White Rose Research Online

eprints@whiterose.ac.uk
https://eprints.whiterose.ac.uk
Universities of Leeds, Sheffield and York

Deposited via The University of York.

White Rose Research Online URL for this paper:
https://eprints.whiterose.ac.uk/id/eprint/241753/

Version: Accepted Version

Proceedings Paper:
UDO, EDIDIONG, BALL, PETER DAVID and Huatuco, Luisa (2026) Big data and resilience in a milk supply chain: A simulation evaluation. In: British Academy of Management conference 2026:proceedings. British Academy of Management conference 2026, 07-11 Sep 2026 British Academy of Management, GBR.

Reuse
This article is distributed under the terms of the Creative Commons Attribution (CC BY) licence. This licence allows you to distribute, remix, tweak, and build upon the work, even commercially, as long as you credit the authors for the original work. More information and the full terms of the licence here: https://creativecommons.org/licenses/

Takedown
If you consider content in White Rose Research Online to be in breach of UK law, please notify us by emailing eprints@whiterose.ac.uk including the URL of the record and the reason for the withdrawal request.

UNIVERSITY OF LEEDS
University of Sheffield
UNIVERSITY of York

Big data and resilience in a milk supply chain: A simulation evaluation

Edidiong Udo[1], Peter Ball[1] and Luisa Huaccho Huatuco[1*]

[1]School for Business and Society, University of York, YO 10 5DD, UK

*Corresponding author: luisa.huatuco@york.ac.uk

Abstract

The purpose of this paper is to address the research question: *How can data-driven analysis be used to measure time to recovery of the milk supply chain and assess the impact of production and logistics disruptions?* This research uses computer simulations of a large milk producers manufacturing facility and SC. Two main types of disruptions were considered: production and logistics disruptions, which were measured against time to recovery. Dynamic capabilities framed the use of big data in sensing disruptions and seizing opportunities to react in a timely manner and transforming to a new normal. The findings show how resilience can be measured in terms of time to recovery. By incorporating the potential of big data for deeper analysis and earlier anticipation of disruptions the detrimental impacts of disruptions were moderated and recovery was faster. The potential impact of using big data to make better predictions of performance earlier in the face of disruptions was demonstrated quantitatively. This paper shows new insights on how resilience can be measured and how disruptions can be moderated.

Keywords: Resilience, disruptions, big data, modelling, supply chain.

Wordcount: 7,168 (excluding title, abstract, figures, tables and references)

1. Introduction

Global food supply chains (SCs), and particularly the milk supply chain, can be impacted by several 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.

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 SC 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 SC can lead to an improvement in the supply chain (Perdana *et al*., 2023).

Big data is becoming increasingly important in the supply chain (SC) as it enables stakeholders to make informed decisions based on accurate, real-time data, particularly in the supply of milk (Belaud *et al*., 2019; Nestlé, 2023). In the past, the milk SC management 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 SC efficiently.

Dynamic capabilities theory informs this research by highlighting the capacity to anticipate and then respond to changes rapidly. Big Data Analytics (BDA) is explored as a tool to enhance dynamic capabilities, enabling organisations to anticipate and mitigate disruptions earlier, thereby enhancing SC resilience.

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.

Therefore, this paper addresses the following research question: *How can data-driven analysis be used to measure the resilience of the milk supply chain and assess the impact of production and logistics disruptions?*

This paper is organised as follows. Section 2 presents the literature review on SC resilience, big data in the milk supply chain and theoretical developments. Section 3 describes the methodology consisting of the computer simulations. Section 4 shows the results on production and logistics disruptions and their effect on time to recovery. Section 5 provides the discussion. Finally, Section 6 shows the conclusions.

2. Literature review

2.1 Supply chain resilience (SCRES)

Resilience is a multidimensional and multidisciplinary concept (Castillo, 2022), which has been generating interest from social scientists and natural scientists alike. Within the physics and engineering communities, resilience is considered as the ability to be able to return to its original form (Castillo, 2022). 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 (Spiegler *et al*., 2012) and is defined as the property within the SC system's ability to retain its original state after a disturbance or advance to a new and more desirable state (Peters *et al*., 2023).

A resilient SC 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 SCs and disaster relief effort (Boin *et al.*, 2010). This implies that parties within the SC must be positioned strategically and be adequately planned for. With the rise of globalisation and the resulting global SC, the longer transportation distance and additional resources used can increase operational disruption (Spiegler *et al.*, 2012). This connotes that developing a resilient SC needs to incorporate strategies for dealing with risks at operational level as well as risks at SC level.

2.1.1 Resilience strategies

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 SC (Michel-Villarreal *et al*., 2021). Improved visibility enables better tracking and management of the SC and can help to identify and mitigate risks before they become disruptive. Additionally, enhanced visibility can improve coordination and collaboration within the SC, leading to better decision-making and a more efficient response to disruptions.

Furthermore, risk management has also been highlighted as an essential factor for achieving SC resilience (Soni *et al*., 2014). The use of risk management techniques can help companies identify and mitigate risks before they occur and 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 have also been studied as means of enhancing SC resilience (Pavlov *et al*., 2019). These strategies attempt to forecast possible disruptions and minimize their effects and financial damage.

The adoption of BDA can be used as a proactive strategy to improve visibility (Kamble and Gunasekaran, 2020), collaboration and enhanced tracking across the SC or can also be applied as a reactive strategy to support decision making for the optimal inventory levels that support customer satisfaction across the SC (Vieira *et al*., 2020). This paper proposes that the resilience strategy for the milk SC incorporates insights into the vulnerabilities and capabilities of the milk SC and analysis of proactive and reactive strategies.

