Analytics for Supply Chain Resilience: Exploring Paths and Obstacles

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Abstract

Supply chain disruptions, ranging from epidemics to geopolitical tensions, have been especially evident in recent years and have consequently become a hot topic in both boardrooms and academic literature. Supply chain resilience (SCR) denotes the ability to prepare, respond, recover, and facilitate growth during disruptions and is usually thought of as consisting of several enablers. Initial evidence suggests that one such enabler could be analytics, which broadly refers to the processing of data to support decision-making. This thesis aims to explore the use of analytics for SCR. The research design comprise one conceptual component followed by two empirical components consisting of a survey and interviews. The findings reveal six application areas for analytics in SCR. Three paths to SCR are also identified in terms of configurations of analytics and other SCR enablers, only one of which does not seem to be contingent on the level of supply chain complexity. Finally, obstacles to the use of analytics were identified. Clear consensus was noted for low data availability and/or quality as a major obstacle to SCR, while a somewhat consensus existed concerning the hindrance to quick decision-making, lack of a data-driven culture, and insufficient benefits and/or use.

The thesis contributes to the nascent stream of research on the use of analytics and SCR by complementing individual observations with broader and deeper insights through the spectrum of application areas, configurations of analytics and complementary SCR-enablers, and finally, obstacles. For practitioners, the thesis provides insights into using analytics as a potential enabler for SCR. Firms can evaluate their current use of analytics for SCR and adjust their set of application areas and configurations of SCR-enablers as per the options outlined in the findings to better align with their specific needs and prerequisites. Finally, guidance is provided on what obstacles to be cognizant of and attempt to mitigate.

Keywords: Supply chain resilience, Analytics, Supply chain disruptions, Enablers, Obstacles, Fuzzy-set qualitative comparative analysis, Collaborative research
Sammanfattning

Störningar i försörjningskedjor, orsakade av händelser såsom pandemier och geopolitiska spänningar, har varit särskilt påtagliga under de senaste åren och har därmed blivit ett hett ämne både i näringslivet och akademien. Begreppet Supply chain resilience (SCR) avser försörjningskedjans förmåga att förbereda sig, reagera, återhämta sig och stödja tillväxt under sådana störningar. Det anses vanligtvis bestå av flera möjliggörare. Initiala bevis i litteraturen tyder också på att en av dessa möjliggörare kan vara analytics, som i stora drag betyder bearbetning av data för att stödja beslutsfattande. Denna avhandling syftar till att utforska användningen av analytics för SCR. Forskningsmetoden bestod av en konceptuell studie, följt av två empiriska studier i form av en enkät och intervjuer. Resultaten visar sex tillämpningsområden för analytics med avseende på SCR. Dessutom identifierades tre vägar till SCR när det gäller konfigurationer av analytics och andra SCR-möjliggörare, varav endast en konfiguration är oberoende av försörjningskedjans komplexitetsnivå. Slutligen identifierades hinder för användning av analytics för SCR. Det fanns en tydlig konsensus kring låg tillgänglighet och/eller kvalitet på data, medan det fanns viss enighet om hinder för snabba beslut, bristen på en kultur att basera beslutsfattande på analytics och slutligen otillräcklig nytta och/eller användning.

Avhandlingen bidrar till forskning om användningen av analytics för SCR genom att komplettera enskilda observationer med bredare och djupare insikter om spektrumet av tillämpningsområden, konfigurationer av analytics och kompletterande SCR-möjliggörare, och slutligen, hinder. För praktiker ger avhandlingen insikter i att använda analytics som en potentiell möjliggörare för SCR. Företag kan utvärdera sin nuvarande användning av analytics för SCR och förändra tillämpningsområden och konfigurationer av SCR-möjligare enligt de identifierade alternativen för att bättre tillgodose sina behov och förutsättningar. Slutligen ges vägledning om vilka hinder man bör vara medveten om och försöka mildra.
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The support from colleagues has been a valuable enabler for the completion of this thesis. Thank you for supporting and inspiring me in every way you saw possible. Our discussions have truly been appreciated and important sources of motivation. I am also immensely thankful to the team responsible for research education. Your positivity and active involvement have been extremely appreciated.

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Finally, a special thanks go to friends and family for looking after me throughout this process.
Appended papers

The following papers are enclosed as appendices.

**Paper 1 (P1)**

*Analytics for supply chain resilience: developing a unifying framework*

Early draft presented at the 29th International Annual EurOMA Conference, Berlin, Germany, July 1–6, 2022.

**Paper 2 (P2)**

*Paths to supply chain resilience*

Early draft presented at the 32nd International Annual IPSERA Conference, Barcelona, Spain, April 2–5, 2023.

**Paper 3 (P3)**

*Obstacles to the use of analytics for ensuring supply chain resilience*

Early draft presented in the doctoral workshop of the 32nd International Annual IPSERA Conference, Barcelona, Spain, April 2–5, 2023.
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1. Introduction

This chapter outlines two broad contemporary topics—recent disruptions and advances in analytics—in supply chain management. The motivation for and relevance of the thesis is provided, followed by the purpose and research questions. This is followed by a description of the scope and delimitations of the thesis. Finally, the outline of the remaining thesis is presented.

1.1. Background

The collective role of focal firms and their up- and downstream partners in competition is a fundamental cornerstone of supply chain management (SCM) (Ketchen & Hult, 2007; Lambert & Cooper, 2000). However, when supply chains (SCs) become complex (e.g., multi-tiered or globalized), as is often the case today, there is inevitable exposure to disruptions (Bode & Wagner, 2015; Craighead et al., 2007); these disruptions are “unplanned and unanticipated events that disrupt the normal flow of goods and materials within a supply chain” (Craighead et al., 2007, p. 132). Every activity along the SC has inherent risks and disruptions propagate in the SC due to the interconnected structure (Ponomarov & Holcomb, 2009), a phenomenon that some authors refer to as the ripple effect (Dolgui et al., 2018; Ivanov et al., 2014).

These disruptions have been especially evident recently. Even before the COVID-19 outbreak had spread out of China, many SCs suffered from disruptions due to the country’s dominant role in global trade (Deloitte, 2020; Linton & Vakil, 2020). Global firms in the automotive industry, such as Volkswagen, General Motors, Hyundai, and Toyota, were significantly affected as Wuhan, China, the epicenter of the outbreak, is a manufacturing hub for automotive components (Belhadi et al., 2021). Even more recently, the war in Ukraine has also resulted in SC disruptions, affecting global supplies of petroleum, grains, fertilizer, and neon gas (Simchi-Levi & Haren, 2022). Sanctions against Russia have also significantly restricted import and export, which means that supply and demand nodes have become
unavailable.\textsuperscript{1} Other recent disruptions include the 2021 obstruction of the Suez Canal, one of the busiest trade routes in the world as the shortest distance between Europe and Asia for sea freight,\textsuperscript{2} and the global semiconductor shortage that forced companies like Volvo Cars to temporarily suspend production.\textsuperscript{3}

Simultaneously, SCs are also affected by a quite different development: technological advancements (e.g., Dolgui & Ivanov, 2020; Frazzon et al., 2021; Waller & Fawcett, 2013). Increasing data volumes, storage capacity, computational power, and algorithm sophistication have provided new possibilities for processing data in support of decision-making (Henke et al., 2016), i.e., analytics (Davenport & Harris, 2007; Srinivasan & Swink, 2018). More specifically, data in a SC context includes point-of-sales data, customer or supplier inventory levels, and lead times, as well as the geographical location of SC entities and shipments (Nikookar & Yanadori, 2022). Analytics provide processing capabilities through simulation, optimization and visualization to support decision-making (Srinivasan & Swink, 2018). Big data analytics and artificial intelligence both serve as examples of technologies that are part of the development toward more advanced analytics (Davenport, 2018; Duan et al., 2019; Maheshwari et al., 2021; McAfee et al., 2012).

\subsection*{1.2. Research motivation}

Disruptions can cause severe harm to SC material flow continuity and have adverse effects on revenues, costs (Ponomarov & Holcomb, 2009), and stock market valuation (Hendricks & Singhal, 2005). Disruptions also carry a societal dimension, as the inability of a SC inability to provide essential goods, including basic food items and medical supplies, negatively affects individuals’ well-being. During the COVID-19 pandemic, for example, the

\begin{itemize}
\item \textsuperscript{1} https://www.consilium.europa.eu/en/policies/sanctions/restrictive-measures-against-russia-over-ukraine/
\item \textsuperscript{2} https://www.reuters.com/world/middle-east/ever-givens-stranding-suez-canal-2021-07-06/
\item \textsuperscript{3} https://www.reuters.com/business/autos-transportation/chip-shortage-prompts-production-halt-volvo-cars-gothenburg-2021-08-11/
\end{itemize}
supply and demand of canned and dried food, toilet paper, hand sanitizer, disinfectant, and personal protective equipment were highly mismatched.\textsuperscript{4} Similarly, the war in Ukraine has raised concerns of a global food crisis as the supply of grain is at risk.\textsuperscript{5} A final example of societal implications of disruptions is lay-offs.\textsuperscript{6} The impacts of the recent disruptions have been especially severe, catching the attention of scholars (Flynn et al., 2021; Kähkönen & Patrucco, 2022; van Hoek, 2020), practitioners (Bain & Company, 2020; Deloitte, 2020), and governments (The White House, 2021) alike.

Given the current environment, supply chain resilience (SCR), broadly defined as the ability of a SC to prepare for, respond to, recover from (Ponomarov & Holcomb, 2009), and facilitate growth amid disruptions (Tukamuhabwa et al., 2015) is of paramount importance. It should be acknowledged, that a rich body of literature on SCR and its enablers exists (see Ali et al., 2017; Han et al., 2020). One such enabler includes SC visibility (SCV), which concerns information about the identity and location of the different tiers within the SC, as well as supply and demand-related information. These aspects increase situational awareness by highlighting potential threats to the SC, such as delays or shortages (Nikookar & Yanadori, 2022). Another enabler is SC integration (SCI), which allows for strategic collaboration with key partners in the SC, as no single firm possesses sufficient resources to independently manage disruptions (Faruque et al., 2021).

Recent attention has also been directed towards the technological advancements, referring to it as an interesting avenue for research on SCR (Ali & Gölgeci, 2019; Dolgui & Ivanov, 2020; Pettit et al., 2019). Analytics presents itself as an especially interesting candidate in this regard. Decision-making during disruptions is challenging due to the high dynamism,

\textsuperscript{4} https://www.who.int/news/item/03-03-2020-shortage-of-personal-protective-equipment-endangering-health-workers-worldwide  
\textsuperscript{6} https://www.reuters.com/markets/europe/european-companies-cut-jobs-economy-sputters-2023-06-23/
uncertainty, urgency, and complexity (Akter et al., 2021; Dennehy et al., 2021). Analytics has the potential to be a helping hand for SC managers and could plausibly support decision-making through the visualization of key parameters, advance simulation of different scenarios, and quickly solving optimization problems in relation to balancing of supply and demand, among other solutions. Indeed, initial evidence has recently surfaced in the literature illustrating the applicability and usefulness of analytics in SCR. Norrman and Wieland (2020), for example, describe the telecom company Ericsson’s use of a visualization tool that maps both their own and (sub)suppliers’ facilities on a map. By combining these geographical coordinates with that of an incident, in this case, the 2011 earthquake in Japan, potentially affected facilities can be readily identified. A detailed list of the components sourced from each affected site can then be generated and used to swiftly achieve situational understanding and support response measure decisions by providing a rapid first evaluation of the disruption's magnitude.

