The Assessment of Big Data Analytics Based Supply Chain Resilience

A comprehensive tool to assess and benchmark the level of supply chain resilience based on big data analytics enablers in the FMCG industry

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A comprehensive tool to assess and benchmark the level of supply chain resilience based on big data analytics enablers in the FMCG industry

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Preface

February marked the start of my final studying chapter, writing my thesis as part of the TU Delft master program Transport, Infrastructure and Logistics. With my background interest in Big Data Analytics and master specialisation in Supply Chain & Logistics, I went on to find a suitable thesis on the border of both subjects. I found this within the Supply Chain & Procurement department of KPMG in Amstelveen, where I got the opportunity to write my thesis. This has been a great challenge were I have learned a lot on both the subjects of the thesis and the company itself. It has provided me with valuable insights on the consulting industry, and great examples of interesting companies and projects.

I would like to thank the Supply Chain & Procurement department of KPMG for this opportunity. In specific, I would like to thank Jotham Hensen for his great supervision, with meaningful and challenging discussions. It really helped to guide my thesis in the right direction and gave useful suggestions to solve challenging problems. Furthermore, I would like to express my gratitude to my TU Delft supervision committee, with both Tina Comes, Marcel Ludema and Wouter Beelaerts van Blokland. Their knowledge has enhanced my thesis through different academic perspectives.

Most of all, I would like to thank my girlfriend Esmée Mooldijk for her continuous support throughout this challenging thesis journey. This also accounts for my parents, who have guided and supported me throughout my time at the TU Delft.

To conclude, I am grateful to finish my TU Delft chapter, looking back at a wonderful time in which the opportunity was given to learn and developed myself on both a personal and professional level.

Wouter de Wilt
Delft, August 16, 2022

Summary

Background
Supply chain resilience is an increasingly important topic, especially with recent major disruptions such as the Covid crisis. The industry stands for great challenges concerning their global supply chains and to keep supply and demand in line with effective transportation. Furthermore, new technologies under the broad term of Industry 4.0 arise and impact supply chain operations. This also accounts for the developments on Big Data Analytics (BDA), which has comprehensive effects on supply chain resilience. This is especially the case for fast moving consumer goods (FMCG) companies, that have dynamic operations and vast quantities of data. However, the challenge lies in quantifying the impact of such technology on resilience. Assessing the impact would greatly enhance the ability for companies to benchmark their operations and increase their resilience.

Objective
In order to address both the industry and academic background, the general objective is articulated as:

'Designing an assessment tool that helps FMCG companies to create insights on their BDA based supply chain resilience and enable the ability to benchmark with the industry.'

The objective addresses the need of the industry to effectively benchmark resilience, while the academic gap is addressed through a research on supply chain resilience based on BDA. The research is conducted in cooperation with KPMG Advisory, in specific the Dutch department for Supply Chain and Procurement. The objective helps KPMG to create insights for their clients and to kick-start potential new projects on the subject.

Research
The objective is achieved through first researching the subject of BDA and supply chain resilience by literature and empirical study. The relations between the two subjects is stated and serves as the base for the design of the partial resilience assessment tool.

The literature study focuses on five main sections. First, background information is given on the FMCG industry. The next two sections focus on investigating how both BDA and resilience fit in supply chains operations. The fourth section then aims to connect these two subjects and states the relevant resilience enablers that are fueled by BDA. Finally, a literature background is given on supply chain resilience assessment tools, giving clear indications on adequate methodologies to use. The empirical study also partly follows the subjects of the literature research. However, the main difference is that there is also a focus on understanding the actual business related disruptions that the industry faces. Furthermore, the interviews with over 10 supply chain experts are used to complement the findings of the literature research. The experts are both from the industry and KPMG, relating to either BDA or supply chain functions. To conclude, the outcomes of the empirical study are used to gain insights on current challenges that companies face regarding BDA based supply chain resilience.

The main results of the research encompass the relation between the two subjects through BDA based enablers. 14 enablers are found and acknowledged that lie on the intersection

between BDA (predictive, descriptive and prescriptive) and supply chain resilience (proactive, concurrent and reactive). The 14 enablers are the foundation of the BDA based partial resilience assessment tool. The enablers are Agility, Collaboration, Contingency Planning, Digital SC Twin, Disruptions Detection, Flexibility, Knowledge Management, Predicting Disruptions, Scenario Modelling, Situational Awareness, Transparency, Velocity, Visibility and vulnerability assessment.

Assessment Tool
The tool aims to assess the level of supply chain resilience based on BDA, allowing for potential benchmarking and comparisons. It can therefore be seen as a maturity assessment on BDA based resilience. The background academic literature on resilience assessment provides a comprehensive methodology that is partly used. Novelties are clearly defined as the methodology is translated for the specific purpose of this research. Requirements from the industry, KPMG and literature are used to further specialise the tool for BDA based resilience. The general design is presented where a matrix (14x14) is created based on enabler implementation levels (diagonal entries) and corresponding interdependencies (off-diagonal entries). The implementation levels of the enablers are based on questionnaire responses from company experts, while the interdependencies are determined by the author, based on both the literature and empirical research. The quantification of resilience based on BDA lies in the calculation of the matrix permanent, giving a single metric value of resilience. These metric values are collected per respondent and exponentially normalised to create a comprehensive BDA based resilience benchmarking scale, including theoretical minimum and optimum values.

Results are promising with clear insights on effective benchmarking within the industry and reflect well on the research objective. Normalised permanent values of the respondents show average BDA based resilience on 48% of theoretical optimum, with a better practice of 68 %. Limitations are however noted, these are mainly due to the heterogeneous sample of respondents. This decreases reliability of comparisons, due to difference in company types of the respondents. However, the current results are validated with industry experts which at least indicates a reliable industry average based on the respondents. In practice, the tool gives KPMG the ability to further improve the industry benchmark and already allows for a kick-start to client discussions and projects. The tool can be further implemented with a large homogeneous group of respondents. This would allow more effective outcomes of the benchmark which would ensure valid feedback towards respondents on their supply chain resilience.

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Part I

Introduction & Approach

1 Introduction

1.1 Background

Current global supply chains face the change of moving with the times where the developments of the fourth industrial revolution (industry 4.0) are creating great challenges. One of these challenges is the incorporation and implementation of Big Data Analytics (BDA), a main development fueled by the digitisation that industry 4.0 brings. It encompasses the different techniques applied to big data to ensure valuable insights or models. This can improve a broad variety of subjects such as sustainability (Lv, Iqbal, and Chang 2018, Mageto 2021), operational excellence (Mulunjkar et al. 2019, Bag, Gupta, and Wood 2020) and resilience (Alicke, Rexhausen, and Seyfert 2017). Especially in the supply chains of the fast moving consumer goods (FMCG) industry, where digitisation is rapidly evolving which increases the collection of data and the importance of comprehensive BDA. The modern supply chains are based on industry 4.0 and acquire a large impact of digitisation which influences elements such as flexibility, accuracy and pace (Alicke, Rexhausen, and Seyfert 2017). In general, industry 4.0 generates a vast quantity of data that may be used by companies to further improve operations and helps to guide the business in difficult times of pressure by disruptions (Spieske and Birkel 2021; Končar et al. 2020). Over the past decades, scientific research on BDA has increased but still lacks behind the true demand of the subject in a commercial environment (Nguyen et al. 2018; Vieira et al. 2020). Adequate BDA increases competitive advantage but seems to be a pitfall for many companies in understanding how to generate, clean, analyse and value large quantities of data (Tiwari, Wee, and Daryanto 2018).

Due to recent disruptive events such as the Covid crisis, a comprehensive example of a major external and unplanned disruption, the demand for adequate research on the relation between BDA and supply chain resilience has relatively grown. Research shows that BDA as part of industry 4.0 has had considerable benefits when implemented correctly for FMCG companies during Covid (Spieske and Birkel 2021). This also applies to the additional data-driven decision making models that are used when implementing BDA in actual businesses (Madhavi and Wickramarachchi 2021). Sometimes these models may also theoretically apply to other types of disruptions, as BDA can benefit in a wide range of cases. However, few researcher actually specify this when applying BDA to supply chain resilience. This builds forth on the main challenge that global supply chain businesses are facing when related to resilience: With the vast quantity of elements that BDA brings, overview is sometimes lost and opportunity is failed to fulfill. Despite great intentions of BDA within the industry, assessing and measuring the actual business and strategic value of BDA when related to supply chain resilience is thus still a major challenge to consider.

This research is conducted as a master thesis for the Technical University of Delft, in cooperation with KPMG the Netherlands. KPMG is a multinational network of firms focusing on audit, tax and advisory services. The research for this thesis is performed at the supply chain and procurement department of KPMG Advisory situated in Amstelveen.

1.2 Problem description

During preliminary research for this thesis, it became evident that there is a lack of research on how big data analytics can be used to improve supply chain resilience within the FMCG industry. This literature gap has been researched in a theoretically way, but still lacks a quantitative approach or relevant and recent industry insights to verify and further research on the subject (Madhavi and Wickramarachchi 2021; Spieske and Birkel 2021; Ribeiro and Barbosa-Povoa 2018). A simplification of the research gap is given in Figure 1.1, amplifying the question on how the two main subjects are connected. Furthermore, there is little relevant research on assessment tools that may help to map supply chain resilience by integrating big data analytics. The subject is of importance as it describes major challenges within for example the FMCG supply chain industry. Mainly due to the consequence of industry 4.0, the industry and literature call for more extensive research on how the developments, and thus the generation of a vast quantity of data, can influence supply chain operations. This is especially the case when considering supply chain resilience, as due to the Covid crisis the call on resilience of major disruptions has rapidly increased.

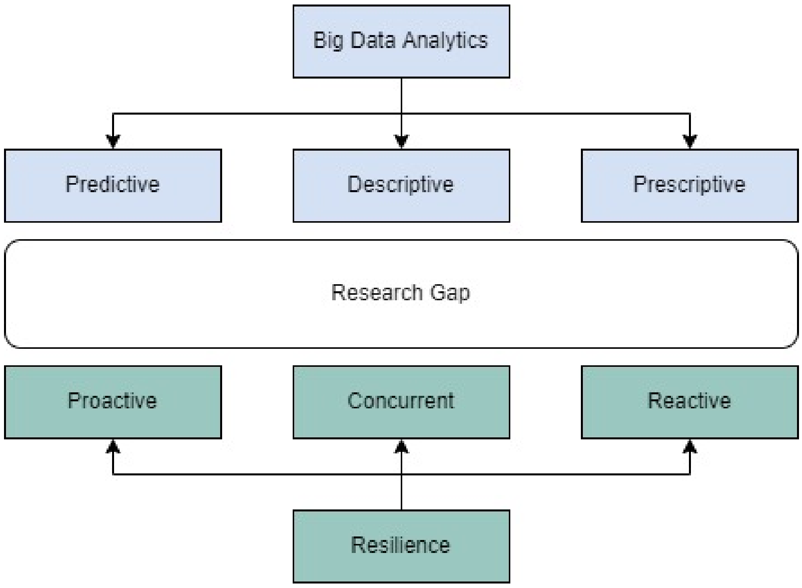

Figure 1.1: Simplification of the research gap

1.3 Relevance

The academic relevance of this research is to firstly fill the found literature gap and thus to increase the knowledge on the important subject of supply chain resilience. This gap is not only found by the preliminary literature research, but is also identified by multiple academic papers. For example, Madhavi and Wickramarachchi 2021 states that the subject of supply chain resilience by using supply chain (big) data analytics is mostly researched from a academic perspective, but without the important combination of mostly quantified insights or assessments. Ribeiro and Barbosa-Povoa 2018 also noted this as there is a lack of quantified tools that may help in the process of mapping supply chain resilience. Furthermore, Ribeiro and Barbosa-Povoa 2018 stated that real practical cases should be explored in especially unique industries with the use of a quantified approach. Nguyen et al. 2018 also discussed that there is a underdevelopment of business related insights within the supply chain resilience research field. Each of the papers gives clear indications on the research gap, giving the subject of BDA based supply chain resilience a high state of academic relevance.

On the other hand, this research also provides a practical relevance to for example the FMCG industry as it helps companies to further enhance their supply chain resilience and incorporate modern data driven practices. Especially with the Covid crisis, companies have noted that supply chain resilience is more important than ever and this research therefore has valuable insights that helps both the industry and society to further develop their resilience. Not only to overcome disruptions like the Covid crisis but also other major disruptions that have happened over the past years. This also has an academic background as for example Li and Gulati 2015 stated that more research needs to be done into resilience based on high impact and low probability disruptions. The final resilience based assessment tool will be valuable to companies to identify current supply chain resilience status based on big data analytics. With a comprehensive assessment tool, companies can benchmark their implementation to peers and acquire relevant advice on potential area's of improvement to enhance BDA based supply chain resilience. This is also inline with the practical needs of KPMG, where there is always a demand for further improvement to help clients excel in their supply chain operations or to give client clear insights in current developments.

1.4 Objective & Deliverable

The objective and deliverable of this thesis research is based on the problem definition and background literature research as described in section 1.2. The objective consists of two main parts: Firstly an extensive analysis of how supply chain BDA relates to supply chain resilience based on both literature and industry insights. Secondly, a supply chain resilience assessment tool based on BDA enablers, showing the partial resilience that BDA helps to improve. The tool is applied to the FMCG industry.

1. **Supply Chain Analysis**
The first objective of this research is to extensively analyse supply chain resilience in relation to supply chain BDA. This means to firstly create an overview on how the (FMCG) supply chain works and which elements are involved. Secondly, it is investigated how BDA is currently used in supply chains and what it brings in terms of performance or operational benefits. Finally the relation is investigated between BDA and supply chain resilience. This analysis will create a appropriate basis for the second objective of this research, since this can only be achieved with considerable knowledge of supply chain resilience and big data analytics. The analysis will mainly consist of a literature research, complemented and validated with industry insights. The industry insights are based on interviews with supply chain or BDA experts and are qualitatively based, however, quantitative examples are also included. The main question that this part thus aims to answer is the following:

'How does BDA relate to supply chain resilience?'

2. **Resilience Assessment Tool**
The second objective of this research consists of the design of an assessment tool, which is tested on a sample of FMCG companies. This tool can be used to determine how well companies use their BDA capabilities for purposes considering supply chain resilience. This assessment tool thus measures the state of a companies BDA usage for partial resilience and identifies possible opportunities. The assessment tool is validated and verified by industry professionals though the KPMG network. The validation will mainly consist of checking whether the tool is useful and adequate for the industry, while the verification is needed to check whether the tool correctly meets all the requirements. In general this objective can be articulated as:

'Designing an assessment tool that helps FMCG companies to create insights on their BDA based supply chain resilience and enable the ability to benchmark with the industry.'

1.5 Scoping

The general scoping of the of this research is presented in Figure 1.2, and shows resilience as a combination of multiple foundation blocks. Each block represent a part of resilience that is influenced by a certain technology or development. In this case, the technologies are linked to industry 4.0. In relation to other I4.0 technologies, it is difficult to quantify the exact contribution of BDA. However, when compared to other technologies like AI, additive manufacturing or cloud computing, BDA has higher implementation levels and greater assumed impact on resilience. For each subject of the research, a brief scoping and explanation is given for more insights in what is taken into account during this research and the corresponding assessment tool. The final definitions for each subject are based on the outcomes of the literature research and industry insights and is discussed in chapter 9.

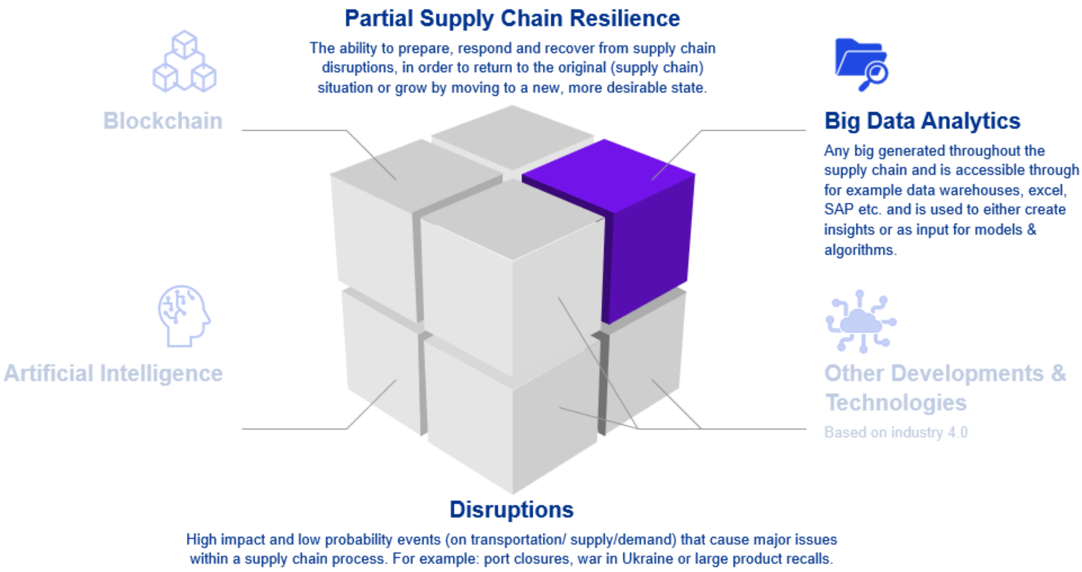

Figure 1.2: General Scoping (blocks are not to scale)

1.5.1 Supply Chains

The first subject that needs to be scoped is that of supply chains, mainly on what type of industry should be incorporated within the research. While the literature research is relatively generic for supply chains, the empirical research and application of the assessment tool need to be down scoped. Industries can be anything varying from automotive, pharmaceutical, fast moving consumer goods and many more. The fast moving consumer goods industry was chosen as a scope since multiple literature reviews insisted on more research on quantitative and industry related research for supply chain resilience for this industry (Madhavi and Wickramarachchi 2021). Furthermore, the industry more easily relates to integrating big data analytics since the fast moving consumer goods industry generates a vast and dynamic quantity of data. Additionally, KPMG has several clients within this sector and will thus help to gain more information on this topic. To further specify, companies throughout FMCG supply chains are approached for industry insights, ranging from suppliers to producers and retailers. For the final assessment tool, the scope of supply chains is further scoped down based on the company using the assessment tool. This means that the company defines its supply chain process as a part of a total FMCG supply chain. The supply chain process consists of the company itself and the concerning supply, demand and transportation unless operations are outsourced.

1.5.2 Big Data Analytics

Big data analytics is seen a an important pillar of the industry 4.0 revolution. Industry 4.0 encompasses multiple new technologies and developments that improve supply chain operations. For supply chain operations, these technologies can be divided in seven parts: cloud computing, internet of thing (IoT), big data analytics (BDA), artificial intelligence (AI), cyber-systems, additive manufacturing and blockchain technologies. Each technology has the potential to influence supply chain resilience (Spieske and Birkel 2021). However, this would be to broad to define within a research, therefore the scope for this research focuses on the impact of only big data analytics on supply chain resilience. Other I4.0 technologies do generate a vast quantity of data, such as the internet of things and blockchain technologies. The data of these other technologies might be analysed within big data analytics, however, the technology that generates the data will be considered out of scope. The scope is visualised in Figure 1.3 and the content of the general term of big data analytics is further research within chapter 5. Big data analytics within supply chains can be seen as any big data (e.g. minimal of a thousand data points) generated throughout the supply chain and is accessible through for example data warehouses, excel, SAP etc. and is used to either create insights or as input for models/algorithms.

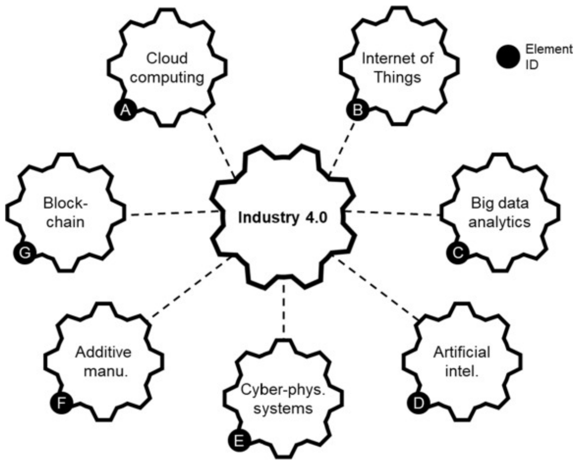

Figure 1.3: Big data analytics as part of Industry 4.0, based on Spieske and Birkel 2021

1.5.3 Partial Resilience

Resilience is a broad subject that consists of different elements that can be organised in three main categories: pre-disruption (readiness), during-disruption (responsiveness) and post-disruption (recovery), as presented in Figure 1.4. As the goal of this research is to find what impact big data analytics has on supply chain resilience, it is important to first fully research the broad term of resilience in order to see where big data analytics may have potential impact. Resilience is thus not scoped before hand, but down scoped during the research as it becomes more clear what the impact of big data analytics is. The comprehensive framework of Ali, Mahfouz, and Arisha 2017 will be used in section 4.1 to identify all resilient elements that are connected to big data analytics in chapter 6. This thus signifies that different elements and capabilities of the framework by Ali, Mahfouz, and Arisha 2017 will remain due to correlations with BDA and some will be scoped out. Furthermore, resilience is scoped down based on the input as only Big Data Analytics based resilience will be considered. This thus means that the outcome of this research only shows a partial supply chain resilience, but all types of resilience influenced by BDA are considered.

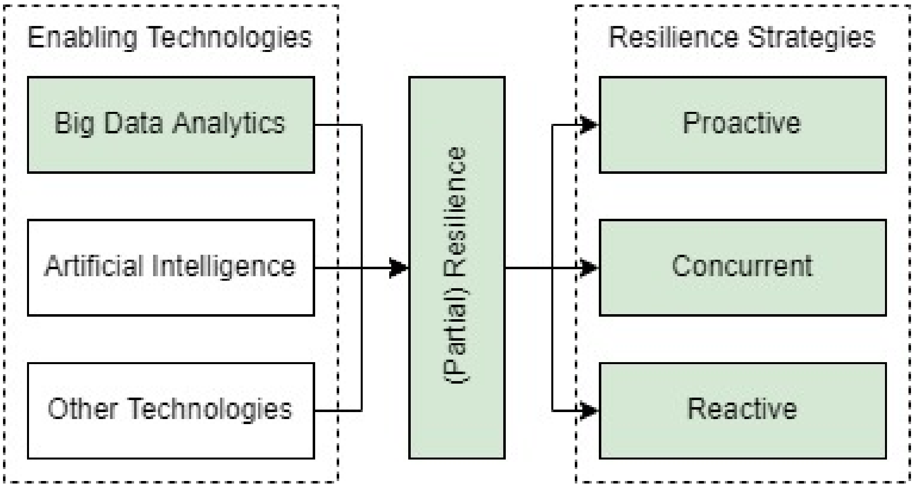

Figure 1.4: General layout of supply chain resilience (work author)

1.5.4 Disruptions

Disruptions are processes or events that rapidly change the potentially affected industry or operation. Disruptions may come in many forms and can have differences in external/internal, planned/unplanned, high or low probability, and measurements of impact. For example, the Covid crisis is a external disruption that has had major impact on the supply chains of practically every company. It is a high impact but low probability disruption, where many companies lacked in resilience. The academic research on the resilience of companies on the Covid crisis has been extensively researched in 2021 (Spieske and Birkel 2021). The research on Covid crisis resilience also fills earlier proposed research gaps. For example, Li and Gulati 2015 proposed that more research is needed on disruptions that have a high impact but low probability, thus something like the Covid crisis. However, the current main issue is that research is specified on the Covid crisis and academic literature therefore lacks in research on other major disruptions. Therefore this research aims to take into account other major external disruptions, which is mainly scoped for the designed assessment tool ensuring specified results. The scoping of disruptions is also visually presented in Figure 1.5. Examples of these disruptions in 2021 are the closure of the Suez canal, the global shortage of computer chips and the abnormally high container prices which can be seen either as a disruption or as an effect of the container shortage and Covid crisis. Background information on these disruptions will mainly be based on interview findings, as the industry has had the best knowledge on what disruptions they have encountered. For clarification on the scope, digital high impact and low probability disruptions such as cyber attacks are not taken into account due to the high difference in disruption type.

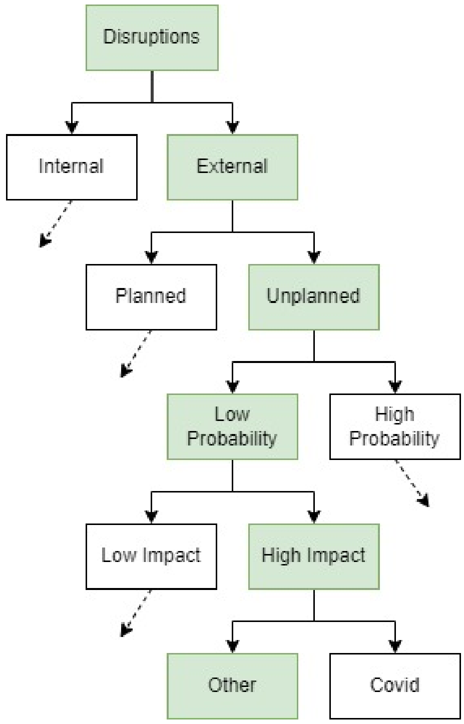

Figure 1.5: Scope for Disruptions (work author)

1.6 Report Layout

This section gives a small overview of the report layout. The report is divided in 5 main parts, corresponding to 13 chapters.

Introduction & Approach
The first part is the introduction in chapter 1 where the background, problem description, relevance, objective and scoping are all discussed. The second part is chapter 2 where the main approach of the research is presented, which also follows the report layout.

Literature Research
The literature research consist of five chapters: First, background information of fast moving consumer goods is given in chapter 3. Additionally, chapter 4 to chapter 6 cover the background literature on the subjects of big data analytics, supply chain resilience and the combination between the subjects. Finally, chapter 7 discusses the literature concerning methodologies for (partial) resilience assessment tools.

Empirical Research
The empirical research consist of the results of interviews held with industry experts, it consist of only chapter 8. The chapter discussed both supply chain disruptions, BDA based resilience and the corresponding challenges of implementation.

Assessment Tool
The assessment tool is covered in chapter 9, chapter 10 and chapter 11. The chapters represent the design, results and the validation & verification respectively.

Concluding Chapters
The final part of the report covers the concluding chapters of the discussion (chapter 12), which covers both implication and limitations, and the combined conclusion and recommendations in (chapter 13).

2 | Thesis Project Approach

2.1 Overview

The approach of this thesis mainly consists of three parts: background literature research, empirical industry insights and the design of an assessment tool. An overview of the approach is presented in Figure 2.1. Each part of the approach if further defined below and consists of several sub questions or components.

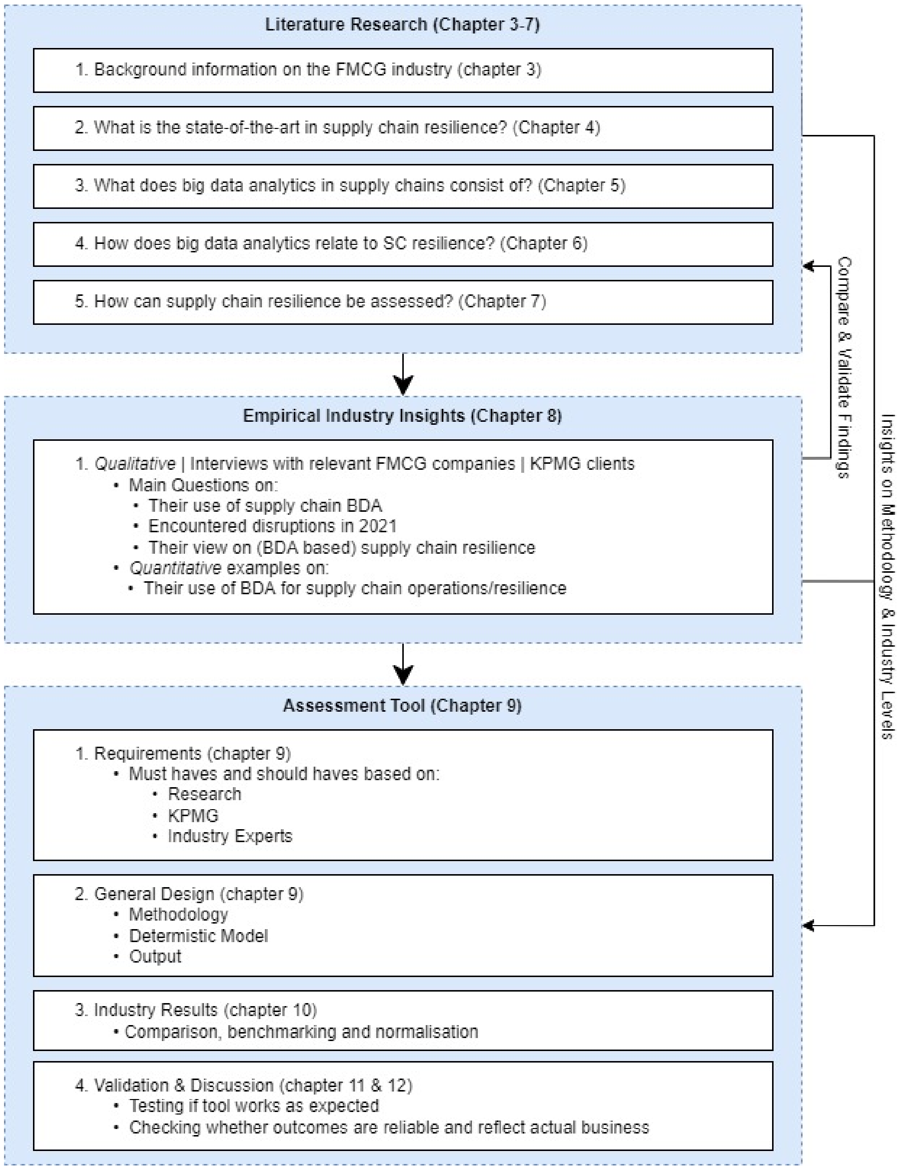

Figure 2.1: Overview of thesis project approach

2.2 Part 1: Literature Research

The first part of this thesis project is to answer important background questions though a thorough academic literature research. The research is divided in multiple research questions, defined below. The first literature chapter serves as background information on FMCG supply chains, the following chapters aim to answer the main objective in order to relate the subjects of supply chain resilience and BDA.
Reference: chapter 3, chapter 4, chapter 5, chapter 6, chapter 7.

1. **Goal**
   Define the relation between supply chain resilience and big data analytics and gain insights on potential assessment tool options and the FMCG industry.

2. **Method**
   First, chapter 3 gives background literature information on the FMCG industry in order to understand the scope of especially the assessment tool. Furthermore, the following research questions are answered through literature research.

   Research Questions

   1. What is the state-of-the-art in FMCG supply chain resilience? (chapter 4)
   2. What does big data analytics in supply chains consist of? (chapter 5)
   3. How does big data analytics relate to SC resilience? (chapter 6)
   4. How can supply chain resilience be assessed? (chapter 7)

   The third research question is based on the previous two and will be used to relate to the results of the empirical research. The fourth research question servers as an academic background to the resilience assessment tool.

2.3 Part 2: Industry Insights

The second part of the project approach is mainly to define and gather industry insights that help to enhance the findings from the previous part. This will ensure that the outcome of the research will also include industry related insights and thus gives a more well defined result for the assessment tool.
Reference: chapter 8.

1. **Goal**
   To further improve and validate the findings of the literature research with relevant industry insights gaining insights on resilience enabler implementations. Additionally, the goal is also to create an understanding of supply chain disruptions and challenges faced by the industry.

2. **Method**
   This part mainly consists of interviews with industry experts of supply chain or data analytics departments. The interviews are subject to the opportunities provided by KPMG's client network.

   1 | Interviews
   Interviews with relevant experts within the FMCG supply chain industry, forming the main part of collecting insights from the industry. Through the network of KPMG, multiple clients will be interviewed that are positioned throughout departments of supply chain or data analytics, ensuring both subject to be incorporated. The interviews will follow are semi-structured way in order to encourage discussions on relevant topics. The aim will be to interview at least 10 experts from within the industry to ensure a wide variety of answers and interviewees. It is of course difficult to ensure reliability with 10 interviews, this will also be noted in the final discussion depending on the outcomes of the interviews.

   2 | Quantitative examples
   It is important to incorporate quantitative examples during interview to this research to comprehensively give insights in how BDA is used within the FMCG industry. Quantitative examples may be in the form of data dashboards or models used by companies to increase certain supply chain resilience elements. The type of examples depend on the outcomes of the interviews and the level of BDA based methodologies that FMCG companies use. Mostly, these examples will only be shown during interviews and will be summarised in chapter 8 due to company confidentiality.

2.4 Part 3: Assessment Tool

The final part of this thesis approach it to build towards the objective of designing a comprehensive resilience assessment tool that is based on the use of supply chain BDA. The assessment tool is not only designed, but also validated to check the reliability and reflection on real world problems and disruptions.
Reference: chapter 9

1. **Goal**
   Define and design a comprehensive assessment tool to assess the state of (partial) FMCG supply chain resilience based on big data analytics enablers that provides industry benchmarks.

2. **Method**
   In order to define and design an assessment tool, multiple steps are taken which are described below. Starting with setting up the requirements, followed by the general design and results, finishing with the validation. The information used to define and design the assessment tool is based on all findings and outcomes of the literature research and the additional industry insights. An important note is of course that a design cycle is iterative, meaning that the different steps may also be subject to change later on in the process.

   1 | Setting up requirements
   The requirements for the assessment tool are based on literature research, empirical study and KPMG. All findings of these parts are prioritised and may be divided into so called must haves and nice to haves. This should ensure that assessment tool is adequate and consist only of what is truly needed.

   2 | General Design
   The general design consists of the iterative step of designing the deterministic model that represents the assessment tool. A functional tool is presented as output of this process, giving the opportunity to test and validate possible outcomes.

   3 | Industry Results
   The designed tool is used to assess input from industry experts. The goal is to acquire a sufficient quantity of input in order to effectively validate and verify the assessment tool.

   4 | Validation & Verification
   The final step is of importance in order to check whether the tool works as expected, but also to check whether the outcomes are reliable and reflect to the actual business. These steps are conducted with both expert discussions with FMCG clients and KPMG personnel.

Part II

Literature Research

3 | Fast Moving Consumer Goods

This chapter elaborates on fast moving consumer goods (FMCG). It serves as a background for understanding the scope of this research, which for FMCG mainly reflects towards the assessment tool and empirical study. This chapter briefly elaborates on both the product and industry characteristics of the FMCG industry. Additionally, the FMCG supply chain is visualised.

3.1 Fast Moving Consumer Goods

Fast moving consumer goods (FMCG) consist of products that sell relatively quickly and at a low purchasing cost. Other known terms for the subject are consumer goods or consumer packaged goods (CPG). The product can be both durable and non-durable (perishable) with examples ranging from food and beverages to cosmetics and easy accessible drugs. Important characteristics of FMCG products can be divided in two points of view: from the consumer perspective and from a vendors perspective. The most important characteristics for each perspective are presented below and are based on Varma and Ravi 2017.

