal (Borshchev and Filippov, 2004). This is ideal because the system's dynamic approach to simulation considers the behaviour of a complex system as the result of its structure. Sterman (2010) discusses systems dynamics as a specific type of continuous simulation where the system is represented as stocks and flows. Due to the characteristics of the system dynamics, it is more utilised in the study of cause and effect between systems quantities (Cagliano and Rafele, 2008).

Table 3. 4: Characteristics of Simulation Approaches

Characteristics	Systems Dynamic (SD)	Discrete Event Simulation (DES)	Agent Based Modelling (ABM)
Focus	System-oriented; focus is on modelling the system observables	Process-oriented; focus is on modelling the system in detail	Individual-oriented; focus is on modelling the entities and interactions between them
Numerousness	Homogenized entities; all entities are assumed have similar features; working with average values	Heterogeneous entities	Heterogeneous entities
Representation	No representation of micro-level entities	Micro-level entities are passive 'objects' (with no intelligence or decision-making capability) that move through a system in a pre- specified process	Micro-level entities are active entities (agent) that can make sense the environment, interact with others and make autonomous decisions
Driver(s)	Feedback loops	Event occurrence	Agents' decisions & interactions
Time handling	Continuous	Discrete	Discrete
Experimentation	By changing the system structure	By changing the process structure	By changing the agents' rules (internal/interaction rules) and system's structure
Structure	System's structure is fixed	The process is fixed	The system's structure is not fixed

Discrete event simulation is based on a model which is governed by a clock and list of events ordered chronologically (Behdani, 2012). With discrete events simulation, the assumption is that time only exists at specific predetermined points. Given this assumption, events can only take place at those specific points and need to have been previously scheduled (Robinson, 2004). Any change within this approach to modelling will only be triggered by these predetermined discrete events (Behdani, 2012). A discrete event will start by inputting a base event from the events list to run and then continues as an infinite loop, executing the next event at the top of the event list. This will continue until the events stop or the list becomes empty (Behdani, 2012). Discrete events simulation allows for the interaction of processes as well as scanning of activities. Additionally, entities with the system can compete for available resources, which is why it is often applied to support decision making (Cagliano and Rafele, 2008).

Agent Based Modelling is a simulation approach which focuses on representing the individuals - people or companies- within the system (called agents) and how they interact with each other and the environment (Behdani, 2012). ABM focuses on understanding behaviour and analysing several strategies for operating a system. Agents in ABM are autonomous and are programmed to follow some rules for behaviour, however, agents can choose the action to perform from a set of possible actions (Cagliano and Rafele, 2008; Behdani, 2012). ABM is more suitable when considering social entities and social level complexities of a system (Behdani, 2012).

This research runs a deterministic computer simulation of supply chain resilience to generate understanding on how the supply chain works and provide a basis for experimentation, while introducing disruptions at specific predetermined points in the simulation. However, the interaction of the supply chain actors is taken into consideration as well as the available resources, but the rules followed by the agents does not change which makes ABM unsuitable for this thesis. The thesis carries out interviews to understand the supply chain system (as-is) and this does not change in experimentation as the intention of this research is to understand the effect of disruptions on the current system and not a changed system. This also makes SD an unsuitable approach. Hence, the Discrete Event Simulation (DES) is chosen as the best suited simulation approach to capture the essence of the current study.

3.7 Computer Simulation

To adequately test out a system, Law and Kelton (2000) hold that an experiment must be carried out. The experiment can either be carried out either by experimenting with the actual system or experimenting with a model of the actual system (Figure 3.3). Given the potential economic effect on a supply chain, this research will experiment on a model of the supply chain and not on the actual supply chain. Experimenting on a model can be carried out by making use of a physical system of a mathematical model. The financial implication of building a real-life physical replica of a supply chain for the purpose of testing makes the mathematical model more appropriate for the purpose of this study.

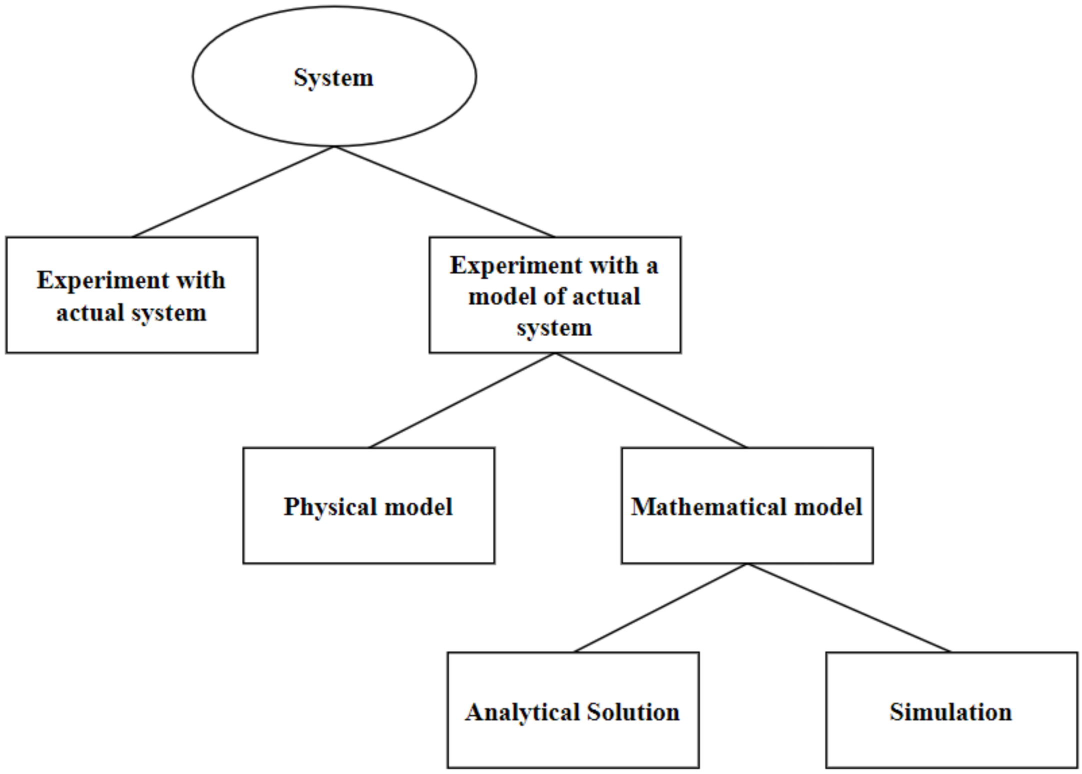


Figure 3. 3: How to study a system (Law and Kelton, 2000 pp. 4)

The idea at this point is to take advantage of the method that best answers the research questions. Simulation modelling is essential when studying supply chain disruption resilience (Carvalho et al., 2012; Macdonald et al., 2018) and in operations management (Davis et al., 2007), especially where the focus of the research is nonlinear, processual, and can expose the interactions of several supply chain and organisational processes (Davis et al., 2007; Macdonald et al., 2018).

These conditions are adequately met in this study, which considers resilience as a mitigation strategy for supply chain disruption. Simulations provide for the application of a simplified imitation of a system and its progress, processes, and operations over time for the purpose of understanding and potentially improving the system (Robinson, 2004).

Various supply chain simulation models have been developed in literature to support the design of supply chains (Van Der Vorst et al., 2000; Gunasekaran, 2004; Kleijnen, 2005; Meixell and Gargeya, 2005). Research by Kleijnen and Smits (2003) provides four distinct types of simulation for supply chain research: spreadsheet simulation, business games, discrete event simulation and system dynamics. Business games simulations are mainly suggested as a technique used in educating and training users. Discrete event simulation provides quantitative insights and results, taking complexities into account. Finally, systems dynamics is mostly focused on qualitative insights. Discrete event simulation is applied in this research as a quantitative method for data collection and analysis.

The Discrete Event Simulation Tool (DES) is available in several commercial software packages. However, to select the software package to be utilised, it became relevant to review available software. Mourtzis et al. (2014) carried out a detailed comparison of some of the available software such as AnyLogic, Arena, FlexSim, Plant Simulation and WITNESS. These software applications were awarded between one and five stars where one star was inadequate, and five stars were outstanding. As evidenced in Table 3.5 all the researched software applications had specific criterion for which they had outstanding performance and other criterion for which they only had adequate performance.

This research has however decided to use the WITNESS software package developed by Lanner Group for the following reasons:

- accessibility to the researcher,
- in built flexibility,
- ease of organising training for software use, and
- possession of common supply chain modelling requirements.

Table 3. 5: Simulation Software Comparison (Mourtzis et al., 2014)

Criteria Groups	Comparison Criteria	Simulation Software Tools				
		AnyLogic	Arena	Flexsim	Plant Simulation	Witness
Hardware and Software	Coding aspects	****	***	**	****	**
	Software compatibility	***	**	***	****	***
	User support	****	**	****	****	***
General features	Purpose	General	General	General	General	General
	Experience required	***	****	**	***	**
	Ease of use	***	**	**	***	****
Modelling assistance	On-line help	****	**	****	***	**
	Library and templates	***	**	****	****	***
	Comprehensiveness of prompting	***	**	***	***	***
Simulation capabilities	Visual aspects	****	**	*****	****	***
	Efficiency	****	**	****	****	***
	Testability	****	***	****	****	***
	Experimentation facilities	***	***	****	****	***
	Statistical data	****	***	****	****	****
Input / Output	Input/output capabilities	****	***	****	*****	****
	Manufacturing capabilities	****	**	****	****	*****
	Analysis capabilities	***	***	****	****	***

3.8 Big Data Analytics in the Supply Chain of Interest

In order to simulate the implication of Big Data Analytics on the milk supply chain, it was essential that this research collects data that aligns with the Big Data requirements set out in literature (Table 1.2). Hence, the focal organisation in this supply chain needed to have adopted Big Data in their activities. This section discusses how the manufacturer from where data is collected meets the Big Data requirement of this thesis.

Discussions with operators within the supply chain (participant 8) and additional evidence from the focal organisation used with organisational permission reveals that the focal organisation within the supply chain of interest in this research incorporates Big Data Analytics (BDA) similar to those presented in Table 1.2 extensively in daily activities. The milk manufacturing company is owned by thousands of active and inactive partners who contribute resources and efforts needed to supply milk and milk products to end users. With several staff and branches across the globe, they produce products known all over the world. In terms of revenues, the organisation generates billions of pounds (GBP) annually. In terms of Big Data incorporation into the organisational framework, the IT department is responsible for data and analytics, and creating data foundations. This department has over 50 people working on self-service analytics, standard reporting, financial reporting dominantly using a Business Warehouse (SAP BW), and advanced analytics building more advanced applications on top of Microsoft Azure with Power BI (Business Intelligence) as the front-end tool. At the core of all of this is their data foundation and their vision, which is basically enabling analytics everywhere within the organisation. The focal organisation however faced a major challenge initially with enabling big data and self-service analytics, and they introduced Power BI across the organization, which really put a big tick in enabling self-service and big data practices organisation wide. This was a scalable solution that could handle large amounts of data and provide real-time analytics to support their business operations. They chose Microsoft Azure as their cloud provider and used various Azure services, such as Azure Data Factory and Azure Analysis Services, to build their data platform. They also used Power BI as their front-end reporting tool to enable self-service analytics for their users.

The focal organisation here utilises the Azure Data Factory to extract data from various sources and load it into their data lake in Azure. They also used Azure Analysis Services to create semantic models and provide a single source of truth for their data. Power BI was then used to create dashboards and reports that could be accessed by their users. Section 6.4 of this thesis provides more details on how Big Data warehouse was used to support computer simulation in a Big Data context within this research. Figure 3.4 provides a summary on how Big Data Analytics (BDA) is being used in the focal milk manufacturing organisation within this supply chain. The implementation of Big Data in this supply chain corroborates the study by Vieira et al. (2019) on how Big Data was implemented in their research. Implementing Big data can lead to business benefits and some of the benefits that this organisation has seen since implementing their data platform and Big Data infrastructure include being able to reduce the time it takes to produce reports and provide real-time analytics to support their business operations. Improvements in data quality is another benefit recorded and have been able to make better-informed decisions based on their data.

In conclusion, the focal company which is the milk manufacturer within this supply chain incorporates key Big Data Analytic practices by implementing a strong data foundation and self-service analytics using cloud services, particularly Microsoft Azure and Power BI. These practices are believed to extend through the supply chain hence why they emphasise scalability in handling large amounts of data and providing real-time analytics to support business operations. The data foundation allows for the incorporating of data from various sources and creating a single source of truth for all data, enabling the company to make data-driven decisions.

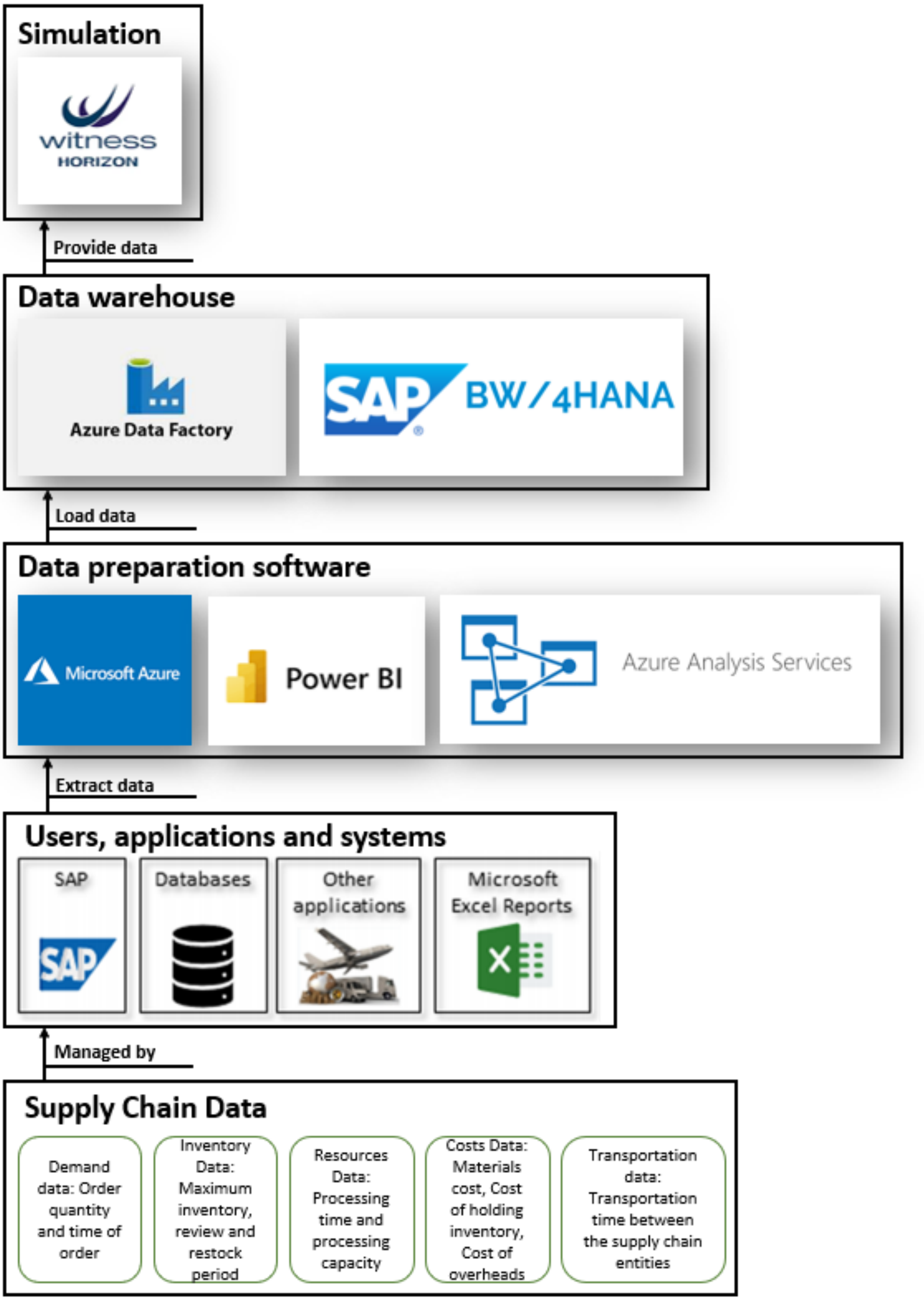


Figure 3. 4: Big Data Application in the Focal Milk Supply Chain

3.9 Big Data Warehousing in Milk Supply Chain Simulation

Simulation has been largely discussed in literature to support Big Data research and supporting technologies (Vieira et al., 2019), given the high volume of data which require analysis in a big data context. Supply chain systems are generating data at very high rates, volumes and in a variety of formats which is characteristic of big data (Vieira et al., 2019). Given the novelty of research in big data, it is difficult to provide a well-accepted threshold for what constitutes big data. The work of Arunachalam et al. (2018) provide for quadrants with which a supply chain's big data analytics capabilities can be assessed (Figure 3.5). According to their research, supply chains are assessed based on five dimensions (data generation, data integration, data management, Data driven culture and analytics and visualisation capabilities) and categorised into one of the four quadrants.

However, the widely acceptable characteristic of big data is that the volume of data exceeds the capacity of storage and processing available using traditional tools (Vieira et al., 2019). Hence, the need for big data warehousing. Big data warehouses allowed for data but has been extracted, transformed and loaded to be stored pending analysis and decision making. Based on the infrastructure available within the focal supply chain, and supporting infrastructure and technology provided by the University of York, the current study adapts the framework developed by Vieira et al. (2019) in simulating resilience in the milk supply chain based on data extracted from several databases, transformed to suit the need of the research and loaded on to a staging area. These data are transferred on to the big data warehouse for analysis using the simulation software chosen (Figure 3.6).

The milk supply chain data was obtained from participating organisation, managed using various databases such as Excel, Microsoft access, SAP, and other internal applications. Usually in formats that are not compatible with each other and some of the data missing. A data preparation software was then used to extract the data, transformed into a usable and compatible format and then loaded onto a staging area within the Big Data infrastructure of the focal supply chain. Once the data has been thoroughly cleaned and suitable for analysis, they are then stored in a Big Data Warehouse which is also a part of the Big Data infrastructure within the focal supply chain. The simulation software provided by the University of York is then fed data from the warehouse, allowing for ease of analysis and findings.

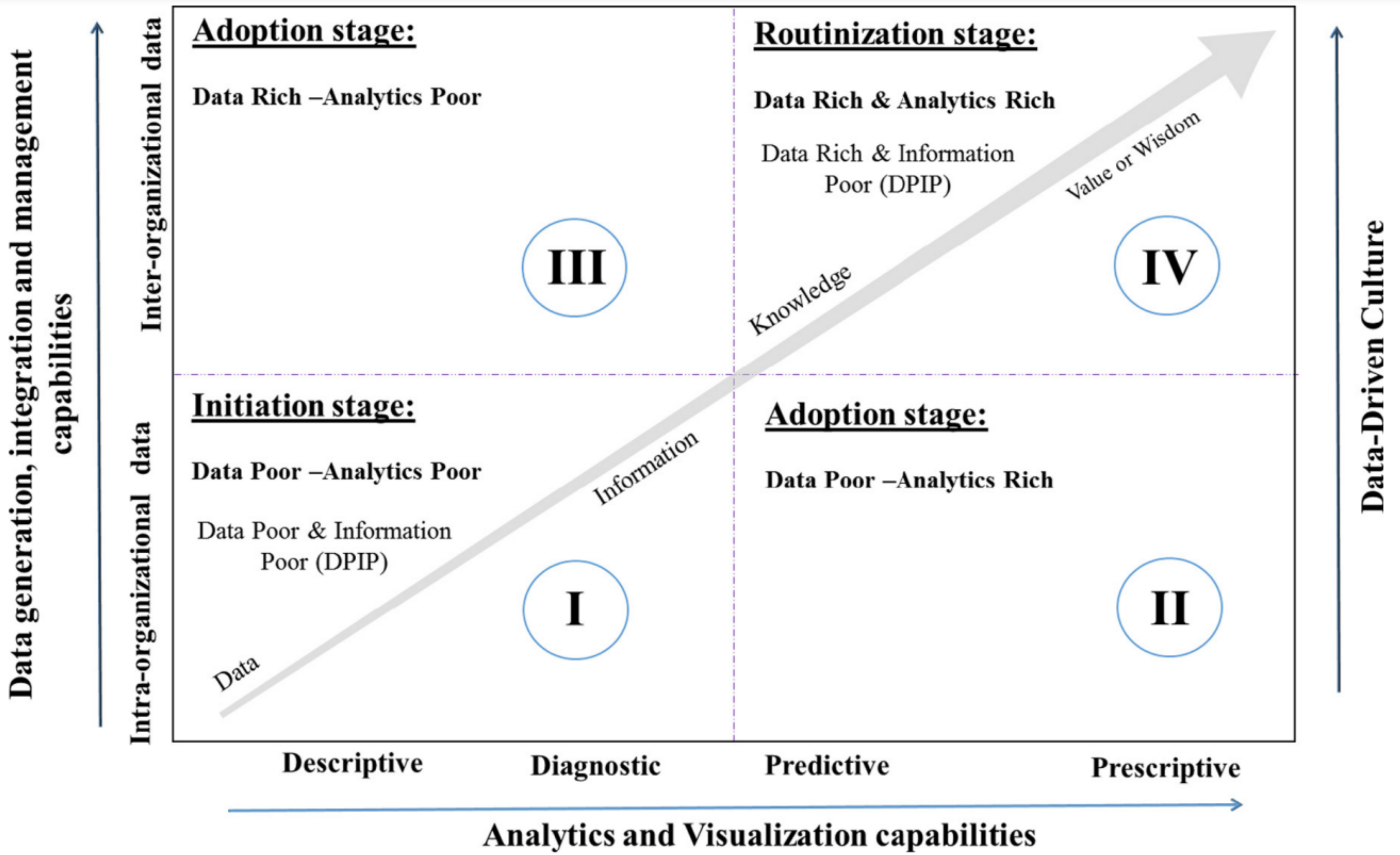
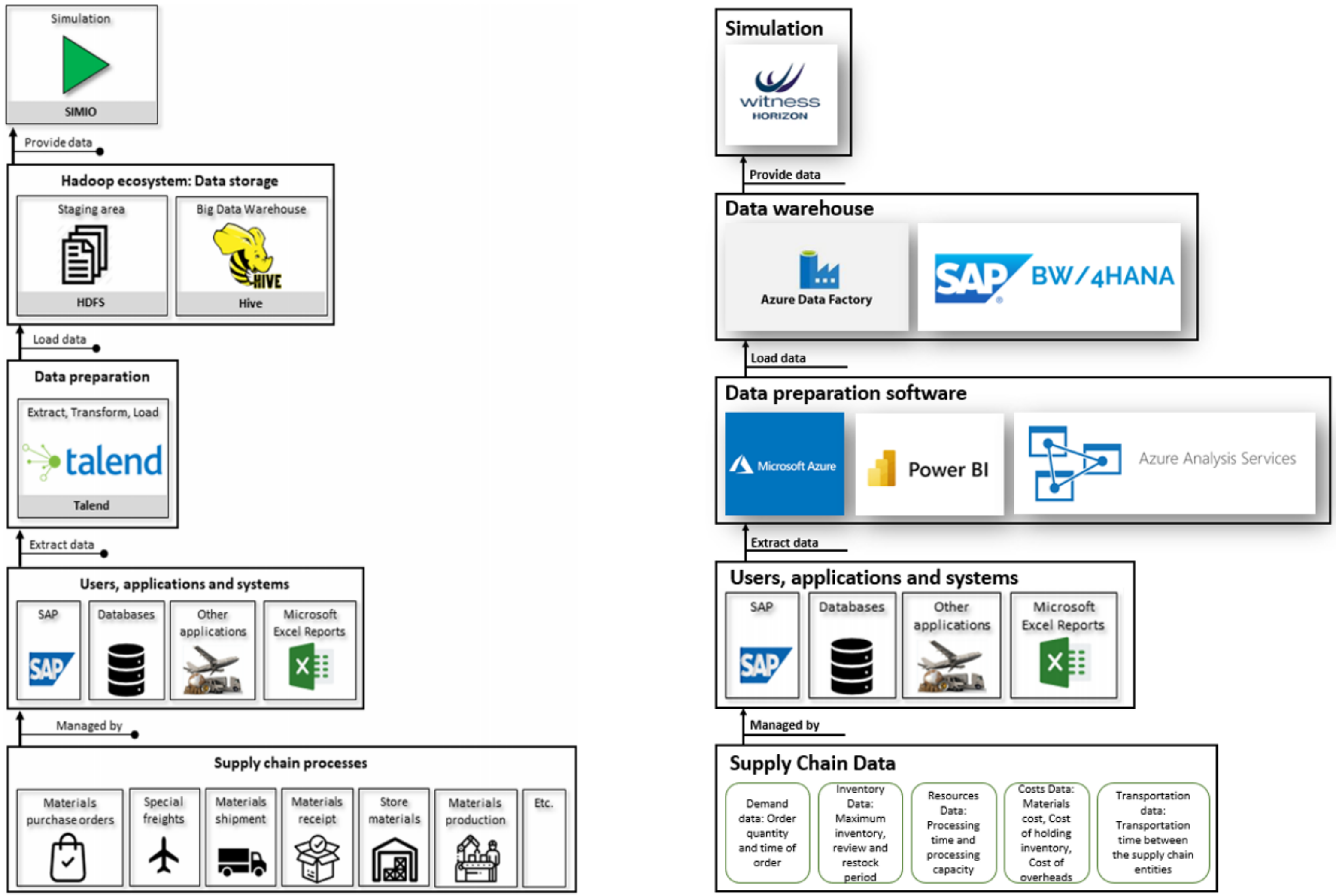


Figure 3. 5: BDA capabilities framework for a supply chain (Arunachalam et al., 2018)



(a) (b)

Figure 3. 6: Framework used to develop (a) the BDW and the simulation model (Vieira et al., 2019 pp. 6) and (b) how this is adapted for the current study.

3.10 Data to be Inputted in Simulation

Based on existing literature, the resilience equation presented in section 2.5 and the work of Carvalho et al. (2012) who simulated the redesign of supply chains to achieve resilience, this research gathers the following data which is inputted in the simulation model for analysis:

- Demand data: Order quantity and time of order
- Milk supply chain design (manufacturers, retailers, consumers)
- Inventory Data: Maximum inventory, review and restock period
- Resources Data: Processing time and processing capacity
- Costs Data: Materials cost, Cost of holding inventory, Cost of production, transportation cost
- Transportation data: Transportation time between the supply chain entities.

3.11 Ethical Considerations

To ensure ethical considerations, the research implements ethical practices both before and during the period of the study. Primarily, the ethical consideration parameters set by the University of York are met by the research and ethical approval received before research participants are contacted (see Appendix G). The research also obtained the consent of the participants prior to conducting the interviews. This consent is essential for the validity and credibility of the research results (Given, 2008). Hence, consent forms are used to inform the participants of the research aim, objectives, and their role as the research participants. They are informed of their right to withdraw from the research at any time without any questions asked. The consent form included information about the expected time commitment as well as the researchers contact details to ensure that they could reach the researcher if they had further questions about the research. Appropriate emails and phone numbers were provided to the participants where they can inform the researcher of their choice to opt out of the research. Hence, only willing participants took part in the study. Signing the consent form indicated that the participant had read and agreed that they will voluntarily participate in research and are assured of their confidentiality. This research maintains anonymity by providing a very broad description of the sector being researched and the roles of individual participants.

Specific details that could help identify organisations or individuals are withheld. All research associated documents are stored following the university's guidelines and using secure locations provided by the University of York. All interview data and notes are stored in this secure location for a maximum of five years following the publication of this study, after which, both hard and soft copies are destroyed.

According to Rallis and Rossman (2003) being able to withdraw from a study is the right of all research participants. For this research, Individual participation in the research was voluntary and participants were informed that they can withdraw their participation at any time, without any repercussions.

The limitations in research could also represent the gaps for further study. Researchers need to be aware of this and highlight them in order to reduce any barriers or issues to the minimum level and provide more authenticity and robustness to the research. The current research is limited by time and as such may be unable to test a wide array of variables.

3.12 Conclusion

This chapter explains the research methodology adopted for this study. The researcher assuming an interpretivist philosophy explores the milk supply chain. The research also adopted a mixed method with interviews as the qualitative method and computer simulations as the quantitative method. The adoption of mixed methods contributes strongly to the research rigour and helping to broaden our understanding of Big Data Analytics and its possible contribution to the field of Supply Chain Management, specifically to supply chain resilience in tackling disruption. Combining interviews with computer simulations also ensures that the complexities of the milk supply chain is accounted for and holistic and substantial information regarding the milk supply chain being investigated is captured. The chapter goes further to discuss how Big Data warehousing is utilised in other studies to explore the implications of big data to a supply chain and how the focal supply chain in this study is applying big data warehousing as part of the big data strategy. Finally, the chapter documents the ethical considerations made as part of this research.

Chapter 4
INTERVIEW RESULTS

4.1 Introduction

As companies look for ways to gain a competitive edge and improve efficiency in their operations, one that has been the focus of research is the interaction between members of the supply chain. To this end, this research carried out semi-structured interviews with 10 key informants within the food supply chain. The interviews aimed to investigate how different actors in the supply chain build their resilience to disruptions in the context of big data and this included asking questions surrounding big data utilisation and supply chain resilience. The in-depth interviews were conducted to gather detailed information about the participants' practices and attitudes towards sharing information, including the types of information shared and the tools used to share it. In analysing the results, four key themes emerged including collaboration, flexibility, data management and supply chain design; in addition to these, there are additional themes which help provide a more robust outlook on the findings. This chapter presents the results of the interviews, starting with how the interview data was collected and analysed, the chapter then highlights the key themes that emerged from the analysis of the interview data before proceeding to discuss each theme in detail. The chapter ends by discussing the Big Data implication for the key themes discussed.

4.2 Interview Data Collection and Data Analysis

Consistent with the objectives of this research, this study adopted semi structured interviews as one of the methods of data collection as this would facilitate the collection of rich data which help the participant express their views (Saunders et al., 2019), while allowing the required degree of flexibility and structure (Merriam, 1998). This data collection method also ensure reliability by allowing for a data collection process that can be replicated (Yin, 2013). This research also takes advantage of synchronous interviews administered online using the video conferencing platform Zoom, which allowed the researcher to reach participants who may have been otherwise unavailable due to the COVID-19 pandemic. The interviews with members of the supply chain took place between November 2020 and September 2022 due to the intervention of the COVID-19 pandemic which caused scheduling issues, each lasting approximately 60 minutes.

The development of interview questions was supported by theoretical frameworks (RBV and DC) which provide lenses for understanding how organisations leverage their resources and capabilities to achieve competitive advantage and resilience in dynamic environments. Interview questions related to the identification and assessment of key resources and capabilities within the milk supply chain were aligned with RBV principles. These questions aimed to explore participants' perceptions of valuable, rare, inimitable, and non-substitutable resources and capabilities that contribute to supply chain resilience. For example, participants were asked to identify critical resources such as technology infrastructure, supplier relationships, and organisational knowledge, and to discuss how these resources enable resilience in the face of disruptions.

Similarly, questions addressing adaptability, learning, and integration of new technologies within the supply chain were informed by the concepts of Dynamic Capabilities. Participants were prompted to share insights into how their organisations develop and deploy dynamic capabilities to respond to disruptions and seize opportunities.

While the interview questions were adapted from existing literature such as Singh and Singh (2019b) and Acharya et al. (2018) , they were tailored to the specific context of the milk supply chain and cognisant of the RBV and Dynamic Capabilities theories. The adaptation process involved refining and customising the questions to ensure they effectively captured the relevant aspects of Big Data capabilities and resilience within the supply chain context. Appendix A provides the interview guide which consisted of three main parts namely A: Introductory and Supply chain description questions, B: Big Data utilisation questions and C: Supply Chain Resilience questions. Themes for parts B and C of the interview were determined by reviewing the Supply Chain resilience and Big Data Analytics literature. Open ended questions were utilised to explore Big Data technologies currently utilised by organisations to promote resilience; as well as the experiences and resilience of supply chains through recent disruptions especially the COVID-19 pandemic.

To ensure that findings of this study are considered trustworthy, the research followed the four principles by (Guba, 1981; Guba and Lincoln, 1994) which include credibility, transferability, dependability and conformability. To ensure credibility, interviews were recorded with consent and participants were allowed to review the interview guide prior to the interview sessions. This ensured that the sessions could be revisited over and over again to avoid any misunderstanding or omissions. Transferability was ensured by interviewing a variety of participants who represented variances in positions, responsibilities and experiences across the supply chain. Table 4.1 shows the summary of participants interviewed – across the various participant groups with ≥ 3 years of working experience in supply chain. Appendix H provides more details on the interviewee profile including their working history and experience level. The research also provides clear information on the number and type of participant, data collection process and interview period. Dependability and conformity were guaranteed by comparing codes developed with codes from similar research in literature as well as carrying out regular reviews of data analysis process. Findings are also supported by quotes to minimise judgemental bias.

Table 4. 1: Summary of Participants Interviewed

Participant Group	Inclusion Criteria	Number of Participants interviewed
SC Professionals/Operators	≥ 3 years working experience in SC	6
SC Consultants	≥ 3 years of consulting experience for major operators within the SC industry	2
Academics	Significant publications in Food SC or SC disruptions	1
Authors/Modelling experts	Book publication in Computer Simulation or relevant/equivalent experience in SC Modelling	1

The data analysis of the structured interviews was carried out based on the three phase thematic analysis approach proposed by Miles and Huberman (1994). This guided the data coding and data categorisation processes summarised in Figure 4.1 and Table 4.2.

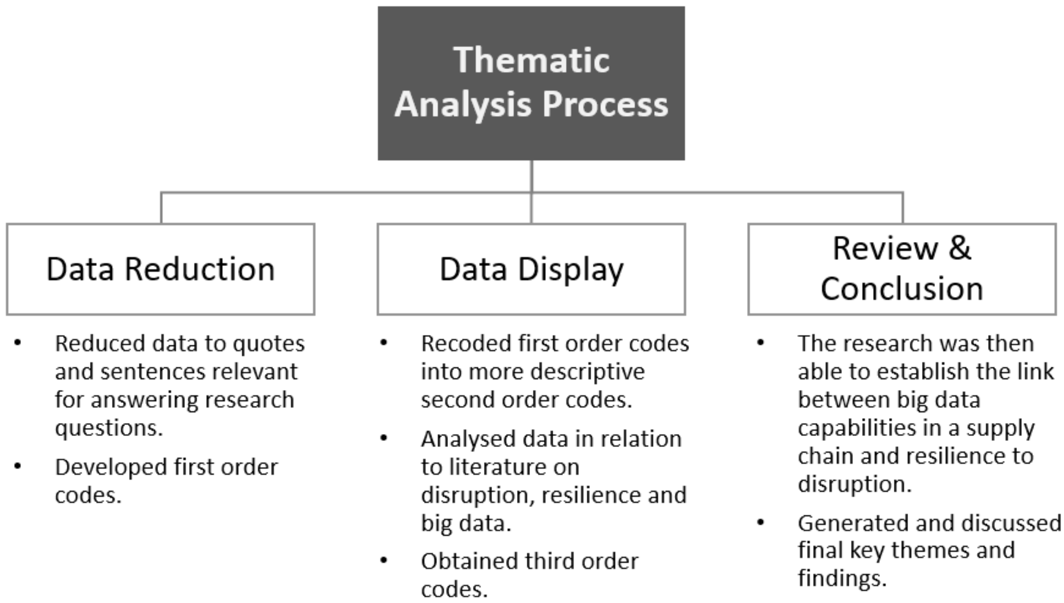


Figure 4. 1: Thematic analysis process adopted in this study based on Miles and Huberman (1994).

A number of criteria were used to ascertain the integrity and/or quality of the results from the research (Lincoln and Guba, 1985). These include interviewing participants with the ability to provide reliable information, considering the positions of interview participants within their organisations and the supply chain and relying more on primary data collected directly instead of secondary data (Chen, 2019). The method applied in this study entailed monitoring the coding process from start finish. A critical part of the documenting the process involved collating and organising verbatim quotes associated with specific codes. These associations link participants' words/phrases (raw data) to the researcher's inferences and interpretations (Michel-Villarreal et al., 2021). This approach affords the basis for the research findings to be adjudged and critique fairly. Hence, a list of codes created during the thematic analysis was compiled together with direct quotes to explain the codes.

On the other hand, transferability of the findings was assessed by comparative analysis of emerging themes with existing literature (Miles and Huberman, 1994). This can be done by reviewing similarities and contradictions and attempting to establish reasons for the variations. Finally, a "thick description" of conclusions and emerging themes are discussed.

4.3 Thematic Analysis Process

The interview data was analysed in line with the three steps postulated by Miles and Huberman (1994) which are data reduction, data display and conclusion. The research started by reducing the data into quotes, sentences and where necessary paragraphs which were essential for answering research questions (first order quotes).

The research then went ahead to examine and analyse the data in relation to literature, and first order codes were further coded into more descriptive second order categories. This allowed for a better understanding of how the supply chains operated pre-disruption (COVID-19 pandemic), as well as how these supply chains reacted when faced with a disruption event. It also provided insight into the big data capabilities, tools and techniques that were currently being utilised within and in support of supply chains. Furthermore, it enabled the research to deduce third order themes in disruption and Big Data.

In the next step of data analysis, the research examined the data in relation to supply chain resilience which allowed for a link to be deduced between big data capabilities in the supply chain and resilience to disruption. This also allowed for final key themes and findings to be generated for this research and the report written up.

Table 4.2 provides a structure on how the data coding was carried out with selected evidence and quotes from the interviews. It provides a clear thought process on how quotes became aggregate codes. Each quote has one code associated with it as the first order code, multiple first order codes are grouped into second order codes, and this informs the choice of aggregate codes. However, the evidence in the table were carefully selected from a wider range of quotes derived from the interview and these reflect the aggregate codes. Therefore, Table 4.2 presents the structured way in which the data gathered from the interview was coded systematically from quotes to first order, second order and finally the aggregate codes.

Table 4. 2: Selected quotes and data coding structure

Selected quotes	First order codes	Second order codes	Aggregate codes
• "*So, we have an IT we have a business systems and IT function right other than that, there are no forums where we get together specifically on the topic of data*" - Participant 5 • *"Also, other segments as well, for example, gum or drinks or confectionery, all these other brands from other segments also send stock to the warehouse to be stored"*- Participant 2 • "*So, it's not just the data is not speaking to each other. It's also the people using the data*"- Participant 5	• Lack of Organisational collaboration among data teams • Cross functional collaboration • Communication barrier to effective collaboration	Vertical collaboration	**Collaboration**
• "*There seems to be a lot of business-to-business collaboration on being very innovative and trying to upset the norms of the industry and create new value and do different things*"- Participant 6 • *"And there's lots of systems integration between suppliers, retailers on forecasting"*- Participant 6	• Innovation based on Inter-organisation collaboration • Systems integration based on the collaboration across the supply chain	Horizontal collaboration	
• *"Organisations as a result of the pandemic are investing more in digital technologies and big data, and also trying to reduce the dependency on low-cost country sourcing"*- Participant 7 • *"Onshore some of these sourcing requirements and do*	• Investing in digital technologies and big data to increase sourcing flexibility • Changing the	Sourcing flexibility	

Selected quotes	First order codes	Second order codes	Aggregate codes
sourcing with suppliers closer to home, which reduces the dependency on low-cost countries, which by the way, was the reason why supply chains failed during a pandemic"- Participant 7 • *"Because, we have already placed our orders, we ended up holding some stock in Europe"*- Participant 1	materials sourcing strategy of the supply chain. • Utilisation of buffer stock for inventory management		**Flexibility**
• *"We had to discontinue a lot of the lines just because we didn't have the stock to provide to the customers and the producers couldn't produce so quickly, so much stock"*- Participant 1 • *"And maybe if I had somehow forecasted it [demand] in a better way, then we could have planned that production increase in a different way in a better way"*- Participant 2	• Possible stockouts due to production disruption. • Production planning based on demand forecasting	Production flexibility	
• *"But, following those periods of very high sales, and subsequently very high production volume within our factory, sales just dipped"*- Participant 2 • *"And that meant it required very good storage management and inventory management"*- Participant 2	• Inventory management problems due to inaccurate demand forecasting • Storage management	Storage flexibility	
• *"So, all the systems that we would normally use were completely redundant"*- Participant 5 • *"You've got legacy systems and legacy data that isn't really fit for purpose"* - Participant 5	• Redundant infrastructure • Legacy systems	Data infrastructure capabilities	

Selected quotes	First order codes	Second order codes	Aggregate codes
• *"You could spend a billion pounds on modernising your data and making it cloud based and agile and all talking to each other, you're not going to get the benefit of that back"*-Participant 5 • *"Companies invest as little as they can to solve the problems of the next 12 months and how that data talks to each other"*- Participant 5	• Poor understanding of Big Data/Interest in Big Data • Poor investment in Big Data	Investment in Big Data	**Data Management**
• *"To take full advantage of the digital technology and big data, you need to change your processes. You've really got to change your processes, and embed digital technologies in those processes"* - Participant 7 • *"So, the reason why it takes a while for the digital transformation to be implemented an organisation is because of the change management, change of behaviours, change of processes, replacement of legacy systems training, making sure people comfortable the system also deep learning interfaces with your suppliers again they need to be managed"* - Participant 7	• Process improvement • Business process re-engineering	Data processing capabilities	
• *"As I mentioned, we have an international supply supplier from Asia that supplies us. We source seventy five percent of our non-food product"* - Participant 1 • *"There is no longer the intermediate step of buying, keeping the ordering volumes to the supplier"* - Participant 1	• Limited suppliers • Fewer supply chain members	Simple supply chain	

Selected quotes	First order codes	Second order codes	Aggregate codes
• *"Our customers are usually the end users"* - Participant 1 • *"75 percent of the products we source from the same suppliers"* - Participant 1	• Contact with end users • Extremely limited suppliers		**Supply Chain Design**
• *"The structure of it is we have three manufacturing plants in the UK. And we have one national distribution centre, which is a warehousing and transport operation. And then we have a customer service and logistics function where we manage production planning"* - Participant 2 • *"We have several suppliers where we will buy more materials from. And we'll have several suppliers that provide our caps and our closures and where we buy aluminium and glass for now, our procurement guys will be responsible for having a number of core suppliers that they will use"* - Participant 5	• Multiple locations • Multiple suppliers	Multi-tier supply chain	

4.4 Research Themes

Analysing the interviews with industry experts reveal the themes of collaboration, flexibility, data management and supply chain design. The interviews also show the disruptions faced by the food industry and the strategies employed to build resilience, including the implementation of big data or lack thereof. One disruption in recent times which has affected the food supply chain is the British exit from the European Union (Brexit) and some participants acknowledged the impact this had on disruption planning and preparations.

A key insight from the interviews was an appreciation of the unique challenges experienced by the operators of food supply chains during another disruption which was the COVID-19 pandemic. The first is the exponential (drastic) increase in demand for food products. This creates a scenario where most suppliers cannot meet up with demand; and for the few that do meet up with demand, the supplied stocks were exhausted in a matter of hours instead of weeks in 'business as usual' scenarios. Another critical challenge faced by food supply chains in disruptive events is that the sales pressure experienced does not necessarily reflect as significant increase in net revenue – particularly because the profit margins of food items are generally low. This is in line with literature as disruption situations affect different organisations and supply chains differently. Baghersad and Zobel (2021) noted that while some disruptions may be relatively easy to manage, others may result in short-term financial losses and/or significant impacts on supply chain's long-term performance which may take months for full recovery.

The next section will discuss the strategies and best practices employed by the experts to build resilience in their supply chains and overcome disruptions, providing insight on how to improve the overall resilience and sustainability of the global food supply chain system in the light of the key themes.

4.4.1 Collaboration

Collaboration among members of the supply chain acts as a 'glue' which hold the various nodes and elements within the supply chain together (Christopher and Peck, 2004). This indicates that working collaboratively within the supply chain allows for a collective response to disruption events which promotes resilience. These collaborative relationships can be formed either vertically or horizontally (Barratt, 2004; Mason et al., 2007). Barratt (2004) identifies four collaborative relationship partners to include suppliers and customers vertically, complementors and competitors horizontally. Their research also noted that an internal collaboration can occur across departments within the same organisation who seek to optimise processes. This research will discuss the collaborative efforts uncovered during the interviews and their effect on the supply chain resilience.

In order for the impact of a disruption to be assessed adequately and to support supply chain recovery, it is essential that collaborative tools be used by organisations (Ivanov et al., 2019). This research found that collaboration does exist in the supply chain when it comes to sharing information about demand and supply but not much else. There was no evidence of collaboration technologies such as a collaborative purchasing platform suggested by Ivanov et al. (2019). Most participants reported that they share some form of information with their partners, and most of them stated that sharing information helps them to make better decisions and improve their operations. However, this research also found the collaboration did not exist extensively through the supply chain as organisations experienced barriers to collaboration.

Participant 1 stated, *"But now, when we start a project, we discuss with our business partner and we create a tool that looks at everything we want to look at*". Participant 6 highlighted the value of business-to-business collaboration, "*There seems to be a lot of business-to-business collaboration on being very innovative and trying to upset the norms of the industry and create new value and do different things*". Participant 6 also noted the integration of systems between suppliers and retailers for forecasting, "*And there's lots of systems integration between suppliers, retailers on forecasting*". Participant 7 highlighted the cost advantages of collaboration, "*Cost advantages are also involved, improved productivity, for your workers and your staff who are involved in running the supply chain, as well as the benefits as well in terms of working more collaboratively with your suppliers"*. This shows collaborative efforts within supply chains with participants understanding the role of collaboration in creating value and obtaining a cost advantage.

Additionally, participant 6 noted that while some food supply chains had the flexibility to respond during the COVID-19 pandemic, challenges arose due to the demand signals and unusual data patterns, "*I think one of the challenges that I* *understand they faced when they go into COVID was: they had the flexibility to respond, it was more about the demand signals that were going nuts, because people were panic buying etc., which was causing the problem. They have the ability to respond, they had the ability to do what they needed to do, but because the data coming in was so bad, and unusual. That's what caused them a challenge in the way they collaborate"*. This participant highlights that certain food supply chains had to ability to manufacture more or less or even make adjustments in their manufacturing process to suit customer demands. However, the supply chain struggled with receiving accurate demand signals to make these decisions. This may be due to poor collaboration when it comes to data sharing within this supply chain.

However, the application of big data led to improved communication in the way people work as participant 1 stated "*The reason why our performance with big data is improving is because our company has put in place new departments and more users*". This improved communication is evidently based on commitment from the wider organisation.

Participant 3 acknowledged that collaboration was essential in getting through difficult times especially during a major disruption and stated "*So, there's a big challenge associated with infrequent large impact activities or challenges. So, you have to make sure that, that your preparedness doesn't build in an unaffordable level of cost. Some of that is about collaboration*".

Another participant emphasised the increase of trust due to data-based collaboration saying "*You're exchanging data in real time, there's more trust*".

Participant 5 who is a large manufacturer and supplier of alcoholic beverages to pubs and restaurants also stated "*Yeah, so any kegs that has been what we call breached any keg that's been opened. That was the pubs responsibility to dispose of that liquid. Right? Any keg that was still sealed, we, we took that keg back from the customer. So, there's a bit of a collaboration there, between who's got the liability for the for the keg, at what point now*".

This shows that collaboration can help reduce liability and build trust. However, several participants also highlighted some barriers to collaboration and effective sharing of information. Participant 5 stated, "*So, we have an IT we have a business systems and IT function right other than that, there are no forums where we get together specifically on the topic of data*". Participant 5 also noted a lack of knowledge and understanding of the tools used to analyse and share information, "*People in supply chain wouldn't know what Tableau is, they wouldn't know how to use it, they wouldn't know what benefit it brings them. The guys in IT are not very good at coming to us and explaining how it can solve our problems, because they don't really know why our problems are*". Additionally, participant 5 highlighted the importance of communication and understanding of the data and its context, "*So, it's not just the data is not speaking to each other. It's also the people using the data*". This implies that while data may be shared with members of other organisations within the supply chain, the collaboration intra-organisation needs a little more effort and collaboration between departments. This could include things such as training and tool/software demonstration to boost understanding.

Summarily, this research finds evidence that collaboration does exist in the supply chain when it comes to sharing information about demand and supply. The findings indicate that supply chain actors and participants are increasingly using data analytics tools and various communication platforms to share information and improve their operation; it also highlights the importance of sharing information in supply chain management and the benefits of using various tools to do so. However, technological advancement provides better tools (Singh et al., 2019; Ivanov et al., 2019) to aid more seamless collaboration that supply chain are not yet maximising; additionally, the few big data tools and capabilities being used do not appear to be used at full capacity. The research findings also indicate some barriers that can make collaboration difficult, it's important for supply chain managers to understand these barriers and take steps to overcome them. Supply chain managers should consider implementing strategies to encourage and facilitate information sharing, provide proper training and resources, and establish cross-functional collaboration to improve their operations and gain a competitive advantage.

4.4.2 Flexibility

Another key theme that emerged from the interviews carried out in this research was flexibility. Achieving resilience in a supply chain requires flexibility, which in this research refers to the ability to adjust quickly to partners' requirements and environmental conditions (Stevenson and Spring, 2007). There are various practices that supply chains can engage to enhance supply chain resilience, including flexible transportation, flexible working arrangements, flexible sourcing and supply base, and order fulfilment flexibility (Pettit et al., 2013). Chopra and Sodhi (2004) suggest that flexibility can be applied both at the organisational level and to the entire supply chain, thus enhancing its ability to adapt to turbulence and increasing its resilience. Christopher and Holweg (2011) support this argument, stating that flexibility improves the supply chain's short-term adaptability during disruptions. Furthermore, a flexible supply chain facilitates quick reaction and recovery, as emphasised by Sheffi and Rice (2005).