While the above example suggests the relevance of analytics as an enabler for SCR, a thorough exploration of analytics use for SCR is still warranted to provide more insights, especially those that extend beyond what can be captured by isolated individual observations. Investigating how analytics can be used for SCR across a range of application areas or which, if any, complementary SCR enablers are needed to achieve SCR are potent avenues to advance research. Another example is what obstacles that impede analytics use for SCR. These insights would also benefit practice as they can describe the use of analytics in a more detailed and usable form. Inquiry in this direction could provide an opportunity for practitioners to make informed assessments by judging analytics use for SCR based on both its merits and its potential perils.
1.3. Purpose and research questions

Based on the background discussed above, the purpose of this thesis is:

*To explore the use of analytics for supply chain resilience*

A natural first target in such an exploration is to clearly delineate how analytics can be used to improve SCR. Indeed, the literature does provide some insights on this matter, such as the previously cited Ericsson case. However, individual observations fall short in demonstrating the complete spectrum of prospective application areas. A delineation of how analytics could be used for SCR may also highlight if complementary SCR enablers are needed in combination with analytics and, if so, in what combinations. This relates to analytics only being useful for supporting decision-making, and not, for instance, provide the means to also execute these decisions. On this note, a broader discussion in the SCM discipline contend that outcomes are the result of multiple factors and their interactions, and that there might be multiple such configurations or paths that lead to the same outcome (Ketchen et al., 2021). To provide an example of interdependencies between analytics and other SCR enablers, Srinivasan and Swink (2018) stress that “each [SCV and analytics] demands and supports the other” (p. 1853). To conclude, understanding how analytics can be used for SCR helps offer a spectrum of application areas and configurations of analytics and other SCR enablers.

Thus, the following research question (RQ) is proposed:

**RQ1.** How can analytics be used for supply chain resilience?

When identifying how analytics can be used for SCR, it is important to also investigate any potential obstacles. Understanding these obstacles can help explain what might make the use of analytics for SCR difficult or unattainable, and thus affect its availability as an enabler. A recent survey among Fortune 1000 firms found that less than a quarter of the surveyed firms characterized themselves as data-driven (i.e., relying on analytics in decision-making) and that this reflects “that becoming data-driven is a long and difficult journey that organizations increasingly recognize playing out over years or decades” (NewVantage Partners, 2023, p. 6). Extant literature touching on obstacles to the use of analytics tend to not take any specific application area in
consideration (e.g., Vidgen et al., 2017). Hence, it remains worthwhile to revisit obstacles specifically in relation to analytics use for SCR. As previously explained, decision-making during disruptions is characterized by high dynamism, uncertainty, urgency, and complexity, which could mean that previous findings will not be transferable to these situations.

Thus, to address this uncertainty, a second RQ is proposed as follows:

RQ2. What are the key obstacles to the use of analytics for supply chain resilience?

1.4. Scope and delimitations

As previously discussed, disruptions occur in inter-firm flows of physical goods and may affect multiple firms along the SC depending on their severity. As SCR is a SC-wide capability, the unit of analysis within this thesis is the SC, with the perspective captured through the viewpoint of focal firms. In other words, focal firms will be the center point from which the collective capabilities of said firms and their SC partners will be evaluated, a common practice in SCM literature (e.g., Golgeci & Ponomarov, 2013).

Given the focus on disruptions to the flow of physical goods, the empirical context will be manufacturers, retailers, and wholesalers within Sweden. According to a report by the World Economic Forum (2018), Sweden is among the top ten countries in the world when it comes to technology and innovation. This assessment is based on several factors, including firms’ technology investment and adoption of emerging technologies; business models enabled by information and communication technology; cybersecurity; research and development expenditure; and patent applications. Sweden also has a high level of imports and exports, according to the same report. As a relatively small economy that is dependent on global trade, Sweden also faces a high level of exposure to disruptions in global SCs. These circumstances make Sweden an ideal context for research on SCR and analytics.

Given the focus of analytics use for SCR, the use of analytics in this thesis specifically concerns decisions-making related to the SC material flow,
following the lead of Srinivasan and Swink (2018) and S. Zhu et al. (2018). In this way, relevant data could entail various aspects of supply and demand from different entities in the SC, such as inventory levels and lead times (Nikookar & Yanadori, 2022).

1.5. Thesis outline

The next section of the licentiate thesis, Chapter 2, presents the frame of references in which key concepts used throughout the thesis are defined. Chapter 3 discusses the research methods, including the research setting, design, and process, as well as the procedures for developing data collection instruments, sampling and data collection, and data analysis. Quality issues and ethical considerations are also outlined. Chapter 4 presents the findings, which is followed by a discussion on the potential research and practical implications in Chapter 5. Finally, Chapter 6 provides concluding remarks and suggestions for future research.
2. Frame of References

This chapter provides an overview of the main concepts addressed in the thesis. It opens with a discussion of SC complexity and its association with disruptions and SCR enablers. The different perspectives of SCR are then outlined, both in terms of its different phases as well as its different enablers. Finally, the concept and role of analytics are defined and obstacles are summarized. Figure 1 at the end of this chapter presents a working conceptual model that illustrates the different concepts covered in this chapter and constitute the foundation of the research in this thesis.

2.1. Supply chain complexity

Supply chain complexity (SCC) is determined by the characteristics of the SC structure, such as the number of entities, transactions, and interconnected material, monetary, and information flows (Bode & Macdonald, 2017). Extant literature has demonstrated that multi-tier and globalized SCs have greater exposure to disruptions, as exemplified by events such as the COVID-19 pandemic (Blackhurst et al., 2011; Bode & Wagner, 2015; Craighead et al., 2007; Ponomarov & Holcomb, 2009). Hendricks et al. (2009), for instance, found that firms with a larger geographic footprint and greater reliance on outsourcing experience more negative stock market reaction following SC disruptions.

There are also indications that SCC not only affects the frequency or severity of disruptions but also affects the way in which they can be managed. Christopher and Lee (2004) argued that high SCC leads to extended response times in decision-making. Brandon-Jones et al. (2014) further revealed a strong moderating effect of one dimension of SCC on the relationship between supply chain visibility (SCV) and SCR, indicating that SCV becomes particularly vital in the context of high SCC. It must be noted that SCC is characterized by high ambiguity in the literature; that is, SCC is acknowledged as exacerbating the frequency and severity of disruptions but, is also thought to increase SCR by allowing for certain enablers (Wiedmer et al., 2021). This dual role makes SCC especially research worthy.
2.2. Supply chain resilience

Although research on SC risks, disruptions, vulnerability, and volatility appeared earlier (e.g., Christopher, 2000; Sheffi, 2001; Svensson, 2000; Zsidisin et al., 2000), the term “resilience” was first explicitly used in the SC context by Rice and Caniato (2003). Its use was sparked by discussions on the impacts of terrorism on SCs, a relevant topic at that time (Ali et al., 2017). In the years that followed, others, including Christopher and Peck (2004) and Sheffi and Rice (2005), continued building the foundation of the emerging research field and the scholarly interest in SCR has significantly increased (Ali et al., 2017; Ali & Gölgeci, 2019; Han et al., 2020).

Over the years, efforts have been made to continuously review and redevelop the concept through further refinement and extension. Today, SCR is viewed as a multi-dimensional concept that encompasses different chronological phases as well as enablers (Ali et al., 2017), as elaborated on in the coming subsections. First, however, SC disruptions are briefly defined.

2.2.1. Defining supply chain disruptions

SC disruptions are often conceptualized as disturbances to the flow of goods and material that are unplanned, unanticipated (Craighead et al., 2007), infrequent, and high-impact (Azadegan et al., 2020; Ivanov & Dolgui, 2021). They can be the result of natural disasters, manmade events, accidents, of quality issues (Ketchen & Craighead, 2020). Disruption risks can be contrasted with operational risks—uncertainties to demand, supply, and costs—which may have only a minor impact on the continuity of SC operations (Tang, 2006).

2.2.2. Supply chain resilience in terms of phases

SCR denotes remedies to supply chain disruptions. Some studies define SCR in more general terms. To illustrate this, SCR is in the viewpoint of Wieland and Wallenburg (2013) thought of as “the ability of a supply chain to cope with change” (p. 301). Furthermore, a bulk of literature take a phasic perspective when defining SCR, which can be noted to slightly shift over time (Ali et al., 2017). Early definitions were rather narrow, addressing only
response to and/or recovery from disruptions (e.g., Christopher & Peck, 2004; Rice & Caniato, 2003; Sheffi & Rice, 2005). As one of the first researchers to define SCR, Christopher and Peck (2004) drew on the original definition of resilience from the science of ecosystems to underline recovery or the move to a new state (the latter often referred to as growth in other definitions). This definition highlights the phase after the disruption has occurred. More recent definitions have adopted a broader view that also includes prevention or preparedness, i.e., the phase before the disruption has occurred (e.g., Kamalahmadi & Parast, 2016; Ponomarov & Holcomb, 2009; Tukamuhabwa et al., 2015). An overview of the phases emphasized in definitions within the extant literature is provided in Table 1.
Table 1: Phases in SCR definitions in select studies

<table>
<thead>
<tr>
<th>Authors</th>
<th>Phases</th>
<th>Prevention or preparedness</th>
<th>Response</th>
<th>Recovery</th>
<th>Growth</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rice and Caniato (2003, p. 25)</td>
<td></td>
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<td>X</td>
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<td>Christopher and Peck (2004, p. 2)</td>
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<td>Sheffi and Rice (2005, p. 41)</td>
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<td>X</td>
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<tr>
<td>Ponomarov and Holcomb (2009, p. 131)</td>
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<td>X</td>
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<tr>
<td>Brandon-Jones et al. (2014, pp. 55-56)</td>
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<tr>
<td>Hohenstein et al. (2015, p. 108)</td>
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<tr>
<td>Tukamuhabwa et al. (2015, p. 5599)</td>
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<tr>
<td>Chowdhury and Quaddus (2016, p. 712)</td>
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<tr>
<td>Kamalahmadi and Parast (2016, p. 121)</td>
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</table>

Hohenstein et al. (2015) offered an alternative differentiation of phases that is both simple and sophisticated, differentiating between the proactive components of SCR in the pre-disruption phase, comprising preparedness, and the reactive components in the post-disruption phase, comprising response, recovery, and growth. This differentiation of phases has gained considerable support in the literature (Chowdhury & Quaddus, 2017; Tukamuhabwa et al., 2017).
Within this thesis, SCR will be defined in line with the contemporary literature conceptualizing it as a multi-dimensional concept comprising preparedness, response, and recovery, and growth. Preparedness is part of the proactive pre-disruption phase, while response, recovery, and growth are part of the reactive post-disruption phase.