Characteristics

Consumer Perspective	Vendor Perspective
• Low prices	• Low margins
• Frequent purchases	• High turnover
• Short shelf life	• High volumes
	• Large scale distribution

As for the FMCG market in general, there are numerous characteristics that define the state and competitive balance. First of all, due to the high volumes and low margins of the product type, competitive rivalry is relative high compared to other markets. This is fueled by the high bargaining power of consumers, as many substitutes of FMCG products are available and a slight price differences can quickly change buyer preferences. As an example, consumers have had a change of preference in the past decade towards more healthier and sustainable products which has had a massive impact on FMCG vendors to maintain there client base and competitive position (Newman, Howlett, and Burton 2014). The competitiveness also has a positive impact as it creates an environment of state-of-the-art innovation on both product characteristics, marketing and operational excellence in order for companies to maintain an edge on rivals (Varma and Ravi 2017). The innovation also relates the the technological advancements that the industry is facing. These range from the implementation and development of e-commerce to the enhancement of predictive demand analysis that is highly needed in the current market competition. All innovations and developments can be combined under the umbrella term of industry 4.0 (Reza et al. 2020).

3.2 FMCG Supply Chain

The supply chain of the FMCG industry is based on regular stakeholders ranging from the supplier until the retailers or consumers. However, there are some distinct differences between regular supply chains and those of the FMCG industry. These differences are either due to FMCG characteristics or due to recent developments within the industry. Most academic papers visualise the FMCG supply chain by 5 main stakeholders: suppliers, manufacturers, distributors, retailers and consumers. This is widely agreed upon, however the main differences lie in how products arrive at the consumers. Few papers incorporate the fast-paced developments within the FMCG industry of home delivery, where retailers directly deliver goods from the distribution centre to the consumer (Manders, Caniëls, Paul, et al. 2016). As for the past year, home delivery already accounted for 6% of FMCG retailer sales and is expected to grow to 15-20% at the end of the decade (Rol and Lambregts 2021). Another main difference of the FMCG supply chain is the scale of the operations, as all chains mostly consist of a large quantity of stakeholders. An example of a FMCG supply chain is shown in Figure 3.1, where recent developments are also integrated. However, the (second tier) suppliers are left out from the visualisation. Other important key elements integrated in the figure are the sales of out-of-home stores and the integration of cross docks. Cross docks are innovative and well coordinated distribution centers where products are directly moved from the unloading to the loading dock. Products are thus never actually stored in cross docks, the dock only provide as a passage way.

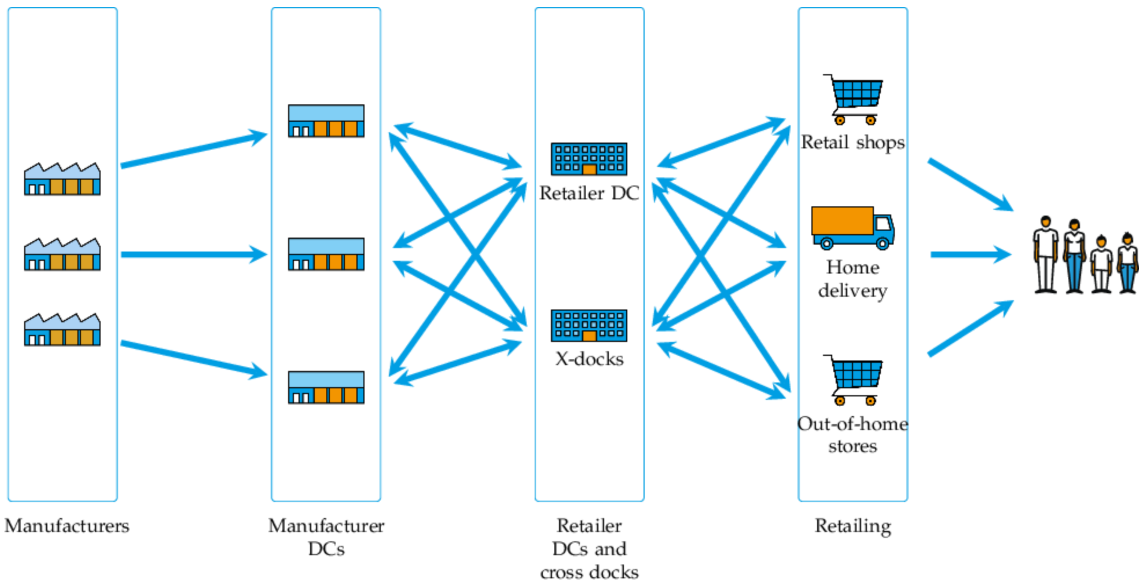

Figure 3.1: Visualisation of a FMCG supply chain, Kok, Dalen, and Hillegersberg 2015

Transportation within the industry can be based on multiple mode types. Between all chains of the supply chain, transportation is needed the move the products from one stakeholder to another. All blue arrows within Figure 3.1 can be associated with transportation. This transportation is mainly done by road, especially at the final stages of the supply chain, as distribution centres and retailers are relatively close by. At the other end of the chain, transportation can consist of different mode types. Suppliers can sometimes be located on other continents due to natural resources or favourable agricultural conditions. This also applies to the FMCG industry, as suppliers of for example fruits are mainly situated in warmer climate based countries compared to northern Europe. These goods are than either transported by ocean carriers or in some special cases by air. Throughout the supply chain, products can thus encounter different transportation modes and travel vast distances before arriving at the final retailer.

A final important note on FMCG supply chains is the strategy used to determine how demand and supply is planned. Products can either be shipped or produced based on actual demand or based on potential demand in the future, also know as make-to-order or make-to-stock. With make-to-order, products are only produced and shipped once an actual order is obtained. Make-to-stock focuses on producing products without knowing to precise demand but with the assumption that the stock will be sold somewhere in the nearby future. This also applies to the FMCG supply chain, as the supply chain works based on the make-to-stock principle. Retailers always need shelves to be filled without knowing exactly when products will be sold, or even if products will be sold when having for example a short shelf life.

3.3 Conclusion

This chapter has provided insights in the fast moving consumer goods industry, mainly focusing on the characteristics of the product, industry and corresponding supply chain. Key takeaways are the characteristics of FMCG, being mainly its large scale, low margins and frequent purchases. The supply chain of FMCG generally follow the normal operations of any supply chain, from raw resources to the end-user or in this case the consumer. Key differences of FMCG supply chains lie in the field of novel retailing and distribution capabilities, such as home delivery and cross docks distribution centres.

4 Supply Chain Resilience

This chapter provides insights on supply chain resilience. Resilience is discussed in relation to practices and an elaboration is given on what supply chain resilience consists of. The main question this chapter answers is the following:

What is the state-of-the-art in supply chain resilience?

4.1 Supply Chain Resilience

Resilience is a broad term that can be interpreted in a variety of ways. Within literature, multiple definitions can be found on what supply chain resilience actually means over the past decades. Definitions may differ in key elements, especially in more older and specific papers as stated by (Ribeiro and Barbosa-Povoa 2018). On the other hand, more recent definitions are mostly taken in a broader perspective and rely on multiple sub relations that resilience brings. Two interesting definitions are presented below and represent two relatively modern interpretations of supply chain resilience.

"The apparent ability of some supply chain to recover from inevitable risk events more effectively than others, based on the underlying assumption that not all risk events can be prevented." (Jüttner and Maklan 2011)

"Supply chain resilience is the supply chain's ability to be prepared for unexpected risk events, responding and recovering quickly to potential disruptions to return to its original situation or grow by moving to a new, more desirable state." (Hohenstein et al. 2015)

The interpretations give interesting insights in different underlying principles of resilience. Main subjects that can be extracted are either to prepare, prevent, respond or recover from uncertainties and risk based events. These are all subject to resilience but identify different possibilities of presenting feasibility. However, in general, resilience can be defined in modern literature as the ability to withstand changes that disrupt the steady-state of a supply chain and work back towards either the same state or an improved version of that state (Ribeiro and Barbosa-Povoa 2018). In order to further clarify the conceptual subject of resilience, Ali, Mahfouz, and Arisha 2017 propose a framework that maps all found concepts in literature in a more clarified overview. Besides the definitions of supply chain resilience, the framework aims to incorporate both strategic capabilities as well as industry practices and key elements. The framework is presented in Figure 4.1 and provides the broad overview of supply chain resilience. An important distribution in the framework in the concept division of resilience in three main pillars; pre-, during- and post disruption. This clarifies the differences that may be focused on within modern day supply chains. Examples of pre-disruption resilience might be to improve forecasting demand or to optimise supplier selection. For during-disruption resilience, supply chain operations need to focus on the agility of the supply chain which is enhanced by the implementation of efficient visibility and velocity (Spieske and Birkel 2021). In this case, the velocity of the supply chain refers to the extent of speed to which operations can be changed. This is intensified by the use of modern innovation as referred to by the term of industry 4.0. Furthermore, the post-disruption resilience of a supply chain is defined by the ability to regain control and to return to the steady or improved supply chain state.

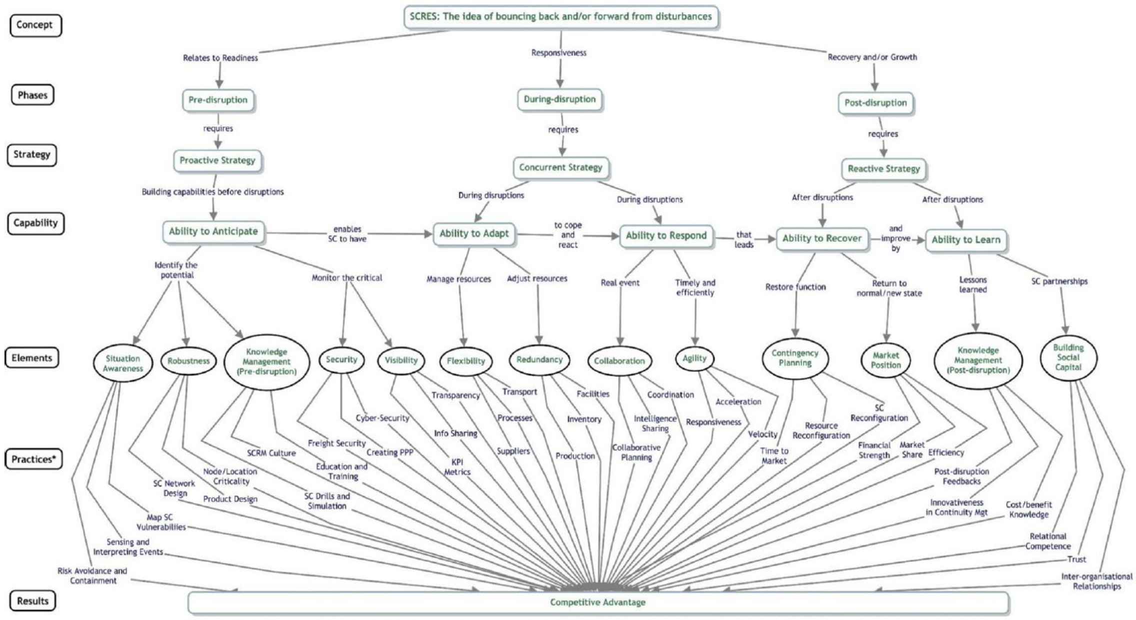

Figure 4.1: Concept Map of Supply Chain Resilience, Ali, Mahfouz, and Arisha 2017

4.1.1 Pre-Disruption

Pre-disruption resilience relies on the level of capabilities that a company may have before a certain disruptions happens. It is a proactive attitude in order to create an ability that enables a company to effectively anticipate on disruptive events. Each element of pre-disruption resilience in relation to a proactive strategy is discussed below.

Situational Awareness | The main idea with situational awareness is the essence of creating a environment where the supply chain is anticipated on potential disruptions. this consists of being able to map supply chain vulnerabilities and by avoiding general risk that may be expected. It is also ensured by implementing a variety of systems that may help in the detection of disruptions or help to implement early warning systems. It is however a difficult resilience element as it needs many stakeholders of information sources to be properly implemented. Both coordination, data sources and personnel knowledge are needed to effectively implement situational awareness. This is enforced by the need for situational awareness to acquire external market information to effectively analyse the situation of the supply chain. External information mostly consist of data sources that require subscriptions or payments since they do not refer to any internal company generated data.

Robustness | With robustness, the resilient elements consist of creating a stable and in a sense healthy supply chain that ensures toleration for certain events. This is implemented by ensuring efficient supply chain configuration in the field of complexity and supply chain density. Furthermore, this is also established by using a segmented supply chain that may easily be tolerant in relation to disturbances. The main goal of the element of robustness is to verify whether the supply chain can continuously function when interfered with disruptions.

Visibility | This resilience element could add value to all types of resilient phases, but is placed under pre-disruption by Ali, Mahfouz, and Arisha 2017. Visibility is one of the most important resilient elements as it enables and improves other elements like flexibility, transparency and agility. With visibility, supply chains can be monitored with the use of tracking tools and visualisation methods in order to create awareness on for example changes in KPI performance. The implementation mostly relies on the use on information technology (IT) and well coordinated connectivity of different sources. When enabled, efficient supply chain visibility can minimise the impact that a disruption might have by aligning capabilities.

Security | Supply chains tend to more recently be targeted by cyber attacks which can cause major disruptions in operations. Therefore, creating a secure online supply chain environment is a key resilient element that grows in importance. In recent years, the industry has shown that the importance of ensuring (cyber) security has been something where companies have lacked in to implement. Mostly waiting for an actual cyber attack before considering implementing expensive security systems. This resilient element has especially gained popularity with the developments towards industry 4.0 and will therefore remain essential.

Knowledge Management | This entails the capabilities of human resources within supply chain operations. Ensuring knowledge by implementing training, exercises, drills and simulations increases the capabilities of personnel and in that way improve resilience. It is a relevant support for other resilient elements, since these elements can only be correctly and effectively implemented with the right knowledge management.

4.1.2 During-Disruption

The resilience within the during-disruption phase is based on concurrent strategies that thus simultaneously happen with a certain disruption. It enables the abilities for a supply chain to adapt or respond to an event which help to cope and react on possible outcomes. The during disruption resilience mainly focuses on four elements: flexibility, redundancy, collaboration and agility.

Flexibility | An important element to enable the ability to adapt is the level of supply chain flexibility. This consists of for example flexible management of supply and demand, to effectively adapt to changes. Flexibility is fueled by the supply chain visibility as adapting to changes is highly dependant on being able to know what is happening within the supply chain. It is increased by maintaining and facilitating flexibility in different processes from order fulfilment to operational efficiencies.

Redundancy | This is primarily a resilience element based on the ability to maintain excess capacity to ensure that a supply chain can rearrange supply and demand to increase adaptability. It both impacts within transportation services, inventory management and storage capabilities.

Collaboration | Collaborative planning is a sometimes missed out in supply chain resilience elements, since effects may not directly be noticed. However, sharing information and knowledge on a high level with supply chain partners is of great essence to ensure resilience, as many stakeholder are normally involved in especially FMCG supply chains. With effective collaboration on both horizontal and vertical levels resilience can be improved or other resilience elements like flexibility and visibility can be enhanced.

Agility | The velocity of the ability to change is mainly the definition of supply chain agility. Especially in the FMCG industry, where products and processes rapidly change and move, the agility is of high importance. It defines the reaction time and is highly correlated with supply chain flexibility. As flexibility is the ability to adapt, agility ensures the responsiveness to an disruptive event. This is particularly the case with disruptions that face changes in demand and supply where a supply chain should quickly be able to respond to sudden changes.

4.1.3 Post-Disruption

Post-disruption resilience is defined by the ability to not only recover but to also learn from processes that happened before and during a disruption. It calls for planning, market position, knowledge management and social capital. The final outcome of especially post-disruption resilience is to enhance competitive advantage to withstand and learn from disruptions better than industry competitors.

Contingency Planning | Post-disruption resilience is mainly based on learning from disruptions and implementing new plans based on how these disruptions were handled. Enabling contingency plans is related on being able to reconfigure both the supply chain, resources and scenario analytics. Implementing well defined contingency plans helps a company to better recover or face future disruptions and to more easily return to the normal supply chain state.

Market Position | The resilience element of market position is a highly debatable element as a company might not have a direct impact on its market position. A strong market position however improves resilience as such company is assumed to have high financial capabilities, good customer relationships and thus a high competitive advantage. These factors play a role in resilience as companies can use these capabilities to adapt or recover from disruptive events.

Knowledge Management | Enabling well coordinated knowledge management is both important in the pre- and post-disruptions phase. It increases the ability to efficiently learn form disruptions and a supply chain can be altered based on the outcomes of such learnings. Main capabilities that empower knowledge management are feedback loops, cost and benefit analyses and risk analysis. Depending on the type of disruption, knowledge management can be of great importance, especially for disruptions that are categorised by a high probability or disruptions that are planned ahead such a new product implementations.

Social Capital | This elements builds forth on the during-disruption collaboration. With increased communication and collaboration in the post-disruptions phase, different stakeholders enable each other to learn and recover from disruptions. It may build trust between supply chain partners and increase overall learning abilities.

4.2 Conclusion

This chapter has provided insights supply chain resilience, with the following research question:

What is the state-of-the-art in supply chain resilience?

For the resilience of a supply chain, literature follows comprehensive frameworks that discuss different resilience elements. These elements or enablers fall under three main categories combined with an operating strategy: pre-disruption / proactive, during-disruption / concurrent and post-disruptions / reactive. Each enabler has its own partial contribution towards general resilience, by providing different strategies that companies can follow to ensure supply chain resilience. The state of the art thus consist of the vast variety of these resilience enablers and the corresponding techniques and strategies.

5 Big Data Analytics in Supply Chains

This chapter elaborates on the definition and use of big data analytics within the supply chain industry. The chapter firstly describes what big data is and how big data analysis is used both in general and when related to the FMCG industry. With this information as a base, the final part of the chapter extensively analyses how BDA contributes to SC resilience according to literature research. The main question this chapter aims to answer is the following:

What does big data analytics in supply chains consist of?

5.1 Big Data

It is important to first understand what Big Data is in terms of characteristics and potential usages. Fosso Wamba et al. 2015 gives the most well-known characteristics of big data by presenting it as 5V's. These V's are volume, variety, velocity, veracity, and value. This is also shown in Figure 5.1. The volume describes the vast quantity of the data that is collected and/or analysed. Velocity is the speed at which the data is generated and the variety represents the different sources and characteristics that the data may have. Veracity is one of the characteristics that is becoming more important as it describes the trustworthiness of the data. This is of importance because with the increase of data quantity at companies it also increases the difficulty of validating the data and finding the data source. Besides, big data is used more frequently within big data analytics to create insights for critical decision making at large companies, making the trustworthiness of data of the at-most importance. Finally, value is the last characteristic that describes big data as it is important to note what data can actually mean or improve. Big data is thus defined by these V's as large, unstructured, complex and valuable data that can be computationally processed in order to be of use in analytical operations.

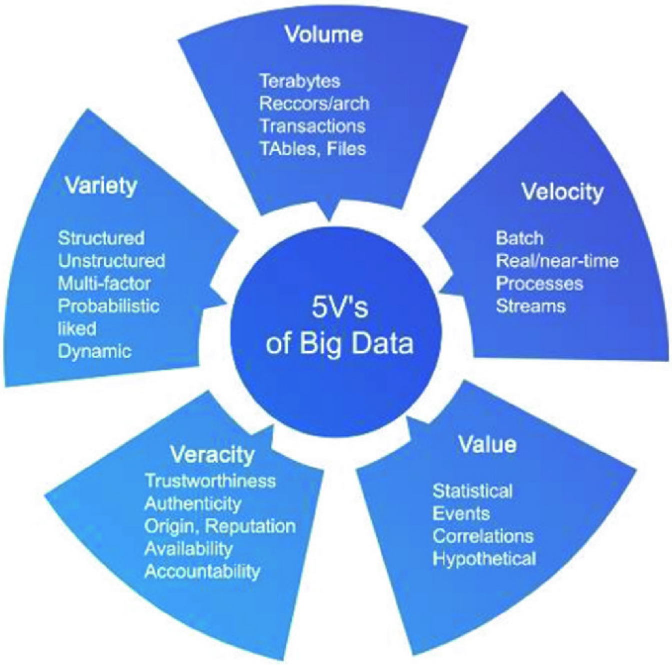

Figure 5.1: 5V's of Big Data, Mazzei 2020

5.2 Big Data Analytics

In relation to the 5V's, data used for supply chain operations and resilience is also primarily defined as big data. New developments of technologies such as RFID and sensors also enhance the generating capacity of data with large amounts of variable data. This is further increased by external data which can either be bought from other companies or can be part of a contract deal that enablers data transparency. For example, sales data from retailers is sometimes sold to producers and vendors to increase their insights on their own product sales. For the most part, BDA has extensive impacts on a wide variety of operations which companies can use to develop and improve business. In general, BDA can bee seen as all tools, processes and techniques that use either structured or non/semi structured data to create valuable insights to use within (critical) decision making (Spieske and Birkel 2021). For example, improvements through BDA that can easily be seen are increases of key performance indicators (KPI) (Raman et al. 2018, Kamble and Gunasekaran 2019) These KPIs can be anything ranging from customer satisfaction to operational excellence. Other well known indicators are cost savings and lead times. The impact of BDA on supply chains can also be indicated though comprehensive frameworks. For example, Raman et al. 2018 proposes the Supply Chain Operation Reference Model (SCOR) which aims to relate data analytics to supply chain management. More concrete research on the implementation of BDA in supply chains by Ionica et al. 2019 presents insights on the lack of research on security technologies and cloud computing. Although out of scope for this research, it does indicate the importance of the subject. In a more broader perspective, BDA is acknowledged to have strategic benefits for companies where is should be seen as a strategic asset instead just only information (Varela Rozados and Tjahjono 2014). This is important to state since the value of BDA as a strategic asset increases with improved developments on digitisation and thus data generation. As a strategic asset, BDA can increase competitive advantage for companies with especially predictive analytics. Through statistical algorithms or more basic regression analyses, companies can try to predict future states of operations in order to improve their insights or increase efficiency. These tools and methodologies are also mentioned in the relevant and recent literature review of Nguyen et al. 2018 where the different types of techniques and models are discussed that are used within supply chain BDA. The paper presents a classification framework that incorporates both the level of analytics, BDA models and BDA techniques and is shown in Figure 5.2.

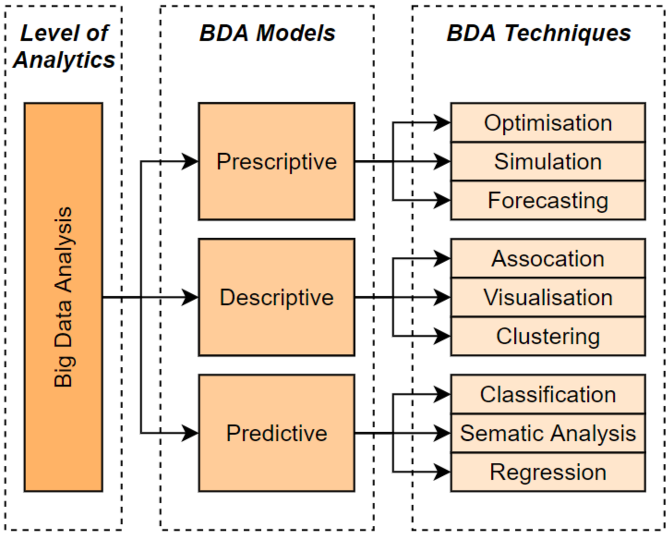

Figure 5.2: Classification Framework, based on Nguyen et al. 2018

An important side note is that the classification network of Nguyen et al. 2018 does miss out on one other potential sub classification: diagnostic data analytics. With diagnostic big data analytics, the main goal is to find out why something happened or why a certain relation is found. This is however out of scope for this research, since the main aim is to investigate major disruptions with high impact and low probability. This thus decreases the need to understand why for example such disruption happens, since it would not give any clear insights on other major disruptions. For example, finding the root cause of the Covid crisis, Suez canal blockage or lack of computer chips would be ineffective and time consuming. The root cause would in this cause not improve competitive advantage, increase resilience or improve general operations and may thus be left out of scope.

The classification framework of Nguyen et al. 2018 in Figure 5.2 describes the three most important BDA based models with prescriptive, descriptive and predictive analytics. Each type or category of BDA relates to specific BDA techniques than are further described below. The general categories are related to supply chain resilience in chapter 6.

5.2.1 Descriptive BDA

Descriptive data analytics derives information from large data sets by describing and analysing what is currently happening (Souza 2014). It tends to find internal relations within the data that may hold valuable information and insights. Descriptive data analytics uses visualisation methods like clustering and scatter plots to both find and describe relations. Another possibility is that data is used to acquire quantitative insights that are not visualised but are presented in numbers. Examples of this are calculating an average or median based on large data sets. As for the use of both descriptive visualisations and calculations, common and innovative practice is the use of data dashboards. These dashboards present real-time data that can be used to both analyse and track current business insights. Examples of software used for these dashboard are PowerBI and Tableau, well known management tools within practically every data-driven industry. The dashboards are important for a wide range of companies as they incorporate different data sources and combine it in a single comprehensive and clear dashboard. The real time insights that the dashboard presents helps to implement effective data-driven decision making or enables empowerment of employees. The use of descriptive data analytics can also be linked to supply chain resilience, as it can be seen as a concurrent resilience element. More elaboration on this relation is discussed in section 6.2.

5.2.2 Predictive BDA

Predictive analytics is the term for analysing data and using it to determine what will be or could be happening in a future state. In order to determine a future state, different methods may be used ranging from regular regression towards complicated machine learning algorithms. It is key to state that for any given method used in predictive analytics, a future state can never be determine with 100% certainty. For example, using predictive analytics to forecast on demand or supply is never completely accurate, it merely gives an approximation of what demand may be. This is however still very useful information to guide decision making processes, as forecasting still gives valuable insights on general demand trends and flows. Due to possible inaccuracies, predictive models from all types of complexities are iterated once a forecast is matched with the actual future states. This ensures continuous improvements and could for example also improve resilient indicators. More elaboration on the relation between predictive analytics and resilience is discussed in section 6.1 where predictive analytics is linked with proactive resilience elements.

5.2.3 Prescriptive BDA

Prescriptive analytics can be seen as the final phase of analytics that derives information and insights from both predictive and prescriptive methodologies. It concern the analytics of what should happen within processes, by defining optimal decisions or methods. This thus also encompasses the question of why something happens and how to deal with potential consequences. Frequently used methodologies to implements prescriptive strategies are simulation and optimisation.

An example of prescriptive analytics is presented in Souza 2014 where Coca-Cola is mentioned as a company that successfully implemented prescriptive analytics. The fleet of Coca-Cola needed to be partly replaced from diesel trucks to electric trucks. However, the main question was what the ratio between the two truck types should be, taking into account that only one type of trucks would not be sufficient. With the use of data on diesel prices, demand and historical maintenance and purchasing costs, Coca-Cola managed to implement a dynamic programming model to calculate the optimal ratio of diesel vs electric trucks. This is a comprehensive example of how prescriptive analytics can work in actual business related challenges. Such optimisation models are commonly performed in programming languages as Python, R or Java which enable complex algorithms or modelling. In relation to supply chain resilience, prescriptive analytics also has an impact on different resilience elements. These element are described and discussed in section 6.3.

5.3 General FMCG BDA

In order to fit the scope of this research, where the relation between BDA and supply chain resilience is applied to the FMCG industry, this section gives more information on BDA within the FMCG industry. For FMCG companies, BDA can improve operations through not only resilience but also efficiency and effectiveness. The FMCG industry especially generates large quantities of data through new technologies such as RFID, as mentioned before. Developments such as RFID are also acknowledged in literature to be beneficial to supply chain operations, especially when the corresponding data is analysed (Bottani and Rizzi 2008, Bottani, Montanari, and Volpi 2010). In specific, this also holds for the bullwhip effect that can be decreased when BDA is sufficiently implemented with for example RFID data to identify and potentially increase safety stocks. For the FMCG industry, the implementation of BDA can greatly increase KPIs or lower costs in different operations through optimisation. However, on the other side, it should also be noted that the costs of the transition to a data-driven organisation should be taking into account. These costs should be tested though pilot projects to get an understanding of the complete scope of a data-driven organisation. In addition, this enables the comparison between investments costs and actual business improvements. Recent research (Sanders 2016) also acknowledges this by defining that pilots projects are of importance to make sure that implementations are widely understood with regards to for example BDA complexity. This is further driven by other new technologies and developments that have an impact on the FMCG industry. As stated during scoping, the developments fall under the broader term of industry 4.0, including BDA (Frederico et al. 2019). It is stated that especially with BDA, FMCG supply chains can effectively reduce their general costs and therefore improve operations. Additionally, the impact of BDA on FMCG supply chains also has an effect on the agility of operations, described by multiple case studies (Manders, Caniëls, Paul, et al. 2016) and relates to resilient measures.

Further and more recent papers show that quantitative approaches have also been researched over the past couple of years in relations to how BDA is developing in the FMCG industry. An extensive literature review of Madhavi and Wickramarachchi 2021 elaborates on decision making models for supply chains, which are regularly used for resilient purposes. However, most models are empirically based and thus not depend on quantitative data nor are data-driven models really explored. Furthermore, the review of Madhavi and Wickramarachchi 2021 is very recent and relates to the Covid-crisis, the issue is that most practices and models that were found and used in the review are from mid 2020 and could therefore be biased to only the Covid crisis. Nevertheless is this review still of essence for this research as it gives insights in how FMCG supply chains could and have coped with a major, low probability, high impact disruption. Another recent study on supply chain data analytics is presented by Mariani and Wamba 2020 where digitisation is explored within consumer good companies, a type of FMCG. The main point related to supply chains is the influence BDA has on effectively managing supply chain risks by streamlining different operations and implementing big data analytic capabilities (BDAC).

5.4 Conclusion

This chapter aimed to answer the following question:

What does big data analytics in supply chains consist of?

The answer lies in first decomposing the question in sub definitions. By researching the essence of big data first, which is defined by its characteristics of high Volume, Velocity, Value, Veracity and Variety. Based on data sets with these high characteristics, big data analytics can be used to acquire valuable insights through visualisation or models and algorithms. With big data analytics, descriptive, predictive and prescriptive are the three main categories discussed that are relevant for the scope of FMCG supply chains. Descriptive analytics are used to analyse current and past states through primarily visualisation in BI dashboards. Predictive analytics entails the use of data through predictive model, determining possible future states of supply chain operations. Prescriptive mainly consists of answering the question of what should happen, using big data to analyse operations in order to for example optimise. These BDA categories are subsequently used to improve business operations within (FMCG) supply chains, fueled by new developments such as digital warehouses or RFID tags that increase the need of adequate BDA.

6 | Big Data Analytics Based Resilience

This chapter combines the previous chapters and creates insights on the impact of BDA on supply chain resilience. The main question to be answered is:

How does Big Data Analytics relate to supply chain resilience?

Both chapter 4 and chapter 5 are used to develop frameworks that visualise relationships between resilience and BDA. The relation between BDA and resilience also refers to the general research gap as discussed in Figure 1.1. The main resilience enablers that BDA has an impact on according to literature research are presented in Table 6.1. The term 'enablers' is used as an umbrella term for both techniques and capabilities for resilience. This is specifically chosen as the umbrella term of enablers will fit the corresponding assessment tool in chapter 7 where interdependence defines the relation between either a technique or capability. This ensures that both techniques and capability can be used accordingly. Subsequently, enablers are categorised based on proactive, concurrent and reactive resilient strategies respectively. For each strategy, resilience enablers and the corresponding BDA technologies are discussed in subsections and are summarised in comprehensive frameworks. Each framework follows the main idea of Figure 6.1, where the relation is addressed between BDA categories and resilience strategies. The resilience elements can also be seen as second tier resilience enablers, having interdependence through the impact of the first tier enablers.

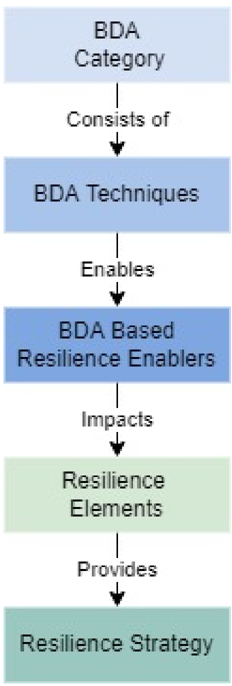

Figure 6.1: Overview of frameworks from section 6.1, section 6.2 and section 6.3.

Table 6.1: Resilient enablers supported by BDA

Resilience Enabler	Supporting Literature of Relation to BDA
Proactive	
Transparency / Visibility	Ramirez-Peña et al. 2020, Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Predicting disruptions	Kara, Fırat, and Ghadge 2020, Bag, Gupta, and Wood 2020
Early warning systems	Kara, Fırat, and Ghadge 2020, Dubey, Gunasekaran, Childe, et al. 2021
Disruption Detection	Kara, Fırat, and Ghadge 2020, Ivanov and Dolgui 2021
Scenario Modelling	Ivanov and Dolgui 2021
SC Vulnerability Assessment	Ramirez-Peña et al. 2020, Kara, Fırat, and Ghadge 2020
Concurrent	
Transparency / Visibility	Ramirez-Peña et al. 2020, Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Velocity / Agility	Zouari, Ruel, and Viale 2020, Kahiluoto, Mäkinen, and Kaseva 2020, Dubey, Gunasekaran, and Childe 2019
Digital SC Twin	Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Organisational flexibility	Dubey, Gunasekaran, Childe, et al. 2021
Flexibility	Dubey, Gunasekaran, and Childe 2019, Hosseini, Ivanov, and Dolgui 2019
Collaboration	Chae 2015, Hosseini, Ivanov, and Dolgui 2019
Reactive	
Identification of risk relationships	Kara, Fırat, and Ghadge 2020
New skill developments	Ralston and Blackhurst 2020
Scenario Modelling	Ivanov and Dolgui 2021

6.1 Proactive Resilience

Proactive resilience within supply chain operations is defined and discussed earlier in subsection 4.1.1 and concludes that it is defined by resilience in the pre-disruptions phase where the emphasis lies on the ability to anticipate on both the potential and critical impacts that may occur due to disruptions. A general framework of the main relation between BDA and proactive resilience is presented in Figure 6.3 and describes the resilience enablers with corresponding BDA techniques.

The link with BDA mainly relates to the both predictive and descriptive analytics that potentially increase resilience. BDA based proactive resilience can be divided in different elements that mainly encompass the prediction of disruptions and the assessment for supply chain vulnerabilities. For the prediction of disruptions, BDA techniques like linear and decision tree regression can be used to analyse potential disruptions (Kara, Fırat, and Ghadge 2020). Even thought these techniques mainly relate to predicting smaller disruptions or risks within supply chain, like fraud detection, it may still also relate to major disruptions that are in the scope of this research (Kara, Fırat, and Ghadge 2020). For example, with the use of regression analytics, FMCG companies could analyse public available data on weather or traffic to detect or predict potential (major) disruptions. Therefore these analytics techniques can help improve supply chain resilience on disruptions detection as well as early warning systems. This is also encouraged by Dubey, Gunasekaran, Childe, et al. 2021 where it is stated that especially data driven supply chain visibility can increase not only the impact of disruptions but also the potential probability.

Besides disruptions detection and early warning systems, it is also possible to use data driven software such as AnyLogistix to simulate a supply chain and to create a digital supply chain twin (Ivanov and Dolgui 2021). This would create the ability to run different scenarios which gives insights in how to handle disruptions. In addition, with the use of external data sources such as power grid, financial market and weather data, it is possible to filter and simulate events to better understand its consequences. An example on how this could be integrated is presented by Ivanov and Dolgui 2021 in Figure 6.2. The figure explains the steps taken in order to understand which process steps are needed.