Participants in this research discussed the flexibility in the supply chain's sourcing options, production options and inventory options. This section discusses the flexibility in the food supply chains and the application of big data supported with a series of quotes from industry professionals who were participants in this research. It evident from the results obtained that there are a variety of different approaches to managing flexibility during disruptions in supply chains, each with their own strengths and weaknesses. This research found that there is reduced flexibility is some supply chains where suppliers were limited, and lead times were very long. Some supply chains had a major supplier where demand was placed a year in advance, especially where the food items were already processed and had longer shelf life. This does not provide the organisation with a lot of flexibility to adjust demands up or down where a disruption in demand occurs as experienced during the COVID-19 pandemic; additionally, the main supplier who supplies nearly 75% of the items could easily be the single point of failure within that supply chain in a disruption. This research also found that barriers existed to production flexibility where significant investment had been made in production lines that were considered ideal before a disruption especially where those production lines could not be adapted to changing needs within a supply chain in a disruption.

One of the main findings that emerged from the interviews is the level of careful planning and long lead times that is required for the distribution of stock in some sections of the food industry. According to participant 1, "*We do that distribution of stock in the different regions in the country twelve months in advance. So, this is very I mean, this this doesn't give us a lot of flexibility*", this implies that this food supply chain requires a significant amount of advance planning in order to ensure that stock is distributed to the right regions at the right time. As noted by (Spiegler et al., 2012), long lead times and transportation can directly affect how resilient a supply chain is. However, it is also important to note that this participant works within the more processed section of the food supply chain which entails a longer life span, supporting these longer lead times. Additionally, participant 1 mentioned that "*75 percent of the products we source from the same suppliers*" suggesting a certain level of predictability in that food supply chain. This is supported by the statement from participant 1, "*So, it's a lot more streamlined, the supply chain for my product range*". While the quality management and cost perspective could be positive as the relationship with the supplier gets stronger, over-reliance on one supplier could also lead to reduced resilience in a disruption situation (Christopher and Peck, 2004).

Another finding that emerges is the reliance on a small number of suppliers and the impact this has on flexibility. For example, Participant 1 who is a food retailer saying, "*We have very big lead times, and we order the volumes a year in advance*", suggests that this food supply chain is dependent on a limited number of suppliers and require significant lead times in order to secure the necessary materials. This limits the flexibility of the supply chain as a whole. However, Participant 2 who is a food manufacturer says "*Our factory, as I said, is operating 24 hours a day*" which highlights the high demand and pressure on the food supply chain, it indicates high-level of production volume. Participant 5 who is an alcoholic beverage manufacturer also discussed the challenges with production flexibility in a disruption saying, "*The lines that are designed to put beer into kegs are very different from the lines that put the same beer into a glass bottle*". This implies that while production flexibility is required in a disruption where buying behaviours of customers change, there is a significant barrier to being flexible especially where significant investment has gone into buying and setting up production lines and machines which cannot be easily altered. Another significant barrier to flexibility involves the regulatory challenges that can arise in food supply chains. As participant 3 stated, "*If you're going to sell a product somewhere, there's an approval process you have to go through. And that approval process requires input from technical people from commercial people from all sorts of other actors*". The different actors and the complexity of the approval process can add a level of uncertainty and inefficiency to the supply chain and prevent flexibility.

During the COVID-19 disruption, participant 1 discusses sourcing flexibilities and the utilisation of buffer stocks to increase resilience "*Because, we have already placed our orders, we ended up holding some stock in Europe*" while also acknowledging challenges with logistical and production flexibility "*In logistics, there was so much stock that we needed to shift but there weren't enough lorries",* adding *"We cancelled a lot of lines*" referring to production. *"We had to discontinue a lot of the lines just because we didn't have the stock to provide to the customers and the producers couldn't produce so quickly, so much stock*". Contrastingly, highlighting the periods following the COVID-19 disruption participant 2 stated "*But, following those periods of very high sales, and subsequently very high production volume within our factory, sales just dipped" "and that meant it required very good storage management and inventory management*". This shows that while during the disruption, extensive buffer stocks were considered, bought and even stored abroad but this caused a logistical challenge in getting these stocks to the customers when they were needed. When some supply chains considered that storing buffer stocks abroad may not work, they chose the option of discontinuing some lines to allow them focus on a few lines in order to satisfy those lines effectively. Some of these resilience strategies worked more than others but at the end of the disruption period, the high demands experienced in the food supply chain during the disruptions dipped.

Organisations such as restaurants providing pre-packed meals also experienced challenges in their production and storage flexibilities which supports the statement from Participant 2 that *"Food is being packed into plastic and paper box, each bag has different shelf life…So obviously, if you produce lots of lots of stock, because you think you're going to sell it and sales do not come through in effect. Therefore, that means that stock will stay in the warehouse and eventually it will go to waste*". This provides evidence that during the COVID-19 pandemic which caused disruption in the food supply chain, there was increased sales on certain food items especially food items that were considered staple as participant 1 stated *"as I said, they were buying essential foods like grocery that have a very low profit margin"* and the supply chain was tasked with ensuring customers received these food items. To support this spike in demand, production of those items had to be increased; the supply chain also had to consider the storage and logistics for these items. Flexibility in production, storage and logistics to adapt to the changing need was essential but some supply chains struggled with that. The period following that then experienced a huge drop in demand and the increased production, storage and delivery capacity was no longer essential which meant that flexibility within the supply chain to handle the reduced demand would help reduce waste.

Similar to Fisher's Model (Fisher, 1997), some of the participants suggest that while their supply chain may be efficient, it may not necessarily be flexible or agile. For example, participant 1 stated *"The company that I work for is very lean and efficient in the structure of the supply chain, so we are not very agile. We are more reactive than proactive; we try to be proactive but the systems are not very flexible*". Participant 2 added in describing their supply chain during the COVID-19 pandemic "*I would say resilient, I would say flexible, because we recovered our customer service loss, our case fill loss within three weeks, which means that we are able to source the materials on time and we're able to produce as much as possible, what the customer wanted*" which implies that certain supply chains may be able to recover from disruptions quickly but it might not be necessarily flexible or proactive in avoiding disruptions. This is unsurprising as existing literature suggests that supply chains can be efficient or responsive but not necessarily both (Fisher, 1997; Fisher et al., 1997) and deciding what supply chain is ideal has to be based on the products are passing through that supply chain. The study suggests that efficient supply chains are ideal for functional products, but innovative products require a more responsive supply chain.

Supply chains attempted different strategies to mitigate the disruption, increase flexibility and help the supply chain perform. Whilst employed in different ways, it was apparent that most supply chains turn to inventory management in the event of a disruption. Participant 3 stated *"There was one primary way (to manage the disruption) and that would involve stock management, primarily increased stock holding, so if organisations imported raw materials, then they increased their raw material stock within the UK where they could… And where they were exporting outside the UK into the EU, particularly, then they try to get ahead and export earlier the whole finished product stock in market".* Some supply chains focused on diversion of stock. As stated by participant 1, *"There was a disruption with our suppliers, manufacturers, producers…because, we have already placed our orders, we ended up holding some stock in Europe".* Additionally, participant 6 discusses the streamlining of the range of products on offer to ensure that organisations could continue to meet a better managed customer expectation *"Okay with retailers. So, they did things like slashing to the core range, making it much more efficient,* *changing the space in store. So doing all the right things to get a grip of what core lines we need to sell and keeping stock on how we do that and then manage that with most of the customers… they just slashed everything down but they manage the supply aspect of it really well".* This method of mitigating a disruption event can be effective and is corroborated by Schmitt and Singh (2012) who used discrete event simulations to analyse the role that inventory reserve and management plays in supply chain performance in the event of a disruption. They found that the impact on performance is positive and can also be amplified to outlast the disruption themselves. However, the work of Christopher and Peck (2004) highlighted that surplus buffer stock, surplus capacity and inventory can very easily lead to waste but could be ideal if maintained at critical points within the supply chain. Hence, it is essential to re-examine the redundancy and efficiency trade off when using buffer stocks.

In summary, the findings highlight that some food supply chains require significant planning and lead time and are dependent on a limited number of suppliers which can be detrimental to the resilience of the supply chain. The findings also highlight that while supply chain participants understand that there is a need for production flexibility, storage flexibility and logistics flexibility, it can sometimes be challenges for a supply chain to be flexible and responsive in this manner due to investments which have been made in setting up a functional supply chain. Additionally, the interview results illustrate barriers such as regulatory challenges and bureaucratic factors that can limit the flexibility and agility of the food supply chains.

4.4.3 Data Management

Another theme which was explored in the interviews was the adoption of big data analytics in the food supply chains and how data is managed. Govindan et al. (2018) had argued that this research theme is becoming more and more popular because of the potential to drive performance and to gain new insights from operation. Organisations made efforts in recruiting more employees to be part of the business intelligence unit created to help with data analysis. Participant 1 noted *"The reason why our performance with big data is improving is because our company has put in place new departments and more users*". However, this unit is only engaged with processing, analysing and visualising existing data [which may not necessarily be classed as big data]. It may be that organisations need to consider new ways of generating relevant data frequently. As at the time of the interview, this participant noted that efforts to generate new data was considered 'below average' within their organisation. This could potentially suggest that there may be inadequate data available for predictive analysis which may be pivotal for addressing and mitigating possible future disruptions.

Studies have underscored the relevance of big data analytics tools and techniques to data-driven decision making within supply chains, particularly because of the capacity for real-time analysing and interpretation of results to enhance appropriate decisions for customer satisfaction (Çakici et al., 2011; Tan et al., 2015; Govindan et al., 2018). A study by Koh et al. (2019) also pointed out that Big Data Analytics are imperative for competitive advantage.

Interview participants also acknowledged the potential of big data and digital technologies to improve supply chain resilience when utilised properly, as evidenced when participant 7 states: "*Big data, and digital technologies, can enable organisations to be resilient, and to identify and mitigate risks in a supply chain, before they become incidents that result in severe disruption to normal business operations"* and adds *"It means that your ability to know who exactly is sorting what and when is very, very difficult unless you've got the data to manage that and unless you've got the visibility across the supply chain"*. Participant 7 also acknowledges a shift in the way organisations use and invest in big data infrastructure as a result of a very severe disruption during the COVID-19 pandemic saying, "*Organisations as a result of the pandemic are investing more in digital technologies and big data, and also trying to reduce the dependency on low-cost country sourcing".* This shows that supply chains are increasingly considering localising their supply chains as a way to remain resilient. This is supported by the work of Ivanov and Dolgui (2018) who suggest that a more localised supply chain may be more resilient in the event of a disruption. However, designing this more resilient supply chain is strongly dependent on data which is why participant 1 suggests "*I think we should definitely create a report or have a pool of data that show exactly the changes in demand in the different products group".* Participant 1 also adds that the data that will be used in the supply chain must be easily accessible and clear saying "*If you have this data in a user-friendly format, there will be bigger transparency among the suppliers and the supply chain users. There will be better visibility*". This accessible and clear data also needs to be readily available for analysis in order to work as noted by participant 1 who states, "*When you have such big disruptions, you need to be able to analyse the data and react fast, otherwise, you miss the boat"*. This indicates that supply chain participants understand the role of big data in ensuring a more responsive and resilient supply chain. Participants emphasised the importance of data and visibility across the supply chain for effective management and decision-making. They also acknowledged the need for data in a user-friendly format for greater transparency and visibility. These suggest that having access to accurate and timely data can help organisations make better decisions and identify potential problems before they occur, which can help improve supply chain resilience.

However, participants also acknowledged the challenges of utilising big data, such as the need for advanced software and the need for more efficient data reporting. Participant 1 highlights that where activities within a supply chain are fast paced, there may be a time constraint to always drawing insights from available data to support decision making. *"We just don't utilize them because we are not generating the right reports and we don't have the time to look at them as much as we should"*. Another challenge highlighted by participant 1 is the reliance on legacy systems which may not have the capacity to support the frequently generated, high volume big data *"With a lot of data, to be honest, it's quite intimidating because our systems as I mentioned are very old school systems and we don't have a lot of advanced software to use big data"*. Participant 2 also adds the financial investment required which could also be a barrier to supply chains fully adopting big data analytics, saying *"All I'm worried is if some businesses want to incorporate big data in their processes, do they have enough money? Basically, do they have the budget to invest on this or can the people be trained on that aspect as well, within the business?"*. Another barrier to fully incorporating big data analytics highlighted by participant 1 is the knowledge and skill relevant to use the technologies and infrastructure available *"We also have access to these data but we do not really know how to create the kind of report on Excel and other tools that we use but mainly Excel"*. Another challenge organisations face in utilising big data is the training necessary. Participant 2 also acknowledged that the "*Big Data is not widely known, with other teams to put together things, maybe they need to be coached somehow on this aspect of just thinking",* which can hinder its adoption. It is then clear that while the focal organisation and milk manufacturer in the research supply chain of interest makes extensive use of Big Data, other milk supply chains are still behind on the adoption of Big Data.

In terms of data infrastructure, participants recognized the importance of data communication and point-of-sale data for product information, but also acknowledged the difficulty in linking systems and data sharing between different partners. Participant 6 notes that external pressure may have to come from other member of the supply chain in order for a supply chain to be aligned with big data practices. *"So, the thing that would change it would be if a retailer said, [one of the biggest food retailers in the UK] you know what this big data thing we're getting behind it, we want all your systems to link to us, and we want to create this incredibly new powerful thing, then they do it because they'll be forced to do it".* This indicates that while financial investment and other barriers may exist, supply chain participants may be more willing to adopt it if it is already being used by other members of the supply chain who also encourage them to adopt it.

Additionally, participant 5 also mentioned the following *"I don't think we'll go back to pre-COVID; I think the supply chain will be different. I don't think we know what different is yet, because we're still in it. We're still in the global pandemic. I think it's difficult to say what different might look like from a systems perspective, I'm not sure we will use any different systems or any different data. When we go back to the new normal. You know, I think we might hold more stock, we might maintain a warehouse".* This indicates the significant impact of a disruption situation such as the COVID-19 pandemic which influenced supply chains to reconsider resilience options including the dependability of their data infrastructure and data capabilities. Participant 1 also adds that supply chains are looking to use more data and make regular data driven decisions as a result of the experiences during the disruption caused by the pandemic *"Even behind the strategic decisions now, we are going to see more data". "Yes, we are making use of big data in decision making?".* This further reinforces the idea that big data and digital technologies can play a crucial role in improving supply chain resilience by providing organisations with the ability to identify and mitigate risks before they become disruptive incidents. Therefore, highlight the ongoing uncertainty and unpredictability of a global pandemic and its impact on supply chains, with participants noting that it is difficult to say what the "new normal" will look like from a systems perspective.

It is worth noting that in a disruption situation such as the COVID-19 pandemic where supply chains should have relied more on data to make decisions, participant 5 reported that existing systems became redundant saying “*So, all the systems that we would normally use were completely redundant and we had to use manual spreadsheets to determine which customers were going to get which volume on any given day in any given week, and how that would change depending on how much finished goods we got available*”. This redundancy in systems when they were most needed may breed a level of reluctance in supply chain members as participant 2 noted “*Lots of people are depending on Power BI [Business Intelligence] reports. It's a big data report. But do they build knowledge on how to do the job themselves in case those systems do not work*?" Participant 3 added "*Big Data is something which is which is used by entities, which look at big systems, and most players in supply chains, see one contact upstream and one contact downstream, they don't see the whole system*", further showing a reluctance to rely on technologies to support the supply chain. This highlights a concern amongst supply chain actors that while big data is being used in the supply chain to make it more efficient, it also raises concerns about how dependent the supply chain is on these systems and how prepared the players are if the systems were to fail. The potential for a failure in the system may have been due to the legacy systems prevalent in current supply chains as noted by participant 1 "*Our systems are very old school. We have a bespoke system which is from the 90s or early 2000s. We use a lot of Excel*". This lack of advancement in technologies used can make systems susceptible to failure and this is not ideal when a supply chain faces disruptions and needs to make data driven decisions.

Summarily, the findings suggest that big data and digital technologies have the potential to improve supply chain resilience, but that there are also challenges to be addressed in terms of data infrastructure, data processing, and investment. In light of these challenges, it is important for organizations to invest in advanced software and data infrastructure, and work to improve data communication and sharing among members of the supply chain. Additionally, it's important for organizations to invest in educating and training their personnel on big data and its uses to fully realize the potential benefits of big data.

4.4.4 Supply Chain Design

Supply chain design refers to structural formation (Ivanov and Dolgui, 2018) and the way in which a supply chain is organised and one of the main characteristics in the supply chain design is the number of critical nodes within the supply chain (Craighead et al., 2007). This includes the number of suppliers, manufacturers, retailers, etc. within that supply chain. The supply chain design in food supply chains plays a crucial role in ensuring resilience in the face of unexpected disruptions. This is seen in the work of Dolgui et al. (2018) where it is suggested that the supply chain design can lead to a greater or lesser ripple effect in the supply chain in the event of a disruption.

One key aspect of supply chain design experienced in this research is the structure of the supply chain itself. Some of the supply chains discussed where the research participants belonged are linear characterised by a straightforward flow of goods from supplier to end user, often only having one actor in each supply chain node (Lahane et al., 2020) while others have multiple tiers, with intermediaries involved in the distribution process. These supply chain with multiple tiers may also have several actors in each node (Tachizawa and Wong, 2014; Sarkis and Zhu, 2017; Jabbour et al., 2019). For instance, participant 1 mentioned that "*There was a disruption with our suppliers, manufacturers, producers*" which indicated a linear design in their supply chain causing a direct ripple effect to the disruption in the supply chain. The present research aims to examine the supply chain design in food supply chains, specifically analysing information from interview research participants in the food industry. The interviews reveal key insights into the structure and dynamics of the supply chains under examination.

One of the key findings that emerged from the interviews is the streamlined nature of the supply chains being discussed. Participant 1 notes that "*there is no longer the intermediate step of buying, keeping the ordering volumes to the supplier*" and also states "*so, it's a lot more streamlined, the supply chain for my product range*." This suggests that these supply chains have a direct relationship between the supplier and end user, which can be more efficient in meeting customer demands but can also be detrimental and lead to reduced resilience when a disruption occurs (Christopher and Peck, 2004). Another important aspect of the supply chains discussed is the presence of international suppliers, with participant 1 stating that "*we have an international* *supply supplier from Asia that supplies us. We source seventy five percent of our… product*." Given a linear supply chain with limited suppliers, it is essential that this supply chain manages lead times very carefully in order to ensure that customer demands are met, and customers are not being lost to competitors. This is noted by participant 2 who states "*now the problem is that some materials are coming from Europe, right? So, they're not coming from UK, but also, they have lead times"*. Here, participant 2 expresses the concern of having to worry about lead times on materials that are being supplied from a distant geographical location to the focal organisation. This may be because an early arrival of the items may cause storage problems, but a late arrival can lead to lack of confidence from the customers and reputational damage.

The interviews also provide insight into multi-tiered supply chains, with participant 2 mentioning "*the structure of it is we have three manufacturing plants in the UK. And we have one national distribution centre, which is a warehousing and transport operation. And then we have a customer service and logistics function where we manage production planning.*" Additionally, the role of imported raw materials in the food supply chain is emphasized by participant 5 stating "*we do import, you know, raw materials, caps, closures, things that go into our finished goods"*. Here, participants discussed having multiple tiers in their supply chains and having more than one actor in each tier. Also, importation occurs in a more considered way where the production happens locally but supporting parts such as packaging are imported. Furthermore, the importance of supplier relationships and the role of procurement in managing them is emphasized, with Participant 5 saying "*we have several suppliers where we will buy more materials from. And we'll have several suppliers that provide our caps and our closures and where we buy aluminium and glass for now, our procurement guys will be responsible for having a number of core suppliers that they will use*". In designing a supply chain, it is essential to consider the geographical location of each member of that supply chain and the lead times necessary to receive the goods or services that they provide to that supply chain. This will allow the supply chain to continue to meet demand and maintain a good level of resilience. It is also worth considering if it is better to import all raw materials from distant suppliers or if key parts of the input needed in that supply chain can be localised (Ivanov and Dolgui, 2018) to improve access in the event of a disruption and increase resilience.

When designing a supply chain, it is vital to bear resilience in mind if that supply chain is expected to be resilient (Klibi and Martel, 2012; Pavlov et al., 2018). However, participant 4 highlights that the concept of resilience is fairly new and not yet well explored *“this term resilience is a fairly new one that's come out fairly recently”*. Where there is no clear understanding of what a resilient supply chain looks like, it may be difficult to design a supply chain that is truly resilient. This lack of understanding can become a significant barrier to building a resilient supply chain. Participant 3 discusses how challenging it is to understand the full impact of disruption events *“With Brexit, you don't know exactly how it will end up in the in the future”* also supporting it with the statement *“Look at what organisations were doing to prepare themselves for Brexit, because they didn't know what the outcome was going to do post Brexit”*. This indicates that supply chains experiment with different options where it is unclear how exactly to achieve resilience. Participant 5 notes the difficulty faced in planning *“There is no silver bullet, where we should have said, if we'd have done x, we wouldn't have had that problem. And there's no way you can plan for something like a global pandemic, there's no way you can plan for needing to have 30% more capacity in your warehousing”.* This negates the literature which shows that the availability of data could have helped the planning process and predictability for needing more capacity.

Existing supply chain literature suggested firms who adopt big data analytics capabilities will be better able to develop resilience and design better supply chains (Singh and Singh, 2019a). This data is also essential to actively invest in a long-term disaster plan in order to adequately prepare for, respond to and recover from both current and future disasters (Papadopoulos et al., 2017b). However, one of the insights derived from this study is the lack of information and usable data. Collecting data to help design resilient supply chains has to be a conscious process however, some of these organisations appear to have little interest in collecting the relevant data or consider the data collection not to be a priority for their organisation. Participant 5 in several statements noted the following *“(At the height of the disruption) we had to use manual spreadsheets to determine which customers were going to get which volume on any given day in any given week… so it's very fragmented, you tend to have systems that are very old, that don't talk to each other and don't connect with each other. So, you've got legacy systems and legacy data that isn't really fit for purpose… And to modernise them, you know, you could spend* *a billion pounds on modernising your data and making it cloud based and agile and all talking to each other, you're not going to get the benefit of that back… So invariably, companies invest as little as they can to solve the problems of the next 12 months… Big data is almost irrelevant".* It is essential that this participant is from a large food manufacturing organisation and the statements above reflect the attitude of that organisation towards gathering and using Big Data. This type of attitude could be a barrier to designing a resilient supply chain. This attitude could be due to poor understanding or misinformation on the applications of big data in the supply chain for optimal performance. However, the research also found that where a more central member of the supply chain adopts a positive outlook towards big data, other members of the supply chain will align. Participant 6 states *"So, the thing that would change it would be if a retailer said, if a [one of the Big 4 food retailers] said, you know what this big data thing we're getting behind it, we want all your systems to link to us, and we want to create this incredibly new powerful thing, then they do it because they'll be forced to do it"*. This proposes a solution where some members of the supply chain adopt a big data approach and encourage other members of the supply chain to adopt big data as well in order to increase the resilience of the overall supply chain.

In summary, the interview research participants in the food industry reveal key insights into the structure and dynamics of supply chains in the food industry. The streamlined nature of the supply chains, the presence of international suppliers, and the importance of supplier relationships are all critical factors in ensuring the resilience of food supply chains. It is also evident that supply chain design for resilience is essential and has to be a conscious effort. To achieve a resilient design however, data is essential, but some member of the supply chain may have a poor attitude towards adopting data and big data practices which can be a barrier to achieving resilience. In which case, key members of the supply chain may go ahead and adopt data practices which would encourage other members of the supply chain to join in, leading to a better synced and resilient supply chain. Additionally, the use of big data can aid in identifying potential vulnerabilities and implementing strategies to mitigate them.

4.5 Big Data Implication for Key Themes

Key themes highlighted in this research include collaboration, flexibility, data management and supply chain design. This section highlights the key findings and discusses how Biga Data can be applied to the key themes.

Firstly, the collaboration theme indicated that supply chain participants in the milk industry are increasingly using big data analytics and communication tools to collaborate and share information on demand and supply, enhancing their performance. The importance of information sharing and the advantages of employing various tools for collaboration are emphasised (Kache and Seuring, 2017). However, the research also identifies challenges that can hinder effective collaboration.

Big data technology has the potential to revolutionize the milk supply chain by providing valuable insights and facilitating more efficient collaboration among chain stakeholders (Kache and Seuring, 2017). By collecting, storing, and analysing large amounts of data from multiple sources, big data enables a comprehensive and accurate view of the supply chain (Kache and Seuring, 2017). It can improve customer service by analysing customer behaviour and preferences, leading to an enhanced customer experience and stronger relationships (Kamal et al., 2018). Transparency is another benefit of big data, as it provides real-time visibility into the entire supply chain and fosters trust among participants (Ji et al., 2017).

Predictive maintenance is another area where big data can make a significant impact in the milk supply chain (Lee et al., 2014). Analysing sensor and operational data enables processors and retailers to identify potential issues and take preventive measures, minimizing disruptions (Lee et al., 2014). Optimizing logistics is also achievable through big data analysis, helping retailers and processors improve supply chain operations, reduce waste, and explore collaboration opportunities (Lamba and Singh, 2017; Kache and Seuring, 2017).

The flexibility theme underscores the importance of meticulous and proactive planning in milk supply chain operations, as well as the reliance on a limited number of suppliers. Interviews conducted as part of the research also reveal challenges such as regulatory barriers, political uncertainty, and technological limitations that can restrict the flexibility and adaptability of food supply chains. The findings further indicate that factors like production volume, just-in-time deliveries, and varying lead times can impact the flexibility of food supply chains.

The integration of big data technology in supply chain management has the potential to enhance the flexibility of milk supply chains by providing accurate and real-time information on various aspects such as demand, alternative suppliers, product availability, and location, as well as alternative delivery routes (Navickas and Gružauskas, 2016). This enables improved planning and decision-making processes, reducing the risks associated with over-reliance on a limited number of suppliers. However, it is important to recognize that, like any technology, the use of big data in milk supply chains also carries potential risks.

One significant advantage of employing big data technology in supply chain management is the ability to gain a comprehensive and precise understanding of consumer demand (Navickas and Gružauskas, 2016). This empowers milk suppliers and manufacturers to anticipate changes in demand more effectively and adjust their production and logistics accordingly. For instance, by analyzing data from social media, online sales platforms, and other sources, suppliers can obtain insights into consumer preferences and trends, enabling them to align their production and distribution strategies accordingly. Furthermore, real-time monitoring of inventory levels and logistics using big data technology allows suppliers to promptly respond to shifts in demand, avoiding inventory shortages or excess (Ji et al., 2017).

The data management theme highlights that Big Data technology has the potential to bring about a revolutionary change in how organisations manage their supply chains, including the milk supply chain. The increasing availability of data from diverse sources, such as sensors, GPS, and social media, enables organizations to gain a comprehensive and detailed understanding of their supply chain operations. This enhanced understanding facilitates the identification of potential risks and vulnerabilities, empowering organisations to make well-informed decisions to improve the resilience of their supply chains. However, the implementation of big data technology in the milk supply chain also presents several challenges that organisations must address.

A significant implication of big data technology in the milk supply chain is the ability to enhance visibility and traceability. This can be accomplished through the utilization of sensors and other digital technologies that collect data on various aspects of the supply chain, such as production, transportation, and distribution (Gupta and Rani, 2019). Analysing this data enables the identification of patterns and trends, shedding light on potential risks and vulnerabilities. For instance, data on temperature and humidity during transportation can help identify conditions that may lead to spoilage, while data on truck location and speed can highlight potential bottlenecks in the supply chain (Gupta and Rani, 2019). By identifying and addressing these issues, organisations can improve the resilience of their supply chains.

Moreover, big data technology empowers organisations to make more informed decisions. Data on consumer preferences and demand, for example, can be utilised to optimize production and distribution operations (Ji et al., 2017; Gupta and Rani, 2019). This optimisation helps organisations avoid overproduction, reduce waste, and enhance efficiency. Additionally, data on consumer sentiment can serve as an early warning system, enabling organisations to proactively address potential issues (Yang et al., 2017). For instance, if social media data indicates growing consumer concerns about the use of antibiotics in milk production, organisations can take corrective measures before the issue escalates. It is important to consider the complexity of the data itself as well. The milk supply chain is a complex system, and the data collected from it can be equally intricate. Organisations need the capability to process and analyse this data, which may necessitate specialised software and skilled personnel (Ivanov et al., 2018). Additionally, organisations must ensure the accuracy and reliability of the data and its appropriate utilisation, which can be a considerable challenge as they may lack the expertise or resources to ensure data quality.

The supply chain design theme provides evidence that Big Data has a broader impact on supply chain in the milk industry beyond the previously discussed areas. It provides organisations with detailed information about the entire supply chain, enabling them to identify bottlenecks, inefficiencies, and areas for improvement. Through data analysis across the supply chain, organisations can pinpoint opportunities to reduce costs and enhance efficiency. Additionally, big data technology supports the improvement of sustainability in milk supply chains. Organisations can analyse data on the environmental impact of milk production and transportation to identify measures for reducing their carbon footprint and enhancing operational sustainability. The visibility of sustainability practices among supply chain participants allows organisations to assess the environmental implications of their partners' actions. For instance, by scrutinising data on the environmental impact of milk production, organisations can identify strategies to minimise their carbon footprint and bolster sustainability.

Moreover, big data technology contributes to enhancing the traceability of milk products across different tiers and nodes in the supply chain. By analysing data on the movement of milk products, organisations can detect and address issues such as contamination or spoilage. This proactive approach enables organisations to take preventive measures and improve the safety of milk products. For example, through data analysis of milk product movement, companies can identify potential food safety concerns and take appropriate actions. An important aspect of big data technology is its application of predictive analytics. By analysing large volumes of data, organisations can make predictions about future events such as demand, inventory, and logistics. This empowers companies to improve their planning and respond more effectively to disruptions. For instance, leveraging predictive analytics allows companies to enhance their ability to forecast future demand for milk products, aiding in better production and logistics planning.

In summary, big data technology in the milk industry encompasses various aspects, including supply chain design, sustainability improvements, traceability enhancement, and the application of predictive analytics. By leveraging data analytics, companies can unlock valuable insights, optimise their operations, and make informed decisions to drive efficiency, sustainability, and safety across the milk supply chain.

4.6 Conclusion

This chapter answers research question 1 (How can Big Data be effectively applied in the development of a disruption-resilient milk supply chain?) by highlighting key themes in supply chain management where Big Data can be applied to develop a more resilient supply chain and further discussing how to effectively apply Big Data to the themes in section 4.4. The results here show that Big Data can be applied effectively in the development of a disruption-resilient supply chain by applying those technological capabilities to the themes presented in this chapter. For example, a supply chain can apply Big Data capabilities in supporting flexibility and collaboration to mitigate disruption and enhance resilience. This also supports the thesis to meet research objective 4. The chapter also answers research question 2 (What are the challenges faced by the milk supply chain and how resilient is it to recent disruptions?) in part by discussing the challenges faced during a disruption and this also meets research objective 1. Some of the challenges discussed by participants in this research include lack of visibility across the supply chain, logistical challenges, decision making around the supply chain costs, lack of access to relevant Big Data technologies across supply chain members, inability to predict demand accurately during a disruption, production challenges during disruptions etc (see section 4.4). Parts of the qualitative data collected in the interviews is used to build the model in Chapter 5 and 6 which is used in Chapter 7 for experimentation.

This chapter presented the qualitative findings from semi-structured interviews in detail, reviewing the key themes of collaboration, flexibility, data management and supply chain design. The research found that some participants in supply chains understood the essence of collaboration and shared data effectively but in supply chains where collaboration was poor, demand signals were also poor. Receiving poor demand signals meant that production and logistics could not be planned properly which can be detrimental and expensive when a disruption occurs.

The research findings suggest that food supply chains require significant planning and lead time and are dependent on a limited number of suppliers. The interview results illustrate challenges such as regulatory challenges, uncertainty due to political factors, and technological factors that can limit the flexibility and agility of the food supply chains. High level of production volume, just in time deliveries, and varying lead times are also discussed as factors that can impact the flexibility of the food supply chains. The research also found that to support flexibility and improve resilience supply chains employed strategies such as procuring extensive buffer stocks and holding them in various locations, including storing them abroad but logistical considerations had to be made. They also employed the resilience strategy of focusing on fewer production lines and discontinuing other lines for some time.

Participants expressed that Big Data capabilities enabled a more responsive and resilient supply chain, but the data needed to be user-friendly in order to ensure transparency and visibility. The findings highlight that while big data and digital technologies have the potential to improve supply chain resilience, organisations face challenges in terms of data infrastructure, data processing, and investment. Organisations need to invest in advanced software and data infrastructure, and work to improve data communication and sharing among partners in the supply chain. To fully realise the potential benefits of big data, organizations should also invest in educating and training their personnel on big data and its uses.

Two supply chain designs were expressed by participants in this research with one of the supply chains relying on one main supplier in a distant geographical location and this presented several challenges during a disruption. The other supply chain design supports multiple suppliers in several locations. This research notes that it is vital that supply chains are consciously designed to improve resilience, and this can be achieved by adopting big data practices that support collaboration and flexibility.

The interview results contribute to advancing Resource-Based View (RBV) and Dynamic Capabilities theory in the milk supply chain. Firstly, they validate the theoretical concepts by providing empirical evidence of how Big Data capabilities when applied effectively can contribute to resilience.

Understanding contextual dynamics within the food supply chains through professional and operators offered insights into the applicability and effectiveness of theoretical strategies proposed within RBV and DC in real-world settings. For example, while RBV and DC hold that a dynamic capability such as BDA may offer competitive advantage, interviews with operators within the supply chain offers insights into the possibility of application.

Finally, the practical implications derived from interview findings can bridge the gap between theory and practice, facilitating the implementation of theoretical concepts in supply chain management.

Chapter 5
QUANTITATIVE DATA COLLECTION AND DESCRIPTIVE ANALYSIS AND TEST MODEL

5.1 Introduction

In this chapter, the key features of the supply chain are based on insights from the quantitative data collected, narrowing in on the production processes from the farm where milk is collected to the retail point (final member of the supply chain) where the final customer purchases it. This research goes on to conduct deterministic experiments based on this data to examine the resilience of the supply chain of interest.

The chapter also examines the information within the data collected, providing a descriptive analysis and extracting information that can be useful in understanding production patterns, volumes and logic within the supply chain of interest. The chapter provides the test model, which is expanded in later chapters for experimentation, as well as the assumptions made as part of developing the model. The chapter then concludes by examining the possible limitations of the data that has been collected and its applicability.

5.2 The Supply Chain of Interest

The focal organisation here is a large manufacturer of dairy products, such as: cheese, butter, yoghurt and various types of milk including skimmed, semi-skimmed and whole milk. This milk manufacturer is a key member of their supply chain as they have interactions with almost all parts of the milk supply chain as documented by Ong et al. (2014) in Figure 5.1, starting from the milk in the farms to the collection and delivery to the manufacturing/bottling plant and then on to the retailers in the stores where customers go to make the purchase.

The organisation owns a small farm of animals who produce the milk but largely work in collaboration with local farmers who go through an auditing process to ensure high standards and quality of milk production. This organisation sends out trucks and tankers to the farms to pick up all available milk from the farmers. One truck may pick up from various farmers and this could lead to milk from one farmer contaminating the whole tanker of milk from the other farmers. Hence, great care must be taken to ensure that they only work with farmers who produce the best quality milk. Due to the short shelf life of milk (10-12 days), and the biological component that cows have to be milked daily to ensure viability of the milk and a continuous flow, this organisation takes an inflow of milk daily and also supplies its customers daily. While this organisation produces a variety of dairy products, for this study, the focus will be on the milk products (semi skimmed, whole and skimmed milk).

Figure 5.2 shows a graphical representation of the milk supply chain adapted from Figure 5.1 and updated based on the information derived from interviewing a manager at the focal company. Figure 5.2 also shows the direction in which supply and production travels in this supply chain as well as the direction of travel for demand and information which is in the opposite direction.

Farmers would normally milk cows twice a day (Mottram, 2016) using a milking machine. The milk will then be refrigerated in a tank at the farmer's site until the next day when a milk tanker is sent by the manufacturers for collection. Upon arrival, a sample of the milk at each farm is taken to ensure no foreign bodies are present before being pumped into the milk tanker and taken to the manufacturer's site where a further examination is carried out to check for antibodies, after which the milk is pumped into silos. The milk then undergoes pasteurisation which separates the milk from most of its bacteria content; further processing is then done which separates the fat content from the milk. At this point, the fat that has been separated from the milk undergoes a separate form of processing which can turn it into other dairy products such as cream etc. or kept in the raw fat form which will later be re-introduced into the milk to make full fat milk option. The milk also undergoes a different form of processing which allows it to be made into skimmed and semi-skimmed options; the milk can also be introduced into an additional filtration process which holds all bacteria in the milk, leading to the filtered milk option for customers. Once all product options have been made, they are packaged and refrigerated below 4°C for quality preservation.

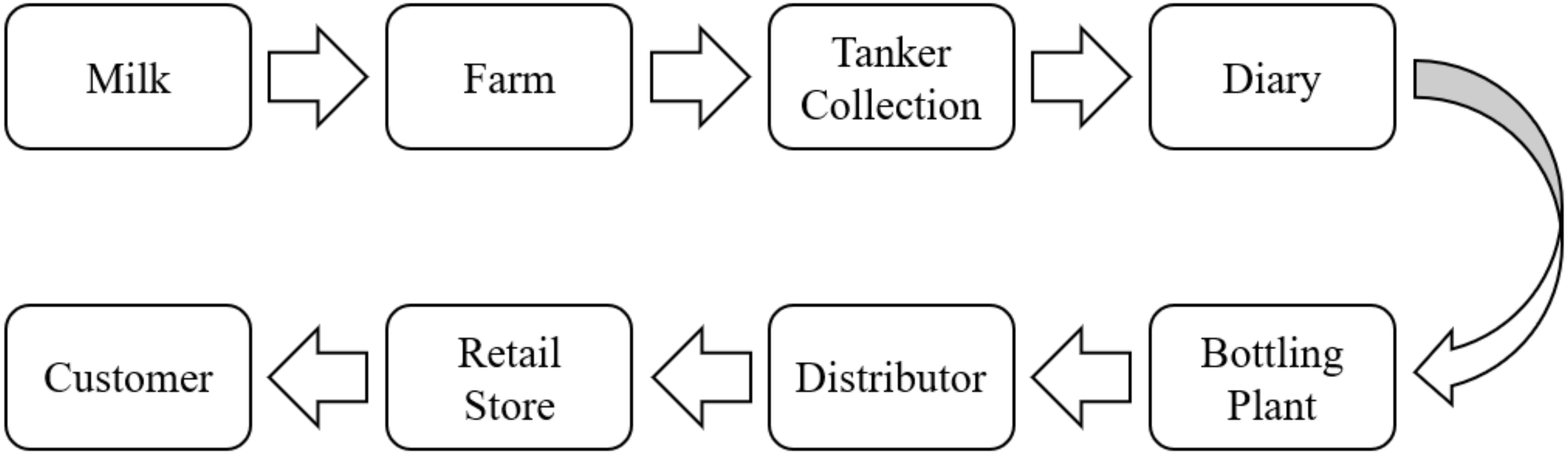


Figure 5. 1: The milk supply chain based on Ong et al. (2014)

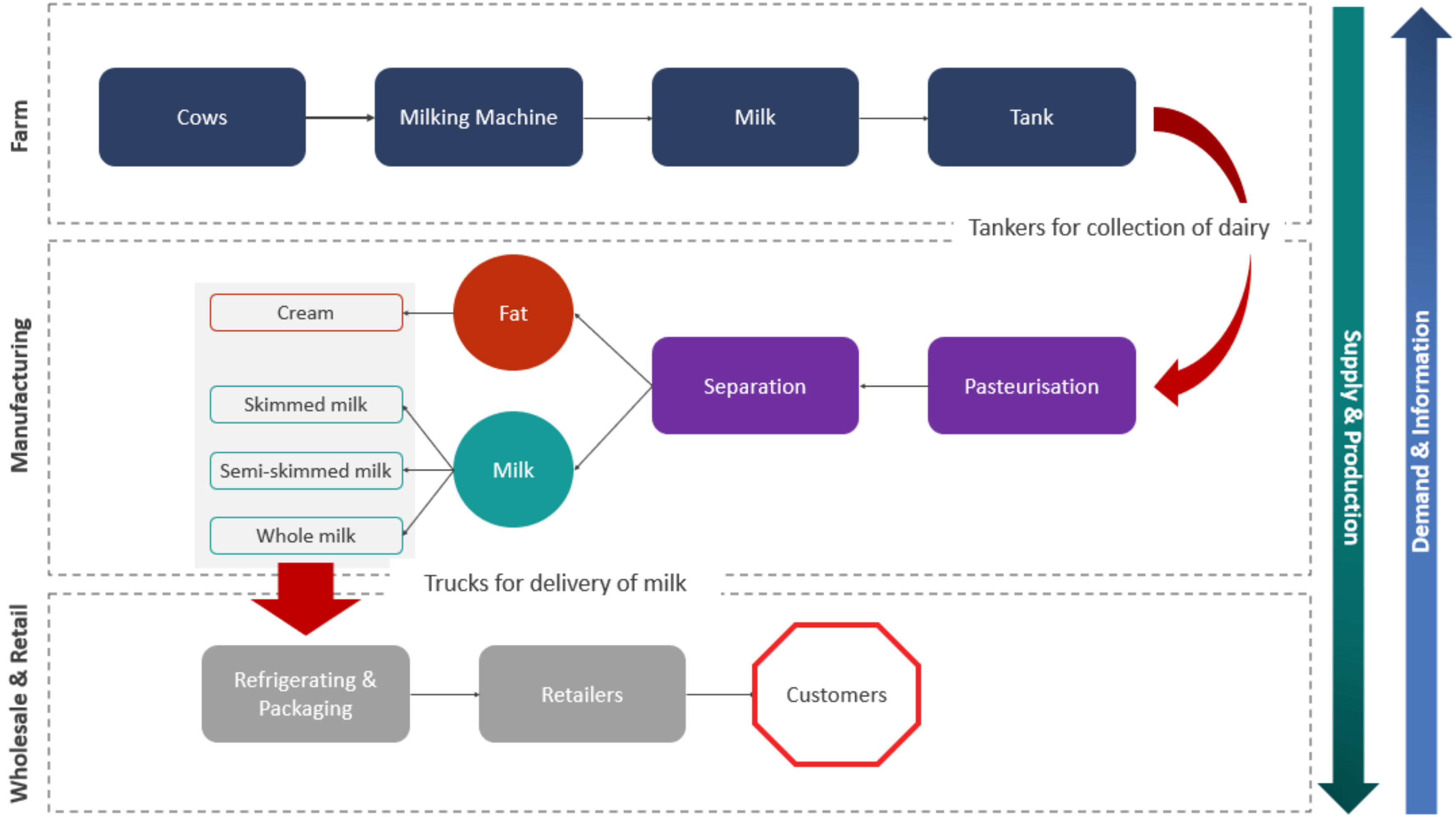


Figure 5. 2: Milk Supply Chain and Information Flow

Retailers participating in this supply chain will then place orders and a truck from the manufacturing organisation delivers their orders to them at their store locations. Milk is high in nutritional value; however, it has a short shelf life, and the quality has to be managed very closely to ensure that it meets food hygiene requirements and organisations can guarantee customers quality. The organisation incurs cost in transportation (farm to plant and plant to retailers) and ensuring a high quality in its products; however, customers will only return to purchase products which they consider to be of high quality. To this end, retailers who purchase from this manufacturer all have set standards of milk which they will be willing to purchase from the manufacturer as this is the same standard which they have promised the end users. Hence, the manufacturer must communicate the same quality to the farmers who will then implement policies and procedures to ensure said standard.

5.3 Descriptive Analysis

The quantitative dataset essential for the simulation carried out in this research was collected from a large manufacturer of dairy products with manufacturing and distribution points in the Yorkshire region of the United Kingdom. The dataset collected was mainly the production data which spanned over 3 years and 3 months from November 2018 to February 2022. The data collected showed data captured with only a few seconds/milliseconds interval which is characteristic of a big data set. This dataset allowed the researcher to understand key activities within the supply chain and provided the basis for the quantitative data inputted in the simulation model. As part of this research, the big data tool Power BI is used in the first instance to import the data from the data source held by the organisation. This tool provided the basis for the initial analysis and data visualisation for insights.

The following section discusses in detail a descriptive analysis of insights drawn from the dataset collected for this research. It evaluates the retailers who regularly purchase from the manufacturing plant or distribution centres, the quantity of milk purchased at any point from the manufacturer and the types of milk regularly purchased.

5.3.1 The Top Retailers

Data was collected from a milk manufacturer within the supply chain. In this specific supply chain, they carry out other functions besides manufacturing. Other such functions include food hygiene monitoring, logistics and farm auditing. Figure 5.3 shows the top retailers within this supply chain for the timeline of data collection which is 3 years and 3 months spanning from November 2018 to February 2022. An initial analysis of data collected from the milk manufacturer shows that the manufacturer is responsible for milk manufacturing for several retailers. However, only 4 of those retailers account for over 90% of the demand as shown in Figure 5.3. To this end, the study will focus on the activities and demands of these retailers.

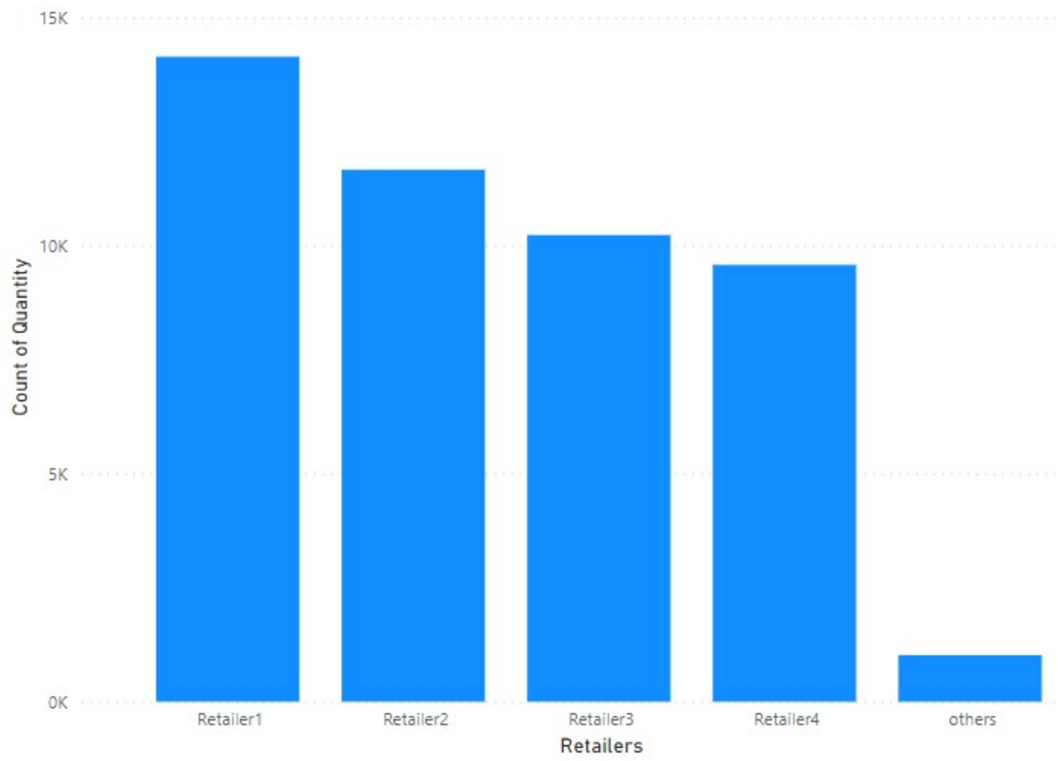


Figure 5. 3: The top retailers

5.3.2 Milk Types per Retailer

As noted in section 4.3.1, four retailers account for over 90% of the manufacturer's demand for milk and this research has chosen to focus on these 4. Figure 5.4 presents the types of milk purchased by these retailers regularly. While the manufacturer makes 4 main types of milk, all the retailers purchase a wide varying amount of semi skimmed, skimmed and whole milk. Retailer 1 and Retailer 3 do not make any purchases of standardised milk while Retailer 2 and Retailer 4 only purchase limited amounts when compared with their purchase of other milk types.