2.2.3. Supply chain resilience in terms of enablers

An alternative means of discussing SCR is through its associated enablers. Although a multitude of enablers have been associated with SCR as conflicting views exist, consensus has been reached on some of them, although they have been referred to in an inconsistent way. Jüttner and Maklan (2011) contended that four enablers, labeled flexibility, velocity, visibility, and collaboration capture the essence of SCR. Quite similarly, Nikookar and Yanadori (2022) identified visibility, responsiveness, and flexibility as collectively covering SCR. As a final example, Gligor et al. (2020) emphasize agility, adaptability, and alignment to be important when operating in a dynamic environment. These enablers relate to reacting (referred to as velocity, flexibility, responsiveness, agility, or adaptability), having information (visibility), and integrating with SC partners (collaboration or alignment). As informed by the extant literature and to avoid conceptual overlaps, visibility, responsiveness, and integration have been selected as the enablers of study for this thesis. The following paragraphs define the terms, mention their conceptual overlaps with adjacent concepts, and discuss them in relation to SCR.

Supply Chain Visibility

According to Williams et al. (2013), SCV is defined as "access to high-quality information that describes various factors of demand and supply" (p. 545). In this case, "high-quality" encompasses multiple dimensions, including the accuracy, timeliness, completeness, and usefulness of the information. SCV includes both upstream and downstream flows, covering supply and demand information, respectively (Barratt & Barratt, 2011; Brandon-Jones et al., 2014). This supply and demand information can be categorized into two groups (Williams et al., 2013): market-level information, which involves information at an aggregated level (e.g., prices, availability), and partner-level
information, which includes information from the focal company's supply chain partners (e.g., point-of-sale data, demand forecasts, customer or supplier inventory levels, lead times, delivery dates, and shipment notices). Beyond supply and demand information, knowledge of the identity and geographical location of different entities in different tiers of the SC is also counted as part of SCV (Nikookar & Yanadori, 2022).

Visibility plays an important role in supporting SCR by providing valuable information about potential threats, such as delays or shortages (Nikookar & Yanadori, 2022). By offering firms situational awareness, visibility enables informed decision-making in the event of a supply chain disruption (Brandon-Jones et al., 2014). It ensures that the supply chain can respond in a well-informed and appropriate manner, avoiding the implementation of incorrect or counter-effective measures when attempting to handle the disruption (Christopher & Lee, 2004).

**Supply Chain Responsiveness**

Supply chain responsiveness (SCResp) is a measure of the ability to swiftly adapt to environmental changes (Yu et al., 2019). Vachon et al. (2009) define SCResp as “the ability of a supply chain to respond quickly to market movements” (p. 324). These market movements and environmental changes can be related to evolving buyer or supplier needs, as well as shifts in competitor strategies (Yu et al., 2019). Like SCV, the environment encompasses both downstream and upstream actors in the SC, but it also includes actors outside the focal firm’s SC, such as competitors. It should be noted that SCResp is often used interchangeably with other related concepts like flexibility or agility, due to different conceptualizations of the terms within the literature (see Williams et al., 2013; Yu et al., 2019). However, some scholars specifically view agility and flexibility as antecedents of SCResp (Shekarian et al., 2020). There are also authors that do not do not discuss SCResp, but rather refer to agility and adaptability as the reaction to short-term and long-term changes, respectively (Gligor et al., 2020). In this view, flexibility is part of both agility and adaptability (ibid.). These definitions can nevertheless be noted to conceptually overlap with that of SCResp, outlined above. To avoid conceptual overlaps within this thesis, only SCResp is used.
In the context of SCR, responsiveness plays a vital role in facilitating a swift response and recovery to mitigate the negative impact of disruptions (Nikookar & Yanadori, 2022). SCResp provides the means to develop and distribute new products rapidly in response to changes in demand or supply (Yu et al., 2019). Ponomarov and Holcomb (2009) definition of SCR emphasizes the importance of adaptability and maintaining continuity during SC disruptions. The ability to withstand adverse influences is sometimes distinguished from SCR and labeled as robustness (Brandon-Jones et al., 2014). It is worth considering whether adaptability and maintaining continuity are mutually exclusive. In the view of Brandon-Jones et al. (2014), adaptations provide the foundation for maintaining continuity. Quick reactions and adaptability facilitated by SCResp play a crucial role in withstanding the negative impacts of disruptions and maintaining continuity.

Supply Chain Integration

Q. Zhu et al. (2018) defined SCI as the "degree to which the focal firm strategically collaborates with its key supply chain partners and collaboratively manages inter-organizational processes to provide maximum value to the customer" (p. 213). Others use the somewhat adjacent concept of alignment, that is expressed along similar lines: “coordinates supply chain members to work together to maximize performance of the entire chain” Gligor et al. (2020, p. 162). SCI has been identified as particularly advantageous in uncertain and dynamic environments (Huang et al., 2014; Wong et al., 2011) and especially for enhancing SCR (Durach et al., 2020; Scholten & Schilder, 2015). This rationale lies in the fact that no single firm possesses sufficient resources to independently manage disruptions (Faruque et al., 2021). Additionally, due to the ripple effect, disruptions spread throughout the SC, which makes them a shared concern (Dolgui et al., 2018; Ivanov et al., 2014). As a specific example of SCI during the COVID-19 pandemic, an online retailer engaged in collaborative initiatives with its suppliers, including streamlining procurement procedures, modifying payment terms and conditions, collaborating on delivery systems and assistance with deliveries, and coordinating promotional activities (Shen & Sun, 2021).
2.3. Analytics

The first decision-support systems for businesses were put to use in the 1960s (Wixom & Watson, 2010) and the term “intelligence” was first introduced as a concept within the artificial intelligence community in the 1950s (Chen et al., 2012). A plethora of overlapping and evolving terms has since been used to express data-driven decision-making, such as “expert systems” until the shift of the millennium and “knowledge-based systems” beginning in the 1980s (Duan et al., 2019). The term “business intelligence” was established as a concept in the 1990s (Chen et al., 2012; Wixom & Watson, 2010). In the following decade, the closely associated term “business analytics” was popularized and is now common in the field (Davenport, 2006). For this thesis, the term analytics is used as defined below.

2.3.1. Definitions

The terms intelligence and analytics are sometimes referred to as in combination (e.g., Chen et al., 2012), though some make subtle distinctions between the terms. Davenport and Harris (2007), for instance, claimed that business intelligence includes data access and reporting, as well as analytics. Analytics, in their view, describes the advanced end of business intelligence. Derivatives of the term analytics are also used interchangeably, including big data analytics, data analytics, business analytics, and supply chain analytics, as noted by several scholars (Srinivasan & Swink, 2018). In general, however, there is an emphasis on the processing of data to support decision-making. As defined by Davenport and Harris (2007), analytics is “the extensive use of data, statistical and quantitative analysis, explanatory and predictive models and fact-based management to drive decisions and actions” (p. 7). Along the same lines, Chen et al. (2012) contend analytics includes “techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions” (p. 1166). In contrast to these more general definitions, Srinivasan and Swink (2018) emphasized simulation, optimization, regression, and visualization to simplify the interpretation of complex information, in the form of so-called “dashboards”. It should also be highlighted that the decision-making process can either involve human intervention, with analytics serving only as decision support,
or be entirely automated, with analytics also making the final decision (Davenport & Harris, 2007).

Analytics can moreover be classified into three types: descriptive, predictive, and prescriptive analytics (Grover et al., 2018; Maheshwari et al., 2021). This division has been popular in conceptual frameworks in the extant literature (e.g., Belhadi et al., 2019; Lepenioti et al., 2020; Nguyen et al., 2018; Wang et al., 2016). Descriptive analytics report on both past events and what is happening in the present (Grover et al., 2018; Lepenioti et al., 2020). Diagnostic analytics (sometimes referred to as inquisitive analytics; Belhadi et al., 2019), which provide insights into the causes of past and present events, are usually seen as an extension of descriptive analytics. Overall, descriptive analytics aim to answer the questions “What has happened and why?” and the more present-looking “What is happening?” (Lepenioti et al., 2020). Predictive analytics forecast future events (Grover et al., 2018), answering the question “What will happen and why?” (Lepenioti et al., 2020). Finally, prescriptive analytics recommend an optimal course of action (Grover et al., 2018) which provides guidance as to “What should be done and why?” (Lepenioti et al., 2020).

The relevant literature has adopted a broad perspective on analytics, as does this thesis. It should also be mentioned that analytics is an umbrella concept and is constantly evolving thanks to technological advancements. Recently, the emergence of big data and artificial intelligence (e.g., machine learning) has introduced novel capabilities to analytics (Davenport, 2018). Here, analytics is specifically applied to the SC context, as the processing of data from multiple entities (see subsection on SCV).

### 2.3.2. Obstacles

Several obstacles to the use of analytics, related both to technological aspects and softer elements, have surfaced in the literature. Data-related issues concerning data access, integration, sharing, and quality are common obstacles related to technological aspects (e.g., Lismont et al., 2017; Vidgen et al., 2017). The obstacle of cybersecurity has gained attention as vulnerabilities can exist in different tiers of the SC, which could hinder data sharing (Haddud et al., 2017). However, it must be noted that there are studies
within the literature that suggest that there is no negative relationship between cybersecurity concerns and the use of analytics (Kalaitzi & Tsolakis, 2022). Obstacles concerning softer elements are usually related to the availability of skills, the existence of a supporting strategy, or the extent to which the return on investments can be assured (e.g., Berndtsson et al., 2020; Vidgen et al., 2017). Scant support from senior management and other competing strategic priorities may also serve as roadblocks (LaValle et al., 2011). The culture and mindset of decision-makers have also been highlighted. A data-driven culture refers to the mindset of decision-makers to rely on data, as opposed to entirely on their own on experience and intuition (McAfee et al., 2012).

2.4. Working conceptual model

Figure 1 presents a working conceptual model of the concepts discussed in this chapter and their relationships. SCR has been described both in terms of different chronological phases and in terms of its enablers. SCC impacts exposure to disruptions but could also have an influence on SCR. As this thesis is concerned with exploring the use of analytics for SCR, analytics is also treated as an SCR enabler (illustrated by the dashed line around analytics in the lower right corner of Figure 1). The three types of analytics and obstacles are also represented in the figure.
Figure 1: Working conceptual model
3. Methods

This chapter describes the research methods used in the thesis. First, brief background information is provided on the research project and research setting that serve as the platform for this thesis. Next, the research design is outlined. The timeline of the research process is explained in the subsequent section. Detailed information on the development of data collection instruments, sampling and data collection, and data analysis is then provided for the two empirical research design components. Finally, quality and ethical considerations are addressed.

3.1. Research setting

The research presented in this thesis was conducted as part of a subproject within the AFAIR research profile. AFAIR was started in January 2021 and takes a multidisciplinary approach in studying the application of artificial intelligence in industry. It employs a collaborative approach with several partnering manufacturing firms. The empirical results presented in this thesis, however, do not solely rest on insights from AFAIR partners. Details on how AFAIR has served as a platform for this thesis are provided throughout the chapter.