Overall, while both proactive and reactive strategies are important for achieving SC 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 SC resilience.

2.1.2 Quantitative measures of SCRES

When a disruption occurs, it is usually due to an unplanned and unanticipated event; as a result, these disruptions will normally disrupt the typical flow of goods and materials in a SC (Macdonald *et al*., 2018). Once a SC has been disrupted, the performance of that SC will be jeopardised (Carvalho *et al*., 2012). In the case of milk SC, disruptions can occur due to a production problem at the milk manufacturer, transportation challenges affecting milk delivery, or a spike or reduction in demand. The ability of the SC to withstand these disruptions and maintain its operations is crucial for the sustainability of the entire system (Hishamuddiin *et al*., 2015).

To measure the resilience of milk SC, quantitative parameters are needed such as the time it takes for the SC to recover (Ponomarov and Holcomb, 2009). This parameter is influenced by the level of preparedness of the SC to respond to disruptions. A resilient SC should be able to recover quickly and resume normal operations (Pavlov *et al*., 2018). 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. Thirdly, the ability of the SC 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 SC.

There is no 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 SC on a multi-country basis quantified resiliency on: customer service level, 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.

2.2 Big data in the milk supply chain

One of the main roles of big data in the milk SC 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 SC. For example, 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 SC. By monitoring the quality of milk at every stage of the SC, from the farm to the processing plant, stakeholders can ensure that milk meets the required quality standards.

Big data technology has the potential to revolutionise the milk SC by providing valuable insights and enabling more efficient and effective collaboration between the different players in the chain (Kache and Seuring, 2017), which can help to improve forecasting, increase transparency, optimize logistics, and improve customer service. One of the main benefits of big data technology in SC 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.

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 using sensors and other digital technologies that can collect data on various aspects of the SC such as production, transportation, and distribution (Gupta and Rani, 2019).

Predictive maintenance is another area where big data technology can have a significant impact in the milk SC (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.

Big data technology can also help to optimise logistics in the milk SC (Lamba and Singh, 2017). By analysing data on transportation, inventory, and other logistics, retailers and processors can optimize their SC operations and reduce waste.

2.3 Barriers to applying big data in the milk supply chain

The milk SC 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). 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). 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.

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.

2.4 Simulating SCs and Disruptions

SC simulation is an important tool for understanding and mitigating the impact of SC disruptions (Ivanov and Rozhkov, 2020). It involves creating virtual models of the SC to test different scenarios and identify potential risks and vulnerabilities (Vieira *et al*., 2019). Researchers have explored different methods for simulating SCs, including system dynamics models, agent-based models, and network-based models. These models can help stakeholders to identify potential risks and vulnerabilities in the SC and develop strategies to improve its efficiency and resilience.

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

Another approach to simulating SCs is using agent-based models which involves creating virtual agents in the SC, 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,

Wu *et al*. (2013) developed an agent-based simulation model that considers how consumers respond to stockouts for different products.

Finally, network-based models are another approach to simulating SCs. Network-based models focus on the structure of the SC and the relationships between different actors. These models can help to identify potential bottlenecks or vulnerabilities in the SC 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.

2.5 Theoretical underpinning

2.5.1 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 BDA (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 to address a rapidly changing environment.

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, the SC responds in a favourable way both to the organisations and the SC. 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). It can then be argued that possessing dynamic capabilities in an organisation, such as the ability to gain insight from BDA, can enable organisations to anticipate and mitigate events which could potentially lead to a disruption, and possibly build a competitive advantage through resilience.

Figure 1 proposes an initial theoretical framework for the study of the potential impact of BDA on SC Disruption. This research attempts to explore the benefits of BDA in building resilience for mitigating SC 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 SC is resilient in the case of a disruption.

[Insert Figure 1 around here]

3. Methodology

To review the impact of big data on resilience, the research must first simulate the target supply chain. It was essential that data collection aligned with the big data requirements set out in literature. Hence, the focal organisation in this supply chain needed to have adopted big data in their production and distribution activities.

The focal milk manufacturing company runs an IT department employing over 50 people who work 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 enables analytics throughout the organisation. The

adoption of Power BI supports self-service and big data practices organisation wide as staff can instantly view the implication of activities based on data added. For example, a front-end staff could update that 500 litres of milk have just been shipped out to a retailer in the north and immediately, the accounts team may be able to view the financial implication of that shipment while the logistics team can also view the operational implication. This was a scalable solution that could handle large amounts of data and provide real-time analytics to support their business operations.

The focal organisation 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. *Figure 2* provides a summary on how 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.

This research proceeded to collect a portion of the data from a big data enabled supply chain to support the simulation conducted as part of the study. 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.

Modern SC 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) provides four quadrants with which a supply chain's BDA capabilities can be assessed. According to their research, SCs 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. Based on the infrastructure available within the focal supply chain, and supporting infrastructure and technology provided by hosting institution, the current study adapts the framework developed by (Vieira *et al*., 2019) in simulating resilience in the milk SC 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.

The milk SC data was managed using various front-end databases, such as MS Excel, MS Access, SAP. Once the data has been thoroughly cleaned and suitable for analysis, then it is 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 hosting institution is then fed data from the warehouse, allowing for ease of analysis and visualisation of results.

Based on existing literature, the resilience measurement 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.

To validate the model, a simple set of test data (data for a period of one month) was synthesised and used to validate the results expected.

[Insert Figure 2 around here]

4. Results

4.1 Overview of the SC

This section presents the results from the computer simulations starting with highlighting the experiments which are carried out in this research. The section 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 to measure the resilience of the SC. The section concludes by discussing how big data is applied to measure SC resilience.