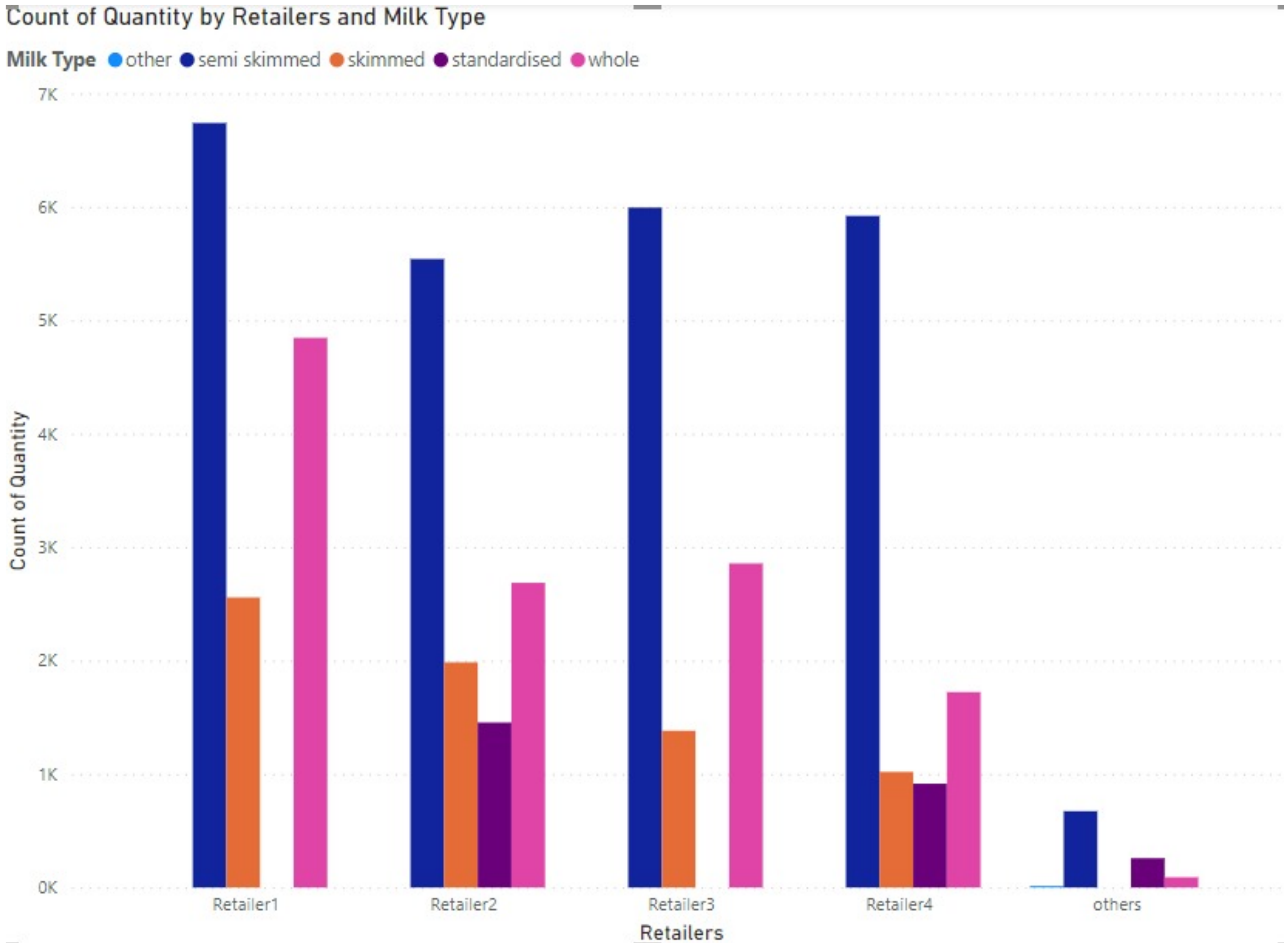


Figure 5. 4: Milk Types per Retailer

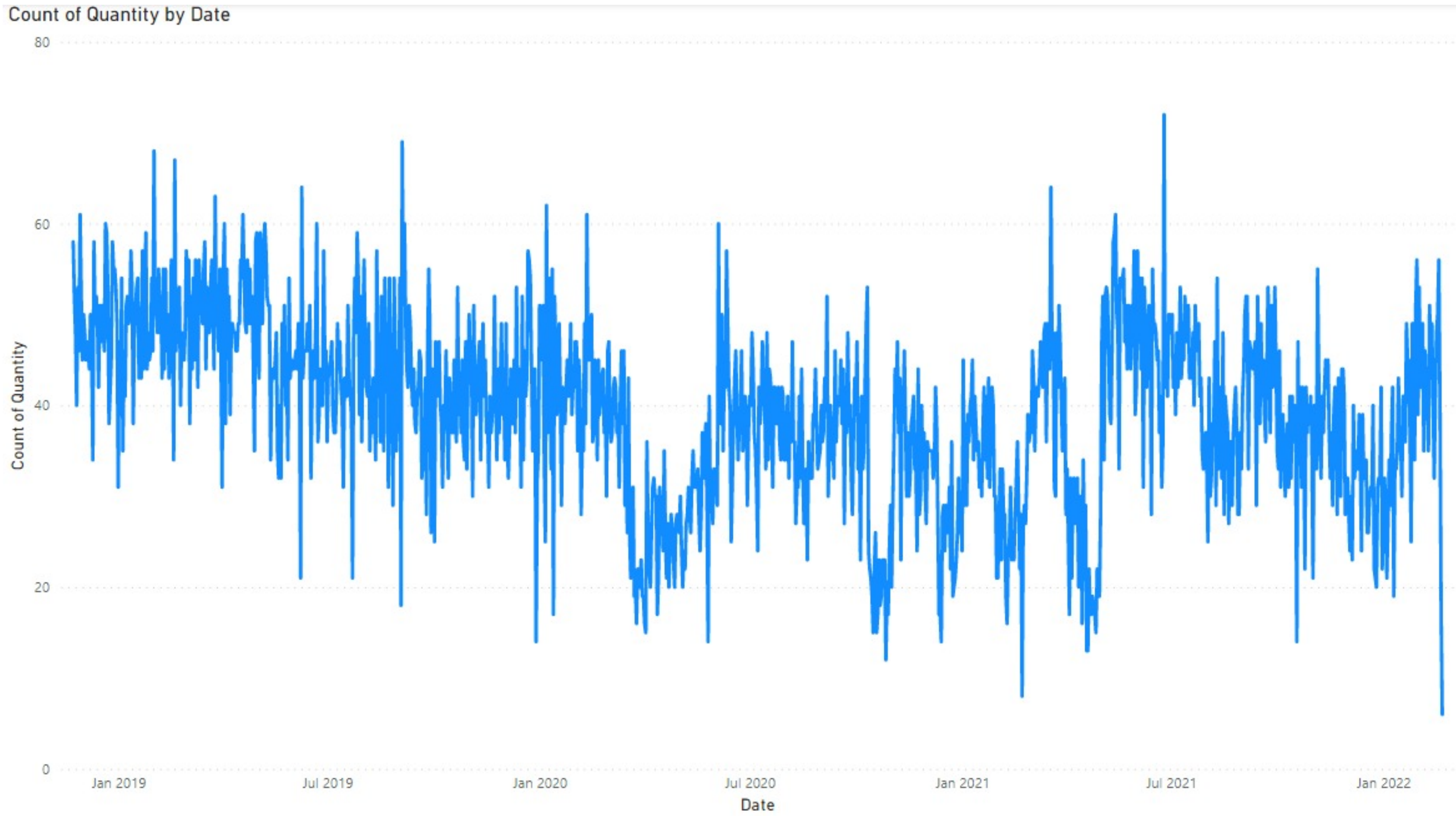


Figure 5. 5: Milk Production

5.3.3 Milk Production

The production of milk displayed in Figure 5.5 covers the data collected from November 2018 to February 2022, although labels appear to have shortened due to the 6-month interval label used in this figure. However, it is clear that the milk production seems to be fairly stable across months and years. From interviews with the manufacturer, this is attributed to an understanding between manufacturers and retailers in the food supply chain where retailers have to purchase everything that has been manufactured as they would only have been manufactured based on a standing agreement. This was also corroborated in an interview with a milk retailer (from a different supply chain) - Participant 9, who noted that they purchase a fairly stable amount of milk at an interval which is known by the manufacturers in their own supply chain. This formed the basis for generating a synthetic consumption data which mirrored closely but not exactly, the milk production data. Also, due to the nature of milk, which can only be produced in specific volumes e.g., 2 pints, 4 pints, 6 pints etc. Noteworthy however is the indication within the data that the highest volumes produced were produced during the COVID-19 pandemic lockdown period.

5.3.4 Production Time of Day

Data collected from the manufacturer and analysed in Figure 5.6 indicates that most of the milk is produced in the morning hours before noon. However, according to interviews with a manager at the company, the milk is not yet sent to retailers until the next day. This period allows for quality control as it could be devastating for the organisation to send out a batch of milk that is later found out to be below the quality expected. This also supports findings from other studies who state in their study that perishable items with an average shelf life of 21 days usually get delivered within an average of 1.2 days (van Donselaar et al., 2006). It can be inferred that an item like milk with a shorter shelf-life may will be delivered to the retailer within a shorter time frame, while allowing time for quality controls and checks.

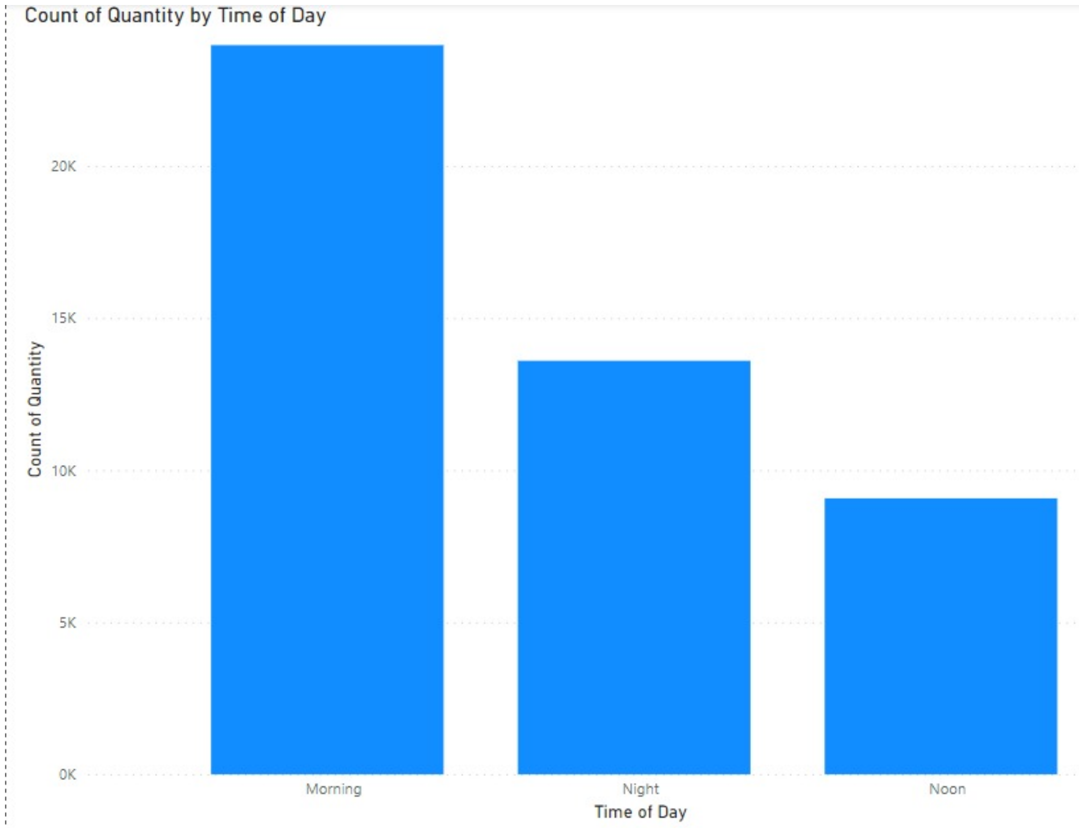


Figure 5. 6: Production Time of Day

5.4 Data extracted for Simulation

Analysis of the data received (November 2018- February 2022) and interviews with a manager at the focal organisation provided input for the model developed in this research. The following data was extracted and used as input for the simulation:

- The number of retailers,
- The different types of milk manufactured for each retailer,
- The frequency of manufacturing,
- The volume/quantity manufactured each time,
- The times of day when most of the manufacturing occurred,
- The interconnectivity of the supply chain,
- Interactions between supply chain members.

Figure 5.7 depicts a supply chain map based on the initial analysis of the supply chain (Figure 5.2), its members and the above data. Figure 5.2 provides an understanding of the milk supply chain, while Figure 5.7 indicates sections of the supply chain which inform conceptual model that is converted into the simulation model to allow the research carry out experiments and obtain relevant results. Figure

5.2 provides a detailed visual representation of the milk supply chain, illustrating the various stages from milk production at farms, through processing and packaging, to distribution and retail. This figure helps in understanding the flow of milk and the interactions between different members within the supply chain. Figure 5.7, on the other hand, highlights specific sections of the milk supply chain that are particularly relevant for the conceptual model. This model is then translated into a simulation framework, enabling the research to conduct experiments and analyse the impact of various disruptions and interventions. By focusing on these critical sections, the simulation can generate relevant results that offer insights into how Big Data Analytics can enhance the resilience and efficiency of the milk supply chain.

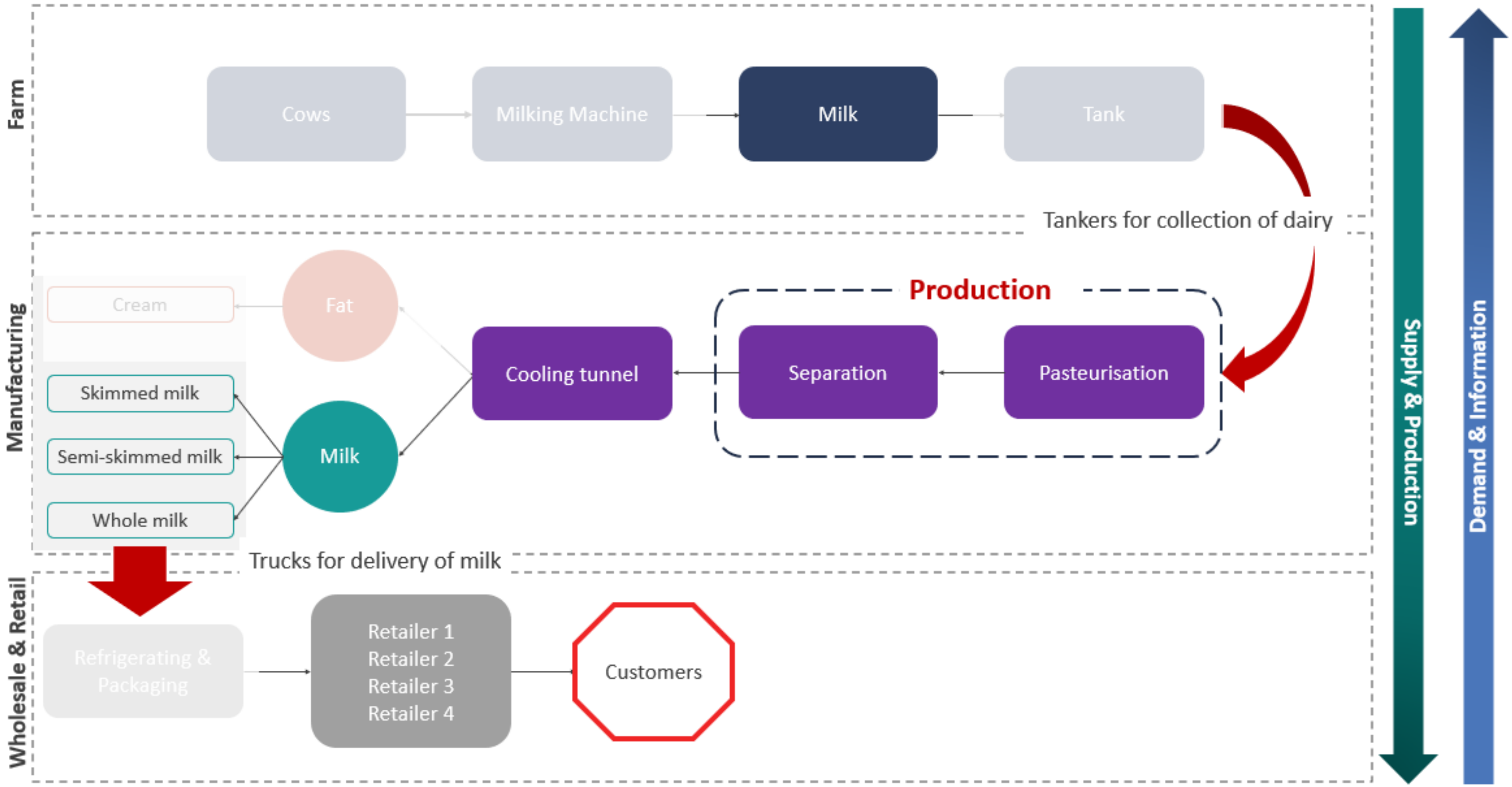


Figure 5. 7: Supply Chain Map

The data made it clear that while the manufacturer handled milk production for several retailers, four key retailers accounted for most of the production volume and as such, this research only modelled activities at four retail points. It was also evident from the dataset that the activities from the various farms were not included in the data shared with this research and as such, the research does not include all activities at the farm level (see figure 5.2). However, this research makes the assumption that all milk received that arrive at the manufacturing plant is an accurate representation for the milk that has been received from the farms. The data also made it clear that while the manufacturer produced several types of milks with varying levels of fat content, the top four retailers purchased three main types of milk: skimmed, semi-skimmed and whole. This research only includes these three types of milk in the model as including or removing the other types of milks will not have a significant impact on the ability of this research to test the resilience levels of the supply chain in the event of a disruption. The dataset also provided evidence for how frequently manufacturing was done for each retailer up to the millisecond and the quantities manufactured each time. This information is also taken into consideration in the simulation to ensure accuracy. Information on the time of day when production occurs is also clear from the dataset received and analysed. While not included in the dataset, interviewing the manager in the focal organisation gave insights into the interactions between supply chain members and their interconnectivity. This information is also used to build the initial test model which is later expanded.

5.5 Test Model, Verification, Validation and Assumptions of the Model

The relevant data extracted is used to inform the design of a test model using the witness horizon software. A simple version (test model) of the target model was built with one manufacturer and one retailer providing only one type of milk to its customers (see Figure 5.8). A simple set of test data (data for a period of one month) is also synthesised and used to validate the results expected. To verify the model, the supply chain map (Figure 5.7) is verified with the manager at the manufacturer who confirms the supply chain map as realistic. Additional verification is received from 2 simulation experts on how the research transforms the problem into the simulation software and confirm it as representative, which ensures the research is building the model right. To validate the model, events are triggered within the model to allow the research to assess the resulting behaviour. This is then used to ensure the accuracy of model implementation, meaning the research is able to ensure that that the model is behaving in the way that is expected and responding to prompts and data inputted. Once the simple model and its accompanying results are validated, the model is then expanded into what is now called the as-is model as depicted in section 7.2.1. The next chapters will go into a more detailed description of how the final expanded model is built to allow the research carry out experiments. Data such as the units of milk produced, the units of milk sold, the time frame for producing each pint of milk, the number of pints producible per time/batch, storage capacity, etc., which have been discussed in this chapter is also input to enable the software model the supply chain.

To ensure that the test model and invariably the expanded (as-is) model is as realistic as possible, some key assumptions made, and characteristics of the model include:

- Events within the model only occur at predetermined points and times.
- Milk arriving at manufacturing plant is all the milk received from the farmers.
- Farmers in this supply chain only supply milk to this manufacturer.
- Raw milk quantity received is equal to the quantity of manufactured milk.
- Manufacturers and retailers can be either fully functional or not functional at all.
- Every customer order which is not fulfilled is either lost or fulfilled elsewhere, and could lead to a loss of reputation, indicating a reduction in resilience.
- Simulation can start with zero inventory and a ‘warm up’ period allowed for a steady state supply chain and observation before a disruption is introduced.
- Prior to a disruption, all milk manufactured for a specific retailer will be delivered to and received by that retailer.
- Disruptions can be introduced at supplier, manufacturer and retailer stage and the reaction of the supply chain observed.
- Disruptions can also have predetermined duration and frequency at each stage.

- The model will also not intervene or alter the supply chain design after a disruption has occurred.
- Demand can be programmed to be fairly stable or consistent.
- The longer customers have to wait to be served, the more impatient they may grow and ultimately can decide to go somewhere else.

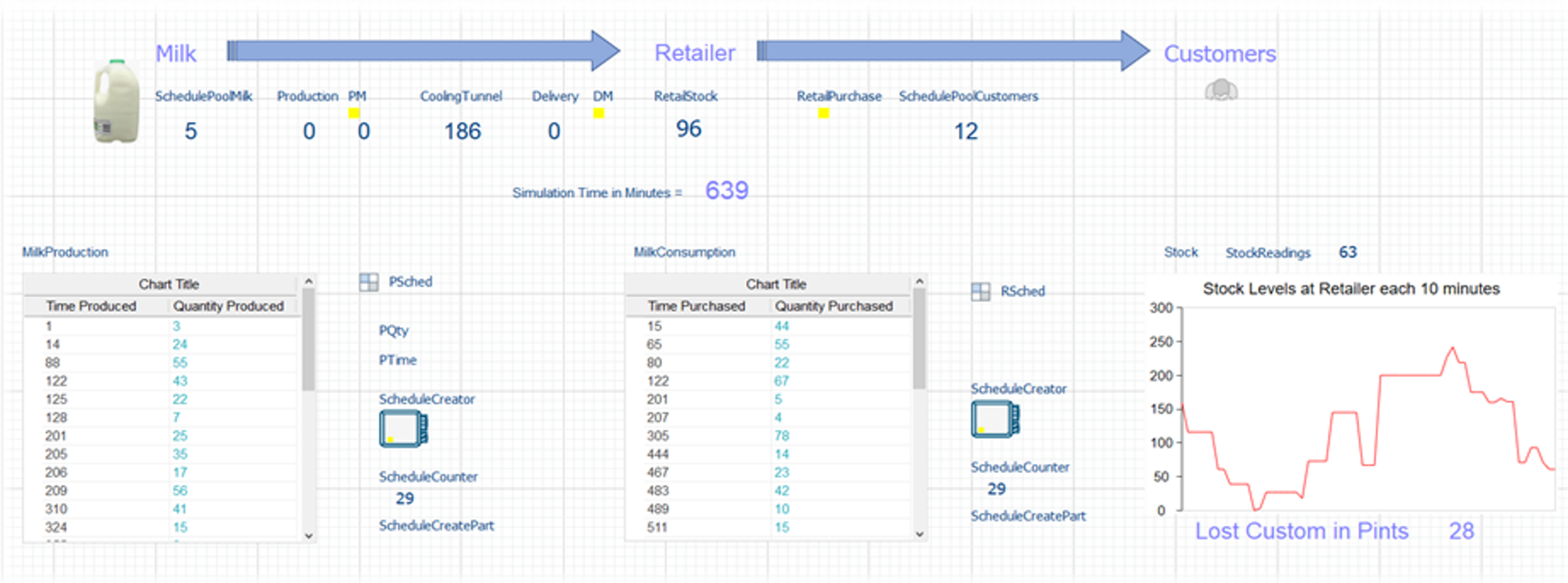


Figure 5. 8: The Research Test Model

5.6 Data Considerations

The research considered the background and operations of the milk supply chain; however, the research only had access to a key participant at the milk manufacturer (participant 8) who works in a managerial position. For this reason, some disadvantage existed when it came to assessing and ascertaining the accuracy of information provided. Hence, the research took extra care to ensure that the data gathered was as accurate as possible using triangulation with literature and additional participant interview (participant 9).

The objective of this study is to examine the whole supply chain and a few organisations were considered, but this organisation was selected due to its large size, over 50 years of experience, willingness to cooperate with this study by sharing data and participating in interviews. This UK based organisation was also ideal because of the active drive and investment in big data practices as detailed in section 3.8. Additionally, this research is only able to review the activities of one organisation within the supply chain which makes the results specific to the focal organisation. However, as noted in section 5.3.3, the research generates synthetic consumption data based on the quantitative data collected from the manufacturer and the feedback of other interview participants (see Appendix I).

5.7 Conclusions

The chapter discussed the focal supply chain and the key members of that supply chain. The chapter also provides the descriptive insights from the raw data collected from the focal supply chain as part of the research. Insights from the dataset shows the top retailers who make up this supply chain in line with the types of milk product frequently purchased by each retailer. The typical milk production volumes and production times are also considered as well as the limitations of the dataset. The chapter goes further to discuss how the data received is extracted and used to inform the research and computer simulation of a test model in the first instance.

The theoretical background served as a guiding framework throughout this chapter which focused on quantitative data collection, descriptive analysis, and test model development. It informed the selection of variables and metrics used to measure key constructs related to the Resource-Based View (RBV) and Dynamic Capabilities within the milk supply chain context. For example, variables related to Big Data Application, such as technological infrastructure and variable related to resilience such as supplier relationships, were identified based on RBV principles.

In terms of descriptive analysis, the theoretical framework provided a lens through which to interpret the quantitative data. Descriptive statistics were used to summarise the distribution and characteristics of key variables, allowing the research to identify patterns and trends that align with theoretical expectations. For example, if certain production levels supported by Big Data usage were found to be consistently associated with higher levels of resilience, it would support RBV propositions regarding the essence of valuable resources.

The theoretical background informed the development and testing of statistical models to explore relationships between variables based on theoretical propositions. For example, the research tests the relationship between Big Data as a valuable resource and Resilience as a Dynamic Capability, drawing on theoretical insights from the RBV and Dynamic Capabilities literature.

Overall, the theoretical framework provided a systematic and structured approach to quantitative data collection, analysis, and model testing, ensuring that the study's findings were grounded in theoretical concepts and contributed to advancing theoretical understanding within the field of supply chain management. The Information and insights drawn in this chapter contributes immensely to the expansion of the computer simulation discussed in subsequent chapters.

Chapter 6
MODEL CONFIGURATION

6.1 Introduction

Food supply chains in the modern era are consistently faced with disruptions (Ali et al., 2023; Alabi and Ngwenyama, 2023), which in most cases are unanticipated and being resilient to these types of disruptions requires the collation and thorough processing of large amounts of supply chain related data (Singh and Singh, 2019a). Additionally, to maintain a resilient supply chain, the efforts of several supply chain actors must be coordinated (Ivanov et al., 2014). This chapter discusses the steps that are taken to build the model of a milk supply chain for testing and measuring resilience. This model will provide the basis for further simulations within this thesis; so, the chapter starts out by discussing the phases involved in building the milk supply chain model, focusing on creating the map of the supply chain and gathering relevant data including the members, the boundaries, the flow of material and data within the supply chain. Data relating to the supply chain processes and functions is also gathered. The model discussed in this chapter expands on the test model discussed in Chapter 5 and provides the basis for measuring resilience in Chapter 7.

6.2 Building the Milk Supply Chain Model

Food sectors in modern society have to operate under regulated conditions (Navickas and Gružauskas, 2016). In some instances, raw materials, technology and processes used for food production may be sourced from around the world (Alabi and Ngwenyama, 2023). These introduce a higher level of complexity for food supply chain members and emphasises the need for having a simple approach to gather data, process, analyse and gain insight from this data which would allow supply chain members to make better decisions with regards to production and distribution. This also implies that where data has not been analysed properly or erroneous insights are drawn, there could be vast implications including reduced resilience to the risk of a disruption. This research has now developed a model (using the phases depicted in Figure 6.1) to measure the resilience of the milk supply chain to a disruption.

The milk supply chain model developed is carried out in three phases:

1. Creating a full map of the focal milk supply chain.
2. Defining the types of disruption for the milk supply chain in focus and identifying the impact of such a disruption on that supply chain.
3. Defining what constitutes a resilient supply chain, measuring the resilience of the milk supply chain to the disruption risk.

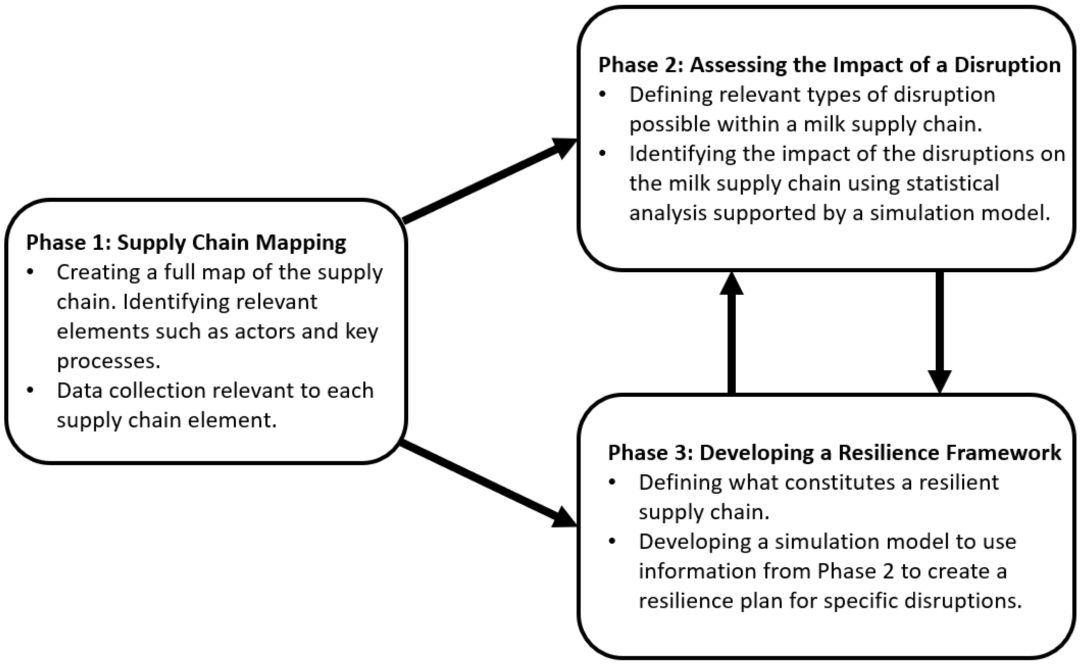


Figure 6. 1: Phases in building the Milk Supply Chain Model

The theoretical framework plays a crucial role in guiding the configuration of the model used in the research. In the context of supply chain resilience and the application of Big Data analytics, the theoretical framework provides the conceptual basis for understanding the relationships between various members, functions and processes within the supply chain. The theoretical framework informs the selection of variables to be included in the model. Based on the concepts and propositions outlined in the theoretical framework, this research identifies key variables that influence supply chain resilience based on the effectiveness of Big Data analytics.

These variables may include logistics, dynamic capabilities, external environmental factors (such as demand preferences), and technological advancements.

The theoretical framework provides the lens through which the research interprets the results of the model. It helps contextualise the findings within existing theoretical perspectives and offers insights into the underlying mechanisms driving observed relationships. By grounding the analysis in theory, this research is able to draw meaningful conclusions about the implications of the results for supply chain practice and theory development (see section 10).

To provide structure and clarity, the work that is done in each phase of the model is divided into several tasks; the tasks are further divided into the sub-tasks that need to be carried out in order to facilitate the required depth of analysis. This is illustrated in Figure 6.2 and given that the supply chain in focus for this research is the milk supply chain, the tasks and sub-tasks reflect the complexities within a milk supply chain.

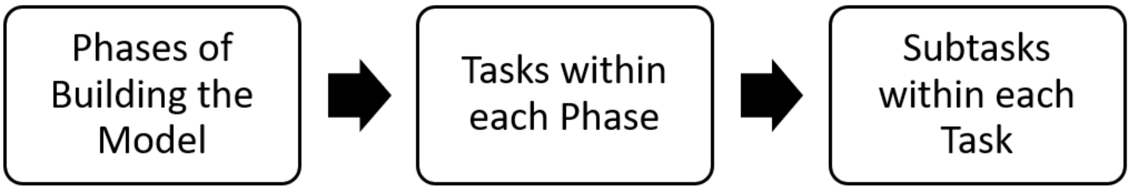


Figure 6. 2: Sub-tasks flow within the supply chain model

6.2.1 Phase 1 Overview

The first phase of building the milk supply chain model dealt with creating a full map of the supply chain in focus. This provided a clear insight into the structural elements that comprise the supply chain as well as show the way in which the supply chain is interconnected and how it operates. It also provided clarity on the functional parts of the supply chain that are relevant to this research. The basic components mapped within the supply chain include: the supply chain members, the flow of materials, the flow of information, the interconnectivity within the supply chain and the data related to each supply chain element. This phase culminated in the building of a map of the food supply chain (see Figure 5.7) from a physical and logical point of view, allowing for a better understanding of each element within the supply chain.

Figure 6.3 shows the supply chain members, materials, processes and functions within the supply chain which are essential to an effective operation and captured as part of mapping out the supply chain in phase one. This research will include in its simulation, the manufacturer, the retailer and the customers. The simulation implies that the milk produced at the manufacturing level came from the farmers, but it does not directly simulate the activities that occur at the farm. This is because the research did not gather data from the farmers or data that can imply the activities at the farm accurately. Furthermore, the simulation of the supply chain does not include wholesalers and wholesale activities are distributed between the manufacturer and the retailers. Phase one as depicted in Figure 6.3 also highlights the gathering of all required data within the various elements of the supply chain, gathering of data related to key members within the supply chain, materials (in this case, different types of milk: skimmed, semi skimmed, whole) and other resources relevant for effective operation of the milk supply chain.

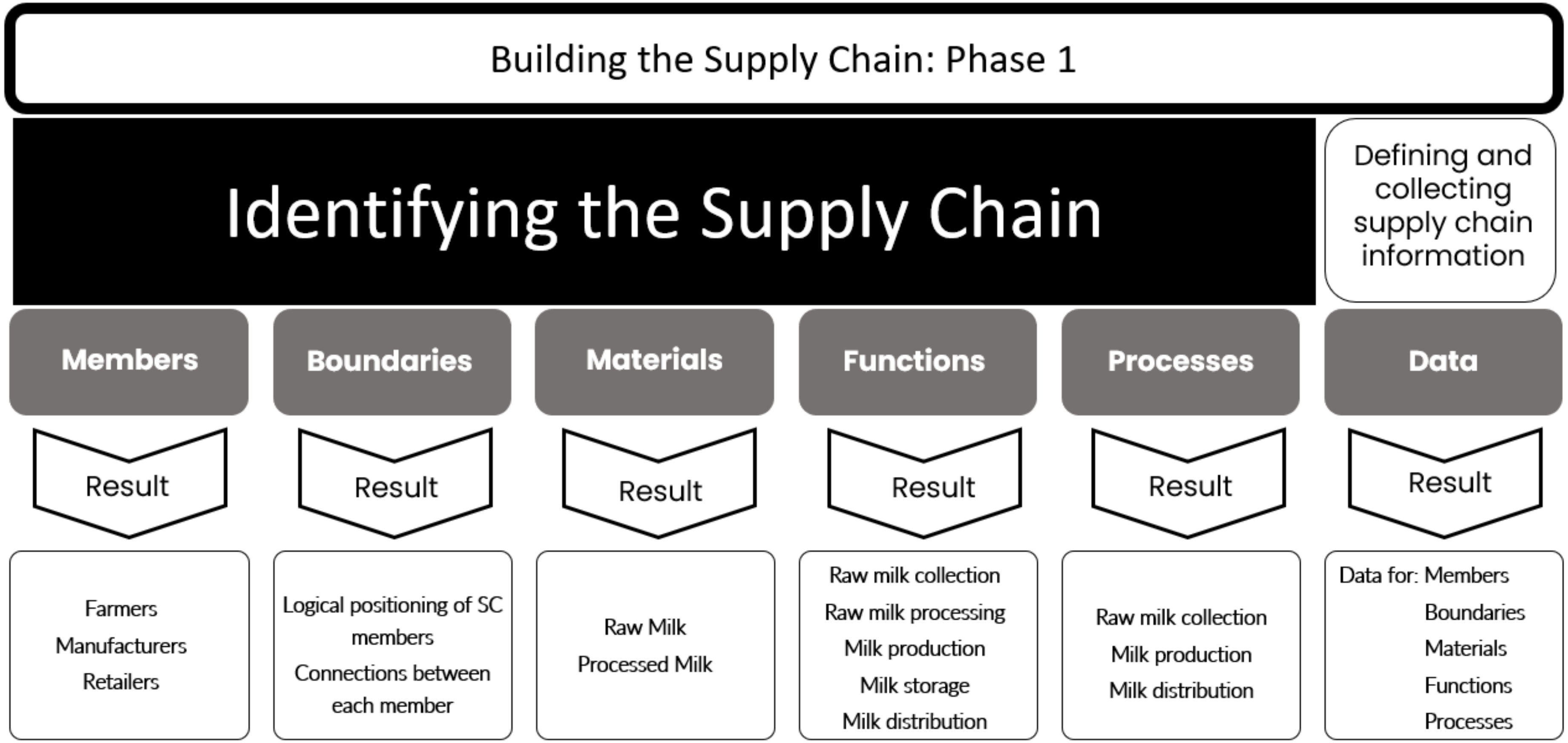


Figure 6. 3: Phase 1 Overview adapted from Tsiamas and Rahimifard (2021)

6.2.2 Phase 2 Overview

Phase 2 of building the milk supply chain model deals with identifying disruptions that can affect the milk supply chain. These disruptions form a basis for the disruptions that will be examined by the model. Table 6.1 examines the internal and external causes of milk within supply chains as documented in the work of Tsiamas and Rahimifard (2021) and the areas of the milk supply chain that are most affected by these disruptions. This research examines the internal disruptions of the milk supply chain as the data collected as part of this research includes only internal supply chain data and does not include data for external factors that can cause disruptions such as weather. Specifically, three disruption types are investigated as part of this research: production disruption, logistics disruption and demand disruption. This is because these three types of disruption represent a disruption at key nodes, affecting key members of this supply chain identified in Figure 6.3, allowing the research to examine the impact of a disruption at each node on the rest of the supply chain.

Table 6. 1: Internal and External causes of Supply Chain Disruption and the affected Milk Supply Chain activities adapted from Hishamuddiin et al. (2015) & Tsiamas and Rahimifard (2021)

	Affected activities within the milk supply chain			
	Milk Production in Farms	**Milk Collection**	**Milk Processing and Manufacturing**	**Milk Distribution**
A. External causes of Supply Chain Disruption				
Global social events e.g., pandemics	X	X	X	X
Brexit		X	X	X
Extreme climate events e.g., floods, snow, drought	X	X		X
Other Natural Events e.g., wildfires, landslides	X	X		X
Other social Events e.g., epidemics	X	X	X	X
B. Internal causes of Supply Chain Disruption				
Labour shortage during epidemics/pandemics	X	X	X	X
Production facility shutdown	X	X	X	X
Shortage of production resources	X	X	X	X
Retail facility shutdown			X	X
Shortage of transport facilities		X		X

6.2.3 Phase 3 Overview

Phase 3 involves defining what constitutes a resilient supply chain and how that is to be measured. It also considers the impact of the three types of disruption identified in phase 2 on the resilience of the milk supply chain in focus. Based on literature, three key parameters have been used to measure resilience: time to recovery, supply chain costs and customer service levels (Christopher and Peck, 2004; Sheffi and Rice, 2005; Ponomarov and Holcomb, 2009). This research adopts these parameters to measure the resilience of the milk supply chain to the disruptions simulated.

Chapter 7 explore phases two and three more critically by providing more detail how these resilience parameters apply to the current study and exactly how they are measured (phase 3). Chapter 7 also explores the different types of disruptions identified in phase 2 by introducing it in the milk supply chain model built. The results and impact of these disruptions on the resilience of the milk supply chain are also discussed in detail in chapter 7.

The next sections in this chapter will explore phase one more critically; expanding on the various tasks involved in completing phase one and the sub-tasks to be carried out within each task.

6.3 Phase 1: Creating the map of the milk supply chain

This section discusses the tasks involved in creating the milk supply chain map documented in Figure 5.7. Phase 1 of creating the supply chain map involves two tasks to complete this phase as shown in Table 6.2. The first task identifies the supply chain members, the flow of materials, supply chain functions and processes, while the second task involves the collection of data associated with the supply chain elements from task one. Table 6.3 depicts the various tasks involved in the two tasks of phase one. The information and data collected in phase one will then be used to understand the impact caused by each disruption defined in phase 2 the supply chain model.

Table 6. 2: Phase 1 and associated tasks

Phase 1	**Creating a Map of the Focal Food Supply Chain**
	1.1 Identifying relevant supply chain elements such as members and key processes (Task 1) 1.2 Data collection relevant to each supply chain element (Task 2)
Phase 2	Assessing the Impact of a Disruption on the milk supply chain
Phase 3	Measuring the resilience of the milk supply chain to the disruptions identified in phase 2

Table 6. 3: Phase 1: tasks and sub-tasks

Phase 1	**Creating a Map of the Focal Food Supply Chain**
Task 1	**Identifying relevant supply chain elements such as actors and key processes**
Sub-task 1	Milk Supply Chain members
Sub-task 2	Materials and Information Flows in a milk supply chain
Sub-task 3	Defining the Supply Chain's functions and processes
Task 2	**Data collection relevant to each supply chain element**
Sub-task 1	Data collection for supply chain members
Sub-task 2	Materials flow
Sub-task 3	Data for supply chain functions

6.3.1 Phase 1 Task 1: Identifying and Defining the Relevant Supply Chain Elements

Phase 1 task 1 identifies relevant supply chain members, their operational boundaries, the supply chain processes and functions, how the materials flow and the rules that govern demand and supply within the milk supply chain. This step is essential for planning and building the supply chain model as it allows the research to compare the supply chain elements with the data received and understand parts of the data and their corresponding supply chain element. For example, how much milk is produced daily, and of that amount, how much of it is sent to the retailer daily? Who is responsible for transportation? How is risk managed? etc. This task also allows for the model to represent in a realistic manner, the real-life activities and decision-making within the supply chain in focus. This task is further broken down into various sub-tasks which have to be carried out in order to build a model that is capable of measuring the resilience of the milk supply chain to the disruptions identified.

6.3.1.1 Sub-task 1: Milk Supply Chain Members

An overview of the milk supply chain is presented in Figure 6.4, highlighting the key supply chain members and the existing relationships. The focal supply chain member for this research is the milk manufacturer due to this manufacturer maintaining interactions with all other parts of the supply chain directly (see section 5.2). This manufacturer collects the raw milk from multiple farmers pre-approved for specific retailers and takes it through the process of pasteurisation and separation shown in Figure 5.2 to ensure that it meets the retailer and customers' expectations and makes the delivery to the retailers. The retailers in this supply chain act both as the storage and distribution point for the manufacturer and customers.

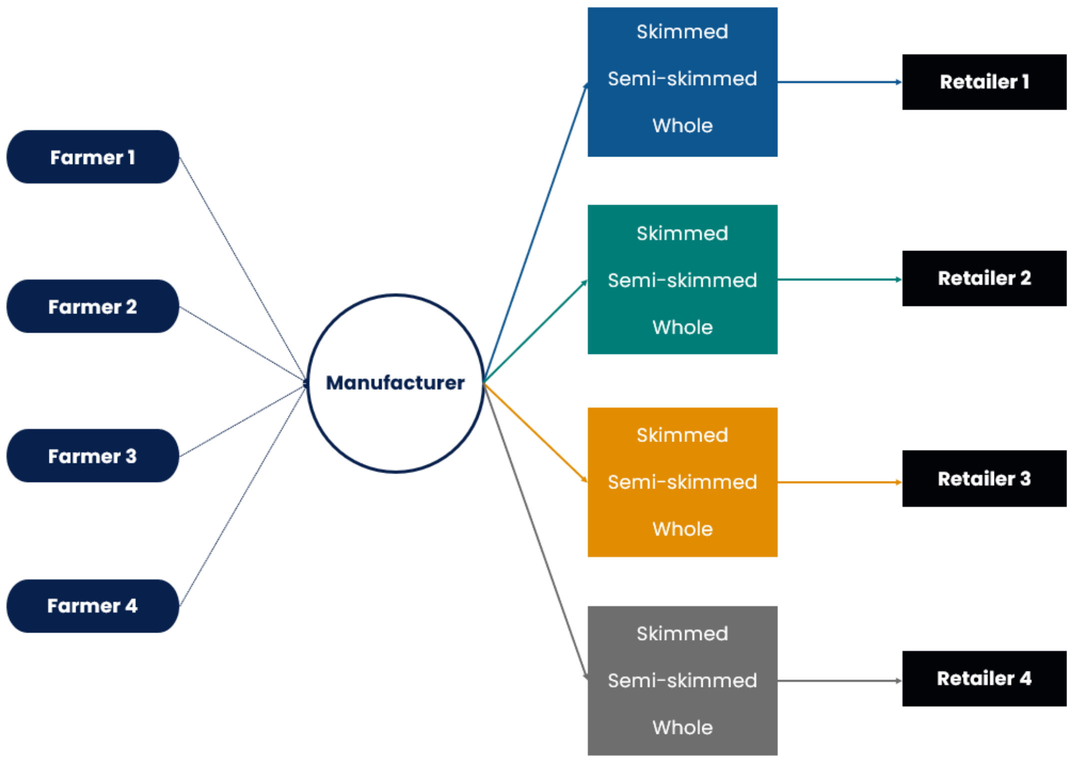


Figure 6. 4: Milk supply chain members and material flow

6.3.1.2 Sub-task 2: Materials and Information Flows in a milk supply chain

The relevant data to the milk supply chain (Appendix B) has been collected systematically and analysed to explore the supply chain members, the scope of the supply chain, the processes, functions, materials and their relevance to the supply chain in focus. In a typical supply chain, there are five groups of members which include: suppliers, manufacturers, wholesalers, retailers, and customers.

Figure 6.5 provides a simplified diagram depicting the logical positioning of actors within the supply chain with emphasis on the flow of materials and the flow of data between these actors. Each category in the figure is explained next.

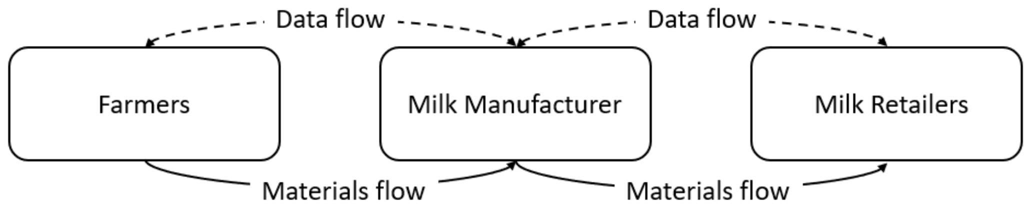


Figure 6. 5: Materials and Information Flow

The activities of the milk supply chain members can be separated into: the milk farming, the milk collection from the farmers and transportation to the manufacturers, the manufacturing process needed to separate milk into three separate finished products, the distribution and delivery of produced milk and the actual retail process (storing and the sales to customers). Figure 6.5 depicts the flow of materials amongst members of the supply chain as well as the flow of data within the supply chain. The type and nature of data which is transferred between the supply chain actors will be described in more detail in Section 6.3.2.

The supply chain boundaries are typically defined by the different member groups within the supply chain and the number of members within each group (Busse et al., 2017; Behnke and Janssen, 2020; Tsiamas and Rahimifard, 2021), for example, the number of milk farmers or the number of milk retailers within the supply chain. The boundaries will also consider the position of each actor member logically and geographically and how they are organised across the milk supply chain. Additionally, with defining the boundaries of the milk supply chain, it is not unusual to strongly consider the geographic dispersion where the supply chain remains active. Some research would consider things, such as the morphology, the physical location of its supply chain access, the roads, the available transport network, etc. (Busse et al., 2017; Behnke and Janssen, 2020; Tsiamas and Rahimifard, 2021). However, this research will not be taking the geographical boundaries into consideration but would look more critically at the logical placement and positioning of each supply chain actor and their interconnectivity. This research focuses on examining the logical placement and interconnectivity of supply chain actors over geographic boundaries as this milk supply chain is characterised by complexity, digitalisation, and dynamic operations, where traditional geographic constraints are becoming less relevant. By prioritising this approach, this research is able to gain deeper insights into supply chain dynamics and review adopted risk mitigation strategies within the network.

It is important to note here that the boundaries include the manufacturer and retailers as the core parts of the supply chain and customers as the part of the supply chain causing stochasticity and enjoying the goods and services delivered by the supply chain. as noted in section 6.2.1, wholesalers are not included as they do not make up part of this supply chain and farmers are implied but not simulated.

The main material which flows through the milk supply chain is milk. The milk first comes in as raw milk and is then processed to become skimmed milk, semi-skimmed milk, whole milk, standardised milk, etc. but this research will focus on the first three types of milk identified by fat content and volume e.g., litres, pints etc.

6.3.1.3 Sub-task 3: Defining the Supply Chain's functions and processes

In this sub-task, the processes and functions of the focal supply chain are described and defined. This gives clarity by providing a step-by-step guide to each supply chain process. While the milk supply chain is complex in its operations and architecture, the supply chain in focus here is mostly coordinated by the milk manufacturer. The activities which are carried out within the supply chain are grouped under specific logic depending on the result that is being targeted. These activities may be carried out by a single supply chain member or a combined effort of more than one member. For example, activities may be carried out from the farmer to the manufacturer or from the manufacturer to the farmer or from the manufacturer to the retailer. Each activity within a function may be guided in a predefined format and may require the use of support from equipment, data flow, human resources and other time bound actions. These activities within the function may be carried out in a consecutive manner or in series. To understand more effectively what constitutes the processes, functions and activities within a supply chain, the process and functions must be clearly defined. Hence, for the purpose of this research, supply chain functions and supply chain processes are defined as follows:

i. A supply chain function is a group of cooperating participants who take advantage of available resources and means to produce a pre-defined result. This will usually be done by following a set process or applying a specific procedure.
ii. The supply chain processes are the given set of instructions usually followed by the supply chain actors to produce the predefined result of a function.

As depicted in Figure 6.5, there is an interaction between the farmer and the manufacturer where the farmer delivers milk and data is exchanged which is relevant to the farmer's role as a raw milk supplier. This is usually carried out as previously detailed in a milk collection plan that would have been set up at the end of a farm audit when the farmer is prequalifying to supply raw milk to be manufactured for a specific retailer. Hence, milk delivery and the corresponding exchange of data with the manufacturer are supply chain functions that are carried out by the farmer in relation to the manufacturer.

There is also an interaction between the retailer and the manufacturer in the supply chain (see Figure 6.5) where data is being exchanged which is relevant to the retailer's role as a client to the manufacturer. This exchange may be guided by data present in a distribution list which shows the order for a specified quantity of milk. The retailer then receives the quantity of milk that was ordered based on that distribution list or based on a pre-set distribution plan. Hence, the milk distribution which involves the manufacturer providing a pre-ordered quantity of milk to the retailer and the exchange of data that follows this interaction is another supply chain function.

The manufacturer will interact with each pre-approved milk farmer in order to collect available milk and exchange data related to the process. Therefore, the milk collection and exchange of data will be classified as a supply chain function that relates the farmer and the manufacturer (see Figure 6.5). Additionally, the same manufacturer interacts with different retailers by receiving an order from each one, providing the quantity of milk for each order and exchanging relevant data in this process. The exchange of milk, the placing of an order and subsequently receiving the order as well as exchanging relevant data will also be classed as a supply chain function within this milk supply chain. While the manufacturer carries out the primary functions listed above within the supply chain, there are other supporting functions Such as human resource management, finance and marketing. These will not be included as part of the supply chain functions as they are extraneous to the supply chain even though they support the supply chain. The activities which are embedded in a supply chain function are carried out according to set processes and guidelines which are designed specifically to ensure that each function results in satisfactory quantity, quality and meet the required coordination for its supply chain. The processes for the supply chain in this research may run concurrently within a series or parallel to each other. The supply chain processes may be disrupted and the impact of a disruption on the supply chain process will be reviewed in the next phase of the simulation. The supply chain functions within this supply chain are discussed next:

Function 1: Collection of milk from the farmers by the manufacturer

The process here involves the collection of milk from the farmer and transferring the raw milk to the manufacturer location. It consists of three activities which include loading the milk onto the manufacturers refrigerated truck, transporting the raw milk from the farm to the manufacturers plant and transferring the milk from the truck to the manufacturer's cold tanks at the manufacturing plant.