3.2. Research design

Given the nascent stage of research on analytics for SCR and the goals of this thesis, an explorative research approach was deemed appropriate. The research design makes use of three sequential components—conceptual development followed by two empirically oriented components—to investigate the purpose of the thesis from multiple angles. The first empirical component was quantitatively oriented and designed to provide an overview and capture general patterns, while the second component was qualitatively oriented.

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7 Abbreviation for “Ambidexterity, Flows, and Artificial Intelligence for Responsiveness”. Funded by the Knowledge Foundation (KK-stiftelsen).
oriented to allow for more in-depth inquiry. The components and their links are illustrated in Figure 2.

![Diagram of research design components]

**Figure 2: Research design components**

A key purpose of the explorative approach used in this research was to define and describe analytics for SCR through conceptual development, thus the first research design component addressed RQ1, see Figure 2. While important on its own in addressing the purpose, the conceptual development was also conducted as an important piece of preparation for the empirical components by provide working definitions, among other things. In terms of execution, typologies of analytics and SCR typologies were identified and subsequently merged to generate a unifying typology tying the two concepts together. Examples derived from the literature are used to illustrate the applicability of the typology. The typology and associated examples describe how analytics can be used for SCR (RQ1). Within the working conceptual model of the thesis, as shown in Figure 3, the conceptual research design component touches on the SCR phases as well as the different types of analytics (note that numbering in Figure 3 refers to the sequential order of research design components).
Figure 3: Research design components in relation to the working conceptual model

For the first empirical component, a survey instrument was designed by adopting established scales from extant literature. Insights on the definitions of analytics and SCR gained in the preceding conceptual component were used when developing the survey (Figure 2). The intention of this component was to generate an overview of how analytics interacts and forms configurations with other distinct SCR enablers and, more importantly, how these configurations associate with SCR. Additionally, SCC is regarded as a contextual factor (Figure 3). In other words, the first empirical component also describes how analytics can be used for SCR (RQ1), complementing the previous conceptual component in this regard. To allow for a configurational approach, fuzzy-set qualitative comparative analysis (fsQCA) was used (Ragin, 2008). This method places the “configurations of causes in relation to an outcome of interest” (Fiss, 2011, p. 395), and has previously been used in the literature for explorative inquiry (e.g., Arellano et al., 2021). fsQCA was deemed suitable in this stage as it is flexible in exploring empirical patterns and associations, which could provide insights on how analytics is used for SCR (RQ1). To explain this, a key strength of fsQCA is that it accounts for causal complexity; that is, conjunctural causation (outcomes might be the
result of a combination of conditions and their interaction), equifinality (might not only be one way to an outcome), and asymmetrical causation (absence of a condition normally associated with an outcome does not have to imply the absence of that outcome) (Misangyi et al., 2017; Schneider & Wagemann, 2010).

Descriptive analysis of the survey data revealed low levels of analytics use (an average of 3.43 on a 7-point Likert scale). This insight partly inspired the use of an expert interview study in the second empirical component, as illustrated in Figure 2. More specifically, this component was intended to explore obstacles to the use of analytics for SCR (RQ2), shown in Figure 3. Expert interviews have been described as suitable for exploratory phases of research and allow for timely and strong results (Bogner et al., 2009), and are popular within SCM research as evidenced by multiple recent applications (e.g., Gruchmann et al., 2019; Meyer & Henke, 2023). A key decision in this component was to respect the explorative research orientation by focusing the interviews on the experts’ cumulative knowledge and experiences, and not solely their current firm or SC affiliation. It should also be mentioned that the outputs of the conceptual component—individual definitions, analytics–SCR typology, and associated examples—were used to ensure that the respondents clearly understood the area of interest before conducting the interviews (Figure 2).

Moreover, AFAIR’s collaborative approach was built into the research design. Both during and in between the research design components, the researcher interacted with industry representatives to identify interesting paths for further research inquiry and evaluate their practical relevance, pilot test the survey instrument (first empirical component), and report and discuss preliminary results. The close collaboration with practitioners was especially helpful given the exploratory nature of this research, as they helped feed the continuous ideation process. For instance, in parallel with the conceptual development component, open discussions on analytics and SCR were conducted with several industry representatives. These discussions revolved around, but were not limited to, the disruptions they had experienced, their ideas about how to achieve SCR, and their reflections on analytics. Insights strengthened the rationale of utilizing conceptual development to clarify the overlap between analytics and SCR and provided inspiration for the two subsequent empirical
phases. It should be reemphasized that empirical data collection in the later research stages was not limited to the AFAIR partners. More information on the sampling approach is provided in later sections.

3.3. Research process

The research presented in this thesis began in early 2021 and was concluded in mid-2023. Excluding the writing of this kappa, the research process consisted of two main phases. The first phase (Ph1), containing the initial ideation process and the conceptual component, spanned the entirety of 2021, while the second phase (Ph2), containing the two empirical components, was initiated in early 2022 and concluded in mid-2023. Additional details of the two phases are provided below and illustrated in the timeline in Figure 4.

<table>
<thead>
<tr>
<th></th>
<th>2021</th>
<th></th>
<th>2022</th>
<th></th>
<th>2023</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Q1</td>
<td>Q2</td>
<td>Q3</td>
<td>Q4</td>
<td>Q1</td>
</tr>
<tr>
<td>Ph1</td>
<td></td>
<td>RP</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Ph2</td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
</tbody>
</table>

Figure 4: Timeline of the research process

In the first phase, the literature on topics relevant to AFAIR was explored, which informed a parallel ideation process. Specifically, this meant browsing the literature to identify emerging topics, state-of-the-art or influential works, key streams, theoretical frameworks, and suggestions for further research. The business press also provided ideas for interesting topics. Potential research areas for this thesis project went through multiple iterations throughout this period before being presented in a research proposal (RP) in the autumn of 2021 (Figure 4). Based on the ideation process, one subproject within AFAIR was adapted and specifically aligned to accommodate research at the
intersection of analytics and SCR. Furthermore, the execution of the conceptual component was performed in the latter part of the first phase. This work was reported in a paper titled “Analytics for supply chain resilience: developing a unifying framework” (P1) and presented at the 29th International Annual EurOMA Conference in Berlin, Germany, in the third quarter of 2022 (Figure 4). P1 address RQ1 through a typology for the use of analytics for SCR that illustrate a set of general application areas, see Figure 5.

![Figure 5: Associations between papers and research questions](image)

The second phase (Ph2) included the execution of the two empirical components. A survey instrument was designed and data collection was conducted during the spring of 2022. It should be mentioned that the launch of the survey was aligned with the requirements of the he subproject within AFAIR that supported this thesis project. Analysis and the write-up of a second manuscript titled “Paths to supply chain resilience” (P2) took place primarily during the autumn of the same year. A draft version of the manuscript was finalized in the second quarter of 2023 and presented at the 32nd International Annual IPSERA Conference in Barcelona, Spain, shortly thereafter. P2 address RQ1 by illustrating distinct paths to SCR as configurations of analytics and other SCR enablers (Figure 5).
The execution of the second empirical component began in mid-2022 and data was collected until mid-2023. An early draft of a paper titled “Obstacles to the use of analytics for ensuring supply chain resilience” (P3) was presented in the doctoral workshop of the same conference as mentioned for P2. In terms of RQ, P2 address RQ2 by presenting obstacles to the use of analytics for SCR.

3.4. Development of data collection instruments

This section describes the development of the data collection instruments used in the two empirical research design components. A survey instrument was developed in the quantitative component, whereas the qualitative component involved a guided interview.

3.4.1. Quantitative component

Exploratory survey research generally adopt open-ended questions, as it can be difficult to determine the appropriate fixed response alternatives beforehand, though open-ended responses can be difficult to interpret and analyze (Ghauri et al., 2020). This survey utilized closed-ended questions not just for this reason, but also because operationalization of all constructs of interest (SCR enablers, see Section 2.2.3) already exists in the extant literature. The survey instrument was designed by adopting scales developed, used, and tested in prior research, as recommended by Malhotra and Grover (1998). Adopting scales from prior literature is one strategy to improve validity, as the scales have already been tested (Ghauri et al., 2020). To ensure consistency, items across all constructs were measured using the same seven-point Likert scale, ranging from “strongly disagree” (1) to “strongly agree” (7), to simplify interpretation. Introductory text was included before the measurement items in each construct to provide an explanation of the scope of that construct. In the first section of the survey, an open-ended question was included in which participants were to state their job title and provide confirmation that their firm manages a physical flow. Another open-ended question was included at the end of the survey, allowing respondents to provide feedback or leave any additional comments with relevance to the contents of the survey. Finally, a cover letter was developed to accompany the
survey and introduce the purpose of the survey, assurance of confidentiality, and contact information to the researchers, following the recommendation by (Ghauri et al., 2020). A summary version of the survey instrument is provided in Table 2 below, and a complete version is available in P2, appended to this thesis.

The scales were translated to Swedish (i.e., the respondents’ native language) and underwent minor refinements so as not to lose essential nuances in the translation while remaining easy to understand. The language was carefully revised, as language is crucial for validity (Ghauri et al., 2020) and reliability (Ruel et al., 2016). Pilot testing survey instruments is suggested to test validity and to improve the survey design (Creswell, 2014). An expert panel of six researchers in disciplines of relevance was asked to critically assess and provide feedback on both format and content. They were specifically asked to comment on the validity of the operationalizations, i.e., if the construct(s) (measurement scales) seem to capture all dimensions of the corresponding theoretical concepts to ensure face validity (Creswell, 2014; Ghauri et al., 2020) and, indirectly, content validity (Forza, 2016). Another expert panel consisting of seven practitioners with profiles corresponding to the target respondents, most of whom were affiliated with AFAIR, were asked to assess the overall relevance, interpretability, time consumption, and their ability to fill in the survey with respect to current job title. Finally, adjustments were made to the survey instrument based on feedback gathered in the pilot test revising items that were ambiguous or difficult to interpret, thereby improving reliability (Forza, 2016).
Table 2: Survey instrument

<table>
<thead>
<tr>
<th>Survey section</th>
<th>Specification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Background information</td>
<td>Respondent job title (open ended).</td>
</tr>
<tr>
<td>SCR</td>
<td>This section deals with disruptions, i.e., major disturbances that occur infrequently but that have a major impact on the flow of goods, such as pandemic, war, or natural disasters. Please take your closest partners (e.g., suppliers, distributors) also into account. Measured through 6 items, based on Golgeci and Ponomarov (2013).</td>
</tr>
<tr>
<td>SCV</td>
<td>This section concerns your knowledge about other actors in your supply chain and availability of data from them. Measured through 4 items, based on Nikookar and Yanadori (2022).</td>
</tr>
<tr>
<td>Analytics</td>
<td>This section deals with data management and analysis techniques to support decision making within supply chain management. Data concerns various aspects of supply and demand from different entities in your supply chain (e.g., inventory levels or lead times). Measured through 5 items, based on Srinivasan and Swink (2018).</td>
</tr>
<tr>
<td>SCResp</td>
<td>The following section concerns your supply chain’s ability to quickly respond to changes. Measured through 5 items, based Yu et al. (2019).</td>
</tr>
<tr>
<td>SCI</td>
<td>The following section concerns relationships among the actors in your supply chain. Measured through 5 items, based on Q. Zhu et al. (2018).</td>
</tr>
<tr>
<td>SCC</td>
<td>This section deals with the structure of your supply chain. Measured through 4 items, based on Bode and Macdonald (2017).</td>
</tr>
<tr>
<td>End section</td>
<td>Space to leave other comments (open ended).</td>
</tr>
</tbody>
</table>
3.4.2. **Qualitative component**

A combined interview guide and response sheet was developed to facilitate data collection in the second empirical research component. It consisted of an Excel file with separate sheets and writable cells, as well as excerpts of the definitions of SCR and analytics and references to the presentation material from the introductory meeting (discussed later in Section 3.5.2). The general instructions asked respondents to provide answers based on their collective experience, not only their current firm or SC affiliation.

