JÖNKÖPING UNIVERSITY
School of Engineering

Doctoral Thesis

In Times of Disruption

A Study of Analytics Capability and Supply Chain Resilience

Martin Seif

Jönköping University
School of Engineering
Dissertation Series No. 103 • 2026

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Abstract

Recent years have seen a surge of supply chain disruptions, including a global pandemic and geopolitical conflicts, which have reinforced the importance of strengthening supply chain resilience. In parallel, advances in data availability and processing have increased the interest in analytics capability to support decision-making. The purpose of this dissertation is *to investigate the nexus of analytics capability and supply chain resilience*. The dissertation adopts a mixed-methods research design and comprises five appended papers together with a comprehensive summary (kappa). The quantitative strand is based on a cross-sectional survey of manufacturing, retail, and wholesale firms and applies both regression analysis and fuzzy-set Qualitative Comparative Analysis. The qualitative strand comprises expert interviews. In addition, a systematic literature review is included as a complementary component of the research. Findings show that analytics capability contributes to supply chain resilience, but that it is neither necessary nor sufficient on its own. Instead, analytics contributes to resilience primarily when combined with other enabling capabilities, namely supply chain visibility, responsiveness, or integration, forming multiple alternative configurations whose viability depends on supply chain complexity. Performance implications are also highlighted. The qualitative findings identify several obstacles and enablers, spanning multiple dimensions. Research at the nexus of analytics capability and supply chain resilience is advanced by underscoring a configurational and context-sensitive perspective, as well as the identification of obstacles and enablers and illustrating how these relate to disruption characteristics, such as sporadic nature and high urgency. Practical guidance is also provided.

Keywords: Supply chain resilience, Analytics capability, Mixed-methods, Dynamic capabilities view, Configuration theory, Contingency theory.

Sammanfattning

De senaste åren har antalet störningar i försörjningskedjor ökat markant, bland annat till följd av pandemin och geopolitiska spänningar, vilket i sin tur har tydliggjort vikten av resiliens i försörjningskedjor. Samtidigt har den tekniska utvecklingen ökat möjligheterna för data-drivet beslutsfattande, så kallad analytics. Syftet med avhandlingen är att undersöka skärningspunkten mellan analytics och resiliens i försörjningskedjor. Avhandlingen använder en kombination av kvantitativa och kvalitativa metoder samt består av fem bilagda artiklar och en kappa. Den kvantitativa delen baseras på en enkätstudie bland tillverknings-, detaljhandels- och grossistföretag. Den kvalitativa delen består av expertintervjuer. Dessutom omfattar avhandlingen en systematisk litteraturöversikt. Resultaten visar att analytics bidrar till resiliens i försörjningskedjor, men att det varken är en nödvändig eller tillräcklig förutsättning i sig. Analytics behöver i stället kombineras med andra kompletterande förmågor i konfigurationer. Flera sådana konfigurationer blev identifierade där typen av försörjningskedja avgör vilken/vilka som är tillämpliga. De kvalitativa resultaten identifierar ett antal hinder och möjliggörare, vilka spänner över flera dimensioner. Sammantaget bidrar avhandlingen till forskningen genom att betona ett konfigurativt och kontextkänsligt perspektiv, identifiera hinder och möjliggörare samt belysa hur de präglas av störningarnas egenskaper, såsom sporadisk förekomst och tidskritiska natur. Avhandlingen ger även praktisk vägledning för beslutsfattare.

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Martin

Jönköping, April 2026

Appended papers

The following papers are enclosed as appendices.

Paper 1 (P1)

Seif, M., & Jafari, H. Analytics for Resilience: A Systematic Review of the Field and Explanation of Mechanisms

Manuscript under review in an international journal

Contribution to paper: I initiated the paper and collected data. Analysis was done jointly by both co-authors. I wrote an early draft, while revision and improvements were done jointly by both co-authors.

Paper 2 (P2)

Seif, M., & Jafari, H. Supply Chain Resilience through Capability Bundles: A Fuzzy-Set Configurational Approach

Manuscript under review in an international journal

Contribution to paper: Both co-authors initiated the study and collected data. I did the analysis while writeup was done jointly by both co-authors.

Paper 3 (P3)

Seif, M. Why Analytics for Supply Chain Resilience Is Far from Trivial: Identifying Key Obstacles

Manuscript under review in an international journal

Paper 4 (P4)

Seif, M., & Jafari, H. (2026). Unpacking the role of analytics for supply chain resilience and performance: the complex influence of supply chain integration. Production Planning & Control, 37(3), 272–289. https://doi.org/10.1080/09537287.2025.2523901

Contribution to paper: Both co-authors contributed equally.

Paper 5 (P5)

Seif, M., & Jafari, H. Supply Chain Resilience Through Analytics: Experts' Perceptions of Key Enablers

Manuscript under review in an international journal

Contribution to paper: I initiated the paper and collected data. Analysis was done jointly by both co-authors. I wrote an early draft, while revision and improvements were done jointly by both co-authors.

List of Key Abbreviations

AC	Analytics capability
AHP	Analytic hierarchy process
AJG	Academic journal guide
AVE	Average variance extracted
CFA	Confirmatory factor analysis
CMB	Common method bias
CR	Composite reliability
DCV	Dynamic capabilities view
EFA	Exploratory factor analysis
FP	Firm performance
fsQCA	fuzzy-set Qualitative Comparative Analysis
HTMT	Heterotrait–monotrait ratio
IS1-2	Interview study 1-2
KMO	Kaiser–Meyer–Olkin measure
OSCM	Operations and supply chain management
P1–P5	(Appended) Papers 1–5
RQ	Research question
SC	Supply chain
SCC	Supply chain complexity
SCI	Supply chain integration
SCM	Supply chain management
SCR	Supply chain resilience
SCResp	Supply chain responsiveness
SCV	Supply chain visibility
SLR	Systematic literature review
SME	Small and medium-sized enterprise
SNI	Swedish standard industrial classification
SS	Survey study
TI	Technological intensity
TOE	Technology–organization–environment (framework)

Notes

This dissertation builds upon the author's licentiate thesis:

Seif, M. (2023). Analytics for supply chain resilience: Exploring paths and obstacles [Licentiate Thesis, Jönköping University].

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1. Introduction

Supply chain management involves the management of material, information, and financial flows across chains or even forth as networks of interconnected firms (Cooper et al., 1997; Mentzer et al., 2001) and is subject to two key developments. First, a series of recent disruptions has reinforced the importance of supply chain resilience. Second, technological advancements have increased the potential of analytics capability to support decision-making. The Introduction chapter lays the foundation for the dissertation by first introducing these two developments. It then turns to the research motivation by outlining the theoretical and practical relevance of the nexus between analytics capability and supply chain resilience and by identifying literature gaps. Next, purpose and research questions are presented. This is followed by scope and delimitations, before concluding the chapter by detailing the structure of the remainder of the dissertation.

1.1. Background

In recent decades, supply chain management (SCM) has relied on initiatives such as outsourcing of activities to third parties, inventory reduction, and offshoring to low-cost countries. While these well-established initiatives offer advantages, primarily in terms of cost reduction, they are also associated with disadvantages. The structural characteristics of supply chains (SCs), referred to as supply chain complexity (SCC), increase due to globalization and multi-tier interdependencies, which in turn are associated with higher exposure to disruptions (Blackhurst et al., 2011; Bode & Wagner, 2015). These represent an infrequent yet severe form of disturbance to the flow of goods in SCs (Craighead et al., 2007; Hosseini et al., 2019). The underlying logic is that interdependencies cause the disruptions to propagate, or "ripple", across the network of firms (Ivanov et al., 2014), meaning that "the failure of any one element in it [the SC] could cause the whole network to fail" (Rice & Caniato, 2003, p. 22).