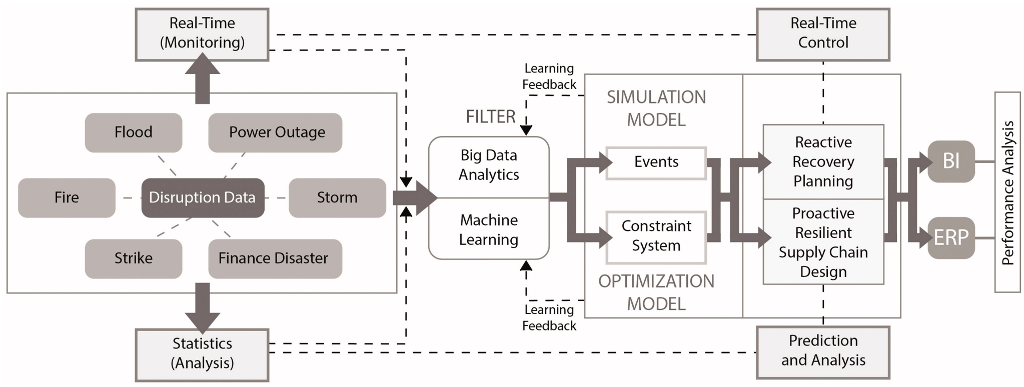

Figure 6.2: Supply chain twin to proactively simulate disruptions, Ivanov and Dolgui 2021

Another important element of proactive supply chain resilience is enabling the potential of assessing vulnerabilities within the supply chain (Kara, Fırat, and Ghadge 2020). Using supply chain data and BDA techniques such as k-means or triagularisation clustering, network relations can be assessed and outcomes may be used to lower the complexity of the supply chain and thus enhance resilience. Assessing vulnerabilities is also linked to scenario modelling or digital supply chain twins as they enable the ability to analyse the supply chain on different levels and expose potential flaws or elements that are extra sensitive to disruptions (Ivanov and Dolgui 2021). Digital supply chain twins are defined by a model that can give the state of a supply chain at any given moment in time. This is a technique that can be used in different settings of resilience, as supply chain twins can give insights for both pre-, during and post-disruption resilience drivers.

Finally, by far the most important BDA element that may improve resilience is visibility, fueled by the increase of a companies transparency (Ramirez-Peña et al. 2020). Visibility encompasses all types of BDA techniques where data is visualised to created better insights in what the data actually describes. This can be in any form of figure, chart or diagram, as long as it is based on supply chain data. All forms are generated with the use of descriptive data analytics ranging for example from visualisation techniques to association and clustering to comprehensive tools such as PowerBI). Supply chain visibility may be based on internal data systems from ERP or WMS but can also be based on external data that can be bought or publicly accessed. A comprehensive example is how Chae 2015 used tens of thousands of twitter messages to identify supply chain operations and managements. Main findings report that with the possible use of this external data source it could relate to supply chain risk, demand and stakeholder analysis and thus has the potential to increase resilience based on visibility and especially knowledge management. The positive effect of BDA on customer or stakeholder information and thus the ability to increase knowledge management is also supported by Dubey, Gunasekaran, and Childe 2019. To conclude, the three main resilient drivers that the above resilience elements improve are thus visibility, but also the creation of situational awareness and knowledge management.

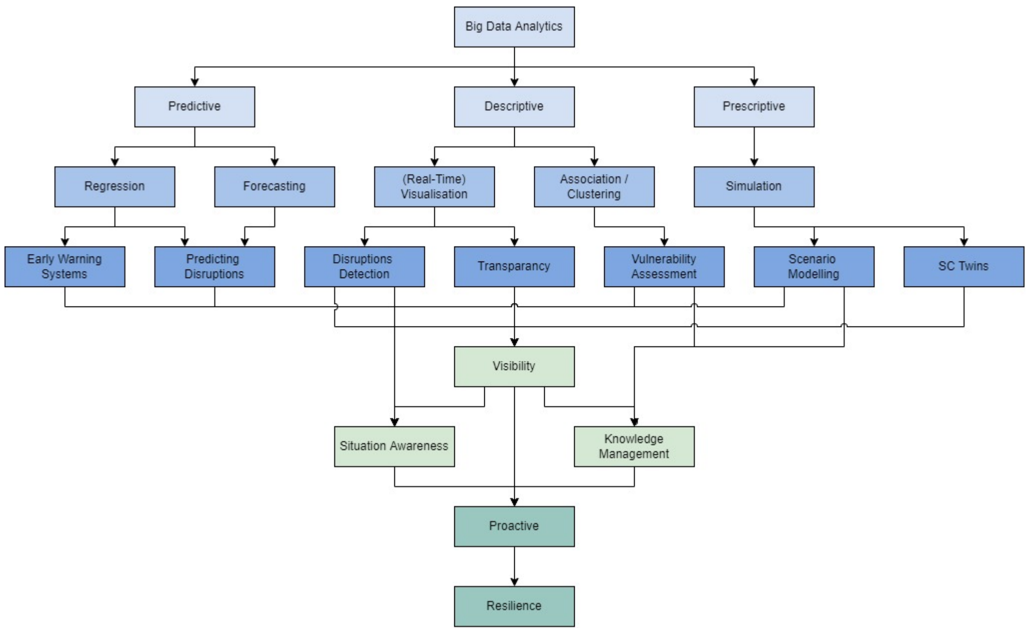

Figure 6.3: Framework op BDA based proactive resilience (work author)

6.2 Concurrent Resilience

A concurrent strategy fits supply chain resilience defined by the during disruption phase. The concurrent strategy evolves around both abilities to adapt and to respond to certain events. More elaboration on during-disruption resilience is discussed in subsection 4.1.2. A general framework of BDA enabled concurrent resilience is given in Figure 6.4.

Visibility is the first major element that increases supply chain resilience with respect to concurrent strategies and based on BDA. As it is also stated in section 6.1, visibility is a comprehensive element that also effects most other resilience elements discussed. It is also stated before that BDA enables to increase transparency and therefore supply chain visibility to improve abilities to see vulnerabilities, this also holds as a concurrent strategy as looking for vulnerabilities can also be done with real-time data analytics (Ramirez-Peña et al. 2020). Using descriptive data analytics methods in a wide range, visibility mostly helps a company to enhance supply chain responsiveness (Zouari, Ruel, and Viale 2020). It is however often stated that BDA has a positive impact on supply chain visibility, but in close relation with other industry 4.0 technologies which further enable capabilities. For example, with the use of BDA algorithms, supply chain operations can improve in efficiency which in turn could also increase resilience (Ramirez-Peña et al. 2020).

Having insights on real-time supply chain operations also has a direct impact on the flexibility, being a complementary factor of visibility and situational awareness (Dubey, Gunasekaran, Childe, et al. 2021). BDA based flexibility mostly relies on these factors, situational awareness leads to effective precaution measures against disruptions, while visibility enhances the ability to quickly adapt to a new situation. Furthermore, BDA based visibility also improves the organisational flexibility of a company, as more information is gathered and presented. Subsequently, managers not only have more possibilities for decisions, the decision making itself also improves in a data-driven way. Flexibility is also in close relation to supply chain agility, as flexibility means to quickly be able to change, while agility also enables on removing barriers that prevent flexibility. Supply chain agility is enhanced by big data analytics thought the capability of velocity, visibility, transparency and collaboration, but especially with valuable insights that allow for better decision making (Zouari, Ruel, and Viale 2020). It also has a two way relation with contingency planning, as reflecting on agility creates the possibility to adapt for future events and contingency plans itself enable agility (Dubey, Gunasekaran, and Childe 2019). There is thus a clear link between the concurrent and reactive resilience strategies. The contingency plans are furthermore also developed based on other BDA enabled techniques such as situational awareness and supply chain visibility.

Furthermore, digital supply chain twins also create a effective environment to increase concurrent resilience. With for example RFID data, the transport chain can be completely visualised in as a digital twin. This can be enhanced, similar to proactive resilience (section 6.2), with the use of data from ERP systems and sensors (Ivanov and Dolgui 2021).

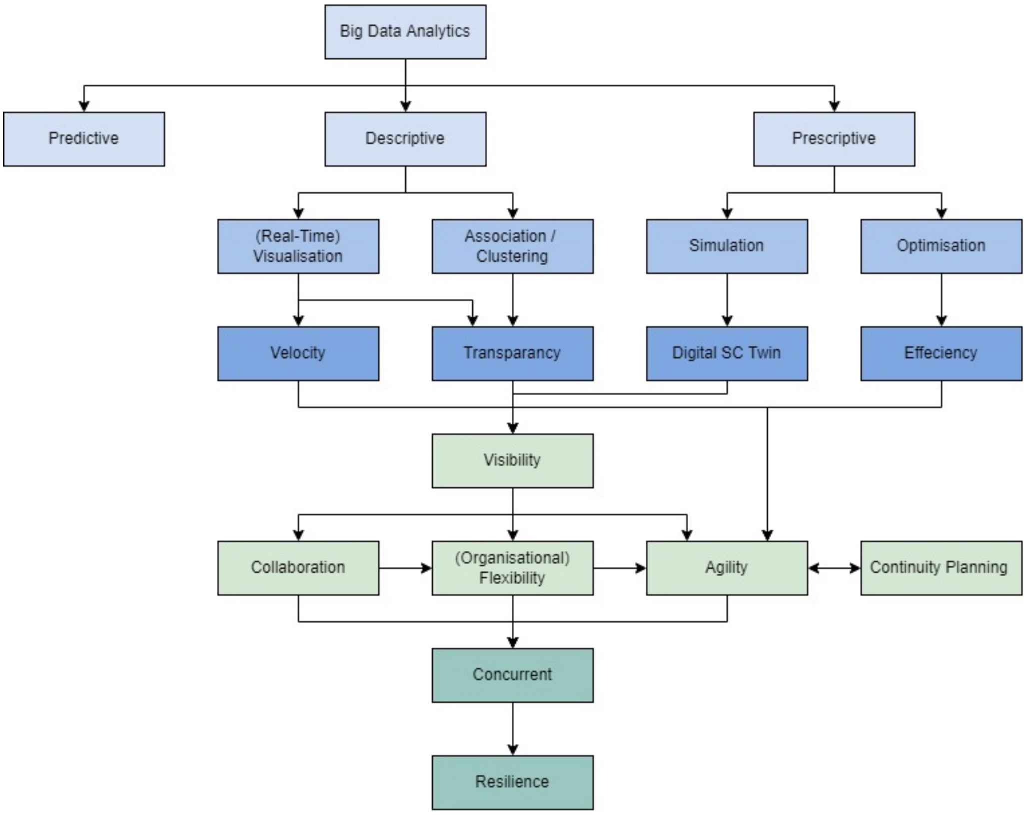

Figure 6.4: Framework op BDA based concurrent resilience (work author)

6.3 Reactive Resilience

Reactive resilience is the final strategy that is involved within supply chain resilience and relies of the two main abilities: to recover and to learn (subsection 4.1.3). There are three main resilience elements that are enabled though BDA as a reactive strategy: developing new skills, knowledge management and contingency planning. The general framework for reactive resilience and its corresponding BDA enabled drivers is given in Figure 6.5.

All elements are fueled by either descriptive or prescriptive BDA techniques, as predictive analytics lacks in applicability for post-disruption resilience. With descriptive visualisation and association techniques, similar to pre- and during disruption resilience, relations within data sets and between different data sources can identify possible vulnerabilities. As a reactive strategy, these vulnerabilities are the basis for developing new skills (Ralston and Blackhurst 2020) and increasing internal knowledge management (Dubey, Gunasekaran, and Childe 2019). Subsequently, both new skills and increased knowledge management have a positive impact on designing and implementing contingency plans. Contingency plans are often data-driven as they require detailed analysis of events and possible outcomes. It thus also required the used of prescriptive simulation techniques that empower resilience drivers such as digital supply chain twins and scenario modelling (Ivanov and Dolgui 2021).

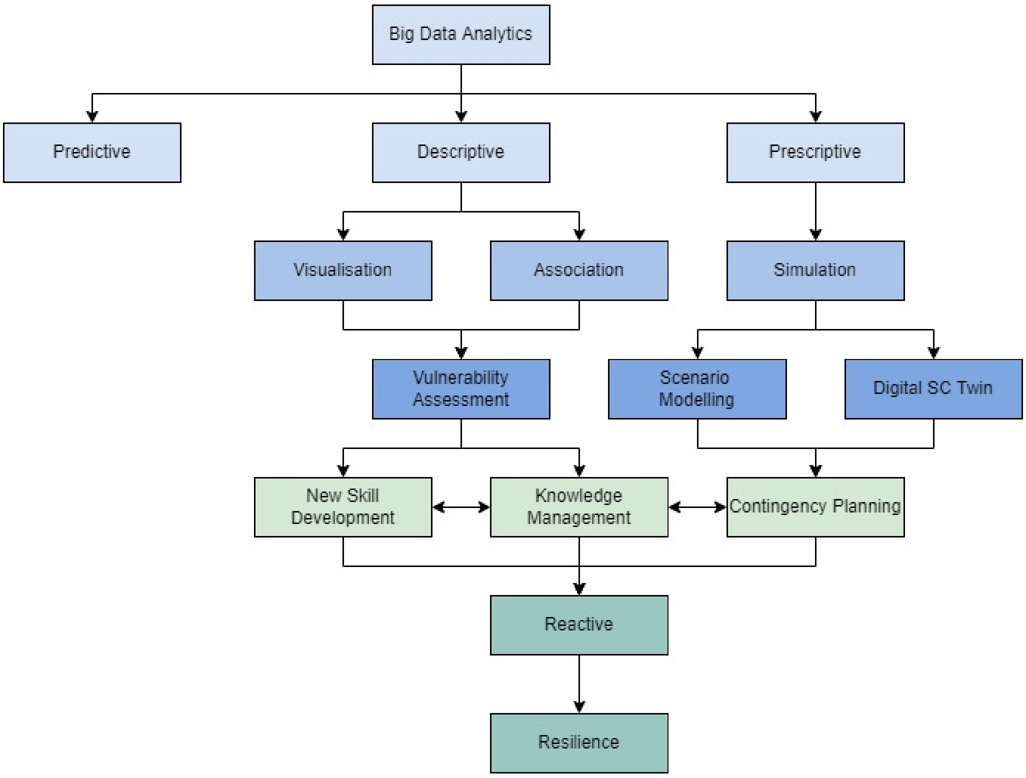

Figure 6.5: Framework op BDA based concurrent resilience (work author)

6.4 Challenges

All relations between supply chain resilience and BDA as described previously in this chapter are based on literature and thus potentially only exist in theory. This is also stated in many of the underlying academic papers as there are multiple challenges faced before being actually able to effectively implement BDA based supply chain resilience. These challenges mainly focus on either the BDA or organisational capabilities of a company. An overview of these challenges is given in Table 6.2.

Table 6.2: Overview of Challenges

BDA	Organisational
Data Availability	Insufficient Training
5V Complexities	Willingness and Mind-Set of Managers
Lack of Trained Personnel	Lack of Resilience Assessment
Digital Maturity	Implementation Costs

6.4.1 Data Challenges

The BDA capabilities form a major challenge according to literature due to the characteristics of big data. As defined in section 5.1, big data relates to the 5V characteristics: Volume, Velocity, Value, Veracity and Variety. These characteristics form the basis of the challenge, as each characteristic makes data more difficult to process or to gain insights on. As more and more decision making models rely on big data as well as the resilience elements enabled by BDA, it becomes more important for a company to precisely enhance their data on validity, completeness and consistency (Ivanov and Dolgui 2021). This is the main challenge for the industry, most companies know what they eventually want to do with big data, but lack in maturity of especially master data management. Master data management can be seen as enabling the correctness and efficiency of the big data characteristics ensuring that well defined analytics can be implemented. For example, big data in especially the FMCG industry can come from multiple sources that have to be linked together and most of the time also have different data formats. These challenges increase the effort and difficulty to effectively clean the data to be used, which still is a major time consuming subject for BDA. Therefore, another importance to effectively implement BDA based supply chain resilience strategies is the availability of well trained personnel (Bag, Gupta, and Wood 2020). This can also be seen as a (organisational) challenge since it proves to be difficult to fill BDA based vacancies.

Besides the complexities of analysing big data, the availability of such data is also a challenge on its own. Especially the on-time availability of data which is needed for real time insights. A company might generate a vast quantity of data, but such data would be useless for real time insights if it cannot be processed accordingly. The availability also depends on the digitisation of (global) supply chains and other industry 4.0 technologies. For example, without sensors, RFID or GPS locators, data on supply chain transport movements is very difficult to generate. This of course also depends on the managerial implications that prevent I4.0 technologies, but is of great essence for BDA based resilience.

A final major challenge for the implementation of effective BDA techniques is the computing power needed to address BDA related issues. It is the capacity needed to analyse the vast quantity of data generated within the FMCG industry, which can count upwards to thousands of terabytes of data. The computing power primarily impacts the time which a BDA algorithm or model needs to run, heavily impacting the effectiveness and level of usefulness of BDA implementations. These challenges are mainly related to the digital maturity of a company, since higher digitised companies can more effectively implement resilience enablers (Zouari, Ruel, and Viale 2020) and have less issues with challenges concerning the characteristics of big data.

6.4.2 Organisational Challenges

To build forth on the BDA challenges, the lack of personnel can also be seen as an organisational challenge. Attracting new employees depends on what an organisation or company has to offer, which in essence relies on organisational decisions ranging from salary to other working conditions. Furthermore, master data management also depends heavily on the willingness of an organisations management to leverage time and money to implement an efficient BDA working structure. This may not always be the case of the willingness of managers, but can also be due to traditional mind-sets or a companies culture which disables new implementations of technology (Bag, Gupta, and Wood 2020). On the other hand, the lack of personnel can be compensated if companies invest time and money in the education and development of their own employee. In theory, this could sometimes be easier than attracting new personnel and should also in general be considered for a consistent and healthy professional development of personnel. However, due to the complexity of BDA and low organisational focus on the subject, training of personnel remains an additional challenge that companies face in effectively implementing BDA practices for resilience.

A final challenge to note is the lack of availability for companies to effectively assess their supply chain resilience. This fuels the lack of organisational capabilities to implement resilience drivers. Without a clear quantification of the effect, managers tend to focus on other problems where the results of can more easily be tracked. There are multiple ways according to literature to implement assessment tools for resilience, but there is still a general lack of business implementation. This is mainly the case due to difficulties of outcomes from literature assessment tools to effectively be compared within the industry. Therefore, the research of this report is highly applicable to the industry with the corresponding design of a comprehensive enabler based resilience assessment tool, as further described in chapter 9.

6.5 Conclusion

Resilience and BDA are widely mentioned within academic literature but the relation between the two subjects lacks in comprehensive research. The connection between the two subjects congregate with multiple resilience enablers that have a partly BDA based foundation. The enablers lie on the intersection between resilience strategies (proactive, concurrent, reactive) and BDA categories (descriptive, predictive, prescriptive). Furthermore, each BDA based resilience enabler also has an impact on other enablers which strengthen the resilience contribution. The found enablers from Figure 6.3, Figure 6.4 and Figure 6.5 form the basis for the research objective, designing a comprehensive assessment tool based on enabler implementation levels. In total, 16 enablers are found from literature with BDA substantiation, these are: Agility, Collaboration, Contingency Planning, Digital SC Twin, Disruptions Detection, Early Warning Systems, Flexibility, Knowledge Management, New Skill Development, Predicting Disruptions, Scenario Modelling, Situational Awareness, Transparency, Velocity, Visibility and Vulnerability Assessment. It is however important to verify BDA based enablers with industry insights, ensuring knowledge on current implementation levels and developments. Additionally, in order to fully understand implementation levels of each enabler, expert discussions should give indications on what these levels are or could be within the current FMCG industry.

7 | Supply Chain Resilience Assessment

7.1 Background Research

As described in section 1.4, the main deliverable of this research is an assessment tool of BDA based supply chain resilience. This chapter offers a preliminary research on how supply chain resilience can be assessed according to current literature. This enables a well defined start for the design of the BDA based resilience assessment tool. The main question to be answered is:

How can supply chain resilience be assessed?

The first step in understanding how to assess supply chain resilience is understanding the basic principle on how supply chain resilience in quantified. A general idea is presented in Figure 7.1 with the resilience triangle. The resilience triangle (Tierney and Bruneau 2007) tends to assess and quantify supply chain resilience by calculating the time of supply chain operations to return to its steady state. The triangle starts at the steady state, meaning that the supply chain is running at normal performance. A disruption than happens which causes the supply chain performance $Q(t)$ to quickly degrade, denoted at time instant t_0. The level of degradation depends on the resilience capability of anticipation and the ability to learn from earlier disruptions. The supply chain performance than slowly returns back to its original steady state, a process that heavily relies on the resilience of such supply chain. Especially the concurrent and reactive strategy that involve capabilities of adaptation, recovering and responsiveness. When the performance of the supply chain is back at steady sate, it is denoted by time instant t_1. The difference between t_1 and t_0 gives a quantifiable indication of the level of supply chain resilience: $t_{recover} = t_1 - t_0$.

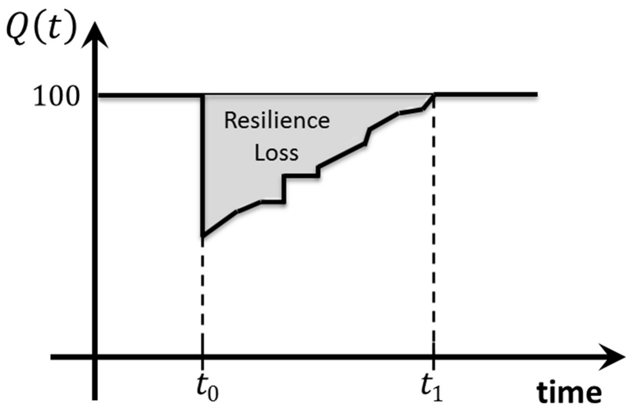

Figure 7.1: Resilience Triangle (Tierney and Bruneau 2007)

At t_0 the performance in the figure degrades with a vertical line to its post disruption performance. This can however also be a time-based decreasing line which could indicate mitigating measures for the disruptive event. However, this is not included in the graph since the scope of this research is low probability and high impact disruptive events where mitigating can already be seen as a step towards recovering. Furthermore, another adjustment of the resilience triangle is the possibility that the performance level does not return to its original state. This may either be because a certain supply chain operation has permanently changed or because counter measures have increased performance. In other words, it could be that performance eventually increases after a disruption due to effective reactive resilience by learning and growing.

This resilience triangle is widely used in literature as a metric form for supply chain resilience. For example, it is used by Falasca, Zobel, and Cook 2008 as a way to define functionality loss compared to a certain performance level. Other metric ways of defining supply chain resilience are related to quantifying different key performance indicators (KPI's) within a certain supply chain. These are mostly based on specific parts of a supply chain since calculation would otherwise involve to many variables. Torabi, Baghersad, and Mansouri 2015 for example presents a metric for resilience that uses a formula based on absorptive, adaptive and restorative strategies for inventory capacity. The formula calculates the value of lost resilience by the loss of capacity and corresponding loss of time. A similar example based on supply chain service loss was conducted by (Ojha et al. 2018).

As for quantifying the supply chain resilience, the resilience triangle and other metric ways of defining resilience also immediately show the main difficulty of assessment. In order to fully understand how resilient a supply chain is and thus how fast supply chain operations return to a steady state, it is important to also understand want would happen without any resilience measures. In other words, the loss of supply chain performance, as described in the resilience triangle, should be effectively compared with and without resilient measures. However, this is not possible for high impact and low probability disruptions as such disruptions mostly tend to not have any equivalent events. The most comprehensive way of calculating such difference in supply chain performance and the time to return to steady state is to effectively simulate a supply chain within simulation software. A supply chain simulation or even better a digital supply chain twin would be the most effective way of measuring the difference between performance loss during a disruptive event while simulating different types of resilience measures. The formula of Torabi, Baghersad, and Mansouri 2015 could then for example be used to calculate resiliency for different types of scenarios. This is done by Moosavi and Hosseini 2021 where the simulation software of anyLogistix is used to simulate a small supply chain of a manufacturing company. The supply chain variables are changed for two main scenario's regarding resilience strategies, being the availability of a backup supplier or inventory. Subsequently, with the formula of Torabi, Baghersad, and Mansouri 2015, for both the scenarios the resiliency is calculated which gives a clear percentage of resiliency difference of between the two strategies. the simulation software of AnyLogistics is also used by Ivanov and Dolgui 2021 to design and simulate a digital supply chain twin to proactively manage supply chain disruptions. Even though the research does not explicitly relate the simulation to resilience assessment, it does contribute to assessing KPI's (arrival times) and supply chain risks which could directly relate to resilience assessment.

Although the methodologies are novel and work well for the given cases, integrating such simulation (Moosavi and Hosseini 2021, Ivanov and Dolgui 2021) for this particular research on the impact of BDA on supply chain resilience would be to extensive to model. Furthermore, from a business point of view, it is mostly a bridge to far as simulating a (complete) supply chain costs to many resources and does not have a clear quantitative direct benefit. Therefore it is important to understand possible other methodologies to quantify supply chain resilience, especially based on BDA enables or elements.

Another thorough way of measuring supply chain resilience is to approach the problem with a deterministic model. Soni, Jain, and Kumar 2014 propose a measurement system that enables supply chain resilience to be identified by a single metric. The metric is based on the identification, ranking and interrelationships of general supply chain resilience enablers that are quantified by both literature and Interpretative Structural Modeling (ISM). ISM focuses on identifying certain interrelationships by the knowledge of domain experts though mostly qualitative methods. The main idea of of the research is thus to propose a metric index that gives a measurement of supply chain resilience based on resilience enablers, as presented in Equation 7.1.

$$SC_{resilience} = f(Resilience\ Enablers) \tag{7.1}$$

The metric thus differs from other academic methods as it describes resilience not based on a certain direct impact of for example performance loss of recovering time but identifies resilience based on the corresponding enabling elements. The discussion of Soni, Jain, and Kumar 2014 does call for more research on the supply chain resilience enablers as well as implementing the methods for specific industries and different geographic locations other that the scope of the research (India).

7.2 Choice of Assessment

In general, section 7.1 presents three main types of assessment possibilities to quantify the level of supply chain resilience of a company. Firstly by calculating resilience based on different KPI outcomes during a disruption, as for example the time it takes to return to a steady state. Secondly, a supply chain can be simulated which enables the possibility to compare different resilience strategies and to see what those strategies do within the simulation. Finally, it is also possible to calculate resilience based on a function of the implementation level of different resilience enablers. In order to effectively chose the type of assessment for this research, all three types are compared to ensure a fitting choice.

Output KPI Assessment | Assessing supply chain resilience though the calculation of certain KPI's is the most effective and clear way for assessment. It allows company managers to clearly see a quantitative number in for example how fast the supply chain returns to steady-state during a disruption. However, the main issue with assessing though KPI's is the problem that for high impact and low probability disruptions, the KPI output is very difficult to compare to other disruptions. In other words, the quantification of the KPI does not give an indication on how well a certain implemented resilience element is because there is no reference possibility to other disruptions. This is mainly due to the nature of high impact and low probability disruptions. The level of implementation of BDA based resilience, the goal of this research, is than thus not possible to effectively present. It is therefore that the assessment of resilience though KPI calculation does not seem fitting for this research.

Simulation | Simulating supply chains enables the opportunity to effectively compare different resilience elements and their potential impact on supply chain operations. For BDA based resilience enablers, this would thus fit since each enabler can be analysed on their impact. However, most simulation models are only for small sub sections of supply chains and thus not ensure effective assessment of overall supply chain resilience. Furthermore, a simulation model is less applicable within the consultancy industry, as a simulation model for a company only works if tailor fitted to the company's needs. Within consultancy, it is important to establish general frameworks and models that are applicable to multiple clients. Therefore, the assessment technique though simulating supply chains does not seem fitting for this research.

Function of Enablers | The final type of assessment technique is through calculating the supply chain resilience based on the implementation level of different resilience drivers. It is thus not the intention to show how well resilient a supply chain is during a disruption, but more on how well a company is doing on implementation steps for different enablers. This would fit the research well since all found resilience enablers as presented in chapter 6 can be integrated in such model based on implementation levels. This type of assessment technique is thus chosen for this research. However, more in-depth research is needed on potential models that define such type of assessment. Mainly because not only implementation levels should be considers, but also for example the different interdependencies of BDA based resilience elements. Therefore, section 7.3 aims to elaborate on potential academic resilience assessment to further define the methodology of Equation 7.1 (Soni, Jain, and Kumar 2014).

7.3 Enabler based Assessment

This section aims to further explain the methodology presented in Soni, Jain, and Kumar 2014 as it forms the basis for the assessment tool in chapter 9. As stated in Equation 7.1, the paper aims to quantify and assess supply chain resilience based on the enablers that enable resilience. In total, 10 enablers are identified such as agility, sustainability, trust among stakeholders and visibility. The different steps taken for the methodology are shown in Figure 7.2, a simplified example with three enablers is used to clearly explain the steps. The academic methodology that holds the foundation for this research is Interpretive Structural Modelling (ISM), and is widely used in literature even in relation to supply chains (Pfohl, Gallus, and Thomas 2011).

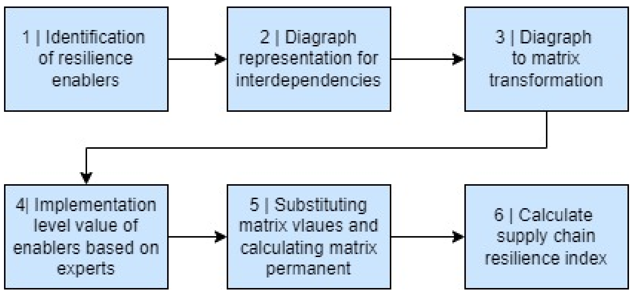

Figure 7.2: Assessment steps overview, Soni, Jain, and Kumar 2014

$\boxed{1.}$ Identification of resilience enablers

The first step is to identify different elements that enable supply chain resilience. For this example, the elements of supply chain visibility, collaboration and agility are used. Each enablers is based on an extensive literature research on supply chain resilience, and is backed by different academic papers, similar to the representation of Table 6.1.

- Visibility

- Collaboration
- Agility

2. Digraph representation for interdependencies

The second part consists of a digraph representation of interdependencies of enablers. The interdependencies show a form of importance of each enablers, a high level of interdependence links to a more important resilience driver. The digraph for the example with three enablers is given in Figure 9.2. The digraph is a representation of a set of nodes and edges given Equation 7.2 and Equation 7.3, where the nodes represent the enablers and the edges represent dependence. the level of dependence is thus defined by the connection between enabler N_i and enabler N_j. If both nodes are dependent, it means that interdependence occurs which allows for a closed digraph representation loop of N_{ij} and N_{ji}.

$$Nodes \rightarrow N_i \qquad i \in Enablers \tag{7.2}$$

$$Edges \rightarrow N_{ij} \qquad i, j \in Enablers \tag{7.3}$$

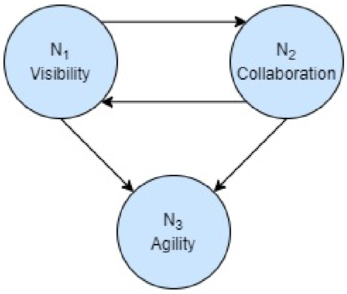

Figure 7.3: Example of a digraph

3. Digraph to matrix transformation

In order to clearly state interdependencies, the digraph is translated to a Structural Self Interaction Matrix (SSIM though Interpretative Structural Modeling (ISM)). The matrix presents the edges through one of four different relationships:

- V | Enabler i influences enablers j
- A | Enabler j influences enablers i
- X | Enablers i and j influence each other
- O | Enablers i and j are unrelated

For the example enablers, the translation of the digraph towards a SSIM is presented in Table 7.1.

Table 7.1: Example SSIM

		N_3	N_2	N_1
N_1	Visibility	V	X	-
N_2	Collaboration	A	-	-
N_3	Agility	-	-	-

The next step is to use the information of Table 7.1 to compose a Resilience Variable Characteristic Matrix (VCM-RM). The matrix is defined by two elements: the Variable Characteristic Matrix (VCM) with diagonal entries N_i for $i \in Enablers$ and the Resilience Matrix (RM) with off-diagonal entries N_{ij} for $i, j \in Enablers$.

$$VCM - RM = \begin{bmatrix} N_1 & -N_{12} & -N_{13} \\ -N_{21} & N_2 & -N_{23} \\ 0 & 0 & N_3 \end{bmatrix} \tag{7.4}$$

The goal is still the representation of the level of resilience environment of a certain supply chain. However, with the current negative entries, the determinant of VCM-RM will not show complete insightful information. Therefore another matrix function is introduced by calculating the matrix permanent, a polynomial including all matrix entries. First, in general, $VCM + RM$ is given in Equation 7.5. Secondly, the matrix is translated to the corresponding example (Equation 7.11), given only valid entries ‘based on the interdependencies. The matrix now presents the impact of critical enablers (diagonal entries) and the interdependencies (off-diagonal).

$$\begin{bmatrix} N_1 & N_{12} & N_{13} \\ N_{21} & N_2 & N_{23} \\ N_{31} & N_{32} & N_3 \end{bmatrix} \tag{7.5}$$

$$VCM" - "RM = \begin{bmatrix} N_1 & N_{12} & N_{13} \\ N_{21} & N_2 & N_{23} \\ 0 & 0 & N_3 \end{bmatrix} \tag{7.6}$$

4. Matrix Permanent

The matrix permanent is used as it is defined by a polynomial of entries giving a relative clear insight through a single metric index number. The permanent of a matrix is calculated with Equation 7.7 where A ($A = N_{ij}$) is a matrix of n by n and σ is the permutation of symmetric groups.

$$perm(A) = \sum_{\sigma \in S_n} \prod_{i=1}^{n} N_{i,\sigma(i)} \tag{7.7}$$

For the example calculation, the permanent would be the following.

$$perm(\begin{bmatrix} N_1 & N_{12} & N_{13} \\ N_{21} & N_2 & N_{23} \\ N_{31} & N_{32} & N_3 \end{bmatrix}) = N_1N_2N_3 + N_{12}N_{23}N_{32} + N_{13}N_{21}N_{32} + N_1N_{23}N_{32} + N_{12}N_{21}N_3 + N_{13}N_2N_{31} \tag{7.8}$$

5. Enabler & Interdependencies Values

For both types of matrix entries, the values of N_i and N_{ij} are determined by industry experts and academic input respectively. The entries of N_i represent the level of resilience element implementation of a company and may be defined as a number between 1-9 ranging between exceptionally low and high. The entries of N_{ij} are the level of interdependencies and may be quantified by a level ranging form 1-5, defined between very weak and very strong levels of interdependencies. For the example resilience enablers, the corresponding example values are given in Table 7.2, which can be seen as possible values given by a company.

Table 7.2: Example Matrix Values

Resilience Enabler	Level of Implementation	Level of Interdependency
Visibility	7	5
Collaboration	4	3
Agility	5	0

6. Supply Chain Resilience Index

The final step is to calculate the index for supply chain resilience, though the permanent of the matrix with quantified entries. This gives the general formula of Equation 7.9.

$$Supply\,Chain\,Resilience\,(SCRES) = Per(VCM" - "RM) \tag{7.9}$$

However, a more effectively quantified way is by identifying the relative supply chain resilience index by first using Equation 7.9 to calculate the optimal or ideal value for SCRES. This can be done by using ideal values for the matrix entries. Subsequently, the relative index for supply chain resilience can than be calculated by Equation 7.12

$$SCRES_R = \frac{SCRES}{SCRES_{optimal}} * 100\% \tag{7.10}$$

As for the exmaple resilience enablers, the resilience index would be the following.

$$(VCM" - "RM)_{company} = \begin{bmatrix} 7 & 5 & 5 \\ 3 & 4 & 3 \\ 0 & 0 & 5 \end{bmatrix} \quad , \quad (VCM" - "RM)_{optimal} = \begin{bmatrix} 9 & 5 & 5 \\ 3 & 9 & 3 \\ 0 & 0 & 9 \end{bmatrix} \tag{7.11}$$

This leads to the final calculation of the resilience relative resilience index.

$$SCRES_R = \frac{SCRES}{SCRES_{optimal}} * 100\% = \frac{215}{864} * 100\% = 24.89\% \tag{7.12}$$

7.4 Conclusion

Based on preliminary research, three main types of assessment tool were described to assess BDA based supply chain resilience: KPI Assessment, Simulation and Function of Enablers. The decision is made to use an assessment tool based on a function of enablers, following on the research of Soni, Jain, and Kumar 2014. The methodology encompasses both enabler implementation level as well as the level of interdependencies between the enablers. These values are used to determine a matrix permanent, which is used to define a resilience level metric, ensuring well defined comparability for industry companies. However, distinct differences compared to the methodology are made to design a novel assessment tool for BDA based supply chain resilience. Especially, concerning the found enablers, different variables and implementation levels, specific industry and benchmarking.