4.2 Experimentation in a big data context

The aim of the experiments is to provide a comprehensive understanding of how different types of disruptions affect the resilience of the SC, and to identify some critical factors that determine the resilience of SC. To achieve this, the experiments were designed to simulate various scenarios that may occur in a real-world SC 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 time to recovery of the SC? Is it different from when a disruption occurs in the SC logistics? The experiments carried out are presented in *Table 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 SC.

[Insert table 1 around here]

The first step within the simulation is the development of an As-Is model which presents how the milk SC operates prior to any interruptions or disruptions and provides this research a baseline with which to compare the SC after a disruption. The next steps involve the introduction of disruptions to the as-is model which necessitates the running of the model in two scenarios to reflect the disruption at the manufacturing level, and the delivery to the retailer level. It should be noted that in all scenarios, there is a potential for ripple effects and all actors within the SC 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 SC at a time.

4.3 Simulation process overview

The process of simulation is the imitation (on a computer) of a milk SC as it progresses through time (Robinson, 2004) and involves the conversion of the SC map into a conceptual model and then on to a computer simulation software. This model considers the relevant entities in the milk SC and utilises the WITNESS simulation tool to approximate real-world behaviour as closely as possible. *Figure 3* illustrates the conceptual model that serves as the precursor to the test model and consequentially, "as-is" model developed in the simulation tool.

[Insert Figure 3 around here]

In the as-is model, the standard entities provided by the WITNESS Horizon software are used to represent processes and workings within the SC. 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 SC'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 expanded. 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 assumes 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 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).

[Insert Table 2 around here]

The as-is model represents the SC prior to any disruption. While the as-is model reflects a SC without major disruptions, the standard scheduled maintenance of machines by the manufacturer is simulated to reflect the reality of the manufacturer as much as possible. The as-is model showcases the SC 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 SC to function effectively, all retailers must 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 SC. The number may reduce as customers continue to make purchases while the

retailer waits for the next delivery from the manufacturer, but the SC 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. This could mean that a customer who is unable to be served may choose a different retailer who does not belong to this SC to fulfil their demand. This research assumes that the longer customers must 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, which is usually over very quickly and can be foreseen and planned for.

This research focuses on the impact of specific disruption types on the resilience of the milk SC. Specifically, the study examines the impact of each disruption type on the SC'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 consider the day-to-day "natural" variations that may occur in the SC due to random or stochastic effects as these can be managed with good SC 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 SC can be made more resilient and better able to cope with planned and unplanned disruptions; and support this research in meeting its aim and objectives.

Following the scheduled maintenance, the SC has exhibited evident signs of a minor disruption, as seen in *Figure 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 SC 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.

[Insert Figure 4 around here]

Similar experiments were carried out with retailers 2-4.

4.4 Measuring resilience

The milk SC resilience in this research is measured using the time it takes for the SC to recover following a disruption. Measuring the resilience of the milk SC is essential for ensuring the sustainability and efficiency of the system. By focusing on the time to recovery, organisations can identify areas of improvement and enhance the resilience of their SC.

The research specifically explored the impact of the two types of disruptions identified in literature: production and logistics disruptions.

- 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.
- 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.

Each type of disruption is simulated for a one-week period as this provides 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 SC resilience conducted by (Carvalho *et al*., 2011). The output results are retrieved from the simulation tool, analysed and discussed extensively in the next section.

4.4.1 Time to recovery results

Time to recovery considers the amount of time it takes for the SC 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 SC to recover after a disruption to stock levels similar to 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 (Muñoz and Dunbar, 2015a). According to (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 SC management, time to recovery has been identified as an important performance measure of SC resilience (Sheffi and Rice, 2005).

4.4.2 Production disruption

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

As considered in the 'as-is' scenario, 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 SC inventory levels drop below this and where it does, how long does it take for the SC to bounce back to these levels or higher 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 5*, the drop in performance was almost immediate without any staggering effect and this may be due to the lack of backup stock.

[Insert Figure 5 around here]

Similar experiments were conducted for retailers 2-4.

The research found that, for the time to recovery from a production disruption, different retailers showed varied recovery times. *Table 3* shows the approximate time in hours taken for the SC to recover similar levels recorded prior to the disruption or a better state.

[Insert Table 3 around here]

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.

The key findings underline the influence of stock levels, backup stock availability, and inventory management on retailer reactions and recovery times during a SC 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 SC disruption. Retailer 1's lack of backup stock resulted in a longer time to recovery, while retailers 2, 3, and 4 were able to recover more quickly due to their effective inventory practices.

4.4.3 Logistics disruption

The impact of a logistics disruption on the time to recovery created multiple long lasting disruption points in the SC. While each retailer recorded multiple impacts from this type of disruption, this section will only discuss one typical time to recovery during logistics disruption.

Retailer 1 experienced the highest level of impact during the disruption, with a total stock out time averaging 130 hours for skimmed milk (*Figure 6*). 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.

[Insert Figure 6 around here]

Similar experiments were conducted for retailers 2-4.

[Insert Table 4 around here]

It is evident that retailers can face significant impacts on their stock levels and performance due to disruptions in SC 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 4* 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 SC 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. 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 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.

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.

[Insert Table 5 around here]

The results in *Table 5* provide additional evidence to support the findings in this research that logistics disruption has had the highest impact on the SC. Previous research also shows that logistics disruptions can have a severe impact on SCs. For example, (Hishamuddiin *et al*., 2015) found that within their research, transportation disruptions in the SC can lead to a more significant effect on the entire SC than the supply disruption investigated. Similarly, (Singh *et al*., 2020) found that disruptions in transportation can lead to a reduction in SC responsiveness.

This highlights the significant impact that logistics disruptions can have on the stock levels in the milk SC. 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.