During the 2020s, the frequency and severity of disruptions have become increasingly evident. These developments have prompted scholars to use terms like "extreme conditions" (Sodhi & Tang, 2021), "new normal" and "unprecedented times" (Alexander et al., 2022) to underscore the peculiarities of contemporary SCM. The COVID-19 pandemic triggered simultaneous supply, demand, labor, and transportation shocks (Belhadi et al., 2021; van Hoek, 2020), exposing the downsides of globalized SCs. Even before the Coronavirus had spread globally, disruptions emerged as the initial outbreak region represented a crucial supply hub for numerous Western firms (Deloitte, 2020; Linton & Vakil, 2020). The automotive industry, with manufacturers such as Volkswagen and Toyota, was impacted almost immediately as the epicenter of the outbreak was an important production hub for automotive parts (Belhadi et al., 2021). A similar situation was noted for the global supply of pharmaceuticals and personal protective equipment (Sodhi & Tang, 2021).

Accidents and geopolitical conflicts have further stressed SCs. The Suez Canal blockage in 2021 halted one of the world's busiest maritime corridors linking Europe and Asia (Reuters, 2021b). The Russian invasion of Ukraine in 2022, resulting in conflict zones and sanctions, disrupted supply of various essential commodities (European Council, 2025; Simchi-Levi & Haren, 2022), and is, at the time of writing, still ongoing. Furthermore, semiconductor shortages exacerbated by trade wars and natural disasters forced some automakers to suspend production lines (Reuters, 2021a, 2025b). The tariffs imposed by the United States have been acknowledged as "the most significant disruption to global supply chains since the onset of the COVID-19 pandemic" (Miller et al., 2025, p. 4). As an urgent response to impending tariffs, Apple ramped up production and transported 600 tons of iPhones via air freight from its manufacturing facilities in India (Reuters, 2025a). Even more recently, the war on Iran has been said to cause the "largest disruption in history to oil supplies" (Financial Times, 2026) and has also forced the Swedish mining company LKAB to shut one of its iron ore plants for six months, resulting in a production loss of roughly two million tons, as the closure of the Strait of Hormuz prevented customers from receiving shipments (SVT, 2026).

Events like these have pushed disruption-related challenges to the forefront of attention in SCM scholarship and practice. It is widely known that disruptions impose a major impact on operational and financial performance. The negative effects may also go as far as influencing firms' stock market valuation (Hendricks & Singhal, 2005). Beyond purely economic concerns, disruptions also carry societal implications, as the uninterrupted provision of essential goods such as food, medical supplies, and personal protective equipment is vital to public wellbeing (WHO, 2020). On this note, supply chain resilience (SCR) has emerged as a central concept, referring to the capability of a SC to prepare for, respond to, and recover from disruptions (Ponomarov & Holcomb, 2009). It could also entail growth and improvement, allowing for progression to a more favorable position after the disruption (Hohenstein et al., 2015).

In parallel with the disruptions, SCM has also been subject to the broader wave of technological advancements that improve the opportunities for data collection and processing (Kache & Seuring, 2017; Schoenherr & Speier-Pero, 2015; Waller & Fawcett, 2013). In essence, these advancements entail increased data volumes, storage capacity, computational power, and algorithm sophistication (Henke et al., 2016). A key concept in this regard is analytics capability (AC), which denotes the ability to process data to support decision-making (Chen et al., 2012; Davenport & Harris, 2007). The literature has conceptualized AC as multidimensional, encompassing technological, managerial, and competency dimensions (Wamba et al., 2017), underscoring the importance of considering both technological and "softer", non-technological dimensions (Öhman et al., 2021). AC comprises techniques such as simulation, statistical regression, optimization, and visualization (Srinivasan & Swink, 2018) and is often divided into three types depending on sophistication: descriptive which reports on the past and current, predictive refers to future states, and prescriptive which provide normative insights on what decisions that should be taken (Grover et al., 2018; Souza, 2014). Additionally, given the recent technological advancements, it has evolved to also integrate components of, e.g., big data and machine learning (Davenport, 2018; Duan et al., 2019; Maheshwari et al., 2021).

1.2. Research motivation

While SCR has been positioned as a capability itself, it is frequently conceptualized as an outcome emerging from other capabilities (Ali et al., 2017; Ali & Gölgeci, 2019). Here, capabilities denote the mobilization and integration of tangible and intangible resources to enable action and achievement of desired outcomes (Helfat & Peteraf, 2003; Olavarrieta & Ellinger, 1997). AC represents an emerging area of interest in this regard (Dubey et al., 2021; Ivanov & Dolgui, 2021; Melnyk et al., 2024) and "thrives in navigating emergency situations" (Akter et al., 2021, p. 1469). Below, the theoretical and practical relevance of AC for SCR are first elaborated. Next, some literature gaps are outlined at their nexus.

1.2.1. Theoretical and practical relevance

AC is useful for decision-making to adjust and generate new plans, e.g., what-if analyses or assessment of alternatives regarding reallocation or redirection of SC flows, when business environments are volatile and processes complex by being interdependent (Srinivasan & Swink, 2018). It could include so-called digital twins that leverage analytics to support proactive and reactive decisions, like dashboards for visualization of information, simulation for SC "stress-testing" in hypothetical disruptions, and assessment of recovery alternatives (Ivanov, 2023; Ivanov & Dolgui, 2021). AC is particularly valuable during disruptions, when decision-making is characterized by several challenges, including high dynamism, uncertainty, urgency, and complexity (Akter et al., 2021; Dennehy et al., 2021), as highlighted during the pandemic that impacted multiple regions, sectors, and dimensions of supply and demand simultaneously (Sodhi & Tang, 2021; van Hoek, 2020). Under such conditions, the frequency of exception scenarios can quickly overwhelm managers (Srinivasan & Swink, 2018), yet, "[i]n any crisis decision speed and accuracy can be the difference between recovering versus relapse and repeat" (Finkenstadt & Handfield, 2021, p. 1). AC could support decision-making by addressing these challenges as well as compensating for cognitive biases and limitations of the decision-maker (Srinivasan & Swink, 2018).

The usefulness of AC is also reflected from a theoretical standpoint. The dynamic capabilities view (DCV) contends that capability renewal is a necessity in a rapidly changing environment (Eisenhardt & Martin, 2000; Teece et al., 1997), which extends the more static thinking in other perspectives like the resource-based view of the firm (Barney, 1991). DCV differentiates static or ordinary capabilities that allow for day-to-day operations from dynamic capabilities, which are instead concerned with creating or renewing static capabilities (Winter, 2003). More specifically, three different capacities of dynamic capabilities have been suggested, namely *sense* emerging threats (or opportunities), *seize* opportunities, and finally, *improve, combine, and reconfigure* resources (Teece, 2007). From this perspective, AC can be motivated for SCR because it supports sensing through processing data, making complex and evolving situations easier to interpret. Additionally, AC assists in identifying opportunities and threats by offering decision support through the evaluation of various responses to disruptions.

From a practical standpoint, some concrete evidence has surfaced in the literature that substantiates the value of AC for SCR. Examples have shown how firms use visualization tools to map the locations of their own, suppliers', and sub-suppliers' facilities. By linking these locations to that of a disruptive event, the firm in question was able to rapidly identify potentially affected sites and components, enabling faster situational assessment and more informed response decisions (Norrman & Wieland, 2020). A further example refers to an intelligent demand forecasting platform that could generate predictions even when representative historical data was unavailable. By incorporating disruption-related data, the application was able to forecast demand more accurately and in real time for products heavily affected by sudden demand distortion (Shen & Sun, 2021). These examples illustrate analytics applications used during the Fukushima disaster in 2011 and the more recent COVID-19 pandemic, respectively.

1.2.2. Gaps

Raj et al. (2025, p. 2) stress that "[d]espite using various tools to gain insights from data, many firms have faced significant supply chain challenges during unprecedented events like the COVID-19 crisis." This statement raises some important questions, especially given the previous discussion of the theoretical and practical relevance of AC for SCR: does the contribution of AC for SCR emerge beyond a few success cases (like those exemplified earlier), is it potentially insufficient, context-dependent, or constrained by obstacles that limit its full potential? Below, some knowledge gaps expand on these questions.