Part III

Empirical Research

8 | Empirical Industry Insights

Industry insights are an important element to a valuable research. It enhances the findings of the literature research and provides relevant information on how literature findings are currently used within actual business. Furthermore, understanding supply chain disruptions is more effective when talking to companies that actually underwent these events. Relating to a resilience assessment tool, interviews can give indications on how far companies actually are with implementing BDA based resilient strategies. The information can thus effectively be used for the design for such assessment tool, but also as a way to validate the assessment outcomes. This chapter therefore has three main objectives:

1. Understand FMCG industry disruptions over the past years
2. Compare literature findings of chapter 6 in relation to the resilience enablers and industry implementation levels
3. Create an understanding of the challenges faced by the industry concerning BDA and supply chain resilience

In order to achieve these objectives, multiple interviews have been performed with relevant experts from within the industry. The interviews can be divided into two main parts, interviews with relevant KPMG personnel and interviews with experts from the FMCG industry that work within the supply chain and/or data & analytics departments. An overview of the different interviewees and their job titles are given in Table 8.1 and Table 8.2. As for KPMG related interviews, the discussions with the Supply Chain & Procurement Department were not noted as specific interviews, but have had significant impact on the research through continuous guidance. Some interviews were confidential in the sense that the information can only be used if anonymised, these interviewees are given a imaginary company name but with the correct job title. Interviews with KPMG personnel mainly focused on different consulting projects that were done within the FMCG industry and related to either supply chain or big data analytics. The findings from these interviews are summarised in this chapter and are subsequently used to answers the main chapter objectives.

Table 8.1: Interviewees with KPMG

Reference	Date	Company	Job Title
KPMG1	17/03/2022	KPMG	Partner Strategy & Operations Former Director Global Supply Chain (FMCG)
KPMG2	21/03/2022	KPMG	Partner Data & Analytics
KPMG3	24/03/2022	KPMG	Lead Data Scientist
KPMG4	11/04/2022	KPMG	Senior Consultant Strategy & Operations
KPMG5	Multiple	KPMG	Supply Chain & Procurement Department

Table 8.2: Interviewees with the FMCG industry

Reference	Date	Company	Job Title
FMCG1	24/02/2022	Transport Innovator	Director Software Development
FMCG2	19/04/2022	Beverage Producer	Group Director Purchasing
FMCG3	12/04/2022	Beverage Producer	Director Supply Chain Development
FMCG4	28/04/2022	Mid-Sized Retailer	Executive
FMCG5	28/04/2022	(Medical) Supplier	Executive Supply Chain
FMCG6	12/05/2022	Global Food Cooperation	Head of Supply Chain Data Product

Besides the interviews, the subject of this research was also discussed during a Dutch supply chain director event. During this event, round table discussions were held with around 25 supply chain directors. All interviews were semi-structured, meaning that no strict list was followed of questions. This allowed for more open interviews, leading with discussions and subjects that well fitted the company or person. However, the main subjects of all interviews were the same and can be summarised into the points shown below. A general sense of the interview layout is also given in Appendix B.

- Function Background
- Encountered SC Disruptions
- Handling of Disruptions
- Relation to BDA
- General SC BDA

In total, 10 interviews were held, with the additions of the discussions within the Supply Chain & Procurement department and the supply chain director event table conversations. Primarily, 12 interviews are seen as the saturation point for effective and reliable empirical insights (Guest, Bunce, and Johnson 2006). This thus means that two additional interviews would benefit the research, however it can be argued that with the additional discussions, empirical saturation is still achieved.

8.1 Supply Chain Disruptions

For the most part in the previous chapters, disruptions have only been mentioned in a broad perspective and related to high impact and low probability. This chapter section presents further clarification on what these disruptive events are from the perspective of industry professionals, focusing on disruptions from the past couple of years. For global FMCG supply chains, interviews showed that disruptions can be divided in three main aspects: transport, supply and demand. For each aspect, the disruptions stated during interviews have been summarised in Figure 8.1, where the top most disruptions for each aspect can also be seen as the one which was most mentioned. This section primarily describes the disruptions, whereas the subsequent sections focus on explaining resilience measures against these disruptions.

Transport	• Closed ports • Container prices • Closed Suez canal • Brexit • Road disruptions ◦ (Perishable Goods)

Supply	• Low product availability
	  ◦ Bad harvest
	  ◦ War (Ukraine)
	• Product recalls
	• Forecasting not aligned

Demand	• New product
	• Covid crisis
	  ◦ Major demand spikes (hoarding/stockpiling)
	  ◦ Low demand (lockdowns)
	• Forecasting not aligned

Figure 8.1: Most mentioned disruptive events during interviews

8.1.1 Transport Disruptions

As a direct consequence of disruptions such as closed ports and the Covid crisis, the balance of containers throughout the globe changed drastically. The balance of containers is defined by the difference between where empty containers are and where the empty containers should be. For example, especially during the Covid crisis, the number of empty containers in Europe was exceptionally high while there was a lack of empty containers in China. This means that in essence, empty containers should be shipped back to China, a very costly business. This caused the abnormal increase in container freight rates, which sometimes exceeded 5/6 times the normal rates. Even though the increase of container freight rates is a ongoing process and thus relates less to the true definition of disruptive events, it is still mentioned in this research since most interviewees stated the freight rates as the most important change in supply chain operations. For reference, Figure 8.2 shows the course of the container freight rates over the past years for containers transported between the port of Shanghai and the port of Rotterdam (Murray 2021). It can clearly be seen that the increase of freight rates may be mentioned as an disruptive event, due to the relative fast pace of increase. The composite index is defined by a group representation of the eight global major routes container shipping routes. The index shows a staggering increase of almost 300%, a new record for the past decade. Compared to historical values, it also clearly relates to low probability and high impact disruptions, since the container prices have generally been stable of the past decades.

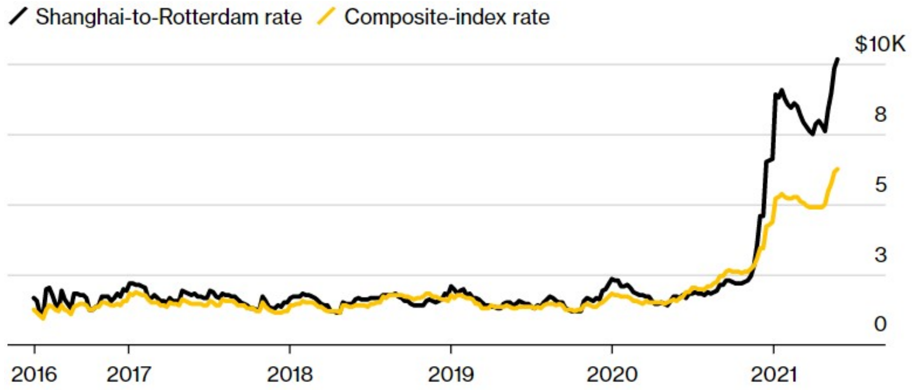

Figure 8.2: Container Freight Rates, Murray 2021

The logical consequence of the increased container freight rates was the subsequently increased costs for companies to transport goods by ocean shipping. This called for comprehensive resilience strategies to lower supply chain costs and especially to prevent high passing on of costs to customers. The passing on of costs is in principal also a driver for disruptions related to demand, as higher costs could potentially drive customers away.

A driver of the high container prices, but also disruptions on its own, are the closure of ports and major transportation routes such as the Suez canal. Port closures, particularly in China due to the Covid crisis, form great supply chain threats though creating for example major backlogs. Ports may not be actually completely closed, but ships often have high waiting times to berth or containers and general goods cant reach the port at all from inland locations due to Covid restrictions on personnel. These are mainly personnel working as truckers that have to show negative Covid tests, which decreases efficiency and working capacity. The closure of the Suez canal due to the Even Given container ship is a similar disruption causing backlogs and route changes. Besides it being a disruption for the interviewed companies, the disruptions also causes global supply chain ripple effects that continuously cause problems months after the main disruption. These disruptive effects thus call for changes in shipping routes by discharging at different ports than initially intended, or using other major routes to use as disruption detours.

A relatively smaller disruption, but still with high impact, are the transportation disruptions as a consequence of the Brexit. These where mentioned by companies trading and transporting to the United Kingdom and where seen as a major disruption for especially perishable goods, with for example high waiting times at the Dover terminal reaching up to 30 hours. The perishable goods lowered in quality which decreased prices or where sometimes even beyond selling point. As mentioned by an interviewee that facilities and analyses transportation networks, an interesting discussion point was also made considering lower impact and high probability disruptions. Disruptions such as truck cooling failures where seen as more structural disruptions that could, when added together, also be seen as high impact events. However, the question then does arise to which extent such structural events can still be called disruptions, due to the nature of the event and the frequency of it happening.

8.1.2 Supply Disruptions

The primary source of supply disruptions within the FMCG industry are stated as consequence of low product availability. The low availability may be seen as a consequence of a major disruptive event such as bad harvests or international wars, however due to the frequency of the subject being mentioned during interviews and the impact it has on FMCG companies, low product availability can be seen a disruption on its own. Different sources for low availability can be found in for example bad harvests due to unexpected weather and climate change. Furthermore, the current war in Ukraine has had major impact on the availability of wheat which is one of the most important base ingredients for a considerable part of FMCG products.

Another interesting source of low product availability was mentioned during interviews with experts working in the soft drink industry. It was stated that the availability of CO_2 sometimes occurs as a major disruption. This is due to the fact that CO_2 is not really produced but is a by product of many chemical processes in other industries. The issue is that if demand and production for the main product decreases, so does the production of CO_2. Without any actual CO_2 production site, the lack of the main product thus causes a major disruption for soft drink producers as CO_2 is a vital ingredient.

An additional disruption in the same industry of soft drinks and beverages is the disruptive event of product recalls. It can both be seen as supply or demand disruptions, but was mentioned specifically as a supply disruptions during interviews. A product recall occurs when a delivered product is of other quality than expected, in such way that the quality can harm the reputation of the company or endangers the safety of customers. The particular example was about partly broken bottles on pallets, leading to potentially selling bottles with glass shards. For these disruption causes, most companies tend to err on the side of caution which in this case would mean recalling large batches of products. Consequently, this leads to major supply and demand misalignments which in turn leads to for example high costs, lower revenue and loss of customers.

8.1.3 Demand Disruptions

Demand disruptions can mostly be divided in two main elements, new product launches and forecasting misalignments. As for new products launches, these in theory fall outside of the original scope of this research. New products are always planned by the launching company, but are still disruptive because the reaction of customers and consumers can never be precisely predicted. On the other side, new product launches does fall under the research scope since it can also be seen as a disruptive event for competitive companies. Especially new innovative products can lead to changes in market equilibrium and have the potential to drive other companies out of certain businesses. For example, FMCG businesses specialising in the meat packing industry may see the continuous launching of vegetarian alternatives as major disruptive threat to their growth potential. It asks for many resilience measures, sometimes as part of a long going process to not only recover but also the survive.

Furthermore, in the light of the Covid crisis, forecasting misalignments have been the biggest issue over the past years within the FMCG industry. Direct consequences of the crisis lead to high variable changes in demand, either causing an abnormal high or low demand. These demand vs. supply misalignments were however different for sub sectors within the FMCG industry. Companies specialising in (alcoholic) beverages saw major loss of demand due to the closure of restaurants and bars. This had less effect on other consumable product companies as they are less dependant on restaurants and bars, but rely more on grocery stores. Besides the beverage sector, other companies with perishable goods also had more impact though misalignments. Non-perishable goods have the ability to stay in stores or restaurants throughout the duration of a lockdown, while perishables costs more due to the goods perishing. On the other side, the complete FMCG industry did have multiple events having industry wide disruptive consequences. While lockdowns lead to low general demand, unexpected lockdown endings caused disruptive demand spikes. Additionally, especially at the start of the crisis, stockpiling was seen as the highest impact misalignment event as it even created empty store shelves.

8.2 BDA Based Resilience

The main goal of the interviews was to generate industry insights on different subjects, the most important being BDA based supply chain resilience. In general, it became evident that companies do not actively seek BDA based supply chain resilience within their operations. However, resilience enablers are implemented indicating that most companies do actually indirectly strive for increased resilience. These enablers are generally inline with literature findings, with most enablers being acknowledged by industry experts. A summary of the literature enablers and corresponding acknowledgements by empirical research are shown in Table 8.3. The following sub sections discuss the different outcomes of the interviews and further explain the findings in more detail.

Table 8.3: BDA based enablers, empirical vs literature

Enabler from literature	Acknowledged?	Reference	Comments
Agility	Yes	KPMG1, FMCG2, FMCG5	
Collaboration	Yes	FMCG2, FMCG6	
Contingency Planning	Yes	FMCG6	Reactive based
Digital SC Twin	Yes	KPMG1, FMCG3	
Disruptions Detection	Yes	KPMG2, FMCG6	Primarily in relation to internal KPI detection
Early Warning Systems	No	-	To much related to disruptions detection
Flexibility	Yes	FMCG1, FMCG2, FMCG5	
Knowledge Management	Yes	FMCG2	
New Skill Development	No	-	No acknowledgements
Predicting Disruptions	Yes	KPMG2	Based on external data models
Scenario Modelling	Yes	KPMG1, KPMG4, FMCG4, FMCG5	Also through forecasting models
Situational Awareness	Yes	FMCG2, FMCG4	External data on e.g. ports
Transparency	Yes	FMCG3, FMCG6	
Velocity	Yes	FMCG3	
Visibility	Yes	All	E.g. dashboard and BI-tooling
Vulnerability Assessment	Yes	FMCG2, FMCG4	Primarily reactive based

8.2.1 Proactive

Proactive resilience has a wide base in BDA, with all BDA categories (predictive, descriptive, prescriptive) giving multiple resilience enablers. Furthermore, it is the only resilience strategy that has enablers based on predictive data analytics. These predictive analytics also come forth within the industry, regarding predicting disruptions and situational awareness. For predicting disruptions, data driven process KPI can be used to track and potentially predict possible disruptions. However, it became clear that this would mostly only work for high probability and low impact disruptions and thus less relates to the scope of this research being low probability and high impact disruptions. In specific, the prediction of disruptions would for example work with predictive maintenance, where equipment KPI's are analysed to see when something would potentially fail or need maintenance, which would be an effective resilience strategy in warehouse and transportation operations. The predictive part of situational awareness has the same issue as predicting disruptions, however it does have a great impact on resilience through descriptive analytics. This was greatly mentioned by interviewees stating that there is a high importance of situational awareness to understand the industry, transportation networks and (global) markets. The awareness is partly created by descriptive data analytics, as companies import external data to analyse current developments. For example, one company mentioned that they bought external data from international ports to analyse cargo flows in order to understand how the market is developing. Based on found outcomes of such analyses, a company can proactively steer their strategy to potentially create a competitive advantage and better prepare for disruptive events. Other descriptive resilience enablers that impact proactive resilience are visibility and transparency. These were stated during interviews as mainly enablers that fuel other (concurrent strategy) enablers. However, it was also indicated that creating supply chain visibility through descriptive analytics forms the basis for almost all enablers, as visibility may be noted as the first step in BDA maturity. A final descriptive proactive resilience enabler is the ability to effectively detect disruptions. The clear difference with predicting disruptions is that with predicting, the data is used in a (regressive) model to predict possible outcomes, while disruption detection only considers actively monitoring both internal and external metrics. These metrics range from internal KPI's to external market prices for raw resources where active detection would increase resilience. The relation towards BDA is also evident, since especially KPIs are always formed based on company progress data.

Additionally, proactive resilience also has prescriptive BDA based enablers such as scenario modelling and digital supply chain digital twins. Here the difference with literature became evident, as especially digital supply chain twins a no where near the theoretical capability proposed in literature. Companies do initiate scenario modelling to digitise a certain process and create the ability to change variables which gives insights in how operations could go during disruptions. This in turn increases the capabilities of supply chains to prepare, adapt and respond to disruptive events. However, most companies mentioned that scenario modelling is mostly qualitatively done, where there are still lacks in data driven processes. The main goal of scenario modelling is primarily to analyse 'what if?' questions regarding possible new product releases, customer developments or major downfalls like the war in Ukraine. One of the companies did have a very extensive demand planning algorithm, which can be seen as a scenario model. The company bought external data of weather, promotions and even birth rates to fuel the machine learning model in order to effectively predict demand but also to prepare operations for unforeseen events. External data is bought for millions of euros, but is earned back through improved demand and/or supply alignment. As variables can easily be changes within machine learning algorithms, it helps companies to improve their supply chain resilience. In contrast, the same company did indicate that the supply models where still very immature, mostly only done though simple Excel based analytics. A clear contrast is thus given in implementation levels, even within the same company, let alone the differences of implementation levels within the industry.

8.2.2 Concurrent

Following on the proactive resilience strategy, many enablers also impact resilience based on a concurrent strategy. These are mainly the enablers of visibility, transparency and collaboration, which in turn empower more general enablers such as agility and flexibility. The main difference is that concurrent visibility relies on real-time data, which thus creates the ability to respond to disruptive events in real time. This can for example be seen in transportation processes, where an interviewee mentioned the company of Transporeon. This company is a perfect example of how data is used to digitise the industry and indirectly improve resilience through BDA based visibility, transparency and agility. Transporeon facilitates a management platform directed on (global) transportation, it ensures its client with not only market intelligence insights but also facilitates a platform where client tenders and transporters are connected. The first element of market intelligence insights can be seen in Figure 8.3, were an example is given of a comprehensive dashboard. Dashboard likewise create the ability for companies to translate real time insights into decision making, for example through real time euro per km prices. This ensures data driven resilience as the insights ensure higher flexibility and agility for supply chain disruptive events. Secondly, both resilience enablers of flexibility through adaptation and agility through responsiveness are empowered by the online platform where freight or shipments are managed and executed and where supplier and transporters are brought together. Transporeon has more to offer than the above, but within interviewees, the above subjects were mostly mentioned and are actively used. Another important note to define on these developments of resilience is that the supply chain needs to first be digitised in order to generate the needed data. One of the interviewees worked at a transport innovator, designing and delivering innovation that generate valuable data such as smart pallets. Given clients the ability to more easily follow their shipments and ensures an indirect base for facilitators as Transporeon.

Figure 8.3: Example of Transporeon Dashboard

Bringing supplier and transporters together is also another resilience enabler that may be fueled by BDA in essence of collaboration. Many companies indicate that BDA has a positive impact on cross supply chain collaboration, thus between both the company and external stakeholders involved throughout the supply chain process. Insights and analytics help during discussions and negotiations between stakeholders and increase the level of objectiveness. This also enhances resilience by ensuring well defined and healthy relations between stakeholders, which ensures better abilities to respond during disruptions. It is especially of importance for companies that outsource their transportation or warehousing operations. For these companies, it has become more important to contractually predetermine the data flows between stakeholders to ensure transparency throughout their supply chain. Without the given data transparency, many BDA based resilience enablers are less possible, such as visibility and data-driven collaboration.

Prescriptive analytics is also involved with concurrent resilience, similar to the enablers with a proactive strategy. A prescriptive project, with the goal of taking the most optimal action, can also be found in BDA based resilience through for example contingency planning. These are however less noted during interviews, most interviewees tend to describe an optimal situation where data-driven contingency plans are present for different kind of supply chain disruptions, but the companies are merely far enough in tooling and capacity to comprehensively implement such resilience enabler. This also accounts for prescriptive data analytics to enable a digital supply chain twin. There is thus a major difference with literature theories and the actual industry implementation for prescriptive and concurrent resilience strategies.

8.2.3 Reactive

The reactive strategy is by far the most mentioned and used supply chain resilience strategy within the industry. However, this does not necessarily account for reactive BDA based resilience. Companies intent to not really think about resilience until an actual disruptive event happens. It that case, companies are mostly to late and only have the ability to mitigate certain outcomes or to prepare for future new disruptive events. This would mean that companies actually use reactive resilience to initiate proactive measures. As for example mentioned by an interviewee, with the current war in Ukraine, supplier vulnerability assessment has become a serious topic. As Ukrainian suppliers fall out, companies have to look for sustainable replacements to divert their supply chain operations. For the Ukrainian war, this has been a reactive strategy to look for supply chain vulnerabilities and change suppliers. However, it also created the urge for companies to also assess supply chain operations on vulnerabilities without actual disruptive events already happening, thus enabling pro-activeness. These supply chain vulnerabilities can also occur within the transportation operations. A comprehensive example was mentioned by an interviewee related to the disruption concerning Brexit and the corresponding truck transportation problems at Dover. The disruption created issue with lead times, distribution centre and other insecurities with especially trucks. Therefore the following strategy was used to address the issue in an adequate and resilient way, partly based on BDA.

1. *Security of Supply* | The first step is to ensure supply by increasing stocks. Even if this is bought against relative higher prices, the general saying is that in the beginning of a disruption, losses are most of the time the lowest.

2. *Critical Assessment of Vulnerabilities* | The second step is to reactively assess vulnerabilities, in this case the vulnerabilities where the transportation done by trucks between EU mainland and the United Kingdom. A data driven analysis was done

to calculate the costs and benefits of other transportation modes. It concluded that the option to charter a barge would be beneficial to ensure security of supply.

3. *Calculating, Explaining and Passing On Costs* | The third step is not always noted but is easily as important as other steps. Companies need to make sure the calculate costs differences and pass them on to the customer. However, it is of at most importance for stakeholder relations to fully explain and substantiate the costs differences to the customer. ensuring transparency.

4. *Draw Lessons* | The final step is to ensure that lessons are drawn for this disruptive issue, complying with BDA based resilience enablers such as knowledge management and new skill development.

The other BDA category that relates to reactive resilience is prescriptive analytics, which mostly concerns increasing supply chain resilience through the optimisation of operations. However, this is were a contradiction was noted through the assessment of both literature and the different interviews. As companies tend to use prescriptive analytics to ensure data driven optimisation as supply chain operations, it also negatively impacts certain concurrent BDA based resilience enablers. For example, the more a supply chain is optimised or runs efficiently, the less room there is for changes. This thus means that prescriptive resilience enablers such as scenario modelling and digital supply chain twins could both increase general resilience but also decrease the capability of supply chain agility and flexibility. However, as noted during interviews, it became apparent that most companies are no where near theoretical implementation levels for prescriptive BDA based resilience and thus making this contradiction of less importance for the time being.

8.3 Challenges

The challenges the industry face to implement BDA based resilience tend to be very similar to what is described in literature. The main challenges lie in the nature of the subject: the 5V's of big data. Companies struggle to align their master data management, in order to effectively use their vast quantity of data generated. Especially for global companies, aligning data proves to be difficult due to differences in files, data types, and the programs used to analysed or process the initial data. Harmonising and documenting company wide data should be of high priority, building an efficient and effective data architecture or warehouse where data can be accessed throughout the company. The intellectual capacity and time needed for BDA based developments are also a major drawback. It enhances the managerial implications of focusing on short term supply chain visions, fueled by the fast digitisation and events that supply chains encounter, making it difficult to create long term resilience developing plans. The implications can be noted with BDA based resilience enablers such as a digital supply chain twin which is frequently mentioned as an ideal form for scenario modelling and supply chain resilience in general, but seems to be far away from actual business implementation. An interesting notation was also made on the implementation level of BDA technologies, the higher the level, the higher the probability of BDA or big data in general being a possible disruption on its own. Decision making relying heavily on big data insights would have issues when data suddenly becomes invalid of available. This is especially the case for large data driven machine learning algorithms, that are used in demand and supply forecasting. This also relates to another topic noted by the interviewees from larger companies, as larger companies tend to optimise as much as possible, it becomes more difficult to design a supply chain for agility and flexibility. While on the other side, smaller consumer good businesses have more adaptation abilities. Finally, as stated before, many companies do not actually intend on having resilience strategies, but indirectly develop their supply chain and BDA enablers to improve resilience. It mainly relates to the nature of the FMCG business, where products are relatively easily replaceable by counterparts. In contrary to a manufacturing industry of for example cars, where each part is essential for the final product, making resilience a more important topic.

8.4 Conclusion

This chapter had three main objectives to be answered:

1. Understand FMCG industry disruptions over the past years
2. Compare literature findings of chapter 6 with industry insights
3. Generate insights on the BDA based resilience enabler implementation levels of companies

The supply chain disruptions have been analysed based on transportation, supply and demand disruptions. The mentioned disruptions during interviews have shown great insights in the challenges the industry face, amplifying the need for adequate BDA based resilience. Disruptions ranged from large transportation events such as closed ports, to major issues in supply and demand through for example product recalls. The second objective proved to relatively be inline with literature, as most enablers of resilience are also acknowledges within the industry. The main difference is that enablers are mostly not directly mentioned in the industry as resilience related, but create indirect consequences that impact supply chain resilience. This also relates to the final objective, as industry insights have proved that there are distinct differences between literature theories and industry implementations. Especially on enablers such as a digital supply chain twins, theory is much further than actual implementation. Mostly having companies note the enablers, but simultaneously admitting that the challenges of big data and required staff are still barriers towards full BDA based supply chain resilience.

8.4.1 Combined Literature and Empirical Framework

The final input for the assessment tool, based on both the literature and empirical study, is shown in Figure 8.4. The figure presents all enablers that were acknowledged in both studies, including the relation towards a resilience strategy or BDA category. In total, 14 enablers remain out of the 16 enablers found in literature.

		Big Data Analytics		
		Predictive	Descriptive	Prescriptive
Supply Chain Resilience	Proactive	• Predicting Disruption • Situational Awareness	• Disruption Detection • Transparancy • Vulnerability Assessment • Visibility • Situational Awareness	• Scenario Modelling • Digital SC Twin • Visibility • Knowledge Management
	Concurrent	-	• Visibility • Collaboration • Flexibility • Agility • Velocity • Transparancy	• Digital SC Twin • Agility • Contigency Planning
	Reactive	-	• Knowledge Management • Vulnerability Assessment	• Scenario Modelling • Digital SC Twin • Contigency Planning

Figure 8.4: All BDA based resilience enablers

Part IV

Partial Supply Chain Resilience Assessment Tool

9 | Assessment Tool | Design

This chapter aims to design and validate a comprehensive assessment tool to quantify and assess the level of BDA based supply chain resilience of a company. First, the different requirements for the tool are stated on which the general layout of the tool will be based. Secondly, a deterministic model is presented that elaborates on the configuration of the tool. Different subsections are dedicated to elements of the model, where a resilience index calculation represents the output. Finally, the tool is validated by industry professionals and a discussion is dedicated to model related challenges.

Tool Novelties

As a result of chapter 7, it became evident that the methodology of Soni, Jain, and Kumar 2014 would fit the objective of this research the most, focusing on the determination of a quantifiable resilience index based on resilience enablers. The paper is one of the few academic insights that presents an assessment tool for resilience not based on KPI changes or simulation, but as a function of resilience enablers. It therefore fits this research since the goal is to assess the level of BDA based supply chain resilience. The methodology will be used as a guideline, given this research the novelty of implementing the model while focusing only on BDA based supply chain resilience. Despite the general layout of the methodology of Soni, Jain, and Kumar 2014, the assessment tool for this research still follows a regular design cycle as different elements of the tool are subject to specific requirements from literature, industry and KPMG. Furthermore, the deterministic model of this research differs on multiple critical areas from Soni, Jain, and Kumar 2014.

BDA Based Enablers | First of all, the model differs in its primary essence, as enablers are only chosen and graded based on BDA background. This gives a clear difference as literature mainly aims to assess resilience either in general, or based on a deep dive of a specific enabler. The enablers not only differ based on their background, but are also tailored to be applicable to the industry. This also gives literature a more comprehensive example on a specified assessment tool which would greatly help when adapting such methodology to other subject like sustainability or operational excellence.

Suited Grading Levels | Secondly, the grading levels of enabler implementation and interdependence levels are more reliable and are adjusted for empirical findings. The changes are made due to the novelty of implementing tool requirements based on KPMG and industry insights. This especially accounts for the interdependencies, as these will be predefined according to expert discussions instead of depending it on assessment tool company input. As defined in chapter 7, the grading levels are both different for implementation levels and interdependence and range from 1-9 and 1-5 respectively. Empirical research showed that especially grading of 1-9 would be ineffective and lack reliability. Therefore grading levels of only 1-5 are used for the assessment tool.

Benchmark | Thirdly, the output of the tool is translated through an exponential fit into a novel benchmark, giving companies a clear indication of their BDA based resilience implementation level compared to peers. By combining the enumeration of above novelties, the tool ensures to fill the missing literature gap on resilience assessment tools. It provides a tool that can be dedicated on a technology that ensures different resilience enablers. Furthermore the benchmark capability ensures an effective and direct contribution to the industry.

Questionnaire | In order to efficiently generate an industry benchmark, a large quantity of respondents is needed. Therefore, a questionnaire is used to gather BDA based enabler implementation levels from companies, instead of extensive interviews. This enhances the effectiveness of the assessment tool, if sufficiently validated.

Subject Definitions
In order to clarify the assessment tool for both research and respondents, definitions of primary research subjects are discussed. These definitions are also presented in the questionnaire, ensuring respondents to have the same idea of how to interpret the subjects. The definitions are given to address the assessment tool and are thus more tailored and specified compared to the general subject definitions used in the research scoping and literature review.

Big Data Analytics | Any big data (e.g. minimal of thousand data points) generated throughout the supply chain and is accessible through for example data warehouses, excel, SAP etc. and is used to either create insights or as input for models/algorithms.

Supply Chain | The supply chain process of the concerned company, meaning the company itself combined with their supply and demand operations and transportation. The supply chain process is defined by the company in the questionnaire which gives insights in potential outsourced operations.

Stakeholders | Any external parties that are needed for the fully functional supply chain process as defined above.

Disruptions | High impact and low probability events (on transportation/supply/demand) that cause major issues within a supply chain process. For example: port closures (Shanghai) (transportation), war in Ukraine (supply) or large product recalls (supply/demand).

9.1 Requirements

Besides the choice made in section 7.2 to partly incorporate the methodology of Soni, Jain, and Kumar 2014, the assessment tool is also subject to various requirements based on either literature, KPMG or industry experts. The tool is more than the academic methodology found, as for example, the questionnaire will generally be subject to especially industry expert and KPMG requirements. Not all requirements or functionalities are integrated in the final design, but may still have a potential value as a discussion point. The most important requirements, divided in must and should haves, are presented below.

1 | Research Based
The research based requirements are addressed to ensure the novelty of the assessment tool and have valuable references to academic papers. Practical requirements are sometimes also given in literature, but in this case are left out due to the extensive practical requirements already given by KPMG.

1. *The tool must have a quantitative (metric) outcome of supply chain resilience*
   Regardless of the method, a quantifiable level of resilience mainly preferred in literature as it helps to understand and scale the assessment. This can be seen for both the resilience triangle (Tierney and Bruneau 2007), KPI's by models (Torabi, Baghersad, and Mansouri 2015) and simulation (Moosavi and Hosseini 2021). Therefore using a quantifiable outcome of the assessment to is a must have for this design.

2. *The tool must provide an outcome that is based on a function of BDA based enablers*
   Using BDA enablers as a foundation of the assessment tool will ensure novelty, especially since it connects a specific I4.0 technology with supply chain resilience. This effectively creates a partial or hybrid resilience model that is of great value for increasing academic knowledge on the topic (Hosseini, Ivanov, and Dolgui 2019).

3. *The tool must include enabler interdependencies*
   The interdependencies are needed to effectively incorporate the methodology of Soni, Jain, and Kumar 2014 into the BDA based resilience assessment tool. As the interdependencies form the bulk of the resilience matrix, they are needed to calculate the matrix permanent and must thus be used in the methodology.

4. *The tool should show visualised industry comparisons*
   Visually comparing different companies based on the assessment tool output is based on academic reasoning where it is stated that more empirical research is needed to validate and address findings (Spieske and Birkel 2021). This research would then also contribute to the research gap, as company comparisons improve insights on preliminary empirical research.

2 | KPMG Based
The requirements based on KPMG are formed throughout discussion with employees ranging from senior consultant to partner. The essence of these requirements lies in the practical implementation and usefulness for KPMG.

1. *The tool must be user friendly for the client in both time and complexity*
   Limitations on time and complexity are important in order to ensure that client will actually use the tool.

2. *The tool must give an output that gives a clear call to action/opportunities*
   Consulting is defined by asking the right questions and helping clients to improve their business. Therefore the assessment tool should also call for action or opportunities which can be used by KPMG as a kick-start towards the client relations. These opportunities also give KPMG indications on the areas where valuable advice can be given.

3. *The tool should be extensively peer checked before implementation*
   In order for KPMG to use the tool with client, is should be extensively peer checked and validated so the outcomes of the tool also provide substantiated results.

4. *The tool should be easy to update by adding new enablers or changing implementation levels*
   KPMG stated that is the assessment tool turn out to be a success, it should then also be sustainable for future use. Therefore, new enablers or old irrelevant enablers should be able to be added or removed from the methodology with relative ease.

5. *The tool should be translatable for other industries than FMCG*
   Comparable with the previous requirements, it should be possible to translate the tool to other industry or subject, thus given clear indication on the methodology and implementation.

6. *The tool should be compatible with both quantitative and qualitative input*
   It is important to be able to use the tool both in a passive and active way. KPMG stated that the tool should be both implemented by a quantifiable input and by qualitative outcomes from interviews with experts.

7. *The tool should provide the ability to compare output with peers*
   Expert should be able to compared themselves to other companies, not only by getting advice from KPMG consultants. It helps experts to better understand their market position, sometimes more valuable then just an assessment.

8. *The tool should take into account industry bias (objectiveness)*
   Benchmarking tend to increase bias from experts, as they fill out their own implementation levels. Therefore, bias should be minimised as much as possible, ensuring valid and useful outcomes.

3 | Industry Based
Industry based requirements are formed through the interviews done with supply chain and data analytic experts from within the FMCG industry. The requirements mainly relate to the practical side and should increase sufficient responses.

1. *The tool must have a clear and straightforward input*
   Experts stated that the tool must have straightforwards input, otherwise respondent might lose their interest and more easily be distracted.

2. *The tool must give insights in opportunities or actions*
   Experts get many requests for questionnaires or interviews, therefore it is important to clearly define the benefits that the tool brings. These benefit are required to be in the form of advice on opportunities or actions that the expert can take to improve their supply chain resilience score.

3. *The tool should not require experts to dedicate more than 30 min on the input*
   The industry is very busy at the moment and expert thus have limited time available for e.g. questionnaires. The 30min mark was stated to be an absolute maximum of time needed for the expert to fill out the assessment tool.

4. *The tool should first state clear definitions of all subjects*
   Both in literature and within the industry, different definitions occur for a wide variety of subjects, including supply chain resilience. Therefore, experts stated that all subjects have to be defined beforehand in order to reduce uncertainties and to ensure experts can effectively use their time on the tool.