5. Discussion

This paper addressed the research question: *How can data-driven analysis be used to measure time to recovery of the milk supply chain and assess the impact of production and logistics disruptions?*

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 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.

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.

Based on results from the computer simulations, time to recovery is used to measure resilience and a set of experiments and disruptions simulated to test the resilience within a selected milk SC. The experiments conducted yielded significant insights into the critical factors influencing the time to recovery. The findings emphasise the distinct impacts of production and logistics disruptions on the SC, highlighting the importance of addressing these areas for effective resilience and cost management.

For time to recovery, the experiments demonstrated that disruptions, particularly logistics disruptions, have a substantial impact on the recovery timeline.

By simulating production and logistics disruptions, the research has shown how these disruptions can significantly impact the time to recovery within the SC network. The findings suggest that SCs 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 supply-side disruptions, inventory levels, transportation, and supplier risks. Ultimately, this research provides a framework for assessing the resilience of the milk SC, which can be used to identify areas for improvement and enhance the sustainability, efficiency and resilience of the system.

6. Conclusions

The findings of this study highlight the importance of considering the time to recovery when assessing SC resilience which corroborates previous studies (Ponomarov and Holcomb, 2009, Jin *et al*., 2026) as different types of disruptions can have varying recovery times. This information can be used by SC managers to develop strategies for improving SC resilience and reducing the impact of disruptions on SC performance.

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 a MS Excel spreadsheet and additional WITNESS capabilities to enhance accuracy and timeliness. This includes data on milk types, order quantities, production and logistic disruptions that can affect the SC's resilience. By integrating real-time data, the simulation provided more up-to-date and dynamic assessments of the SC's performance and vulnerability to disruptions.

Thirdly, big data-driven techniques enable scenario analysis. By simulating different disruptions, such as production disruption, or logistics disruption, the simulation can project the potential impact on key

performance metrics like time to recovery. This allows SC 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 SC and provides valuable insights for decision-making, risk management, and improving overall resilience.

Limitations of the research include the focus on two types of disruption only and the time to recovery performance, which could be expanded to other types and performance metrics. So, future research could include customer demand, and/or environmental disruptions, as well as SC costs and/or customer service levels.

Furthermore, alternative methodologies can be used to complement the current research. Case studies including interviews with managers could be used to provide richer explanations for the performance metrics affected by disruptions. BDA research should include more prescriptive approaches (Jahani *et al*., 2026).

References

AHDB 2022a. Agriculture and Horticulture Development Board (AHDB). *UK milk deliveries*. [Online]. [Accessed 27 February 2026]. Available from: https://ahdb.org.uk/dairy/uk-daily-milk-deliveries.

Alzubi, E., Shbikat, N. and Noche, B. 2023. A system dynamics model to improving sustainable performance of the citrus farmers in Jordan Valley. *Cleaner Production Letters*. 4, pp.1–15.

Belaud, J.-P., Prioux, N., Vialle, C. and Sablayrolles, C. 2019. Big data for agri-food 4.0: Application to sustainability management for by-products supply chain. *Computers in Industry*. 111, pp.41–50.

Boin, A., Kelle, P. and Clay Whybark, D. 2010. Resilient supply chains for extreme situations: Outlining a new field of study. *International Journal of Production Economics*. 126(1), pp.1–6.

Brandon-Jones, E., Squire, B., Autry, C.W. and Petersen, K.J. 2014. A Contingent Resource-Based Perspective of Supply Chain Resilience and Robustness. *Journal of Supply Chain Management*. 50(3), pp.55–73.

Carvalho, H., Barroso, A.P., MacHado, V.H., Azevedo, S. and Cruz-Machado, V. 2012. Supply chain redesign for resilience using simulation. *Computers and Industrial Engineering*. 62(1), pp.329–341.

Castillo, C. 2022. Is there a theory of supply chain resilience? A bibliometric analysis of the literature. *International Journal of Operations and Production Management*.

Chopra, S. and Sodhi, M.S. 2014. Reducing the risk of supply chain disruptions. *MIT Sloan management review*. 55, pp. 73-80.

Côrte-Real, N., Oliveira, T. and Ruivo, P. 2017. Assessing business value of Big Data Analytics in European firms. *Journal of Business Research*. 70, pp.379–390.

Dubey, R., Gunasekaran, A., Childe, S.J., Papadopoulos, T., Blome, C. and Luo, Z. 2019. Antecedents of Resilient Supply Chains: An Empirical Study. *IEEE Transactions on Engineering Management*. 66(1), pp.8–19.

Ghaithan, A.M., Alarfaj, I., Mohammed, A. and Qasim, O. 2022. A neural network-based model for estimating the delivery time of oxygen gas cylinders during COVID-19 pandemic. *Neural Computing and Applications*. 34(13), pp.11213–11231.

Gupta, D. and Rani, R. 2019. A study of big data evolution and research challenges. *Journal of Information Science*. 45(3), pp.322–340.

Hishamuddiin, H., Sarker, R. and Essam, D. 2015. A simulation model of a three echelon supply chain system with multiple suppliers subject to supply and transportation disruptions. *IFAC-PapersOnLine*. 28(3), pp.2036–2040.

Ivanov, D., Das, A. and Choi, T.-M. 2018. New flexibility drivers for manufacturing, supply chain and service operations. *International Journal of Production Research*. 56(10), pp.3359–3368.

Ivanov, D. and Rozhkov, M. 2020. Coordination of production and ordering policies under capacity disruption and product write-off risk: an analytical study with real-data based simulations of a fast moving consumer goods company. *Annals of Operations Research*. 291(1–2), pp.387–407.