Extant research has attempted to establish the link between AC and SCR, yet empirical evidence remains scattered and inconclusive. Empirical studies to date have largely examined this link in specific contexts, such as developing economies (Dubey et al., 2021; Iftikhar et al., 2023; Munir et al., 2024), humanitarian aid SCs (Dennehy et al., 2021), and manufacturing firms (Dubey et al., 2021), leaving open the question of whether the AC–SCR relationship holds across a broader range of contexts. This is especially important as prior research has reported mixed results (Jiang et al., 2025). In addition, variations in how AC and SCR are operationalized, together with limited attention to alternative causal logics, indicate that it could be worth investigating further. From another angle, it is important to capture whether AC, by enabling SCR, ultimately also translates into improved performance outcomes (Raj et al., 2025). Establishing this link is crucial, as it provides insights into how the benefits of AC are further channeled through SCR. This is in line with mainstream SCM research that often incorporates performance measures to understand the wider implications of capabilities, or the interactions thereof (e.g., Juan & Li, 2023; Munir et al., 2022).

A second gap concerns capability interaction and configurations. A growing recognition in management scholarship highlights the importance of considering configurations of capabilities, rather than focusing on them in isolation (Fiss, 2007; Ketchen et al., 2021). These ideas rest on configuration theory, which posits that outcomes are the result of coherent sets of interdependent and internally aligned elements (Meyer et al., 1993; Miller, 1986; Ward et al., 1996). The literature hints at such capability complementarities. Srinivasan and Swink (2018) distinguish between *awareness* of what to change (supported by AC) and the *ability to execute* change (supported by other capabilities), which also resonate with the distinct capacities of dynamic capabilities (Teece, 2007). Similarly, prior SCR research has acknowledged that different capabilities serve distinct roles, either by treating them as configurations or in parallel by focusing on their independent contributions (e.g., Gomes & Silva, 2025; Nikookar et al., 2024; Nikookar & Yanadori, 2022). Despite these advances, empirical evidence on how AC interacts or forms configurations with other SCR-enabling capabilities is still sparse, leaving an important gap. Notable exceptions that prove the relevance of this area, have examined how dimensions of AC and SC integration form configurations (Jiang et al., 2024) and how flexibility complements AC for SCR (Dubey et al., 2021). These tendencies are also reflected in case-based research, where AC is employed in tandem with other capabilities (Shen & Sun, 2021). Further research could build on these insights and extend the understanding of how AC contributes to SCR when considered alongside other enabling capabilities, and whether multiple equivalent configurations exist.

A third gap relates to contextual contingencies. There is broad agreement that the returns of capabilities are context-dependent, which rests on the principle of achieving a 'fit' with the surrounding environment (Donaldson, 2001; Schilke, 2014). As a contextual contingency, SCC is of particular interest given its dual role in increasing exposure against disruptions (Blackhurst et al., 2011; Bode & Wagner, 2015) as well as enhancing SCR through redundancies like availability of alternative suppliers or freight carriers (Wiedmer et al., 2021). At the same time, SCC has been suggested to constrain SCR, as it may hinder disruption identification and thereby delaying responses (Bode & Macdonald, 2017; Christopher & Lee, 2004). Nevertheless, scholars highlight that the connection between SCC and SCR remains understudied (Akın Ateş et al., 2022). Investigating the contingent role of SCC can address this ambiguity and highlight how the prerequisites for AC–SCR vary across structurally diverse SCs.

The fourth and final gap is drawn from practice. Findings from a study on Fortune 1000-firms reveal that a minority, less than one in four firms, would describe themselves as data-driven that incorporate AC in their decision-making processes (NewVantage Partners, 2023). On this end, the authors concluded that "becoming data-driven is a long and difficult journey that organizations increasingly recognize playing out over years or decades" (p. 6). AC research has a tradition of investigating factors like obstacles (e.g., Vidgen et al., 2017) and enablers (e.g., Kalaitzi & Tsolakis, 2022; Lai et al., 2018). In this dissertation, obstacles and enablers are broadly defined in relation to AC as anything that "hinders or complicates" and "supports, facilitates or accelerates", respectively. Reflecting the multidimensional nature of AC (Wamba et al., 2017; Öhman et al., 2021), these factors span technological (e.g., data availability and quality; Lismont et al., 2017; Vidgen et al., 2017) and non-technological issues (e.g., data-driven culture; Gupta & George, 2016; McAfee et al., 2012).

Extant research has taken a broad perspective on these factors, in the sense of concerning AC more generally, albeit with some rare exceptions that focus on specific contexts, such as a particular industry (e.g., Zhao et al., 2024). It is therefore unclear whether previous insights are relevant for specific application areas like SCR. As previously mentioned, disruptions constitute decision-making conditions that may overwhelm and expose the cognitive limitations of decision-makers (Srinivasan & Swink, 2018). Such scenarios are characterized by high dynamism, urgency, uncertainty, complexity (Akter et al., 2021; Dennehy et al., 2021), as well as their occasional yet extreme nature (Hosseini et al., 2019), which could be reflected in the obstacles and enablers. Although case studies have illustrated AC in disruption settings (Norrman & Wieland, 2020; Shen & Sun, 2021), obstacles and enablers have not been sufficiently and systematically illuminated. Therefore, research in this direction can deepen the understanding of AC-SCR.

1.3. Purpose and research questions

Taken together, the above gaps lead to the following overarching purpose of the dissertation:

> *To investigate the nexus of analytics capability and supply chain resilience.*

The purpose is addressed through two complementary research questions (RQs), that illuminate different aspects of the AC–SCR nexus. RQ1 focuses on how AC contributes to SCR, which also takes the potential presence of other SCR-enabling capabilities and contextual contingency, operationalized as SCC, in consideration. Broader performance implications of AC's contribution to SCR are also considered. RQ1 is worded as follows:

RQ1 *How does analytics capability contribute to supply chain resilience?*

While RQ1 investigates how AC contributes to SCR, RQ2 addresses the purpose by focusing on obstacles and enablers shaping (i.e., constraining or supporting) AC-SCR, with explicit attention to the multidimensional nature of analytics capability, including both technological and non-technological factors. RQ2 is worded as follows:

*RQ**2*** *How is analytics capability for supply chain resilience shaped by obstacles and enablers?*

1.4. Scope and delimitations

The dissertation treats SCR as a broad capability, and does not disaggregate it into phases (preparing, responding, recovering, and growth; Hohenstein et al., 2015). AC is treated in a similar manner and not disaggregated into types (descriptive, predictive, and prescriptive; Grover et al., 2018) or specific techniques (e.g., optimization; Srinivasan & Swink, 2018). Moreover, while disruptions represent a homogeneous phenomenon (Hosseini et al., 2019, p. 285), this dissertation does not focus on specific disruptions (e.g., one event as a case), but rather addresses them collectively.

The empirical scope of the dissertation is delimited to three industries: manufacturing, retail, and wholesale. These industries were chosen because they manage flows of physical goods and are exposed to disruptions. Regarding the geographical setting of the research, the studies were conducted in Sweden. Although chosen primarily for convenience, this empirical context is suitable for AC-SCR research. Sweden is frequently identified as a leading country in terms of technology and innovation, reflecting high levels of investment, development and adoption of digital technologies (World Economic Forum, 2018). In addition, the Swedish economy is highly dependent on international trade, which exposes firms to disruptions in international SCs (World Economic Forum, 2018).

1.5. Dissertation outline

The rest of the dissertation is structured as follows. The Frame of References (Chapter 2) introduces the core concepts and theoretical perspectives. Next, Methods (Chapter 3) outlines the mixed-methods research design and provides information on the execution of the different studies. It concludes with research quality and ethical considerations. The Summary of Papers (Chapter 4) briefly introduces the five papers (P1-5) appended to the dissertation. Findings and Analysis (Chapter 5) address the two RQs. This is followed by the Discussion that elaborates on implications for research and practice. Finally, the Conclusion (Chapter 7) provides some concluding remarks and discusses future research.