9.2 General Design

Based on both the preliminary research and the requirements stated in section 9.1, the general layout for the assessment tool is constructed and presented in Figure 9.1. The layout is partly based on the methodology of Soni, Jain, and Kumar 2014, mostly for calculating the permanent of the corresponding matrix. Each of the four main sub sections of the layout are discussed separately in the following paragraphs.

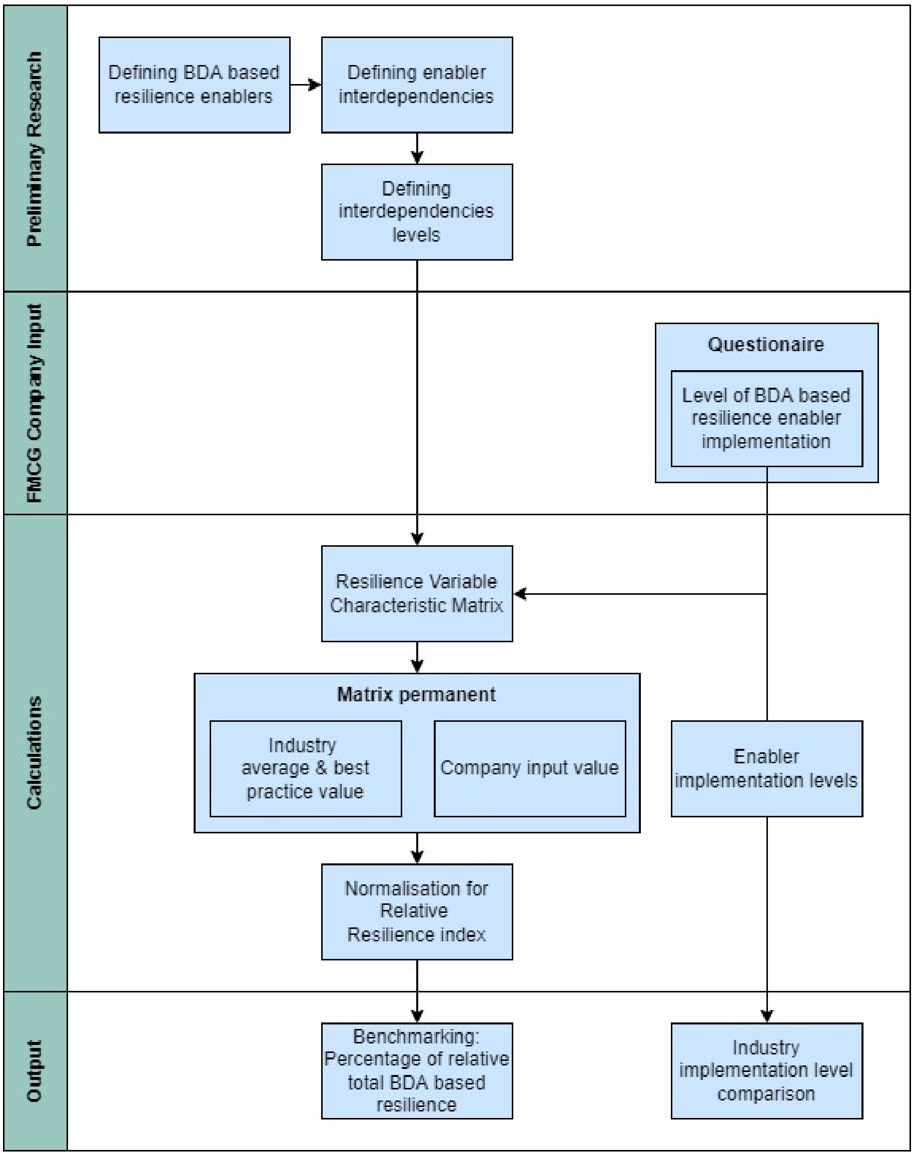

Figure 9.1: Tool Design, Overview of assessment tool

9.2.1 Preliminary Necessities

The first step of the assessment tool is to define the preliminary necessities such as the different BDA based resilience enables and corresponding interdependencies. Brief definitions of each enabler as used within the assessment tool are given in Table 9.1.

Table 9.1: Tool Design, Enabler Definitions

Enabler	Definition
Agility	The ability to quickly respond to disruptions
Collaboration	Cross supply chain collaboration with external stakeholders
Contingency Planning	Having pre-described plans on how to handle certain disruptions
Digital SC Twin	A simulation of the complete supply chain in (real-time) digital form
Disruptions Detection	The ability to detect disruptions through internal BDA, focusing on KPI abnormalities
Flexibility	The ability to quickly adapt to disruptions
Knowledge Management	Well defined use of knowledge sharing and processing within the organisation
Predicting Disruptions	The ability to use external data to predict disruptions
Scenario Modelling	The ability to digitally simulate a process to model different scenario's
Situational Awareness	Knowing what is happening in the global market, politics, health (covid), transport etc.
Transparency	Having complete and easy access to all supply chain data
Velocity	The speed of being able to change supply chain operations
Visibility	Enabling digital insights in all supply chain processes
Vulnerability Assessment	Comprehensively assessing (internal) supply chain elements on potential vulnerabilities for disruptions

1. Defining BDA Based Enablers

The enablers of supply chain resilience, based on BDA, are used from the concluding remarks of chapter 8 where the different enabling elements are stated. In total, 14 elements of resilience enablers can be traced back to BDA and are alphabetically stated below. Two enablers are left out compared to literature: 'Early warning systems' and 'new skill development'. Early warning systems was taken out due to the high correlation with the enabler of 'disruption detection'. The enabler 'new skill development' was also taken out due to negligible mentioning during industry expert interviews, making the enabler unnecessary for the assessment tool. A representative variable is given to each enabler to ensure efficiency during calculation steps, given N_i for $i \in Enablers$.

1. N_1 Agility
2. N_2 Collaboration
3. N_3 Contingency Planning
4. N_4 Digital SC Twin
5. N_5 Disruption Detection
6. N_6 Flexibility
7. N_7 Knowledge Management
8. N_8 Predicting Disruptions
9. N_9 Scenario Modelling
10. N_{10} Situational Awareness
11. N_{11} Transparency
12. N_{12} Velocity
13. N_{13} Visibility
14. N_{14} Vulnerability Assessment

2. Digraph Representation

All enablers are presented in a digraph which visualises the different interdependencies of variables. The interdependencies are based on the outcomes of the frameworks of chapter 6 and form the basis for the Structural Self Interaction Matrix (SSIM). The specifics of the interdependencies are based on the author's assessment in order to ensure efficiency and practicality of the tool. This thus however decreases the academic substantiation for the interdependencies. For example, Soni, Jain, and Kumar 2014 uses an empirical research where respondents are asked to assess each possible interdependence. In the case of this research, this would mean that each respondent would have to assess 81 interdependencies. It was therefore concluded that it would not be practical to ask this from the interviewees, especially when taking into account the number of interviewees and the scarce time available for each interview. This also holds for the quantification of the interdependencies.

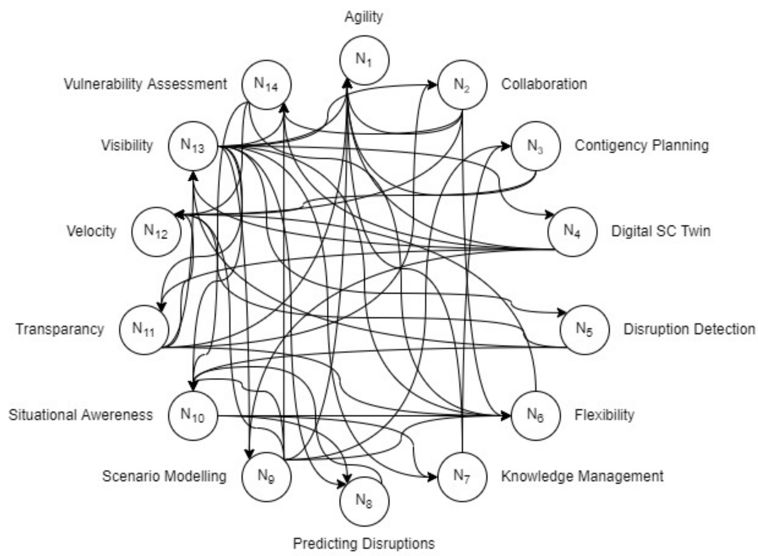

Figure 9.2: Tool Design, Digraph Representation

$\boxed{3.}$ Structural Self Interaction Matrix

The SSIM is presented in Table 9.2 and represents the different interdependencies N_{ij} for $i, j \in Enablers$. Interdependencies are described using the following four variables. The SSIM is transformed to a regular matrix to ensure matrix calculation can be performed (Equation 9.1). A SSIM can be seen as a table form of the previously stated di-graph.

- V | Enabler i influences enablers j
- A | Enabler j influences enablers i
- X | Enablers i and j influence each other
- O | Enablers i and j are unrelated

Table 9.2: Tool Design, SSIM Matrix

		N_{14}	N_{13}	N_{12}	N_{11}	N_{10}	N_9	N_8	N_7	N_6	N_5	N_4	N_3	N_2	N_1
N_1	Agility	O	A	O	A	O	A	O	A	O	O	A	A	A	-
N_2	Collaboration	V	A	V	A	O	O	O	O	V	O	O	O	-	-
N_3	Contingency Planning	O	O	V	O	O	A	O	A	O	O	O	-	-	-
N_4	Digital SC Twin	V	X	O	V	O	V	O	O	O	O	-	-	-	-
N_5	Disruptions Detection	O	X	V	O	V	O	O	O	O	-	-	-	-	-
N_6	Flexibility	A	A	V	A	A	A	O	O	-	-	-	-	-	-
N_7	Knowledge Management	O	A	O	O	O	A	O	-	-	-	-	-	-	-
N_8	Predicting Disruptions	O	A	O	O	X	O	-	-	-	-	-	-	-	-
N_9	Scenario Modelling	V	A	V	O	V	-	-	-	-	-	-	-	-	-
N_{10}	Situational Awareness	A	A	O	O	-	-	-	-	-	-	-	-	-	-
N_{11}	Transparency	O	X	V	-	-	-	-	-	-	-	-	-	-	-
N_{12}	Velocity	A	A	-	-	-	-	-	-	-	-	-	-	-	-
N_{13}	Visibility	V	-	-	-	-	-	-	-	-	-	-	-	-	-
N_{14}	Vulnerability Assessment	-	-	-	-	-	-	-	-	-	-	-	-	-	-

$$\begin{bmatrix}
N_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
N_{2,1} & N_2 & 0 & 0 & 0 & N_{2,6} & 0 & 0 & 0 & 0 & 0 & N_{2,12} & 0 & N_{2,14} \\
N_{3,1} & 0 & N_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{3,12} & 0 & 0 \\
N_{4,1} & 0 & 0 & N_4 & 0 & 0 & 0 & 0 & N_{4,9} & 0 & N_{4,11} & 0 & N_{4,13} & N_{4,14} \\
0 & 0 & 0 & 0 & N_5 & 0 & 0 & 0 & 0 & N_{5,10} & 0 & N_{5,12} & N_{5,13} & 0 \\
0 & 0 & 0 & 0 & 0 & N_6 & 0 & 0 & 0 & 0 & 0 & N_{6,12} & 0 & 0 \\
N_{7,1} & 0 & N_{7,3} & 0 & 0 & 0 & N_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & N_8 & 0 & N_{8,10} & 0 & 0 & 0 & 0 \\
N_{9,1} & 0 & N_{9,3} & 0 & 0 & N_{9,6} & 0 & 0 & N_9 & N_{9,10} & 0 & N_{9,12} & 0 & N_{9,14} \\
0 & 0 & 0 & 0 & 0 & N_{10,6} & N_{10,7} & N_{10,8} & 0 & N_{10} & 0 & 0 & 0 & 0 \\
N_{11,1} & N_{11,2} & 0 & 0 & 0 & N_{11,6} & 0 & 0 & 0 & 0 & N_{11} & N_{11,12} & N_{11,13} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{12} & 0 & 0 \\
N_{13,1} & N_{13,2} & 0 & N_{13,4} & N_{13,5} & N_{13,6} & N_{13,7} & N_{13,8} & N_{13,9} & N_{13,10} & N_{13,11} & 0 & N_{13} & N_{13,14} \\
0 & 0 & 0 & 0 & 0 & N_{14,6} & 0 & 0 & 0 & N_{14,10} & 0 & N_{14,12} & 0 & N_{14}
\end{bmatrix} \tag{9.1}$$

$\boxed{4.}$ Quantification of N_{ij}

Each interdependence described in Table 9.2 is given a value with corresponding qualitative level. In this case, the different levels of interdependence are given between the following range described below. The final values are given based on discussions with supply chain experts of KPMG and the industry, relating the values to the industry knowledge of (consulting) professionals. The values are directly filled into the matrix of Equation 9.1, short explanations on the values can be found in Appendix D. As with the interdependencies, the specific quantification are based on the author's final assessment.

- 5 | Very High
- 4 | High
- 3 | Medium
- 2 | Low
- 1 | Very Low

$\boxed{5.}$ Matrix Representation

The final output of this first part of the assessment tool is the matrix composed of both the still to be determined enabler implementation levels N_i for $i \in Enablers$ and the already determined levels of interdependence N_{ij} for $i, j \in Enablers$. The final matrix to use in the consecutive steps is presented in Equation 9.2.

$$\begin{bmatrix}
N_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
3 & N_2 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 2 \\
5 & 0 & N_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 0 \\
4 & 0 & 0 & N_4 & 0 & 0 & 0 & 0 & 4 & 0 & 3 & 0 & 4 & 3 \\
0 & 0 & 0 & 0 & N_5 & 0 & 0 & 0 & 0 & 3 & 0 & 3 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & N_6 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\
1 & 0 & 2 & 0 & 0 & 0 & N_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & N_8 & 0 & 2 & 0 & 0 & 0 & 0 \\
3 & 0 & 4 & 0 & 0 & 2 & 0 & 0 & N_9 & 2 & 0 & 3 & 0 & 4 \\
0 & 0 & 0 & 0 & 0 & 1 & 3 & 2 & 0 & N_{10} & 0 & 0 & 0 & 0 \\
3 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & N_{11} & 3 & 2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{12} & 0 & 0 \\
5 & 3 & 0 & 2 & 4 & 5 & 3 & 5 & 5 & 4 & 5 & 0 & N_{13} & 3 \\
0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 2 & 0 & 2 & 0 & N_{14}
\end{bmatrix} \tag{9.2}$$

9.2.2 FMCG Company Input

The second part of the design for the assessment tool is to set up a questionnaire in order to acquire the BDA based resilience enabler implementation levels of FMCG companies. These values represent the matrix variables of N_i for $i \in Enablers$. The questionnaire needs to comply with the determined requirements from both the industry as well as the requirements from KPMG.

1. Desired Outcomes

The outcomes needed from FMCG companies are the values for N_i for $i \in Enablers$. These values represent the level of implementation of BDA based supply chain resilience enablers. The values range is different from literature, where the numbers between 1 and 9 are used. Instead, the range is decreased to 1-5 after discussions with supply chain consultants where it was noted that 1-9 would be to difficult to comprehend for industry experts to chose a single implementation level. Choosing a value between one and nine would be to difficult, as the difference between for example six and seven is very unclear. With the range of 1-5, there are only three undefined levels that are much easier to understand for industry experts. For each enabler, the lowest and highest level of implementation are pre-described, after which the company's representative can determine how far the company is within the given range. The pre-described levels are defined though a thorough discussion with supply chain experts. The desired outcomes from the questionnaire are thus 14 values, each representing the implementation level of one enabler.

2. Questionnaire set-up

The questionnaire is defined by all 14 enablers, each described by a lowest and highest level of implementation. An example of one of the enablers is given in Figure 9.3, where the enabler of BDA based visibility is used. The full questionnaire is given in Appendix C, also including the general introduction and explanation needed for supply chain experts to effectively fill in the questionnaire. The objective for a supply chain expert would thus be to fill in all the 14 levels of implementation based on the given lowest and highest explanations. Besides the implementation levels, the company representative is also asked to fill in general questions on the scope of their supply chain, personal function, company size and elaboration on implementation levels if needed. The full questionnaire is presented in Appendix C, where an introduction, subject definitions and further explanations are given.

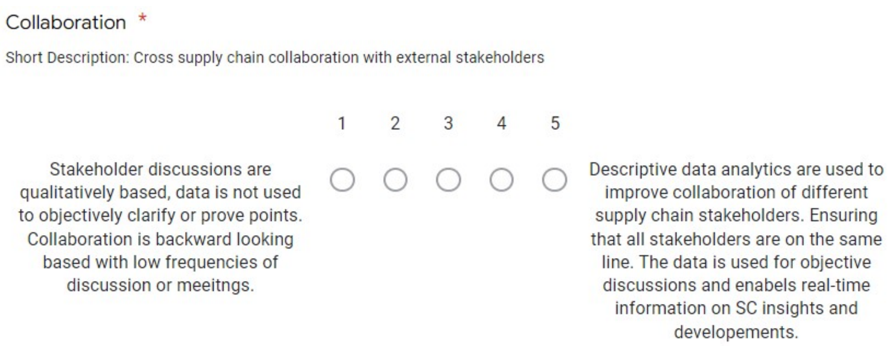

Figure 9.3: Tool Design, Questionnaire Example

3. Example final matrix

With all previous steps completed, the final input matrix (Resilience Variable Characteristic Matrix (RVCM)) for the assessment tool calculation can be determined. As for clarification of the assessment tool concept, the matrix is Equation 9.3 has filled in diagonal entries, that are taken at random. These entries will be filled in by company experts, shown in the assessment tool results section.

$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 3 & 4 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 2 \\ 5 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 0 \\ 4 & 0 & 0 & 5 & 0 & 0 & 0 & 0 & 4 & 0 & 3 & 0 & 4 & 3 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 3 & 0 & 3 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 2 & 0 & 0 & 0 & 0 \\ 3 & 0 & 4 & 0 & 0 & 2 & 0 & 0 & 3 & 2 & 0 & 3 & 0 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 3 & 2 & 0 & 2 & 0 & 0 & 0 & 0 \\ 3 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 4 & 3 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 5 & 3 & 0 & 2 & 4 & 5 & 3 & 5 & 5 & 4 & 5 & 0 & 2 & 3 \\ 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 2 & 0 & 2 & 0 & 5 \end{bmatrix} \tag{9.3}$$

9.2.3 Deterministic Model

The deterministic model has the objective of calculating a BDA based resilience index. This index can be compared to an ideal state index, which gives the relative BDA based resilience index number. The background of the calculations are discussed in section 7.3.

1. VRCM Permanent

The first step of the deterministic model is to calculate the matrix permanent which gives a single comprehensive value. The permanent is first calculated for the RVCM based on the values given by a FMCG company expert. In this case, the same example is used as in Equation 9.4.

$$perm \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 3 & 4 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 2 \\ 5 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 0 \\ 4 & 0 & 0 & 5 & 0 & 0 & 0 & 0 & 4 & 0 & 3 & 0 & 4 & 3 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 3 & 0 & 3 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\ 1 & 0 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 2 & 0 & 0 & 0 & 0 \\ 3 & 0 & 4 & 0 & 0 & 2 & 0 & 0 & 3 & 2 & 0 & 3 & 0 & 4 \\ 0 & 0 & 0 & 0 & 0 & 1 & 3 & 2 & 0 & 2 & 0 & 0 & 0 & 0 \\ 3 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 4 & 3 & 2 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 5 & 3 & 0 & 2 & 4 & 5 & 3 & 5 & 5 & 4 & 5 & 0 & 2 & 3 \\ 0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 2 & 0 & 2 & 0 & 5 \end{bmatrix} = 4.85 \times 10^6 \tag{9.4}$$

$\boxed{2.}$ Best Practice & Average VRCM Permanent

After calculating the company's RVCM permanent, the permanent can now be calculated of the best practice RVCM (Equation 9.5). The optimal RVCM represents the industry better practice value for the BDA based implementation of resilience enablers. After acquiring many responses of company experts, the optimal RVCM can also be replaced by the industry average RVCM. This would give a relative resilience index compared to the average industry, instead of the best practice implementation levels.

$$SCRES_{BP} = perm \begin{bmatrix} N_1 & \dots & N_{1,14} \\ \vdots & \ddots & \vdots \\ N_{14,1} & \dots & N_{14} \end{bmatrix} = x \tag{9.5}$$

$$SCRES_{Avg} = perm \begin{bmatrix} N_1 & \dots & N_{1,14} \\ \vdots & \ddots & \vdots \\ N_{14,1} & \dots & N_{14} \end{bmatrix} = \overline{x} \tag{9.6}$$

$\boxed{3.}$ Relative BDA Based Resilience Index

$$SCRES_{Relative,BP} = \frac{SCRES}{SCRES_{BP}} * 100\% \tag{9.7}$$

$$SCRES_{Relative,Avg} = \frac{SCRES}{SCRES_{Avg}} * 100\% \tag{9.8}$$

9.2.4 Output

Given the calculation presented above and a company filling in the questionnaire, the results can be presented to the company composed of two main elements. First, the company can match itself against the industry average resilience index and the best practice. Second, the company also gains insight on the relative implementation levels of each enabler, also compared to both the industry average and best practice.

1. Relative BDA Based Resilience Index

The metric value that is calculated of the RVCM and compared to industry average and best practice is visually presented to a company though Figure 9.4.

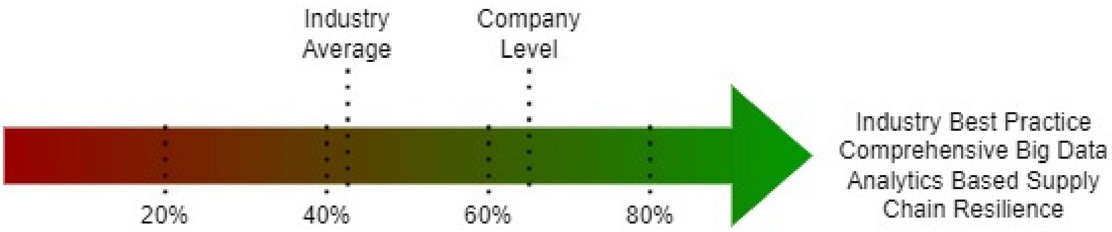

Figure 9.4: Tool Design, Result Scale

2. Implementation Level Industry Comparison

The second part consists of comprehensive radar diagrams that present the company with insights on relative enabler implementation levels compared to the industry. An example is given of a radar plot given a imaginary company and industry average result in Figure 9.5. Additionally, Figure 9.6 gives the visualisation of comparison for a company with the industry better practice. The better practice is calculated based on the resilience index, this means that the a company could still outperform the best practice on some enablers, but not when the comprehensive index is calculated.

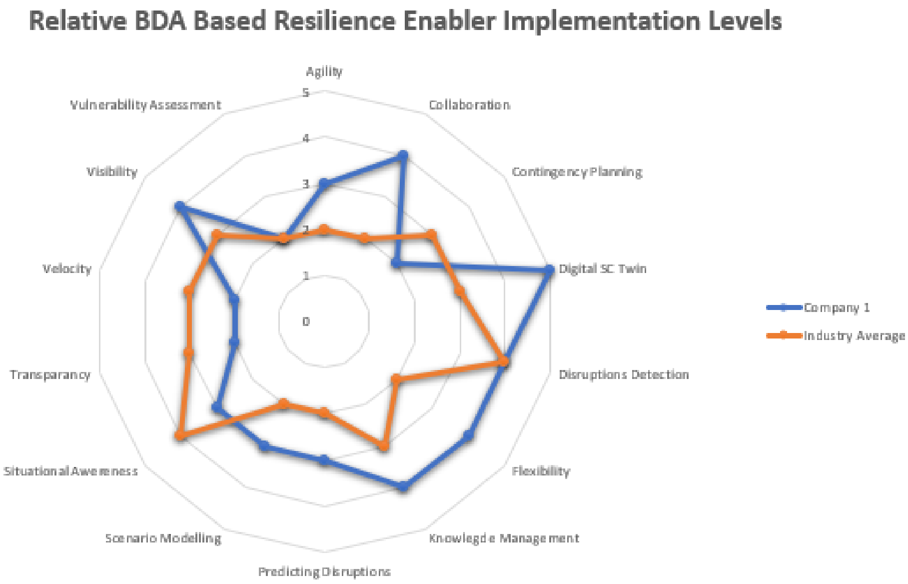

Figure 9.5: Tool Design, Example Result, Average

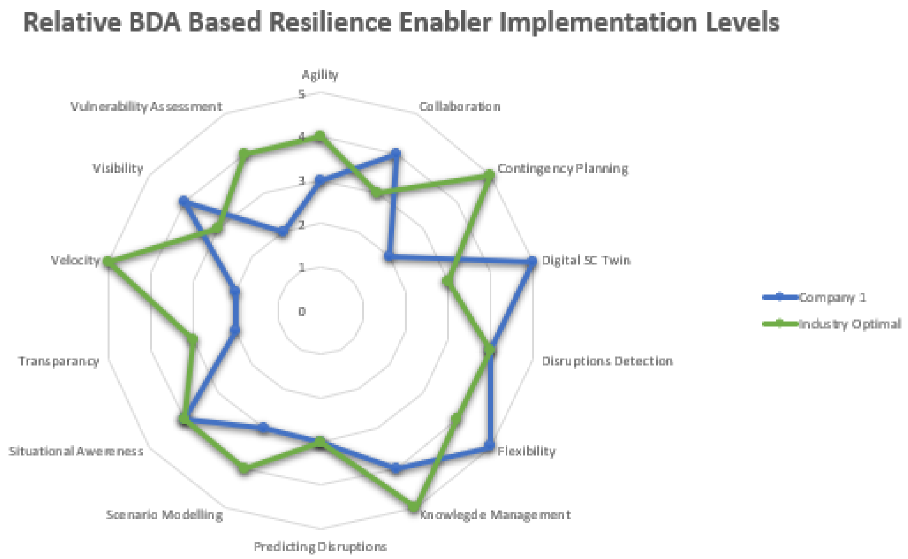

Figure 9.6: Tool Design, Example Result, Best Practice

3. Advice for Improvements

With the output comparison of different implementation levels of enablers, companies can see how they perform compared to peers. These form the kick-start to discussion with KPMG experts where personal advice can be given on how to improve on certain BDA based enablers. Personal advice would be best given during face to face conversations, ensuring suited suggestions for each company. Furthermore, it is also noted during empirical research that most companies already know what they should do to improve BDA based resilience, however the challenges they face currently prevent than from improving. Therefore, the benchmark ability to compare to peers is in this case more important as it gives companies an indication on the importance of the subject and sets improvements to higher priority.

$\boxed{4.}$ Strategy based output

Both the relative resilience index and the industry comparison can also be applied to specific resilience enabler matrices subdivided by resilience strategy and BDA category, similar to the conclusion presented in Figure 8.4. The subdivided matrices are presented in Table 9.3 and are based on underlying literature that connects BDA and supply chain resilience through its enablers. For each of these matrices, the permanent can be calculated which allows for specific bench marking possibilities. For example, the matrix that connects descriptive BDA and concurrent resilience can be seen as the matrix that allows for the calculation of partial concurrent resilience provided impacted by descriptive BDA. These are however only possibility given, but will not be extensively processed in the actual results of the research.

		Big Data Analytics		
		Predictive	Descriptive	Prescriptive
Supply Chain Resilience	Proactive	$\begin{bmatrix} N_8 & 2 \\ 2 & N_{10} \end{bmatrix}$	$\begin{bmatrix} N_5 & 3 & 0 & 1 & 0 \\ 0 & N_{10} & 0 & 0 & 0 \\ 0 & 0 & N_{11} & 2 & 0 \\ 4 & 4 & 5 & N_{13} & 3 \\ 0 & 2 & 0 & 0 & N_{14} \end{bmatrix}$	$\begin{bmatrix} N_4 & 0 & 4 & 4 \\ 0 & N_7 & 0 & 0 \\ 0 & 0 & N_9 & 0 \\ 2 & 3 & 5 & N_{13} \end{bmatrix}$
	Concurrent	0	$\begin{bmatrix} N_1 & 0 & 0 & 0 & 0 & 0 \\ 3 & N_2 & 4 & 0 & 4 & 0 \\ 0 & 0 & N_6 & 0 & 4 & 0 \\ 3 & 2 & 3 & N_{11} & 3 & 2 \\ 0 & 0 & 0 & 0 & N_{12} & 0 \\ 5 & 3 & 5 & 5 & 0 & N_{13} \end{bmatrix}$	$\begin{bmatrix} N_1 & 0 & 0 \\ 5 & N_3 & 0 \\ 4 & 0 & N_4 \end{bmatrix}$
	Reactive	0	$\begin{bmatrix} N_7 & 0 \\ 0 & N_{14} \end{bmatrix}$	$\begin{bmatrix} N_3 & 0 & 0 \\ 0 & N_4 & 4 \\ 4 & 0 & N_9 \end{bmatrix}$

Table 9.3: Tool Output, Strategy Based

9.2.5 Theoretical Minimum & Optimum

The theoretical optimum of the matrix permanent can be calculated when all implementation levels of the resilience enablers are on the highest level. This thus means that the complete diagonal entries of the matrix are all of value 5. For the minimum theoretical value, these diagonal entries are all set to 1. The equation for the theoretical minimum and optimum is presented in Equation 9.9. In order to understand what happens between these two theoretical values, the behaviour of the matrix permanent is tested for a small matrix example.

$$perm\begin{bmatrix}5&0&0&0&0&0&0&0&0&0&0&0&0&0\\3&5&0&0&0&4&0&0&0&0&0&4&0&2\\5&0&5&0&0&0&0&0&0&0&0&5&0&0\\4&0&0&5&0&0&0&0&4&0&3&0&4&3\\0&0&0&0&5&0&0&0&0&3&0&3&1&0\\0&0&0&0&0&5&0&0&0&0&0&4&0&0\\1&0&2&0&0&0&5&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&5&0&2&0&0&0&0\\3&0&4&0&0&2&0&0&5&2&0&3&0&4\\0&0&0&0&0&1&3&2&0&5&0&0&0&0\\3&2&0&0&0&3&0&0&0&0&5&3&2&0\\0&0&0&0&0&0&0&0&0&0&0&5&0&0\\5&3&0&2&4&5&3&5&5&4&5&0&5&3\\0&0&0&0&0&3&0&0&0&2&0&2&0&5\end{bmatrix}_{Opt} = 1.40\times 10^{10} \quad \vdots \quad perm\begin{bmatrix}1&0&0&0&0&0&0&0&0&0&0&0&0&0\\3&1&0&0&0&4&0&0&0&0&0&4&0&2\\5&0&1&0&0&0&0&0&0&0&0&5&0&0\\4&0&0&1&0&0&0&0&4&0&3&0&4&3\\0&0&0&0&1&0&0&0&0&3&0&3&1&0\\0&0&0&0&0&1&0&0&0&0&0&4&0&0\\1&0&2&0&0&0&1&0&0&0&0&0&0&0\\0&0&0&0&0&0&0&1&0&2&0&0&0&0\\3&0&4&0&0&2&0&0&1&2&0&3&0&4\\0&0&0&0&0&1&3&2&0&1&0&0&0&0\\3&2&0&0&0&3&0&0&0&0&1&3&2&0\\0&0&0&0&0&0&0&0&0&0&0&1&0&0\\5&3&0&2&4&5&3&5&5&4&5&0&1&3\\0&0&0&0&0&3&0&0&0&2&0&2&0&1\end{bmatrix}_{Min} = 1.75\times 10^{2} \tag{9.9}$$

Behaviour of Matrix Permanent

It is important to analyse the behaviour of the matrix permanents, as it is a novel area compared to the foundation research of Soni, Jain, and Kumar 2014. In order to test the behaviour of the matrix permanent for a n by n matrix, a python code (Appendix F) is written to show the behaviour when 100.000 permanents are calculated. As input for the code, a 3x3 matrix is used where only the diagonal is variable, comparable to the actual research assessment tool. Larger matrices are difficult to process, since computational power increases exponentially. Therefore it is also not possible to test the permanent behaviour of the 14x14 matrix used for this research for large quantities. The 3x3 matrix should however give a clear indication. For each of the three diagonal variable entries, a random number generator is used between 1 and 5, which relates to the implementation levels used in this research. The results of the 100.000 matrix permanent calculation are shown in Figure 9.7.

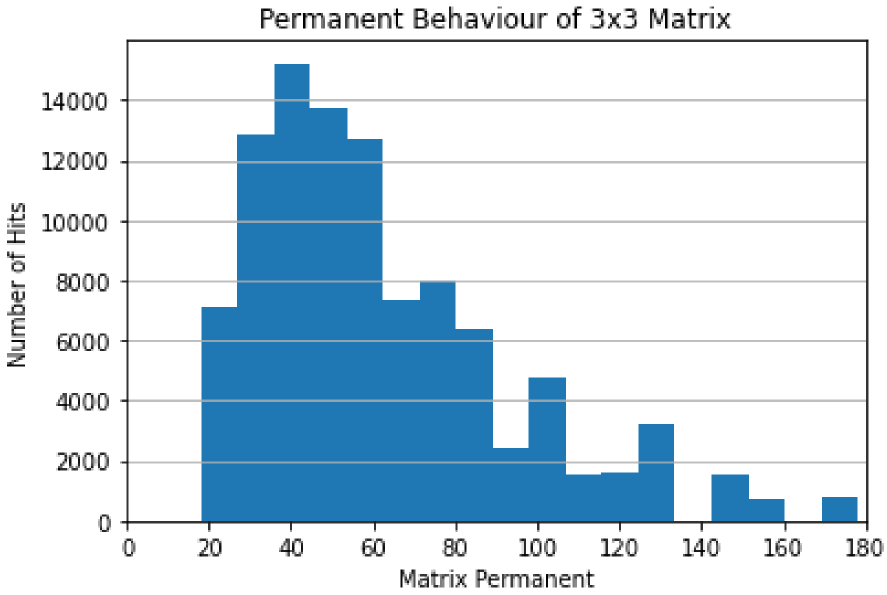

Figure 9.7: Tool Design, Matrix Permanent Behaviour

It can clearly be seen that there is no linear course of output, thus indicating that a fitting trend line should be used for the benchmarking visualisation. Especially since the complexity of matrix permanents increases exponentially with larger matrices. Therefore it is also presumed that the difference between the theoretical optimum and average value will also increase both relative and absolutely. Furthermore, it is also tested that a quantity of 100 respondents already gives a clear indication on the distribution of outcomes. Starting from a 1000 inputs, the distribution becomes practically the same as for any other higher input distributions.

To conclude, the final results of the assessment tool will need to be standardised for an exponential fit, which automatically corresponds to a logarithmic scale in order to keep visualisation understandable. This will ensure that the benchmark results will give perspective for companies and clarifies the metric outcomes.

9.3 Sensitivity

A sensitivity analysis is performed where the different quantification's for each enabler are tested. In this case, all enablers implementation levels are kept at a constant of 3 (being the center level) while one specific enabler is changed from implementation level, ranging from 1 to 5. Main results show that the highest variability is found in multiple enablers such as agility and flexibility, while the enabler of visibility has the lowest variability. On first sight, this seems counter intuitive as visibility has the most interdependencies. However, it follows that visibility actually has the highest base contribution to the permanent, but then continues with lower variability. Overall the sensitivity follows the expectation when compared to enablers interdependence. Larger differences of variability could however be realised, but only if more interdependencies are defined, given less zeros with the permanent matrix.