The first Excel sheet asked general questions about the expert’s current job title and previous experience. The second sheet contained open-ended questions touching on obstacles and prerequisites for the successful use of analytics. Within the interview guide, obstacles were broadly defined as reasons that impede the use of analytics, including those that decrease willingness. The third and final sheet contained the structured part of the interview guide with closed-ended questions. 29 distinct, pre-labeled obstacles were listed for participants to evaluate (for the complete list, see P3, appended to this thesis). In an attempt to build on the extant literature and help the respondents articulate demotivating factors, the list was compiled using obstacles identified in the extant literature. Additional obstacles were added to the list based on the researcher’s own elaboration and an iterative peer-review process. Within the Excel sheet, the respondent was prompted to:

A) Rate each listed obstacle on a scale of 1 (low relevance) to 10 (high relevance);

B) Select the top-five most critical obstacles;

C) Provide concise comments on as many obstacles as possible (at least on the factors selected in B);

D) Add to the list of obstacles (optional).

The final sheet within the Excel file was devoted to capturing respondents’ miscellaneous comments and feedback.
3.5. **Sampling and data collection**

The sampling procedures in the two empirical components were distinct, though they shared some key commonalities. First, the empirical context was the manufacturing, retailing, and wholesale industries within Sweden, as explained in Section 1.4. Due to the SC perspective and focus on aspects related to decision-making and physical flows, target respondents in both empirical components were required to hold senior positions that were involved in inter-firm material flows and relationships. This was to ensure that the respondents were representative of the unit of analysis (Forza, 2016). Managers within SC, operations, logistics, purchasing, etc. were targeted with titles including (senior) vice president, director, chief officer, and manager. It was assumed that individuals within these roles would have insights into physical flows, decision-making, cooperation, and the capabilities of their closest SC partners. When none of these roles were available, such as in the case of smaller firms, the chief executive officer was deemed acceptable. As previously mentioned in Section 1.4, the SC was the unit of analysis, while the unit of observation was the focal firm, as respondents were asked to evaluate the collective capabilities of their own firm and their SC partners.

3.5.1. **Quantitative component**

In the quantitative empirical component, the target population consisted of firms with either primary or secondary industry classification codes 10–31 (manufacturing), 46 (wholesale, except motor vehicles and motorcycles), and 47 (retail trade, except motor vehicles and motorcycles), based on classifications by Statistics Sweden (2007). The target sample frame was extracted from the Amadeus database (provided by Bureau van Dijk, publisher of business information), using the above industry classification codes and Sweden as the empirical context. Only firms with registered phone numbers and financial information for the preceding fiscal year (2020) were extracted. The financial information was used to ensure that the firm is not inactive or bankrupt and to determine the firm size as defined by the European Commission (2021). Due to technical constraints when generating the target sample frame, only the top fifty thousand firms based on revenue were extracted (corresponding to around 1 MSEK and above).
A professional market research company was tasked with selecting respondents from the target sample frame using stratified random sampling. The split was set to 50/50 between manufacturing as one stratum, and wholesale and retail as the second. A cross-sectional survey design was chosen and data collection was performed through telephone interviews by the marketing research company, using the structured survey instrument based on the seven-point Likert scale. The raw data set contained responses from a total of 200 cases, with an equal split between the two strata. The response rates were 12% for manufacturing and 10% for wholesale and retail, which is deemed sufficient (Forza, 2016).

As a final step before proceeding with data analysis, the raw data was screened and cleaned to increase validity (Ruel et al., 2016). First, a visual inspection was conducted to identify potential entry errors or disqualified responses (e.g., due to industry or respondent title not being within the scope). No issues were detected in this initial screening. Responses missing with than ten percent of the data points were disqualified from further analysis, leaving 165 cases. Next, responses with suspicious patterns were investigated by computing standard deviations, and identifying whether there were any responses with a very low standard deviation, as that is a sign that the respondent was unengaged and consistently chose the same response. No such patterns were discovered, and all 165 responses were retained. Sample demographics of the final sample are shown in Table 3. Missing data points (in responses missing less than ten percent of data points) were replaced by the sample median. Items were also screened (i.e., column-wise). Only one item (SCC, item #1) appeared to be problematic, missing more than ten percent of data points, for the remaining sample. This item was retained, however, for the subsequent validity and reliability tests, after which it was dropped.
Table 3: Sample demographics, quantitative component

<table>
<thead>
<tr>
<th>Sample composition (n=165)</th>
<th>Sample (n)</th>
<th>Sample (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Respondent job title</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Warehouse, Factory Manager, or similar</td>
<td>19</td>
<td>11.5 %</td>
</tr>
<tr>
<td>SC, Logistics, Purchasing Manager, or similar</td>
<td>39</td>
<td>23.6 %</td>
</tr>
<tr>
<td>Chief Executive Officer</td>
<td>81</td>
<td>49.1 %</td>
</tr>
<tr>
<td>Miscellaneous</td>
<td>26</td>
<td>15.8 %</td>
</tr>
<tr>
<td>Size (European Comission, 2021)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Large</td>
<td>16</td>
<td>9.7 %</td>
</tr>
<tr>
<td>Medium</td>
<td>21</td>
<td>12.7 %</td>
</tr>
<tr>
<td>Small</td>
<td>42</td>
<td>25.5 %</td>
</tr>
<tr>
<td>Micro</td>
<td>86</td>
<td>82.1 %</td>
</tr>
<tr>
<td>Industry (Statistics Sweden, 2007)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Manufacturing (SNI code 10–31)</td>
<td>84</td>
<td>50.9 %</td>
</tr>
<tr>
<td>Wholesale (SNI code 46) and Retail (47)</td>
<td>81</td>
<td>49.1 %</td>
</tr>
</tbody>
</table>

Screening was followed by statistical tests to ensure the validity and reliability of the data. Internal consistency (i.e., that items within the same construct are statistically related) was checked as a measure of reliability by computing Cronbach’s alpha (Creswell, 2014; Ruel et al., 2016). The threshold for Cronbach’s alpha was set to 0.7 (Hair et al., 2018). A value below that threshold indicates that an individual item within a construct should be dropped from the analysis (Ruel et al., 2016). Convergent and discriminant validity (i.e., construct validity (Forza, 2016)) were checked by computing the average variance extracted (AVE) and the square root of AVE, respectively. The threshold for AVE was set to 0.5, and the square root of AVE should always be greater than the inter-construct correlations (Hair et al., 2018). For detailed information on the statistical validation of the
constructs and dropped items, refer to P2, appended to this thesis. Descriptive statistics including measures of central tendency (mean) and dispersion (standard deviation) were also calculated and are presented in Table 4.

Table 4: Construct descriptive statistics

<table>
<thead>
<tr>
<th>Construct</th>
<th>Mean</th>
<th>Standard deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCR</td>
<td>4.40</td>
<td>1.27</td>
</tr>
<tr>
<td>SCV</td>
<td>4.64</td>
<td>1.44</td>
</tr>
<tr>
<td>Analytics</td>
<td>3.43</td>
<td>1.80</td>
</tr>
<tr>
<td>SCResp</td>
<td>4.65</td>
<td>1.23</td>
</tr>
<tr>
<td>SCI</td>
<td>4.48</td>
<td>1.31</td>
</tr>
<tr>
<td>SCC</td>
<td>4.40</td>
<td>1.60</td>
</tr>
</tbody>
</table>

3.5.2. Qualitative component

In the qualitative empirical component, a combination of criteria and convenience sampling was utilized for sample selection. The target respondents were defined according to the above description, albeit with one key exception. Respondent candidates within the qualitative component were also considered if they had experience in development or sales (e.g., key account manager) at software companies specializing in industrial analytics applications. This respondent category also possesses extensive experience with obstacles that appear during use of analytics. Furthermore, as the cumulative knowledge and experiences of potential respondents were important, previous job titles were also of interest in addition to their current role when identifying suitable candidates.

Convenience sampling was utilized due to time constraints. Data collection overlapped with disruptions caused by COVID-19, the war in Ukraine, etc., affecting the availability of SC managers for interviews. Participants in AFAIR were an appropriate starting point both for this reason and because they had previously participated in research components and consequently
knew about the research topics and had experience being interviewed about complex topics. Candidates were also drawn from the pool of industry contacts of the author’s institution. All candidates were subject to an initial eligibility screening by collecting information on their experience from LinkedIn and checking it against the eligibility criteria outlined earlier.