2. Frame of References

Following the structure of the Introduction, this chapter opens with outlining two contemporary and interrelated supply chain challenges – disruptions and complexity. The chapter then proceeds with providing an overview of the main concepts and theoretical perspectives used in the dissertation. First, an overview of supply chain resilience is provided, elaborating on definitions and enabling capabilities. The chapter then proceeds with analytics capability[1]. Finally, the theoretical perspectives guiding the research, the dynamic capabilities view, configuration theory, and contingency theory, are presented and discussed in terms of how they inform and are applied in the dissertation.

2.1. Contemporary supply chain challenges

This section defines SC disruptions and complexity in more depth. With respect to disruptions, key characteristics are presented, contrasted with ordinary disturbances, and illustrated through typical examples. Next, complexity is defined and discussed in relation to disruptions.

2.1.1. Supply chain disruptions

SC disruptions typically refer to low-likelihood, unplanned, and unanticipated events that can have high short- or long-term impacts on the normal material flow (Craighead et al., 2007; Hosseini et al., 2019). Due to their temporary and irregular nature, these phenomena are challenging to identify and forecast (Hosseini et al., 2019). Yet, they pose a "serious threat" (Bode & Wagner, 2015, p. 216) and have significant adverse consequences on both operational and financial performance (Ponomarov & Holcomb, 2009). The negative effects may also extend to firms' stock market valuation. Hendricks and Singhal (2005) show that public announcements of disruptions lead to substantial and persistent decline in stock prices, as these events reduce

[1] For an extensive review of recent literature on the nexus of analytics and resilience, refer to P1.

shareholders' expectancy of future cash flows. Moreover, because SCs are highly interconnected and disruptions have significant effects, the impact often propagates from the initial trigger point across the chain or network of entities. This phenomenon is commonly referred to as the "ripple effect" (Dolgui et al., 2018; Ivanov et al., 2014) and was clearly highlighted during the COVID-19 pandemic, as China's role as a major manufacturer led to supply problems for downstream producers and customers (Belhadi et al., 2021; Sodhi & Tang, 2021).

Disruption risks can be contrasted with operational risks or ordinary disturbances which only have a minimal impact on the continuity of material flows (Tang, 2006), like demand or lead-time fluctuations (El Baz & Ruel, 2021). Ordinary disturbances are also more frequent by being recurrent (Dolgui et al., 2018), which allow reasonably accurate estimation of risks in terms of occurrence likelihoods and impacts (Manuj & Mentzer, 2008). However, this proves inadequate for disruptions, as low-frequency events result in lack of historical data and therefore prevent effective risk identification and quantification (Pettit et al., 2013; Pettit et al., 2010). Disruptions are typically characterized as low-frequency-high-impact whereas ordinary disturbances are the opposite, high-frequency-low-impact (Dolgui et al., 2018), as illustrated in Figure 1.

		Severity of impact	
		Low	**High**
Occurrence frequency or probability	**Low**		Disruptions
	High	Ordinary disturbances	

Figure 1: Differences between ordinary disturbances and disruptions Based on Dolgui et al. (2018) and Pettit et al. (2010).

Typical examples of disruptions include natural disasters, terrorist attacks, strikes, supplier insolvency (Craighead et al., 2020), political turmoil, financial crises, accidents (Ali & Gölgeci, 2019), geopolitics (Miller et al., 2025; Moradlou et al., 2024), and more. Disruptions may occur both at the upstream and downstream end of the SC, with a major product recall as an example of the latter (Bode & Wagner, 2015). As illustrated by these examples, disruptions represent a heterogenous phenomenon and may “unpredictably vary in type, scale and nature” (Hosseini et al., 2019, p. 285). Craighead et al. (2020) argue that the pandemic differed from other disruptions along three key parameters: scope, spillover, and shifts. While typical disruptions are often geographically or sector-specific, the pandemic affected multiple regions and industries simultaneously (scope). Moreover, instead of a single shock that gradually weakens as in a typical disruption, pandemic-induced disruptions propagate repeatedly across different sectors or between different locations and can even be intensified by government interventions such as border closures and mobility restrictions (spillover). Finally, pandemics can trigger extreme and simultaneous fluctuations in both supply and demand, as illustrated during COVID-19 by sudden, extreme surges in consumer goods demand alongside the collapse of entire markets, revealing a level of disruption not observed in more isolated events (shifts).

2.1.2. Supply chain complexity

Building on the definition of SCM, which centers on the flow of material, information, and finances among interconnected firms (Cooper et al., 1997; Mentzer et al., 2001), it is important to recognize that these chains or networks can take a variety of forms. This diversity in characteristics has significant implications for SCM, and especially in relation to disruptions. The characteristics of a SC can be described as the degree of SCC, comprising the number of entities, transactions, flows, and their interrelatedness, which, if high, may lead to an intricate network that is difficult to easily get an overview of (Bode & Macdonald, 2017). Thus, SCC captures both structural complexity (number of entities) and dynamic complexity (interactions, such as number of transactions) (Bode & Wagner, 2015). Akın Ateş et al. (2022, p. 3) summarize these characteristics when defining SCC as the:

> “extent to which the supply chain of an organization is made up of a large number of varying elements that interact in unpredictable ways”

Some authors also extend SCC to consider other complexity dimensions beyond the number and interdependences of entities ("scale complexity", Brandon-Jones et al., 2014). These include geographical dispersion as distant suppliers are more challenging to manage and introduce uncertainties in quality and lead-times, delivery complexity as longer lead-times require more planning efforts, and finally, differentiation relates to differences between suppliers that make maintenance of relationships more challenging (Brandon-Jones et al., 2014, building on other authors). Bode and Wagner (2015) discuss number of tier-1 suppliers (horizontal complexity), total number of upstream tiers (vertical complexity), and geographical dispersion (spatial complexity) as three complexity dimensions.

Extant research has examined the relationship between SCC and disruptions. Craighead et al. (2007) demonstrate that SCC causes more severe disruptions, defining severity as the number of nodes affected by disrupted inbound or outbound flows. Quite similarly, Bode and Wagner (2015) find that all studied complexity dimensions (horizontal, vertical, and spatial complexity) lead to increased disruption frequency as every additional entity adds to disruption exposure[2], increasing number of tiers further allow disruption propagation, and geographical dispersion leads to longer material flow paths where the transportation route and handling points (e.g., ports) introduce additional possibilities for disruptions. They also note that the three dimensions interact by amplifying disruption frequency, leading the authors to recommend practitioners to "simplify your supply chains (within the limits of your business model)!" (p. 224). As a final example, Hendricks et al. (2009) show empirically that firms in geographically dispersed networks and higher adoption of outsourcing face more severe stock market reactions following disruptions.

[2] The authors differentiate between disruption *frequency* and *severity*. While multi-sourcing may lead to higher disruption frequency (due to higher horizontal complexity), it may simultaneously also lead to lowered severity (Bode & Wagner, 2015).

2.2. Supply chain resilience

This section introduces the concept of supply chain resilience. It reviews the origins and evolution of the concept, discusses prominent definitions, and presents enabling capabilities.

2.2.1. Background

Resilience is a widely used concept and has been studied in numerous domains, including psychology, ecology, and economics (Ponomarov & Holcomb, 2009). One of the earliest adopters was the science of ecosystems, where Holling (1973, p. 17) defined resilience as the:

> "persistence of relationships within a system and is a measure of the ability of these systems to absorb changes […] and still persist".

In engineering sciences, another early domain where the concept of resilience was adopted, it was instead defined as the ability to quickly recover and return to equilibrium (Holling, 1996). These ideas have served as inspiration for newer domains, like SCM (Wieland & Durach, 2021). Resilience was first explicitly introduced to SCM by Rice and Caniato (2003), following the terrorist attacks around the shift of the millennium (Ali et al., 2017). Following the seminal works of Rice and Caniato (2003), other important contributions were made to the establishment of SCR (e.g., Blackhurst et al., 2011; Jüttner & Maklan, 2011; Pettit et al., 2010; Ponomarov & Holcomb, 2009). Over time, scholars have continually refined and expanded the concept. As a result, it is now understood as multidimensional that spans distinct chronological phases and involves various enabling capabilities, as discussed in 2.2.2 and 2.2.3, respectively.