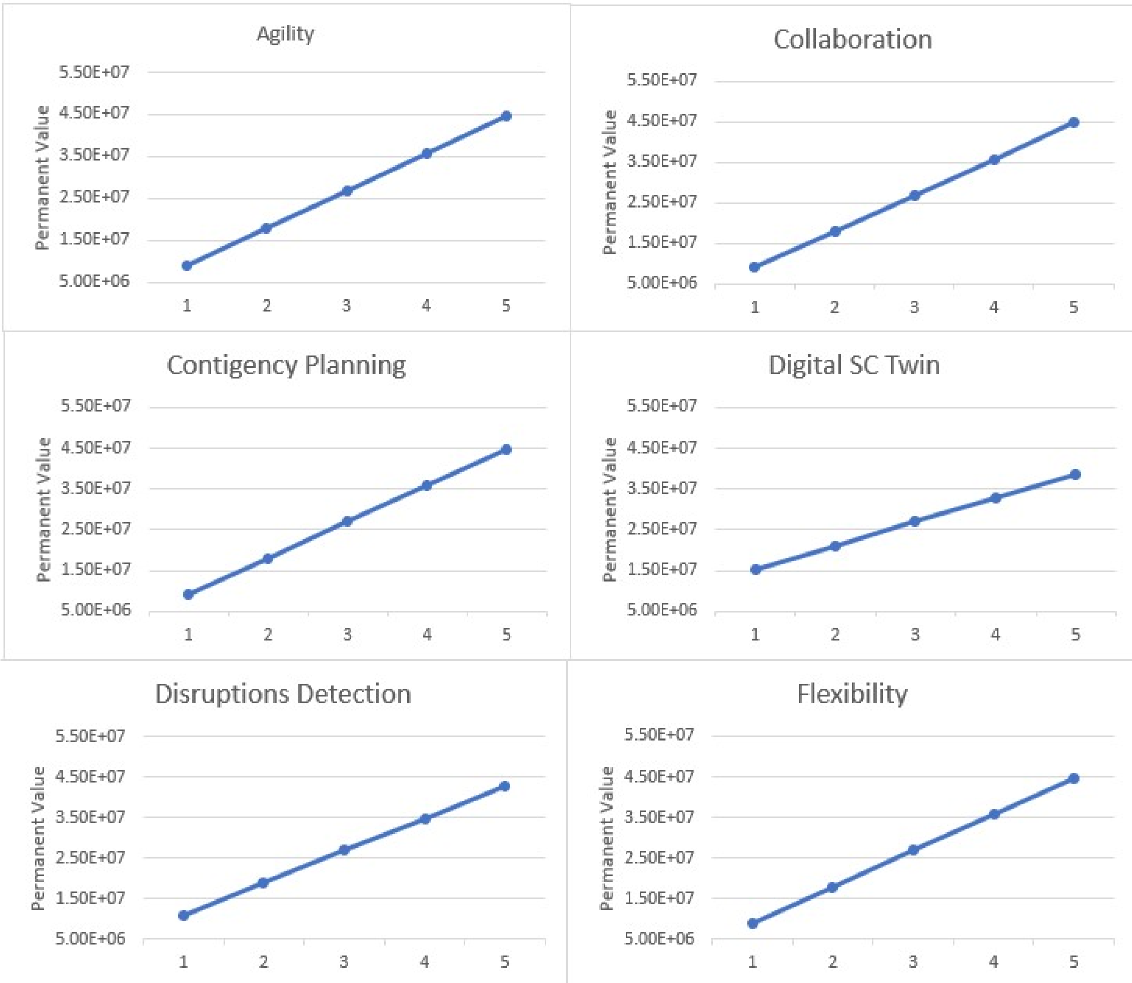

Figure 9.8: Tool Design, Sensitivity 1

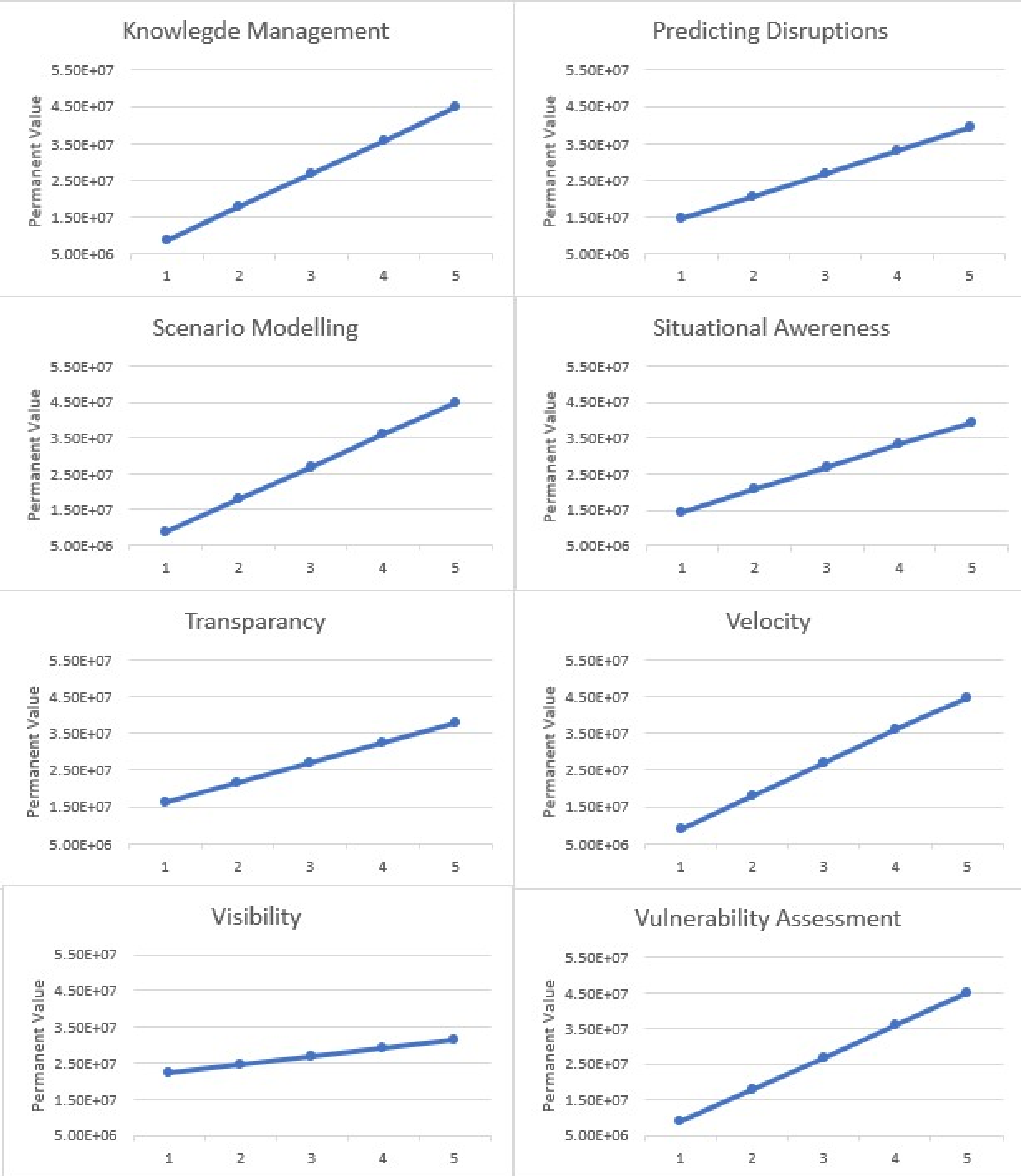

Figure 9.9: Tool Design, Sensitivity 2

10 | Assessment Tool | Results

This chapter presents the results from the resilience assessment tool. There are three main outcomes that the assessment tool gives: an industry average, better practice and specific assessment tool responses. In an ideal state, the industry average and better practice are determined based on the output of a large quantity of questionnaire response (>100). However, the goal of this research is to design and validate an assessment tool leaving the task of acquiring a large number of questionnaire responses for further research. Therefore, the industry average and better practice are based on the responses on the questionnaire. Additionally, the estimated outcomes based on empirical and literature research are compared with actual response on the questionnaire.

$\boxed{1.}$ Expected Industry Average & Best Practice

The matrices for the industry average and better practice are presented below with the corresponding matrix permanent, short descriptions on the implementation levels of the enablers are described in Appendix E. The values are estimated based on the outcomes of the expert interviews and are compared to actual outcomes of the results. These estimates can also give a good indication of the reliability of questionnaire responses. In essence, the average and better practice of the questionnaire responses should be close to the estimated value based on the interviews.

$$perm \begin{bmatrix} 2&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 3&2&0&0&0&4&0&0&0&0&0&4&0&2 \\ 5&0&2&0&0&0&0&0&0&0&0&5&0&0 \\ 4&0&0&1&0&0&0&0&4&0&3&0&4&3 \\ 0&0&0&0&3&0&0&0&0&3&0&3&1&0 \\ 0&0&0&0&0&2&0&0&0&0&0&4&0&0 \\ 1&0&2&0&0&0&2&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&1&0&2&0&0&0&0 \\ 3&0&4&0&0&2&0&0&2&2&0&3&0&4 \\ 0&0&0&0&0&1&3&2&0&3&0&0&0&0 \\ 3&2&0&0&0&3&0&0&0&0&3&3&2&0 \\ 0&0&0&0&0&0&0&0&0&0&0&2&0&0 \\ 5&3&0&2&4&5&3&5&5&4&5&0&4&3 \\ 0&0&0&0&0&3&0&0&0&2&0&2&0&2 \end{bmatrix}_{Avg} = 4.85 \times 10^6 \quad \vdots \quad perm \begin{bmatrix} 4&0&0&0&0&0&0&0&0&0&0&0&0&0 \\ 3&3&0&0&0&4&0&0&0&0&0&4&0&2 \\ 5&0&3&0&0&0&0&0&0&0&0&5&0&0 \\ 4&0&0&3&0&0&0&0&4&0&3&0&4&3 \\ 0&0&0&0&4&0&0&0&0&3&0&3&1&0 \\ 0&0&0&0&0&4&0&0&0&0&0&4&0&0 \\ 1&0&2&0&0&0&3&0&0&0&0&0&0&0 \\ 0&0&0&0&0&0&0&3&0&2&0&0&0&0 \\ 3&0&4&0&0&2&0&0&4&2&0&3&0&4 \\ 0&0&0&0&0&1&3&2&0&4&0&0&0&0 \\ 3&2&0&0&0&3&0&0&0&0&4&3&2&0 \\ 0&0&0&0&0&0&0&0&0&0&0&3&0&0 \\ 5&3&0&2&4&5&3&5&5&4&5&0&5&3 \\ 0&0&0&0&0&3&0&0&0&2&0&2&0&4 \end{bmatrix}_{BP} = 1.92 \times 10^8 \tag{10.1}$$

$\boxed{2.}$ Questionnaire Responses

Figure 10.1 present the results of the questionnaire filled in by different experts from within the industry. Each implementation level is given from the unique BDA based supply chain resilience enablers. Furthermore, the calculated matrix permanent is also presented in the lower row. The difference between industry results and the theoretical optimum is very large, however this is understandable due to the behaviour of the matrix permanent for large matrices. This has also been researched in subsection 9.2.5.

Company	Solar Nederland	Royal Philips	Heineken	Refresco	Action	Mustad	Online Mealkit Retailer	BROSPER
Function	VP Operations	VP Spend Management SC	Global SC Director	Director SC Development	Director SC	SC Director	Head of SC Management EU	Owner
Enabler	Company 1	Company 2	Company 3	Company 4	Company 5	Company 6	Company 7	Company 8
Agility	2	2	2	2	1	2	4	1
Collaboration	2	2	3	3	2	1	2	3
Contigency Planning	2	2	3	3	4	4	3	2
Digital SC Twin	1	2	4	2	1	1	1	2
Disruptions Detection	2	2	2	3	2	2	3	2
Flexibility	2	2	2	2	1	2	3	1
Knowlegde Management	3	2	3	1	2	1	4	2
Predicting Disruptions	2	2	2	1	2	1	1	2
Scenario Modelling	1	2	4	2	4	3	2	3
Situational Awereness	2	3	3	2	3	3	2	3
Transparancy	3	3	4	2	2	2	4	3
Velocity	2	3	5	4	3	3	3	1
Visibility	2	4	4	3	4	2	3	3
Vulnerability Assessment	3	2	4	3	2	2	4	3
Matrix Permanent	801792	706560	31104000	1016064	384000	185472	8875008	185760

Figure 10.1: Tool Results, Questionnaire Output

3. Matrix Permanents

The calculations of the partial resilience matrix permanents, including the interdependencies, are presented below in Figure 10.2 where the permanent for each of the respondents is plotted. Furthermore, the permanents are also visualised compared to the theoretical optimum in Figure 10.3.

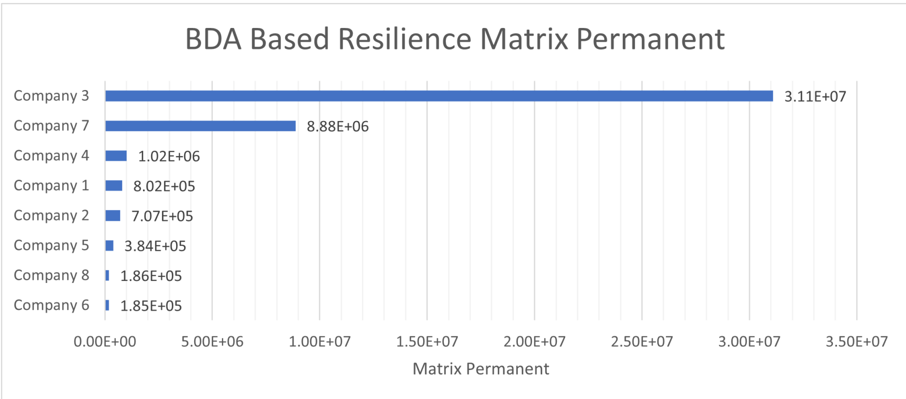

Figure 10.2: Tool Results, Matrix Permanent

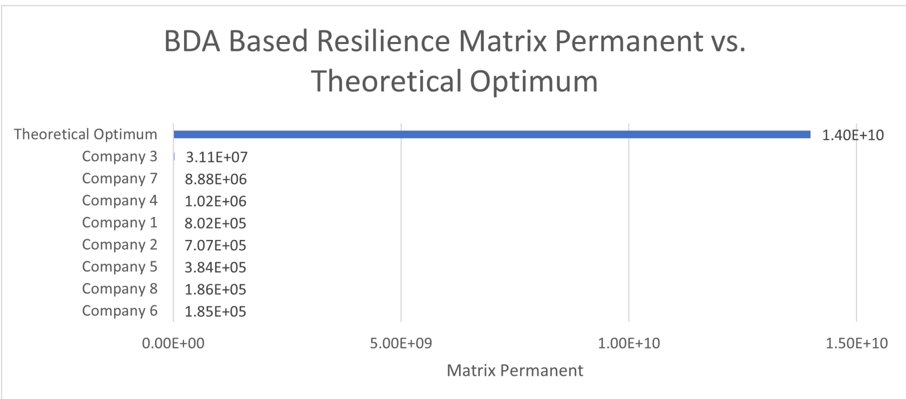

Figure 10.3: Tool Results, Matrix Permanent vs. Theoretical Optimum

The figures present insights in the large differences between permanent outcomes, especially compared to the theoretical optimum. These are expected as the behaviour of the matrix permanent was researched in subsection 9.2.5. Furthermore, literature also acknowledges the benefits of exponential scaling with logarithmic scales (Mahajan 2018). It translated that the permanent values are best presented when fitted to and exponential line with a underlying logarithmic scale. The exponential function is plotted through the theoretical minimum and optimum, giving a straight line on the logarithmic scale. Using the found fitted exponential line, the results of the companies permanents are calculated backwards to find the corresponding x value between the theoretical values. The results of the scaling are shown in Figure 10.4 and give the base for the benchmark visualisation.

In general, the fitted exponential is the following formula where the theoretical minimum is equal to y = 0 (0%) and optimum is equal to y = 10 (100%):

$$y = 175 \times e^{18.197 \times x} \tag{10.2}$$

The backward calculation finds the benchmark percentage of a companies matrix permanents compared to the theoretical optimum. Giving an example for company 4 with permanent 1.02×10^6:

$$\frac{\ln(\frac{1.02 \times 10^6}{175})}{18.197} = 47.63\% \tag{10.3}$$

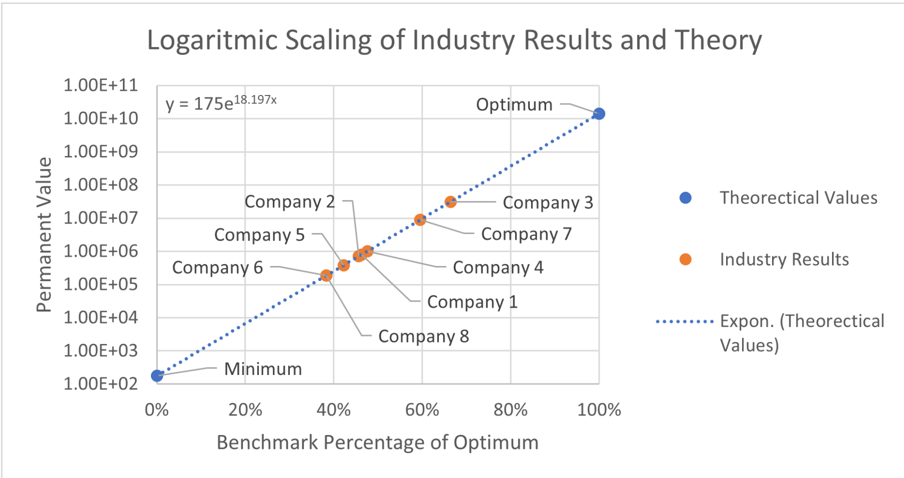

Figure 10.4: Tool Results, Scaling

The calculated percentages on the exponential fitted line form the input for the final partial resilience benchmark visualisation. The final version of the visualisation is therefore made and presented in Figure 10.5.

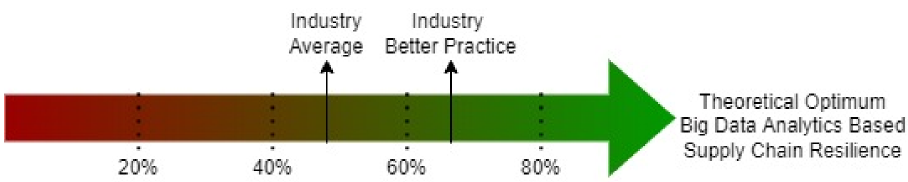

Figure 10.5: Tool Results, Final Visualisation

3. Enabler Implementation Levels

Finally, the visualisations are presented of the individual implementation levels of BDA based resilience enablers. The average and better practice results from the questionnaire are presented along side the expected values for each enabler. Figure 10.6 present the industry average results and Figure 10.7 present the industry better practice results.

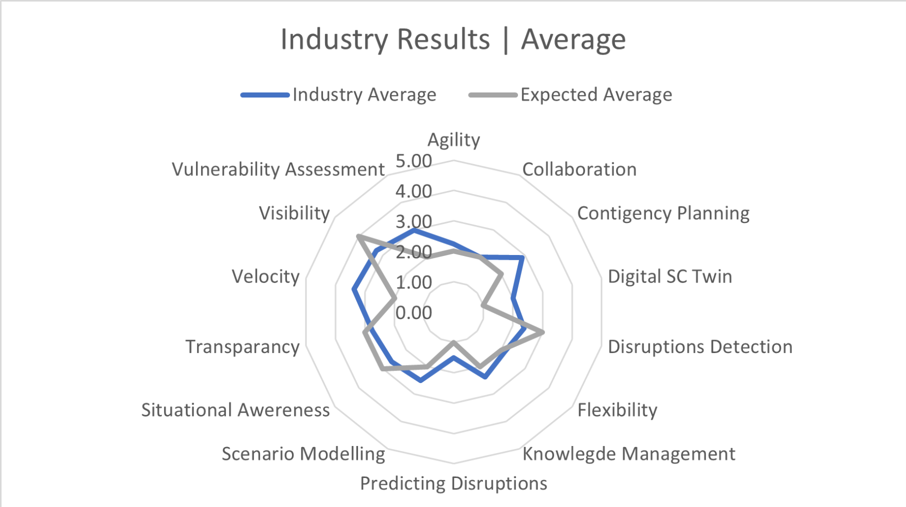

Figure 10.6: Tool Results, Industry Average

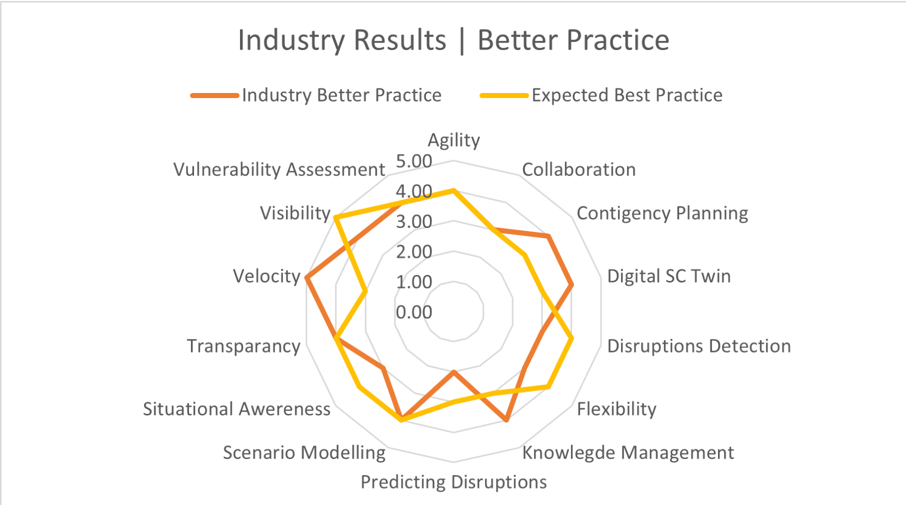

Figure 10.7: Tool Results, Industry Better Practice

11 | Assessment Tool | Validation & Verification

This chapter presents the validation and verification of the designed and executed BDA based resilience assessment tool. The assessment tool is both validated on initial requirements, discussed with experts and verified on outcomes.

11.1 Verification of Requirements

The requirements presented in section 9.1 are validated in relation to the final design. A division is made between the three main requirements background of research, KPMG and industry. The validations are presented in Figure 11.1, Figure 11.2 and Figure 11.3 respectively. In general, most requirements have been met, with only a few being partially met due to tool simplifications made on especially the questionnaire in order to keep the assessment tool comprehensible.

Requirement	Met?	Explanation
1 | Research Based		
1. The tool must have a quantitative (metric) outcome of supply chain resilience	Yes	The tool uses the required input to calculate a matrix permanent, transforming the input to a single metric expression.
2. The tool must provide an outcome that is based on a function of BDA based enablers	Yes	The matrix permanent is a polynomial function of matrix entries where the entries are the implementation levels of different BDA based resilience enablers.
3. The tool should include enabler interdependencies	Yes	The off-diagonal mtrix entries are the enabler interdependencies that are based on expert discussion and are used for the permanent calculation.
4. The tool should show visualised industry comparisons	Yes	The tool provided several visual outputs representing the benchmarking scale and specific enabler implementation level comparisons.

Figure 11.1: Verification Requirements Research

Requirement	Met?	Explanation
2 | KPMG Based		
1. The tool must be user friendly for the client in both time and complexity	Yes	The only needed input of respondants is to fill in a questionaire which can be done in 15min. Furthermore, the user is guided through the questionaire with descriptions and definitions.
2. The tool must give an output that gives a clear call to action/opportunities	Yes	The tool present the user with short advice on enablers where the user lacks in compared to industry peers. The advice can be used by the user to implement or change or improve current BDA practices.
3. The tool should be extensively peer checked before implementation	Partially	The tool has been checked through validation and verification, but only with a few industry experts. Ideally, this number would have been greater.
4. The tool should be easy to update by adding new enablers or changing implementation levels	Yes	The matrix that is used for calculation can easily be improved or changed, for example by adding new BDA based enablers.
5. The tool should be translatable for other industries than FMCG	Yes	The tool in relatively generic and can easily be translated to other industries. Only some implementation level descriptions might need to be altered.
6. The tool should be compatible with both quantitative and qualitative input	Yes	A questionnaire can be use to gain quantifiable insights of the compny, however it Is also possible to use interviews for qualitative input which can thereafter be translated in quantatative model input.
7. The tool should take into account industry bias (objectiveness)	Partially	The bias that might occur when a user fill in the questionnaire is partly removed due to the interdepencies taking into account. However, this does not fully remove the industry bias.
8. The tool should provide the ability to compare output with peers	Yes	The tool presents multiple figure of output where the user can see their performance compared to industry average and industry best practice.

Figure 11.2: Verification Requirements KPMG

Requirement	Met?	Explanation
3 | Industry Based		
1. The tool must have a clear and straightforward input	Partially	The questionnaire gives the user the oppertunities to provide implementation levels of different BDA based enablers where the highest and lowest level are predefined. However, the user must imaginate the implementation levels between 1 and 5.
2. The tool must give insights in opportunities or actions	Yes	The tool provided the user with advice on enablers where the company performance is below industry average. This gives an indication of oppertunities and actions.
3. The tool should not require experts to dedicate more than 30 min on the input	Yes	The questionnaire, the only input needed from the user, can be filled in within 15min.
4. The tool should first state clear definitions of all subjects	Yes	The questionnaire begins with comprehensive definitions of the main research subjects.

Figure 11.3: Verification Requirements Industry

11.2 Expert Validation

Validation from expert insights is collected through feedback, discussions and responses from the questionnaire. Feedback was for example provided by a senior consultant and a partner of the supply chain department of KPMG. Furthermore, during a supply chain director event, the topic of BDA based supply chain resilience was discussed and directors had the ability to respond to the questionnaire. The questionnaire also provided insights on feedback, as it finishes with two open questions for respondents to explain their reasoning or feedback. The validation is divided in two sections, general impressions and feedback respectively.

General Impressions

The general impressions on the assessment tool, in specific the questionnaire, were primarily positive. Impressions described that the questionnaire covered most relevant topics. Furthermore, the definitions given at the beginning of the questionnaire were experienced as very helpful, as most respondents have different ideas on the subjects. Overall, the idea and goal of the tool was also clear, giving respondents the indication of what to expect of the results. The methodology was partly validated, since is mainly consists of literature background. However, general impressions were positive and described as useful with clearly defined novelties and implementation purposes.

Feedback

Feedback also consisted of primarily suggestions and improvement points on the questionnaire with additional remarks on the methodology. Main feedback on the questionnaire was the following

1. Supply chain risk management could also be added as an enabler
2. Questions assume BDA implementation, which narrows down the level interpretation
3. No direct correspondence of results

These feedback points are all valuable input, which might improve the interpretation of respondents and increase overall tool results. The supply chain risk management addition was primarily mentioned due to many respondents and supply chain directors being familiar with the topic, as risk management is already incorporated in companies in relation to for example finance. However, the risk management is already encompassed throughout the assessment tool as risk management can be differentiated in for example enablers as scenario modelling. It does give the impression that risk management should be incorporated in one way or another so no questions or uncertainties would occur with respondents. Furthermore, the second feedback point is also valid as the essence is of course to look for BDA based resilience. It is however noted that for especially low implementation level companies, the pre-determined levels might be to vague. This is validated as only companies with low permanents have mentioned this topic. Lastly, no direct correspondence of results is done during testing and validation of the tool. It is however the general idea to have automatic correspondence once the tool is fully functional.

11.3 Validation of Results

Results presented in chapter 10 can also be validated based on the outcomes. These values can be validated through either expert validation session or by comparison with outcomes of the empirical research.

Average Results

For the average results of respondents, the value are in line with findings from the empirical research. This thus indicates that values are relatively reliable. The differences between the expected implementation values and the average values of respondents is presented in Figure 11.4. It indicates that the questionnaire effectively extracts the reliable implementation levels of companies as the average values are relatively inline with expected values based on extensive interviews. Small difference occur, of which the biggest one is related to digital supply chain twin and velocity. These results however do reflect on the high values of the industry better practice.

Enabler	Industry Average	Questionnaire Average	Difference Avg
Agility	2	2,25	11%
Collaboration	2	2,00	0%
Contigency Planning	2	2,88	30%
Digital SC Twin	1	2,00	50%
Disruptions Detection	3	2,38	26%
Flexibility	2	2,13	6%
Knowlegde Management	2	2,38	16%
Predicting Disruptions	1	1,50	33%
Scenario Modelling	2	2,50	20%
Situational Awereness	3	2,63	14%
Transparancy	3	2,75	9%
Velocity	2	3,38	41%
Visibility	4	3,25	23%
Vulnerability Assessment	2	3,00	33%
		Average:	22%

Figure 11.4: Results Validation Average, Absolute Difference

Better Practice

Furthermore, the permanent of the better practice is relative high compared to other respondents. Therefore, a validation session is conducted with the supply chain director responsible for the better practice result. The outcome of the specific questionnaire is presented in Figure 11.5 and are based on the response from a brewing company. The results show that the company scores primarily higher than average, as expected. The biggest differences are noticed with the digital SC twin and scenario modelling. The validation session showed that this is in fact applicable for this company when compared to outcomes from the empirical research. The supply chain director stated that the company had a complete data driven backbone within the organisation, where country based operation had practically 100% digital data twins. The backbone includes the connection with the global SAP system, with integrated cloud solutions. Of course, their are always missing data sets that can still be integrated which primarily consist of external data. Therefore it is reliable to state that the value of 4 for the digital supply chain twin is validated. This is enhanced by the empirical research, as no interviewee stated such implementation levels on data integration. Furthermore, the high level of digital twin also enhanced the capabilities on scenario modelling. It was stated that throughout a week time, multiple scenario algorithms can be runned to determine optimal planing operations. The algorithms are fueled by relative harmonised master data, but are mainly limited by computational power. Only one other company during the empirical research stated to have a comprehensive demand forecast modelling. As this level was thus an exemption, it can be stated that the value of 4 for scenario modelling is adequate. The results from these algorithms can directly be implemented in supply chain operations, including financial impact analysis. This is also in contradiction with empirical results, validating the high level of velocity filled in by the director. Finally, with high levels of organisational data management, other enablers such as transparency and visibility are also enhanced. Additionally, with implemented Azure systems and high levels of dashboarding, the values for descriptive data analytics enablers are also adequate.

Enabler	Company 3	Industry Average	Difference (%)
Agility	2	2,3	88,89%
Collaboration	3	2,0	150,00%
Contigency Planning	3	2,9	104,35%
Digital SC Twin	4	2,0	200,00%
Disruptions Detection	2	2,4	84,21%
Flexibility	2	2,1	94,12%
Knowlegde Management	3	2,4	126,32%
Predicting Disruptions	2	1,5	133,33%
Scenario Modelling	4	2,5	160,00%
Situational Awereness	3	2,6	114,29%
Transparancy	4	2,8	145,45%
Velocity	5	3,4	148,15%
Visibility	4	3,3	123,08%
Vulnerability Assessment	4	3,0	133,33%

Figure 11.5: Industry Better Practice, Relative Difference

Part V

Concluding Chapters

12 | Discussion

12.1 Research Reflection

This research has provided insights on the relation between big data analytics and FMCG supply chain resilience. The relation has been researched both through literature and empirical industry insights. This has proved the bases for a resilience assessment tool, based on BDA resilience enablers. Main conclusions of both the literature and empirical study stated roughly the same, the differences where mainly related to enabler implementation levels. However, the contradiction mentioned during interviews, where it was stated that BDA can also has a negative impact on supply chain resilience, was not comprehensively found in literature. The contradiction stated that with BDA, many supply chain processes are optimised which might decrease resilience enablers such as agility and flexibility. Since optimising supply chain operations, based on costs or lead times, primarily creates less room for changes and specifies many operations in advance. Furthermore, a general note on results defines the literature writing more from the 'what is possible' point of view, while the industry mentions primarily 'why not (yet) possible'. This translates to the enablers where most companies only provide small implementations on mainly reactive resilience and descriptive BDA. It is also inline with the challenges that the industry faces concerning the characteristics of big data and the organisational inquiries still needed to effectively implement BDA based resilience.

Results

The results of the assessment tool indicate high levels of usefulness and relative good reliability. With the average values of respondents being inline with findings of the empirical research, the tool presents an effective way to quickly benchmark companies. However, the better practice is still very dependent on unique cases. As stated by Guest, Bunce, and Johnson 2006, the number of respondents are almost enough to effectively state average values. This is however not the case with the calculation and background of the better practice. Even though the better practice has been validated, it may not represent the actual industry better practice as this is very difficult to find with only around 8 respondents. Since the better practice is unique and relatively differs from most other respondents, it is difficult to state that the current better practice also reflects the actual industry. Furthermore, the results indicate that maturity on BDA based supply chain analytics is relatively low. Most companies only intend on effective strategies relating to descriptive analytics and reactive resilience. This is also inline with the findings of the empirical research, where the lack of high implementation levels is related to the vast quantity of data and organisational challenges. Additionally, comments and feedback on the tool were recognised and may be incorporated in future assessment tool iterations. First of all with the focus on risk management. Secondly, and of higher importance, using the tool output to also give respondents direct reaction on their outcomes. This is however still difficult, as the becnhmarking tool only works with higher quantities of respondents.

Company Based Results

An interesting discussion is also possible on the results based on the which company filled in the questionnaire. Unfortunately, not all respondents actually represent the FMCG industry, most important contribution are from Heineken, Refresco, Online Mealkit Retailer and Brosper. The industry better practice, Heineken, shows a significant high permanent value. The logic behind the results can be interpreted in two ways. First, Heineken is a very large global company, with prosperous results and high possibilities for investments, given the ability to also invest in BDA and its relation to resilience. On the other side, sometimes global and older companies can be more conservative and may have difficulties in their digitisation and adaptation of industry 4.0. This is more the case with Refresco and Brosper, although by far not as old as Heineken, the companies have difficulties in implementing BDA capabilities. Furthermore, young companies with a high and direct digital integration are more advanced in their BDA capabilities. This can be seen with the Online Mealkit Retailer, a presumably young company that relies on online sales. Thus it has a great need in digital solutions and more easily converts to BDA implementation. As for the other companeis, they are more difficult to compare due to the differences in industry. It may however be argued that companies like Philips and Action are closely related to the FMCG industry, with also highly dynamic supply chains, but without perishable goods.

12.2 Implications

This research has provided comprehensive insights in the BDA based enablers that can enhance supply chain resilience within the FMCG industry. It builds forth on the literature gaps mentioned by a variety of academic papers. As stated in the problem definition in section 1.2, three main papers where found on the subject of quantitative or I4.0 based supply chain resilience enablers. Spieske and Birkel 2021 stated the need of more empirical background on the subject between I4.0 and resilience, where this research has decreased the gap concerning the implementation of BDA. It has provided clear empirical industry insights that improve the quality of the conclusion and better defines the relation of differences between literature and the FMCG industry. Furthermore, literature gaps are also found on quantitative approaches on decision making models for resilience (Madhavi and Wickramarachchi 2021, Spieske and Birkel 2021). This is not entirely addressed within the scope of this research, however, the assessment tool does provide a quantitative outcome for resilience. The outcome can be used by decision makers to improve specific resilience enablers.

Furthermore, the layout and methodology of the assessment tool also provides the ability to apply the tool to other potential subjects. For example, a BDA based enabler assessment tool can also be designed for the relation between BDA and sustainability or operational excellence. The methodology would relatively be the same, except for the change in the types of BDA enablers. This would greatly increase academic knowledge on input based assessment tools for different subjects, especially sustainability where there is also a lack of input based assessment tools (Singh et al. 2009). The relation between BDA and supply chain sustainability is for example already researched (Shokouhyar, Seddigh, and Panahifar 2020), giving an extensive basis for a potential assessment tool.