Function 2: Milk Production

The milk production process aims to achieve the standard and quality that was agreed upon with the retailers. The raw milk is taken through a pasteurisation and homogenisation process which separates bacterial content and the milk, leaving behind the appropriate content for the specific (skimmed, semi-skimmed, whole) pasteurised milk. While this process will produce other dairy products, this research is focused on different types of pasteurised milk produced for each retailer (see Figure 6.4). For instance, the production process might end in skimmed milk and semi skimmed milk for one retailer but whole milk and skimmed milk for another retailer as would have been pre-agreed with the retailers. The produced milk is then transferred to the cooling tunnel where it will await distribution.

Function 3: milk distribution to retailers from the manufacturing plant

This involves the transfer of produced milk from the manufacturer to the retailer and would usually consist of the following activities. First, requested quantities of each milk type are loaded on a cold truck. Secondly, this milk Types are transported outbound from the manufacturer's premises and finally, the milk is delivered at the premises of the retailers.

6.3.2 Phase 1 Task 2: Data collection for each supply chain element

Based on identification and definition of supply chain members, the supply chain boundaries, the flow of materials, the supply chain functions and the supply chain processes in phase 1 task one, it is now essential to gather data related to the identified supply chain element in the current task (Phase 1 task two) as this data will be used in phase 2 of building the supply chain model. The data to be collected will relate to the number of members in each group, for example, the number of retailers. The research will also collect data relating to the types of milk produced for each retailer, how the milk is stored, transportation, volumes of production, production times and frequency, quantities delivered per time and process timings. The data that is collected contains static data (e.g., quantities and capabilities) and dynamic data (e.g., operational activities, data related to decision-making and day-to-day planning). The direction of data exchange is shown in Figure 6.5.

6.3.2.1 Sub-task 1: Data collection for supply chain actors

For the purpose of this research, an assumption is made that farmers supply all the milk to the specific manufacturer within this supply chain. This is based on the evidence gathered from interviewing a manager at the milk manufacturer (Participant 8); it has been gathered that the manufacturer, the retailer and the farmers have an understanding or an agreement where milk from a specific farm is only processed and produced for the relevant retailer where the farmer has been pre-screened to meet expectations of quality, hygiene, safety etc.

Where data is to be gathered from the farmer, relevant data may include:

a) The quantity of milk made on a daily basis, and this can be segregated by fat content.

b) The location of the firm, milking facilities, farm capabilities (Daily average milk production, quantity of cows and herd types).
c) Data from the milk collection plan which may include frequency of collection, collection times, etc.

However, this research will focus on the data that is available at the manufacturer's point of the supply chain and will not be collecting data from farmers.

Relevant data to be collected for this research from the manufacturer includes:

a) Production details; for example, storage capacity, number of production lines, average production from each product line.
b) Milk collection plan e.g., collection schedules, transportation schedule.
c) Milk production plan e.g., daily production, production times, production dates, processing time etc.
d) Milk distribution plan e.g., Transportation schedule, distance, truck capacity, how delivery is organised etc.

Table 6. 4: Data collected from supply chain members

Supply Chain Members	Data	Timeline of Data collected
Farmers	No data collected	N/A
Manufacturer	Name, Location, Phone Number, Email Addresses, Plant Capacity, Logical Positioning in the Supply Chain, Milk Production, Milk Warehousing, Milk Distribution, Milk Production Capacity per Milk Type, Other Dairy Products Produced.	3 years and 3 months from November 2018 to February 2022
Retailers	Name, Frequency Of Purchase, Storage Capacity, Logical Positioning in the Supply Chain.	3 years and 3 months from November 2018 to February 2022

It should be noted that for ethical considerations in this research and the lack of consent from the manufacturer, this research did not gather quantitative data from the retailers, however, general food retailers participated in interviews and information provided as part of those interviews are used to support simulations. It should also be noted that for the purpose of this research, it is assumed that retailers will only receive a supply of milk from this focal manufacturer in the supply chain. This is because the scope of this research is limited to the interactions of the retailers with this manufacturer. Relevant data for this research that collected for the retailer include:

a) All interactions with the manufacturer (quantity requested, quantity received, etc.).
b) Milk distribution plan.
c) Frequency of customer purchase.

All the relevant data collected for each supply chain actor is itemised in Table 6.4.

6.3.2.2 Sub-task 2 Materials flow

Raw milk is the most essential raw material that is used in the milk manufacturing process. In this supply chain the manufacturer gets informed of the daily production by the farmer which helps assess the volume of raw milk that needs to be transported from the farm to the manufacturing plant. The relevant data to the manufacturer from the farmer will include the quantity of raw milk and the fat content of the milk.

The second material which flows through the supply chain is the processed (pasteurised and standardised) milk which is the finished product to be delivered to the retailers. The data relevant in this instance is the quantity of each milk type available to be delivered to the retailers. Sometimes, the quantity agreed, and the quantity delivered may vary but this data is transmitted very regularly between the manufacturer and the retailer.

6.3.2.3 Sub-task 3: Data for supply chain functions

This refers to the data collected for the supply chain functions and processes identified in the milk supply chain. It includes data from the milk production, collection and distribution: data supporting raw milk collection sent to the manufacturer by the farmer, milk request and receipt data sent to the manufacturer by the retailer, milk production data generated by the manufacturer, milk distribution data also generated by the manufacturer. The data collected for these functions and processes will be used in Phases 2 and 3 of building the milk supply chain model to assess the impact of disruptions on resilience.

6.4 Big Data Warehousing in the Model Configuration

Sections 6.2 and 6.3 discuss the steps taken to configure the model used in the computer simulation experiments within this research including the data collected as part of this study. It is therefore important to discuss the steps taken in order to provide a semantically valid data to the simulation model based on the Big Data practices within the Big Data Warehouse utilised by the focal organisation in this study and introduced in sections 3.8 and 3.9.

As can be seen from Figure 3.4, the first step is the extract, transform and load (ETL) process. Here, the transportation, cost, order and distribution data which are managed using applications and systems such as Microsoft Excel, System Analysis Program Development (SAP) and other database are extracted, transformed and loaded on to the data preparation software Power Business Intelligence (Power BI), supported by Microsoft Azure and analysed using the Azure Analysis services. The data transformation that occurs in this process is responsible for correcting any synaptic errors that were identified when profiling the data. Afterwards, the insights gained on the supply chain's processes during interviews is combined with data which at this point should contain no synaptic errors to create a model which meets the simulation requirements of this thesis. Given that the model is developed based on the Big Data simulation needs, there is no need to search for value during run time which should be avoided in Big Data contexts as this can lead to the simulation running considerably slower. Once the data is prepared in a format that aligns with the simulation and supply chain needs, the data is integrated and stored in a Big Data Warehouse which in this case is the Azure Data Factory. The information in the Big Data Warehouse is then provided to the simulation which has already been validated as documented in section 5.5 and experiments are carried out according to the research or business needs.

6.5 Conclusion

This chapter discussed the steps taken in the model configuration for this research, building on the test model in Chapter 5. The steps taken to build the supply chain map, showing the key elements within the supply chain of interest, including the members of the supply chain (farmers, manufacturers and retailers), the way in which material flow within the supply chain and the direction in which information flows in the supply chain. The chapter ascertains that typically, information flows in the opposite direction of materials as the retailers send data via a distribution list to the manufacturer for quantities needed and the manufacturer uses that information to make decision and send an order request further up to supply chain to the farmers. The materials (milk) then flow from the farmers to the manufacturers and on to the retailers. The research provides evidence that the relationship between each element varies, and each element has to carry out specific processes and function in order for the supply chain to perform as expected; data on each function and process is also gathered.

These are essential because the supply chain map allows the research to build the model using WITNESS Horizon and the data gathered is essential to the running of the model.

Phase 2 of this model involves the introduction of the types of disruption identified in this chapter and that is carried out in Chapter 7. Phase 3 of this model involves measuring the supply chain resilience to the disruptions introduced in phase 2 and that is also carried out in Chapter 7. Chapter 7 present the results of phase 2 and 3. This chapter serves as the basis for the discussion of results from further experimentation on the supply chain using a simulation.

Chapter 7
SIMULATION EXPERIMENTS AND RESULTS

7.1 Introduction

After the collection and analysis of data for the milk manufacturer and retailers in this milk supply chain, a simulation model is developed to explore the impact of several disruptions within the supply chain. This simulation model is built utilising the WITNESS horizon software (Lanner Group 2016). The model includes three key actors that must be considered within the context of a milk supply chain namely: manufacturers, retailers and customers.

This chapter builds on Chapter 6 and Table 7.1 presents the series of experiments that are conducted (phase 2 and 3). The experiments were designed to investigate and evaluate various measures related to the resilience of supply chain operations in the milk industry. Specifically, the chapter focuses on three disruptions types (see section 2.4) that may occur in the supply chain and their impact on key measures of resilience, such as supply chain cost, customer service levels, and time to recovery discussed in section 7.4.

This chapter presents the results from the computer simulations starting with highlighting the experiments which are carried out in this research. The chapter goes on to provide information on the simulation process taken to conduct the experiments starting with the As-Is model and moving on to the other experiments carried out in order to measure the resilience of the supply chain. The chapter concludes by discussing how Big Data is applied in this research to measure supply chain resilience.

7.2 Experimentation in a Big Data Context

Experimentation in this thesis is carried out in a Big Data context as highlighted in section 6.4 and discussed further in section 7.5. The aim of the experiments is to provide a comprehensive understanding of how different types of disruptions affect the resilience of the supply chain, and to identify some critical factors that determine the resilience of supply chain. To achieve this, the experiments were designed to simulate various scenarios that may occur in a real-world supply chain environment, and to measure the impact of these scenarios on the different resilience measures. For example, where a production disruption occurs, what will be the impact on the customer service levels of the supply chain? Is it different from when a disruption occurs in the supply chain logistics? The experiments carried out are presented in Table 7.1 and the results of the experiments are presented in detail in the following sections and interpreted to draw meaningful conclusions regarding the resilience of the milk supply chain.

Table 7. 1: Simulation Experiments

Resilience Measure (Sections)	**Disruptions**	**Disruption Length**	**Retailer**			
As-Is (7.3)	*Scheduled maintenance (No Disruption)*	24 hours	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Supply Chain cost (7.4.1)	*Production Disruption*	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Demand Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Logistics Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Time to Recovery (7.4.2)	*Production Disruption*	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Demand Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Logistics Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Customer Service Levels (7.4.3)	*Production Disruption*	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Demand Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Logistics Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4

The first step within the simulation is the development of an As-Is model which presents how the milk supply chain operates prior to any interruptions or disruptions and provides this research a baseline with which to compare the supply chain after a disruption. The next steps involve the introduction of disruptions to the as-is model which necessitates the running of the model in three scenarios to reflect the disruption at the manufacturing level, the delivery to the retailer level and the customer level. It should be noted that in all scenarios, there is a potential for ripple effects and all actors within the supply chain are evaluated for impacts, however, examining ripple effects is out of scope for this research and disruptions are only applied to one actor in the supply chain at a time.

7.3 Simulation Process Overview

In this research, the process of simulation is the imitation (on a computer) of a milk supply chain as it progresses through time (Robinson, 2004) and involves the conversion of the supply chain map into a conceptual model and then on to a computer simulation software. This model takes into account the relevant entities in the milk supply chain and utilises the WITNESS simulation tool to approximate real-world behaviour as closely as possible. Figure 7.1 illustrates the conceptual model that serves as the precursor to the test model and consequentially, "as-is" model developed in the simulation tool. The simulation process in this research aligns with the processes of a simulation project documented in (Robinson, 2004)- see Figure 7.2.

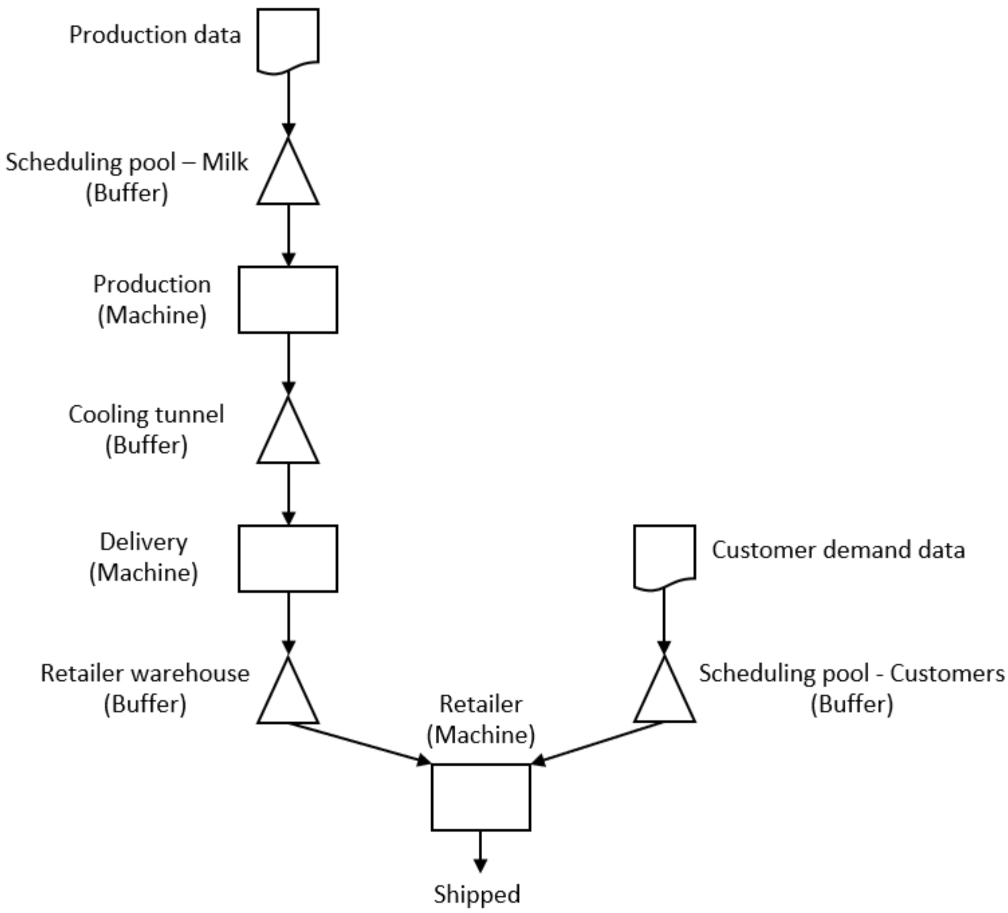


Figure 7. 1: Conceptual Model showing the simulated elements within WITNESS

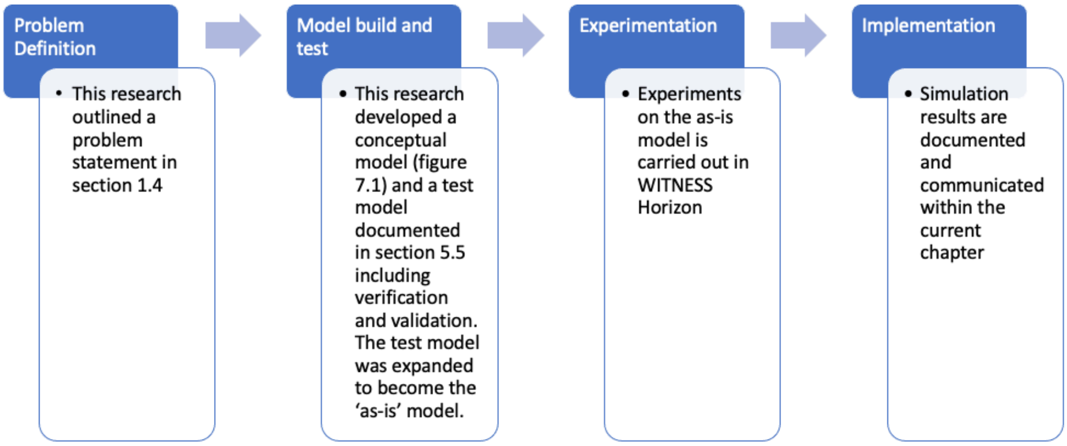


Figure 7. 2: The simulation process, adapted from Robinson (2004)

In the as-is model, the standard entities provided by the WITNESS Horizon software is used to represent processes and workings within the supply chain. Machines entities are utilised to carry out: the production function at the manufacturing level, the delivery function at the wholesale/retail level and the purchase function at the customer's level. This is because a machine entity in WITNESS allows for commands and data to be inputted and output to be recorded which is essential when trying to communicate the usual supply chain's behaviour to the software. Machine entities in WITNESS also provide a direct breakdown, which occurs when the meantime between disruptions is reached, and is fixed when the pre-set time for repairs which has been defined within the machine is expended. This allows the research to simulate a disruption within those machines. Parts are used in this model to represent each pint of milk which is produced separately as they go through the model. The model makes the assumption input (raw milk) is equal to output (processed milk). This is due to the density for raw milk and processed milk ranging from 1.027 to 1.033 gr, respectively (AHDB, 2022a). These densities are very close and as such the lost volume in the production process is insignificant. The buffer entities are used to represent storage at the manufacturing and retailing level. The manufacturer maintains a cooling tunnel which also serves as storage where produced milk is kept prior to delivery to the retailer. The retailers also maintain warehouses and large refrigerators where milk received from the manufacturer is stored and displayed for purchase by customers.

Table 7.2 displays elements that contributed to the simulation and provides a description of what those elements are and how they were applied in this simulation.

Elements considered include how the time was converted into minutes which were compatible with WITNESS Horizon simulation software, the total simulation run time and the repair time (the total time it took for the disruption to end).

Table 7. 2: Simulation Elements

	Elements	Description
1	Simulation Time in Minutes	The simulation time starts from the first day included in data collected which is 23/11/2018 and 00:00. The simulation considers this to be the start of time. The simulation time is the calculated as the number of minutes that have passed since 23/11/2018 at 00:00
2	Simulation run time	The simulation runs for a total of 1573000 minutes
3	Repair time (Minutes)	10080
4	Iterations before disruption	The iterations before a disruption utilises a uniform distribution between 1400 and 1600 operations

The as-is model represents the supply chain prior to any disruption. While the as-is model reflects a supply chain without major disruptions, the standard scheduled maintenance of machines by the manufacturer is simulated in order to reflect the reality of the manufacturer as much as possible. Figure 7.3 summarises the simulation results for an experiment with no disruption and is captured prior to any disruption that may have been caused by scheduled maintenance which occurs every six months and ensures that the baseline shows the standard performance of the supply chain.

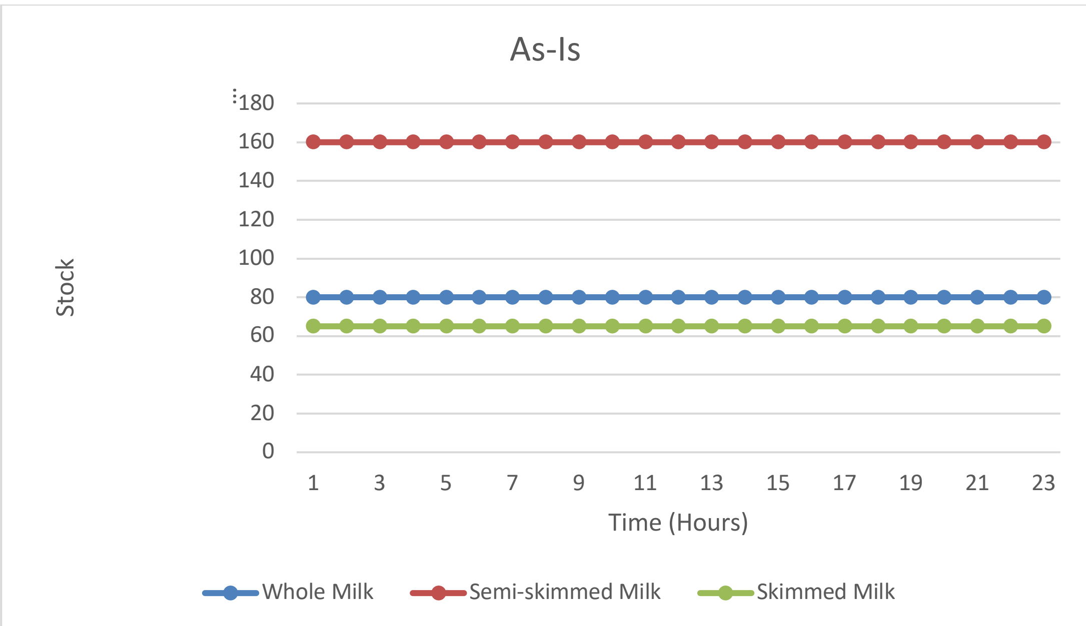


Figure 7. 3: The supply chain As-Is

Figure 7.3 showcases the supply chain in its current state before a disruption where a stock level of 80 pints of whole milk, 65 pints of skimmed milk and 160 pints of semi-skimmed milk is maintained to ensure a stable performance in the event of a disruption. These numbers hold true at Retailer 1, Retailer 2, Retailer 3 and Retailer 4. This implies that for this supply chain to function effectively, all retailers have to have approximately 300 pints of the different types of milk in stock. The number may be higher or lower at specific times depending on activities at various points on the supply chain. The number may reduce as customers continue to make purchases while the retailer waits for the next delivery from the manufacturer, but the supply chain is exposed to a higher level of risk when the number in stock reaches zero and the manufacturer is unable to supply for an extended period of time. This could mean that a customer who is unable to be served may choose a different retailer who does not belong to this supply chain in order to fulfil their demand. This research assumes that the longer customers have to wait to be served, the more impatient they may grow and ultimately can decide to go somewhere else. The as-is scenario will examine closely, stock out situations that last more than four hours per time as there is no disruption here but a scheduled maintenance (Table 7.1) which is usually over very quickly and can be foreseen and planned for. Additionally, the fact that milk is such a staple in regular eating habits while also having a very short shelf life implies that customers are less likely to wait days to fill their order (especially where the disruption only affects one supply chain) and more likely to take their demands to a competitor who is able to service their demands quicker. This behaviour is implied as milk that has stayed in the model past its shelf life is shipped out of the model and not used to satisfy a customer demand. However, this is not simulated as this is a discrete event simulation implying that "*only the points in time at which the state of the system changes are represented*" (Robinson, 2004).

This research focuses on the impact of specific disruption types on the resilience of the milk supply chain. Specifically, the study examines the impact of each disruption type on the supply chain's ability to recover and maintain its operations. It is important to note that this research has been designed with a specific focus on the impact of specific disruption types that can be prepared for and managed in advance. As such, the study does not take into account the day-to-day "natural" variations that may occur in the supply chain due to random or stochastic effects as these can be managed with good supply chain practices (Chopra and Sodhi, 2014) and are not the focus of this study. Focusing on the disruption types identified should provide insights into how the supply chain can be made more resilient and better able to cope with planned and unplanned disruptions; and also support this research in meeting its aim and objectives.

Figure 7. 4: Retailer 1 after scheduled maintenance

Following the scheduled maintenance, the supply chain has exhibited evident signs of a minor disruption, as seen in Figure 7.4. Specifically, a dip in the available stock levels at Retailer 1 has been observed. Nevertheless, despite this dip, there has been no complete depletion of stock until the 22nd hour, at which point the entire milk supply was depleted. However, it is worth noting that the supply chain quickly recovered at the 28th hour, which suggests a brief six-hour stock outage. Such an occurrence may be attributed to suboptimal planning of retail stock levels to cope with either routine maintenance or scheduled change.

Figure 7.5 shows the reaction of Retailer 2 to the slight disruption caused by the scheduled maintenance. Prior to the maintenance, Retailer 2 possesses slightly higher stock levels than Retailer 1 and evidently could be more resilient than Retailer 1. While the maintenance affected Retailer 2 as seen in Figure 7.5 where stock levels have a slight drop below initial performance levels, this retailer is still able to retain enough stock to satisfy customer demand. The semi-skimmed milk is the most affected at this retailer but still manages to avoid a complete stock out situation.

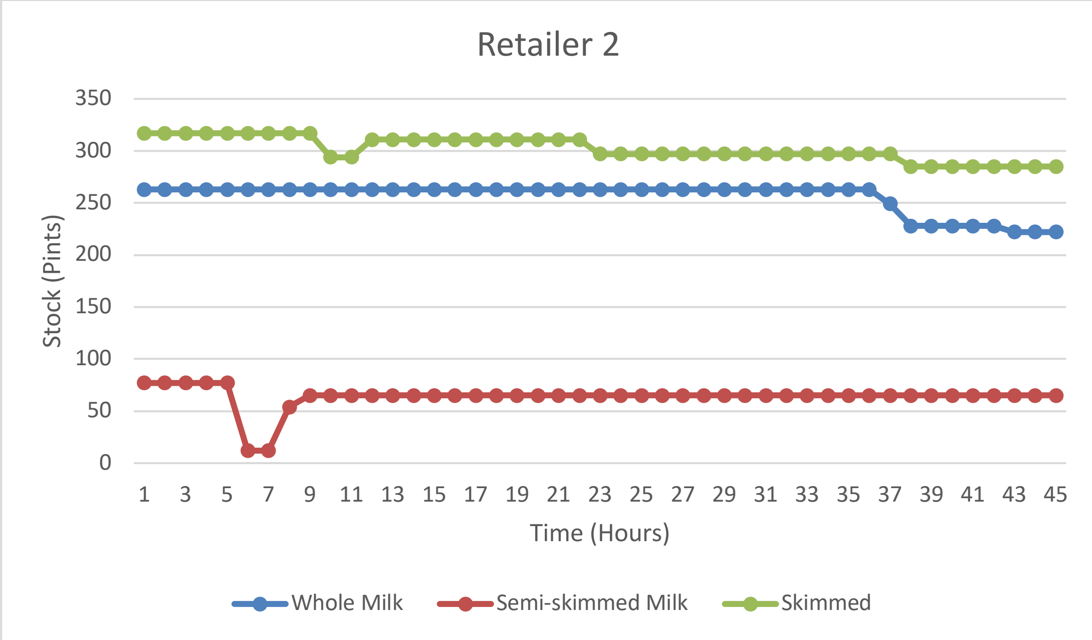


Figure 7. 5: Retailer 2 after scheduled maintenance

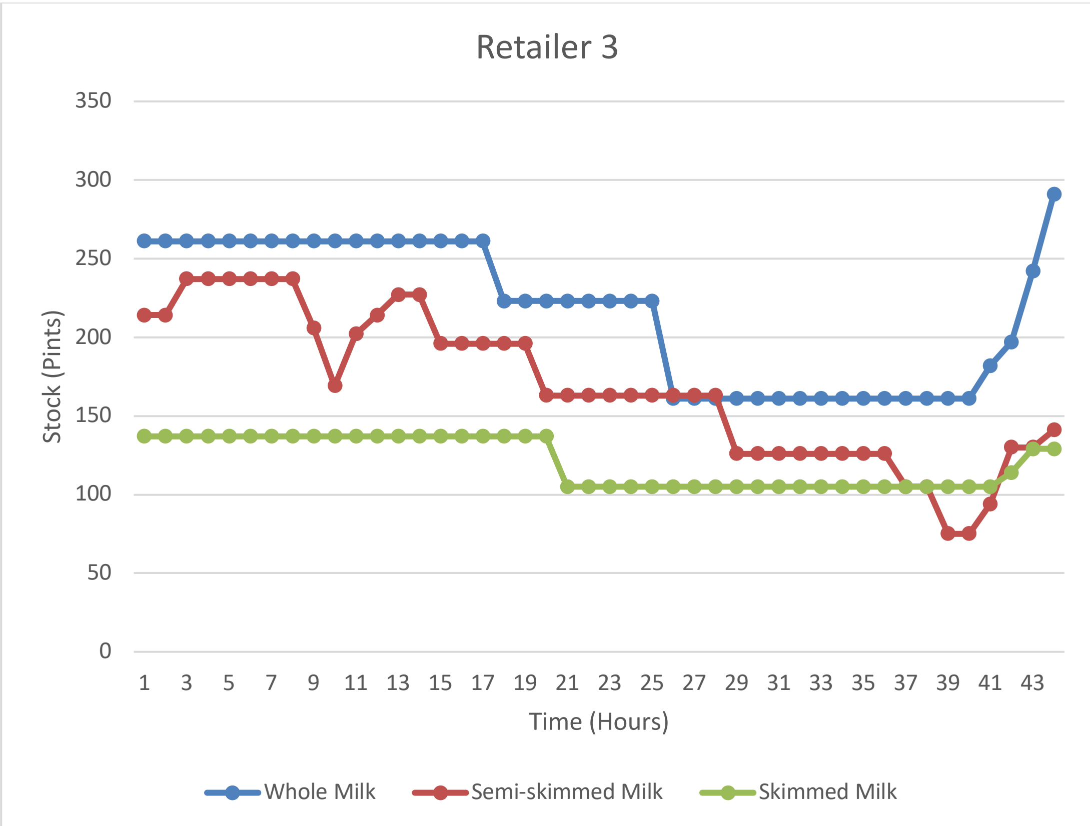


Figure 7. 6: Retailer 3 after scheduled maintenance

Retailer 3 records a continuous decline in stock availability as the whole milk, semi-skimmed, milk, and skimmed milk in Figure 7.6 continue to decline gradually. However, similar to Retailer 2, this retailer does not reach a complete stock out situation and continues with a good performance level at the end of the scheduled maintenance. Notably, this retailer also has higher stock levels than retailer one at the start of the scheduled maintenance. This may mean that, even though the stock levels will reduce along with performance, this retailer is still able to meet customer demands pending the end of the maintenance period and arrival of the next delivery from the manufacturer. However, given that the stock levels at Retailer 1 and Retailer 3 are not significantly different, the difference in performance may be due to planning or levels of customer patronage. This implies that if Retailer 3 has fewer customers patronising it, then it is easier to maintain performance given a similar stock level as Retailer 1.

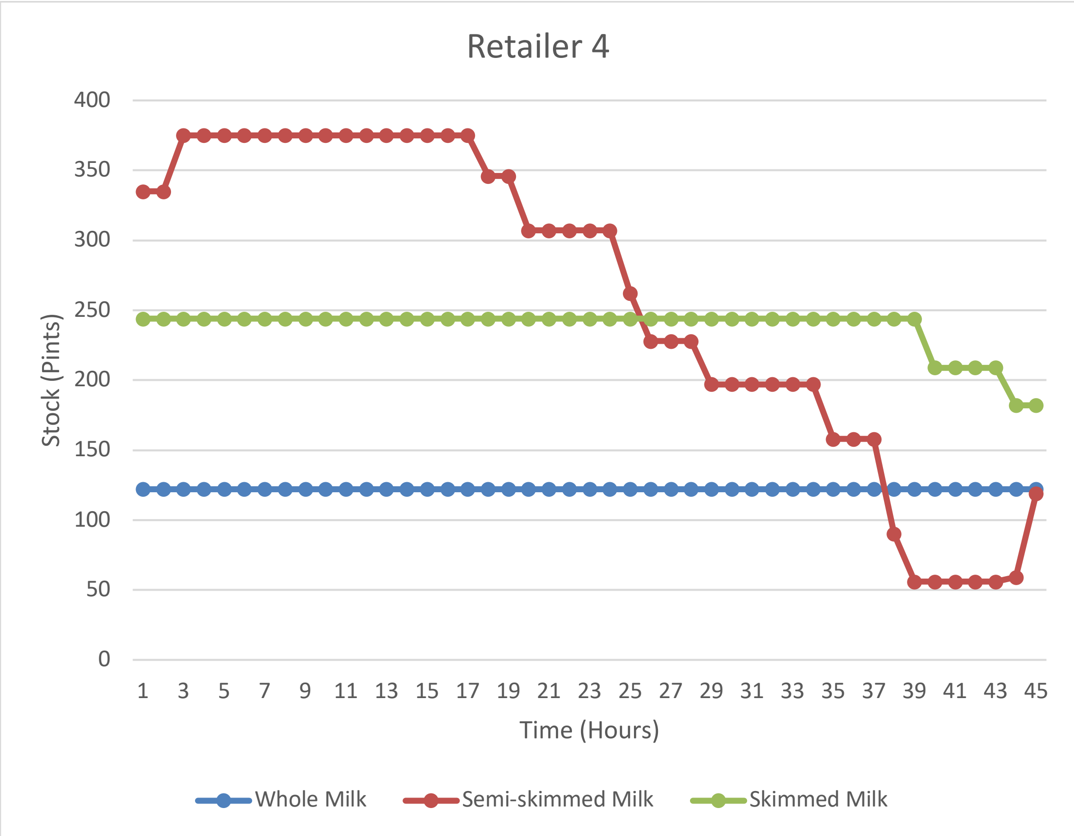


Figure 7. 7: Retailer 4 after scheduled maintenance

Figure 7.7 shows the reaction of Retailer 4 to the scheduled disruption which is a maintenance carried out to ensure that hygiene and health and safety standards are met. This implies that retailers and other members of the supply chain will be provided adequate information regarding this type of maintenance. As evident in Figure 7.7, Retailer 4 manages to maintain a fairly stable stock level for whole milk and skimmed from where they are also able to maintain performance until the end of the period. Semi-skimmed milk shows a steady decline following the disruption and this continues for 27 hours. However, given the level of stock that was present at the start of the maintenance period, this retailer does not reach a total stock-out situation by the end of the disruption but manages to bounce back.

Overall, this section highlights the impact of a scheduled maintenance in this milk supply chain on the retailers' stock levels and performance. It shows that the retailers' ability to cope with the disruption depends on their initial stock levels, planning, and customer patronage. Given that this is the minor disruption which occurs regularly, the supply chain quickly recovers. This quick recovery is to be expected as the retailers are usually informed of an upcoming scheduled maintenance. This may highlight the importance of adequate communication and planning to mitigate the impact of disruptions in supply chains. However, this research will carry out further experiments to ascertain the effects of unplanned and uncommunicated disruptions on the supply chain’s resilience.

7.4 Measuring Resilience

The milk supply chain resilience in this research is measured using three of the key parameters discussed in section 2.7.3. These parameters are: the time it takes for the supply chain to recover following a disruption, the total cost incurred due to the disruption, and the ability of the supply chain to maintain consistent and reliable service levels. The experiments that follow will be structured according to these three parameters. Measuring the resilience of milk supply chain is essential for ensuring the sustainability and efficiency of the system. The parameters used in this research provide a comprehensive framework for assessing the resilience of the supply chain. By focusing on these parameters, organisations can identify areas of improvement and enhance the resilience of their supply chain.

The research specifically explored the impact of the three types of disruptions identified in literature in section 2.4 on these parameters: production disruption, demand disruption, and logistics disruption.

- Production disruption examines a scenario where the manufacturer is unable to produce due to the breakdown of a machine or other issues that affect production capacity. This type of disruption can lead to shortages in the supply of milk, which can negatively impact customer service levels by causing delays or unfulfilled orders.

- Demand disruption refers to a scenario where customers suddenly change their purchasing habits, such as during a crisis or pandemic. For example, the COVID-19 pandemic has led to a shift in consumer behaviour, with some customers stockpiling food items and others reducing their consumption. This can lead to a mismatch between supply and demand, which can also negatively impact customer service levels.
- Logistics disruption refers to a scenario where milk cannot be delivered to retailers from the manufacturer due to logistical issues such as transportation disruptions, natural disasters, or other unforeseen events. This type of disruption can lead to delays in delivery and reduced availability of milk in stores, which can negatively impact the parameters being measured.

Each type of disruption is simulated for a one-week period as this provided a longer time frame to differentiate between the scheduled maintenance which had a one-day disruption time. This is also in line with what has been done in previous research on supply chain resilience conducted by Carvalho et al. (2011). The output results are retrieved from the simulation tool, analysed and discussed extensively in the next section.

7.4.1 Supply Chain Cost

The first parameter to be discussed in this research which provides insight into the resilience level of a supply chain is the supply chain cost which refers to the cost incurred by the supply chain as a result of the disruption. Supply chain costs is derived in the WITNESS Horizon simulation software by multiplying each pint of milk lost by the calculated total costs. The costs taken into consideration include material costs (MC), production costs (PC), transportation costs (TC) and inventory costs (IC) (Subbaiah et al., 2009; Sale et al., 2021). Material cost is calculated using equation 7.1 which was derived from Sale et al. (2021).

$$\boldsymbol{MC = \sum C_M * A_{RP}} \qquad \textbf{Eq 7.1}$$

In equation 7.1, C_M is the cost of raw material (milk purchased from vendor). A_{RP} is the amount of raw milk a specific company procures.

$$\boldsymbol{PC = \sum C_P * R_{PF}} \qquad \textbf{Eq 7.2}$$

Equation 7.2 calculates the production costs in a milk supply chain and is derived from Sale et al. (2021) where C_P is the cost of production of commodities by the manufacturing facility and R_{PF} is the number of products which the manufacturing facility produces.

Transportation costs is calculated using the formula given in equation 7.3 derived from Sale et al. (2021).

$$\boldsymbol{TC = \{\sum TC_{FF} * R_{RTFF}\} + \{\sum TC_{FC} * R_{PFCS}\} + \{\sum TC_{CR} * R_{CSTR}\}} \qquad \textbf{Eq 7.3}$$

In equation 7.3, TC_{FF} is the transportation cost of raw milk from the farmer to facility, R_{RTFF} is the amount of raw milk which is being transported from farmer to facility. TC_{FC} transportation cost of products from facility to cold storage, R_{PFCS} is the number of products which is transported from manufacturing facility to a cold storage. TC_{CR} is the transportation cost of products from cold storage to retailer and R_{CSTR} is the number of products transported from cold storage to retailer. This research only considers the transportation costs applicable to this specific manufacturer in this specific supply chain; and that includes the transportation costs incurred in transporting raw milk from the farmer to the manufacturing facility and the transportation cost incurred to transport the finished goods to the retailer. This manufacturer is not responsible for storage as that risk is borne by the retailers.

The final cost of the supply chain which is the inventory cost is calculated using the formula provided in equation 4 derived from Sale et al. (2021).

$$\boldsymbol{IC = \{\sum C_{HR} * A_{RF}\} + \{\sum C_{HP} * A_{PF}\} + \{\sum C_{HC} * A_{PCS}\}} \qquad \textbf{Eq 7.4}$$

In equation 7.4, C_{HR} is the Inventory cost of raw milk, A_{RF} is the amount of raw materials inventory within the facility. C_{HP} is the Inventory cost of finished products, A_{PF} is Inventory of finished products produced at the manufacturing facility. C_{HC} is the Inventory cost of finished products in cold storage and A_{PCS} is the inventory of products in cold storage. This research does not include the inventory cost as it focuses on the supply chain costs relevant to the manufacturer in this supply chain. The cost of inventory, warehousing and storage in this supply chain is borne by the retailer while the manufacturer bears the cost of distribution, transportation and logistics. This help to share the risks within the supply chain evenly among participants.

The manufacturer offers a 21 pence per litre (ppl) compensation in purchase of materials (raw milk) to the farmers as evidence in the interview where participant 8 states *"milk, each litre we pay the farmers, each litre is 21p for each litre"* and the Agriculture and Horticulture Development Board (AHDB) places the cost of the milk manufacturing process to the manufacturers at 35ppl (AHDB, 2022b). The farming forum discusses the cost of transportation as being approximately £1.50 per litre for 30 miles (The Farming Forum, 2018); this brings the cost of transportation to about 0.05 pence per litre per mile. The transportation cost is recorded twice to account for the transportation from farm to facility and from facility to the retailer. Thus, bringing the total cost to 0.66ppl (~37.6pence per pint) which is reflected in the simulation by multiplying each pint lost in the supply chain by 38pence.

The next sections provide the results of experiments within this research which consider the impact of the different types of disruption on the supply chain cost. First, the thesis takes a look at the impact of a production disruption on supply chain cost and discuss the implication on the resilience of each retailer. Then the research considers a demand disruption and a logistic disruption, experimenting on the impact of each disruption on the supply chain cost and examining this in light of the resilience of each retailer within the supply chain.

7.4.1.1 Production disruption

The results obtained from the simulation of a production disruption and its impact on supply chain costs in the milk industry are in line with existing literature on supply chain disruptions. According to Hishamuddiin et al. (2015) supply chain disruptions can result in significant increases in costs, which can be attributed to the disruption in the flow of goods and services within the supply chain network. The disruption in the production of milk in this simulation resulted in an increase in supply chain costs for all retailers, with some experiencing significantly higher costs than others.

Table 7.3 shows the supply chain costs for each retailer experiencing production disruption in a simulated supply chain system. The results indicate significant supply chain costs for all retailers after the production disruption. These findings are consistent with previous studies that have demonstrated the negative impact of supply chain disruptions on costs (Hishamuddiin et al., 2015; Olivares-Aguila and ElMaraghy, 2021).

Table 7. 3: Supply Chain Costs (Production Disruption)

Retailers	After Production Disruption (£)
Retailer 1	3266
Retailer 2	594
Retailer 3	795
Retailer 4	763

The results also highlight Retailer 1 as having the highest supply chain cost associated with the production disruption. This is unsurprising as Figure 5.3 indicates that this retailer has the highest milk purchase which is indicative of customer numbers and activities. The high supply chain cost may be attributed to the usual number of sales and exchange of goods. However, Retailer 3 and Retailer 4 have a close similarity in supply chain cost even though retailer 3 has a significant number of orders more than Retailer 4 (Figure 5.3). This may indicate that Retailer 4 is less resilient to a production disruption than Retailer 3. Retailer 2 who has a high sales and order number than Retailer 3 and Retailer 4 (see Figure 5.3) managed to keep the financial impact of a production disruption lower than Retailer 3 and Retailer 4. This may indicate that Retailer 2 is more resilient to a production disruption than Retailer 3 and Retailer 4. These findings suggest that production disruptions can have a significant impact on costs, which highlights the importance of developing robust and resilient supply chain systems that can better withstand disruptions (Chen et al., 2019).

Key findings in the experiment examining the impact of a production disruption on supply chain costs show that the higher the activity level, the higher the cost that is incurred during a production disruption which is the experience of Retailer 1 and this holds true for Retailer 2 and Retailer 3 who have costs impact commensurate with their activity levels. However, Retailer 4 has an impact that is not commensurate with their typical activity level and that reflects a reduced resilience level. Retailer 2 demonstrates higher resilience by having a reduced supply chain cost than commensurate.

7.4.1.2 Demand Disruption

The simulation of demand disruption also had an impact on the supply chain costs for all retailers. Table 7.4 shows the impact of demand disruption to the retailers, and it is evident that all retailers experienced financial impacts to this disruption in varying levels. Retailer 1 also had the highest impact level which is similar to the production disruption scenario, and this could also be due to the fact that Retailer 1 in general has the highest activity level (Figure 5.3) in terms of orders, demands and volume. The higher cost may only be a reflection of that level of volume and activity for this retailer. Contrary to production disruption scenario (Table 7.3), the demand disruption scenario sees Retailer 3 having a significantly less supply chain cost implication than Retailer 4 even though Retailer 4 typically handles less volume than Retailer 3 (see Figure 5.3). This could indicate that Retailer 3 is more resilient to a demand disruption than Retailer 4 which is similar to the production disruption scenario. However, the demand disruption scenario makes it more conspicuous as the difference in supply chain cost is higher. Retailer 2 has managed to keep the supply chain cost incurred in the demand disruption scenario fairly consistent with the production disruption scenario.

Table 7. 4: Supply Chain Costs (Demand Disruption)

Retailers	After Demand Disruption (£)
Retailer 1	2623
Retailer 2	583
Retailer 3	275
Retailer 4	653

It is essential for supply chains and the specific members of the supply chain to maintain consciousness of the disruptions that could affect their supply chains and take steps to reduce and mitigate the impact. This is evident with Retailer 3 who significantly has a reduced impact in the demand disruption scenario when compared with production disruption.

Key findings from the experiment examining the impact of a demand disruption on the supply chain cost suggest that different types of disruptions can have varying impacts on supply chain costs, depending on the specific factors involved. In the case of a production disruption, there can be significant increases in supply chain costs due to the loss of production and customers. However, in the case of a demand disruption, the supply chain also experiences costs associated with scrappage where milk has to be discarded and costs associated with lost revenue and both scenarios can be mitigated in different ways.

7.4.1.3 Logistics Disruption

The simulation of logistics disruption showed a significant increase in supply chain costs across all retailers. This is in line with previous research that has shown that disruptions in the supply chain can have a significant impact on costs (Hishamuddiin et al., 2015; Olivares-Aguila and ElMaraghy, 2021) and that disruptions from the supply side (which includes logistics) have a higher impact on the supply chain than disruptions on the demand side (Choudhury et al., 2022). Logistics disruptions can result in delays and increased transportation costs, which can affect the entire supply chain.

Table 7. 5: Supply Chain Costs (Logistics Disruption)

Retailers	After Logistics Disruption (£)
Retailer 1	9346
Retailer 2	781
Retailer 3	5896
Retailer 4	4642

Table 7.5 indicates a significant increase in supply chain cost for Retailer 1, Retailer 3 and Retailer 4. Retailer 1 maintains the highest supply chain cost considering the significant cost increase, while Retailer 3 and Retailer 4 also see a dramatic increase in the cost associated with logistic disruption when compared with the production disruption and demand disruption scenarios. Retailer 3 had seen a reduction in cost in the event of demand disruption, but the logistic disruption presents a different cost association where Retailer 3 experiences high-cost impact. Retailer 2 however experiences a lower cost impact when compared with the other retailers even though Retailer 2 experiences a slightly higher cost in logistic disruption than in demand disruption and production disruption. This is indicative of the higher level of resilience for Retailer 2 who appears stable with limited impact across all three disruption types.

The results of this simulation highlight the importance of having contingency plans in place to mitigate the impact of disruptions in the supply chain. This can include having alternative transportation methods or backup suppliers to ensure that the supply chain remains resilient in the face of disruptions (Dolgui et al., 2018). Furthermore, the impact of logistics disruptions can also be influenced by the location of the retailers and the manufacturer. Research has shown that the location of suppliers and customers can have a significant impact on the costs of transportation and logistics (Hishamuddiin et al., 2015; Singh et al., 2020; Tsiamas and Rahimifard, 2021). Therefore, companies need to consider the geographical distribution of their suppliers and customers when designing their supply chain networks to minimise the risk of disruptions.

Key findings from the simulation of a logistic disruption showed a significant increase in supply chain costs and highlighted the importance of contingency planning and the geographical distribution of suppliers and customers in designing resilient supply chains.

7.4.2 Time to Recovery

The next parameter to be discussed as part of this research which measures the resilience of the milk supply chain is the time to recovery after disruptions. Time to recovery considers the amount of time it takes for the supply chain to return to its normal state or better following a disruption (Carvalho et al., 2012). Hence, this research calculates the time to recovery for each disruption type as the time it took for that supply chain to recover after a disruption to stock levels similar with the As-Is stock levels.

This study found that the time to recovery varied depending on the type of disruption. The concept of time to recovery as a measure of resilience has been widely discussed in the literature (Carvalho et al., 2012; Munoz and Dunbar, 2015a). According to Pavlov et al. (2018) and Dubey et al. (2019), resilience is a function of both the ability to withstand disruptions and the ability to recover from them quickly. Similarly, Ponomarov and Holcomb (2009) and Brandon-Jones et al. (2014) define resilience as the ability of a system to withstand stress and recover from disruption. In the context of supply chain management, time to recovery has been identified as an important performance measure of supply chain resilience (Sheffi and Rice, 2005). Resilient supply chains are those that can recover quickly from disruptions, minimizing the impact on customers and minimising supply chain costs.

The findings of this study highlight the importance of considering the time to recovery when assessing supply chain resilience which corroborates previous studies (Christopher and Peck, 2004; Sheffi and Rice, 2005; Ponomarov and Holcomb, 2009) as different types of disruptions can have varying recovery times. This information can be used by supply chain managers to develop strategies for improving supply chain resilience and reducing the impact of disruptions on supply chain performance.

The next sections provide the results of experiments within this research which consider the impact of the different types of disruption on the time to recovery. First, the thesis takes a look at the impact of a production disruption on recovery time and discuss the implication on the resilience of each retailer. Then the research considers a demand disruption and a logistic disruption, experimenting on the impact of each disruption on the time to recovery and examining this in light of the resilience of each retailer within the supply chain.

7.4.2.1 Production Disruption

This section reviews the impact of a production disruption at the manufacturing plant on the time to recovery of the milk supply chain. In simulating the time to recovery of the supply chain from a production disruption, the research found that each retailer's reaction and recovery time was different. This is due to a number of factors.

As seen in Figure 7.3, the retailers maintain a controlled stock level for each milk type to allow resilience. Semi-skimmed milk is maintained at 160 pints in inventory, Skimmed milk at 65 pints and whole milk at 80 pints. This research considers whether the supply chain inventory levels drop below this and where it does, how long does it take for the supply chain to bounce back to these levels or higher in order to ensure resilience.

After a production disruption, the research finds that Retailer 1 was out of stock for all three types of milk, despite maintaining a higher stock level for both skimmed and semi-skimmed milk compared with the stock level for whole milk. However, Retailer 1 managed to bounce back to the required stock levels to ensure resilience after a period of over 155 hours for whole milk, 160 hours for semi-skimmed milk and 150 hours for skimmed milk. As represented in Figure 7.8, the drop in performance was almost immediate without any staggering effect and this may be due to the lack of backup stock.