2.2.2. Definition

SCR captures the ability of a SC to manage disruptions, with different studies offering varying definitions of the concept. Some scholars define SCR in broad, general terms rather than elaborating on specific elements or mechanisms on how disruptions are managed. In fact, some definitions do not even explicitly mention "disruptions". For instance, Wieland and Wallenburg (2013) define SCR as "the ability of a supply chain to cope with change" (p.

301). In contrast, other authors offer more comprehensive definitions, and often by specifying distinct chronological phases in relation to disruptions. These phasic definitions can also be noted to slightly differ over time as the concept has matured (Ali et al., 2017). The early definitions emphasized only one or two phases. For instance, Christopher and Peck (2004) underlined recovery to the original state or growth to a new, better state. In comparison, newer definitions expand SCR to also encompass the period before a disruption occurs, emphasizing aspects such as prevention or preparedness (e.g., Kamalahmadi & Parast, 2016; Ponomarov & Holcomb, 2009; Tukamuhabwa et al., 2015). For example, the widely recognized and frequently cited definition by Ponomarov and Holcomb (2009, p. 131) details preparation, response and recovery when defining SCR as:

> *"the adaptive capability of the supply chain to prepare for unexpected events, respond to disruptions, and recover from them by maintaining continuity of operations at the desired level of connectedness and control over structure and function."*

These phases have different objectives. Based on a literature review, Ali et al. (2017) argue that readiness or recovery typically deal with anticipating potential disruptions by monitoring changes in the environment and recognizing early signals. Next, the response phase reflects adapting and acting during the disruption to limit the impacts and sustain performance. Finally, recovery and growth capture restoration after a disruption and to learn from the event, using experience to improve performance and SCR in the future.

Besides detailing phases, and therein encompassing a holistic perspective on SCR, the definition by Ponomarov and Holcomb (2009, p. 131) includes an additional noteworthy aspect: 'maintaining continuity'. While some authors define this separately from resilience as robustness (Brandon-Jones et al., 2014, pp. 55–56), it has found relevance in extant SCR conceptualizations (e.g., Golgeci & Ponomarov, 2013; Scholten & Schilder, 2015) and is a legacy of resilience definitions from the science of ecosystems Holling (1973). As SCR "is based on the underlying assumption that not all risk events can be prevented" from happening (Jüttner & Maklan, 2011, p. 246), it is essential to lowering their impact once they occur and cope with them by maintaining continuity.

Consistent with the literature, the dissertation employs a phase-based perspective encompassing preparation, response, recovery, and growth (Hohenstein et al., 2015; Tukamuhabwa et al., 2015), that also includes the facet of maintaining continuity despite disruptions (Ponomarov & Holcomb, 2009).

2.2.3. Enabling capabilities

It is important to distinguish the concept of SCR (*what* it is) from the means through which it is achieved (*how* it can be enabled). To address the latter aspect, the literature has often pointed to several other distinct concepts (Ali et al., 2017; Ali & Gölgeci, 2019), contending that "resilience is an output measure which is dependent on capabilities" (Brandon-Jones et al., 2014, p. 58). The dissertation employs the term (enabling) capabilities, which in line with Olavarrieta and Ellinger (1997, p. 536), are regarded as "complex bundles of individual skills, assets and accumulated knowledge" and denote the capacity to leverage and combine different resources or routines to carry out activities and achieve desirable outcomes (Helfat & Peteraf, 2003; Peng et al., 2008; Winter, 2003). Below, three enabling capabilities are briefly defined and discussed in relation to SCR.

Supply chain visibility

Supply chain visibility (SCV) is a foundational capability. It has been defined as the "access to high-quality information that describes various factors of demand and supply" (Williams et al., 2013, p. 545). Information (or *data*) on demand and supply can be expressed in different ways, with one concerning the location, status, and estimated arrival times of shipments transiting the SC (Francis, 2008). SCV also considers information on other SC partners in terms of their identity and geographical locations (Nikookar & Yanadori, 2022). Other examples include sales data, demand forecasts, inventory levels, and lead times from both upstream suppliers and downstream customers (Williams et al., 2013). Importantly, data availability and quality go hand in hand for visibility to be useful (Barratt & Barratt, 2011; Barratt & Oke, 2007).

As disruptions represent unforeseen events, historical data is not useful in the same way as under stable conditions (Browning et al., 2023; Melnyk et al., 2024), which emphasize the importance of current and up-to-date data for

SCR. The recent review by Swink et al. (2024) note a steady stream of research connecting SCV to SCR. Visibility is well-established in the SCR literature (e.g., Jüttner & Maklan, 2011; Kleindorfer & Saad, 2005) given its key role in fostering awareness of potential disruptions by providing insight into the structure of the SC and real-time supply and demand data (Nikookar & Yanadori, 2022). Thus, SCV has been associated with informed decision-making during SC disruptions, as knowledge about disruptions can prompt development of continuity plans (Brandon-Jones et al., 2014). Christopher and Lee (2004) position SCV as an important measure to increase *confidence* in the SC, which in turn promotes informed and appropriate decisions rather than over-reactions or wrong decisions. Given these benefits, SCV is indirectly tied to monitoring to identify signals before a disruption (Ali et al., 2017) and the quick reaction and response during disruptions (Wieland & Wallenburg, 2013) which has been deemed to potentially reduce both the probability and impact of disruptions (Brandon-Jones et al., 2014). Poor SCV is acknowledged as exacerbated shortages of personal protective equipment during the pandemic, as decision-makers lacked visibility into where inventory was located in the SC and where shipments were being directed (Finkenstadt & Handfield, 2021). Examples of issues that inhibit data sharing in SCs are concerns about confidentiality or security (Bag et al., 2024; Sharma et al., 2020).

Supply chain responsiveness

The concept of SC responsiveness (SCResp) refers broadly to the ability to react and adapt to changing conditions. Yu et al. (2019, p. 791) define it as the:

> "extent to which a firm along with its supply chain partners responds to changes in the business environment"

Changes in the business environment, which by other authors is denoted dynamic environmental conditions (Richey et al., 2022) or market movements (Vachon et al., 2009), are key in SCResp by steering reaction and adaptation. It may refer to changes related to SC partners, such as shifting supplier conditions or customer needs, as well as dynamism in competitor behavior (Kim & Lee, 2010; Yu et al., 2019). Extant definitions often assert that the reaction should be *purposeful* and *timely* (Bernardes & Hanna, 2009; Holweg, 2005), underscoring intentional reaction aiming at specific objectives while also being quick. The reaction could be multifaceted and entail introduction of new products, adjustment of production volumes, changes in product variety, or modification of existing offerings (Roh et al., 2022). However, following Yu et al. (2019), the dissertation focuses on the overall essence of SCResp (quick response in relation to customer, suppliers, competitors, and market), without disaggregating it into specific dimensions or antecedents. Moreover, the reaction needs to be done with "less penalty in terms of cost, time and quality than its competitors" (Roh et al., 2022, p. 836), which signifies that SCResp is a relative concept.

SCResp has been acknowledged as important in relation to SCR. Munir et al. (2022, p. 1584) find support for SCResp as a prerequisite for SCR and make a subtle distinction between the concepts; SCResp deals with response more generally, while SCR is instead concerned with response specifically to disruptions. These insights are also echoed by findings from other studies (Nikookar et al., 2025; Nikookar & Yanadori, 2022). SCResp has been identified as an indispensable (i.e., necessary) prerequisite for SCR, meaning that "[a]ny effort to improve resilience without responsiveness would be wasteful", meaning that it cannot be substituted by any other capability (Nikookar et al., 2025, p. 2).