From this point, the remaining respondent screening and data collection was conducted in three consecutive steps, as illustrated in Figure 6. All respondent candidates who passed the initial screening were invited to an online meeting. These meetings lasted approximately one hour and in most cases were conducted one-on-one with the researcher to avoid candidates being influenced by each other. The candidates were first asked to introduce themselves and their professional experience to verify the information collected through LinkedIn. The researcher then defined key concepts. The candidates were invited to provide their own examples of SC disruptions, the experience they had managing them, and their views on SCR and analytics in general. This was done to ensure that the candidates’ professional profiles matched their actual experiences. Finally, the scope of the research was presented by the researcher. Upon completion of the introductory meeting and agreement to participate in the study, presentation slides and the combined interview guide and response sheets were sent to the experts by e-mail. A total of 18 candidates participated in the introductory meetings, and 10 continued on to data collection. Table 5 provides demographic information for these respondents (labeled A–J) and illustrates their lengthy industrial tenures. Data from 10 respondents was deemed sufficient, as prior research indicates that a sample size of 6 to 12 interviews is generally considered appropriate for thoroughly describing and exploring patterns within a homogenous participant group (Guest et al., 2006).
In some cases, the discussion on SC obstacles was first initiated during the introductory meetings. However, all expert respondents were invited to a dedicated interview (step 3), giving them a minimum of one week to prepare and reflect on obstacles with the interview guide as a basis (step 2). They were asked to go through the interview guide and fill in their reflections in the response sheets before the upcoming interview. If relevant comments had been provided during the introductory meeting, they were already added to the response sheets by the researcher for the experts to approve and extend while preparing for the dedicated interview. To provide time for the researcher to review their reflections and prepare follow-up questions, the experts were asked to submit their responses a few days before the interview. Each individual follow-up meeting with the 10 experts was conducted online with screen-sharing and lasted between 30 and 120 minutes. The experts were prompted to further elaborate on their reflections and, in the case of misinterpretation or change of heart, adjust their comments and corresponding ratings. Their additional comments were summarized and recorded in the interview guide by the researcher during the interviews, which were able to be validated instantaneously thanks to screen-sharing. The interviews were also recorded upon permission from the interviewee.
<table>
<thead>
<tr>
<th>ID</th>
<th>Experience (years)</th>
<th>Job titles (selection)</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>20+</td>
<td>Manager Sales and Operations Planning</td>
</tr>
<tr>
<td>B</td>
<td>20</td>
<td>Manager Strategic Logistic &amp; Development</td>
</tr>
<tr>
<td>C</td>
<td>20+</td>
<td>Logistic manager; Deputy Plant manager</td>
</tr>
<tr>
<td>D</td>
<td>10</td>
<td>Project Procurement Manager; Supply Chain Manager; Purchasing Manager</td>
</tr>
<tr>
<td>E</td>
<td>10</td>
<td>Purchasing Manager; Purchasing and Logistics Manager; Segment Leader (within purchasing); Commodity Sourcing Manager; Project Sourcing Manager</td>
</tr>
<tr>
<td>F</td>
<td>20</td>
<td>Senior Supplier Manager; Manager Production Planning; Acting Head of Global Material Management; Director Supplier Management; Director Inbound Supply; Head of Digitalization &amp; Automation, Business Transformation (advanced technology)</td>
</tr>
<tr>
<td>G</td>
<td>20</td>
<td>(S)VP Supply Chain; Supply Chain Manager (specific business area); Logistics Manager</td>
</tr>
<tr>
<td>H</td>
<td>15</td>
<td>Head of Factory Support; (Deputy) Production Manager; Supply Chain Planner</td>
</tr>
<tr>
<td>I</td>
<td>20</td>
<td>Key Account Manager (software company)</td>
</tr>
<tr>
<td>J</td>
<td>15</td>
<td>Supply Demand Planning Manager; Warehouse and Material Handling Manager</td>
</tr>
</tbody>
</table>
3.6. Data analysis

The following section describes the data analysis procedures used in the two empirical components.

3.6.1. Quantitative component

The analytical process of QCA follows the approach of Arellano et al. (2021) and consists of five steps: 1) definition of the outcome; 2) selection of causal conditions; 3) calibration of outcome and causal conditions; 4) truth table generation; and 5) truth table minimization.

The outcome was naturally defined as SCR. The selection of causal conditions was more challenging, as it should be based on theoretical or substantive knowledge of links between causal conditions (when present) and the outcome (Fiss, 2011) and not be the result of “fishing expeditions” (Ketchen et al., 2021, p. 14). A moderate number of causal conditions must be carefully selected, as it is impossible to include all causal conditions that might influence the outcome (Russo et al., 2019). Insights from the large body of literature on SCR and its enablers (see Section 2.2.3) generally informed the selection of the causal conditions, though some adaptations were necessary (e.g., Jüttner & Maklan, 2011; Nikookar & Yanadori, 2022). Analytics was included as the point of interest for the thesis and enablers that overlapped conceptually were avoided. Additionally, SCC was included as a contextual factor to split the sample into two subsets, allowing for an examination of whether the paths are contingent on the SCC level.

Calibration of the outcome and causal conditions is the third step in the QCA process (Arellano et al., 2021) and refers to the process of turning raw Likert-scale data to fuzzy-set membership scores to “highlight differences in kind and in degree among cases” (Greckhamer et al., 2018, p. 488). These fuzzy-set membership scores range from a lower cut-off point of 0.0 (representing the qualitative anchor of full non-membership) to an upper cut-off point of 1.0 (full membership), with 0.5 as the cross-over point (Ragin, 2008). The multi-item scales were first merged into one measure by calculating the arithmetic mean (e.g., Leischnig et al., 2018). Then, an empirical calibration principle was chosen to better reflect the empirical reality. In this approach, the 95th
percentile was used for full membership, the median for the cross-over point, and the 5th percentile for full non-membership, as outlined in (Pappas & Woodside, 2021). A common alternative conceptual calibration approach utilizes 6, 4, and 2 as the upper bound, cross-over point, and lower bound, respectively, across all measures (e.g., Pappas et al., 2020). However, as evidenced by the computed thresholds in Table 6, empirical calibration using percentiles resulted in values in the vicinity of 6, 4, and 2 for most constructs. The median aligns with the midpoint of the 7-point Likert scale (i.e., 4; Table 6), indicating that the calibrated values maintain the intended verbal and linguistic interpretation of the responses on the Likert scale. Calibrated fuzzy-set membership scores also range across the entire allowed spectrum (0.0 to 1.0), indicating that differences in degree and in kind have been captured successfully. A constant of 0.001 was added to all fuzzy-set membership scores equal to exactly 0.5 (Fiss, 2011), to avoid dropping those scores in the subsequent analysis (Ragin, 2008).

Table 6: Calibration reference points

<table>
<thead>
<tr>
<th>Construct</th>
<th>Full non-membership (5th percentile)</th>
<th>Crossover point (median)</th>
<th>Full membership (95th percentile)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SCR</td>
<td>2.00</td>
<td>4.67</td>
<td>6.00</td>
</tr>
<tr>
<td>SCV</td>
<td>2.00</td>
<td>4.50</td>
<td>7.00</td>
</tr>
<tr>
<td>SCA</td>
<td>1.00</td>
<td>3.40</td>
<td>6.40</td>
</tr>
<tr>
<td>SCResp</td>
<td>2.33</td>
<td>4.67</td>
<td>6.60</td>
</tr>
<tr>
<td>SCI</td>
<td>2.25</td>
<td>4.50</td>
<td>6.95</td>
</tr>
</tbody>
</table>

Two truth tables were generated in the fourth step, one for low SCC (<4) and one for high SCC (>4). Truth tables contain $2^k$ rows, with all logically possible paths for $k$ number of causal conditions and information on the frequency of empirically observed cases associated with each row (Greckhamer et al., 2018). One path may consist of a single causal condition or configurations of two or more causal conditions. Thus, for 4 causal conditions, 16 rows ($2^4$)
were generated in each truth table. Empirical instances were observed for all 16 logically possible paths in conditions of both low and high SCC.

The fifth and final step was truth table minimization. Truth table minimization is conducted by performing Boolean algebra operations on the truth table rows to determine sufficiency and necessity, which are the two dimensions of causality in QCA (Ragin, 2008). Sufficiency means that a configuration of causal conditions is a subset of the outcome, while necessity means that the outcome is a subset of a configuration of causal conditions (Greckhamer et al., 2018). Consistency and coverage are two key measures for evaluating sufficiency and necessity. Consistency measures “how closely a perfect subset relation [between a (configuration of) causal conditions and an outcome] is approximated” (Ragin, 2008, p. 44), or, in other words, the proportion of cases of a particular configuration that also exhibit the outcome (Greckhamer et al., 2018). Coverage assesses “empirical relevance or importance” (Ragin, 2008, p. 44), or the proportion of the outcome covered by a particular configuration (Greckhamer et al., 2018).

Initial consistency and frequency cut-offs were set to 0.80 and 1, respectively, for the sufficiency analysis (Greckhamer et al., 2018; Pappas & Woodside, 2021). In this analysis, it was evident which configurations could be associated with the presence and absence of SCR (the latter denoted “~SCR”). Multiple configurations, however, exhibited simultaneous membership in both SCR and ~SCR. These are referred to as “contrary configurations” and are considered logically erroneous. Contrary configurations were resolved by checking the proportional reduction in inconsistency (PRI) measure against the threshold of 0.50 (Greckhamer et al., 2018). The process of resolving contrary configurations also led to a marginal increase in consistency cut-off to 0.81 and 0.84 for low and high SCC, respectively, making the final consistency cut-offs more conservative than the general recommendations. Necessary condition analysis was performed for all causal conditions, using 0.90 as the consistency threshold (Greckhamer et al., 2018). No necessary conditions were identified. Three types of solutions were generated at the end of the sufficiency analysis: complex, parsimonious, and intermediate. The comparison of parsimonious and intermediate solutions is used to identify core and peripheral conditions (Fiss, 2011). However, in this study, the parsimonious and intermediate solutions were found to be identical due to the
non-existence of logical remainders (i.e., configurations with no empirical instances). As a result, it was not possible to distinguish between core and peripheral conditions.

3.6.2. **Qualitative component**

In the analysis stage, responses for the listed factors were aggregated row-wise; the ratings, the number of times it was selected as critical, and comments from all respondents were summarized for each of the listed factors. Additional coding was deemed unnecessary for the comments as they were already connected to thematically distinct factors in the questionnaire. Finally, the list was sorted in descending order based on the assessment of critical obstacles. It should be mentioned that only two respondents chose to add additional obstacles to the list, with both adding a singular obstacle. These obstacles also overlapped qualitatively with obstacles on the original list (see P3 for further details).

3.7. **Research quality and ethical considerations**

Since the research presented in this thesis encompasses a combination of both qualitative and quantitative research design components, quality criteria must be applicable to both approaches. Thus, following the suggestion of Riege (2003), four composite quality criteria are used. Construct validity and confirmability deal with non-subjectiveness in relation to the operational measures of theoretical concepts or the interpretation of data. (1; numbering refers to the corresponding column in Table 7) Construct validity and confirmability were ensured through peer review of data collection instruments, data analysis, and results, and the use of established constructs (i.e., operational definitions) that match nominal definitions. The second composite criterion, internal validity and credibility (2), refers to the correctness of inferences about cause-and-effect relationships and empirical phenomena in general. Peer review of results and respondent approval of data were used to satisfy this criterion. External validity and transferability (3) relate to generalization, or the extent to which the findings can be extended to a broader context. To address this criterion, a clear description of the overall scope of the thesis study has been provided, including sample design, to
highlight the opportunities for and the boundaries of generalization of the results. Finally, reliability and dependability (4) focus on the possibility of replication of the research process and findings. Clear descriptions of research design and execution, the use of structured data collection instruments, and the preservation of raw data increase the likelihood of replication. Table 7 summarizes the techniques that were employed to ensure that the four composite quality criteria were satisfied. As illustrated in the table, some techniques relate to more than one criterion. For further details on quality issues, refer to P2 and P3, appended to this thesis.