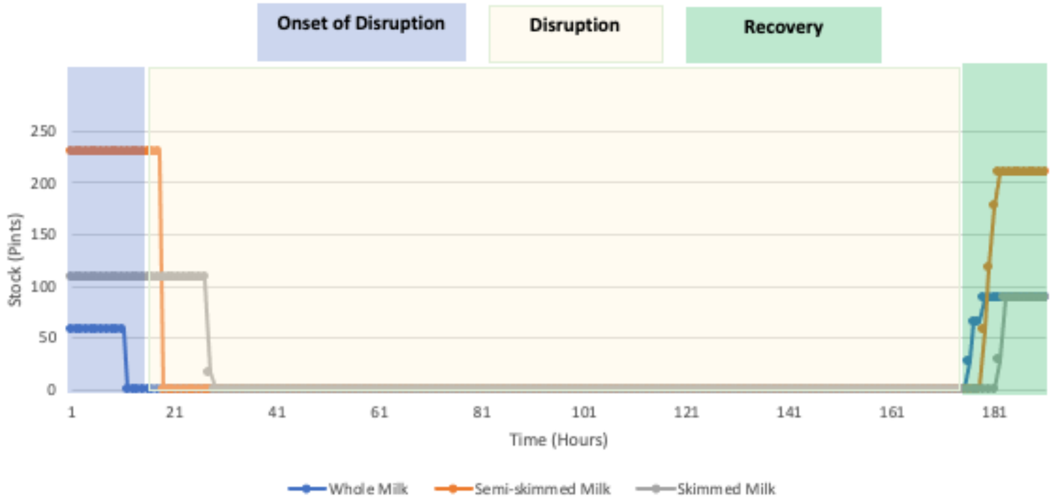


Figure 7. 8: Time to recovery after production disruption-Retailer 1

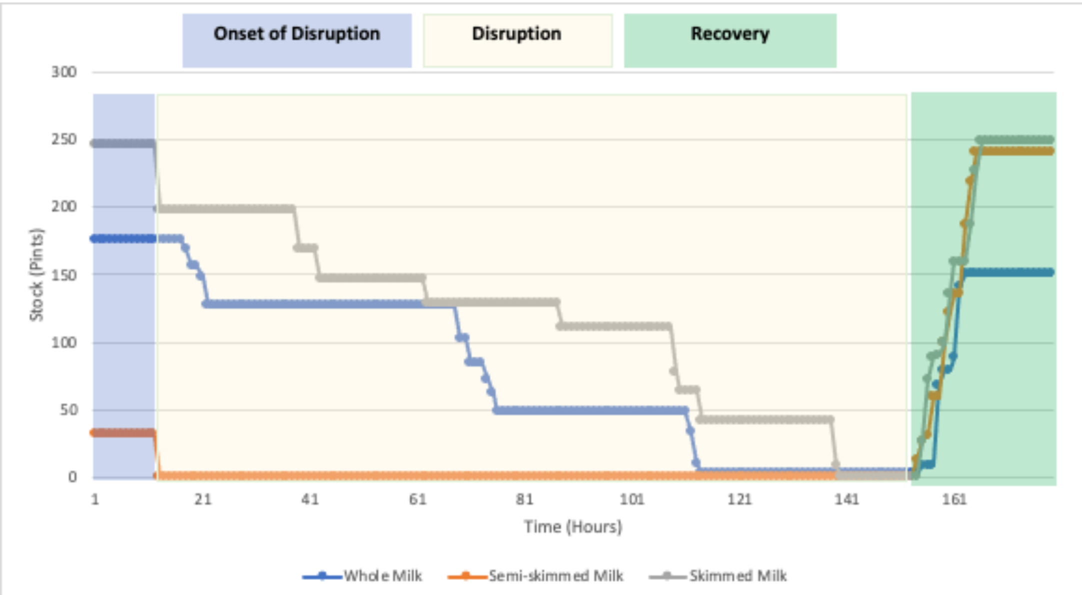


Figure 7. 9: Time to recovery after production disruption-Retailer 2

Retailer 2 on the other hand, maintained a lower level of stock for semi skimmed milk, than Retailer 1 and a higher level of stock for skimmed milk and whole milk, when compared to Retailer 1. Figure 7.9 shows that retailer 2 was out of stock on its semi skimmed milk for over 140 hours with a quick drop in performance but whole milk and skimmed milk reflected a staggered drop in performance. The effect of the disruption on retailer 2 lasted on the whole milk for about 131 hours and skimmed milk for about 138 hours; however, an extreme outage where the stock levels reached 0 was delayed for both the whole milk and skimmed milk. This may be due to the ability of retailer 2 to use the excess stock as back up, allowing for a reduced time in extreme outage to about 30 hours. Retailer 2 achieved a full recovery, bouncing back after a disruption to inventory levels recorded in Figure 7.3 and higher in some instances.

With Retailer 3, results in Figure 7.10 present whole milk and skimmed milk with higher stock levels than the stipulated stock levels in Figure 7.3 which reflects backup stock. Prior to the disruption, Retailer 3 maintained higher stock levels of about 190 pints of whole milk as against the usual 80 pints, 110 pints of skimmed milk as against the usual 65 pints. Retailer 3 also maintained a lower than usual stock level for semi-skimmed milk where only 80 pints are in stock as against the usual 160. This retailer showed a staggered reduction in performance and picked up very quickly in the recovery period. Skimmed milk maintained a stable stock level for longer than whole milk and semi-skimmed milk and picked up alongside the other two types of milk at this retailer. Skimmed milk recovered after 100 hours to stock levels pre-disruption, while whole milk was out for 130 hours and semi-skimmed milk for 144 hours. This may once again be due to stock levels available, and inventory kept by the retailer allowing for the supply chain to cope effectively when disrupted and to recover quickly.

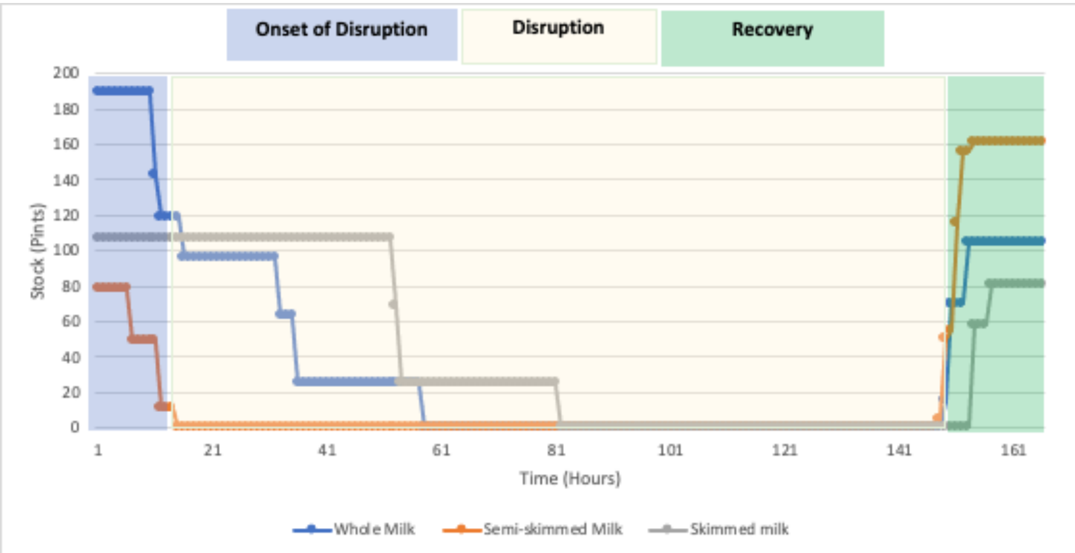


Figure 7. 10: Time to recovery after production disruption-Retailer 3

Retailer 4 in Figure 7.11 interestingly was able to maintain a standard level of stock for whole milk due to having high enough stock levels. Skimmed milk and semi-skimmed milk showed a relatively low staggering in performance reduction, taking about 101 and 113 hours to recover from the effects of a production disruption. The whole milk may have maintained a consistent performance level due to reduced patronage while stock for semi-skimmed milk and skimmed milk with higher patronage showed staggered performance reduction in a disruption.

The findings in this research show that holding backup stock supports resilience across all disruption types which is contrary to the work of (Ivanov, 2019) who holds that safety and backup stock will only mitigate some types of disruption and offer limited resilience. This also contradicts other studies who purport that holding backup stock could be considered inefficient (Aldrighetti et al., 2019). The results in this thesis highlight the importance of retailers' ability to manage their inventory effectively and quickly adapt to a disruption in the supply chain (Balcik et al., 2010).

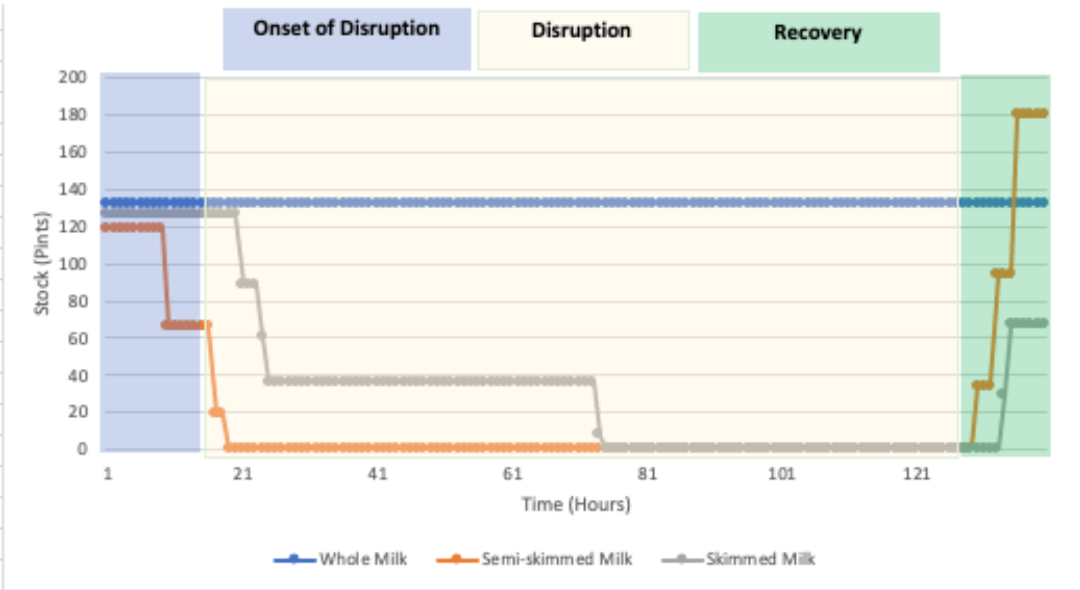


Figure 7. 11: Time to recovery after production disruption-Retailer 4

The research found that, for the time to recovery from a production disruption, different retailers showed varied recovery times. Table 7.6 shows the approximate time in hours taken for the supply chain to recover similar levels recorded in Figure 7.3 (prior to the disruption) or a better state and the associated supply chain costs.

Table 7. 6: Summary of Time to Recovery after production disruption

Disruption Type	Retailer	Milk Type	Time to Recovery (Hours)	Cost (£)
Production Disruption	Retailer 1	Whole	155	3266
		Semi-skimmed	160	
		Skimmed	150	
Production Disruption	Retailer 2	Whole	131	594
		Semi-skimmed	140	
		Skimmed	138	
Production Disruption	Retailer 3	Whole	130	795
		Semi-skimmed	100	
		Skimmed	144	
Production Disruption	Retailer 4	Whole	N/A	763
		Semi-skimmed	113	
		Skimmed	101	

Summarily, Retailer 1 experienced prolonged stock-out situations for all milk types despite higher stock levels for certain types. Retailer 2 had a quicker decline in performance for one type of milk but managed to utilise excess stock as backup, reducing outage time. Retailer 3 demonstrated staggered performance decline due to varying stock levels, while Retailer 4 maintained consistent performance for one type of milk but staggered decline for others. Stock levels and backup availability played a significant role in the retailers' ability to cope and recover during disruptions. It is also evident from Table 7.6 that in the event of a production disruption the longer the time to recovery, the higher the supply chain costs incurred by the retailer. Retailer 1 incurs the highest supply chain cost which can be associated with the length of time it took for that retailer to recover. However, Retailer 4 who has no stockout for whole milk incurring higher costs than Retailer 2 who had stockouts for all milk types. This may be associated with adequate planning for associated costs such as the cost of inventory.

The key findings underline the influence of stock levels, backup stock availability, and inventory management on retailer reactions and recovery times during a supply chain disruption. The results show that excess and back up stock when combined with adequate planning can support resilience and reduce the impact of associated costs. This suggests that retailers' ability to manage their inventory effectively, maintain high stock levels, and use excess stock as backup can reduce the time to recovery in a supply chain disruption and keep supply chain costs low. Retailer 1's lack of backup stock resulted in a longer time to recovery and higher supply chain costs, while retailers 2, 3, and 4 were able to recover more quickly due to their effective inventory practices.

7.4.2.2 Demand Disruption

The research also simulated demand disruption to measure the time it takes for the supply chain to recover after a demand disruption. The demand disruption here simulates a situation with a change in customer buying behaviour as discussed in section 2.4 and experienced during the COVID-19 pandemic. The research measures the time it takes for the supply chain to recover from that disruption and go back to performance levels prior to disruption recorded in Figure 7.3. The results of the demand disruption on the time to recovery of the supply chain are discussed next.

Figure 7.12 shows a clear decline in the quantity of stock available at Retailer 1 for whole milk and semi-skimmed milk with whole milk disrupted for 20 hours and semi-skimmed milk being disrupted for 11 hours. However, skimmed milk retained stock levels through the period of disruption, showing partial resilience. This may be due to adequate planning of stock levels and the levels of patronage for each milk type.

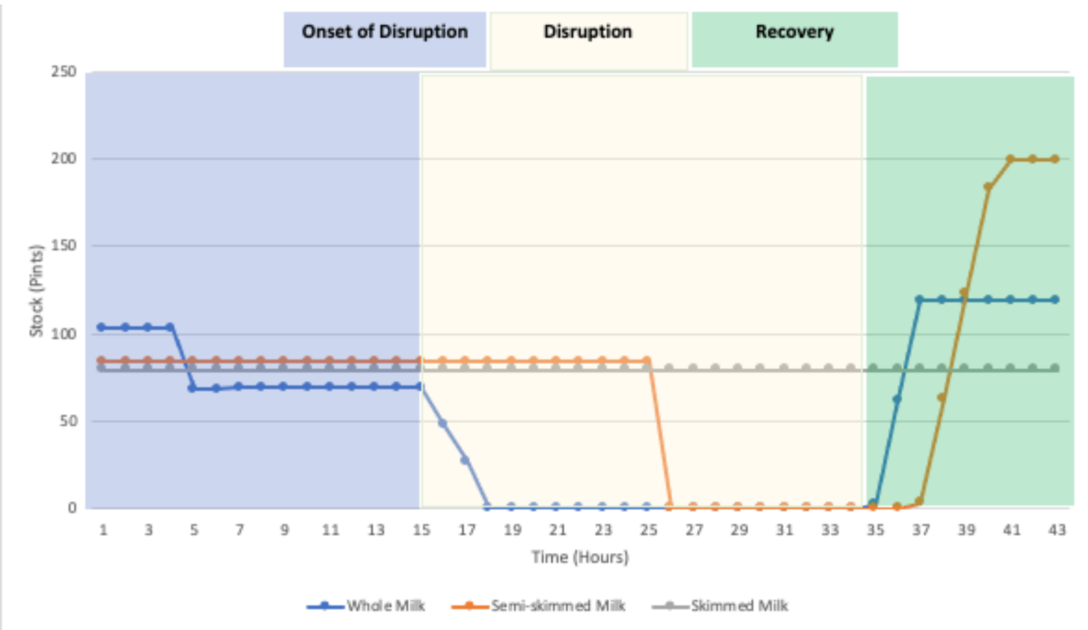


Figure 7. 12: Time to recovery after demand disruption-Retailer 1

Figure 7.13 demonstrates how retailer 2 reacts to the demand disruption. This retailer has slightly higher stock levels than retailer 1 and is therefore more resilient for longer. The disruption causes a slight drop in stock levels, particularly for semi-skimmed milk, but the retailer manages to retain enough stock to satisfy customer demand and avoid a complete stock-out situation.

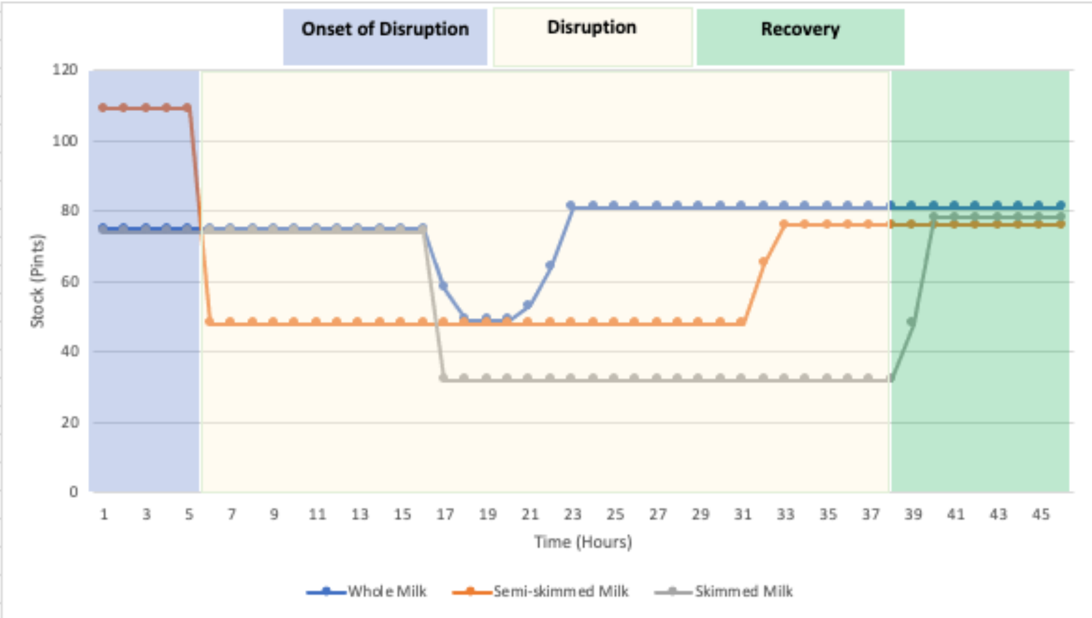


Figure 7. 13: Time to recovery after demand disruption-Retailer 2

Retailer 3 experiences a continuous decline (Figure 7.14) in stock availability across all types of milk, but it does not reach a complete stock-out situation during the demand disruption. This retailer has higher stock levels than Retailer 1 at the start of the disruption period, suggesting that it can meet customer demands despite reduced performance. Whole milk at Retailer 3 declines in performance for about 22 hours and skimmed milk declines in performance for 18 hours while semi-skimmed milk declines for 26 hours. The difference in performance between Retailer 3 and Retailer 1 may be due to planning or levels of customer patronage.

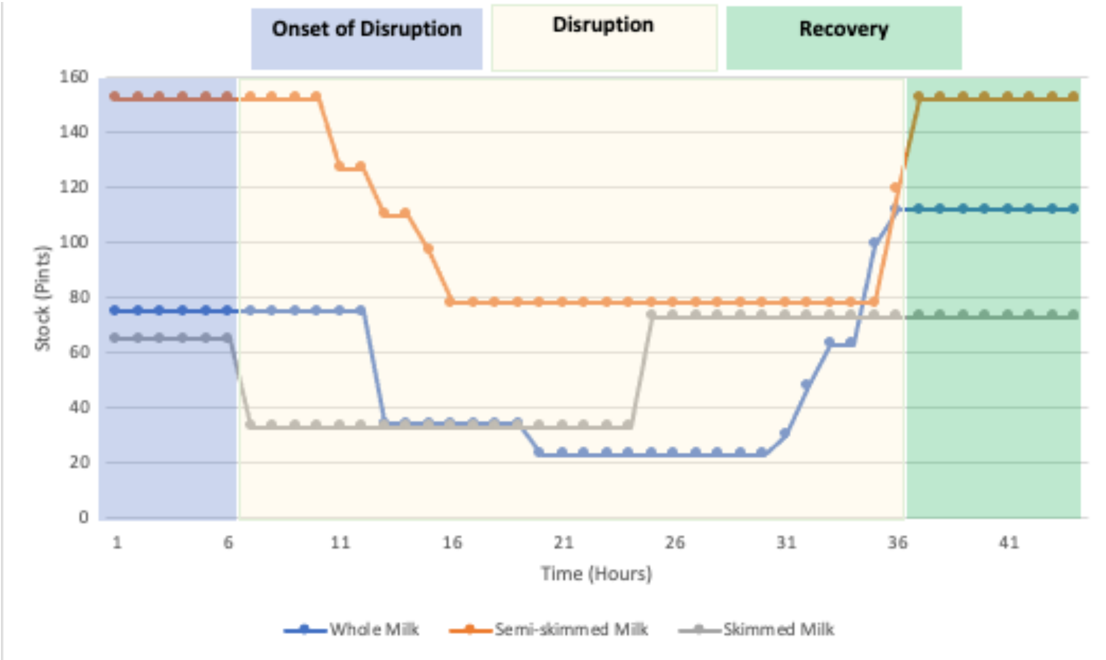


Figure 7. 14: Time to recovery after demand disruption-Retailer 3

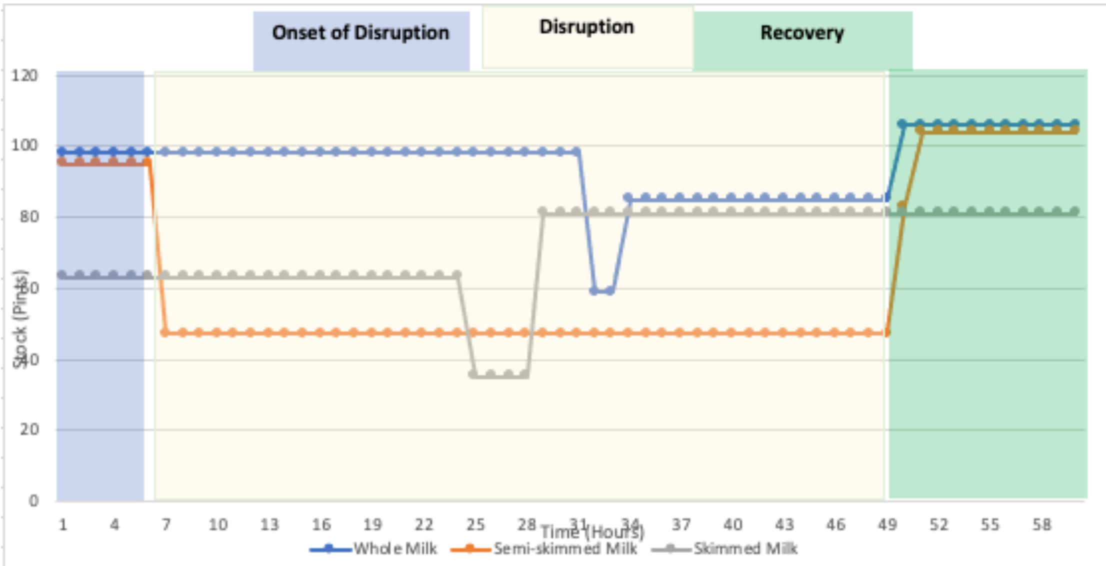


Figure 7. 15: Time to recovery after demand disruption-Retailer 4

Figure 7.15 illustrates how retailer 4 responds to demand disruption. This retailer manages to maintain a fairly consistent stock level for whole milk and skimmed milk and therefore maintains performance throughout the disruption period. Semi-skimmed milk shows a steady decline following the disruption, but the retailer does not reach a total stock-out situation due to the level of stock present at the start of the disruption period.

The results recorded in the demand disruption when measuring the time to recovery parameter for resilience is very similar to the results recorded when measuring the supply chain costs and customer service levels. The demand disruption had the least impact on all parameters as seen in Table 7.7 (compared with Table 7.6 and Table 7.8) which summarises the time it takes for the retailers to reach stock levels recorded in Figure 7.3 or higher; as well as the supply chain costs associated with the disruptions.

Table 7. 7: Summary of Time to Recovery after demand disruption

Disruption Type	Retailer	Milk Type	Time to Recovery (Hours)	Cost (£)
Demand Disruption	Retailer 1	Whole	20	2623
		Semi-skimmed	11	
		Skimmed	N/A	
Demand Disruption	Retailer 2	Whole	6	583
		Semi-skimmed	26	
		Skimmed	21	
Demand Disruption	Retailer 3	Whole	22	275
		Semi-skimmed	26	
		Skimmed	18	
Demand Disruption	Retailer 4	Whole	19	653
		Semi-skimmed	43	
		Skimmed	4	

Overall, several key findings emerged from the study. Retailer 1 encountered a decrease in stock availability for whole milk and semi-skimmed milk during the disruption, with both reaching stockouts, whereas skimmed milk displayed partial resilience, likely due to effective planning of stock levels and understanding of customer demand. However, Retailer 1 maintained the highest supply chain costs associated with this type of disruption (demand) when compared with other retailers. Retailer 2, with slightly higher stock levels than Retailer 1, demonstrated greater resilience by managing to meet customer demand and avoid complete stock-out situations. This kept the supply chain cost for Retailer 2 low compared to Retailer 1. Retailer 3 experienced a continuous decline in stock availability for all milk types during the disruption but did not reach a point of complete stock-out, possibly due to starting with higher stock levels and being able to meet customer demands despite reduced performance. This also kept the associated supply chain for Retailer 3 low when compared to Retailer 1 and Retailer 2. In contrast, Retailer 4 maintained consistent stock levels and performance for whole milk and skimmed milk, and although there was a decline in stock for semi-skimmed milk, the retailer did not face a total stock-out due to having sufficient initial stock levels.

Hence, the key points to note here include that effective stock planning and understanding of customer demand patterns are crucial in enabling retailers to recover efficiently from demand disruptions. It is also evident that reaching a complete stockout increases the supply chain cost because where retailers did not experience any stockout even though they were impacted by a disruption, those retailers recorded lower associated supply chain costs. Finally, demand disruption had the least impact on time to recovery.

7.4.2.3 Logistics Disruption

The impact of a logistical disruption on the time to recovery created multiple long lasting disruption points in the supply chain and this corroborates the findings when measuring other resilience parameters where this type of disruption recorded the highest impact to supply chain costs and customer service levels. While each retailer recorded multiple impacts from this type of disruption, this section will only discuss one typical time to recovery during logistics disruption. This is because of very close similarities with the other multiplicities, a selection of additional data to show multiple impacts is shown in Appendix A.

Retailer 1 experienced the highest level of impact during the disruption, with a total stock out time averaging 130 hours for skimmed milk (Figure 7.16). Semi-skimmed milk and whole milk experienced a reduction in performance lasting 123 hours and 120 hours respectively. These extended periods of low performance and eventual stock outs can have a significant impact on customer loyalty as customers may turn to other retailers to satisfy their needs. The staggered reduction in performance with higher levels of stock for whole milk can be attributed to the ability of the retailer to manage their inventory levels effectively. However, the drastic and quick drop in performance for semi-skimmed milk with high stock levels suggests that the retailer may have had difficulty managing their inventory levels and planning for the levels of patronage for this product in the event of a disruption.

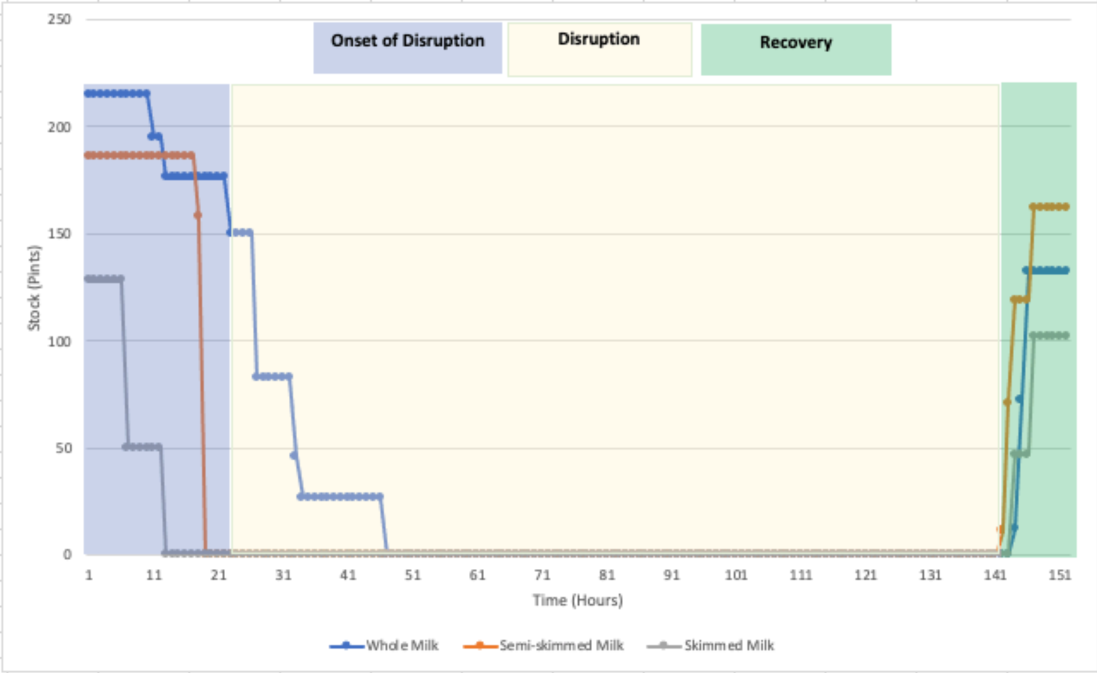


Figure 7. 16: Time to recovery after logistics disruption-Retailer 1

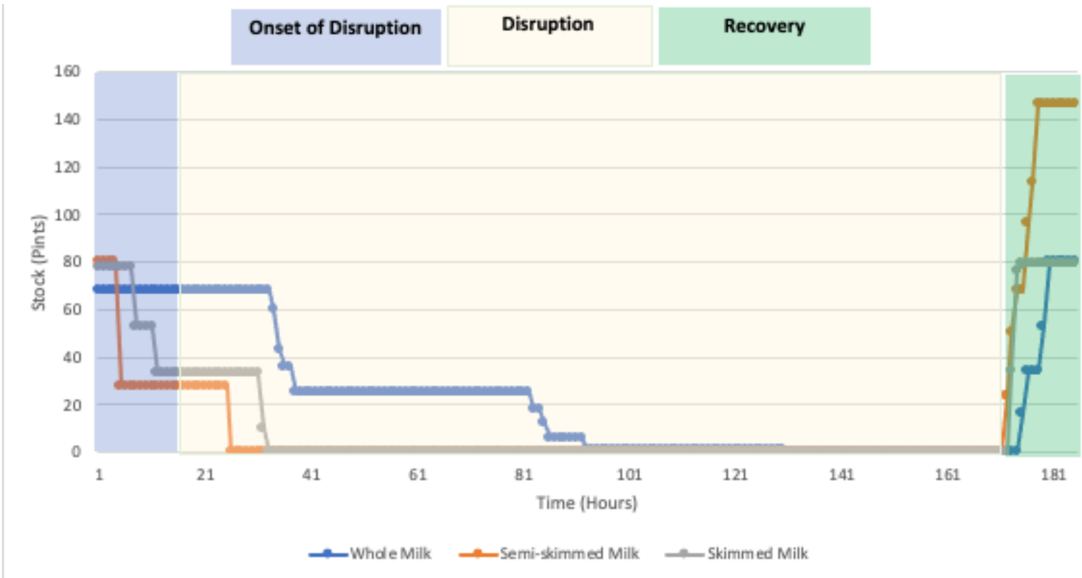


Figure 7. 17: Time to recovery after logistics disruption-Retailer 2

Retailer 2 was able to stagger the reduction in performance for both whole milk and skimmed milk as long as possible but still experienced a complete stockout situation with semi-skimmed milk for an average of 150 hours as depicted in Figure 7.17. Whole milk and skimmed milk experience the impact of the disruption and were only able to recover after 130 hours and 145 hours respectively. However, the quick recovery of performance as soon as the disruption ended suggests that the retailer was able to recover quickly and effectively. This retailer had lower levels of stock than was recorded in the as-is model (Figure 7.3) and was able to recover to performance levels averaging 80% of what was expected as per the as-is model. This could reflect a change in ordering choices by the retailer due to experiences during the disruption.

Retailer 3 maintained lower levels of stock and experienced an immediate reduction in performance (Figure 7.18). The time to recovery at the retailers took 148 hours for whole milk, 150 hours for semi-skimmed milk and 153 hours for skimmed milk. These long periods of reduced performance can have significant impacts on the supply chain. This can have a significant impact on customer loyalty, as customers may perceive the retailer as unreliable or unable to meet their needs. According to a study by Sahagun and Vasquez-Parraga (2014), customer loyalty is critical in the retail industry where consumers operate in a low-switching cost environment and as such, can decide to switch to a competitor after just one negative experience.

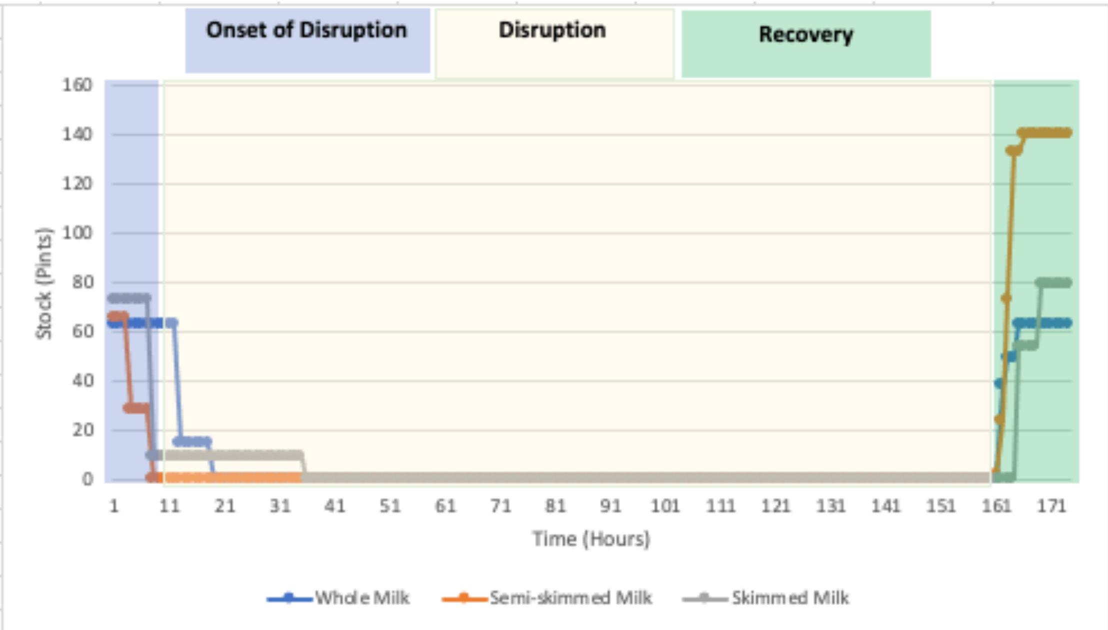


Figure 7. 18: Time to recovery after logistics disruption-Retailer 3

Retailer 4 maintained a slightly higher stock level than retailer 3 and was able to have more of a staggered reduction in performance as evidenced in Figure 7.19. However, this retailer still had significant periods of stock outage where they were unable to serve customers with disruption effect lasting 136 hours for whole milk, 157 hours for semi skimmed milk and 140 hours for skimmed milk.

Having a staggered performance decline provides the retailer with time to manage customer expectations and provide information on current market situations, allowing customers to make more informed choices. Effective communication during a disruption can help to mitigate the impact on customer loyalty and ultimately contribute to the long-term success of the retailer.

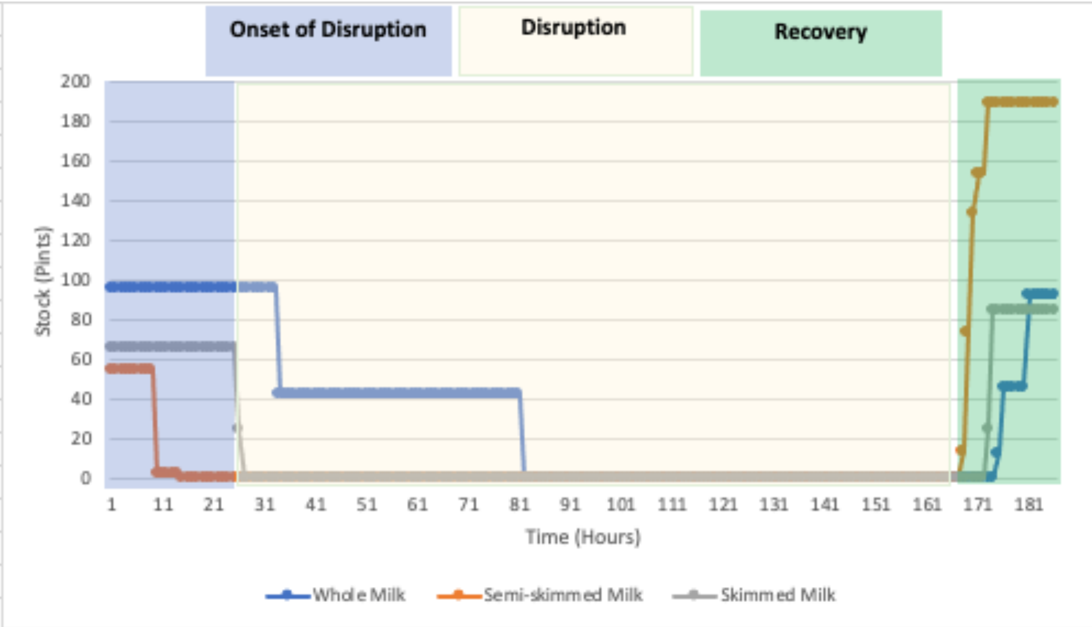


Figure 7. 19: Time to recovery after logistics disruption-Retailer 4

Table 7. 8: Summary of Time to Recovery after logistics disruption

Disruption Type	Retailer	Milk Type	Time to Recovery (Hours)	Cost (£)
Logistics Disruption	Retailer 1	Whole	120	9346
		Semi-skimmed	123	
		Skimmed	130	
Logistics Disruption	Retailer 2	Whole	130	781
		Semi-skimmed	150	
		Skimmed	145	
Logistics Disruption	Retailer 3	Whole	148	5896
		Semi-skimmed	150	
		Skimmed	153	
Logistics Disruption	Retailer 4	Whole	136	4642
		Semi-skimmed	157	
		Skimmed	140	

It is evident that retailers can face significant impacts on their stock levels and performance due to disruptions in supply chain delivery. However, effective inventory management and communication during such disruptions can help mitigate the impact on customer loyalty and contribute to the long-term success of the retailer. Table 7.8 summarises the time it takes the retailer to recover to pre-disruption levels for each milk type after a logistics disruption and the costs associated with this type of disruption for each retailer.

In conclusion, examining the impact of logistical disruption on the time to recovery of the supply chain yielded several notable observations. Retailer 1 encountered the greatest impact during the disruption, experiencing prolonged periods of low performance and stock-outs for skimmed milk, semi-skimmed milk, and whole milk. This supports the evidence that this retailer experienced very high supply chain costs. Effective inventory management led to a gradual reduction in performance for whole milk, whereas difficulties in managing inventory levels resulted in a swift decline for semi-skimmed milk. Retailer 2 demonstrated a staggered decrease in performance for whole milk and skimmed milk but faced a complete stock-out situation for semi-skimmed milk. Nevertheless, Retailer 2 exhibited prompt and efficient recovery once the disruption ended. Retailer 2 also experienced the lowest associated supply chain cost in the event of a logistic disruption. Retailer 3 maintained lower stock levels and faced an immediate decline in performance across all milk types, leading to substantial recovery times. Such prolonged periods of reduced performance can have a detrimental impact on customer loyalty. Retailer 4 sustained slightly higher stock levels compared to Retailer 3, which facilitated a staggered decline in performance, albeit with notable stockout durations. These findings underscore the importance of staggered performance declines in managing customer expectations and emphasise the significance of effective communication during disruptions to mitigate the impact on customer loyalty.

Both Retailers 3 and 4 experienced a significant increase in supply chain cost in the event of a logistic disruption which is explained by the increased stock out durations for both retailers. Key findings from examining the impact of a logistics disruption on time to recovery show that the disruption has the highest impact on the time to recovery; however, building a loyal customer base may support resilience. It is also the position of this research that overall, that supply chain costs have a direct relationship with the time to recovery as it is evident that where retailers take a longer time to recover, the associated supply chain costs also increase significantly.

7.4.3 Customer Service Levels

Customer service levels are a commonly used parameter to measure the resilience of a supply chain (Olivares-Aguila and ElMaraghy, 2021). This parameter measures the ability of a company to continue to meet the needs of its customers despite disruptions in the supply chain. Research carried out by Munoz and Dunbar (2015) explores the resilience of the supply chain by measuring the order fill rate, investigating how regularly demand is being satisfied. Factors that can affect customer service levels in the milk supply chain include the availability of milk, the responsiveness of suppliers and distributors, and the effectiveness of logistics and inventory management (Ong et al., 2014).

The research first simulated the supply chain as-is model and found that retailers typically retain certain stock levels (Figure 7.3) to ensure they continue to meet demand. However, during a disruption, these stock levels reduce, making it challenging for the retailers to continue to service their customers. This research will consider the availability of stock when measuring customer service levels. This is based on previous studies who have measured customer service levels based on fulfilment and availability (Carvalho et al., 2011; Ong et al., 2014).

The milk supply chain is a complex and dynamic system that involves various actors and disruptions can have a significant impact on the availability of milk (Ong et al., 2014). As part of this research into the milk supply chain, computer simulations were carried out to examine the impact of disruptions on customer service levels as a measure of resilience. These simulations allowed the researcher to model different scenarios to assess the ability of the supply chain to continue to meet the needs of its customers despite these disruptions (Ong et al., 2014; Munoz and Dunbar, 2015). The results of the computer simulations revealed that customer service levels were strongly affected by disruptions in the supply chain.

The next section provides more details on each simulation experiment carried out to explore the customer service levels after each type of disruption starting with production disruption, then demand disruption and then logistics disruption.

7.4.3.1 Production Disruption

To examine the impact of disruptions on customer service levels in the milk supply chain, computer simulations were conducted. The research simulated a one-week production disruption in the milk supply chain which revealed a notable impact on customer service levels as seen in Table 7.9. Table 7.9 also takes into consideration the supply chain cost associated with this disruption. These results indicate that the production disruption had a significant effect on the ability of the supply chain to maintain customer service levels. It is important to note that the figures for customer service levels during a disruption takes the lowest point reached into consideration.

Table 7. 9: Customer service level: Stock Availability in a production disruption

Retailer	Milk Type	Stock levels before Production Disruption (Pints)	Stock levels during Production Disruption (Pints)	Stock levels at Recovery (Pints)	Cost (£)
Retailer 1	Whole	58	0	88	3266
	Semi-skimmed Milk	229	0	209	
	Skimmed Milk	108	0	88	
Retailer 2	Whole	176	0	150	594
	Semi-skimmed Milk	32	3	240	
	Skimmed Milk	245	0	248	
Retailer 3	Whole	189	0	104	795
	Semi-skimmed Milk	78	0	161	
	Skimmed Milk	107	0	81	
Retailer 4	Whole	132	132	132	763
	Semi-skimmed Milk	119	0	180	
	Skimmed Milk	126	0	67	

Table 7.9 shows the stock available for each milk type at the different retailers before the disruption, during the disruption and after the supply chain recovered from the disruption. It is evident that in the production disruption scenario, Retailer 4 was able to maintain stock levels for whole milk and thus, continue to serve its customers. However, Retailer 4 was unable to maintain stock levels for semi-skimmed milk and skimmed milk. This reflects a reduced customer service level however, given the nature of milk, it may be possible for customers to switch

between milk types at a retailer if that retailer was able to provide at least one milk type. Retailer 1 on the other hand during a production disruption experienced complete stock out across all three milk types. This meant that Retailer 1 is unable to service its customers, making this retailer less resilient than Retailer 4. This is also reflected in the associated supply chain cost where Retailer 1 experiences higher supply chain cost than Retailer 1. This implies an inverse relationship between customer service levels and supply chain cost where the higher your customer service level during a disruption, the lower the associated supply chain cost. Retailer 2 experienced reduced services for semi-skimmed milk without complete stock out. However, Retailer 2 experienced stockout with whole milk and skimmed milk while Retailer 3 experienced total stockout for all milk types during a production disruption. This indicates that Retailer may be more resilient than Retailer 3. This is also reflected in the supply chain costs where Retailer 2 incurs a lower cost than Retailer 3 as Retailer 2 maintains a higher customer service level during a production disruption.

It is clear that the impact of a production disruption on customer service levels and the associated supply chain cost is not uniform across all retailers and is different from the results after a scheduled maintenance. This is supported by existing literature that suggests that the duration of a disruption can have a significant impact on the effectiveness of buffer stock in mitigating the effects of the disruption (Macdonald et al., 2018). For shorter disruptions such as the 6 monthly shut down of the manufacturing plant for maintenance which lasts for one day as shown in the as-is model, the buffer stock may be sufficient to prevent a significant reduction in stock availability. However, building on the as-is model for the one-week disruption yearly, the buffer stock was depleted, and the supply chain was not able to respond effectively to the increased demand for milk.

Additionally, the low stock levels and eventual stock-outs experienced by the retailers during the production disruption could be due to the difficulty of predicting the length and severity of the disruption. Research has shown that uncertainty in supply chain disruptions can make it challenging to determine the appropriate level of buffer stock to hold (Macdonald et al., 2018). In this case, the supply chain may have held an insufficient amount of buffer stock to account for the longer duration of the disruption.

Key results from the simulation of a production disruption in the milk supply chain shows lower stock availability for most retailers when compared to the as-is model. This implies that the retailers are unable to service the demands of the customers as there is no milk available in stock. Customer service levels in a production disruption reflected an inverse relationship with supply chain costs where costs were higher when customer service levels were low. The longer duration of the disruption and the uncertainty surrounding the disruption may have contributed to the increased impact on customer service levels and invariably, the cost. These findings highlight the importance of supply chain resilience and the need to develop strategies to mitigate the impact of disruptions on customer service levels.

7.4.3.2 Demand Disruption

In addition to the production disruption, a simulation was also carried out to test the impact of a demand disruption on the customer service levels. This also involved simulating a one-week period where demand for milk at the four retailers was disrupted. Table 7.10 compares the typical stock levels before demand disruption, the stock levels after demand disruption and stock levels at recovery. Table 7.10 also highlights the supply chain costs associated with this disruption type at each retailer. The stock levels allow the retailer to successfully meet customer demands and low stock levels means a reduced ability to meet those demands (performance) and a stockout situation refers to a situation where the retailer has zero (0) stock available with which to service customer demands. The ability to maintain a stock level closer to the as-is model during a disruption represents a higher level of resilience for the retailer as they will still be able to perform at the levels that their customers are used to despite the disruption.

Table 7. 10: Customer service level: Stock Availability in a demand disruption

Retailer	Milk Type	Stock levels before Demand Disruption (Pints)	Stock levels during Demand Disruption (Pints)	Stock levels at Recovery (Pints)	Cost (£)
Retailer 1	Whole	103	0	119	2623
	Semi-skimmed Milk	84	0	199	
	Skimmed Milk	79	79	79	
Retailer 2	Whole	75	49	81	583
	Semi-skimmed Milk	109	48	76	
	Skimmed Milk	74	32	78	
Retailer 3	Whole	75	23	112	275
	Semi-skimmed Milk	152	78	152	
	Skimmed Milk	65	33	73	
Retailer 4	Whole	98	59	106	653
	Semi-skimmed Milk	95	47	104	
	Skimmed Milk	63	35	81	

Similar to the production disruption scenario, results displayed in Table 7.10 show that the higher the customer service level, the lower the associated supply chain cost in a disruption. This is possibly due to high customer service levels meaning that you are able to meet demand and cover your costs. Table 7.10 also provides evidence that demand disruption had the least impact on customer service levels when compared with production disruption (Table 7.9) and Logistics disruption (Table 7.11). This is because with a demand disruption, Retailer 2, Retailer 3 and Retailer 4 maintain customer service levels without reaching stockouts and these three retailers maintain costs that are lower when compared with Retailer 1 who was unable to maintain customer service levels. Retailer 1 who is the only retailer to reach a stockout level during a demand disruption continues to have stock availability for skimmed milk when whole milk and semi-skimmed milk reached stockouts. This may be due to poor planning of inventory levels and lack of flexibility. Reaching stockout on two milk types as opposed to other retailers who do not reach stockout makes Retailer 1 the least resilient to a demand disruption within the supply chain. This leads this retailer to also incur higher costs than the other retailers.

The difference in the reactions of retailers to the different disruptions makes it imperative to consider multiple disruption types in supply chain disruption simulation. Previous studies have also emphasized the importance of considering various variables in supply chain disruption simulations. For example, Hishamuddiin et al. (2015) noted that the inclusion of multiple disruption scenarios and factors such as inventory levels, transportation, and supplier risks can lead to more comprehensive and accurate results. Similarly, research has highlighted the importance of considering both demand and supply-side disruptions in simulations to capture the full impact on supply chain performance (Klibi and Martel, 2012; Shen and Li, 2017; Singh et al., 2020). These simulation results further demonstrate the need to consider a wider range of variables and factors in future simulations. It is worth considering and possibly comparing the impact of demand and supply side disruptions on the associated supply chain costs.

Summarily, Retailer 2, 3 and 4 maintained stock levels and were able to continue serving their customers but Retailer 1 experienced stockout for two milk types and incurred higher supply chain cost due to reaching stockout levels and possibly losing customers. This further emphasises the need for the supply chain to plan accurate stock levels and remain flexible (see section 4.4.2) in order to remain resilient in a disruption. This flexibility can be supported by Big Data technologies to boost the resilience of the supply chain.

7.4.3.3 Logistics Disruption

This research also simulated disruption in logistics to assess its impact on customer service levels in the milk supply chain. This allowed the research to explore what happens where a manufacturer is unable to deliver manufactured milk to the retailer as scheduled, similar to the first two disruptions discussed, this disruption was also simulated for a week. Table 7.11 compares the availability of stock levels before logistics disruption, the availability of stock in a disruption and recovery stock levels. Table 7.11 also takes into account the cost associated with this type of disruption for each retailer.