Supply chain integration

SC integration (SCI) is a relational concept that involves the effective coordination and collaboration among various stakeholders. Different perspectives on the exact scope of SCI exist in terms of locus of integration. Some authors take a wider view, contending that it involves both inter- and intra-organizational integration (Flynn et al., 2010; Schoenherr & Swink, 2012), while others only consider integration with external SC partners, like customers or suppliers (Zhu et al., 2018, p. 213). Research has also shown that internal integration acts as an enabler for external integration, as firms need to be internally integrated before having the prerequisites for successful external integration (Zhao et al., 2011). For the dissertation, SCI is not considered in the broader sense but rather along the second, narrower and external-looking perspective, defined by Zhu et al. (2018, p. 213) 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"

Typically, SCI manifests through practices such as aligned and collaborative planning, decision-making, and mutually developed key performance indicators and processes with other SC partners (Vanpoucke et al., 2017). Moreover, it concerns shared problem solving, proactively exchanging information about changing requirements, jointly setting goals, mutual support and working together to address challenges, and fair distribution of benefits (Zhu et al., 2018). Given this broad scope, informational, operational, and relational integration have been recognized as the key dimensions of SCI (Jiang et al., 2024; Leuschner et al., 2013; Zhu et al., 2017). Overall, SCI should result in an ideal state where "firm boundaries flow smoothly into each other so that a separation into specific actors is no longer possible" (Kotzab et al., 2021, p. 26). Despite benefits, it should be noted that varied findings regarding SCI's impacts has also been observed (Qi et al., 2023; Wiengarten et al., 2019), potentially due to coordination costs or structural rigidities (Wieland & Wallenburg, 2013).

As the "ripple effect" cause disruptions to propagate beyond the original trigger point (Dolgui et al., 2018; Ivanov et al., 2014), they naturally become a shared concern for all affected SC partners. SCI plays a key role by allowing firms to pool resources and jointly tackle challenges (Durach et al., 2020; Scholten & Schilder, 2015) that would likely exceed any single firm's capacity (Faruquee et al., 2021). Integrated SC partners can spot disruptions and shift resources through joint planning and interpretation of information (Qi et al., 2023). The COVID-19 pandemic offered a concrete practical example when showcasing how an online retailer engaged in collaborative practices with its suppliers by sharing infrastructure to assist with inbound deliveries, adjusting payment terms and conditions, and coordinating promotions (Shen & Sun, 2021).

2.3. Analytics capability

Using computers for processing data to support managerial decision-making is not at all a new concept. However, the literature has referred to this concept using inconsistent terminology. The earliest traces of these concepts date back to the 1950s, when "artificial intelligence" was first introduced (Chen et al., 2012). However, it was not until the 1960s that decision-support systems for business applications began to emerge (Wixom & Watson, 2010). Over the years, concepts such as "expert systems" and "knowledge-based systems", have been introduced to the vocabulary. More recently, "business intelligence" and "business analytics" become popularized in the 1990s (Chen et al., 2012; Wixom & Watson, 2010) and 2000s (Davenport, 2006), respectively. While some refer to intelligence and analytics collectively (e.g., Chen et al., 2012), others make distinctions by perceiving analytics to denote the advanced end of business intelligence (e.g., Davenport & Harris, 2007).

For the dissertation, AC is adopted and used in a broad sense, defined by Srinivasan and Swink (2018, p. 1851) as the:

> "organizational facility with tools, techniques, and processes that enable a firm to process, organize, visualize, and analyze data, thereby producing insights that enable data-driven operational planning, decision-making, and execution".

This definition reflects a widespread understanding in the literature, that similarly describe AC as a broad concept for processing and presenting data to support decision-making (Chen et al., 2012; Davenport & Harris, 2007). Some authors even go as far as defining AC as "all the activities that transform data into action" (Öhman et al., 2021, p. 2). This definition also signifies the importance of data availability and quality in relation to AC (e.g., Lismont et al., 2017; Vidgen et al., 2017). Research has differentiated analytics into three types based on output and level of sophistication. Descriptive analytics focus on reporting past events as well as current conditions, predictive analytics extend this perspective by forecasting future outcomes, and finally, prescriptive analytics provide explicit recommendations on optimal actions (Grover et al., 2018; Lepenioti et al., 2020; Souza, 2014). In term of specific techniques, it may involve the use of simulation, optimization, statistical regression, and visualization (Srinivasan & Swink, 2018). Furthermore, decision-making may use analytics to complement human judgment, or it may be fully automated, with analytics both generating and executing the decisions (Davenport & Harris, 2007).

The definition of Srinivasan and Swink (2018) emphasize "organizational facility" and "processes", thereby reinforcing the view of analytics as a capability. Similarly, Öhman et al. (2021) approach analytics from a broader organizational perspective, defining analytics not merely as a set of technologies or tools, but also including other aspects. They state that analytics gives rise to "new skills being needed, practices developed and governance principles established", which broadens AC development to also include "governance, culture, and competencies" (p. 2), echoing arguments by McAfee et al. (2012) and others. To exemplify, organizational or cultural aspects such as an appealing return on investment (LaValle et al., 2011; Vidgen et al., 2017), data-driven culture, i.e., tendency to rely on data in decision-making (Gupta & George, 2016; McAfee et al., 2012), ability to combine analytics and experience (Browning et al., 2023; Rengarajan et al., 2022), readiness (Egwuonwu et al., 2024; Kalaitzi & Tsolakis, 2022) and top management support (Egwuonwu et al., 2024; Lai et al., 2018) are as important as technology for AC.

From this perspective, various sub-dimensions of AC have been recognized. Technology capability (Akter et al., 2016; Fosso Wamba & Akter, 2019) and infrastructure flexibility (Wamba et al., 2017) capture aspects like connectivity, compatibility and modularity of systems. Next, talent capability (Akter et al., 2016; Fosso Wamba & Akter, 2019) and personnel expertise (Wamba et al., 2017) emphasize different skill categories, including technical and domain knowledge. Finally, management capability (Akter et al., 2016; Fosso Wamba & Akter, 2019; Wamba et al., 2017) highlight planning, governance, and control. Another way of capturing the multidimensional nature of AC is through the Technology–Organization–Environment (TOE) framework, that categorizes key factors across the three dimensions that has given the framework its name (Tornatzky & Fleischer, 1990). Technology-related factors include infrastructural and compatibility aspects, while organizational characteristics address softer elements such as routines, resources, skills, and cultural norms, and finally, external factors that frame the context in which firms act in terms of stakeholders, industry dynamics as well as regulatory pressure are captured in the environment-dimension (Hao

& Demir, 2025; Kalaitzi & Tsolakis, 2022; Lai et al., 2018; Oliveira et al., 2014).

2.4. Theoretical perspectives

The dissertation combines three complementary theoretical perspectives. First, the dynamic capabilities view provides a lens for understanding the distinct roles of the selected enabling capabilities. Then, configuration theory is used to emphasize that supply chain resilience may emerge from configurations of enabling capabilities. Finally, contingency theory is applied to account for potential variation in these configurations depending on contextual contingencies.

2.4.1. Dynamic capabilities view

A central point of departure in DCV is change and dynamism related to a firm's environment or shifts in technology, which demands equal change and renewal of static capabilities (Teece et al., 1997). Static capabilities (also called ordinary, operational or zero-level capabilities) denote capabilities that (only) ensure firms to "make a living in the short term" (Winter, 2003, p. 991). Dynamic capabilities, on the other hand, modify or develop new static capabilities (Eisenhardt & Martin, 2000; Teece et al., 1997; Winter, 2003), and are defined as:

> "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments and achieve new and innovative forms of competitive advantage" (Teece et al., 1997, p. 516).