Table 7: Techniques employed to ensure quality

<table>
<thead>
<tr>
<th>Employed technique</th>
<th>Quality criteria</th>
</tr>
</thead>
<tbody>
<tr>
<td>Peer review of data collection instruments (survey instrument and interview guide)</td>
<td>1</td>
</tr>
<tr>
<td>Key concepts clearly defined (interviews) and use of established constructs to ensure that operational definitions match nominal definitions (survey)</td>
<td>1</td>
</tr>
<tr>
<td>Respondent review and approval of data and interpretation (interviews)</td>
<td>1 2</td>
</tr>
<tr>
<td>Test of construct validity (test of convergent and discriminant validity of survey data)</td>
<td>1</td>
</tr>
<tr>
<td>Peer audit of data analysis process</td>
<td>1 2</td>
</tr>
<tr>
<td>Peer examination of preliminary results</td>
<td>1 2</td>
</tr>
<tr>
<td>Raw data (survey data set and interview recordings) available for confirmatory audit, i.e., reanalysis</td>
<td>1 4</td>
</tr>
<tr>
<td>Patterns (similarities) identified within scope and sample through rich descriptions and consensus (interviews) and systematic identification of patterns among concepts (survey)</td>
<td>2 3</td>
</tr>
<tr>
<td>Clear description of scope and sampling</td>
<td>3</td>
</tr>
<tr>
<td>Clear description of research design and execution</td>
<td>4</td>
</tr>
<tr>
<td>Structured data collection instruments used (survey questionnaire and interview guide)</td>
<td>4</td>
</tr>
<tr>
<td>Cronbach’s alpha (survey)</td>
<td>4</td>
</tr>
<tr>
<td>Pilot testing of survey instrument</td>
<td>4</td>
</tr>
</tbody>
</table>
Ethical considerations were incorporated into the research process to comply with the ethical principles of Vetenskapsrådet (2017). First and foremost, efforts were made to explain the scope and purpose of the research before commencing data collection to the respondents. The respondents were guaranteed confidentiality of the information that they provided. Interviews were recorded only once permission had been granted by the participant. Respondents were assured that their identities and firm affiliations would not be disclosed to third parties and would be removed from published and presented findings. Participation in the empirical components was voluntary and respondents were informed of their right to decline further participation at any time.
4. Findings

This chapter presents the findings as they relate to each of the two RQs in the thesis, followed by a discussion of said findings.

4.1. How can analytics be used for supply chain resilience?

The findings of this research illuminate two perspectives on how analytics can be used for SCR. Insights revealed by the typology developed in the conceptual research design component and reported in P1 show that analytics can be used for SCR through six distinct application areas. This is complemented by the insights from the configurational analysis that was performed in the quantitative research component and reported in P2, which revealed that analytics can be used for SCR through the development of three distinct configurations with other SCR enablers.

4.1.1. Application areas

The conceptual framework represented by a two-dimensional, 3x2 matrix, shown below in Figure 7, illustrates a typology for the analytics–SCR nexus. The intersections in the matrix illustrate six general application areas which, together, conceptually capture the entire spectrum of possible application areas in the analytics–SCR nexus. These six alternatives collectively explain how analytics can be used for SCR. Some brief examples of the application areas are provided below to further explain how analytics can be used for SCR (for a more detailed description, see P1, appended to this thesis).

In the pre-disruption phase, descriptive analytics can be utilized to retrospectively evaluate the impact of previous SC disruptions, as well as the success of associated response measures. This can be achieved by extracting historical data on lead times, supply, capacity levels, etc. during a previous disruption. The data should also cover the time preceding and succeeding the disruption to allow possible changes over time to be illustrated. The data
should be processed and presented in a suitable format, such as purposefully selected aggregated key performance indicators (KPIs). Visualization techniques, such as simple line charts, may also be employed to facilitate interpretation of the data. The extraction of historical SC data from a previous disruption and subsequent computation and visualization of KPIs can also be used to prepare for future disruptions. By adjusting parameters that correspond to capacity levels, costs, lead times, etc., and analyzing how KPIs of interest might be affected, different response measures can be tested and evaluated in preparation for future disruptions.

Computation and visualization of important KPIs are also useful in the post-disruption phase to monitor disruption impacts and the success of implemented response, recovery, and growth measures. Ideally, the descriptive analytics in the pre-disruption phase will be used to provide insights on important KPIs and what products, nodes, or links in the SC require more ambitious monitoring efforts during SC disruption. Visualization of the SC network is another example of how descriptive analytics might be used in the post-disruption phase. By comparing the geographical coordinates of the incident with the sites of SC partners, a preliminary impact assessment can be performed.

Examples of predictive analytics in the pre-disruption phase include the prediction of disruptions, simulation of different SC configurations (nodes and links) and operational policies (e.g., capacity levels), and simulation of disruption for suppliers within the same geographical area and the associated impact on KPIs. Predictive analytics can be used in a similar manner in the post-disruption phase but with real-time data from the ongoing disruption. Examples include response and recovery simulation, prediction of demand during disruptions, and prediction of excess demand from panic hoarding through the simulation of different lockdown decisions with regard to timing and duration.

In the pre-disruption phase, prescriptive analytics is concerned with supplier segmentation and/or selection when disruption risks are considered. Re-configuration and re-optimization of the distribution network can be utilized in both pre- and post-disruption phases. Distribution network configuration and optimization refers to deciding which transportation routes should be used
and which products or regions a certain distribution center should serve, as well as having an optimal plan with details on how, when, or which products should be transported in the network. In the pre-disruption phase, constraints or disruptions must be hypothetical and based on qualified guesses and knowledge about vulnerabilities in the SC. This approach can enable the proactive development of response measures. If a specific node or link within the SC becomes unavailable or significantly constrained at some date, prior knowledge of appropriate modifications to the distribution network configuration and operational policies can be highly advantageous. Other examples of prescriptive analytics in the post-disruption phase include the automatic generation and submission of replenishment plans and emergency order allocations to suppliers to allow for quick responses during the disruption.
<table>
<thead>
<tr>
<th>Analytics</th>
<th>Pre-disruption phase</th>
<th>Post-disruption phase</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Descriptive analytics</strong></td>
<td>Computation and visualization of KPIs—focus on retrospective assessment of the impact of previous disruptions and the effectiveness of implemented measures. Test and evaluation of different response measures using data from previous disruptions.</td>
<td>Computation and visualization of KPIs—focus on monitoring disruption impact and the effectiveness of implemented measures. Visualization of the geographical location of an incident and nearby sites.</td>
</tr>
<tr>
<td><strong>Predictive analytics</strong></td>
<td>Prediction of disruptions at first-tier suppliers. Simulation of different SC configurations and operational policies. Simulation of disruptions and evaluation of impacts.</td>
<td>Simulation of response and recovery using real-time data. (Excess) demand prediction.</td>
</tr>
<tr>
<td><strong>Prescriptive analytics</strong></td>
<td>Supplier segmentation and/or selection Distribution network reconfiguration and/or re-optimization</td>
<td>Distribution network re-configuration and/or re-optimization Automatic generation and submission of replenishment plans and emergency order allocation to suppliers</td>
</tr>
</tbody>
</table>

*Figure 7: A typology for the use of analytics for SCR*
4.1.2. Configurations with other SCR enablers

Three paths to SCR are available when SCC is low. All three paths comprise pairs of enablers, i.e., analytics complemented by one of the other enablers (SCV, SCResp, or SCI). However, when SCC is high, only one path to SCR seems to be viable—the analytics–SCI pair. This means that the configuration of analytics and SCI is feasible regardless of SCC level. This also means that a total of three unique paths for SCR exist when analytics is included.

4.2. What are the key obstacles to the use of analytics for supply chain resilience?

The findings of this study suggest that a multitude of obstacles to the use of analytics for SCR exist. Specifically, 21 distinct obstacles were assessed as critical by at least one expert respondent. Despite dispersion in assessments of critical obstacles, some consensus was noted in relation to four obstacles:

1. Low data availability and/or quality;
2. Hindrance to quick decision-making;
3. No data-driven culture; and
4. Insufficient benefits and/or use.

Low data availability and/or quality clearly stands out, as it was deemed critical by eight experts. The other three obstacles listed were considered critical by four experts. These obstacles are elaborated on below.

Most experts agree that poor availability and quality of data from SC partners pose significant challenges, especially during disruptions, and may consequently serve as a reason for not implementing or using analytics for SCR. Experts also note that recent disruptions have not stimulated increased data-sharing among SC partners, with security precautions mentioned as a possible reason. While it is essential to have external, real-time data during disruptions, findings suggest that internal and historical data can serve as a sufficient starting point for analytics for SCR-related purposes.
Four of the interviewed experts agreed that the associated hindrance to quick decision-making was a reason for not implementing or using analytics for SCR. The lengthy process of developing and validating analytics tools leads to challenges for reactive tool development during disruptions. Additionally, the process becomes even lengthier when there is already a backlog of tools waiting to be developed and validated. Another issue that hinders quick decision-making is the need for (additional) data collection. Respondents also highlighted the time-consuming nature of analyzing and formulating plans to address a wide range of scenarios. It is also worth noting that many of the recent SC disruptions were not anticipated or even deemed to be plausible.

The absence of a data-driven culture was another obstacle considered critical by four of the interviewed experts. A multitude of overlapping reasons was mentioned as to why decision-making tends to be based on factors other than analytics, such as experience and intuition. The reasons include a lack of trust in analytics, previous unsatisfactory experiences, data quality issues, skepticism, complexity, and the criticality of decision-making during disruptions. Multiple experts underscored the potential limitations of analytics in accurately taking into consideration all facets and available information. To illustrate the issue, an instance during the COVID-19 pandemic was described where data contradicted reality as it did not capture all the relevant dimensions that determined demand. Findings also suggest an influence of the decision-maker’s personality and seniority on the inclination to rely on analytics. A middle manager’s faulty decision might go unnoticed, for instance, which could allow for greater risk-taking when making decisions.

Insufficient benefits and/or use was the final factor identified as critical by four experts. Developing analytics exclusively for SCR-related purposes was considered unnecessary, especially due to the unknown timing and characteristics of future disruptions. Findings specifically suggest that the use of analytics before a disruption has occurred is considered uneconomical. This is due, in part, to the fact that it is not certain whether these efforts will ever pay off.
5. Discussion

This chapter discusses the implications of this thesis for research, practice, and society.

5.1. Research implications

This exploration of the use of analytics for SCR carries multiple implications for research. First and foremost, the thesis contributes to the general stream of research on SCR. The recent SC disruptions have increased the importance and practical relevance of research on SCR, as evidenced by the increased attention in the literature (e.g., Flynn et al., 2021; Kähkönen & Patrucco, 2022; van Hoek, 2020). In particular, empirical data collected during the recent disruptions provide a unique and invaluable opportunity to conduct research on SCR. On a general note, the scarcity of empirical SCR research has been a key concern in the literature (Scholten et al., 2020; van Hoek, 2020). The primary contribution of this research is to the nascent stream of research on the nexus of analytics and SCR, in response to the calls of Sarkis (2021), Queiroz et al. (2020), Ali and Gölgeci (2019), and others to provide more space for technology within SCR research. Focusing on the analytics–SCR nexus represents an attempt to bridge two disciplines (SCM and information systems) and create a unified body of knowledge. The thesis has contributed towards an interdisciplinary research agenda which will avoid duplication of work in the respective disciplines.