Jahani, H., Jain, R. and Ivanov, D. 2026. Data science and big data analytics: a systematic review of methodologies used in the supply chain ad logistics research. *Annals of Operations Research*, 359, pp. 1297-1354.

Ji, G., Hu, L. and Tan, K.H. 2017. A study on decision-making of food supply chain based on big data. *Journal of Systems Science and Systems Engineering*. 26(2), pp.183–198.

Jin, S., He, Y., Ivanov, D. and Chen, W. 2026. To act or wait: The impact of disruption duration estimates on manufacturer's response strategies. *IISE Transactions*, 58(1), pp. 16-32.

Kache, F. and Seuring, S. 2017. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations and Production Management*. 37(1), pp.10–36.

Kamble, S.S. and Gunasekaran, A. 2020. Big data-driven supply chain performance measurement system: a review and framework for implementation. *International Journal of Production Research*. 58(1), pp.65–86.

Kırılmaz, O. and Erol, S. 2017. A proactive approach to supply chain risk management: Shifting orders among suppliers to mitigate the supply side risks. *Journal of Purchasing and Supply Management*. 23(1), pp.54–65.

Lamba, K. and Singh, S.P. 2017. Big data in operations and supply chain management: current trends and future perspectives. *Production Planning and Control*. 28(11–12), pp.877–890.

Lee, J., Kao, H.A. and Yang, S. 2014. Service innovation and smart analytics for Industry 4.0 and big data environment. *Procedia CIRP*. 16(2014), pp.3–8.

Macdonald, J.R., Zobel, C.W., Melnyk, S.A. and Griffis, S.E. 2018. Supply chain risk and resilience: theory building through structured experiments and simulation. *International Journal of Production Research*. 56(12), pp.4337–4355.

Michel-Villarreal, R., Vilalta-Perdomo, E., Canavari, M. and Hingley, M.K. 2021. Resilience and digitalization in Short Food Supply Chains: A case study approach. *Sustainability*. 13(5913), pp.1–23.

Muñoz, A. and Dunbar, M. 2015a. On the quantification of operational supply chain resilience. *International Journal of Production Research*. 53(22), pp.6736–6751.

Navickas, V. and Gružauskas, V. 2016. Big Data Concept in the Food Supply Chain: Small Markets Case. *Scientific Annals of Economics and Business*. 63(1), pp.15–28.

Nestlé 2023. Accelerating data-driven digitalization. [Accessed 27 February 2026]. Available from: https://www.nestle.com/investors/annual-report/digitalization.

Ogbuke, N.J., Yusuf, Y.Y., Dharma, K. and Mercangoz, B.A. 2020. Big data supply chain analytics: ethical, privacy and security challenges posed to business, industries and society. *Production Planning and Control*. 33(2–3), pp.123–137.

Pavlov, A., Ivanov, D., Dolgui, A. and Sokolov, B. 2018. Hybrid Fuzzy-Probabilistic Approach to Supply Chain Resilience Assessment. *IEEE Transactions on Engineering Management*. 65(2), pp.303–315.

Pavlov, A., Ivanov, D., Pavlov, D. and Slinko, A. 2019. Optimization of network redundancy and contingency planning in sustainable and resilient supply chain resource management under conditions of structural dynamics. *Annals of Operations Research*.

Perdana, T., Tjahjono, B., Kusnandar, K., Sanjaya, S., Wardhana, D. and Hermiatin, F.R. 2023. Fresh agricultural product logistics network governance: insights from small-holder farms in a developing country. *International Journal of Logistics Research and Applications*. 26(12), pp.1761–1784.

Peters, E., Knight, L., Boersma, K. and Uenk, N. 2023. Organizing for supply chain resilience: a high reliability network perspective. *International Journal of Operations and Production Management*. 43(1), pp.48–69.

Ponomarov, S. and Holcomb, M. 2009. Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*. 20(1), pp.124–143.

Pourhejazy, P., Kwon, O.K., Chang, Y.T. and Park, H. (Kevin) 2017. Evaluating resiliency of supply chain network: A data envelopment analysis approach. *Sustainability*. 9(2), pp.1–19.

Priya Datta, P., Christopher, M. and Allen, P. 2007. Agent-based modelling of complex production/distribution systems to improve resilience. *International Journal of Logistics Research and Applications*. 10(3), pp.187–203.

Robinson, S. 2004. *Simulation: The Practice of Model Development and Use*. John Wiley & Sons, Inc.

Sahagun, M.A. and Vasquez-Parraga, A.Z. 2014. Can fast-food consumers be loyal customers, if so how? Theory, method and findings. *Journal of Retailing and Consumer Services*. 21(2), pp.168–174.

Sheffi, Y. and Rice, J.B. 2005. A supply chain view of the resilient enterprise. *MIT Sloan Management Review*.

Sher, P.J. and Lee, V.C. 2004. Information technology as a facilitator for enhancing dynamic capabilities through knowledge management. *Information and Management*. 41(8), pp.933–945.

Singh, N.P. and Singh, S. 2019a. Building supply chain risk resilience: Role of big data analytics in supply chain disruption mitigation. *Benchmarking*. 26(7), pp.2318–2342.

Singh, S., Kumar, R., Panchal, R. and Tiwari, M.K. 2020. Impact of COVID-19 on logistics systems and disruptions in food supply chain. *International Journal of Production Research*. 59(7), pp.1993–2008.

Sivarajah, U., Kamal, M.M., Irani, Z. and Weerakkody, V. 2017. Critical analysis of Big Data challenges and analytical methods. *Journal of Business Research*. 70, pp.263–286.