Table 7. 11: Customer service level: Stock Availability in a logistics disruption

Retailer	Milk Type	Stock levels before Logistics Disruption (Pints)	Stock levels during Logistics Disruption (Pints)	Stock levels at Recovery (Pints)	Cost (£)
Retailer 1	Whole	215	0	132	9346
	Semi-skimmed Milk	186	0	162	
	Skimmed Milk	128	0	102	
Retailer 2	Whole	68	0	80	781
	Semi-skimmed Milk	80	0	146	
	Skimmed Milk	78	0	79	
Retailer 3	Whole	63	0	63	5896
	Semi-skimmed Milk	66	0	140	
	Skimmed Milk	73	0	79	
Retailer 4	Whole	96	0	92	4642
	Semi-skimmed Milk	55	0	189	
	Skimmed Milk	66	0	85	

The results show that disruption in logistics within the supply chain has a very high impact on all retailers. This impact is seen in the stock levels and the supply chain costs associated with this disruption. The retailers in this supply chain experience stockouts during the disruption which is evident in reaching zero (0) stock levels in the event of a disruption; this implies that the entire supply chain may have been unable to service customer needs at times in the disruptions. This low customer service levels are also reflected in the higher supply chain costs incurred which this research has established have an inverse relationship. The results in Table 7.11 also show Retailer 1 unable to meet pre-disruption stock levels for all milk types at recovery. However, Retailer 2 meets and exceeds pre-disruption stock levels for all milk types which may be evident of a change in stocking decisions based on experiences during the disruption. Retailer 3 barely matches pre-disruption stock levels for whole milk and skimmed milk at recovery; semi-skimmed milk however exceeds pre-disruption levels at recovery. Retailer 4 exceeds pre-disruption stock levels for semi-skimmed milk and skimmed milk at recovery and nearly matches pre-disruption stock levels for whole milk at recovery.

Table 7.11 shows a significant gap between the stock levels before the logistics disruption and the stock levels during the logistics disruption. The high increase in the impact of the disruption on customer service levels in our study may be due to the criticality of the logistics function to the milk supply chain. One potential reason is that the impact of a production disruption can be cushioned by the manufacturer with existing inventory which can still be delivered to the retailers for sale, whereas a disruption in logistics can have an immediate and severe impact on customer service levels. This is also reflected in the cost where each retailer incurs a significantly higher supply chain cost in a logistics disruption than in a production or demand disruption.

Key results in measuring the customer service levels during a logistic disruption shows retailers struggling to catch up with pre-disruption customer service levels. This makes logistics disruption critical to supply chain due to the high impact on customer service levels. This is probably because while a disruption type like production disruption can be cushioned with backup or excess inventory at the manufacturing level, in a logistic disruption, once the retailer runs out, there is little that can be done until the cause of the disruption is lifted.

In summary, all the experiments in this thesis underscore the significance of addressing time to recovery, supply chain costs, and customer service levels in the face of disruptions. By implementing effective strategies such as robust backup stock, accurate inventory management, contingency planning, and proactive communication, supply chains can enhance their resilience, minimise costs, and maintain optimal customer service levels. By acknowledging the unique challenges posed by production, demand, and logistic disruptions, organizations can proactively prepare for potential disruptions and safeguard their supply chain performance and financial outcomes.

Table 7.12 provides a summary of all the experiments carried out in this research and the results measuring the resilience of each retailer, and by extension, the supply chain. The cost of each disruption type is presented per retailer. Table 7.12 also presents the average time to recovery for each retailer per disruption type, taking all three milk types into consideration. The average stock level during each disruption is also displayed, taking into account all three milk types, pre-disruption, disruption and post-disruption stock levels. Table 7.12 builds on Table 7.1 where the intended simulation experiments for this thesis was presented.

Table 7. 12: Summary of Results 1

Resilience Measure (Sections)	Disruptions	Disruption Length	Retailer (Results 1)			
As-Is (7.3)	*Scheduled maintenance (No Disruption)*	24 hours	Retailer 1 *(No Disruption)*	Retailer 2 *(No Disruption)*	Retailer 3 *(No Disruption)*	Retailer 4 *(No Disruption)*
Supply Chain cost (7.4.1)	*Production Disruption*	1 week	Retailer 1 (£3266)	Retailer 2 (£594)	Retailer 3 (£795)	Retailer 4 (£763)
	Demand Disruption	1 week	Retailer 1 (£2623)	Retailer 2 (£583)	Retailer 3 (£275)	Retailer 4 (£653)
	Logistics Disruption	1 week	Retailer 1 (£9346)	Retailer 2 (£781)	Retailer 3 (£5896)	Retailer 4 (£4642)
Time to Recovery (7.4.2)	*Production Disruption*	1 week	Retailer 1 (155 Hours)	Retailer 2 (136 Hours)	Retailer 3 (124 Hours)	Retailer 4 (71 Hours)
	Demand Disruption	1 week	Retailer 1 (10 Hours)	Retailer 2 (18 Hours)	Retailer 3 (22 Hours)	Retailer 4 (22 Hours)
	Logistics Disruption	1 week	Retailer 1 (124 Hours)	Retailer 2 (141 Hours)	Retailer 3 (150 Hours)	Retailer 4 (144 Hours)
Customer Service Levels (7.4.3)	*Production Disruption*	1 week	Retailer 1 (86 Pints)	Retailer 2 (122 Pints)	Retailer 3 (80 Pints)	Retailer 4 (99 Pints)
	Demand Disruption	1 week	Retailer 1 (82 Pints)	Retailer 2 (69 Pints)	Retailer 3 (84 Pints)	Retailer 4 (76 Pints)
	Logistics Disruption	1 week	Retailer 1 (102 Pints)	Retailer 2 (59 Pints)	Retailer 3 (54 Pints)	Retailer 4 (64 Pints)

The results in Table 7.12 provide additional evidence to support the findings in this research that logistics disruption has had the highest impact and demand disruption had the least impact on the supply chain. Previous research also show that logistics disruptions can have a severe impact on supply chains. For example, Hishamuddiin et al. (2015) found that within their research, transportation disruptions in the supply chain can lead to a more significant effect on the entire supply chain than the supply disruption investigated. Similarly, Singh et al. (2020) found that disruptions in transportation can lead to a reduction in supply chain responsiveness, which can negatively impact customer service levels.

This highlights the significant impact that logistics disruptions can have on the stock levels in the milk supply chain. As such, companies should proactively prepare for and mitigate the potential negative effects of such disruptions to ensure the highest possible levels of customer satisfaction and retention. This can also lead to reduced supply chain cost for members of the supply chain.

7.5 Big Data in Simulating and Measuring Resilience

The simulation carried out in this chapter is done using Big Data shared with this research from the milk supply chain. In the context of this thesis, "Big Data" refers to the extensive amounts of structured and unstructured data that are collected from various sources within the milk supply chain. This encompasses data on production, transportation, inventory levels, customer demand, and other pertinent factors. These big data was collected from the participating milk manufacturer who gather the Big Data using the Big Data infrastructure discussed in section 3.8. The Big data gathered by the milk manufacturer and shared with this research is characterised by its high volume, high velocity, high variety, and high veracity.

Hence, big data is employed as the basis for data-driven simulation involving the utilisation of advanced software, codes and algorithms to analyse and interpret the large datasets. The simulation harnesses the insights derived from big data to experiment scenarios and assess the impact of potential disruptions on the resilience of the milk supply chain.

The research utilises big data in several ways within the simulation. Firstly, historical data is gathered and processed to identify patterns and trends. This historical data assists in establishing baseline performance measures (as-is model) and serves as a reference point for evaluating the impact of disruptions.

Secondly, real-time data is incorporated into the simulation process using an Excel spreadsheet and additional WITNESS capabilities to enhance accuracy and timeliness. This includes data on milk types, order quantities, production disruption, logistic disruption, and demand disruption that can affect the supply chain's resilience. By integrating real-time data, the simulation can provide more up-to-date and dynamic assessments of the supply chain's performance and vulnerability to disruptions.

Thirdly, big data-driven techniques enable scenario analysis. By simulating different disruptions, such as production disruption, demand disruption, or logistics disruption, the simulation can project the potential impact on key performance metrics like time to recovery, customer service levels, and supply chain costs. This allows supply chain managers to assess the effectiveness of different strategies and contingency plans in mitigating the disruptions and enhancing resilience.

Thus, the use of big data in the simulation process enhances the accuracy, complexity, and comprehensiveness of the analysis. It enables a deeper understanding of the dynamics of the milk supply chain and provides valuable insights for decision-making, risk management, and improving overall resilience. The next section reviews how additional resilience decision making can be carried out given the availability of Big Data.

7.6 Inclusion of Stochastic Elements

To address the deterministic nature of the simulation presented in Chapter 7, the research introduces stochastic elements to the simulation. The aim of introducing these stochastic elements is to capture the inherent uncertainty and 'noise' present in the real world of a milk supply chain. These stochastic elements introduce variability which better represents the supply chain operations. To represent the expected variability the research uses profiles that allow the simulation to use random values that are representative of the profiles over a 3-year period, similar to the deterministic model. The primary focus here is the introduction of stochastic variation in delivery times; given that this is an area where big data can provide significant enhancements and logistics disruptions appeared to have the highest impact on the supply chain in the previous experiments, making it a crucial aspect of the milk supply chain operations.

The research introduces a new variable within the code in WITNESS referred to as "DeliveryFactor" using the code below:

DeliveryFactor = Uniform (0.95,1.05)
SCHEDULE "Disruption Event", TIME + 1440, Disruption ()

This code allows the research to capture the variations in delivery times, and its components are explained as follows. A uniform distribution is used to model the variability which allows delivery time fluctuations within a range of + or – 5%. While this range may appear to be narrow, it is typical for this supply chain because there is extensive coordination and understanding between members of the supply chain which reduces disparity as highlighted in Chapter 4. The choice of a uniform distribution is based on its simplicity and allows the balancing between typical behavioural patterns and practical observation within the context of disruption, aiming for a reasonable representation of real-world scenarios.

Another critical factor within the stochastic model is the "Disruption" function. This function introduces variability into the "DeliveryFactor" variable. It achieves this by resampling from the Uniform distribution and generating new values for "DeliveryFactor" to reflect the dynamic nature of supply chain operations.

Figure 7.20 shows the results for the stochastic simulation of logistics disruption. As highlighted in section 7.6, a logistics disruption is selected for further experimentation as this had the highest implications on the resilience of the milk supply chain based on the results discussed in section 7.4; additionally, Retailer 1 is also selected for further experimentation as this retailer tends to have the highest stock and activity levels across all retailers. Figure 7.20 allows for comparison with Figure 7.8 which shows the deterministic results for Retailer 1. Figure 7.20 shows the initial deterministic simulation adopted from Figure 7.8 which shows the time to recovery for three milk types. This figure also includes the stochastic simulation that was carried out for each milk type; this stochastic simulation was conducted in 5 runs, changing the random number sequence. However, the overall time to recovery averages out at a similar position to the deterministic simulation. This shows that while various simulations may provide deferring quantities before and after a disruption, the average quantity and time to recovery is similar to the deterministic simulation. Hence, this research holds that the deterministic simulation provides a realistic view of disruption events and resilience within the milk supply chain.

Additionally, the results from this stochastic simulation shows that the overall time to recovery exhibits some variation, the main distinction occurs in the temporal patterns at the onset of the disruption. This difference in the response can be attributed to the stochastic elements, which have now been integrated into the simulation. In the deterministic simulation, the response to the disruption unfolds in a smoother manner due to the absence of variability. The absence of random fluctuations leads to a consistent and predictable progression throughout the disruption event.

In contrast, the stochastic simulation which incorporates inherent randomness exhibits more pronounced peaks and troughs during the onset of disruption and recovers gradually as opposed to the deterministic model. These are indicative of the inherent uncertainty introduced by the stochastic elements. Such fluctuations reflect the dynamic nature of milk supply chain operations.

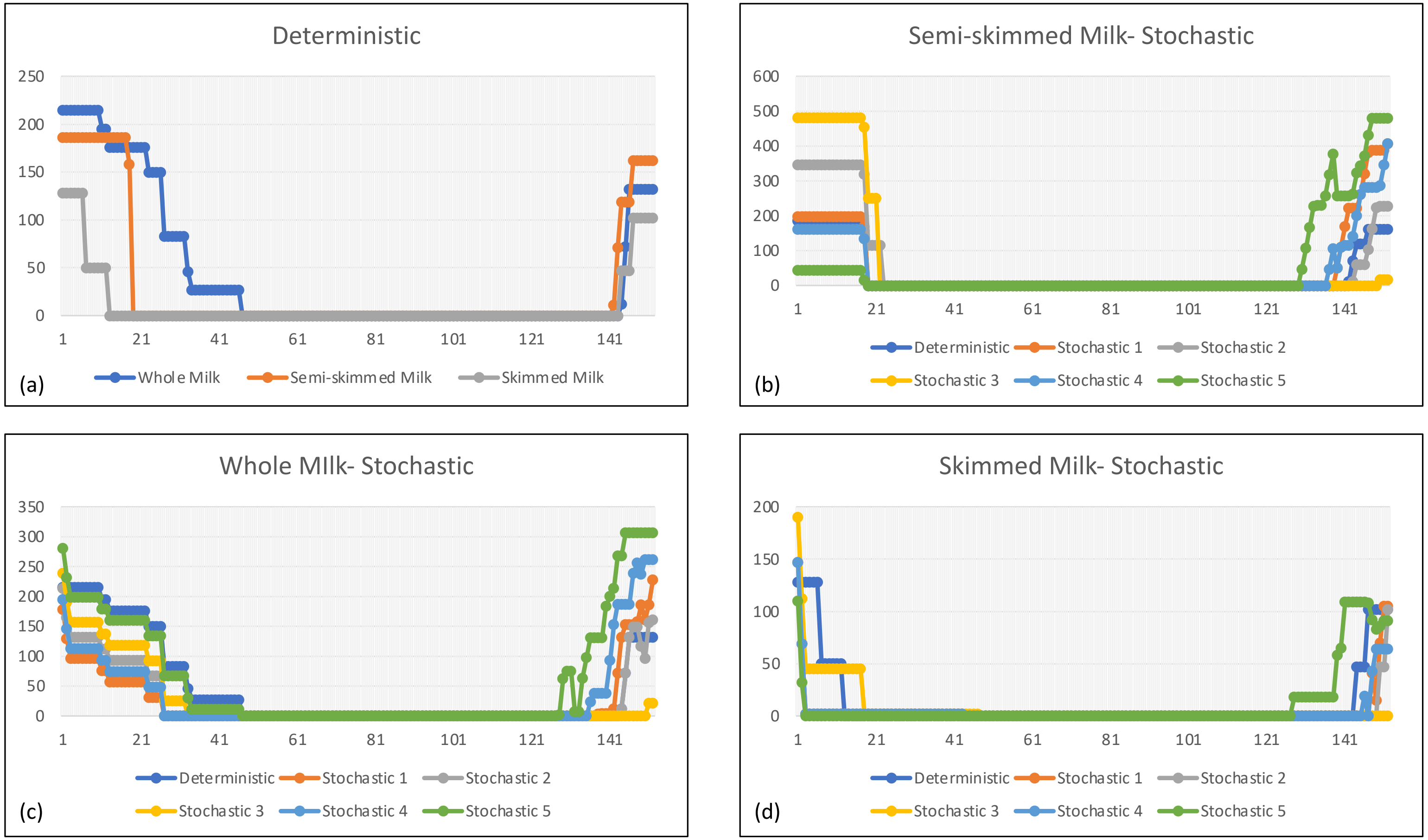


Figure 7. 20: Stochastic simulation results for Retailer 1

7.7 Conclusion

This chapter addresses research question 4 (How can data-driven analysis be used to measure the resilience of the milk supply chain and assess the impact of potential disruptions?) in this study as it discusses the results from the computer simulations carried out as part of this research, the key parameters used to measure resilience and set of experiments and disruptions simulated to test the resilience within a selected milk supply chain. This research has highlighted the importance of measuring the resilience of the milk supply chain, with a focus on three key parameters: time to recover, total cost incurred, and consistent service levels. The experiments conducted yielded significant insights into the critical factors influencing the set parameters. The findings emphasise the distinct impacts of production disruptions, demand disruptions, and logistics disruptions on the supply chain, highlighting the importance of addressing these areas for effective resilience and cost management.

For time to recovery, the experiments demonstrated that disruptions, particularly logistical disruptions, have a substantial impact on the recovery timeline. The ability to promptly recover from disruptions is crucial in minimising supply chain costs and maintaining operational efficiency. Retailer 2 demonstrated efficient recovery, leading to lower associated supply chain costs, while Retailer 1 experienced prolonged periods of low performance and stockouts, resulting in higher costs.

Supply chain costs were found to have a direct relationship with the time to recovery. Retailers that took longer to recover from disruptions experienced significantly higher costs. Effective stock planning, inventory management, and contingency strategies played vital roles in reducing both recovery time and associated costs. Retailers with robust backup stock availability and adequate planning demonstrated greater resilience and lower supply chain costs. However, supply chain costs demonstrated an inverse relationship with customer service levels, the lower the customer service level, the higher the supply chain cost.

Customer service levels were identified as a key aspect affected by disruptions, especially during production disruptions. Lower service levels were associated with higher supply chain costs, indicating the importance of maintaining customer satisfaction and loyalty. Effective communication, accurate stock planning, and resilient supply chain strategies were highlighted as essential components in mitigating the impact on customer service levels and minimising costs.

Among the different types of disruptions, production disruptions resulted in increased supply chain costs due to the loss of production and customers. Demand disruptions incurred costs associated with scrappage and lost revenue. Logistic disruptions led to significant cost increases, highlighting the necessity of contingency planning.

Simulation results in this chapter contributes to RBV and DC theories development by validating and refining the application of both theoretical frameworks within the milk supply chain. These results provide empirical evidence to support theoretical propositions within RBV that Big Data can be a dynamic capability which provides competitive advantage, therefore, leading to the generation of new insights in theoretical understanding of its application in the milk supply chain.

By simulating production, demand, and logistics disruptions, the research has shown how these disruptions can significantly impact the parameters being measured within the supply chain network. The findings suggest that supply chains should proactively prepare for and mitigate the potential negative effects of disruptions to ensure the highest possible levels of customer satisfaction and retention. Furthermore, this research has emphasised the need for comprehensive and accurate simulation models that consider various factors and variables, including demand and supply-side disruptions, inventory levels, transportation, and supplier risks. Ultimately, this research provides a framework for assessing the resilience of the milk supply chain, which can be used to identify areas for improvement and enhance the sustainability, efficiency and resilience of the system.

Chapter 8
BIG DATA AND PREDICTIVE ANALYTICS IN THE MILK SUPPLY CHAIN

8.1 Introduction

In this section, the outcomes of the research pertaining to the predictive ability of Big Data in supply chain management are presented. This chapter emphasises the significance of ensuring the model remains responsive to evolving supply chain conditions such as changing traffic conditions, weather information, strikes etc. The introduction of predictive analytics presents a valuable enhancement to the simulation, equipping it to more effectively address real-world complexities in milk supply chain management. Literature asserts that Big Data is advantageous for decision making based on predictive analytics (see Chapter 2); hence, this research models the consequences of being able to analyse big data for decision making purposes and reviews the benefits that can be derived from having Big Data available and predictively analysing the data for decision making. The chapter also includes the application of predictive modelling to delivery aspect of the supply chain, comparisons between prediction and non-prediction scenarios.

This chapter supports the research in addressing research question 1 which focused on the application and impact of Big Data on supply chain resilience. Predictive Analytics is a core area in which Big Data is expected to be advantageous and this chapter allows the research to empirically explore this notion. This chapter also explores research question 4 which focused on how Big Data can be effectively utilised to develop a disruption-resilient milk supply chain and examines data-driven methods for measuring and enhancing this resilience.

8.2 Predictive Analytics in the Milk Supply Chain

Predictive capacity within the milk supply chain can highlight the possibility of a data-driven decision-making process. With prior knowledge or the ability to predict a problem, such as delays in delivery (traffic, floods, etc.) then some deliveries could be brought forward and production times for instance adjusted accordingly, in a connected world, information can be used to replan. In the milk supply chain, organisations may choose to deliver more promptly based on information from big data as customers may be less likely to wait patiently for a staple yet highly perishable product such as milk. However, in other supply chains, it may be possible to delay delivery by a few days with adequate communication with customers. These types of decisions are best made with more information and the bigger picture in mind. By harnessing the power of predictive analytics and real-time data, simulations can be made based on the analysis of data, adjusting the simulations as necessary based on new information to enable organisations proactively address disruptions, improve operations, and enhance customer service. Predictive analytics is not only a strategic and competitive advantage, but also a necessity in today's dynamic and interconnected supply chain. Hence, Big Data is a key resource for supply chains and provides participating organisations within that supply chain with dynamic capabilities as discussed in section 2.13.

Predictive analytics have gained prominence with the rise of Big Data and advanced analytics technologies such as simulations. In the milk supply chain, these simulations offer a progressive approach to address potential disruptions, such as delays in delivery caused by issues such as traffic congestion, adverse weather conditions, or other events. This section explores the concept of predictive analytics and their application within the milk supply chain.

To execute predictive analytics effectively in a simulation, access to a wide range of relevant data sources is crucial. These sources may include:

- Traffic Data: Real-time traffic data from sources like GPS devices and traffic monitoring systems can support in providing data about road conditions, congestions, and estimated travel times.
- Weather Forecasts: Weather forecasts can provide information that helps predict adverse weather conditions that can impact milk deliveries, such as heavy rainfall, typhoons, hurricanes, heavy snowfall etc.
- Historical Delivery Data: Historical data for the delivery schedules, delivery routes, etc can be examined support the identification of recurring patterns and possible disruptions.
- Order Records: Information on customer orders, scheduled industrial actions such as strikes, production schedules, and delivery requests may be analysed for pre-emptive order processing.

The sources of information considered in the simulation within this research is the traffic data, strikes and weather information. In the predictive analytics simulations in this research, each week a random number is sampled – if Uniform (0,1) is less than 0.1 (i.e., 10% of the time) then the following is made to happen:

- Any deliveries for the day after today are delayed.
- Orders due for production tomorrow are processed today – and if cooling/delivery permits delivered too.

Using a relatively low probability value strikes a balance between maintaining the realism of the simulation and ensuring that disruptions are not overly frequent. In a supply chain, not every day will experience a significant disruption. Therefore, the choice of 10% reflects that the system encounters notable disruptions on an occasional basis. This is further supported by the Predictive Analytics study focused on Big Data in Supply Chains (Wafula et al., 2022) where the authors hold that a 10%-30% constitutes a sizeable sample. The 10% is also flexible and can be modified based on the specific characteristics and objectives of the simulation. Depending on the aim, this probability can be adjusted to represent different levels of disruption frequency. This implies that within the research, in order to simulate predictive analytics based on Big Data, the research explore the scenario where predictability is possible due to the availability of Big Data and the assumption of spare capacity. Hence, the simulation runs under normal conditions 90% of the time but for 10% of the time, the simulation runs in a manner that depicts a scenario where information such as a strike, congestion etc is available and could possibly disrupt milk delivery to the relevant retailer. This information allows the supply chain participant to make decisions, such as produce tomorrow's orders today and make the deliveries today too. Then those orders meant for tomorrow are cancelled in the simulation as they have already been delivered today. Thus, freeing up 'tomorrow' where the business thinks there may be a disruption. This shows the capacity of Big Data to support decision making and replanning.

The simulation contains the following code to set the DeliveryTime variable and a first possible disruption after one week:

Retailer_1.DeliveryTime = 25

SCHEDULE "Disruption Event", 10080, Retailer_1.Disruption ()

The disruption function has the following code:

DIM II AS INTEGER

!

IF Uniform (0,1) < 0.5 !

! Release more milk into production (all the milk due to be released in the next 24 hours) !

FOR II = 1 TO NParts (SchedulePoolMilk(1))
IF SchedulePoolMilk(1) AT II:PTime - 1440 < TIME

NEXT !

SchedulePoolMilk(1) AT II:BF = 1

PRINT II,SchedulePoolMilk(1) AT II:PTime ENDIF

- *! Schedule a delivery time change in 24 hours !*

SCHEDULE "Set delivery time event", TIME + 1440, SetDeliveryTime ()

! ! !

- *! Schedule next disruption test for a week later !*

ENDIF
SCHEDULE "Disruption Event", TIME + 10080, Disruption ()

The new function SetDeliveryTime is run 1440 minutes after the above – this does the following:

DeliveryTime = 25 + 1440
!
! Schedule reset of delivery time
!
SCHEDULE "Reset event for delivery time", TIME + 1440, DeliveryTime = 25

The above code programs the simulation in a manner that if the uniform distribution is less than 0.5, then all the milk due for delivery in the next 24 hours is released into production which allows the milk to be ready for delivery and available at the retailer for customers ahead of a potential disruption. Then the simulation schedules a delivery time change so that the corresponding delivery can be made, missing expected disruption based on data available to supply chain participants. Finally, the simulation rests and schedules the next disruption. Results of prediction and non-prediction scenarios are discussed in section 8.2.1.

8.2.1 Retailer 1 Comparison of Prediction vs Non-Prediction Scenarios

To assess the impact of predictive modelling on supply chain resilience, the research compares scenarios with prediction capabilities and scenarios with no prediction capabilities. This comparative analysis allows the research to review the resilience measures in prediction and non-prediction scenarios. Table 8.1 presents the results of key resilience measures in a simulation with no predictive capabilities and the results in a simulation where predictive capabilities are present.

Table 8. 1: Key Resilience Measures in Prediction vs. Non-Prediction Scenarios: Retailer 1

	Resilience Measure	Prediction Scenario	Non-Prediction Scenario
1	Time to recovery (hours)	23	124
2	Customer Service Levels (pints)	118	102
3	Supply Chain Costs (£)	3465	9346

The results showing supply chain resilience in the prediction vs. non-prediction scenarios of the milk supply chain simulation underscores the substantial benefits of incorporating predictive capabilities supported by Big Data into the milk supply chain.

In the prediction scenario, the time it takes to supply chain to recover from disruptions is significantly shorter, with an average of 23 hours when compared to the 124 hours it took in the non-prediction scenario. This significant reduction in the time to recover shows the effectiveness of predictive analytics in swiftly identifying and mitigating disruptions. In this case, the predictive capabilities enabled proactive decision-making, allowing the supply chain to reschedule deliveries, replan and reorganise production, leading to minimised downtime and ensuring a rapid return to normal operations.

Customer service levels are also higher in the prediction scenario, with an average of 118 pints when compared to the 102 pints in the non-prediction scenario. This outcome may indicate that predictive analytics can contribute to better meeting customer demand during disruptions. By anticipating potential disruptions and taking pre-emptive actions such and the expedited deliveries adopted in this research, the supply chain can maintain a higher customer service level which can lead to increased customer satisfaction and customer retention.

The financial implications to the supply chain as regards predictive analytics are captured within the supply chain costs. In the prediction scenario, supply chain costs for a logistics disruption to retailer 1 are significantly lower at £3,465 compared to £9,346 in the non-prediction scenario. Notably, this type of disruption comprised the highest cost to any retailer within this supply chain and even more so retailer who typically records higher activity levels than other retailers. This reduction in supply chain cost can reflect the efficiency gained through the proactive management of disruption, thereby reducing its impact. Predictive analytics may also allow for optimised resource allocation, reduced overtime expense, and minimised waste, which could result in meaningful cost savings.

These simulation results demonstrate the possible benefits of incorporating predictive analytics using Big Data available in the supply chain to build resilience. Supply chains that embrace predictive analytics may be better equipped to respond to disruptions quickly, provide high customer service levels, and achieve improved cost-efficiency. These findings emphasise the strategic advantage of data-driven decision-making and proactive supply chain management.

8.2.2 Retailer 2 Comparison of Prediction vs Non-Prediction Scenarios

The research also compared prediction scenarios and non-prediction scenarios for retailers 2 (Table 8.2), and the results are discussed in this section. The analysis focuses on the key resilience measures discussed in Chapter 7: time to recovery, customer service levels, and supply chain costs.

Table 8. 2: Key Resilience Measures in Prediction vs. Non-Prediction Scenarios: Retailer 2

	Resilience Measure	Prediction Scenario	Non-Prediction Scenario
1	Time to recovery (hours)	20	141
2	Customer Service Levels (pints)	47	59
3	Supply Chain Costs (£)	707	781

For the time to recovery, the prediction scenario shows a significant decrease to 20 hours, showcasing the effectiveness of proactive measures. Contrastingly, the non-prediction scenario experiences a prolonged recovery time of 141 hours. This difference underscores the potency of predictive analytics in minimising downtime and facilitating a rapid return to normal operations.

Interestingly, customer service levels in the prediction scenario are measured at 47 pints, slightly lower than the non-prediction scenario at 59 pints. This unexpected outcome highlights there are additional nuances involved in managing customer service dynamics during disruptions.

The supply chain costs in the predictive scenario presents a slight reduction with costs amounting to £707. In contrast, the non-prediction scenario incurs slightly higher costs at £781. This result highlights the advantage of proactive disruption management, where resource allocation is optimised, and wastage is minimised, leading to cost savings.

These findings assert the strategic advantages of a predictive analytics in enhancing milk supply chain resilience. By reducing recovery time and optimizing costs, predictive analytics emerges as a valuable tool in navigating disruptions. However, the observed trade-off in customer service levels prompts a nuanced consideration of the contextual factors influencing the effectiveness of predictive measures.

8.2.3 Retailer 3 Comparison of Prediction vs Non-Prediction Scenarios

Table 8.3 shows the prediction and non-prediction scenarios for retailer 3. In the prediction scenario, the time to recovery stands at 20 hours, showcasing the effectiveness of predictive measures. Contrastingly, the non-prediction scenario presents a more prolonged recovery period of 150 hours. This substantial disparity underscores the pivotal role of predictive analytics in minimising time to recovery and facilitating a quick return to normal supply chain activities.

Table 8. 3: Key Resilience Measures in Prediction vs. Non-Prediction Scenarios: Retailer 3

	Resilience Measure	Prediction Scenario	Non-Prediction Scenario
1	Time to recovery (hours)	20	150
2	Customer Service Levels (pints)	89	54
3	Supply Chain Costs (£)	560	5896

The prediction scenario also shows an improvement in the customer service levels, registering at 89 pints. In contrast, the non-prediction scenario records 54 pints. This clear difference highlights the impact of predictive analytics in ensuring a seamless customer experience during disruptions, highlighting its strategic significance in milk supply chain management.

Another noteworthy result emerges in the supply chain costs. The predictive scenario shows an economically efficient supply chain, with costs amounting to a mere £560. On the other hand, the non-prediction scenario incurs a significantly higher cost, reaching £5896. This contrast accentuates the financial advantages of proactive disruption management, where predictive analytics optimises resource allocation and curtails unnecessary costs.

The results affirm the transformative potential of predictive analytics in strengthening the resilience of the milk supply chain. By drastically reducing recovery time, enhancing customer service levels, and optimising costs, predictive measures emerge as an essential in effective supply chain management.

8.2.4 Retailer 4 Comparison of Prediction vs Non-Prediction Scenarios

Finally, Table 8.4 shows the prediction and non-prediction scenarios for retailer 4. In the prediction scenario, the time to recovery shows results of 21 hours, significantly showing an increased resilience with a reduced time to recovery based on predictive analytics. In contrast, the non-prediction scenario results in a prolonged recovery period of 144 hours.

Table 8. 4: Key Resilience Measures in Prediction vs. Non-Prediction Scenarios: Retailer 4

	Resilience Measure	Prediction Scenario	Non-Prediction Scenario
1	Time to recovery (hours)	21	144
2	Customer Service Levels (pints)	39	64
3	Supply Chain Costs (£)	820	4642

Customer service levels in the predictive scenario demonstrates a reduction for retailer 4 with a trade-off in maintaining customer service levels, registering at 39 pints. In the non-prediction scenario, customer service levels are higher at 64 pints. This unexpected outcome prompts further examination, indicating that the effectiveness of predictive measures in ensuring optimal customer service could be context-dependent and some retailers may make better decisions based on available data than others.

The economic implications of predictive analytics are evident in the supply chain costs. The predictive scenario incurs costs amounting to £820, while the non-prediction scenario has significantly higher expenditures at £4642. This underscores the potential cost-saving benefits of predictive analytics-based decision making.

The results for retailer 4 sheds light on the multifaceted impact of predictive analytics on milk supply chain resilience. While predictive measures contribute to a reduction in recovery time and supply chain costs, the observed trade-off in customer service levels necessitates a nuanced understanding of the contextual factors influencing these outcomes.

8.3 Conclusion

In conclusion, the integration of predictive analytics simulations provides a competitive edge to milk supply chains by augmenting their capacity to manage disruptions effectively, thereby improving resilience. It is evident that predictive analytics supported by Big Data can contribute not only to a shorter time to recovery, improved customer service level and reduced supply chain cost, but doing so helps improve resilience in the milk supply chain. This makes Big Data a highly essential resource to the supply chain and predictive analytics a dynamic capability that milk supply chains should aim to own, develop, and use effectively.

The results show the competitive advantage that predictive analytics, supported by Big Data, brings to supply chains. It shortens the time needed for recovery, boosts customer service, and reduces supply chain costs. Each retailer benefits from these advantages, but the study also reveals a nuanced trade-off, particularly in customer service levels, which demands ongoing contextual analysis. Hence, this research positions predictive analytics as a game-changer in modern supply chain management. Its practical benefits, as shown through the different retailers, underscore the need for continuous improvement.

The simulation results significantly advance the Resource-Based View (RBV) and Dynamic Capabilities theories in supply chain management. For RBV, the results provide empirical evidence that Big Data is a valuable resource that enhances competitive advantage and can improve supply chain resilience. For Dynamic Capabilities, the simulations demonstrate how Big Data and predictive analytics enable rapid adaptation to disruptions and can be crucial for maintaining competitive advantage.

Chapter 9
DISCUSSION OF FINDINGS

9.1 Introduction

This chapter systematically discusses the findings of this research based on the qualitative and quantitative data gathered and analysed. This chapter also situates the research findings in the context of literature and highlights how the research aim is achieved. The research aimed to explore the potentials and opportunities of applying the competitive advantages of Big Data in improving resilience and mitigating the risk of disruption in a milk supply chain and posed the following questions:

- How can Big Data be effectively applied in the development of a disruption-resilient milk supply chain? (Answered in Chapter 4)
- What are the challenges faced by the milk supply chain and how resilient is it to recent disruptions? (Answered in Chapter 2 and Chapter 4)
- How can a resilience measuring tool be developed to capture the impact of disruptions within the milk supply chain? (Answered in Chapter 5 and Chapter 6)
- How can data-driven analysis be used to measure the resilience of the milk supply chain and assess the impact of potential disruptions? (Answered in Chapter 7)

This discussion chapter is structured according to these research questions to ensure that the reader follows the flow of thought for this chapter and the research objectives are met.

9.2 Addressing Research Questions

This section highlights each of the research questions listed above and discusses how the findings from this research answers those questions and meets the research objectives. Earlier sections in this thesis have specifically answered these research questions and met the research objectives. For instance, the first research question is answered in Chapter 4 by reviewing the key themes presented by research participant surrounding resilience. The interviews also reveal how supply chains are applying Big Data and areas in which Big Data has been effective and compares this with literature to answer research question 1. The second research question is answered within Chapter 4 by reviewing feedback from participants on what constituted challenges in recent disruption. The research also reviews literature for challenges to the resilience of milk supply chain in recent disruptions documented in literature to answer research question two. Chapter 5 provides the descriptive analysis of the data gathered towards developing a resilience measuring tool and highlights the data that will be used as input. Chapter 6 builds on Chapter 5 to provide a step-by-step guide on how the resilience measuring tool is developed: thereby, answering research question three. Once the resilience measuring tool is built, Chapter 7 uses the tool to measure resilience by conducting experiments to assess the impacts of disruptions and providing the results of those experiments. Hence, answering the fourth research question. While research questions have mostly been answered throughout the research and the results documented in earlier chapters, this section will discuss the findings in detail and highlight how they answer the relevant research questions.

9.2.1 RQ1: How can Big Data be effectively applied in the development of a disruption-resilient milk supply chain?

This research identified key themes within the supply chain which are vital in improving performance and resilience. These areas include collaboration, flexibility, data management and supply chain design. This research adopts Big Data in the first instance as a structural support where organisations can, as done in this research utilise Big Data infrastructure to support sensing capabilities, analysis and decision making. This thesis holds in the second instance that where the structural component of Big Data is applied effectively, Big Data can become a dynamic capability for organisations as presented in section 2.13.

Recent studies by Perdana et al. (2023) and Xu et al. (2023) highlights that a supply chain focussing on Agricultural products such as milk require certain factors such as collaboration, flexibility etc. as being crucial to the performance of that supply chain which aligns with the themes identified in this research (section 4.4), and technology can be applied to achieve this enhanced performance.. This implies that organisations seeking to apply Big Data in improving resilience must look to apply Big Data in improving collaboration, flexibility, data management and supply chain design. In terms of design, this research has indicated that the majority of supply chains in the food industry are either linear or multi-tier in nature and as such, applying Big Data has to be tailored to fit the needs of the different supply chain designs and their collaboration, data management and flexibility needs. In linear supply chains, for instance, big data analytics can be employed to monitor supplier performance and track inventory levels, thus allowing for a more efficient supply chain management as supported in the work of Mari et al. (2014). In multi-tier supply chains, big data analytics can be utilised to manage the complexity and multiple data points, making it easier to track, manage, and analyse the big data. In reverse supply chains, big data can provide valuable data on customer preferences, product durability, and potential areas for improvement.

Previous research shows that Big Data technology has the potential to revolutionise the milk supply chain by providing valuable insights and enabling more efficient and effective collaboration between the different players in the chain (Kache and Seuring, 2017). Big Data technology can also be used to improve the traceability of milk products across the various tiers and nodes within their own supply chain. By analysing data on the movement of milk products through the supply chain, companies can identify any issues or problems that may arise, such as contamination or spoilage. This can help companies to take action to prevent these issues from occurring and to improve the safety of milk products. For example, by analysing data on the movement of milk products through the supply chain, companies can identify potential issues with food safety and take action to prevent them. An important aspect of the big data technology is the use of predictive analytics. By analysing large amounts of data, companies can make predictions about future events such as demand, inventory, and logistics. This can help companies to better plan for the future and to respond to disruptions more effectively. For example, by using predictive analytics, companies can improve their ability to predict future demand for milk products, which can help them to better plan production and logistics. The ability to collect, store, and analyse large amounts of data from various sources can provide supply chain actors with a more comprehensive and accurate view of the supply chain (Kache and Seuring, 2017), which can help to improve forecasting, increase transparency, optimize logistics, and improve customer service.

The focal organisation in this research found that the implementation of Big Data resulted in various business benefits. One of the advantages observed by the focal organisation upon implementing a Big Data strategy is the reduction in the time required to produce reports and the provision of real-time analytics to support their business operations. This implies that planning for manufacturing quantity can be automated within this supply chain as typical order quantities are analysed taking factors such as seasons, animal vaccinations, weather, disruptive activities etc into account. Given that this information is available in real time to their retailers, the retailer can provide instant feedback on whether or not those quantities are accurate. This allows the planning for both the retailer and the manufacturer to be done effectively. As seen the simulations, poor planning led to higher losses in the event of a disruption (see section 7.4.3.3). Collaborating effectively reduces the impact of the disruption as all members of the supply chain have a good understanding of demand and supply within that supply chain. This implies real-time visibility into the entire supply chain, from the farm to the consumer. Sharing the result of the data analysis with the members of the supply chain and ensuring that ideal milk is produced, and customers are served better can help to increase customer loyalty and ultimately lead to greater resilience and adaptability in the face of unexpected disruptions. Customer service levels and its implication for supply chain resilience is discussed in more detail in section 7.4.3. Understanding demand and supply patterns can help all parties in the supply chain to better understand and anticipate disruptions, such as unexpected changes in demand or supply-side issues like farm failures. Increased transparency can also help to build trust among supply chain actors (Ji et al., 2017) as they can see that the data being shared is accurate and reliable. Once trust is built, it becomes easier to share additional information and collaborate better and more frequently. This makes the data even more accurate and reliable.

However, this research found that while supply chain members shared some data relating to demand and supply, in-depth collaboration and information exchanged was not substantial enough to achieve the potential benefits. This may have been due to lack of trust and privacy concerns; the lack of trust among supply chain members can make it difficult for them to share information and collaborate effectively. This can be addressed by building trust among supply chain members through increased transparency and by encouraging members to share information and collaborate more effectively. Data security and privacy is another important issue that needs to be considered (Gupta and Rani, 2019). Supply chain members need to implement robust data security measures to protect the data they collect and store and ensure that personal information is protected. This can include measures such as encryption, firewalls, and regular backups. Additionally, supply chain actors need to have clear data governance policies and procedures in place, to ensure that data is managed appropriately, and that sensitive information is protected.

Where supply chain members have built trust and work collaboratively in data gathering, analysis and dissemination, a challenge that still has to be considered is the lack of standardisation in data collection and analysis, which can lead to inconsistencies and inaccuracies in the data which make it difficult for supply chain members to make informed decisions (Ji et al., 2017). As part of this study, data was collected to support computer simulations; however, data entries from the raw data collected from the manufacturer were done in an inconsistent manner. For example, "skimmed milk" was entered as "skimmed milk", "sk milk", "sk mlk", "skimmed mlk" depending on the person who entered the original information into the software. These inconsistencies can make data analysis challenging or cause an accidental exclusion to some data during analysis. This problem can be addressed by establishing standards for data collection and analysis and encouraging supply chain actors to adopt these standards. A similar issue that needs to be considered is data quality. Supply chain members need to ensure that the data they collect is accurate, complete, and relevant to the decisions they are trying to make. This can be a challenge when dealing with large amounts of data from various sources. Supply chain members need to put in place processes and procedures to ensure that the data they collect is of high quality and that it is cleaned and processed before it is analysed.

Another challenge noted is the high cost of implementation; participant 5 acknowledged this cost "*I've been around the industry a long time. And whenever you go to a group of consultants and say, help us with our data, they come back with a bill that runs into hundreds of millions of pounds, takes two years to implement, and you never really get the data, the usefulness out of it. You know, we can spend 5 million quid on renovating… and get a return on our investment straight away"*. The cost of collecting, storing, and analysing large amounts of data can be substantial, and may be a barrier for small and medium-sized enterprises (SMEs) in the milk supply chain. Additionally, there is also the need for skilled personnel to operate and maintain the systems, which can be a significant cost for organisations. To overcome this, supply chain members can consider adopting a collaborative approach to big data implementation, where they share data and insights, and pool resources to lower the costs of implementation (Navickas and Gružauskas, 2016).

Overall, Big Data can be applied in the milk supply chain to achieve resilience by focusing on increasing collaboration, data management and supply chain flexibility while taking into account the specific design of the supply chain that is being considered. Addressing the barriers to Big Data application will ensure that all members of the supply chain can apply Big Data and obtain the benefits intended.

9.2.2 RQ2: What are the challenges faced by the milk supply chain and how resilient is it to recent disruptions?

This research found that supply chains experienced many challenges in the event of a disruption. Members of the food supply chain who were interviewed as part of this research acknowledged several challenges and could draw on the experiences of their supply chains during the COVID-19 pandemic, which was experienced in 2020, globally. One of the challenges experienced what is the sharp increase in demand as consumers who had not experienced this type of disruption before were uncertain about what to expect and as such engaged in panic buying and hoarding, which in turn made items unavailable in the market, and in unregulated markets, the prices of items which were hoarded soared really high. This hoarding and stockpiling placed an additional pressure on a supply chain that was already fragile. This unexpected increase in demand meant that supply chains had to find ways to cope. Results from simulation in this research however found this type of disruption in normal demand activities presented the least impact to the supply chain as opposed to the logistics demand which had the highest impacts as highlighted in Chapter 7. Nevertheless, the supply chain still needs to find ways to cope with a demand disruption.

One way supply chains coped with this disruption and attempted to be resilient was by increasing production capacity or requesting increased supply from suppliers where possible. However, some parts of the supply chain struggled; for example, participant 3 noted that they were unable to sell goods using the usual routes to the market because customers were not allowed together in public places as a measure to control the spread of the virus. That meant that a lot of the businesses in the hospitality industry which was a major clientele group for had to shut down. However, the demand for food items which could be sold in retail stores soared very high. In an ideal world, it would be a simple decision to repackage based on the new demand criteria to ensure that demand is still being met. However, several other decision points need to be considered. For instance, in the drinks industry, the packaging equipment used to package drinks in bottles is different from that which is used to package in kegs and the capacity of each packaging line does not change. To make adjustments to the packaging lines in order to meet the new demand requirements may become expensive, especially where the manufacturer was unable to determine with any accuracy how long the new demand structure will continue and if the investment in the new packaging line will yield expected returns.

Participant 5 employed the risk sharing strategy with its retailers to maintain a certain level of resilience and reduce financial impact on only one member of the supply chain. To combat this challenge and maintain resilience, the strategy employed was that of risk sharing, where manufacturer was responsible for taking ownership of the collection, transportation, and management of any alcoholic beverages that has been delivered to a business in the hospitality industry, but was on opened at the time, when the business decides to shut down as per the government regulation. However, where the keg had already been opened, the pub or restaurant is responsible for managing the drinks. the manufacturer in this instance would be responsible for picking up the keg after the content had been handled. This strategy allowed the manufacturer to take up some of the financial responsibility and another member of the supply chain to take up the other parts of the financial responsibility, allowing all members of the supply chain to stay in business and minimise huge losses. While this may have benefitted both all involved members of the supply chain, there was no explicit benefit sharing or revenue sharing in this instance which contradicts the work of Scholten and Schilder (2015) who imply that revenue sharing should precede risk sharing and collaboration. However other researchers maintain firmly that for any risk mitigation strategies such as resilience to be successful, supply chain partners should have risk sharing arrangements in place (Jain et al., 2017).

Other supply chains reported having to reduce the number of product lines on offer and adopt a lean approach to satisfying customers' demands. Participant 6 provides evidence that in the food industry especially where pre-packed meals were being offered, organisations were continually driving their range of offerings down as this was what led to improved efficiency. Participants 1 and 2 support this view by adding that during the disruptions they experiences, there was a level of difficulty for food manufacturers as the levels of demands that were coming through were not accurately forecasted and exceeded expectations. This implied that manufacturers were unable to manufacture fast enough to meet the demand levels. To respond to this increased demand and struggling production, supply chain members, especially the retailers reduced their product range.

This contradicts the work of Jabbarzadeh et al. (2016) who postulate that in a demand disruption, organisations should "run fewer number of larger facilities". Their research holds that running larger facilities would allow organisations to take advantage of the economies of scale when purchasing. The participants in the current study found that it was beneficial in the event of a disruption if facility size was either reduced or maintained. However, it was even more beneficial to reduce the lines on offer so the quality of service and production can be maximised over quantity.

Following a period of high demand, participant 2 highlights a quick reduction in demand and sales. It is unclear if this reduction was measured against demand numbers during the disruption or typical demand in business as usual. It is however clear that this reduction also constituted a planning and forecasting challenge within that supply chain. Participant 2 acknowledged forecasting to be a major challenge of the disruption during the disruption "*And also, there was a lot of disruption for us forecasting or trying to plan the volumes, and for the stores*" "*obviously it wasn't forecasted because we didn't know how customers would, would react to that*", also adding "*I would say the only thing that really troubled us during that period was the sales forecast because I don't know if there's a way or I don't know if we didn't foresee even though we saw the signs, but no one prepared us for that*"; however, acknowledging "*And maybe if I had somehow forecasted it in a better way, then we could have planned that production increase in a different way in a better way*".

To combat this challenge of reduced demand right after a period of increased demand, and improve the resilience of the supply chain, the members of this supply chain adopted strategies such as expanding storage to other countries. This meant that raw materials and finished goods that were either sourced or manufactured in other countries within Europe that would have otherwise been shipped straight to the United Kingdom for sales or as an input in the manufacturing process were stored in those European countries where storage was available until further notice. In instances where members of the supply chain have misunderstood disruption demands to mean standard demands and manufactured excess products, this storage strategy allowed them to be stored while the organisation came up with an appropriate way to get those products in the hands of customers by employing other techniques such as discounting and promotional offers in the cases of products with shorter shelf lives. With products with longer shelf lives, business could take the required amount of time to sell off or re-strategize as appropriate. This is in line with research studies who have acknowledged production capacity, storage and transportation routes as some of the strategies often employed in a disruption (Fan et al., 2023). Other resilience strategies adopted included flexible storing solutions where warehouse spaces may be shared by items that alternatively would have been stored separately.

This research supports an inventory planning and flexibility approach where the supply chain has adequate data to sense and forecast demand accurately. This ensures that the supply chain only produces and hold an adequate amount of stock to fulfil expected and accurately forecasted demand. This is even more critical for the milk supply chain where items have a very short shelf-life and planning properly can make a big difference. The simulation results in this research shows that where planning has been a challenge for retailers, they become more impacted by disruption and incur higher supply chain costs. In section 7.4.2.2 evidence is present where Retailer 3 who plans more accurately and maintains the adequate stock level for a disruption shows signs of impact and decline but manages to recover before reaching stockout. However, Retailer 1 who typically has more buying and selling activity and should have more data to support planning encountered a disruption without planning stock levels or having the flexibility in sourcing, and reaches stockout on all three milk types, while also experiencing very high supply chain costs. A recent study by Badakhshan and Ball (2023) discusses the criticality of maintaining a certain level of financial flow in a disruption to the supply chain performance. This shows the criticality of planning and flexibility in maintaining resilience.

Where inventory planning and forecasting constituted a challenge for the supply chain, this research proposes that Big Data technology could have been applied to aid better decision making. However, the activities and strategies employed by some of the supply chains which participated in this research negates findings in literature and they failed to lean on Big Data capabilities where they had some. One of the main implications of applying Big Data technology in the milk supply chain is improved forecasting (Wamba et al., 2015; Ivanov and Dolgui, 2019). The ability to analyse data on weather patterns, consumer demand, and production levels can help farmers, processors, and retailers to better understand demand for their products, allowing them to adjust production accordingly. This can help to prevent overproduction or stockouts, which can disrupt the supply chain and lead to waste. Improved forecasting can also help to reduce the risks associated with unexpected changes in demand or supply-side issues such as crop failures (Ji et al., 2017). This shows that supply chains could have benefitted from using Big Data technology in forecasting for the demand and consequently planning the supply during a disruption. This may have reduced to cost of adopting other strategies such as additional storage and inventory.