Teece (2007) outline three capacities that are embodied within dynamic capabilities: sensing, seizing, and reconfiguring. First, sensing deals with monitoring and gathering insights on developments in the environment related to opportunities and threats (Teece, 2007), which requires the organization to scan, search, and observe developments, enabled by e.g., good relationships with external partners (Wilden et al., 2013). Next, seizing relates to capturing and leveraging the opportunities (Teece, 2007), which involve evaluation of capabilities and potential investments in assets (Wilden et al., 2013). Finally, reconfiguring represents the most significant intervention by transforming and reconfiguring resources and ordinary capabilities (Teece, 2007; Wilden et al., 2013). On their relative importance, it should be noted that they act synergistically and need to be developed and applied simultaneously (Teece, 2007).

Following recent SCR research (Nikookar et al., 2025; Nikookar & Yanadori, 2022), the dissertation uses sensing, seizing, and reconfiguring to motivate the selection of enabling capabilities (Table 1). SCV is linked to sensing, as it provides access to high-quality information on demand, supply, and the status and location of entities and flows in the SC. Trough processing and interpretation of data, AC relates to sensing of developments in the environment and potential disruptions. It also relates to seizing by providing decision support for evaluating alternative responses to disruptions, for example through simulation, scenario planning, or what-if analyses, while not involving the execution of decisions. SCResp aligns closely with seizing, as it reflects the ability to react and adapt purposefully and quickly to changes in the environment. The broadness of SCI reflects sensing, seizing, and reconfiguring at the same time. It relates to sensing through information sharing about changing needs, but not to the extent of SCV in this regard. Its main role is instead attributed to seizing and reconfiguring by enabling joint planning and problem solving, allowing coordinated decisions and adjustments to how activities and processes are carried out across firms. Unlike SCResp, however, SCI does not emphasize ‘quick reactions’. Although not presenting a strict one-to-one association, this framing highlights how the selected enabling capabilities collectively cover the three DCV capacities while also illustrating some overlaps.

Table 1: Selection of enabling capabilities

		DCV Capacities		
		Sensing	**Seizing**	**Reconfiguring**
Enabling capabilities	**SCV**	X		
	AC	X	X[1]	
	SCResp		X	
	SCI	X[1]	X[2]	X
	Notes: [1]Partly; [2]Does not emphasize quick reactions			

2.4.2. *Configuration theory*

Configurations denote a set of distinct but interdependent attributes that together form synergistic bundles and therein associate with performance (Meyer et al., 1993; Miller, 1986; Ward et al., 1996). Fiss (2007, p. 1180) state that organizations should be viewed as "clusters of interconnected structures and practices, rather than as modular or loosely coupled entities whose components can be understood in isolation". Thus, the absence or presence of individual attributes is not of key interest (Venkatraman, 1989b). Instead, once these individual attributes exhibit fit in relation to one another and form coherent "gestalts" or "archetypes", performance can readily be attained (Misangyi et al., 2017; Venkatraman, 1989a).

Configuration theory makes an important deviation from traditional thinking about causality. Instead of assuming that variables have uniform effects, it accepts that "variables found to be causally related in one configuration may be unrelated or even inversely related in another" (Meyer et al., 1993, p. 1178). Configuration theory broadly addresses causal complexity, referring to the idea that multiple factors jointly produce an outcome (conjunctural causation), that there might be multiple such paths to the same outcome (equifinality), and finally, that both the presence and absence of the same attribute may be associated with the outcome (asymmetrical causation) (Misangyi et al., 2017). Fiss (2007) suggests that this phenomenon is often encountered by firm decision makers. It has specifically been advocated in SCM research (Gligor et al., 2020; Ketchen et al., 2021; Russo et al., 2019). To align with these premises, scholars have proposed the use of set-theoretic methods like fuzzy-set Qualitative Comparative Analysis (fsQCA) (Fiss, 2007, 2011; Greckhamer et al., 2018).

A crucial aspect in configurational theorizing is the formulation of a *configurational rationale* (Greckhamer et al., 2018), which in the dissertation relates to why the enabling capabilities would potentially combine to jointly build SCR. This choice is motivated by their differentiated, yet complementary, roles when viewed through the lens of the DCV (2.4.1). Given that the enabling capabilities are positioned as distinct and reflecting different capacities of dynamic capabilities, they might need to be combined as Teece (2007) argues for a holistic perspective on sensing, seizing, and reconfiguring. At the same time, the partial overlaps among these enabling capabilities indicate that they may occasionally compensate for one another, which further motivates a configurational perspective. Thus, using configuration theory, the enabling capabilities are perceived to operate on the same level and allowed to freely combine into configurations to account for potential conjunctural causation and equifinality. This has the advantage of permitting investigation of how distinct, yet complementary, enabling capabilities jointly associate to SCR without assuming a singular and universal sequential relationship.

2.4.3. Contingency theory

Contingency theory has for long been rooted in the operations and supply chain management (OSCM) domain (Sousa & Voss, 2008). It posits that high performance can be attributed to fit between internal factors, like organizational practices, and contextual factors (Donaldson, 2001). Ensign (2001, p. 287) define fit as "the alignment between strategic choices and critical contingencies with the environment (external), organization (internal) or both (external and internal)". Therefore, context may refer to both external and internal contingencies (Danese et al., 2020). In this way, contingency theory build on the assumption that organizations (or SCs) are open systems and exposed to different contingencies that determine performance (Aragón-Correa & Sharma, 2003; Wong et al., 2011). This aligns well with SCM, as relationships with external entities, such as buyers and suppliers, define the external environment in which firms function and interact (Flynn et al., 2010).

Examples of internal contextual contingencies include firm orientations like digital orientation (Chavez et al., 2023) or environmental orientation (Chavez et al., 2021). However, contextual contingencies are typically external to the focal firm and outside the direct control of managers, like national context and culture (Sousa & Voss, 2008), industry sector (Brandon-Jones & Knoppen, 2018), or environmental equivocality, uncertainty (Koufteros et al., 2005), dynamism and munificence (Fainshmidt et al., 2019). These internal and external contingencies may impose an amplifying or dampening effect (Chavez et al., 2021; Sousa & Voss, 2008), underscoring the principle that there are no universally effective strategic choices or operational practices (Wong et al., 2011).

Contingent role of supply chain complexity

As there are several ways to improve SCR, it is crucial, especially from a practical perspective, to determine which approach is most suitable given prevailing environmental conditions (Brandon-Jones et al., 2014). Extant literature has presented SCC as a key contextual contingency in relation to SCR, not only influencing exposure to disruptions (2.1.2), but also the maneuverability needed to manage them. Research has shown that SCC, in the sense of number of nodes, reduces SCR as longer SCs result in longer throughput time for physical goods in the material flow (Blackhurst et al., 2011). In addition, Christopher and Lee (2004) argue that greater SCC undermine SCV due to longer and globalized material flows, which delay managerial awareness and decision-making, and thereby stretching response times. The findings by Bode and Macdonald (2017) refine these claims by showing empirically how higher SCC is negatively associated with disruption recognition and diagnosis, while not having an effect on response planning and execution. They contend that when SCC is high:

> "[…] there is a lot of noise and ambiguity in the information being processed. It becomes difficult for the managers to discern what is happening in the supply chain with the disruption, resulting in the slowdown of the early response stages." (p. 862)

The impact of SCC is further demonstrated in the works of Brandon-Jones et al. (2014). Using a contingency perspective, they show that SCV is more critical for SCR when SCs are structurally complex and involve many interdependent entities (i.e., scale complexity). These findings suggest that under higher SCC, stronger capabilities for sensing, interpreting, and sharing information are important to avoid delayed responses and amplified disruption impacts. SCC has also been associated with redundancies, such as the availability of alternative suppliers or freight carriers, which may support resilience. Therefore, because SCC can also increase exposure to disruptions, it has been characterized as having "both dark and bright sides" in relation to SCR (Wiedmer et al., 2021, p. 338), highlighting ambiguity.

These insights suggest that SCC has a contingent role in relation to SCR, as it influences both the viability of leveraging enabling capabilities and the value they can generate. At the same time, scholars note that the role of SCC has not been sufficiently investigated in conjunction with SCR (Akın Ateş et al., 2022). The dissertation uses contingency theory to account for SCC as a contextual condition that shapes what enabling capabilities link to SCR.