Sokolov, B., Ivanov, D., Dolgui, A. and Pavlov, A. 2016. Structural quantification of the ripple effect in the supply chain. *International Journal of Production Research*. 54(1), pp.152–169.

Soni, U., Jain, V. and Kumar, S. 2014. Measuring supply chain resilience using a deterministic modeling approach. *Computers and Industrial Engineering*. 74(1), pp.11–25.

Spiegler, V.L.M., Naim, M.M. and Wikner, J. 2012. A control engineering approach to the assessment of supply chain resilience. *International Journal of Production Research*. 50(21), pp.6162–6187.

Teece, D.J., Pisano, G. and Shuen, A. 1997. Dynamic capabilities and strategic management. *Strategic Management Journal*. 18(7), pp.509–533.

Vieira, A.A.C., Dias, L., Santos, M.Y., Pereira, G.A.B. and Oliveira, J. 2020. Supply chain risk management: An interactive simulation model in a big data context. *Procedia Manufacturing*. 42(2019), pp.140–145.

Vieira, António A.C., Dias, L.M.S., Santos, M.Y., Pereira, G.A.B. and Oliveira, J.A. 2019. Simulation of an automotive supply chain using big data. *Computers and Industrial Engineering*. 137(August), pp.1–14.

Van Der Vorst, J.G.A.J., Tromp, S.O. and Van Der Zee, D.J. 2009. Simulation modelling for food supply chain redesign; Integrated decision making on product quality, sustainability and logistics. *International Journal of Production Research*. 47(23), pp.6611–6631.

Wu, Y.R., Huatuco, L.H., Frizelle, G. and Smart, J. 2013. A method for analysing operational complexity in supply chains. *Journal of the Operational Research Society*. 64(5), pp.654–667.