Summarily, this research question sought to understand the challenges the milk supply chain faced in the event of a disruption and how resilience was reached in recent disruptions. Empirical evidence from interview showed that the supply chain encountered several challenges including a sharp and unexpected increase in demand which the supply chain had to adapt to; this was quickly followed by a sharp decrease in demand which required adaptation by the supply chain as well. The supply chains found this challenging, however simulation results showed that a disruption in demand has the least impact on the supply chain overall and while there are cost implications, this type of disruption also has the least cost implication. To achieve resilience, evidence in this research shows that supply chains focused on risk sharing, alternative transportation and storage options. However, evidence from simulations show that inventory planning worked out better for the retailers.

9.2.3 RQ3: How can a resilience measuring tool be developed to capture the impact of disruptions within the milk supply chain?

Resilience is a critical aspect of any supply chain management strategy as it enables organisations to withstand and recover from disruptions that may occur in the chain (Huatuco et al., 2010). Developing a resilience measuring tool can help organizations to quantify their resilience and identify potential areas of vulnerability within the chain. This research aimed to develop such a tool for the milk supply chain using the WITNESS Horizon simulation software.

The milk supply chain is an example of a complex supply chain with many different members involved in the production, processing, and distribution of milk products (Perdana et al., 2023). As with other supply chains, disruptions can occur at any point in the chain, and the ability to identify and quantify resilience is crucial to the development of effective supply chain management strategies.

This research sought to develop a resilience measuring tool for the milk supply chain using the WITNESS Horizon simulation software. The development of such a tool required a multi-stage approach that involved collecting data, cleaning and analysing that data, mapping out the supply chain, creating a conceptual model, and testing and expanding that framework using simulation software.

Data collection involved collecting both quantitative and qualitative data from members of the milk supply chain. The quantitative data was obtained from the milk manufacturer and provided information on the frequency of purchases, the types of milk produced and purchased by each retailer, and the typical time of day for production. The qualitative data was obtained through interviews with the milk manufacturer. This data allowed the researchers to gain a deep understanding of the supply chain's structure, operations, and potential vulnerabilities.

The quantitative data obtained from the manufacturer required cleaning and analysis to ensure accuracy and consistency. Data cleaning involved removing duplicate data and ensuring consistency in the entry of data points, such as ensuring that "skimmed milk" was entered consistently across all data points (see section 8.2). Once the data was cleaned, it was analysed to identify patterns and trends, such as the frequency of purchases by each retailer and the types of milk produced and purchased by each retailer (see section 5.3).

The qualitative data obtained from interviews provided valuable insights into the supply chain's operations and potential vulnerabilities. For example, interviews revealed that the chain did not make use of wholesalers and that manufacturers interacted directly with retailers, providing support for the flow of goods and information within the chain. This information was used to create a supply chain map that identified the different members within the supply chain and their roles in the production and distribution of milk.

The data obtained from both quantitative and qualitative sources was used to develop a supply chain map, which was shared with the milk manufacturer for feedback and adjustments were made to incorporate feedback received. The conceptual model was then developed and transferred to the WITNESS Horizon simulation software, which allowed the research to design a test model. The test model included one manufacturer and one retailer and only produced and sold one type of milk. The test model was designed to ensure that the simulation software and model worked as expected and responded to prompts and inputs. Once the test model was functional, it was expanded to the as-is model, which accounted for one manufacturer who produced three types of milk purchased by four retailers.

The as-is model allowed the research to introduce different types of disruptions to the supply chain, such as a disruption in production or customers not ordering milk and measure the supply chain's resilience. The resilience measuring tool developed through this research provides a valuable means of quantifying resilience and identifying potential vulnerabilities within the milk supply chain. The tool can be used to identify areas where improvements can be made, such as improving communication and trust between members.

The research also identified the importance of collaboration and communication among supply chain members in enhancing the resilience of the milk supply chain where the simulation results show that poor planning and communication of needs and demand to the manufacturer made some retailers more vulnerable, reducing the resilience of the supply chain. The resilience measuring tool developed by this research can help in simulating different scenarios and evaluating the effectiveness of different collaboration and communication strategies in mitigating the impact of disruptions. This can enable supply chain managers to identify the most effective strategies and adopt them to enhance the resilience of the supply chain.

Overall, the research findings suggest that a resilience measuring tool can be developed to capture the impact of disruptions within the milk supply chain. The tool can help in identifying and evaluating collaboration and communication strategies. This can enable supply chain managers to take proactive measures to mitigate the impact of disruptions and enhance the overall resilience of the supply chain.

In conclusion, the development of a resilience measuring tool for the milk supply chain is essential in enhancing the resilience of the supply chain. The research findings suggest that the tool can be developed using a combination of quantitative and qualitative data, with the WITNESS Horizon simulation software being used to simulate different scenarios and evaluate the impact of disruptions on the supply chain. The tool can help in identifying critical members of the supply chain, evaluating collaboration and communication strategies, and assessing the impact of disruption on the resilience of the supply chain. This can enable supply chain managers to take proactive measures to mitigate the impact of disruptions and enhance the overall resilience of the supply chain. Future research could focus on applying the resilience measuring tool to other supply chains and evaluating its effectiveness in enhancing the resilience of those supply chains.

Overall, in answering this research question, the thesis builds on the supply chain resilience body of knowledge by applying resilience measures identified in literature to the milk supply chain and simulating these in different disruption scenarios.

9.2.4 RQ4: How can data-driven modelling be used to measure the resilience of the milk supply chain and assess the impact of potential disruptions?

This research uses data driven modelling to measure the resilience of a milk supply chain and assess the impact of a disruption on that supply chain by determining what a resilient supply chain looks like. In this instance, a resilient supply is one that takes a short period of time to bounce back from a disruption, continues to serve its customers and reduces the cost of a disruption to the organisation. The research determines that resilience will be measure based on time to recovery, customer service levels and total cost incurred during a disruption. Having determined this, the research carries out the several experiments (see section 7.4). In order to assess the resilience of the milk supply chain, the study used a range of data-driven modelling techniques, focusing on simulation modelling. These techniques enabled the research to explore the impact of different disruptions within the milk supply chain.

One of the key findings of the research was the importance of inventory management in improving the resilience of the milk supply chain. By maintaining adequate levels of inventory and ensuring that inventory is distributed strategically, supply chains can reduce the impact of disruptions and improve the overall resilience of the supply chain. However, the research holds that the accurate inventory level to be held has to be data driven in order to maximise benefits. Another important factor identified by the research was the need for collaboration and coordination within the supply chain. By working together and sharing information, supply chain partners can improve their ability to respond to disruptions and mitigate their impact. This is can also be supported by big data technology as discussed in section 2.9.

The research also highlighted the importance of transportation infrastructure in ensuring the resilience of the milk supply chain. It is evident in this research that having a disruption in the logistics created the highest impact in the model causing the supply chain to be the least resilient. Poor transportation infrastructure can significantly increase the risk of disruptions, particularly in remote or rural areas where road and rail networks may be limited. Deciding on truck loads and ideal travel route should also be data driven. Organisation can take advantage of sensor data, travel time and weather data. Moreover, the use of data-driven modelling can help supply chain managers to identify areas for improvement and optimise their operations. For example, by analysing delivery routes and transportation costs, managers can identify opportunities for cost savings and increased efficiency.

Overall, the research findings suggest that data-driven modelling can be a valuable tool for measuring the resilience of the milk supply chain and assessing the impact of potential disruptions. By identifying key factors that impact the resilience of the supply chain and using data-driven techniques to quantify and assess these factors, supply chains can improve their ability to respond to disruptions and improve the overall resilience of the milk supply chain.

However, it is important to note that data-driven modelling is not a silver bullet solution and should be used in conjunction with other approaches, such as risk management and contingency planning. Additionally, the accuracy of the models relies heavily on the quality and accuracy of the data inputs; research by Isaja et al. (2023) show that creating a zero-defect system relies heavily on high quality data. This can be challenging in the case of complex supply chains with multiple stakeholders. However, this thesis provides a scientific explanation on how data can be supported by Big Data Warehousing, collected, cleaned, a data driven model built and used in measuring resilience. Thus, providing a framework for future research.

9.3 Conclusion

Supply chains experienced a lot of challenges during the COVID-19 pandemic disruption, particularly in the food and beverage industry. One of the major challenges was the sharp increase in demand, which led to panic buying and hoarding by consumers, causing some items to become unavailable and putting additional pressure on already fragile supply chains. To cope with this, some supply chains increased production capacity, requested increased supply from suppliers, or adopted a lean approach to reduce the number of product lines on offer.

Another significant challenge was the difficulty in forecasting demand accurately, which led to planning and forecasting challenges within the supply chain. This issue was compounded by a sudden reduction in demand after a period of high demand, which presented further challenges for supply chain members.

To improve resilience, some supply chains employed risk-sharing strategies to reduce the financial impact on one member of the supply chain. This allowed all members to stay in business and minimize huge losses. Additionally, some supply chains expanded their storage to other countries, allowing raw materials and finished goods to be stored until further notice. However, this research postulates that big data technology has the potential to greatly improve the resilience and adaptability of the supply chain. To fully realise the potential benefits, it is important to address the challenges and limitations associated with the use of big data, such as the lack of standardisation, lack of trust, data security and privacy concerns, high costs, data quality, and data governance. Supply chain members need to work together to establish standards for data collection and analysis, build trust among each other, and implement robust data security measures to protect the data they collect and store. Additionally, they need to have clear data governance policies and procedures in place, to ensure that data is managed appropriately, and that sensitive information is protected. By addressing these challenges and limitations, supply chain actors can fully realise the potential benefits of big data technology and improve the resilience and adaptability of the milk supply chain in the face of unexpected disruptions.

The development of a resilience measuring tool for the milk supply chain has also been discussed in detail. The study highlights that the process of developing a resilience measuring tool starts with collecting data from the focal supply chain and interviewing members of that supply chain. This process provides a clear understanding of the supply chain in focus and allows for the creation of a supply chain map. The data collected is then cleaned and analysed to obtain relevant insights, which are used to develop a conceptual model for the resilience measuring tool.

The supply chain map was shared with the milk manufacturer for feedback, and adjustments are made to incorporate feedback received. The conceptual model is transferred into simulation software used to design the supply chain model. The simulation model is tested on a smaller scale and then expanded to measure the resilience of the supply chain under different types of disruptions.

The results of this study suggest that the developed resilience measuring tool can be used effectively to capture the impact of disruptions within the milk supply chain. The tool provides a quantitative approach to measure the resilience of the milk supply chain, which can help supply chains identify potential vulnerabilities and improve the resilience of their supply chains.

The use of data-driven modelling is also discussed in this chapter and can be an effective tool for measuring the resilience of the milk supply chain and assessing the impact of potential disruptions. By analysing historical data and simulating different scenarios, supply chain managers can identify vulnerabilities and develop contingency plans to mitigate potential risks.

In summary, this research provides evidence for the potential benefits of data-driven modelling in measuring the resilience of the milk supply chain and assessing the impact of potential disruptions. While there are limitations to this approach, supply chains should consider incorporating it into their risk management strategies as part of a comprehensive approach to improving supply chain resilience.

Chapter 10
CONCLUSIONS AND RECOMMENDATIONS

10.1 Introduction

The previous chapters have explored the potential of Big Data in managing the milk supply chain and identified areas where it can be applied to improve resilience. This chapter discusses the contributions of this research to both the knowledge base and practice of supply chain and big data management. It highlights the practical implications of the resilience measuring tool for practitioners in the milk supply chain industry and recommends areas for further study. Overall, this chapter provides a comprehensive summary of the research findings and their implications for the milk supply chain industry.

This chapter highlights the contributions made by this research to the knowledge base of resilience measurement within the milk supply chain and provides practical insights into key areas that are vital in improving resilience. It also recommends areas for further study to expand upon this work.

10.2 Contributions to Knowledge

This research has contributed significantly to the knowledge base of resilience literature. This study contributes to the Resource-Based View (RBV) of organisations by examining ways in which Big Data either being captured or currently held by organisations can constitute a dynamic capability. This research shows that by applying Big Data strategically, organisations can develop dynamic capabilities, increase resilience, and improve performance. The research identifies key areas within the milk supply chain where Big Data can be applied to improve resilience. These areas include collaboration, flexibility, data management, and supply chain design. Big Data can be used to manage supplier performance, track inventory levels, and provide valuable insights into customer preferences, product durability, and potential areas for improvement. Additionally, by analysing data on the movement of milk products through the supply chain, companies can identify any issues or problems that may arise, such as contamination or spoilage. Big Data technology also provides the use of predictive analytics, helping companies to make predictions about future events such as demand, inventory, and logistics, which can help companies to better plan for the future and to respond to disruptions more effectively. The research also contributes to resilience measurement within the milk supply chain. Specifically, the study has contributed to the following areas:

- **Development of a Resilience Measuring Tool**: The study has developed a resilience measuring tool that captures the impact of disruptions within the milk supply chain. The tool is documented in Chapter 6 and is based on a conceptual model that combines qualitative (Chapter 4) and quantitative data (Chapter 5) to create a model that can simulate the supply chain and measure its resilience. This tool can be used to assess the resilience of supply chains and to identify areas that need improvement.
- **Application of Big Data in Milk Supply Chain**: The study in Chapter 2 and Chapter 4 has applied Big Data in a Milk Supply Chain context which is currently lacking in literature and provides a basis for further research and can be extended into the wider dairy supply chain. This provides an improved understanding of the milk supply chain, particularly in terms of the application of Big Data technologies for performance improvement. The study also allows for the exploration of the ways in which inventory planning and stock availability impacts resilience in the milk supply chain and how Big Data can be harnessed to provide an advantage.
- **Documentation of Impact for Disruption Types**: Chapter 7 of this study has provided objective documentation of the impact disruption types can have on the milk supply chain. These disruption types include production disruption, demand disruptions, and logistic disruptions. While these disruption types are not new to literature, this research modelled and documented the result of the impact to the milk supply chain in an objective and scientific way using a simulation which had not been done previously. This allows for future research to build on objective research findings.
- **Providing a framework for resilience measurement**: This study contributes to the literature on supply chain resilience by providing a framework for measuring resilience that can be applied to other supply chains. Chapters 5, 6 and 7 provide a step-by-step guide on how the framework is developed and resilience is measured. The study has also identified disruptions that can affect the milk supply chain, which can be

used to develop strategies to mitigate the impact of these disruptions in other supply chains. While resilience is not new to supply chain literature, a gap existed in documenting and implementing a guide on measuring resilience using simulations and real-world data; hence, a contribution to the supply chain resilience body of knowledge.

In conclusion, this research has made significant contributions to the knowledge in terms of resilience measurement within the milk supply chain. The resilience measuring tool developed in this study can be used to assess the resilience of the milk supply chain, identify areas that need improvement, and develop strategies to mitigate the impact. The study has also provided an improved understanding of the milk supply chain. The findings of this study can be applied to other supply chains and can contribute to the development of more resilient supply chains.

10.3 Contributions to Practice

This research contributes to the supply chain and big data practice by providing insights into the key themes within the supply chain that are vital in improving performance and resilience. These themes are identified in Chapter 4 and include collaboration, flexibility, data management, and supply chain design, which must be considered when applying big data to improve resilience. The research also highlights the potential benefits of applying big data technology in the milk supply chain, such as improving traceability, increasing transparency, optimising logistics, and improving customer service.

The development of the resilience measuring tool in Chapter 6 for the milk supply chain has several practical contributions that can benefit practitioners in the industry.

Firstly, the tool can be used to identify vulnerabilities and potential areas of disruption within the supply chain. By testing various scenarios and disruptions as done in section 7.4, practitioners can proactively prepare for potential risks and develop strategies to mitigate the impact of disruptions on the supply chain. For example, if the tool identifies that a disruption in milk transportation has a significant impact on the supply chain, practitioners can explore alternative transportation options or implement backup plans to ensure milk delivery is not completely halted in the event of a disruption.

Secondly, the tool can be used to optimise supply chain operations. By simulating various scenarios in section 7.4, it is evident that the tool can support practitioners to identify inefficiencies in the supply chain and develop strategies to improve operations. For example, the tool may identify that a particular retailer orders too frequently, causing increased transportation costs and disruptions to the supply chain. Practitioners can then work with the retailer to adjust their ordering patterns, reducing transportation costs and improving overall supply chain resilience.

Finally, the tool can be used to evaluate the effectiveness of supply chain resilience strategies. Practitioners can use the tool to test different resilience strategies and evaluate their effectiveness in mitigating the impact of disruptions on the supply chain. This allows practitioners to make informed decisions about which strategies to implement and invest in.

Overall, the resilience measuring tool has practical contributions that can help practitioners in the milk supply chain industry to identify vulnerabilities, optimise operations, and evaluate resilience strategies. This can ultimately lead to a more resilient supply chain, benefiting both the industry and consumers.

10.4 Research Generalisability and Limitations

While it is not the aim of this research to produce generalisable results, but the research focuses on understanding the milk supply chain as noted in section 3.2, it is important to note that the generalisability of results from this study on the milk supply chain to other supply chains depends on the similarities and differences between the milk supply chain and those of other industries. If these supply chains share comparable characteristics such as perishable goods, complex distribution networks, and quality control requirements, the findings from the milk supply chain study may have broader applicability.

It is also essential to acknowledge the contextual factors that may limit the generalisability of results. Factors such as regulatory environments, market structures, and technological landscapes vary across industries and may influence supply chain dynamics differently. Therefore, while certain principles of resilience and supply chain management may transcend industry boundaries, the specific contextual factors unique to each industry sector may restrict the generalisability of results.

This research has made significant contributions to the field by developing a tool for measuring the resilience of the milk supply chain and exploring the implications of big data analytics. However, there are several limitations that should be acknowledged. These limitations suggest areas for further study and provide opportunities for expanding on the current research.

- **Data Limitations**: One limitation of this study is the reliance on available data. The research utilised data from a specific milk manufacturer and over a limited time period (3 years and 3 months), which may limit the generalisability of the findings to other contexts. Future research should aim to access a larger and more diverse dataset across several industries to enhance the validity and generalisability of the findings.
- **Scope of Factors**: While this study considered various factors that impact supply chain resilience, such as production disruptions, demand disruptions, and logistics disruptions, there may be additional factors that were not fully explored. Future studies could expand the scope to include other relevant factors, such as weather events, economic disruptions, and regulatory changes, to provide a more comprehensive understanding of resilience and its determinants.
- **Tool Adaptability**: The developed tool for measuring supply chain resilience was specifically designed for the milk supply chain. Its applicability to other industries and supply chains may be limited and require adaptation. Future research should explore the adaptability of the tool to different contexts and industries, considering the specific characteristics and complexities of each supply chain.
- **Technology Advancements**: This research focused on the utilisation of big data analytics for resilience measurement. However, technology is continuously evolving, and new advancements, such as machine learning and artificial intelligence, could further enhance the functionality and capabilities of the tool. Future studies should explore the integration of advanced technologies to improve the accuracy and efficiency of resilience measurement.
- **Ethical and Organisational Considerations**: As big data analytics becomes more prevalent in supply chain management; ethical and privacy concerns arise. Future research should investigate the ethical implications of using big

data analytics, as well as develop guidelines and policies to address these concerns. Additionally, organisational factors, such as organisational culture, leadership support, and resource availability, should be explored to understand their influence on the adoption and implementation of big data analytics in supply chain resilience management.

In conclusion, while this research has made valuable contributions to the measurement of supply chain resilience and the implication of big data analytics, there are limitations that suggest areas for further study. Addressing these limitations will help expand the understanding of resilience, enhance the applicability of the developed tool to different contexts, leverage technological advancements, and address ethical and organizational considerations. By undertaking these avenues of research, practitioners and decision-makers can better improve the resilience of supply chains and effectively respond to disruptions.

10.5 Recommendations for further study

While this research has contributed to the supply chain resilience literature, there are several areas that could be further studied to expand upon this work.

10.5.1 Expanding the Scope of the Resilience Measurement Tool

Future research could expand the scope of the tool to include other factors that can impact supply chain resilience, such as weather events or economic disruptions. Weather-related disruptions, such as hurricanes, floods, or extreme temperature fluctuations, can have a significant impact on supply chain operations. These disruptions can cause transportation delays, damage to infrastructure, and disruptions in the availability of resources. Integrating weather data into the resilience measurement tool would enable practitioners to assess the vulnerability of the supply chain to different weather scenarios. This could include incorporating historical weather data, predictive models, and real-time weather information to simulate the effects of weather events on the supply chain and evaluate its resilience.

Economic factors, such as market fluctuations, changes in consumer behaviour, or financial crises, can profoundly affect supply chains. These disruptions can result in shifts in demand patterns, price fluctuations, or changes in trade policies. Expanding the resilience measurement tool to include economic factors would allow for a more comprehensive understanding of how economic disruptions impact the supply chain's ability to recover and adapt. This could involve integrating economic data, market indicators, and macroeconomic models into the tool to simulate and assess the supply chain's resilience in the face of economic disruptions. This would provide a more comprehensive understanding of the supply chain's resilience and allow practitioners to better prepare for a wider range of potential disruptions.

10.5.2 Exploring the Application of the Resilience Measuring Tool in Other Industries

In addition to its application in the milk supply chain, further research should investigate the potential use of the resilience measuring tool in other industries. Adapting the tool to suit the specific characteristics and complexities of different supply chains and industries would enable practitioners to assess and enhance supply chain resilience across various sectors. Here are some areas of research that can be explored:

- Industry-Specific Adaptation: Each industry has unique supply chain dynamics, challenges, and requirements. Future research could focus on adapting the resilience measuring tool to address the specific characteristics of different industries. For instance, industries with perishable goods, such as the fresh produce or pharmaceutical industry, may require different resilience metrics and parameters compared to industries with durable goods. By tailoring the tool to different industries, practitioners can effectively assess and improve resilience based on their specific needs.
- Supply Chain Complexity: Supply chains can vary in terms of complexity, ranging from simple linear supply chains to highly interconnected and global networks. Further research could investigate how the resilience measuring tool can handle different levels of complexity and accurately capture the interdependencies and vulnerabilities within complex supply chains. This may involve incorporating network analysis techniques and considering factors such as multi-tier supplier relationships, global transportation networks, and information flows.
- Comparative Analysis: Conducting comparative analyses across multiple industries using the resilience measuring tool would offer valuable insights into the similarities and differences in supply chain resilience across various sectors. Such research could highlight industry-specific best practices and identify transferable strategies that can be applied to improve resilience in

different contexts. By benchmarking resilience performance across industries, practitioners can gain valuable knowledge to enhance their own supply chains.

- Integration with Industry Standards: Many industries have established standards and frameworks related to supply chain management and resilience. Future research could explore how the resilience measuring tool can be integrated with existing industry standards, such as ISO 28002 for supply chain security or ISO 22301 for business continuity management. This integration would provide a comprehensive approach to assessing and improving supply chain resilience, aligning with industry best practices.

By exploring the potential application of the resilience measuring tool in other industries, researchers can contribute to a broader understanding of supply chain resilience across diverse sectors. The findings can help practitioners in different industries to assess their supply chain resilience, identify improvement areas, and implement targeted strategies to enhance their resilience capabilities. Ultimately, this research strand can lead to the development of industry-specific tools and guidelines that empower practitioners to build resilient supply chains in various domains.

10.5.3 Exploring the Potential of Machine Learning and Artificial Intelligence in Enhancing the Resilience Measuring Tool

As an expansion from Big Data technology, future research could explore the potential for machine learning and artificial intelligence techniques to enhance the tool's functionality. Machine learning algorithms could be used to automatically identify vulnerabilities and potential disruptions within the supply chain, allowing for more efficient and effective testing of various scenarios. Here are key areas of research that can be explored:

- Vulnerability Detection: Machine learning algorithms can be employed to analyse large volumes of supply chain data and identify patterns or indicators that signify vulnerabilities. By training the algorithms on historical data, they can learn to recognise the factors that contribute to disruptions and determine the areas of the supply chain that are most susceptible to risks. This would allow practitioners to proactively address vulnerabilities and fortify the resilience of critical supply chain components.

- Risk Assessment and Prediction: Machine learning models can be developed to assess and predict the likelihood and impact of potential disruptions on the supply chain. By incorporating relevant data, such as weather patterns, economic indicators, or geopolitical events, these models can generate risk scores or probabilities for different scenarios. This would enable practitioners to prioritise their risk mitigation efforts and allocate resources effectively to minimise the impact of disruptions.
- Scenario Testing and Optimisation: Machine learning techniques can be utilised to simulate and optimise various supply chain scenarios. By generating virtual environments and running simulations, practitioners can evaluate the resilience of the supply chain under different conditions and identify optimal strategies for mitigating disruptions. These simulations can consider multiple factors, such as demand fluctuations, supplier failures, or transportation delays, to provide actionable insights for decision-making.
- Real-time Monitoring and Adaptive Resilience: Machine learning algorithms can be deployed for real-time monitoring of supply chain data streams. By continuously analysing incoming data, these algorithms can detect deviations from expected patterns and trigger proactive responses to mitigate potential disruptions. Furthermore, AI techniques, such as reinforcement learning, can be employed to enable the resilience measuring tool to learn and adapt its strategies based on evolving supply chain dynamics, thereby enhancing its responsiveness to disruptions.

By integrating machine learning and AI techniques into the resilience measuring tool, researchers can unlock the potential for more efficient and effective assessment of supply chain resilience. The tool would have the ability to automatically identify vulnerabilities, predict disruptions, and optimize strategies for enhanced resilience. This advancement would empower practitioners to make data-driven decisions and proactively address risks, ultimately leading to more robust and adaptive supply chains. However, it is crucial to address challenges related to data quality, model interpretability, and algorithmic bias to ensure the ethical and reliable implementation of machine learning in supply chain resilience assessment.

10.5.4 Exploring Ethical and Privacy Concerns in Big Data Analytics for Supply Chain Management

Future research could explore the ethical and privacy concerns related to big data analytics in supply chain management and develop guidelines and policies to address these concerns; also, examining the organisational factors, such as culture, leadership, and resources, that influence the adoption and implementation of big data analytics in supply chain management.

- Data Privacy and Security: Future research should investigate the potential risks and vulnerabilities associated with the collection, storage, and use of supply chain data. This includes examining data privacy regulations and legal frameworks to ensure compliance, as well as developing robust data security measures to protect sensitive information. Moreover, strategies for anonymising or aggregating data should be explored to strike a balance between data utility and privacy protection.
- Ethical Use of Data: Researchers should examine the ethical implications of using big data analytics in supply chain management. This involves exploring issues such as data ownership, informed consent, and transparency. Guidelines and frameworks should be developed to guide practitioners in the responsible and ethical use of data, ensuring that the rights and interests of individuals and stakeholders are respected throughout the data analysis process.
- Organisational Culture and Leadership: Future research should investigate how organisational culture and leadership influence the adoption and implementation of big data analytics in supply chain management. This includes examining factors such as data-driven decision-making, risk appetite, and the role of leadership in fostering a culture that values ethical and responsible data practices. Understanding these organisational dynamics is crucial for successful implementation and ensuring that ethical considerations are embedded in the decision-making processes.

By addressing the ethical and privacy concerns associated with big data analytics in supply chain management, researchers can contribute to the development of responsible and sustainable practices. This research strand should focus on providing actionable guidelines, policies, and frameworks that enable organisations navigate the complex landscape of data ethics and privacy. Ultimately, this will foster trust, enhance stakeholder engagement, and promote the adoption of ethical data practices, leading to more responsible and beneficial use of big data analytics in supply chain management.

In conclusion, while this research has explored the implication of Big Data to the resilience of the milk supply chain and developed a valuable tool for assessing supply chain resilience, there are several areas that could be further studied to expand upon this work and improve the resilience of supply chains more broadly.

10.6 Conclusion

In conclusion, this chapter provides a summary of the key contributions of the research, practical implications of the findings, and recommendations for future research. The study identified key areas within the milk supply chain where Big Data can be applied to improve performance and resilience. It also developed a resilience measuring tool that captures the impact of disruptions within the milk supply chain. The tool can be used by milk supply chain managers to assess the resilience of their supply chains, identify areas that need improvement, and develop strategies to mitigate the impact of disruption. The study contributes to the literature on supply chain resilience and provides insights into the key areas that are vital in improving performance and resilience in the supply chain. The resilience measuring tool has practical contributions that can help practitioners in the milk supply chain industry to identify vulnerabilities, optimize operations, and evaluate resilience strategies. Finally, the study recommends further research to expand the scope of the tool to include other factors that can impact supply chain resilience and explore the potential application of the tool to other industries beyond the milk supply chain.

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Appendices

Appendix A: Interview Guideline

Supply Chain Description Questions

1) Please state your name (optional)
2) What is your role?
3) What is your position in the supply chain (retailer/manufacturer/wholesaler etc)?
4) Briefly describe the supply chain you operate in
5) In the current pandemic, what is your opinion on the performance of your supply chain.
6) Would you describe the supply chain as being equipped for another disruption such as experienced during the pandemic?
7) Can the supply chain in its current state continue functioning in the event of a disruption?

Big Data Utilisation Questions

**Where Big Data is defined as data generated very frequently in varying formats, generated in large volumes and using a variety of tools; please answer the following questions*.*

8) "Please describe what 'Big Data' means to you."
9) Is Big Data widely used across all supply chain participants?
10) Would you describe the supply chain as making use of Big data in decision making?
11) Do you think a wider use of Big Data can be beneficial to the supply chain?
12) Would you describe each firm in the supply chain as investing maximally in data software such as SAPs, track and trace devices, sensors etc?
13) Are members of our supply chain actively encouraged to come up with ideas on how best to utilise Big Data being generated. If they are, in what way?
14) Does the supply chain consistently generate data that are often not relevant to operating the supply chain in a crisis scenario?
15) To what extent are data visualisation tools such as dashboards and Tableau used for decision making.
16) Does your firm contact Big Data experts often to review its Big Data processes?

Supply Chain Resilience Questions

17) In light of the current pandemic, describe the challenges the supply chain faced.
18) Are the challenges faced in the supply chain during the pandemic different from those faced before the pandemic?
19) Describe the consistency of demand during the pandemic
20) Was your supply chain stable during the pandemic? Why?

21) How could a supply chain have better handled the occurrence of such disruption?
22) What should supply chain operators do in the future to prepare for similar situations?
23) During a crisis, describe the areas in which a food supply chain can incur the most losses.
24) Can your supply chain recover quickly to its original state or possibly a new, different but stable state after a disruption such as was experienced during the pandemic? Why do you think so?

Appendix B: Participant Transcription

Supply Chain Description Questions

Q: What is your position in the supply chain (retailer/manufacturer/wholesaler etc)?

A: OK. So, yeah, my supply chain company and the role, fits in, the retailer. And now in terms of my tasks and responsibilities and they are mainly about like optimising the allocations of stock. So, I do the demands analysis like demand planning, demand forecasting. They're different terms for the same thing, essentially. And then monitoring sales on a weekly basis and then making weekly decisions about dropping the prices of the products that I look after are not performing as strongly as we want. Based on that mark, and on a budget that we have like weekly budget, monthly budget, annual budget.

I work with promotional products. So, we call them in and out products because they are in stores for a select period of time, months. until they sell through or until we decide to recall them because they've been on sale for a few weeks and they're not shifting anymore. I also make the weekly decisions about returning stock and writing off stock and or extending a stock.

Q: Briefly describe the supply chain you operate in

A: OK, so the supply chain of the company, I would say, is international in the sense that we have both international and national suppliers. The buyers mainly liaise with the suppliers. But the supply chain team is ordering the volumes. And so, the buyers make the deal of the sale price and the range. The buyers like the purchasing and the buying department of my organisation, they are in direct contact with the suppliers right now. As supply chain department we get more information off the products that will be in the range and we forecast and order the volumes. In particular the products that I am managing because I am managing more non-food products. Mainly, we are a food retailer, but we also have a big non-food range. I manage the non-food range and the seventy five percent of our suppliers. No, actually, 75 percent of the products we source from the same suppliers. So, it's a lot more streamlined, the supply chain for my product range. but this is mainly for the product range that I look after, because, as I said, this, these are the promotional items. So, if you go in a store these are the products that you will find for a selected period of time, they are what we call the listed range. So, the products that are in stores at any time you walk in our store and for these products as a supply chain, we *order directly from the supplier; So daily, weekly, monthly, there is no longer the intermediate step of buying, keeping the ordering volumes to the supplier. Our customers are usually the end users.*

Q: In the current pandemic, what is your opinion on the performance of your supply chain.

A: There were various issues. I mean, I can explain the issues that I face because I work (as in promotional items) with different lead times than the listed range we have in stores. So, for our promotional and non-food items, we have very big lead times. As I mentioned, we have an international supply supplier from Asia that supplies us. We source seventy five percent of our non-food products; so, we have very big lead times and we order the volumes a year in advance. And then we do that distribution of stock in the different regions in the country twelve months in advance. So, this is very I mean, this this doesn't give us a lot of flexibility.

For us, the problem is that the planning had happened so many months in advance and what happened in the pandemic was that people were not buying non-food because they were just rushing in to get their food. For the non-food range that we offer to our stores, which is not our basic product, it's just the range that I manage. I mean, very unexpected, the demand changed unexpectedly, but in the other direction of food. So, people were no longer browsing in stores just to non-food, like to top up their shopping. They were rushing into stores to get their essentials, right? Which means that our demand and our sales dropped a lot. And then we had to jog it around all. And make a lot of, like, changes in the sense that we were trying to stop the stock that was coming in the country. Because, we have already placed our orders, we ended up holding some stock in Europe. And that trying the consolidation centres instead of sending it in the country and our warehouses. We had a lot of stock in the country that we didn't put out on sale on the advertising dates that we had planned. So, we cancelled a lot of lines, but also, we were able to divert some of the stuff that was in transit to the country and keep it in a in one location in Europe rather than sending it to our distribution centres in the U.K

Q: And these all happened in a different direction from the food items?

A: Yeah. Because the food items were flying. Their sales were very strong. And, of course, I mean, you have probably seen that we had empty shelves in the supermarkets and a lot of dissatisfied customers. So, the demand that the customers had for food products like flour, eggs, pasta, even toilet paper. I would class it under…. They are not food, but this range, they are something that we offer to our customers in our stores any time they walk in. So, the demand was too high. And although we were getting a stock from the supplier, it's not like the suppliers *couldn't produce anything. They were producing stock and we were replenishing the store. But they after a few hours, all the stuff was gone. for the food items, we have different lead times. We have like a daily, weekly, monthly. We had to discontinue a lot of the lines just because we didn't have the stock to provide to the customers and the producers couldn't produce so quickly, so much stock. And so, a lot of the lines were discontinued and at the same time, a lot of the lines were available to order. But we were bringing the volumes that they couldn't last stores more than a few hours. They would be gone by midday. So, after like two, three, four hours, you know, the stock would be gone and you couldn't replenish the stock with the same speed that the customers were buying it. But it was just such a shame that even if the stock was coming, you just couldn't replenish it. I think it was the same situation with our competitors, to be honest. But definitely there was a lot of opportunity for even higher turnover, I mean our turnover increased a lot. This doesn't necessarily mean that now our net revenue increased the load because customers, as I said, they were buying essential foods like grocery that have a very low profit margin. And they wouldn't buy like non-food items or some other products that have higher profit margins. And that's another insight to our situation, because on the outside, it looks like, yes, our turnover increased a lot and then we made a lot more money but that doesn't necessarily translate to a higher net revenue as well*

Q: Would you describe the supply chain as being equipped for another disruption such as experienced during the pandemic?

A: I think we are more prepared because this has happened again. But to be honest, I don't, I don't know. I don't think the supply chain is ready to perform better in a similar disruption. I just think that the customers are more educated not to suddenly change their demand so drastically; because if people start to panic buying like they did in March and April, yes we can be more proactive and yes we can do some things we have done before and now we know our processes better in an extreme occasion. But still I don't know if we can meet the customer demand in such a big disruption.

If people react the same way they reacted in March of April, then we will have so many gaps as we had back at the time but we will still have big gaps in our product range and we will still have availability issues. The customer demand is also not as crazy these days which helps the systems and supply chain

Q: Can the supply chain in its current state continue functioning in the event of a disruption?

A: I think the supply chain proved to be more resilient than we might have thought before in this time because it reacted really quickly and it responded and change a *lot of things in the right direction. When I say in the right direction, I mean we didn't make mistakes that would cost us even more issues with availability, I think we responded to the best of our ability and to the best of the system's ability. I think the supply chain was resilient definitely because all the participants stepped up when the time came but if another disruption would come without any changes, I think we will still have problems but not to the extent we had before. I think the biggest disruption would then be with our workload because we plan and then we would have to change all our planning and get out of our way to do things; and that puts more pressure on individuals and employees. But the system itself I think it's more resilient, the supply chain. Yes, it could cause disruption but it was more resilient than before the pandemic even though we haven't tested our limits. For example, the company that I work for is very lean and efficient in the structure of the supply chain, so we are not very agile. We are more reactive than proactive; we try to be proactive but the systems are not very flexible. So, in reality we can't be agile but I think we were able to be very resilient and adapt to the situation very well. And yes, I mean that we are more resilient post pandemic. I didn't expect that people would move or change so quickly in our supply chain before, because our model relies so much on internal processes and admin which makes it difficult to be agile. But we were able to change things faster and react and liaise with our suppliers and the government and take precautions in our stores. And this all happened at a pace I could not imagine you could do.*

Big Data Utilisation Questions

Q: Please describe what 'Big Data' means to you.

A: With a lot of data, to be honest, it's quite intimidating because our systems as I mentioned a very old school systems and we don't have a lot of advanced software to use big data. So when I think of big data, my mind goes to a lot of data but at the same time they're available, we just don't utilise them because we are not generating the right reports and we don't have the time to look at them as much as we should. Also, when you mention the word big data, I wondered how we could select and target the data that we want from all the data that is available. So, for me to issues come up: selection of data and analysis of data

Q: Is Big Data widely used across all supply chain participants?

A: I think this is something that has improved over the past few years not necessarily because of the pandemic because we are generating data frequently and analysing it on a weekly basis. And then we have data on a monthly basis and there are some *frequent data that we look at. I think the way we report Data and the way we run the report is becoming more and more efficient. We analyse the big data weekly and monthly but we also have some ad hoc analysis on days like Black Friday. One more thing I want to say is that the reason why our performance with big data is improving is because our company has put in place new departments and more users. So we have Business intelligence and business partner departments that we didn't have two or three years ago and the company is seeing more and more of the value of having people dealing with data and creating and generating reports for us to look at on top of the reports we run as part of our jobs. This has helped us a lot.*

Q: Do you think other participants in the supply chain are constantly bringing in experts to analyse and provide insights from data

A: Yes, more and more. I think this is a trend and the reason the business intelligence and business partners department have helped us is because I supply chain operators, we wouldn't have the time to invest and prepare all the necessary reports and look at the big data as the business partners of business intelligence department would. So, they run the data and streamline everything.

Q: So how often do you interact with the business intelligence and business partners department

A: they prepare some reports for us weekly and monthly and we interact with our business partners when we decide to run a new project and we want to run the data for this project. So, again, this is something new because in the past we would run the project and whoever was running the project would just do some analysis and run the data which was not always the best analysis you could do. But now, when we start a project, we discuss with our business partner and we create a tool that looks at everything we want to look at.

Q: Where are the data being run by the business intelligence team derived

A: These are pre-existing data in our data system. We also have access to these data but we do not really know how to create the kind of report on Excel and other tools that we use but mainly Excel. We also don't have the time to prepare such efficient tools that can be updated quickly because you can create a tool that will be very slow and will take up a lot of your time. The data is accessible to everyone, and we have a pool of data; it's just that some people are more skilled with putting it together based on what we want to see.

Q: Do you feel that all the participants outside your organisation are taking the same steps

A: I am not really sure as I do you mostly with internal stakeholders and not external stakeholders. So, I wouldn't know if to take the same steps to work with big data

Q: Would you describe the supply chain as making use of Big data in decision making?

A: Yes definitely. We are asked to look at specific reports and when the report is created, we discuss about this report and the fact that we should get in the habit of looking at them and sometimes when we don't look at some reports all the time and the standards slip a bit, we get reminded to. There is also a big push in our meetings when we have a disagreement with a stakeholder, to back our opinion with more data. So, if there is a decision and we are disagreeing with different departments, we need to look at the data more in order to back our decision and try and push for our agenda. Even behind the strategic decisions now, we are going to see more data. It's not just enough if we suggest something because we think or we feel that this is what is going to happen, we need to back it with more data.

Q: Would you describe each firm in the supply chain as investing maximally in data software such as SAPs, track and trace devices, sensors etc?

A: No. that is a very clear answer I can give. The company is investing in growing the teams for reporting (national reporting and international reporting, Business intelligence, business partners) which is a positive thing. However, on the other hand, our systems are very old school. We have a bespoke system which is from the 90s or early 2000s. We use a lot of Excel. This system and Excel allow for a lot of human error; which is why I mention that if things change, we will need to do a lot of manual work in order to change what we had planned because a lot of our processes are very manual. Our company has actually truly invested in SAP internationally, in all the countries that it is operating in; this was a very big project. In our international office and in one of our countries, they were testing the SAP but the test was not successful, so they stopped the project; so now, we are essentially stuck with what we have. Also, in these two years that the company was investing on SAP, nobody in the company was also trying to update our systems, which means that we were left behind and now people just try to maximise our system and work with what we have. This is a bit disappointing because perhaps the company doesn't see the benefit investing or they only see the big cost of an investment in a new software. For us as users, we look at the benefits and we wish we could implement a new software.

Q: Do you think a wider use of Big Data can be beneficial to the supply chain?

A: yes definitely. Because, as I said people make more sophisticated decisions and they will be better reasoning behind decisions; and not just base decisions on experience or something they do weekly that is working

Q: Does your firm contact Big Data experts often to review its Big Data processes?

A: I think that we do; in the sense that there was a justification as to why we didn't end up switching to SAP but I think that the problem is that there was not any follow-up; in the sense that if you try something like an SAP and it doesn't work, then what's next. Do you get stuck with the old software you have been using? I think there could have been some next steps taken. Because, if you want to try something and it doesn't work, that is fine but you have to come up with new ways of optimising it.

Q: To what extent are data visualisation tools such as dashboards and Tableau used for decision making.

A: No, we use Excel. So, they are very good at Excel; if you are very good at excel in our company, you'll progress really well. And that's definitely a constraint in our operation and it's also a bit demoralising for us the users because you see that some very big companies are using the software and you want to be competitive in the market. So, you wish you also knew how to use these software. I think it will also improve our motivation.

Supply Chain Resilience Questions

Q: In light of the current pandemic, describe the challenges the supply chain faced

A: I think with the pandemic it was different because everything happened very fast and very drastically. I guess you can say that you can have big changes without the pandemic but my argument would be that with the pandemic, there was a disruption with all the stakeholders in our supply chain. There was a disruption with our suppliers, manufacturers, producers. In logistics, there was so much stock that we needed to shift but there weren't enough lorries. There weren't enough people to work the stock. Sometimes the stock was in our warehouse but we didn't have a lot of manpower to work the stock and send it to the stores. And also, there was a lot of disruption for us forecasting or trying to plan the volumes, and for the stores. In any *other situation, I think it would have taken us longer to identify the problem which would've taken us longer to react but the challenge with the pandemic was that it was all over the place. So even if we were ordering the right volumes of stock, there weren't enough people in the warehouse to work the stock or the supplier would fail to produce the stock that we wanted.*

Q: What were the typical challenges prior to the pandemic

A: I think the main challenge would have been availability. So, if for example, we didn't manage our suppliers properly or our suppliers were not the best in the market, then we would have a lot of issues and we wouldn't have the stock in the stores. If for instance the availability became poor, this would be a big issue because it will lead our customers to our competitors. If the customers came once or twice a week and did not find what they wanted, they will just go to the competitor. So, there was more pressure to have the stock available. During the pandemic, we didn't have the stock available and our stores were looking poor but this was what was happening everywhere so it wasn't looking as bad. But if for example all our competitors had a good availability of eggs or flour for instance and we didn't have for one or two weeks, then there will be a lot of pressure, and these gaps in the stores would look even worse. So that is one main challenge that we would have if it wasn't the pandemic.

Then another big challenge that we have as a business is to manage the write-off (the stock that doesn't sell) which is one of our KPIs. So, if for instance, our sales dropped and our write-offs increased; then something is very wrong. So that is another challenge that we face but it's an ongoing thing to be honest. It's always us trying to balance these two things, so it's not something new.

Q: how do you manage the inventory levels

A: We try to optimise the regional location of stock. so, when we have the national volume, we try to maximise the allocation that will go to the regional distribution centre and from each distribution centre to the stores. And we also tried to optimise the distribution of stock across the country because you might have one region having too much stock and another region having too little stock; which means that the national volume could have been alright but you just didn't allocate it to the regions properly.

Q: Describe the consistency of demand during the pandemic

A: A few weeks ago, we were still not at a point where it normally would be. So, it took a lot of time to get our availability and to get our missing items to the targets. I think that now, there is a demand point that is more consistent and we can use the details to forecast and have good availability. I think the demand stabilised; we monitor it closely. When the second lockdown was announced, we were more prepared. And when the lockdown is over, we are also more prepared that our demand will drop just because people will be able to go out and have a drink or go out to restaurants again. So, we are monitoring it more and we look at the data more. So, with the combination of stabilised demand and us being more prepared.

Q: How could a supply chain have better handled the occurrence of such disruption?

A: I think in a pandemic, our approach was very good. However, I don't know if the system is ready for such a big shock again. I can't think of many things we could have done better. I can think of a lot of things that we could have done worse. I think we did a lot of things right.

Q: What should supply chain operators do in the future to prepare for similar situations?

A: I think we should definitely create a report or have a pool of data that show exactly the changes in demand in the different products group. I think that would be helpful to all groups. The thing is, if you have this data in a user-friendly format, there will be bigger transparency among the suppliers and the supply chain users. There will be better visibility. I think there's a department (business continuity and crisis management) who have processes in place for when an emergency happens within the company e.g., fire, flooding. It will be important for this department to put something together for a similar situation. We initially did not have this department so we are very lucky because it was created just a few months before the pandemic. I think the part of the supply chain to incur the most losses in this pandemic where the people who miss the opportunity to react quickly and put in please measures to ensure safety for your customers and employees.

Q: Can your supply chain recover quickly to its original state or possibly a new, different but stable state after a disruption such as was experienced during the pandemic? Why do you think so?

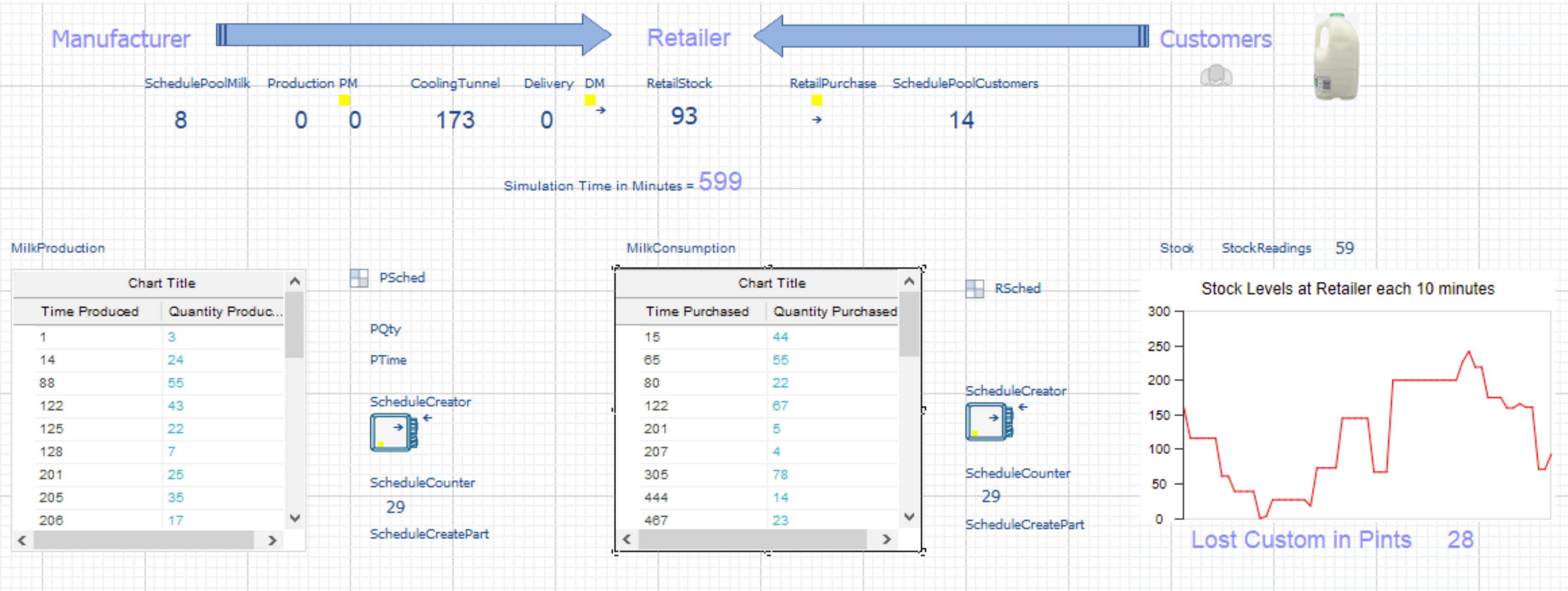
A: I think it will recover for sure. In terms of processes, I don't think the supply chain will have different processes but I think the market share will be different because e-commerce has increased so a lot of people have now turned online shopping so if you are a retailer that is based on physical stores and you don't have *an e-commerce channel, then your market share essentially will decrease. But if you have online channels like Ocado for example, their market share has increased a lot because the market is shifting in a new direction. In terms of the internal operations of the supply chain, after the pandemic, I think it will be more automated because of having to work remotely. People will turn to technology more.*

Q: What are the biggest lessons from this disruption

A: I think it comes down to using the data. When you have such big disruptions, you need to be able to analyse the data and react fast, otherwise, you miss the boat. I think we learnt to work better with data because a simple task of ordering a product daily requires more analysis and thought. However, I think in our case, we were lucky that the demand for our food product was there, we just couldn't fulfil it. The general feeling was positive. I realise we didn't have the opportunity to reflect on what happened and what we learnt; I think it will be important to reflect on what happened during the pandemic and record it, and make it available to be used in a similar situation.