As part of its exploration, the thesis has offered a multidimensional view of how analytics can be used for SCR. It has contributed to conceptual development by developing a typology that describes the complete range of application areas. This contribution enriches the extant literature by offering both a deeper and broader understanding of the role of analytics for SCR, going beyond what can be illustrated by isolated individual cases (e.g., Norrman & Wieland, 2020). The thesis also contributes to the perspective on how analytics can be used for SCR in terms of the configurations of SCR enablers. A configurational perspective was used to investigate SCR enablers collectively, treating SCR as causally complex and utilizing fsQCA. Findings
identified multiple paths to SCR (equifinality) and suggested that complementary SCR enablers are needed in combination with analytics (conjunctural causation), concurring with the literature that has previously suggested these characteristics (e.g., Srinivasan & Swink, 2018). A contribution has also been made to the literature on SCC, which has thus far been described as ambiguous in relation to SCR (Wiedmer et al., 2021). Findings suggest that paths to SCR differ based on the level of SCC level with one exception being the pair of analytics and SCI. An additional contribution involves increasing methodological diversity in the SCM discipline by responding to the calls for employing fsQCA. Interestingly, both Ketchen et al. (2021) and Russo et al. (2019) specifically suggested SCR as a suitable candidate for the application of a configurational approach through fsQCA.

Exploration of the use of analytics for SCR has also revealed several obstacles to implementation. This builds on and complements the general literature on obstacles to analytics use (e.g., LaValle et al., 2011; Lismont et al., 2017; Vidgen et al., 2017). The findings indicate that previously identified obstacles are still relevant when considering SCR, highlighting the rigor of the previous literature. Low data availability and/or quality, the obstacle rated as critical by most experts, has been emphasized as highly important in previous studies (e.g., Lismont et al., 2017; Vidgen et al., 2017). The specific focus on SCR within this research, however, has provided new insights that offer an additional dimension to the extant literature. It was revealed, for example, that data quality is much worse during disruptions and that data sharing between SC members is not stimulated by disruptions.

This research contributes to scholarly debate on SCV and its interplay with other SC concepts (Williams et al., 2013). The findings of this research illuminate two sides of SCV. On the one hand, it is a required complement to analytics when enabling SCR in contexts where SCC is low. This is supported by examples of analytics applications for SCR that require SCV. Visualization of the geographic location of SC partners, for instance, is not possible if the information is not available. Monitoring in the post-disruption phase also requires that supply and demand data are available and reliable across the different tiers of the SC. The relevance of SCV as a complement to analytics is clear. However, on the other hand, SCV seems to be particularly problematic in practice and its absence is a key obstacle to the use of analytics.
for SCR according to the findings. Nevertheless, the findings also indicate that historical data could constitute an adequate starting point for analytics in relation to SCR. If true, it may make the left-hand side column of Figure 7, representing the use of analytics in the pre-disruption phase, more appealing from a practical standpoint.

5.2. Practical implications

The exploration of the use of analytics for SCR has multiple uses for industry and society. From the perspective of a practitioner, the thesis sheds light on analytics as a potential enabler for SCR. The findings provide a platform on which practitioners can assess whether it is worthwhile to develop and use analytics for SCR considering the set of distinct application areas, configurations with other SCR enablers, and potential obstacles. Research of this nature is especially valuable considering the recent SC disruptions. The conceptual development in this thesis can serve as a starting point for mapping and development projects. Firms can assess how many of the six different application areas of analytics for SCR are currently used and evaluate whether the portfolio needs adjustment to better align with current or future needs. Practitioners can also investigate which application areas may be especially valuable for their specific needs and context.

There are also multiple paths that practitioners can choose from in terms of SCR enabler configurations. Findings show that analytics is must be paired with one additional SCR enabler; a singular managerial focus of overinvestment in analytics will therefore likely prove unsuccessful. The pair of analytics and SCResp constitutes an example on synergetic effects that appeared in the findings. Findings showed that SCResp is a complementary SCR enabler to analytics. At the same time, findings also indicate that the hindrance to quick decision-making appeared as a key obstacle to analytics use. However, by combining analytics with SCResp it is possible that the quick reaction enabled by SCResp compensates for the potential lengthy decision-making process when analytics is used. As another key practical implications is that analytics and only one additional SCR enabler is needed, which indicates that building SCR might not be resource-intensive. SC managers can focus their efforts on developing and leveraging specific enabler
pairs, rather than attempting to build an extensive and complex set. The potential for targeted and efficient resource allocation is beneficial as resources are limited in practice and require prioritization. The different available configurations provide practitioners with a “menu” of options that they can choose from based on their current capability portfolio while taking their SCC context into consideration.

Moreover, the identification of obstacles provides practitioners with a list of issues to be cognizant of and to address proactively when considering the use of analytics for SCR. For instance, availability of supply and demand data (SCV) is a complement to analytics, but also problematic in practice (obstacle of availability and/or quality), warrant increased managerial attention. To address this obstacle proactively, SC partners could explore strategies for enhancing data sharing, integration, and validation processes, such as the creation of data-sharing agreements, the cultivation of trust and transparency among partners, and the implementation of secure and efficient data-sharing platforms.

By extension, the thesis also has societal impacts. SCs play a crucial role in providing essential goods to society, including basic food items and medical supplies. The responsibility of SCs to ensure the uninterrupted provision of these goods persists even during disruptions. This responsibility underscores the need for SCs to possess the capability to prepare, respond, recover, and facilitate growth during disruptions. Through the exploration of analytics use for SCR, and the therein managerial implications, the thesis also holds implications for society.
6. Conclusion

The final chapter of this thesis provides concluding remarks and proposes avenues for future research.

6.1. Concluding remarks

The recent SC disruptions have clearly underscored the importance of SCR, and initial evidence suggests that analytics could play an important role in its achievement. On this basis, this thesis aimed to explore the use of analytics for SCR. The exploration generated a typology for the analytics–SCR nexus consisting of six different application areas. Findings also indicated that there are different paths to SCR in terms of configurations of SCR enablers. Three unique configurations, each consisting of analytics and an additional SCR enabler, were identified, though the feasibility of each approach was dependent on the level of SCC. Finally, obstacles to the use of analytics were identified. There was a clear consensus that low data availability and/or quality represents a significant obstacle, but somewhat weaker consensuses concerning the hindrance to quick decision-making, lack of data-driven culture, and insufficient benefits and/or use as obstacles to the use of analytics for SCR.

6.2. Future research

There are several opportunities for future research to further advance the literature on the use of analytics for SCR. Some of these opportunities concern the replication of studies in other empirical contexts. For instance, the data presented in this thesis was collected within a solitary country (Sweden) and limited industries (manufacturing, retailing, and wholesale). Interesting insights could be captured by investigating developing countries, which have begun to receive attention in the SCR literature recently (e.g., Aman & Seuring, 2023; Tukamuhabwa et al., 2017). It is plausible that the utilization of analytics is different in developing countries due to low technological maturity (World Economic Forum, 2018). Furthermore, developing countries
are important for global SCs as they often harbor the upstream end of SCs due to low costs, while also being more exposed and vulnerable to disruptions (Tukamuhabwa et al., 2017). It is important that this empirical context also be reflected in SCR research. Furthermore, while the transportation and warehousing industries were not covered by the sample within this thesis, they are relevant in relation to disruptions to the flow of physical products and SCR. Logistics service providers are by definition service firms and warrant special adaptation in research to accommodate the differences from manufacturing, retailing, and wholesale firms that carry product risk. Replication of the research presented in this thesis in other empirical contexts such as these could prove fruitful.

It is also important to note that data collection was conducted during a period encompassing two significant disruptions, namely the COVID-19 pandemic and the war in Ukraine. Consequently, it is plausible that respondents' perceptions of their SCR may have been influenced by the temporal context comprising these ongoing disruptions and, due to their severity, resulted in potentially lower reported levels of SCR. Replication studies or a longitudinal approach could reveal the extent to which perceived levels of SCR are contingent on specific disruptions, as well as examine the temporal stability of the identified paths or obstacles.

Another suggestion for future research concerns more in-depth inquiry. Although this thesis has indicated some paths to SCR that pair analytics and an additional SCR enabler, it has not investigated in which sequence the enablers in the respective pairs should be developed or how they interact. It is for instance not clear if analytics support the development of SCI, or vice versa, in that pair. Qualitative, in-depth case studies on instances representing each path could offer valuable insights into their development and practical functioning, i.e., in what order the enablers should be developed and how synergistic effects are created. These case studies could specifically shed light on development of different pairs require different levels of investments. More in-depth inquiry may also reveal whether certain application areas or obstacles are more prevalent or problematic in certain industries. Future research could attempt to provide a more nuanced understanding of the use of analytics use for SCR by highlighting such characteristics.
It should be emphasized that both analytics and SCR are evolving concepts, as evidenced by the development of big data and artificial intelligence (Davenport, 2018; Duan et al., 2019; Maheshwari et al., 2021; Toorajipour et al., 2021). Analytics will not be considered in the same way in the future as it is today. Similarly, new theoretical perspectives on SCR have emerged, sparked in part by the recent severe disruptions. These perspectives include antifragile SCs (Nikookar et al., 2021), viable SCs (Ivanov & Dolgui, 2020), and transilience (Craighead et al., 2020), as well as perspectives that emerge by drawing on other theories or disciplines (Wieland, 2021; Wieland & Durach, 2021; Wieland et al., 2023). The evolving nature of these concepts surely represents an opportunity for future research to offer new insights into their intersections.
References


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Vetenskapsrådet. (2017). *God forskningssed*


Analytics for Supply Chain Resilience:
Exploring Paths and Obstacles

Supply chain disruptions, ranging from epidemics to geopolitical tensions, have been especially evident in recent years and have consequently become a hot topic in both boardrooms and academic literature. Supply chain resilience (SCR) denotes the ability to prepare, respond, recover, and facilitate growth during disruptions and is usually thought of as consisting of several enablers. Initial evidence suggests that one such enabler could be analytics, which broadly refers to the processing of data to support decision-making. This thesis aims to explore the use of analytics for SCR. The research design comprise one conceptual component followed by two empirical components consisting of a survey and interviews. The findings reveal six application areas for analytics in SCR. Three paths to SCR are also identified in terms of configurations of analytics and other SCR enablers, only one of which does not seem to be contingent on the level of supply chain complexity. Finally, obstacles to the use of analytics were identified. Clear consensus was noted for low data availability and/or quality as a major obstacle to SCR, while a somewhat consensus existed concerning the hindrance to quick decision-making, lack of a data-driven culture, and insufficient benefits and/or use.

The thesis contributes to the nascent stream of research on the use of analytics and SCR by complementing individual observations with broader and deeper insights through the spectrum of application areas, configurations of analytics and complementary SCR-enablers, and finally, obstacles. For practitioners, the thesis provides insights into using analytics as a potential enabler for SCR. Firms can evaluate their current use of analytics for SCR and adjust their set of application areas and configurations of SCR-enablers as per the options outlined in the findings to better align with their specific needs and prerequisites. Finally, guidance is provided on what obstacles to be cognizant of and attempt to mitigate.