Figures

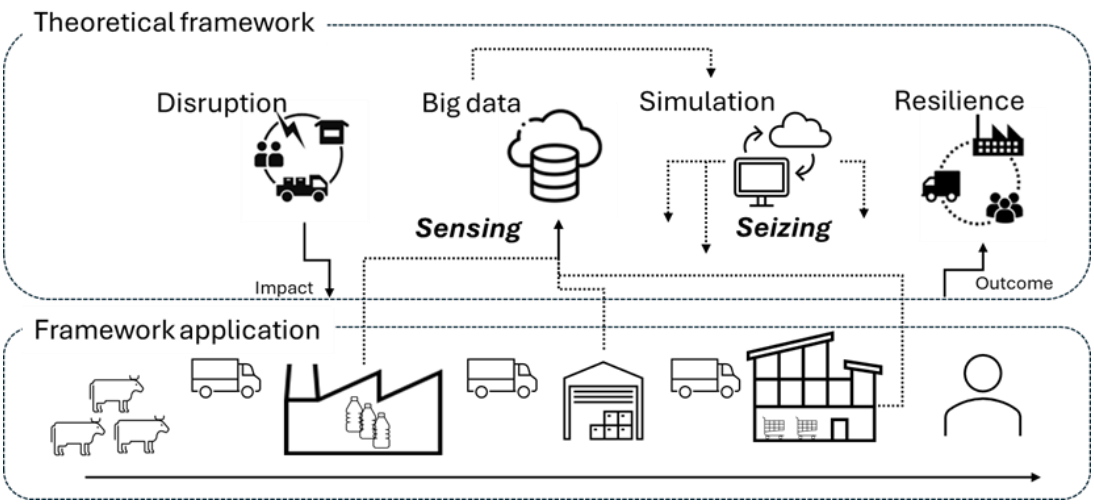

Figure 1: *Theoretical Background – Big Data Analytics and SC*

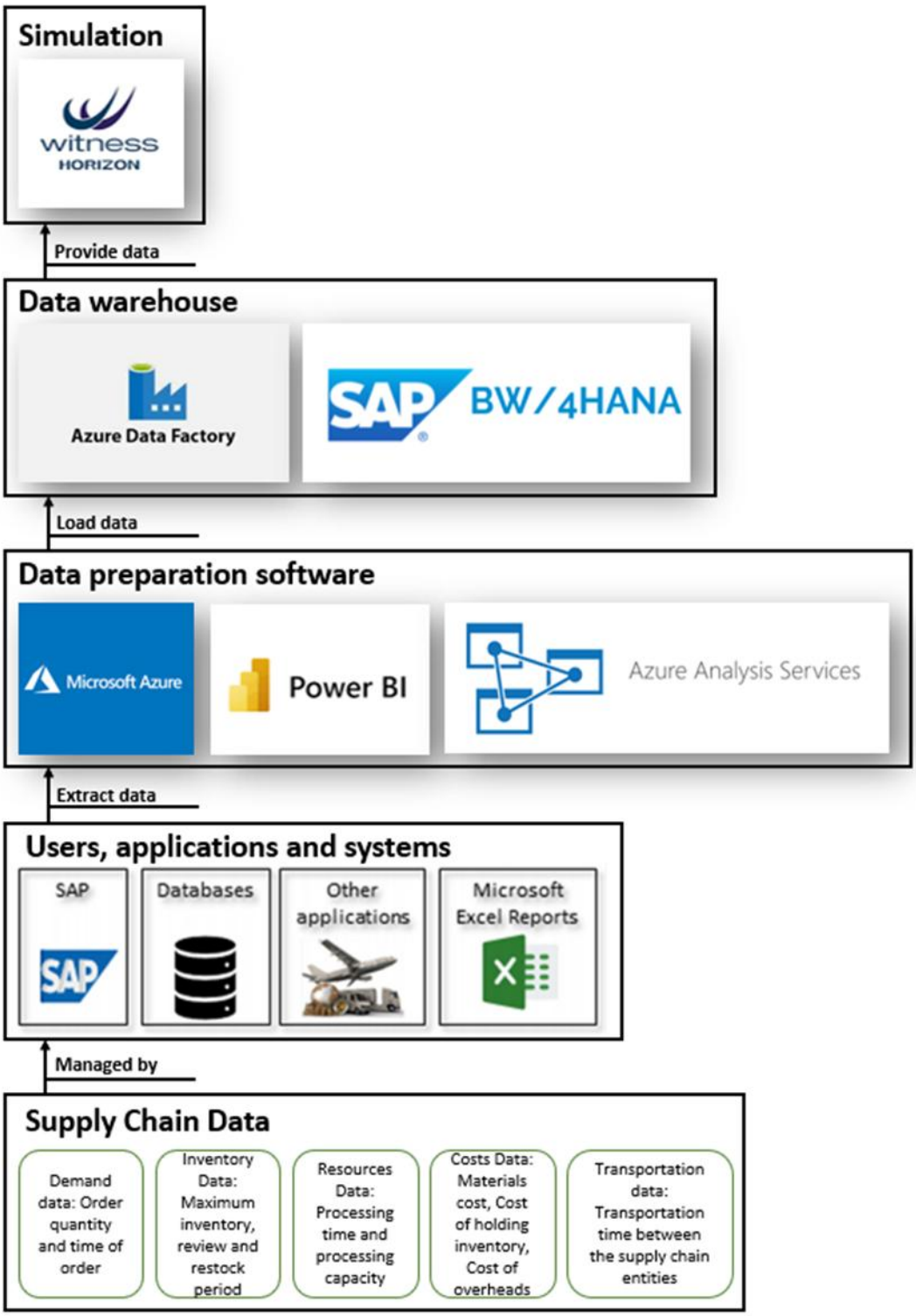

Figure 2: *Big Data Application in the Focal Milk SC*

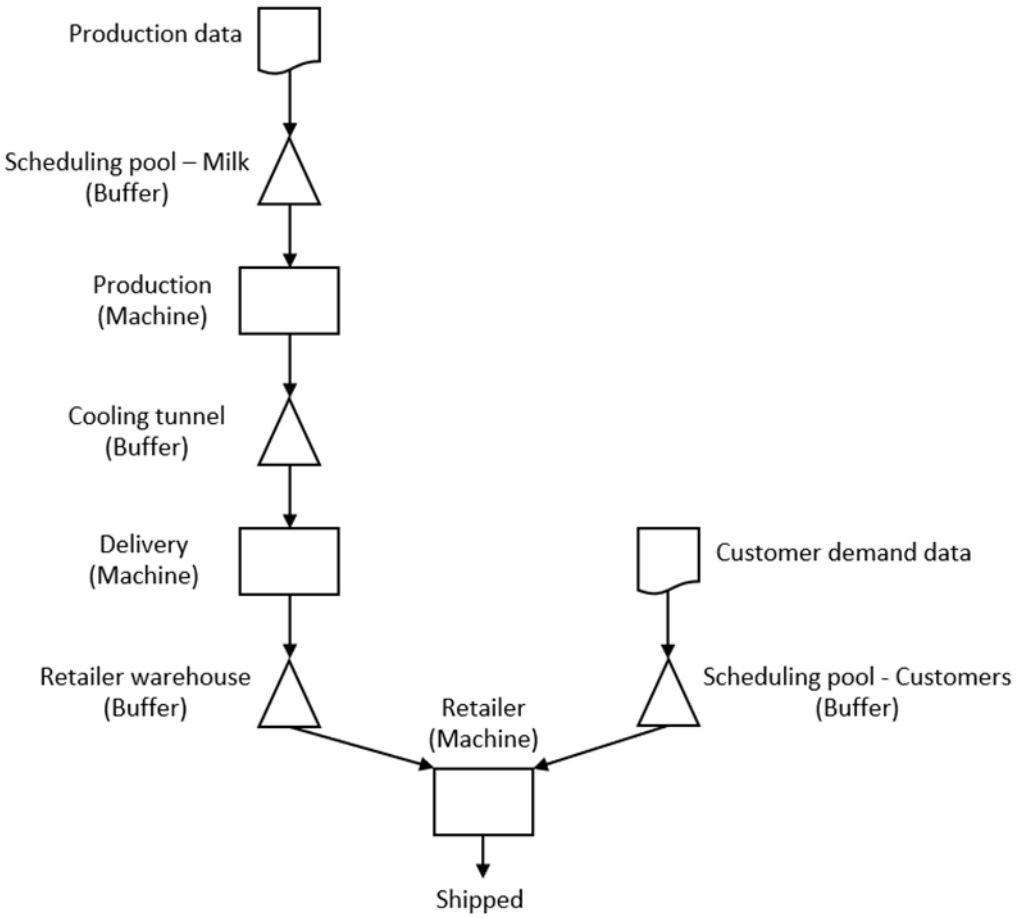

Figure 3: *Conceptual Model showing the simulated elements within WITNESS*



Figure 4: *Retailer 1 after scheduled maintenance*

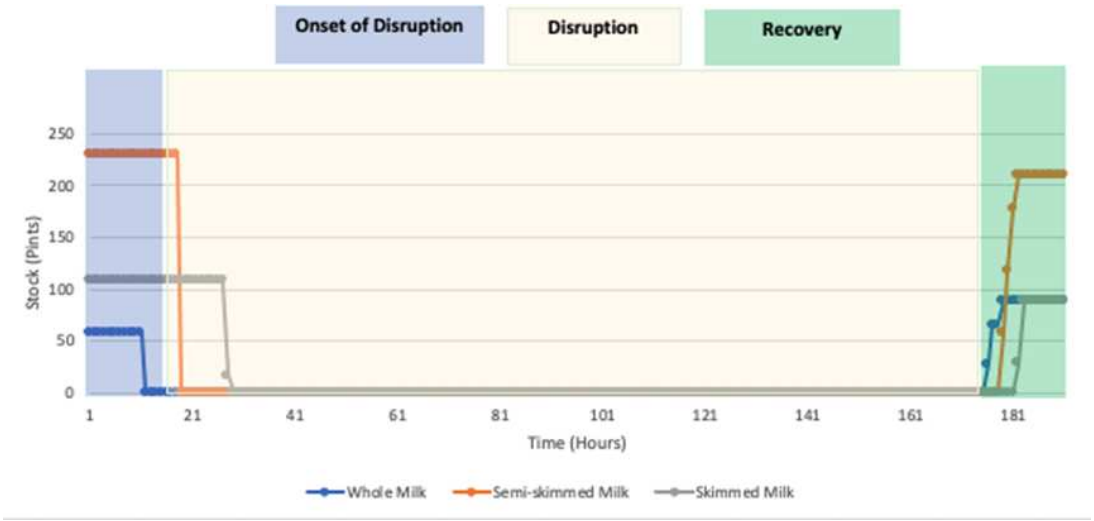

Figure 5: *Time to recovery after production disruption-Retailer 1*

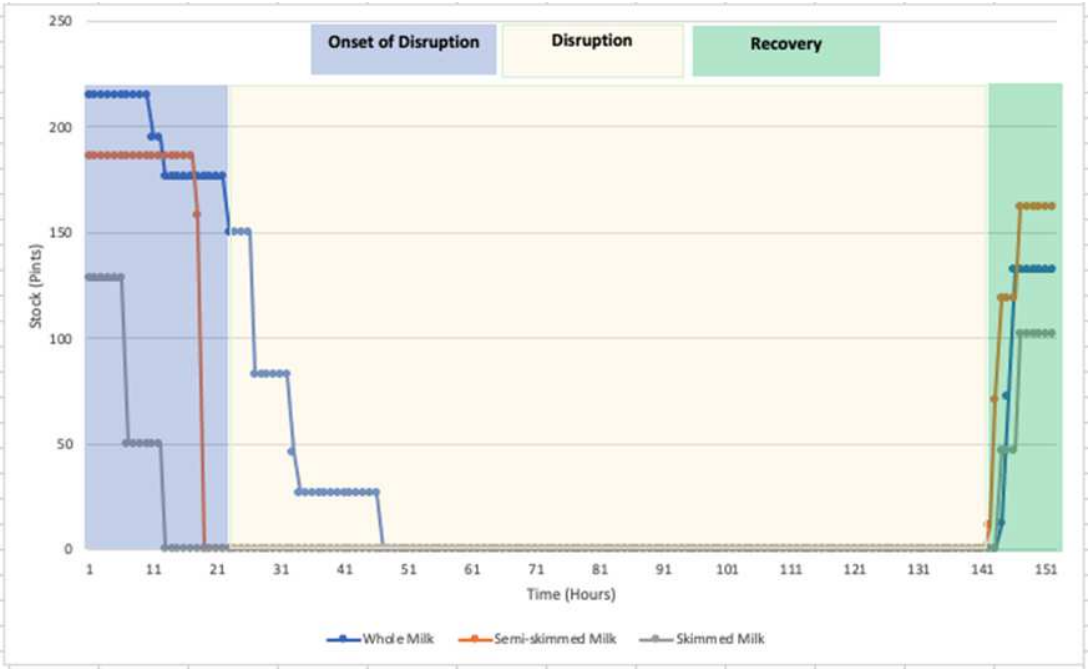

Figure 6: *Time to recovery after logistics disruption-Retailer 1*

Tables

Table 1: *Simulation Experiments*

Resilience Measure	**Disruptions**	**Disruption Length**	**Retailer**			
As-Is	Scheduled maintenance (No Disruption)	24 hours	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Time to Recovery	Production Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4
	Logistics Disruption	1 week	Retailer 1	Retailer 2	Retailer 3	Retailer 4

Table 2: *Simulation Elements*

No.	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 (Minutes)	The simulation runs for a total of 1'573,000 (equivalent to 3 years, assuming a 24/7 operation)