Appendix C: Simulation overview in WITNESS

Appendix D: Test Model



Appendix E: Input Data

Milk Orders and Production		Skimmed= 3 Semi-skimmed= 2 Whole= 1
Time Produced	Quantity Produced	Type of Milk
1693	41	2
2092	45	2
2170	25	2
2622	54	1
2843	25	2
3291	33	2
3512	41	2
3513	22	3
3532	39	3
3713	45	1
3756	37	1
3790	24	3
4204	29	2
4229	48	2
5224	43	2
5244	59	1
6218	25	2
6613	37	3
6628	29	3
7044	26	2
7097	45	1

7506	50	2
7542	41	2
7697	50	2
8245	37	2
8514	38	2
8704	35	2
8882	34	2
8906	33	2
9185	22	3
9245	25	3
9251	38	3
9648	47	2
9658	46	1
9984	49	2
10158	45	2
10338	42	2
10339	37	2
10469	51	2
10638	29	2
10659	40	2
10673	49	2
10900	37	2
11234	26	2
11337	44	2
11340	24	2
11765	47	2
11808	46	2
12013	42	2

12073	41	3
12219	26	3
12238	35	3
12533	44	1
12691	26	2
12967	35	2
13106	27	2
13258	34	2
14261	39	2
14455	31	2
14716	37	2
14719	40	2
14990	32	2
15044	33	3
15111	24	2
15221	38	3
15559	29	3
15651	25	2
15654	27	2
15861	39	2
16095	25	2
16368	49	1
17159	45	2
17387	48	2
17736	27	2
17818	28	3
17823	29	3
17933	27	3

18124	46	1
18612	24	2
18784	25	2
19383	30	3
19489	31	2
19531	31	2
20408	39	2
20697	26	3
20792	41	3
20930	37	2
21099	27	3
21445	33	2
21451	41	2
21453	25	2
22177	47	2
22329	46	2
22447	37	2
22491	43	2
22939	40	2
23527	45	2
23622	35	3
23690	33	3
23914	23	3
23915	68	1
24437	30	2
24782	48	2
24881	46	2
26213	27	2

26335	43	2
27081	25	3
27103	37	3
27111	54	1
27475	26	2
27896	50	2
28426	28	2
28966	43	2
28974	32	2
29343	47	2
29498	26	3
29511	32	2
29522	29	3
29548	26	3
29903	47	1
29956	34	2
30421	26	2
30506	36	2
30615	42	2
30825	44	2
30848	41	2
31738	37	2
31740	37	2
31828	32	2
31919	34	2
32213	27	3
32345	22	3
32345	40	3

32349	32	3
32443	39	1
33223	27	2
33331	36	2
33332	28	2
33345	29	2
33955	54	1
34790	42	2
35059	41	2
35214	21	3
35227	38	3
35447	40	2
36128	51	2
37715	25	2
37940	32	3
38073	22	3
38224	26	3
38984	51	2
39435	35	3
39510	42	3
40210	51	2
40545	46	2
40552	28	2
40690	26	3
40937	25	3
40964	22	3
41617	32	2
41715	40	2

41738	29	2
42520	41	2
42524	51	2
42566	29	2
42670	63	1
42983	43	2
43126	45	2
43425	42	2
43434	36	2
43790	41	3
43791	41	2
43846	42	3
43848	46	2
43949	26	2
44052	50	2
44125	26	2
44383	51	2
44539	37	2
44828	48	2
44876	41	2
44910	25	2
44998	49	2
45025	39	2
45453	47	1
46279	37	2
46331	62	1
49640	33	3
49691	40	3

49694	39	3
50029	55	1
50066	48	1
50253	25	2
50477	40	2
50586	33	2
50713	26	2
51888	48	2
52058	42	2
52349	40	3
52355	27	3
52513	40	3
52579	54	1
52896	50	2
53478	45	2
53562	34	2
53572	29	2
53765	44	2
54013	61	1
54689	48	2
54736	24	2
54757	50	2
55206	22	3
55230	25	3
55283	26	3
55283	22	3
55283	22	3
55296	38	3

55458	41	1
56069	51	2
56265	26	2
56422	36	2
56611	43	2
56765	38	1
56886	39	2
56988	32	2
58207	37	3
58240	28	3
58268	26	3
58543	54	1
59255	29	2
59257	31	2
59398	46	2
60302	51	2
60738	45	2
61014	29	2
61100	32	3
61779	35	2
62020	33	2
62024	26	2
62121	40	2
62297	24	2
62698	44	2
62879	48	2
63001	32	2
63539	44	2

63862	43	3
63927	37	3
64028	41	3
64283	60	1
64940	43	2
64958	37	2
65009	34	2
65180	29	2
65549	55	1
65575	50	1
65672	37	2
65805	47	2
66140	28	2
66179	24	2
66186	39	2
66287	35	2
66313	28	2
67090	39	3
67109	32	3
67223	55	1
67390	24	2
67392	27	2
67533	47	2
67600	40	2
67892	37	2

Appendix F: Output Data

Whole Milk	Semi-Skimmed Milk	Skimmed Milk
96	55	66
96	55	66
96	55	66
96	2	66
96	2	66
96	2	66
96	2	66
96	2	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	66
96	0	25
96	0	0
96	0	0
96	0	0
96	0	0
96	0	0
96	0	0

96	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
42	0	0
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13	200	85
46	200	85
46	200	85
46	215	85
49	259	65
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0	75	0
0	135	0
0	161	0
0	194	27
0	194	87
56	194	91
68	242	91
68	302	54
68	362	54
68	388	34
59	388	62
81	426	62
81	486	62
81	546	62
81	606	62
81	666	62
81	726	62
81	730	118

Appendix G: Approved Ethics Form

THE UNIVERSITY of York

ELMPS Ethics Committee

SUBMISSION FORM

(Version as of 1 July 2018)

This form is intended to enable you and the Committee to ensure that your proposed research is compliant with the relevant codes of practice and ethical guidelines. The University recognises its obligation to the wider research community and to society as a whole to uphold the integrity of academic research. The University also has a responsibility to ensure that the funds it receives are spent in accordance with the legitimate expectations of the funding providers and the law and in the public interest. The University formally endorses the UUK Concordat to Support Research Integrity (2012).

Please ensure that you are familiar with the University's Code of Practice on Research Integrity and the University Data Management Policy as well as any relevant professional guidelines for your discipline (e.g. the Statement of Ethical Practice for the British Sociological Association) or funding organisation (e.g. ESRC Framework for Research Ethics). Useful links include:

https://www.york.ac.uk/staff/research/governance/policies/ethics-code/

https://www.york.ac.uk/staff/research/governance/policies/research-code/

http://www.esrc.ac.uk/about-esrc/information/framework-for-research-ethics/

http://www.britsoc.co.uk/about/equality/statement-of-ethical-practice.aspx

http://www.york.ac.uk/about/departments/support-and-admin/information-directorate/information-policy/index/research-data-management-policy/

Please ensure, **prior to your submission of this form**, that you have consulted the University's guidance on data protection and the General Data Protection Regulation, available at: http://www.york.ac.uk/recordsmanagement/dp/

Internet research may involve new and unfamiliar ethics questions and dilemmas. A good place to start is with the Association of Internet Researchers 2002 Guidelines and the BPS 'Conducting Research on the Internet: Guidelines for ethics practice in psychological research online (2007)'.

Note: If you are collecting data from NHS patients or staff, or Social Service users or staff, you will need to apply for approval through the Integrated Research Application System (IRAS) at https://www.myresearchproject.org.uk/Signin.aspx If you are a staff member please fill in the IRAS form NOT this one. When your IRAS application has been approved you should then send your completed IRAS form to ELMPS. Masters and Undergraduate student applications for approval through IRAS should normally be pre-reviewed by department level ethics committees.

Completed application forms should be submitted by the advertised deadline and **will not be accepted after this date. One signed <u>electronic</u> copy** (including attachments) combined into **ONE pdf file** (email to: elmps-ethics-group@york.ac.uk). We no longer require a signed hard copy. Initial decisions will normally be made and communicated within two weeks of the Committee meeting.

SECTION 1 ABOUT YOU

1a. Please provide the following details about the principal investigator at YORK

Name of Applicant:	EDIDIONG UDO
e-mail address:	Eu546@york.ac.uk
Telephone:	07926338012
Staff/Student Status:	PhD student
Dept/Centre or Unit:	The York Management School
Head of Department:	Prof. Mark Freeman
HoD e-mail address:	mark.freeman@york.ac.uk

Head of Research: (if applicable)	Prof. Jacco Thijssen
HoR e-mail address: (if applicable)	Jacco.thijssen@york.ac.uk
If you are a student please provide details about your supervisor(s)	Supervisor(s) Name: Dr Luisa Huaccho Huatuco; Prof. Peter Ball e-mail address(es): luisa.huatuco@york.ac.uk; peter.ball@york.ac.uk

1b. Any other applicants (for collaborative research projects) Expand as necessary

Name of Applicant:	
e-mail address:	
Telephone:	
Staff/Student Status:	
Dept/Centre or Unit:	
Head of Department:	
HoD e-mail address:	
Head of Research: (if applicable)	
HoR e-mail address: (if applicable)	

SECTION 2 ABOUT THE PROJECT

2.1 Details of Project

Title of Project:	Addressing the challenges of Supply Chain disruptions in businesses: Exploring the Role of Big Data
Date of Submission to ELMPS:	02/07/2020
Project Start Date:	January 2019
Duration:	3 years
Funded Yes/No:	Yes
Funding Source:	Niger Delta Development Commission (NDDC)
External Ethics Board Jurisdictions (if any):	NA

2.2 Aims and objectives of the research

Please outline the aims of your project and key research questions. Show briefly how existing research has informed the research proposal and explain what your research adds and how it addresses an area of importance (**N.B. Max 250 words**).
Organisations are increasingly having a difficult time surviving and competing as independent businesses (Ben-Daya et al., 2019) and operating in supply chains have become a vital way for organisations to survive. However, these supply chains are consistently faced with risks. While several other risks exist, disruption contributes a significant risk within the supply chain (Ivanov et al., 2014). Research carried out by key experts holds that the availability of accurate and timely data and information can aid in the in effective decision making within the supply chain. This research aims to explore the opportunities for applying the competitive advantages of Big Data in mitigating the risk of disruption in a supply chain by: • Critically reviewing and identifying the potential advantages of Big Data Analytics application in enhancing supply chain management through in-depth literature studies. • Establishing a baseline scenario of the current practical approach to supply chain disruption mitigation adopted by operators within the manufacturing sector • Determining how the manufacturing industry can be disruption-resilient through data driven modelling of alternative scenarios • Proposing optimal operations critical to the development of a disruption resilient supply chain infrastructure.

The literature reviewed has helped in shaping the following research questions:

- To what extent does Big Data Analytics offer the benefits detailed in literature?
- Are organisations currently collecting and gathering data targeted at mitigating SC disruption risks?
- How can organisations further develop their Big Data Analysis capabilities?
- How can organisations harness their Big Data Analysis capabilities to mitigate the risk of SC disruption?

2.3 Methods of Data Collection

Provide a brief summary of the method(s) of the research making clear what it will involve for participants (e.g. interviews, observation, questionnaires). If you (or your research assistants) are meeting face-to-face with research participants, specify *where* you will be meeting them (and you will need to address how any risks associated with this will be managed in Section 2.10)

In order to achieve the aims and meet the research objectives listed above, the research will adopt a mixed methods approach. The research will start out by interviewing carefully selected participants with experiences of supply chain disruption and supply chain resilience building and will then move on to computer simulations of disruption scenarios within the supply chain, building alternative scenarios for improving resilience to disruptions.

Interviews: It is the intention of the study to conduct interviews with participants in the food supply chain industry and supply chain academics who may provide vital information for the research to consider. Consultants, academics and computer simulation (modelling) experts as well as SC professionals are being considered under the assumption that they will provide unique insights that will aid a more robust and evidence-based understanding of the supply chain industry within which the current research will be based. This research will identify qualified participants through referrals and by carrying out a thorough online search for candidates matching the defined participant inclusion criteria

Participant Group	**Inclusion Criteria**	**Expected Data**
SC Professionals/Operators (2 – 3 participants)	≥ 3 years working experience in SC	Perspective on the operation of the industry

SC Consultants (2 – 3 participants)	≥ 3 years of consulting experience for major operators within the SC industry	Perspective on the operation of the industry
Academics (1 – 2 participants)	Significant publications in Food SC or SC disruptions	Perspective on relevant research component and insight to support current study
Authors/Modelling experts (1 – 2 participants)	Book publication in Computer Simulation or relevant/equivalent experience in SC Modelling	Perspective on SC Computer Simulation

The participants will be informed that the objective of the research is to capture supply chain disruption and resilience data and no confidential information is required or should be shared.

Computer Simulation: Simulation modelling is essential when studying supply chain disruption resilience (Carvalho et al., 2012; Macdonald et al., 2018) and in operations management (Davis et al., 2007), especially where the focus of the research is nonlinear, processual, and can expose the interactions of several supply chain and organisational processes (Davis et al., 2007; Macdonald et al., 2018). These conditions are adequately met in this study; which considers resilience as a mitigation strategy for supply chain disruption. Simulations provide for the application of a simplified imitation of a system and its progress, processes and operations over time for the purpose of understanding and potentially improving the system (Robinson, 2004). Discrete event simulation is applied in this research as a quantitative method for data collection and analysis.

The Discrete Event Simulation Tool (DES) is available in several commercial software packages. This research has however decided to use the WITNESS software package developed by Lanner Group for the following reasons: Accessibility to the research team, in built flexibility, ease of organising training for software use and possession of common supply chain modelling requirements.

2.4 Sampling and Recruitment of participants

How many participants will take part in the research? How will they be identified – describe your ***sampling*** method? How will they be invited to take part in the study – describe your ***recruitment*** method? If research participants are to receive any payments, reimbursement of expenses or any other incentives or benefits for taking part in the research please give details, indicating what and how much they will receive and the basis on which this was decided.
It is the intention of the field study to conduct interviews Knowledgeable experts in the food supply chain industry who may provide vital information for the research to consider. This research will identify qualified participants through referrals and by carrying out a thorough online search for candidates matching our participant criteria. Participants in the field study will be carefully selected in order to ensure that the research meets its aims and objectives. The participants in the study will have to be currently working senior professionals who can speak directly to the current disruption challenges faced by the modern supply chain. As there is a disruption ongoing at the time of data collection for this research, the participant will be able to draw from recent events. These senior professionals must be working in key positions and roles which directly affect the supply chain such as Supply Chain managers, Risk managers, Supply Chain consultants, Senior academics and experts in supply chain disruption, Supply Chain modelling experts. This research seeks to interview 8-10 participants as part of the study. Data from the field study will be collected using both handwritten notes and digital voice recording to capture inputs by participants. This will later be transcribed and analysed accordingly.

2.5 'Vulnerable' Participants

Please indicate whether any research participants will be from the following groups; if so, please explain the justification for their inclusion. In most cases, researchers working with vulnerable people will need to be registered with ISA (www.isa.homeoffice.gov.uk) which has links with the DBS (formerly the CRB). The DBS offers organisations a means to check the background of researchers to ensure that they do not have a history that would make them unsuitable for work involving children and vulnerable adults.

NB: *If you are collecting data from NHS patients or staff, or Social Service users or staff, you will need to apply for approval through the Integrated Research Application System (IRAS).*

Children under 18	NA
Those with learning disability	NA
Those who are severely ill or have a terminal illness	NA
Those in emergency situations	NA
Those with mental illness (particularly if detained under Mental Health Legislation)	NA
People with dementia	NA
Prisoners	NA
Young offenders	NA
Adults who are unable to consent for themselves	NA
Those who could be considered to have a particularly dependent relationship with the investigator or gatekeeper, e.g. those in care homes	NA
Other vulnerable groups (please specify) – discuss the issues this raises	NA

If yes to any of the above, do you have Disclosure and Barring Service Clearance?
Yes/No
Describe the procedures you are using to gain (a) consent and/or (b) proxy consent if applicable

NA

2.6 'Sensitive' topics

During your study, will anyone discuss sensitive, embarrassing or upsetting topics (e.g. sexual activity, drug use) or issues likely to disclose information requiring further action (e.g. criminal activity)? If so, please give details of the procedures in place to deal with these issues, including any support/advice (e.g. helpline numbers) to be offered to participants. Consider, too, the risks this may pose to the researcher.

Note that where applicable, consent procedures should make it clear that if something potentially or actually illegal is discovered in the course of a project, it may need to be disclosed to the proper authorities.

NA

2.7 Covert research

If the research involves covert data gathering or deception of any kind, please explain and justify the deception. Specify what procedures (if any) will be used to debrief participants after the data have been collected.

NA

2.8 Informed Consent

Please attach (1) the privacy notice/project information sheet to be given to all participants and (2) the informed consent form. In line with the University's Code of Practice on Research Integrity, participants and/or their representatives should be provided with details of a first point of contact through which any concerns can be raised: this should be your Head of Department (or if you *are* a Head then the Pro-Vice-Chancellor for Research).
i. If you are not seeking informed consent It is usually the case that informed consent is required for research with human participants. If you do NOT intend to seek informed consent please explain carefully why you believe this is not necessary for your project. You should explain this with reference to the research ethics guidelines for your discipline and cite other recent published research using your methodological approach or ethics discussions about this to support your case. Not Applicable
ii. Please confirm you have included the privacy notice/project information sheet to be given to all participants with your submission to ELMPS. If these have not been attached, please explain why this is the case.
Privacy notice and informed consent forms attached.

iii. Please confirm you have included all the relevant informed consent forms. If these have not been attached, please explain why this is the case.
Privacy notice and informed consent forms attached.
iv. Are the results to be given as feedback or disseminated to your participants (if yes please specify when, in what form, and by what means). If no, why not?
The result of this research may at the request of the participants be given as a 30 minute presentation, alternatively the published copy of the thesis will be made available to participating organisations.

2.9 Anonymity

In most instances the Committee expects that anonymity will be offered to research participants. Please set out how you intend to ensure anonymity. If anonymity is not being offered please explain why this is the case. Note that if anonymity is not offered (or cannot be guaranteed) this has implications you must address in Section 3 below. Note: if you are using a transcriber or translator you must have a signed confidentiality agreement with them.
This research will maintain anonymity by providing a very broad description of the sector being researched and the roles of individual participants. Specific details that could help identify organisations or individuals (such as participant name, exact job title, company name, company location within the UK, specific company products) will be withheld. In addition, codes will be assigned to each transcript instead of names to ensure an additional level of confidentiality. A separate cross reference sheet held in a different location on the google drive will then be used to identify participants The following descriptors *may* be used as they may be required for research publications resulting from reviewer feedback: - company locality (e.g. Yorkshire, UK) - company size (e.g. SME or large) or structure (e.g. multi-site) - generic job role (e.g. product development lead) or generic title (e.g. design

director) - internal company structure (e.g. engineering team, design team)

2.10 Anticipated Risks or Ethical Problems

Please outline any anticipated risks or ethical problems that may adversely affect any of the participants, the researchers and/or the university, and the steps that will be taken to address them. (Note: all research involving human participants can have adverse effects.) Please also refer to the University's Health, Safety and Welfare Policy Statement and associated Management Procedures, as well as to any ethical guidelines you have consulted. Where relevant, risk assessments should be carried out not only in relation to the researchers themselves, but also for those participating in the project or affected by its conduct, and in relation to any impact on the environment. Researchers should ensure that appropriate insurance is in place, liaising with the University's Insurance Officer as necessary (via standard departmental procedures where these exist).
i. Risks to participants (e.g. emotional distress, financial disclosure, physical harm, transfer of personal data, sensitive organisational information…)
Given the current pandemic, the interviews will be held virtually which should pose very low or no risk to the participants Data to be collected will be limited to only information required for a better understanding of supply chain risks, supply chain disruption and mitigation strategies.
ii. Risks to researchers (e.g. personal safety, physical harm, emotional distress, risk of accusation of harm/impropriety, conflict of interest…)
The research will be carried out virtually and will pose no threat to the researcher. Additionally, participants will be anonymised and as such, there should be no risk of participants being identified
iii. University/institutional risks (e.g. adverse publicity, financial loss, data protection…)
The research will pose no risk to the university
iv. Financial conflicts of interest (e.g. perceived or actual with respect to direct payments, research funding, indirect sponsorship, board or organisational memberships, past associations, future potential benefits, other…) **The research will not offer any financial incentives**

2.11 Research outside the UK

If you are planning research overseas, you should also take account of the ethical standards and processes of the country/countries in question as well as those of the University. If the research is being conducted outside the UK please specify any local guidelines (e.g. from local professional associations/learned societies/universities) that exist and whether these involve any ethical stipulations beyond those usual in the UK. Also specify whether there are any specific ethical issues raised by the local context in which you are conducting research, for example, particular cultural sensitivities or vulnerabilities of participants. **NA**

SECTION 3: DATA PROTECTION

Please ensure you have read the information on data protection at: https://www.york.ac.uk/records-management/dp/ *before you complete this section*

3.1 Does your project involve personal data (as defined by the General Data Protection Regulation): Yes/No. If yes, please provide a description of the data and explain why you need to collect this data.

While sensitive data will not be collected for the purpose of this research, the research will collect information such as job title, position or role in the supply chain, as this is relevant to ensure that participants meet selection criteria and research journals upon eventual publication may request to know the types of people interviewed. However, for the purpose of anonymity, generic identifiers like "supply chain consultant" will be used. Additionally, the research will ensure that company descriptions are fully generic to ensure that both the organisation and the participant remain unidentifiable.

3.2 Does it involve special category personal data (as defined by the General Data Protection Regulation): Yes/No. If yes please provide a description of the data:

No

3.3. If the research will involve any of the following activities please indicate so and provide further details. Explain how this will be conducted in accordance with the General Data Protection Regulation and the Data Protection Act (and/or any international equivalent)

Electronic transfer of data in any form	The researcher's email will be shared with participants. However, this will be for the purpose of setting up meetings, providing consent forms and other relevant information ahead of the interviews. However, this will only take place between their work email and the researcher's University of York email.

Sharing of data with others at University of York	Any data collected during this research will be shared with the supervisory team using the Google Drive provided by the University of York. The participants will be informed of this prior to the research taking place.
Sharing of data with other organisations	No
Export of data outside the European Union or importing of data from outside the UK	No
Use of personal addresses, postcodes, faxes, emails or telephone numbers	Data will be collected using either Zoom account or Google conferencing provided by the University of York. However, where these means are not convenient for the participants, personal phone numbers or skype accounts may be required.
Publication of data that might allow identification of individuals	No
Use of audio/visual recording devices	The interviews will be recorded using a smartphone device or the recording function provided by software used. All software will be password protected while in use, after which the data will be transferred to password protected files (Google Drive)
Use of data management system (e.g. Nvivo, ATLAS.ti)	This research will make use of excel spreadsheets, Nvivo for analysing interview data and WITNESS by Lanner Group for computer simulation.
Data archiving	The research data will be stored in the Google Drive provided by the University of York for the duration of the research, after which is will be transferred to the archive provided by the University of York which offers similar security. Additionally, any personal computers which may be

	used in the course of this research will be password protected to provide an added layer of security.

3.4. If the research will involve storing personal data on any one of the following please indicate so and provide further details.

Manual files (i.e. in paper form)	The findings from this research may later be published in Research journals.	
University computers	Yes	Password protected Yes Encrypted Y/N
Private company computers	No	Password protected Yes Encrypted Y/N
Home or other personal computers	Yes. Given the current pandemic, some part of this research will have to be carried out using a personal computer which is password protected. However, storage will not be done on this personal computer.	Password protected Yes Encrypted Y/N
Laptop computers/ CDs/ Portable disk-drives/ memory sticks	Yes. Given the current pandemic, some part of this research will have to be carried out using a personal computer which is password protected. However, storage will not be done on this personal computer.	Password protected Yes Encrypted Y/N
Websites	NA	Password protected Y/N Encrypted Y/N
Other	NA	Password protected

		Y/N Encrypted Y/N

3.5 Please explain the measures in place to ensure data confidentiality, including details of encryption and anonymisation.

This research will ensure that data provided is **only** shared between the researcher and the supervisory team where necessary. No names of organisations or individual participants will be used. Data gotten during the research will be stored in a secure location provided by the university during the period of the research, after which is it archived in an equally secure location according to University guidelines. The data will be stored for a period of five years and then destroyed. To provide an extra layer of security, codes will be assigned to ensure an additional level of confidentiality.

3.6 Please detail all who will have access to the data generated by the study.

The companies may exchange data (plans, activities, processes, achievements). They will do so willingly. Their act of sharing is voluntary. They will be advised not provide any confidential information. The Researcher may share details of data collected with Supervisors and the University of York

3.7 Please detail who will have control of, and act as custodian(s) for, data generated by the study.

Researcher, Supervisors and the University of York

3.8 Please give details of data storage arrangements, including where data will be stored, how long for, and in what form. Will data be archived – if so how and if not why not. Note the university policy that "Where possible, relevant elements of research data must be deposited in an appropriate national or international subject-based repository, according to their policies. Data should be kept by the researcher in an appropriate manner when suitable subject repositories are not available." http://www.york.ac.uk/about/departments/support-and-admin/information-directorate/information-policy/index/research-data-management-policy/#tab-1

Audio or video data, as well as transcription data will be stored using the University's secure storage system (Google Drive) for the period of the research, after which it will be archived following University guidelines for a period of five years. Following a five-year duration from the date of research conclusion, the data will be destroyed.

If participants choose to share secondary data in written or digital form, similar processes will be followed. All research associated documents will be stored following the university's guidelines and using secure locations provided by the University of York. All interview data and notes are stored in this secure location for a maximum of five years following the publication of this study, after which, both hard and soft copies are destroyed.

3.9. Minimising data collection to what is necessary

A key principle contained in the General Data Protection Regulation (GDPR) is that the data collected must be **limited to what is necessary** to fulfil the purpose for which they are processed.

Are you capturing the minimum amount of personal data/special category data necessary for your research project? If yes, please provide an indication of why this is the minimum amount of personal data/special category data required.

This research will only collect data focused on providing a better understanding of supply chain disruption risk and how organisations are currently mitigating it. The research will not consider data outside the scope of this research and will only collect personal data such as years of experience and role within the organisation to put the participant's response into context.

3.10. Data Protection Impact Assessment (DPIA) Screening Questions

A DPIAs should be undertaken for data processing likely to be high risk under the GDPR. The Regulation does not define 'high risk' but the Information Commissioner's Office has produced a checklist for determining when assessments should be undertaken. This is available on the ELMPS website DIPA Screening Questions (MS Word, 15kb).

Please consult the University of York's guidance on DPIAs prior to completing the declaration below. This is available at: https://www.york.ac.uk/records-management/dp/dataprivacyimpactassessments/

It is your responsibility to ensure that a DPIA is undertaken if it is required for your research project. Please tick **ONE** appropriate statement below:

Declaration	Agreement
1. I have completed the DPIA screening questionnaire and consider that a DPIA **is not required** as the data collected is not 'high risk.'	☒
2. I have completed the DPIA screening questionnaire and consider that a DPIA **is required** as the data collected is likely to be 'high risk.' I have submitted the completed assessment to the University of York's Data Protection Officer for review and **am awaiting a decision on approval.**	☐
3. I have completed the DPIA screening questionnaire and consider that a DPIA **is required** as the data collected is likely to be 'high risk.' The completed assessment is attached to this application and **has been approved** by the University of York's Data Protection Officer.	☐

SECTION 4 SIGNED UNDERTAKING

In submitting this application I hereby confirm that I undertake to ensure that the above named research project will meet the University's Code of Practice on Research Integrity https://www.york.ac.uk/staff/research/governance/policies/research-code/.

Edidiong I. Udo

……………………………………….. (Signed Lead Researcher/Principal Investigator)

02/07/20

……………………………………….. (Date)

……  …………….. (Signed Supervisor (where relevant))

I confirm I have read and approved this application

(*Electronic signature required*)

…………1/7/20……………….. (Date)

Submission Checklist for Applicants

One signed <u>electronic</u> copy (including attachments) in **one pdf file** to: elmps-ethics-group@york.ac.uk

- [x] ELMPS Application form
- [x] Consent form for participants
- [x] Privacy notice/participant information sheet
- [x] ELMPS Compliance form

Participant Consent Form

Participant Identification Number___________________________________

Study Title:
ADDRESSING THE CHALLENGES OF SUPPLY CHAIN DISRUPTIONS IN BUSINESSES: Exploring the Role of Big Data

Lead Researcher:

Edidiong Udo

eu546@york.ac.uk

Consent form for participants

This form is for you to state whether or not you agree to take part in the study. Please read and answer every question. If there is anything you do not understand, or if you want more information, please ask the researcher.

Have you read and understood the information leaflet about the study?	Yes ❒ No ❒
Have you had an opportunity to ask questions about the study?	Yes ❒ No ❒
Do you understand that the information you provide will be held in confidence by the research team?	Yes ❒ No ❒

Do you understand that you may withdraw from the study at any time and for any reason before publication, without affecting any services you receive? Yes ❒ No ❒

Do you understand that the information you provide may be used in future research? Yes ❒ No ❒

Do you agree to take part in the study? Yes ❒ No ❒

If yes, do you agree to your interviews being recorded? Yes ❒ No ❒

(You may take part in the study without agreeing to this).

All data is held by The York Management School, University of York, UK in accordance with the Data Protection Act.

Your name (in BLOCK letters):

____

Your signature:

____

Date:

____

For the research team only:

I hereby confirm that the participant was provided adequate opportunity to ask questions concerning the research and that all questions asked by the participants have been duly answered to the best of my ability. I also confirm that the participant has given this consent voluntarily and is not under any duress.

Interviewer’s name:

____

Your signature:

____

Date:

____

______

Participant Information Sheet

Background

The University of York would like to invite you to take part in the following research project,

Before agreeing to take part, please read this information sheet carefully and let us know if anything is unclear or you would like further information.

What is the purpose of the study?

Organisations are increasingly having a difficult time surviving and competing as independent businesses (Ben-Daya et al., 2019) and operating in supply chains have become a vital way for organisations to operate in today's business environment. However, these supply chains are consistently faced with risks and finding ways to mitigate these risks has become imperative**.**

The aim of this research is to explore the potentials and opportunities of applying the competitive advantages of Big Data in mitigating the risk of disruption in a supply chain. The research will also explore the requirements and advantages of building resilient supply chains as a strategy for mitigating disruption.

Why have I been invited to take part?

In order to achieve the aims and meet the research objectives listed above, the research will adopt a mixed methods approach. The research will start out by carrying a field study which involves a survey, interviewing carefully selected participants. It is the intention of the field study to conduct interviews with knowledgeable experts and participants within a functional supply chain who may provide vital information for the research to consider.

You have been invited to take part because you are a qualified subject matter expert identified by this research as being crucial to supply chains. This makes your input very valuable to this research.

Do I have to take part?

No, participation is optional. If you do decide to take part, you will be given a copy of this information sheet for your records and will be asked to complete a participant information form. If you change your mind at any point during the study, you will be able to withdraw your participation without having to provide a reason.

On what basis will you process my data?

Under the General Data Protection Regulation (GDPR), the University has to identify a legal basis for processing personal data and, where appropriate, an additional condition for processing special category data.

In line with our charter which states that we advance learning and knowledge by teaching and research, the University processes personal data for research purposes under Article 6 (1) (e) of the GDPR:

Processing is necessary for the performance of a task carried out in the public interest

Special category data is processed under Article 9 (2) (j):

Processing is necessary for archiving purposes in the public interest, or scientific and historical research purposes or statistical purposes

Research will only be undertaken where ethical approval has been obtained, where there is a clear public interest and where appropriate safeguards have been put in place to protect data.

In line with ethical expectations and in order to comply with common law duty of confidentiality, we will seek your consent to participate where appropriate. This consent will not, however, be our legal basis for processing your data under the GDPR.

How will you use my data?

Data will be processed for the purposes outlined in this notice.

Will you share my data with 3rd parties?

No. Data will be accessible to the project team at York only which includes the researcher and the supervisory team. Therefore, data collected as part of this research will not be made available to third parties. Additionally, data drawn from this research will be fully anonymised such that no participant identity can be revealed and all publications utilising this data will be done anonymously.

How will you keep my data secure?

The University will put in place appropriate technical and organisational measures to protect your personal data and/or special category data. For the purposes of this project we will make use of the storage technology provided by the University of York, using the Google Drive. However, if you are opposed to your data being stored within the Cloud system under special contract between Google and the University of York, please let the researcher know to ensure appropriate arrangements are made.

Information will be treated confidentiality and shared on a need-to-know basis only. The University is committed to the principle of data protection by design and default and will collect the minimum amount of data necessary for the project. In addition, we will anonymise or pseudonymise data wherever possible.

Will you transfer my data internationally?

No. For the purposes of this research, data will be held within the European Economic Area in full compliance with data protection legislation.

It is however noteworthy to pinpoint that the University's cloud storage solution is provided by Google which means that data can be located at any of Google's globally spread data centres. The University has data protection compliant arrangements in place with this provider. For further information see, https://www.york.ac.uk/it-services/google/policy/privacy/.

Will I be identified in any research outputs?

No, the name of participants and organisations taking part in this research will only be made known to the primary researcher and the supervisory team.

How long will you keep my data?

Data will be retained in line with legal requirements or where there is a business need. Retention timeframes will be determined in line with the University's Records Retention Schedule.

What rights do I have in relation to my data?

Under the GDPR, you have a general right of access to your data, a right to rectification, erasure, restriction, objection or portability. You also have a right to withdrawal. Please note, not all rights apply where data is processed purely for research purposes. For further information see, https://www.york.ac.uk/records-management/generaldataprotectionregulation/individualsrights/.

Questions or concerns

If you have any questions about this participant information sheet or concerns about how your data is being processed, please contact the primary researcher (Edidiong Udo) in the first instance. My email address is eu546@york.ac.uk. Additionally, you may contact one of my two supervisors (Dr Luisa Huatuco) at her email address luisa.huatuco@york.ac.uk.

If you are still dissatisfied, please contact the University's Acting Data Protection Officer at dataprotection@york.ac.uk.

Right to complain

If you wish to lodge a complaint about the researcher or the way this research is currently being carried out and you do not wish to contact the researcher, please contact my supervisor

Dr Luisa D. Huaccho Huatuco

Senior Lecturer in Operations Management

T: 01904 325 077

E: luisa.huatuco@york.ac.uk

If you are unhappy with the way in which the University has handled your personal data, you have a right to complain to the Information Commissioner's Office. For information on reporting a concern to the Information Commissioner's Office, see www.ico.org.uk/concerns.

Compliance Declaration

This declaration must be returned, fully completed, along with each submission made to ELMPS.

On completion, please return a copy of this form by email to elmps-ethics-group@york.ac.uk, **signed by the Applicant and, if applicable, the Applicant's PhD Supervisor**.

Those making a resubmission **must also complete section 6, on page 2.**

1. The Applicant:

Name: Edidiong Udo

Position: Doctoral Researcher

Centre/Department: The York Management School

Contact details: email address: eu546@york.ac.uk Telephone number: 07926338012

2. Supervisors:

Doctoral Supervisors: Dr Luisa Huatuco; Prof. Peter Ball

(if applicable)

Head of Research: Prof. Jacco Thijssen

Head of Department: Prof. Mark Freeman

3. The Project:

Project Title: Addressing the Challenges of Supply Chain Disruptions In Businesses: Exploring the Role of Big Data

How is the project funded?: ☐ Self-Funded ☐**X** External funder

Funder (if applicable): Niger Delta Development Commision (NDDC)

4. Other Jurisdictions:

Please indicate whether your proposal has been considered by any other bodies:

☐ External Sponsor

☐ Another University of York Ethics Committee

☐ NHS Research Ethics Committee

5. Declaration:

I confirm that I have read and understood:

X the ELMPS guidelines on consent; and

X the ELMPS information sheets for researchers working with human subjects; and

X the University of York data protection guidelines.

Signature of applicant:

(Type name if submitting electronically)

Edidiong I. Udo

Date: 06/06/20

I confirm that the applicant and myself have read and understood the ELMPS guidelines on Consent and Data Protection)

Signature of Research Supervisor (if appropriate):

(Electronic signature required)

Date:1/7/20

6. Additional Declaration for Resubmissions:

I have read and understood the ELMPS response to the initial application, and consider that the attached response deals appropriately with its recommendations.

Signature of applicant:

Date:

Please attach an additional sheet/file with a point-by-point response to the recommendations issued by ELMPS.

I have read and understood the ELMPS response to the initial application, and consider that the attached response deals appropriately with its recommendations.

Signature of Research Supervisor (if appropriate):

Date:

Appendix H: Participants Description

Participant 1

Participant 1 works within one of the top international retail suppliers (with over 10,000 stores worldwide) as a Senior Supply Chain Expert, with responsibility spanning across optimising the allocations of stock, demand analysis, planning and demand forecasting. Their role also involves sales monitoring sales with a view to making weekly decisions about price reviews of non-performing products. They also have operational responsibility for promotional products and also deals with returns, writing off of stocks and extending stocks. Thus, this participant is quite versed in the daily operation management of supply chain activities with the UK, and so met the inclusion criteria for this study.

Participant 2

Participant 2 works within a multinational food manufacturing supply chain as a central supply planner, with responsibilities spanning from periodic sales forecast to demand forecast and production planning. They also visualise production and manage organisational capacity to ensure availability and efficiency. This participant is uniquely qualified to discuss potential issues surrounding procurement volumes, demand planning and the effects of a disruption on production planning within the supply chain.

Participant 3

Participant 3 brings over 15 years of supply chain experience consultancy in industries such as construction, textile and development. Key experiences include procurement, logistics and distribution, sales and marketing, operations and manufacturing. This participant works in conjunction with key supply chain experts to analyse and review issues surrounding supply chain sustainability, transportation, supply chain emissions in carbon and water. This participant is involved with reviewing the stress testing ability and modelling of organisational capacity to ensure efficiency and effectiveness.

Additionally, this participant is also involved with the review of organisational policies and procedures with regards to their supply chain activities. Hence, this participant is able to offer viewpoints covering supply chain activities as well as the policies that affect them.

Participant 4

Participant 4 is a simulation and modelling expert with about 20 years of experience which also covers supply chain modelling, working with some of the top automotive companies in the United Kingdom and also top research modelling and simulation organisations. This participant has also worked in conjunction with international telecommunications organisations and as a consultant for organisations looking to optimise their business processes for higher efficiency and clear visualisations.

This participant is also a published author in the modelling and simulation space including supply chain which provides a unique perspective to supply chains, how they are modelled and the existing research surrounding supply chain modelling.

Participant 5

This participant brings about 30 years of working experience within supply chains. Participant 5 is the head of supply chain for one of the largest manufacturers of food within the United Kingdom and has worked with this company for over five years now. Prior to this current organisation, this participant spent 15 years at another multinational food manufacturer within various positions in sales, marketing and supply chain and procurement jobs. Prior to that, this participant worked for 10 years in food retail for one of the top food retailers in the United Kingdom with over 1500 stores.

Hence, this participant has worked as a front-line staff in supply chains through various disruption scenarios including COVID-19 pandemic, Brexit, CO2 Crisis and even the recent blocking of the Suez Canal; which makes this participant well-informed on how disruptions affect supply chains and food manufacturing decision making processes.

Participant 6

This participant brings nearly 30 years of working experience, having worked with suppliers across the fast-moving consumer goods industry for over 10 years; and has also worked in retail supply chains. The participant has now remained a consultant within the supply chain with a relevant PhD and authorship of relevant literature over the past 20 years. Key responsibilities and areas of interests include commercial management, marketing, sales and supply, which make the participant uniquely positioned to offer independent insights on both academic and practical viewpoints within the supply chain industry.

Participant 7

This participant brings over 20 years of combined senior management and consulting experience in procurement and supply chain, with responsibilities including digital transformation change management and procurement. This participant now leverages this vast experience in supply chain and procurement to provide services to one of the largest organisations in digital transformation with a strong focus on providing customer value in sourcing and procurement.

This participant also has experience delivering lectures on supply chain related topics to students at three top ranking universities within the United Kingdom, which makes them uniquely qualified to offer both academic and practical viewpoints to the topic of big data and supply chain resilience.

Participant 8

Participant 8 serves as a supply chain manager at a milk manufacturing company. In this role, they oversee end-to-end supply chain operations, including procurement, production planning, logistics, and distribution. They are responsible for ensuring the efficient flow of materials and products, maintaining optimal inventory levels, and coordinating with suppliers and retailers to meet demand. Additionally, they implement strategies to enhance supply chain resilience and mitigate risks. With over ten years of industry experience, this participant is regarded as a key informant for this research due to their extensive knowledge and expertise in managing and optimising supply chain operations within the dairy sector.

Particpant 9

Participant 9 works at a large national grocery retailer, with responsibilities primarily focused on demand forecasting and planning. Additionally, they are involved in monitoring sales trends, analysing inventory levels, and making weekly purchasing decisions to ensure optimal stock levels. This participant's role requires close collaboration with suppliers and the merchandising team to align supply with consumer demand. With nine years of experience in the retail sector, this participant has advanced to a managerial level, where they utilise their extensive expertise to improve operational efficiency and drive business performance.

Participant 10

Participant 10 specialises in simulation modelling, bringing about five years of experience in this field. In their organisation, they are responsible for developing and implementing simulation models to analyse and optimise various operational processes. Their role involves collecting and interpreting data, creating accurate models to predict outcomes, and providing insights to support decision-making. They work closely with cross-functional teams to ensure that models align with organisational goals and strategies. In this research, their contribution is crucial, as they ensure that the supply chain simulations accurately reflect the information gathered from interviews, thereby enhancing the reliability and validity of the research findings.

Appendix I: Big Data Simulation and Resilience Decision making

One of the advantages of Big Data discussed in literature is its ability to support decision making. With the availability of a Big Data Warehouse and a simulation model, organisations can develop a decision support system, enhancing the quality of decisions made in risk scenarios. An organisation can create what if scenarios and carry out experiments based on data available in real time within the Big Data Warehouse and providing that data to the model to view varying results. Kagermann et al. (2013) highlights the application of computer simulations such as the one carried out within this chapter in analysing the behaviour of supply chains and adds that with the introduction of Big Data into the simulation, various sources can be considered at the same time which allows for better decision making. The study by Vieira et al., (2020) suggests that Big Data from various supply chain sources could even be gathered solely for the purpose of providing that data to a simulation model for analysis and decision making. This beg the question within this research: what if the supply chain of interest within this research had a greater analysis of the Big Data, what insights can be gained?

To answer this question, the research by Vieira et al. (2020) used their simulation interactively to simulate what if scenarios. Hence, this research will answer the question of insights that can be gained from Big Data analysis by analysing a larger set of Big Data. This new set of Big Data is generated based on technological capacity with WITNESS Horizon simulation tool. Having already inputted 3 years data collected into WITNESS, WITNESS is able to learn the patterns within the dataset and is able to generate data set based on the learned pattern for extended period. The next set of experiments is provided in Results 2 expands on Table 7.12 and shows results of a 4-year experiment with production disruption, demand disruption and logistics disruption. This research will compare the results between both sets of experiments to gain additional insights where additional data is available. The resilience measures being taken into account in both experiments is the supply chain cost, the time to recovery and the customer service levels within a simulation time of 2,100,000 minutes.

In the new sets of experiments conducted, the results show supply chain costs increase between the first experiment and the second experiment. However, the increase is not significant across all retailers. The pattern remains the same as in the first set of experiments, where demand disruption incurs the least cost across all retailers and logistics disruption includes the highest supply chain cost.

The difference between the first set of experiments and the second set of experiments may indicate the different factors interacting within the milk supply chain. For example, the market conditions may have changed, retailers may have learnt lessons from previous disruptions and made additional provisions, there may be changes in the dynamics between demand and supply. The degree of change in both experiments varies across the different retailers as seen in Results 2, which reflects the resilience levels of each retailer within the supply chain as well as their unique characteristics

Additionally, the result is consistent in the pattern between both experiments. The demand incurs the least cost and logistics. This version includes the highest cost; providing valuable insight into the cost drivers in the milk supply chain. And as seen in section 7.4, the cost incurred where there is a change in buying behaviour can be mitigated by proper inventory planning. However, the logistics disruption where demand exists and supply exists but transportation is unavailable is not easily mitigated.

The time to recovery in the second set of experiments also increases, however not significantly. This may be indicative of the effectiveness of recovery strategies or the availability of resources which allows the retailers to recover. It is however important to note that the different disruption times result in different recovery times across the retailers, which may also reflect the resilience levels of each retailer.

Summary of Results 2

Resilience Measure (Sections)	**Disruptions**	**Disruption Length**	**Retailer (Results 1)**				**Retailer (Results 2)**			
As-Is (7.3)	*Scheduled maintenance (No Disruption)*	24 hours	Retailer 1 *(No Disruption)*	Retailer 2 *(No Disruption)*	Retailer 3 *(No Disruption)*	Retailer 4 *(No Disruption)*	Retailer 1 *(Not Disruption)*	Retailer 2 *(No Disruption)*	Retailer 3 *(No Disruption)*	Retailer 4 *(No Disruption)*
Supply Chain cost (7.4.1)	*Production Disruption*	1 week	Retailer 1 (£3266)	Retailer 2 (£594)	Retailer 3 (£795)	Retailer 4 (£763)	Retailer 1 (£3568)	Retailer 2 (£600)	Retailer 3 (£810)	Retailer 4 (£790)
	Demand Disruption	1 week	Retailer 1 (£2623)	Retailer 2 (£583)	Retailer 3 (£275)	Retailer 4 (£653)	Retailer 1 (£2922)	Retailer 2 (£585)	Retailer 3 (£277)	Retailer 4 (£659)
	Logistics Disruption	1 week	Retailer 1 (£9346)	Retailer 2 (£781)	Retailer 3 (£5896)	Retailer 4 (£4642)	Retailer 1 (£9708)	Retailer 2 (£786)	Retailer 3 (£5902)	Retailer 4 (£4654)
Time to Recovery (7.4.2)	*Production Disruption*	1 week	Retailer 1 (155 Hours)	Retailer 2 (136 Hours)	Retailer 3 (124 Hours)	Retailer 4 (71 Hours)	Retailer 1 (159 Hours)	Retailer 2 (138 Hours)	Retailer 3 (127 Hours)	Retailer 4 (75 Hours)
	Demand Disruption	1 week	Retailer 1 (10 Hours)	Retailer 2 (18 Hours)	Retailer 3 (22 Hours)	Retailer 4 (22 Hours)	Retailer 1 (12 Hours)	Retailer 2 (20 Hours)	Retailer 3 (25 Hours)	Retailer 4 (25 Hours)
	Logistics Disruption	1 week	Retailer 1 (124 Hours)	Retailer 2 (141 Hours)	Retailer 3 (150 Hours)	Retailer 4 (144 Hours)	Retailer 1 (138 Hours)	Retailer 2 (150 Hours)	Retailer 3 (159 Hours)	Retailer 4 (153 Hours)
Customer Service Levels (7.4.3)	*Production Disruption*	1 week	Retailer 1 (86 Pints)	Retailer 2 (122 Pints)	Retailer 3 (80 Pints)	Retailer 4 (99 Pints)	Retailer 1 (89 Pints)	Retailer 2 (126 Pints)	Retailer 3 (82 Pints)	Retailer 4 (103 Pints)
	Demand Disruption	1 week	Retailer 1 (82 Pints)	Retailer 2 (69 Pints)	Retailer 3 (84 Pints)	Retailer 4 (76 Pints)	Retailer 1 (84 Pints)	Retailer 2 (72 Pints)	Retailer 3 (87 Pints)	Retailer 4 (79 Pints)
	Logistics Disruption	1 week	Retailer 1 (102 Pints)	Retailer 2 (59 Pints)	Retailer 3 (54 Pints)	Retailer 4 (64 Pints)	Retailer 1 (107 Pints)	Retailer 2 (63 Pints)	Retailer 3 (60 Pints)	Retailer 4 (69 Pints)

The results also show an overall increase in the time to recovery when simulated for four years, even though this is not significant. This may suggest that the resilience practices developed based on previous disruptions such as collaboration with suppliers, collaboration with logistics partners, resilient supply chain design, flexible sourcing options and backup stocks are impactful, allowing the supply chain to learn and be more resilient. Evidence in section 4.5 shows that these strategies are enhanced by Big Data technology.

The customer service level, which shows the average volume of milk available for customers to purchase also increased. And this increased customer service level is an indication of overall improvement in the performance of the supply chain. It is also indicative of the learning and adaptation of the supply chain which allowed to supply chain to identify areas to improve and resilience measures to apply.

Retailers may have implemented resilience measures such as communication among supply chain participants, inventory management, flexible sourcing and production, resilient supply chain design etc. allowing the supply chain to react better to more disruptions. A culture of continuous improvement will allow the supply chain to put feedback mechanisms in place to collect data, analyse performance and conduct post disruption reviews which may consistently enhance customer service levels.

Overall, the research observed an improvement in customer service levels in the second set of experiments which reflects the ability of the supply chain to learn and enhance performance. The supply chain showed an increased ability to meet the customers demand, even though only slightly. The time to recovery follows a similar pattern where the demand disruption takes the shortest time to recover, followed by the production disruption, and the logistics disruption takes the longest time to recover; which was also seen in the first set of experiments. The supply chain costs show an overall increase with the demand disruption incurring the lower costs and the logistics disruption incurring the higher costs. Understanding the impact of each disruption time on the resilience measures means that the supply chain can make progress towards being more resilient.