Practical (KPMG/Industry)
On a practical side, this research has provided KPMG Advisory with an assessment tool that can be used as a starting point with new or existing clients. As the tool enables benchmarking, discussions can quickly evolve from the outcome if a client fills out the tool. This gives KPMG the ability to clearly state the resilience enablers where effective

consulting can improve client operations. This ensures effectiveness of the tool and gives KPMG the opportunity to increase and improve business projects. However, the tool does consist of two different main elements, BDA and supply chain resilience. Therefore it is important that projects or discussions that evolve from the tool should be done in cooperation with both the Supply Chain & Procurement and the Data & Analytics department within KPMG Advisory. This would ensure that the client is given valid and comprehensive consult on the broad subject. Furthermore, with long lasting KPMG clients, the assessment tool can be performed on for example yearly bases which would also give clients the insights on the improvement of the subject during a specific time frame. It is an important opportunity as benchmarking the same company over a certain time period would also show the effectiveness of consulting if implementation levels are improved. In general, the usability of the tool for KPMG is thus versatile. The usability for the industry itself is less straightforward, as the tool needs of course to be processed by a company like KPMG. However the tool does create awareness within the industry and encourages companies to further improve on the BDA capabilities in order to increase their resilience. This was also shown during the supply chain directors event, where discussions on the subject and the tool increased their awareness and knowledge of the industry.

12.3 Limitations

Methodology

The methodology used for the assessment tool is academically verified, however there are potential limitations concerning the chosen enablers and interdependencies. The enablers are based on both the literature review and industry insights, but might still lack on some less known or used enablers. These have been intentionally left out of the tool, but could be added for a more comprehensive overview. Furthermore, the interdependencies have a lack of academic substantiation and are mainly based on expert discussions. This decreases reliability of the interdependencies and therefore also the outcome of the benchmarks.

Objectiveness

The objectiveness of the results is also difficult to validate, due to the difference in background of respondents. There might be differences in the outcome of the assessment tool for respondents from the same company but with different functions. This is a limitation to the research as it can only be fully understood when the results of a large quantity of respondents is analysed. It would give more insights on the differences in tool outcomes based on the input of specific respondent groups. For the conclusions of this research, the low amount of actual respondents thus decreases the reliability of the outcomes since they might need to be normalised for specific function groups. However, the general validity of the assessment tool is sufficient as it is both based on literature and expert validation. Furthermore, the assessment tool gives broad strategic level insights for companies, which complies with the objective of this research. However, the BDA enablers used in the tool are all broad subjects which also leaves room for further differentiation in interpretations.

Empirical Industry Insights

Limitations arise when related to the empirical research consisting of 10 expert interviews. The interviews where conducted with both experts from the subject of BDA as well as the subject of supply chain resilience, which are both very different departments within a company. This gives a relative high heterogeneous sample size, also due to the semi-structured nature that gave room for a broad variety of topics with the scope of the research. Therefore, the validation and reliability of the expert interviews might be doubtful. According to Guest, Bunce, and Johnson 2006, a quantity of twelve interviews would give saturation on input and therefore be reliable enough if the sample is relatively homogeneous. Additionally, meta-themes are mostly already found after only six interviews. The number of interviews used in this research would thus be on the low side of what is recommended, being just short of twelve interviews and with a more heterogeneous sample. However it is debatable that the feedback sessions and internal KPMG department discussions have generated the sufficient addition of expert input to create reliability.

Practical

The assessment tool is relatively easily applicable for KPMG to use with supply chain clients. The questionnaire enables efficient tool input, instead of long individual interviews with respondents. The input side is thus relatively easy in terms of practical implementation. However, this does not count for the output side due to the matrix permanent calculation. The permanent calculation for this research has mainly been done through a online web based calculator, which gives the permanent for any given matrix. This is however difficult to implement on a large scale, or when the output of the tool would need to be automated, with automation being that the respondent would get an instant e-mail with the tool outcomes. For the automation of the tool, a web application would need to be build where the matrix permanent is internally calculated. Such application is however far out of scope for the current research, but might be of importance if the tool would be implemented on a large scale.

13 | Conclusion & Recommendations

This research has provided insights on the relation between big data analytics (BDA) and supply chain resilience. Furthermore, it has presented an assessment tool for BDA based partial supply chain resilience that is tested within the FMCG industry.

Big Data Analytics and Supply Chain Resilience
The first part consists of a literature research and an empirical study in order to address the following main question:

'How does big data analytics relate to supply chain resilience?'

The question is answered by four sub questions for the literature research and conclusions formed from the industry insights.

<u>Literature</u>

1. *What is the state-of-the-art in FMCG supply chain resilience?*
   The state of the art of supply chain resilience currently lies in a vast variety of resilience enablers that can be used to improve resilience strategies. The enablers are categorised in either proactive, concurrent or reactive strategies and can be for example supply chain visibility, transparency or agility. These strategies also define the period of time in which it can be implemented compared to a disruption, these are pre-, during and post disruption respectively. Each indicator currently has a more traditional supply chain background with a lack of implementation based on developments of the fourth industrial revolution. The supply chains are changing and therefore the state of the art resilience enablers are also increasingly related to new technologies such as artificial intelligence, internet of things or big data analytics.

2. *What does big data analytics in supply chains consist of?*
   BDA is a broad subject that is defined by the technologies and methodologies used to analyse data in order to create insights or as an input for models and algorithms. Within supply chains, three main categories of BDA can be addressed: predictive, descriptive and prescriptive. Each category has a different effect on supply chain operations. Predictive analytics are mainly based on forecasting by using models ranging from regression to complicated machine learning algorithms. Descriptive analytics are the most used category of BDA within supply chains, as it compels the ability to visualise real-time supply chain operations. Finally, prescriptive analytics are primarily based on optimising supply chain operations through big data based models and algorithms.

3. *How does big data analytics relate to SC resilience?*
   BDA relates to supply chain resilience through a number of general resilience enablers that are fueled by BDA. These enablers thus only partially define the complete capabilities of supply chain resilience. 16 enablers are found where BDA increases the effectiveness or impact of the enabler in relation to resilience. These enablers are Agility, Collaboration, Contingency Planning, Digital SC Twin, Disruptions Detection, Early Warning Systems, Flexibility, Knowledge Management, New Skill Devel-

opment, Predicting Disruptions, Scenario Modelling, Situational Awareness, Transparency, Velocity, Visibility and Vulnerability Assessment. Each enabler lies on a specific boundary between a BDA category and a supply chain resilience strategy, as defined in Figure 8.4.

4. *How can supply chain resilience be assessed?*
   Resilience within supply chains can be assessed through mainly three types of assessment. First, formulas presenting KPI's based on output parameters can be used. These are for example KPI's on supply chain performance based on the resilience triangle. Second, supply chain simulations can be made to compare different scenarios in order to evaluate the difference between theoretical and actual supply chain performance. Third, KPI's can also be calculated based on enabling technologies. Thus not looking at the output of the supply chain, but at the enabling input implementation levels as assessment criteria. The third type of assessment is used within this research to design an assessment tool as it well fits the purpose of designing an assessment tool based on BDA enablers.

<u>Empirical Industry Insights</u>
An empirical study was performed with over 10 supply chain experts, ranging from both supply chain and BDA based function backgrounds. Furthermore, round table conversations with multiple supply chain directors were held during an event, discussing the main subject of this research. Outcomes focused on three subjects: background information on supply chain disruptions, identifying and comparing the relation between BDA and supply chain resilience with respect to the literature research and finally insights on challenges corresponding to BDA based resilience.

1. *Supply chain disruptions*
   Major supply chain disruptions have been identified during expert interviews that can be categorised in three area's: transport, supply and demand. Examples of these disruptions are closed ports, product recalls and demand spikes respectively. These disruptions are defined by low probability and high impact, generating massive financial and operational supply chain issues.

2. *Big data analytics based supply chain resilience*
   Supply chain experts stated that big data is already available for most companies, however, there is a general lack of implementation concerning BDA. BDA enablers found in literature are acknowledged but are mainly stated to be enablers for future implementation. From the 16 enablers found in literature, only two were not acknowledged: Early Warning Systems and New Skill Development. Descriptive analytics had the highest implementation levels concerning supply chain resilience, where most companies stated to have insights through BI-tooling and dashboards. For predictive and prescriptive analytics, responses where very mixed and major differences where found in implementation levels. However, these were primarily based on specific examples. The statements on maturity of BDA within the companies also reflects to the resilience strategies used. The biggest strategy to contribute to resilience was reactive, with the general relation towards descriptive analytics. To conclude, importance of BDA based resilience was acknowledged, with high levels of big data already present. However, the use of big data is generally limited to descriptive analytics due to multiple data and organisational related challenges.

3. *Challenges*
   Lack of BDA implementation within the industry is mainly due to the vast data and

organisational related challenges, similar to the challenges stated in literature. These mainly concern the alignment of big data through master data management or due to the lack of knowledge and personnel.

In conclusion, the literature research provided valuable insights on the theoretical BDA enablers for supply chain resilience and assessment approaches that can be used. Additionally, the empirical study showed background on disruptions and actual business implementation levels of the found theoretical BDA enablers. Comparisons between the literature and empirical study have shown that there are differences between both the BDA enablers as well as the corresponding implementation levels. The combination of both studies, being the 14 acknowledged enablers, are used as the input for the design of the BDA based partial supply chain resilience assessment tool.

Partial Resilience Assessment Tool
A BDA based partial supply chain resilience assessment tool has been presented that defines partial resilience through BDA enablers implementation and interdependence levels. The goal of the design was the following:

'Designing an assessment tool that helps FMCG companies to create insights on their BDA based supply chain resilience and enable the ability to benchmark with the industry.'

The tool uses a matrix permanent to calculate a single metric value which gives the ability to effectively compare and benchmark results.

1. *Design*
   The design of the partial resilience assessment tool is based on requirements from literature, KPMG and the industry. The requirements result in a comprehensive design that includes 14 BDA based enablers for supply chain resilience. These enablers are translated to interdependencies and enabler implementation levels. The interdependencies are based on the empirical and literature research, but with a final quantification assessed by the author due to the large quantity of 91 interdependencies. The implementation levels are acquired through a questionnaire filled in by respondents from the industry. With both sets of values, the resilience characteristic matrix is created which enables the calculation of the matrix permanent. The matrix permanent serves as a comparison metric that can be used to benchmark companies. Additionally, the unique implementation levels are individually compared to the industry average and better practice.

2. *Results*
   Results of the assessment tool are based on 8 respondents and show promising insights on the usefulness of the tool. The calculated matrix permanents of each respondent is normalised on an exponential fitted line through the theoretical matrix permanent minimum and optimum. This creates the benchmarking scale where the average of the respondents partial supply chain resilience is around 48% of the theoretical optimum, while lowest assessed partial resilience was 38%. Furthermore, the best performing company and thus the industry better practice currently stands at 66%.

3. *Validation*
   Validation and verification of the assessment tool firstly focus on the validation of the requirements. Most requirements are met, with only 3/16 being partially met. Secondly, the general impression and feedback from experts showed positive insights,

with some relevant suggestions on for example risk management. Thirdly, validation of the results showed that the average results are relatively in line with the expected values from the empirical research. However, the industry better practice differs from the expected value, but is validated through a discussion session with the respondent. Due to the small heterogeneous sample of respondents, concluding remarks on the industry better practice are difficult to state, but average values are reliable and reflect the actual business.

In conclusion, a comprehensive partial resilience assessment tool based on big data analytics enablers is designed. The design is based on both a literature and empirical industry research and mainly relies on the calculation of matrix permanents. Results are promising and show insights in industry implementation levels and ensures companies the ability to benchmark against industry average en better practice. The tool is validated and verified, but still provides challenges for optimal industry implementation.

13.1 Recommendations

A few recommendations are given, based on the conclusion and limitations discussed in section 12.3. The recommendations may improve overall reliability and effectiveness of the assessment tool.

1. **Tool Methodology**
   It is recommended to further analyse the interdependencies of the BDA resilience enablers which would increase the reliability of the assessment tool. As the interdependencies are currently partly based on the author's assessment and might need to be further tailored for specific purposes of implementation.

2. **Tool Objectiveness**
   The objectiveness of the assessment tool would be enhanced if the sample size of respondents for the questionnaire is increased to either a large (100+) heterogeneous sample, or a smaller homogeneous sample. This would ensure that relations between responses and function backgrounds can be analysed for further improvements on the assessment tool, or for enhanced insights.

3. **Different Subject Application**
   The current design of the assessment tool may also be of use for other relations between subjects, for example the design could also be applied to the relation of sustainability and resilience for a specific industry. It is therefore recommended to further implement the assessment tool related to other subjects to further test and validate the tool with new subject tailored enablers or interdependencies.

4. **Practical**
   This recommendation is purely for the ideal state, and improves the easiness for implementing the assessment tool. It is recommended that an online web application is made where the questionnaire and output is integrated. This gives a respondent the ability to directly see the tool outcomes and thus their benchmark and resilience potential. Furthermore, this could also be integrated in a online dashboard, where direct filters can be applied on the results for the different function backgrounds or companies. It would greatly enhance the effectiveness and usability of the tool.

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Appendices

A | Thesis Paper

The Assessment of Big Data Analytics Based Supply Chain Resilience

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***Abstract*: Big data analytics (BDA) and supply chain resilience are both present and important topics, but research on the relation between the subjects is limited. This also holds for the translation of the subject for a specific industry. This research therefore addresses this relation and translates it to a comprehensive partial resilience assessment tool that provides a benchmark for the Fast Moving Consumer Goods (FMCG) industry. The tool is based on a deterministic model that incorporated 14 resilience enablers and their corresponding interdependence. Results show that current industry BDA based resilience levels are, compared to a theoretical optimum, on average 48% and have a better practice of 66%. It is recommended that the tool is further implemented within the industry to gain more reliable and substantiated results.**

***Keywords*—** Supply Chain Resilience, Big Data Analytics, FMCG, Resilience Assessment Tool

1 Introduction

With the past years overshadowed by the Covid crisis, many global supply chains have endured extensive disruptions. The disruptions are fueled by the crisis and are characterised by for example closed ports and demand/supply misalignments. These disruptions have greatly impacted supply chains on both financial and operational levels (Katsaliaki et al. (2021)). This is also confirmed by the insights of KPMG Advisory, a global consulting firm that collaborates with this research through their Dutch Supply Chain & Procurement department. Consequently, this has (re)-opened the discussion on supply chain resilience in order to counter the various impacts that these events bring. Resilience is a comprehensive subject that, within supply chains, encompasses of the abilities to prepare, respond or recover from disruptive events (Ali et al. (2017)). It is influenced by many different developments and technologies, especially when related to Industry 4.0 over the past decade. This has been researched in various ways, both considering positive and negative influence, (Ralston & Blackhurst (2020), Spieske & Birkel (2021)). In specific, Big Data Analytics (BDA) has gained more interest of both the industry and literature and is one of the more developed I4.0 technologies. BDA can be defined as any big data that is generated throughout the supply chain and is accessible through for example data warehouses, excel etc. and is used to either create insights or as input for models/algorithms. The interest in the subject especially holds for the Fast Moving Consumer Goods (FMCG) industry, where vast quantities and varieties of dynamic data are generated which increases the need for adequate solutions. While the subjects of supply chains and BDA have been extensively researched (Nguyen et al. (2018)), the specified impact of BDA on resilience still lacks in comprehensive academic substantiation. Furthermore, the translation of the related subjects to the FMCG industry has not yet been proposed. Therefore, this research has two main objectives. First, an extensive literature and empirical research answers the question of 'How does BDA relate to supply chain resilience?'. Second, based on the previous results, a comprehensive assessment tool is designed that helps FMCG companies to create insights on their BDA based supply chain resilience and enables the ability to benchmark with the industry. The assessment tool is primarily based on a deterministic model from (Soni et al. (2014)) that uses resilience enablers and their corresponding interdependencies to calculate company based benchmark metrics. The tool thus only assesses the partial resilience contribution that is based on BDA. However, due to relative high developments on BDA, the impact on resilience is assumed to be higher than for other technologies of industry 4.0. Subsequently, the tool is tested and validated by eight respondents holding key positions within the industry.

This paper addresses both the objectives in the following structure. First, the literature reviews is addressed in section 2. Second, an empirical study is presented in section 3 that partly reflects on the literature findings. Third, the assessment tool is discussed in section 4 with the corresponding academic background and methodology. Fourth, the results of the tool are discussed and validated in section 6. Finally, the paper ends with the conclusions and recommendations in section 7.

2 Literature Review

The literature review for this research consists of two main elements. First, an understanding of the background on supply chain resilience and big data analytics is discussed. Second, resilience enablers that have a foundation in BDA are presented.

2.1 Supply Chain Resilience

Supply chain resilience is a extensively researched topic with a large variety of definitions and applications. Most definitions aim at defining resilience through the ability to recover from disruptions (Jüttner & Maklan (2011)) and thus focusing on the post-disruption phase. More comprehensive explanations can be found when both the pre-, during and post-disruption phases are combined. For example, Hohenstein et al. (2015) combines resilience through the ability to prepare, respond and recover. An addition to the definition, although arguably less related to resilience, is the ability to also learn from disruptions and thereby improve supply chain operations (Ribeiro & Barbosa-Povoa (2018)). With all the extensive and different definitions and substantiations of resilience, it is best to chose a comprehensive variant which may easily be related to big data analytics. Therefore, the supply chain resilience framework of Ali et al. (2017) is used as a guideline in identifying current resilience practices, element and abilities. The framework defines supply chain resilience through both the state of time in relation to the disruptions and the strategic definition to cope with the disruptions. This is stated by the disruption phases of pre-, during and post disruption and the strategies of proactive, concurrent and reactive. The elements discussed are for example visibility and agility together with practices like vulnerability assessment and form the base in order to relate BDA to resilience.

2.2 Big Data Analytics

The subject of big data analytics (BDA) is increasing in importance and demand through the digitisation of global supply chains. This is amplified by the fourth industrial revolution, which not only accelerates digitisation, but also enables new data driven technologies such as Radio-frequency identification Bottani et al. (2010). These technologies generate big data and can in turn be analysed for insights or used as input for models and algorithms. While the specific definition of big data is vague, general agreement within literature is that the data should reflect on the five major characteristics: volume, variety, velocity, veracity, and value (Fosso Wamba et al. (2015)). When such data is effectively used through analytics, it can greatly enhance supply chain operations. Either generally by improving business KPI's (Raman et al. (2018) or by helping to make more substantiated critical decisions (Spieske & Birkel (2021)). Therefore BDA should not only be seen as an process but more as a strategic asset of a organisation's supply chain (Varela Rozados & Tjahjono (2014)). In order to fully combine the insights of supply chain resilience and BDA, the main pillars of BDA are identified. These are categorised by predictive, descriptive and prescriptive analytics (Nguyen et al. (2018)).

2.3 Big Data Analytics Based Resilience

Both subjects previously discussed are well mentioned within literature, however the connection between the subjects is often limited. The connection is either researched on a large scale, by relating Industry 4.0 to resilience (Spieske & Birkel (2021)) or by addressing a specific relation through for example quantitative decision making models (Ribeiro & Barbosa-Povoa (2018), Madhavi & Wickramarachchi (2021)). Therefore a literature gap is found surrounding the specific relation between BDA and supply chain resilience. To address this literature gap, the relation is analysed by finding different enablers that lie on the intersection between a BDA category (predictive, descriptive and prescriptive) and a resilience strategy (proactive, concurrent and reactive). Through a literature review, academic papers are identified that discuss enablers that lie on this mentioned intersection. The background papers are presented in Table 1. The table gives an overview of enablers that are used to compare with empirical findings. An enabler is a umbrella term for the different elements, practices/techniques and abilities/capabilities discussed in Ali et al. (2017). The decision is made to combine these subject under the term of enabler since it enhances the ability to effectively address interdependence between the enablers. For example,

Table 1: Overview of BDA based resilience enablers

Resilience Enabler	Supporting Literature of Relation to BDA
Proactive	
Transparency / Visibility	Ramirez-Peña et al. 2020, Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Predicting disruptions	Kara, Fırat, and Ghadge 2020, Bag, Gupta, and Wood 2020
Early warning systems	Kara, Fırat, and Ghadge 2020, Dubey, Gunasekaran, Childe, et al. 2021
Disruption Detection	Kara, Fırat, and Ghadge 2020, Ivanov and Dolgui 2021
Scenario Modelling	Ivanov and Dolgui 2021
SC Vulnerability Assessment	Ramirez-Peña et al. 2020, Kara, Fırat, and Ghadge 2020
Concurrent	
Transparency / Visibility	Ramirez-Peña et al. 2020, Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Velocity / Agility	Zouari, Ruel, and Viale 2020, Kahiluoto, Mäkinen, and Kaseva 2020, Dubey, Gunasekaran, and Childe 2019
Digital SC Twin	Dubey, Gunasekaran, Childe, et al. 2021, Ivanov and Dolgui 2021
Organisational flexibility	Dubey, Gunasekaran, Childe, et al. 2021
Flexibility	Dubey, Gunasekaran, and Childe 2019, Hosseini, Ivanov, and Dolgui 2019
Collaboration	Chae 2015, Hosseini, Ivanov, and Dolgui 2019
Reactive	
Identification of risk relationships	Kara, Fırat, and Ghadge 2020
New skill developments	Ralston and Blackhurst 2020
Scenario Modelling	Ivanov and Dolgui 2021

an ability has high interdependence based on practices. In total, 16 enablers are found that have a BDA based foundation for resilience. Some enablers such as visibility are versatile and therefore correspond to multiple strategies.

2.4 Resilience Assessment

The final part of the literature reviews is aimed at the background of resilience assessment. Different methodologies are briefly discussed and an explanation is given on the final chosen methodology for this research. Main findings showed that assessment of resilience can be done through three main options. First, resilience can be assessed by calculating different KPIs such as the time is take for a supply chain to return to its steady state (Tierney & Bruneau (2007)). Second, supply chains can be simulated to effectively compare scenarios related to disruptions (Ivanov & Dolgui (2021)). Third, it is also possible to determine resilience by assessing the implementation levels of enablers. This gives an indication of how resilient a supply chain is based on the organisational maturity of resilience related to BDA. Both the first and second assessment methodology do not fit this research due to difficulties in effectively comparing companies and since simulation is not generically applicable on multiple companies. Therefore, the choice was made to lay the foundation of the assessment tool methodology on the deterministic model of Soni et al. (2014). The paper describes an assessment form where resilience enablers and their interdependence are used to calculate a single metric to represent resilience.

3 Empirical Study

The empirical study serves two purposes: First, gaining background knowledge on recent disruptive events. Second, comparing literature results with knowledge from industry experts. The empirical study consisted of interviews with either supply chain of data analytics experts from KPMG or from FMCG companies. In total, 10 interviews were held, with various additional discussions with the KPMG Supply Chain and Procurement department and round table discussions during a Dutch Supply Chain Directors event. Although just below the recommended 12 interviews for saturated results (Guest et al. (2006)), it is argued that with the additional discussions the saturation is still achieved.

As this research focuses on the subject of supply chain resilience, it is important to first fully understand to which events resilience is needed. From the empirical study, it became evident that disruptions are categorised by either transportation, supply or demand. With transportation, the main disruptions are caused by closed routes through for example closed ports or the blockade of the Suez Canal. However, as a results of the Covid crisis, the most important transportation disruption mentioned were the extremely high container prices, making it difficult to cost effectively transport goods. On the supply and demand side, the misalignment of the two subjects was primarily mentioned. The misalignment is caused by for example demand spikes due to hoarding or bad (global) harvests of consumables. Furthermore, new product launches can be very disruptive for both entire industries, also effecting the actual company that launches the product. Similarly on the supply side, product recalls due to endangerment are also experienced as highly disruptive.

With the background on disruptions, the empirical research follows by asking the interviewees how they deal with such disruptions and if and how BDA helps. These findings are related to the enablers found in literature, in order to tailor the enablers to the industry accordingly. The 16 enablers found in the literature research where mostly acknowledged by the interviewees. Only the enablers of early warning systems, new skill development and identification of risk relationships were found to be currently irrelevant for the industry. In addition, the enabler of 'knowledge management' was identified as an use full contribution. Other enablers such as visibility and collaboration had considerable acknowledgements, often with comprehensive examples of BDA integration. However, in general the overall implementation of BDA to improve resilience enablers was low. Naturally, proactive resilience was the only strategy were predictive analytics were used. With external data from for example port information, companies are able to predict situations to a certain extent. Descriptive analytics were found to be of use for all resilience strategies, with especially strong impact on supply chain visibility. This was the enabler with the highest mentioned implementation levels, due to BI-tooling capabilities ensuring clear and visible data driven dashboards of supply chain operations. Finally, prescriptive analytics were seen as the most difficult to implement since it concerns more elaborate models. Although some companies stated implementations on big data driven forecasting models, most where still lacking in maturity and therefore had low implementation levels of enablers such as scenario modelling and digital supply chain twins. Additionally, it is also argued that the optimisation of supply chain operations though prescriptive analytics could also decrease resilience. Since higher optimised and efficient operations leave less room for change and therefore weaken enablers such as agility and flexibility.

Overall, when combining the findings from literature and the empirical study, 14 enablers are found and acknowledged to be of high importance. These enablers are used as an input for the partial supply chain resilience assessment tool and have a foundation with BDA. The final enablers are: Agility, Collaboration, Contingency Planning, Digital SC Twin, Disruptions Detection, Flexibility, Knowledge Management, Predicting Disruptions, Scenario Modelling, Situational Awareness, Transparency, Velocity, Visibility and Vulnerability Assessment.

4 Methodology

Both the literature and empirical study have given clear BDA based resilience enablers. These enablers are used as an input for the partial resilience assessment tool, which gives FMCG companies the ability to benchmark their resilience against industry average and better practice. This research will focus on methodology of (Soni et al. (2014)) but with the novelty of translating the results to a benchmark scale. Furthermore, specific research on BDA based enablers ensures academic contribution towards further enhancing such method. The methodology of the tool is therefore based on both enabler implementation and interdependence levels and combines it towards a comprehensive metric.

4.1 Process

The BDA based resilience enablers, combined with general findings from literature and empirical research, are used as an input for the assessment tool. The tool also has a foundation through requirements stated by both KPMG en industry representatives, this ensures that parts of the tool are more tailored with respect to respondents or results. The complete methodology of the tool in described below.

1. *Stating the Enablers*
   There are 14 BDA based resilience enablers found during the combined literature and empirical study, these are: Agility, Collaboration, Contingency Planning, Digital SC Twin, Disruptions Detection, Flexibility, Knowledge Management, Predicting Disruptions, Scenario Modelling, Situational Awareness, Transparency, Velocity, Visibility and Vulnerability Assessment. The enablers are addressed as N_i for $i \in Enablers$ respectively.

2. *Interdependence*
   The interdependence between enablers is based on the combined literature and empirical research. Due to the large amount of possible interdependencies (91), the specific interdependence is assessed by the author for efficiency, taking into account the indications given during interviews. The interdependencies are visualised in a di-graph representation and are translated to a structural self interaction matrix (SSIM) (Table 2). The SSIM shows the different interdependencies according to the legend described below.

Table 2: SSIM Matrix

		N_{14}	N_{13}	N_{12}	N_{11}	N_{10}	N_9	N_8	N_7	N_6	N_5	N_4	N_3	N_2	N_1
N_1	Agility	O	A	O	A	O	A	O	A	O	O	A	A	A	-
N_2	Collaboration	V	A	V	A	O	O	O	O	V	O	O	O	-	-
N_3	Contingency Planning	O	O	V	O	O	A	O	A	O	O	O	-	-	-
N_4	Digital SC Twin	V	X	O	V	O	V	O	O	O	O	-	-	-	-
N_5	Disruptions Detection	O	X	V	O	V	O	O	O	O	-	-	-	-	-
N_6	Flexibility	A	A	V	A	A	A	O	O	-	-	-	-	-	-
N_7	Knowledge Management	O	A	O	O	O	A	O	-	-	-	-	-	-	-
N_8	Predicting Disruptions	O	A	O	O	X	O	-	-	-	-	-	-	-	-
N_9	Scenario Modelling	V	A	V	O	V	-	-	-	-	-	-	-	-	-
N_{10}	Situational Awareness	A	A	O	O	-	-	-	-	-	-	-	-	-	-
N_{11}	Transparency	O	X	V	-	-	-	-	-	-	-	-	-	-	-
N_{12}	Velocity	A	A	-	-	-	-	-	-	-	-	-	-	-	-
N_{13}	Visibility	V	-	-	-	-	-	-	-	-	-	-	-	-	-
N_{14}	Vulnerability Assessment	-	-	-	-	-	-	-	-	-	-	-	-	-	-

- V | Enabler i influences enablers j
- A | Enabler j influences enablers i
- X | Enablers i and j influence each other
- O | Enablers i and j are unrelated

3. *Matrix Representation*
The results from the SSIM can be transposed into a regular matrix representation. The matrix presents both the enabler implementation levels (N_i for $i \in Enablers$) on the diagonal and the interdependencies (N_{ij} for $i, j \in Enablers$) on the off-diagonals.

$$\begin{bmatrix}
N_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
N_{2,1} & N_2 & 0 & 0 & 0 & N_{2,6} & 0 & 0 & 0 & 0 & 0 & N_{2,12} & 0 & N_{2,14} \\
N_{3,1} & 0 & N_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{3,12} & 0 & 0 \\
N_{4,1} & 0 & 0 & N_4 & 0 & 0 & 0 & 0 & N_{4,9} & 0 & N_{4,11} & 0 & N_{4,13} & N_{4,14} \\
0 & 0 & 0 & 0 & N_5 & 0 & 0 & 0 & 0 & N_{5,10} & 0 & N_{5,12} & N_{5,13} & 0 \\
0 & 0 & 0 & 0 & 0 & N_6 & 0 & 0 & 0 & 0 & 0 & N_{6,12} & 0 & 0 \\
N_{7,1} & 0 & N_{7,3} & 0 & 0 & 0 & N_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & N_8 & 0 & N_{8,10} & 0 & 0 & 0 & 0 \\
N_{9,1} & 0 & N_{9,3} & 0 & 0 & N_{9,6} & 0 & 0 & N_9 & N_{9,10} & 0 & N_{9,12} & 0 & N_{9,14} \\
0 & 0 & 0 & 0 & 0 & N_{10,6} & N_{10,7} & N_{10,8} & 0 & N_{10} & 0 & 0 & 0 & 0 \\
N_{11,1} & N_{11,2} & 0 & 0 & 0 & N_{11,6} & 0 & 0 & 0 & 0 & N_{11} & N_{11,12} & N_{11,13} & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{12} & 0 & 0 \\
N_{13,1} & N_{13,2} & 0 & N_{13,4} & N_{13,5} & N_{13,6} & N_{13,7} & N_{13,8} & N_{13,9} & N_{13,10} & N_{13,11} & 0 & N_{13} & N_{13,14} \\
0 & 0 & 0 & 0 & 0 & N_{14,6} & 0 & 0 & 0 & N_{14,10} & 0 & N_{14,12} & 0 & N_{14}
\end{bmatrix} \tag{1}$$

4. *Quantification of N_{ij}*
Research by Soni et al. (2014) suggest to assess interdependence through a comprehensive expert questionnaire, asking to quantify all interdependencies. However, due to the large amount of interdependencies (91) and taking into account to number of interviewees and scarce time available, it was chosen to quantify the interdependencies by the authors assessment. This assessment is however based on the findings from both the literature and empirical study. This gives the following matrix.

$$\begin{bmatrix}
N_1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
3 & N_2 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 2 \\
5 & 0 & N_3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 0 \\
4 & 0 & 0 & N_4 & 0 & 0 & 0 & 0 & 4 & 0 & 3 & 0 & 4 & 3 \\
0 & 0 & 0 & 0 & N_5 & 0 & 0 & 0 & 0 & 3 & 0 & 3 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & N_6 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\
1 & 0 & 2 & 0 & 0 & 0 & N_7 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & N_8 & 0 & 2 & 0 & 0 & 0 & 0 \\
3 & 0 & 4 & 0 & 0 & 2 & 0 & 0 & N_9 & 2 & 0 & 3 & 0 & 4 \\
0 & 0 & 0 & 0 & 0 & 1 & 3 & 2 & 0 & N_{10} & 0 & 0 & 0 & 0 \\
3 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & N_{11} & 3 & 2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & N_{12} & 0 & 0 \\
5 & 3 & 0 & 2 & 4 & 5 & 3 & 5 & 5 & 4 & 5 & 0 & N_{13} & 3 \\
0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 2 & 0 & 2 & 0 & N_{14}
\end{bmatrix} \tag{2}$$

5. *Quantification of N_i*
The quantification of N_i represents the implementation levels for each of the 14 enablers for a specific company. In order to effectively acquire such implementation levels, a questionnaire is set up to identify the levels for a company. The questionnaire mainly consist of 14 questions where the lowest (1) and highest (5) levels of an enabler are predefined. The respondent then needs to address at which level between one and five their company is concerning the enabler. This gives a clear view on their implementation levels and is used as a final input for the diagonal entries of the matrix.

6. *Permanent Calculation*
With all matrix entries known, the matrix permanent is calculated in order to convert the matrix values to a single metric value. The matrix permanent is a polynomial of matrix entries, similar to the determinant but with only positive elements. For the theoretical minimum (1.75×10^2) and optimal (1.40×10^{10}) values, the diagonal of the matrix consists of only ones or fives respectively. These values help to put the results on the industry average and better practice in perspective.

$$perm \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
3 & 4 & 0 & 0 & 0 & 4 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 2 \\
5 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 0 \\
4 & 0 & 0 & 5 & 0 & 0 & 0 & 0 & 4 & 0 & 3 & 0 & 4 & 3 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 & 0 & 3 & 0 & 3 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 4 & 0 & 0 \\
1 & 0 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 5 & 0 & 2 & 0 & 0 & 0 & 0 \\
3 & 0 & 4 & 0 & 0 & 2 & 0 & 0 & 3 & 2 & 0 & 3 & 0 & 4 \\
0 & 0 & 0 & 0 & 0 & 1 & 3 & 2 & 0 & 2 & 0 & 0 & 0 & 0 \\
3 & 2 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 0 & 4 & 3 & 2 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\
5 & 3 & 0 & 2 & 4 & 5 & 3 & 5 & 5 & 4 & 5 & 0 & 2 & 3 \\
0 & 0 & 0 & 0 & 0 & 3 & 0 & 0 & 0 & 2 & 0 & 2 & 0 & 5
\end{bmatrix} = 4.85 \times 10^6 \tag{3}$$

7. *Normalisation*
The theoretical minimum and optimal are extremely far apart, therefore a normalisation is needed to effectively present the results. In order to fully understand the behaviour of the matrix permanent, a Python code is used to simulate a 100.000 permanents calculation for a 3x3 matrix. Results show that the output of such large amount of permanents leads to an exponential distribution. Therefore, an exponential fit is tested between the theoretical minimum and optimal. This gives a linear line on a logarithmic scale, allowing the results of the assessment tool to be visualised on this scale. The normalisation also gives the foundation for the benchmark, as the normalised values are used to compare company with the industry better practice and average. The formula for the normalised line is given by:

$$y = 175 \times e^{18.197 \times x} \tag{4}$$

With y being the percentage of the theoretical optimum and x the permanent value of a company.

8. *Output*
The output of the assessment tool is in twofold. First, a benchmark scale is given where the

permanents of the companies are compared in relation to the industry average and better practice. Second, the individual enabler implementation levels are also compared to industry average and better practice through radar plots. The visualisation of the output is shown in the results section.