3	Repair time (Minutes)	10,080 (equivalent to 1 week)
4	Iterations before disruption	The iterations before a disruption utilises a uniform distribution between 1400 and 1600 operations

Table 3: *Summary of Time to Recovery after production disruption*

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

Table 4: *Summary of Time to Recovery after logistics disruption*

Retailer	Milk Type	Time to Recovery (Hours)
Retailer 1	Whole	120
	Semi-skimmed	123
	Skimmed	130
Retailer 2	Whole	130
	Semi-skimmed	150
	Skimmed	145
Retailer 3	Whole	148
	Semi-skimmed	150
	Skimmed	153
Retailer 4	Whole	136
	Semi-skimmed	157
	Skimmed	140

Table 5: *Summary of Results 1*

Resilience Measure	**Disruptions**	**Disruption Length**	**Retailer (Results 1)**			
As-Is	*Scheduled maintenance (No Disruption)*	24 hours	Retailer 1	Retailer 2	Retailer 3	Retailer 4
Time to Recovery	*Production Disruption*	1 week	Retailer 1 (155 Hours)	Retailer 2 (136 Hours)	Retailer 3 (124 Hours)	Retailer 4 (71 Hours)
	Logistics Disruption	1 week	Retailer 1 (124 Hours)	Retailer 2 (141 Hours)	Retailer 3 (150 Hours)	Retailer 4 (144 Hours)