5 Application

The assessment tool is applied by asking supply chain experts to complete the questionnaire. The questionnaire was both emailed to the interviewees of the empirical study and was presented as a QR-code during the round table discussions of the supply chain directors event. In total, eight supply chain experts completed the questionnaire, with most of the experts representing companies from the FMCG industry. The sample of respondents is therefore defined as relatively small and heterogeneous, but sufficient for testing and the validation of the tool.

6 Results

Results are acquired based on the respondents that completed the questionnaire. The resulting permanent calculations for the respondents and the corresponding implementation levels are given in Table 3. The exponential difference of the results can be seen, which is in line with the expectations of the background research for the normalisation.

Table 3: Tool Results, Questionnaire Output

Company	Solar Nederland	Royal Philips	Heineken	Refresco	Action	Mustad	Online Mealkit Retailer	BROSPER
Function	VP Operations	VP Spend Management SC	Global SC Director	Director SC Development	Director SC	SC Director	Head of SC Management EU	Owner
Enabler	Company 1	Company 2	Company 3	Company 4	Company 5	Company 6	Company 7	Company 8
Agility	2	2	2	2	1	2	4	1
Collaboration	2	2	3	3	2	1	2	3
Contigency Planning	2	2	3	3	4	4	3	2
Digital SC Twin	1	2	4	2	1	1	1	2
Disruptions Detection	2	2	2	3	2	2	3	2
Flexibility	2	2	2	2	1	2	3	1
Knowlegde Management	3	2	3	1	2	1	4	2
Predicting Disruptions	2	2	2	1	2	1	1	2
Scenario Modelling	1	2	4	2	4	3	2	3
Situational Awereness	2	3	3	2	3	3	2	3
Transparancy	3	3	4	2	2	2	4	3
Velocity	2	3	5	4	3	3	3	1
Visibility	2	4	4	3	4	2	3	3
Vulnerability Assessment	3	2	4	3	2	2	4	3
Matrix Permanent	801792	706560	31104000	1016064	384000	185472	8875008	185760

Translating the results to the normalised scale between the theoretical minimum and optimum gives the following result.

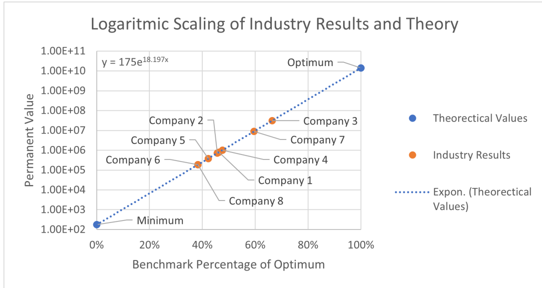

Figure 1: Scaled Results

Final scaled results lead to an industry average value of 48% of the theoretical optimum, while the industry better practice is set on 66% of the theoretical optimum. The corresponding enabler implementation levels for the average and better practice are presented below. Matching with the expectations of the empirical study and literature background, implementation levels are generally low. With high implementation on descriptive analytics enablers such as visibility and low levels on prescriptive enablers such as digital supply chain twins.

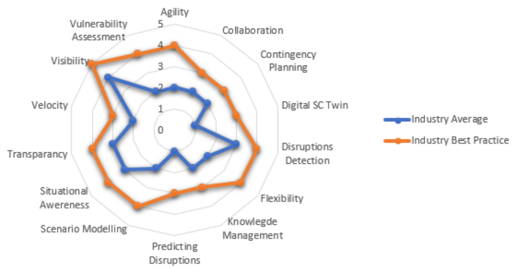

Figure 2: Implementation Level Results

6.1 Validation

The results of the questionnaire, and therefore also the results from the scaled benchmark, are validated through expert sessions and a comparison with interview results. In general, the results where inline with the expectations from the empirical study. Low implementation levels on most enablers with only visibility being one of the best implemented enablers. This ensured that the average values from the respondents where valid, as they compare well to expectations. Furthermore, the industry better practice was extensively validated through an expert session. This concluded that the results of the questionnaire from the respondent where valid, with high implementation levels on for example a digital supply chain twins. These where generated by clear differences in practices by the respondent, especially compared to interview findings. The respondent had for example much higher levels of forecasting models, integrating both internal and external data. However, the reliability of the results being the actual industry better practice are low, since the chance that the better practice is among the respondent is relatively low.

7 Conclusion

Research on the relation between big data analytics (BDA) and supply chain resilience is limited, with especially demand in applicability for resilience assessment in specific industries. This research therefore proposed a comprehensive assessment tool to assess the level of BDA based resilience for the FMCG industry. 14 enablers are found that lie on the intersection between BDA and supply chain resilience and form the input of the tool. Both the implementation and interdependence levels of the enablers are integrated in a matrix for a deterministic model, where the matrix permanent is used to translate to input in a metric outcome. The applicability of the tool shows promising results with a current industry average of 48% and better practice of 66% of the theoretical optimum. The tool gives KPMG the ability to kick-start projects by effectively identifying improvements for resilience. Furthermore, the design and background research helps to address the gap between BDA and supply chain resilience.

7.1 Recommendations

Due to large quantities of enabler interdependence, limitations of the tool mainly concern the assumptions made for these interdependencies. It is therefore recommended to further tailor the interdependence for a specific intention when the tool is implemented. Additionally, due to the relative small and heterogeneous sample size of tool respondents, it is recommended to further test the tool for larger and more homogeneous sample sizes.

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B | General Interview Layout

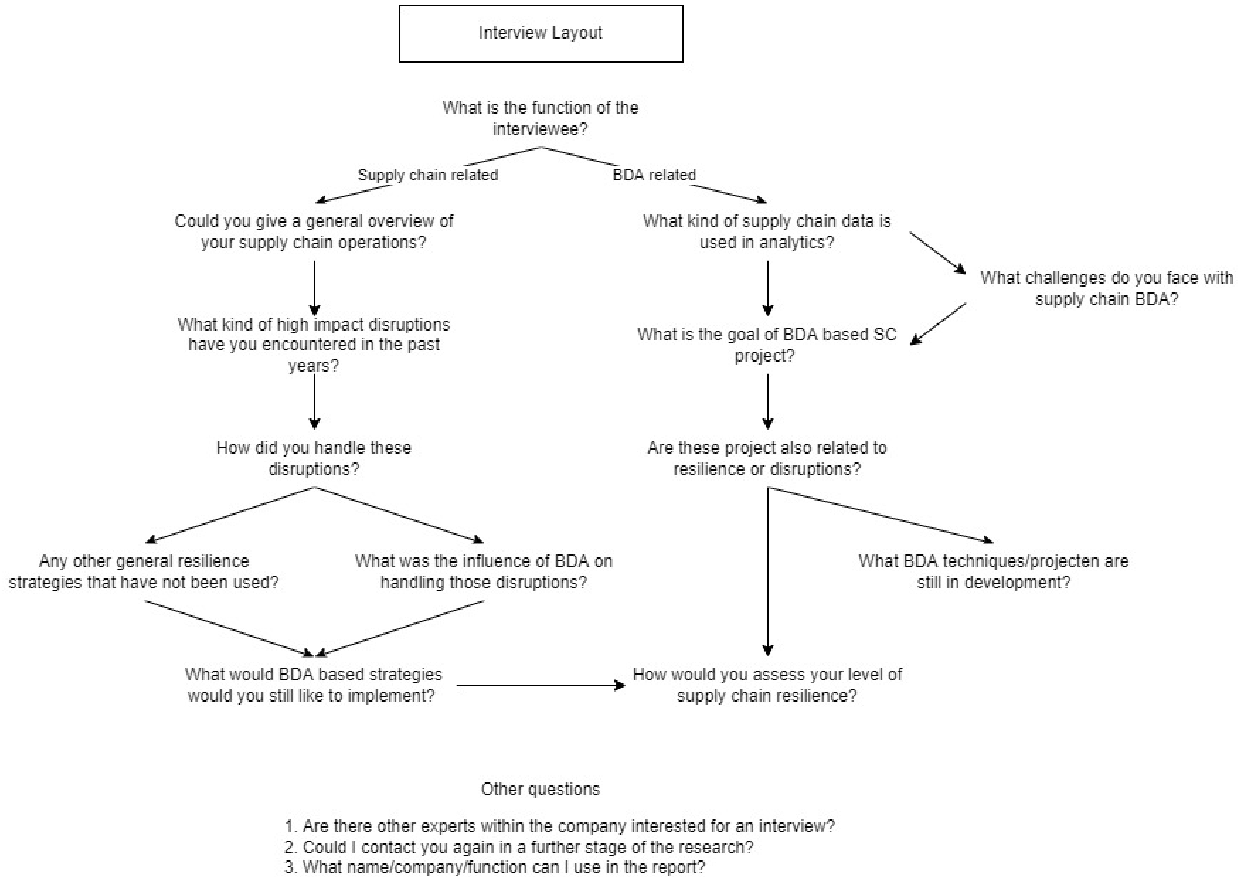

Figure B.1: General Interview Layout

C | Assessment Tool | Questionnaire

Big Data Analytics Based Supply Chain Resilience

| Introduction |

This questionnaire aims to acquire implementation levels of different BDA based supply chain resilience enablers.
Please fill in the questions regarding your company and supply chain, using the lowest and highest implementation level explanations as guidedance.
A BDA based resilience index will be calclutated based on your input, which allows for industry benchmarking aginast average and best practice values.

The results will be send to your email once a sufficient number of respondants is achieved.
Short advice to improve on different resilience enablers will also be given.

| Definitions |

Supply Chain:
The supply chain process of the your company, meaning the company itself combined with the supply, demand and transportation operations. Outsourced operations should be noted in the first question.

Stakeholders:
Any external parties that are needed for your fully functional supply chain process (as defined below).

Big Data Analytics (BDA):
Any big data that is generated throughout the supply chain and is accessible through for example data warehouses, excel, SAP etc. and is used to either create insights or as input for models/algorithms.

Disruptions:
High impact low probability events (on transportation/supply/demand) that cause major issues within a supply chain. For example: port closures (Shanghai), war in Ukraine or large product recalls.

| Contact information |

This questionnaire is part of the master thesis of Wouter de Wilt, graduating in Transport, Infrastructure and Logistics at the Technical University of Delft in coorperation with KPMG.

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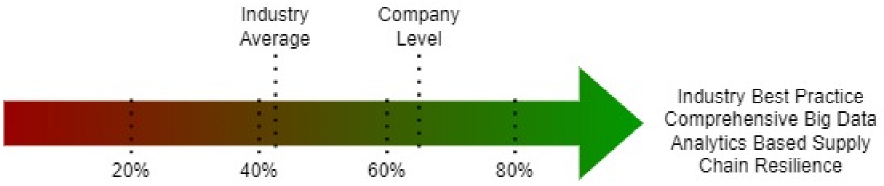
*Vereist

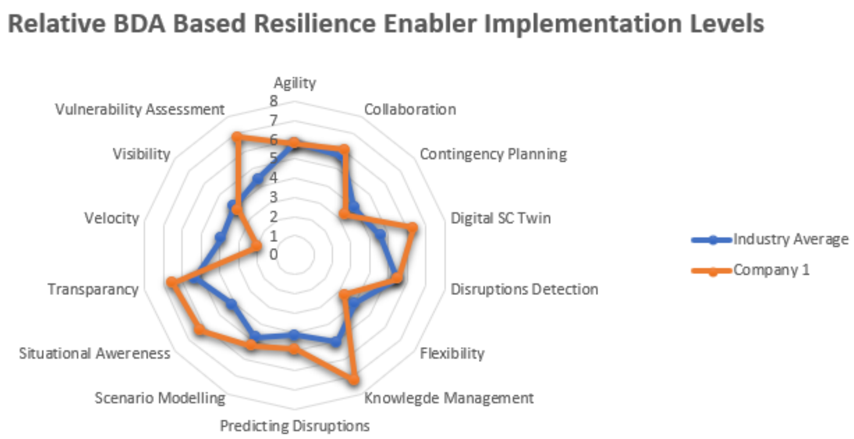
E-mailadres *

Je e-mailadres

Example of results: benchmarking visualisation



Example of results: Enabler comparison



Volgende

Formulier wissen

Big Data Analytics Based Supply Chain Resilience

wwoutdewilt@gmail.com Ander account

*Vereist

General Information

What is the name of your company? Or if confidential, please describe your company (e.g. mid-sized retailer) *

Jouw antwoord

What is your function within the company? *

Jouw antwoord

Vorige Volgende Formulier wissen

Verzend nooit wachtwoorden via Google Formulieren.

Big Data Analytics Based Supply Chain Resilience

wwoutdewilt@gmail.com Ander account

*Vereist

BDA Based Resilience Implementation Levels

Please answer the following questions to the best of your ability.

When answering the questions, keep in mind that the essence lies on big data analytics based implementation levels. A lowest and highest level is described for guidance.

E.g. 'Agility': It is not the question how agile your supply chain is, but to what extend BDA is used to enable agility.

Vulnerability Assessment *

Short Description: Comprehensively assessing (internal) supply chain elements on potential vulnerabilities for disruptions

	1	2	3	4	5	
Supply chain operations are only qualitatively analysed to inspect for possible vulnerabilities.	○	○	○	○	○	Data is effectively used to assess different supply chain operations to analyse potential vulnerabilites.

Transparancy *

Short Description: Having complete and easy access to all supply chain data

	1	2	3	4	5	
No data is shared between supply chain stakeholders, data that is available is difficult to access.	○	○	○	○	○	Data is comprehensively shared and accessible thoughout the supply chain for multiple stakeholders or for internal use.

Situational Awereness *

Short Description: Knowing what is happening in the global market, politics, heatlh (covid), transport etc.

	1	2	3	4	5	
Supply chain data analytics do not encompasse external developments, only internal processess are analysed. There are no subscriptions to external data sources.	○	○	○	○	○	External data is used to analyse market developments or political shifts, enabling clear views on current (global) situations.

Predicting Disruptions *

Short Description: The ability to use external data to predict disruptions

	1	2	3	4	5	
Predictive analytics are not used in supply chain operations in terms of predicting potential disruptions.	○	○	○	○	○	Predictive data analytics methods are used to analyse external data in order to effectively predict potential supply chain disruptions.

Knowlegde Management *

Short Description: Well defined use of knowledge sharing and processing within the organisation

	1	2	3	4	5	
BDA methodologies, information and data are not shared, saved, or processed for potential future use. There are practically no experts on BDA available, meaning that there is also no department for data-analytics.	○	○	○	○	○	BDA methodologies, information and data are structurally shared, saved, or processed for potential future use. These processes are guided through a comprehensive BDA department with experts on both data analytics and data science.

Disruptions Detection *

Short Description: The ability to detect disruptions through internal BDA, focusing on KPI abnormalities

	1	2	3	4	5	
No effort is done to descriptively analyse data in order to assess operations on possible disruptions.	○	○	○	○	○	(Real-time) Internal data is used to detect possible disruptions for any supply chain operation though real time visualisations where (KPI based) abnormalities are can quickly be noted.

Digital SC Twin *

Short Description: A simulation of the complete supply chain in (real-time) digital form

	1	2	3	4	5	
No supply chain processes are digitally simulated.	○	○	○	○	○	There is a complete digital simulation of the entire supply chain, based on (real-time) supply chain data.

Collaboration *

Short Description: Cross supply chain collaboration with external stakeholders

	1	2	3	4	5	
Stakeholder discussions are qualitatively based, data is not used to objectively clarify or prove points. Collaboration is backward looking based with low frequencies of discussions or meetings.	○	○	○	○	○	Descriptive data analytics are used to improve collaboration of different supply chain stakeholders. Ensuring that all stakeholders are on the same line. The data is used for objective discussions and enabels real-time information on SC insights and developements.

Contigency Planning *

Short Description: Having pre-described plans on how to handle certain disruptions

	1	2	3	4	5	
There are no data-driven SC contigency plans available within the company. After disruptions, no data is analysed to understand what has happend making it difficult to design data driven contigency plans.	○	○	○	○	○	By analysing and learning from SC data during earlier disruptions, new contigency plans are made to withstand or prepare for other disruptive events.

Scenario Modelling *

Short Description: The ability to digitally simulate a process to model different scenario's

	1	2	3	4	5	
It is difficult to model different scenario's, disabling data-driven decisions based on potential model outcomes. Scenarios may sometimes be analysed but only through qualitative expert or stakeholder discussions.	○	○	○	○	○	Scenario modelling is widely used to assess potential changes of supply chain operations. The modelling is done through digitial supply chain models (e.g. in Python) where variables can easely be changed. Models are based on either historic supply chain data, or external data of developments.

Visibility *

Short Description: Enabling digital insights in all supply chain processes

	1	2	3	4	5	
"No supply chain data is visualised, given managers no indication of how processes are going."	○	○	○	○	○	"There is a harmonised (real-time) data flow of all supply chain operations. Each supply chain step has its own dashboard (BI-Tools) or is visualised though descriptive analytics to ensure visibility."

Flexibility *

Short Description: The ability to quickly adapt to disruptions | When answering this question, keep in mind that other enablers might also have effect on the outcome of flexibility (e.g. visibility etc.)

	1	2	3	4	5	
BDA in not used to enable effective adaptiveness during disruptions.	○	○	○	○	○	BDA effectively creates the ability to proactively adapt to a possible supply chain disruptions. This is fueled by the implementation levels of other BDA based resilience enablers.

Agility *

Short Description: The ability to quickly respond to disruptions | When answering this question, keep in mind that other enablers might also have effect on the outcome of agility (e.g. visibility etc.)

	1	2	3	4	5	
BDA in not used to enable effective responsiveness during disruptions.	○	○	○	○	○	BDA effectively creates the ability to concurrently respond to supply chain disruptions. This is fueled by the implementation levels of other BDA based resilience enablers.

Velocity *

Short Description: The speed of being able to change supply chain operations

	1	2	3	4	5	
BDA descreases the directness and speed of communication and decisions throughout the supply chain due to the complexities that BDA brings.	○	○	○	○	○	BDA enabels faster (real-time) and more direct communication between stakeholders and internal supply chain operations through clarified and substantiated desicion making.

Are there any other resilience enablers (based on BDA) that you would like to mention?

Jouw antwoord

If needed, this question allows for further explanation of your input or any other topics/feedback you would like to discuss.

Jouw antwoord

Vorige Verzenden Formulier wissen

Verzend nooit wachtwoorden via Google Formulieren.

Big Data Analytics Based Supply Chain Resilience

Thank you for your response!

Nog een antwoord verzenden

D | Assessment Tool | Quantification of Interdependencies

		Vulnerability Assessment N_{14}	Visibility N_{13}	Velocity N_{12}	Transparancy N_{11}	Situational Awereness N_{10}	Scenario Modelling N_{9}	Predicting Disruptions N_{8}	Knowlegde Management N_{7}	Flexibility N_{6}	Disruptions Detection N_{5}	Digital SC Twin N_{4}	Contingency Planning N_{3}	Collaboration N_{2}	Agility N_{1}
N_{1}	Agility	O	A	O	A	O	A	O	A	O	O	A	A	A	-
N_{2}	Collaboration	V	A	V	A	O	O	O	O	V	O	O	O	-	-
N_{3}	Contingency Planning	O	O	V	O	O	A	O	A	O	O	O	-	-	-
N_{4}	Digital SC Twin	V	X	O	V	O	V	O	O	O	O	-	-	-	-
N_{5}	Disruptions Detection	O	X	V	O	V	O	O	O	O	-	-	-	-	-
N_{6}	Flexibility	A	A	V	A	A	A	O	O	-	-	-	-	-	-
N_{7}	Knowlegde Management	O	A	O	O	O	A	O	-	-	-	-	-	-	-
N_{8}	Predicting Disruptions	O	A	O	O	X	O	-	-	-	-	-	-	-	-
N_{9}	Scenario Modelling	V	A	V	O	V	-	-	-	-	-	-	-	-	-
N_{10}	Situational Awereness	A	A	O	O	-	-	-	-	-	-	-	-	-	-
N_{11}	Transparancy	O	X	V	-	-	-	-	-	-	-	-	-	-	-
N_{12}	Velocity	A	A	-	-	-	-	-	-	-	-	-	-	-	-
N_{13}	Visibility	V	-	-	-	-	-	-	-	-	-	-	-	-	-
N_{14}	Vulnerability Assessment	-	-	-	-	-	-	-	-	-	-	-	-	-	-

V | Enabler i influences enablers j A | Enabler j influences enablers i X | Enablers i and j influence each other O | Enablers i and j are unrelated

Figure D.1: Interdependencies

		Agility N_{1}	Collaboration N_{2}	Contingency Planning N_{3}	Digital SC Twin N_{4}	Disruptions Detection N_{5}	Flexibility N_{6}	Knowlegde Management N_{7}	Predicting Disruptions N_{8}	Scenario Modelling N_{9}	Situational Awereness N_{10}	Transparancy N_{11}	Velocity N_{12}	Visibility N_{13}	Vulnerability Assessment N_{14}
N_{1}	Agility	N_{1}	0	0	0	0	0	0	0	0	0	0	0	0	0
N_{2}	Collaboration	3	N_{2}	0	0	0	4	0	0	0	0	0	4	0	2
N_{3}	Contingency Planning	5	0	N_{3}	0	0	0	0	0	0	0	0	5	0	0
N_{4}	Digital SC Twin	4	0	0	N_{4}	0	0	0	0	4	0	3	0	4	3
N_{5}	Disruptions Detection	0	0	0	0	N_{5}	0	0	0	0	3	0	3	1	0
N_{6}	Flexibility	0	0	0	0	0	N_{6}	0	0	0	0	0	4	0	0
N_{7}	Knowlegde Management	1	0	2	0	0	0	N_{7}	0	0	0	0	0	0	0
N_{8}	Predicting Disruptions	0	0	0	0	0	0	0	N_{8}	0	2	0	0	0	0
N_{9}	Scenario Modelling	3	0	4	0	0	2	0	0	N_{9}	2	0	3	0	4
N_{10}	Situational Awereness	0	0	0	0	0	1	3	2	0	N_{10}	0	0	0	0
N_{11}	Transparancy	3	2	0	0	0	3	0	0	0	0	N_{11}	3	2	0
N_{12}	Velocity	0	0	0	0	0	0	0	0	0	0	0	N_{12}	0	0
N_{13}	Visibility	5	3	0	2	4	5	3	5	5	4	5	0	N_{13}	3
N_{14}	Vulnerability Assessment	0	0	0	0	0	3	0	0	0	2	0	2	0	N_{14}

Figure D.2: Interdependencies levels

Short descriptions of the interdependencies are also given on the following pages.

N_{i}	N_{i}	N_{j}	N_{j}	Value	Short Description
N_{2}	Collaboration	Agility	N_{1}	3	Collaboration contributes to agility in a partial way, as there are more enablers that impact agility. There is thus only an average impact of collaboration.
N_{2}	Collaboration	Flexibility	N_{6}	4	Flexibility is simplified by collaboration, as adaptation of supply chain operations due to disruptions mostly concerns other stakeholders. Therefore the relations is above average.
N_{2}	Collaboration	Velocity	N_{12}	4	This also related to the previous interdependence, as velocity is greatly enhanced is efficient collaboration is provided throughout the supply chain. However, velocity is not purely dependant on collaboration, thus next to maximum value applies.
N_{2}	Collaboration	Vulnerability Assessment	N_{14}	2	Vulnerabilities can sometimes originate at external stakeholders, effective collaboration should mitigate this in a noticeable way.
N_{3}	Contingency Planning	Agility	N_{1}	5	Contingency plans can be seen as pre-described agile ways of working and responding on operational levels. If complete contingency plans are available, agility should come naturally.
N_{3}	Contingency Planning	Velocity	N_{12}	5	In principle, with a realistic contingency plans, the velocity of responding would become instant because there is no thinking time on what to do.
N_{4}	Digital SC Twin	Agility	N_{1}	4	Digital twins increase visibility and operational capabilities, thus both indirectly and directly influencing agility.
N_{4}	Digital SC Twin	Scenario Modelling	N_{9}	4	An effective digital twin can be seen as a model where variables can also be changed to model certain scenario's. This serves as an important role and thus has a relative high value.
N_{4}	Digital SC Twin	Transparancy	N_{11}	3	If insightful for more (external) stakeholders, a digital twin also enables increased transparency throughout the supply chain. But only in a passive, simulated way.
N_{4}	Digital SC Twin	Visibility	N_{13}	4	In essence, a digital twin is composed of complete supply chain visibility but never completely presents the real world variation.
N_{4}	Digital SC Twin	Vulnerability Assessment	N_{14}	3	With digital twins, more insights are created which thus enables assessment of vulnerability. However, there are always missing links in a digital twin resulting in sub optimal vulnerability assessment.
N_{5}	Disruptions Detection	Situational Awereness	N_{10}	3	Detection ensures a major part of situational awareness, effective detection ensure quick awareness.
N_{5}	Disruptions Detection	Velocity	N_{12}	3	Detecting disruptions helps to increase the speed of responsiveness given the ability to know what is event is happening.
N_{5}	Disruptions Detection	Visibility	N_{13}	1	Detecting disruption increases visibility, but is only a small part of the visibility concept.
N_{6}	Flexibility	Velocity	N_{12}	4	High flexibility increases the potential to have quick adaptation solutions for different disruptions, thus increasing supply chain velocity.
N_{7}	Knowlegde Management	Agility	N_{1}	1	Better management of knowledge helps to ensure low level responsiveness.
N_{7}	Knowlegde Management	Contingency Planning	N_{3}	2	Increased management of knowledge enables more valuable expert input for contingency plans, making the plans more fitted to specific purposes.

N_{8}	Predicting Disruptions	Situational Awereness	N_{10}	2	With clear prediction of disruptions, the awareness is increased of what could happen en should be done in advance.
N_{9}	Scenario Modelling	Agility	N_{1}	3	Responding to disruptions is increased if different scenario's are pre- determined. This ensures that expert know what to potentially expect, resulting in an average contribution towards agility.
N_{9}	Scenario Modelling	Contingency Planning	N_{3}	4	Running multiple scenario's results in better understanding of disruptive events, and create the ability to compose valid contingency plans.
N_{9}	Scenario Modelling	Flexibility	N_{6}	2	Each scenario could ensure that adaptation through flexibility improves, but is remains difficult to model for low probability disruptions.
N_{9}	Scenario Modelling	Situational Awereness	N_{10}	2	Modelling scenarios improves indications on where more situational awareness is needed, but is not primarily necessary.
N_{9}	Scenario Modelling	Velocity	N_{12}	3	The more simulation are done of scenarios, the greater the knowledge on counter actions and thus on the velocity of operations.
N_{9}	Scenario Modelling	Vulnerability Assessment	N_{14}	4	Similar to situational awareness, scenario modelling provided insights in possible blind spots of the supply chain where more assessment is needed on certain operations.
N_{10}	Situational Awereness	Flexibility	N_{6}	1	A slight impact is generated from situational awareness to flexibility, as it helps to estimate effective adaptiveness.
N_{10}	Situational Awereness	Knowlegde Management	N_{7}	3	Knowledge management also encompasses the external situation, increasing the awareness therefore also ensures improved knowledge on the subject.
N_{10}	Situational Awereness	Predicting Disruptions	N_{8}	2	If external situations are analysed, it becomes easier to see disruptions coming, but doesn't necessarily enhance the prediction.
N_{11}	Transparancy	Agility	N_{1}	3	Responsiveness is increased through transparency by increasing easy and comprehensive access to information, ensuring improved capabilities to respond to disruptions.
N_{11}	Transparancy	Collaboration	N_{2}	2	More transparency enablers better collaboration though trust and visibility.
N_{11}	Transparancy	Flexibility	N_{6}	3	Similar to other interdependencies, flexibility is enhanced by the capabilities that transparencies bring to supply chain operations.
N_{11}	Transparancy	Velocity	N_{12}	3	Transparency increases trust and visibility, thus enhancing abilities to increase supply chain velocity.
N_{11}	Transparancy	Visibility	N_{13}	2	Increased transparency helps to achieve more visibility throughout the supply chain, especially when considering all stakeholders.
N_{13}	Visibility	Agility	N_{1}	5	Without clear visibility on supply chain operations, it is impossible to see disruptive effects and responds towards countermeasures.
N_{13}	Visibility	Collaboration	N_{2}	3	Data driven insights based on descriptive analytics helps to prove and present statements and developments with stakeholders, thus improving collaboration.
N_{13}	Visibility	Digital SC Twin	N_{4}	2	Visibility helps to design and create digital supply chain twins.
N_{13}	Visibility	Disruptions Detection	N_{5}	4	The ability to detect is primarily only possible if comprehensive insights are created.

N_{13}	Visibility	Flexibility	N_{6}	5	Flexibility, thus adaptation, is only possible when there are clear indications on what is effectively happening.
N_{13}	Visibility	Knowlegde Management	N_{7}	3	Knowledge is increased though clear insights of business, which also increase the ability to manage already existing knowledge
N_{13}	Visibility	Predicting Disruptions	N_{8}	5	Without proper visualisation of current and past data, predictive analytics is not possible.
N_{13}	Visibility	Scenario Modelling	N_{9}	5	Scenario modelling is based on real world data and thus can only be achieved when stakeholders have clear insights on these operations.
N_{13}	Visibility	Situational Awereness	N_{10}	4	Visibility is especially important for situational awareness as insights are gained and expressed on external events or situations.
N_{13}	Visibility	Transparancy	N_{11}	5	The main way of being transparent is to be able to share insights with all (external) stakeholders.
N_{13}	Visibility	Vulnerability Assessment	N_{14}	3	Visibility helps to assess vulnerabilities, ensures insights on how operations are going.
N_{14}	Vulnerability Assessment	Flexibility	N_{6}	3	When vulnerabilities are assessed, it becomes easier to effective adapt to different situations.
N_{14}	Vulnerability Assessment	Situational Awereness	N_{10}	2	This assessment helps in understanding where and why certain vulnerabilities can be and is often related to external situations.
N_{14}	Vulnerability Assessment	Velocity	N_{12}	2	Identifying vulnerability gives an upper hand when a disruption happens, it count as a way of preparation.

E | Assessment Tool | Average and Best Practice

Enabler	Industry Average	Short Description	Industry Best Practice	Short Description
Agility	2	Although agility might be relatively high within the industry, it lacks the BDA foundation that is needed for this assessment. Therefore the average value is only set to 2.	4	Examples of companies changing transport modes due to disruptions value the best practice on level 4. These were BDA based due to other enablers such as visibility and velocity that ensured agile resilience in this case.
Collaboration	2	Most companies indentified that BDA would help in collaboration, but lacked on the implementation side of the enabler.	3	Some companies effectively used BDA techniques to clarify and adress operations with internal stakeholders. However,
Contingency Planning	2	Although most companies primarily state that they work on reactive resilience, BDA based contigency plans are not made due to the nature of the scoped disruptions.	3	There where companies that analysed high probability disruptions to plan ahead for the reocurring event, however these are mainly not in scope. However, it does indicate that some companies work on the matter, given the best practrice a value 3.
Digital SC Twin	1	Digital supply chain twins were mentioned as ideal state BDA based resilience, but are still far ahead for most of the industry.	3	Some companies are relatively far on certain scenario modelling, but lack in comprehensively adressing it to the broader supply chain, making 3 a fair best practice value.
Disruptions Detection	3	As defined by mostly KPI and dashboard tracking, most companies do have this in order, but may lack in some inportant supply chain processes.	4	Defined by companies that track the most internal KPI's, but still have improvements due to vastly changing supply chain operaitons.
Flexibility	2	Most companies intend on adaptation, but lacked in BDA foundation.	4	Adaptation ability where high at a specific company by using safety stocks throughout the supply chain based on analytic outcomes.
Knowlegde Management	2	Due to BDA based and organisational challenges, companies lack with knowlegde management.	3	Some companies did have improved knowledge of BDA, but always still noting the challenges that are faced.
Predicting Disruptions	1	Most companies do not intent on analysing external data for disruption detection, only analysing for improved situational awereness.	3	Some companies to analyse external data to predict disruptions on a low scale, but still lacks effective results.
Scenario Modelling	2	FMCG6 was the only one with a comprehensive model, but also noted that these models were not availieble yet for other processes than demand. Thus average value should be relatively low.	4	FMCG6 has a comprehensive demand model based on big data to properly forecast demand. Assuming other company would also have these models on other supply chain processes, it is fair to say that best practice woujld be relatively high.
Situational Awereness	3	Several companies indicated that they analyse external data to better understand the market and current developments. However, each company indicated on different types of external data, thus mosst companies still have ways to improve. Therefore, value 3 is well suited as an industry average.	4	The best practice is just a bit higher than the industry average due to specific companies used more external data than others. However, there are still sources to be investigated and thus ways to improve on situational awereness.
Transparancy	3	Data transparacy throughout supply chain stakeholders was mentioned often, and is initiated by maby companies.	4	Specific companies where further in transparancy, but also noted the relation with data security. Noted that security should firstly be improved before improving best practice data transparacy.
Velocity	2	This is in line with other enablers that are at low implementation levels due to BDA and organisational challenges.	3	Best practice is close to average, most companies use similar systems for data velocity.
Visibility	4	Visbility through for example dashboarding is one of the first enablers that companies work on, industry average should be relatively high.	5	FMCG3 should an very eleborate dashboarding tool weer almost all data was incorporated for certain supply chain processes. Furthermore, visibility is one of the first enablers that companies implement. Thus, value 5 for best practice is appropriate.
Vulnerability Assessment	2	Internal vulnerability analysis was conducted by several companies, especially related to the supplier side of operations. Mostly, assessment lacks on all combining all area's of supply, transport and demand.	4	Best practice is in this case defined by vulnerability assessment of multiple supply chain operations.

F Python Code Matrix Permanent Behaviour

Python matrix permanent.py

```python
#%% Imports
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import scipy as sp
import random

#%% Running Model
b = []

for x in range(100000):
    a = np.array([[random.randint(1,5), 3, 5],
                  [1,random.randint(1,5), 1],
                  [1, 1, random.randint(1,5)]])
    #print(a)

    perm = a[0,0]*a[1,1]*a[2,2] + a[0,0]*a[1,2]*a[2,1] + a[0,1]*a[1,0]*a[2,2] + \
           a[0,1]*a[1,2]*a[2,0] + a[0,2]*a[1,0]*a[2,1] + a[0,2]*a[1,1]*a[2,0]

    #print(perm)
    b.append(perm)
    b.sort()

best_practice = max(b)
average = sum(b) / len(b)

optimum_array = np.array([[5, 3, 5], [1,5, 1], [1, 1, 5]])

theory_optimum = optimum_array[0,0]*optimum_array[1,1]*optimum_array[2,2] + \
                 optimum_array[0,0]*optimum_array[1,2]*optimum_array[2,1] + \
                 optimum_array[0,1]*optimum_array[1,0]*optimum_array[2,2] + \
                 optimum_array[0,1]*optimum_array[1,2]*optimum_array[2,0] + \
                 optimum_array[0,2]*optimum_array[1,0]*optimum_array[2,1] + \
                 optimum_array[0,2]*optimum_array[1,1]*optimum_array[2,0]

#%% Prints
#print(b)
print(optimum_array)
print('Permanent Better Practice =', best_practice)
print('Permanent Average =', average)
print('Theoretical Optimum =', theory_optimum)

#%% Plot Scatter
plt.plot(b)
plt.xlabel("Input Number")
plt.ylabel("Matrix Permanent Value")
plt.title("Permanent Behaviour of 3x3 Matrix")
plt.grid(axis='y')
plt.show()

#%% Plot Histgram
plt.hist(b, bins=18)
plt.xlabel("Matrix Permanent")
plt.ylabel("Number of Hits")
plt.title("Permanent Behaviour of 3x3 Matrix")
plt.grid(axis='y')
plt.xlim([0, 180])
```

Figure F.1: Python Code Matrix Permanent Behaviour