3. Methods

This chapter describes the research methods used in the dissertation. First, the research setting is presented, providing brief background information on the research projects that supported the completion of the dissertation. Next, an overview of the research approach and design is presented. This is followed by information on the execution of the individual studies' data collection and analysis procedures. Finally, the chapter ends by addressing quality and ethical considerations.

3.1. Research setting

The completion of the dissertation project was supported by a research portfolio funded by the Knowledge Foundation[3] named "Ambidexterity, Flows, and Artificial Intelligence for Responsiveness" (AFAIR). AFAIR comprises several subprojects involving multiple industry partners and adopts a multidisciplinary perspective on the application of artificial intelligence. The research is conducted in a collaborative setting in which academic researchers and industry partners jointly address topics of shared interest. I was involved in two of the subprojects, which influenced both the choice of topic and the research methods of the dissertation project.

Throughout the research process, AFAIR served as a platform for ideation, validation, and engagement with practitioners. These interactions occurred both formally, as part of data collection activities, and informally in connection with different gatherings. The early discussions with industry representatives were especially valuable, as they addressed topics such as prior disruption experiences, approaches to achieving SCR, and the role of AC. One of the takeaways, among many, was the relevance of adopting a configurational perspective in response to RQ1. Another was the reinforcement of the decision to formulate RQ2 around obstacles and enablers. The subprojects also provided a valuable platform for pilot testing data

[3] Grant no. 2021/562-411.

collection instruments, conducting data collection, and supporting validation and dissemination of findings. However, while participation in AFAIR facilitated access to potential respondents, the dissertation also relies on insights from other sources.

3.2. Research approach and design

The research approach and design were determined by purpose and RQs, which in turn were crafted based on the state of knowledge on the AC-SCR nexus at the initiation of the dissertation project. In 2021, the literature at the intersection of AC and SCR was relatively limited but existing, comprising some empirical (Dubey et al., 2021; Norrman & Wieland, 2020) and conceptual publications (Ivanov & Dolgui, 2021; Ivanov et al., 2019). Consequently, it was positioned as an area of emerging interest requiring "immediate attention for further investigation" (Ali & Gölgeci, 2019, p. 804). These insights were sufficient to provide an initial understanding of the AC–SCR nexus and to indicate that the two concepts were meaningfully connected. However, despite their intersection being relatively nascent, each of the concepts was individually well established in the literature. Based on the state of knowledge, a "working" purpose and RQs were designed to be multifaceted and illuminate different facets of the AC-SCR nexus. RQ1 was inspired by SCR-literature that often revolves around the association between diverse enabling capabilities and SCR (e.g., Brandon-Jones et al., 2014; Scholten & Schilder, 2015; Wieland & Wallenburg, 2013), while RQ2 was influenced by the frequent emphasis of key obstacles, determinants, or similar factors in AC-literature (e.g., Kalaitzi & Tsolakis, 2022; Lai et al., 2018; Lismont et al., 2017).

The next step was to align the research approach and design with the purpose and RQs. To obtain an encompassing perspective of the AC-SCR nexus and capture the distinct nature of the respective RQs, a mixed-methods research design comprising both quantitative and qualitative approaches was adopted (Creswell & Tashakkori, 2007; Karlsson, 2024). As will be explained shortly, the dissertation warrants both quantitative evidence that captures general patterns and qualitative insights that provide more detailed understanding and meaning. In terms of sequencing and stage of integration, the quantitative and qualitative research processes (i.e., data collection and analysis) were carried out independently and simultaneously, before being combined at the end to address the purpose. This is referred to as a convergent mixed-methods research design (Creswell & Creswell, 2018), and was operationalized using two strands as building blocks: Strand I using a quantitative research approach to address RQ1 and Strand II using a qualitative research approach to address RQ2. By integrating insights from the quantitative and qualitative strands, the overall purpose of the study is addressed.

In terms of methods, Strand I comprised a survey study (SS) to address RQ1, while Strand II comprised two expert interview studies (IS1 and IS2). In addition, a systematic literature review (SLR) study was conducted as a "living" project throughout most of the dissertation process to inform the strands as well as constitute a platform for the Kappa. Each study produced one paper, except SS, which resulted in two papers. More specifically, IS1 produced P3, IS2 produced P5, SS produced both P2 and P4, and the SLR produced P1. The convergent mixed-methods research design is presented in Figure 2. Each study is introduced and motivated briefly below, while detailed information is provided in subsequent sections (3.3-3.6).

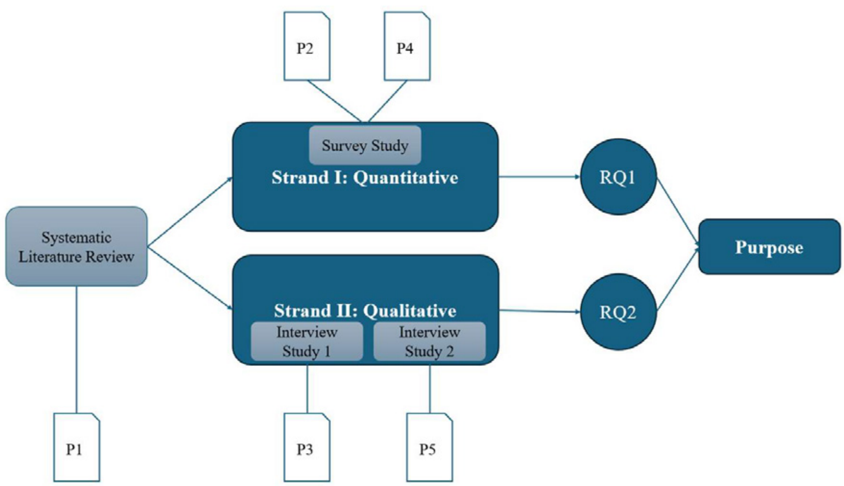

Figure 2: Convergent mixed-methods research design

SLRs are a widely used method for identifying and synthesizing extant literature in a systematic and transparent way (Denyer & Tranfield, 2009; Tranfield et al., 2003), and often used in SCM research (Durach et al., 2017). The SLR served as a common resource for both empirical strands, complementing the Frame of References in the kappa and providing a reference point for the interpretation of findings. In addition to profiling the literature and outlining the state of the art, it covered the main components of the dissertation, namely complementary capabilities to AC for SCR, obstacles and enablers. In this way, the SLR supported the empirical strands and provided a reference point for interpreting the findings. The review was initiated early in the dissertation process and finalized towards the later stages to allow for as large literature base as possible. Further details are provided in 3.3 and P1.

A quantitative SS was deemed appropriate in Strand I since RQ1 is concerned with investigating how concepts are related and that existing research on each of the concepts of interest were sufficiently established and the intersection of AC-SCR not entirely nascent (Forza & Sandrin, 2024), as outlined above. Thus, a survey instrument could be designed by adopting established scales on each concept from literature. Data analysis employed two contrasting logics of causality to investigate how AC contribute to SCR: a variance-based (net-effect) logic using regression analysis (Hayes, 2017) and a set-theoretic logic using fsQCA (Fiss, 2007; Pappas & Woodside, 2021). Further details on SS are provided in 3.4, P2 (fsQCA), and P4 (regression analysis).

In Strand II, two qualitative expert interview studies were conducted. They are particularly suitable for research in which diverse viewpoints and the extensive experience of participants are of central interest (Bogner et al., 2009). Through interviews, researchers can obtain rich, subjective insights into the interviewees' reflections and experiences (Denscombe, 2014), which in turn enables the capture of multiple perspectives and the development of a comprehensive understanding of the phenomenon under study (Creswell & Creswell, 2018). In this regard, experts can be "seen as 'crystallization points' for practical insider knowledge and are interviewed as surrogates for a wider circle of players" (Bogner et al., 2009, p. 15). Reflecting these strengths, expert interviews have gained increasing traction in OSCM research, with several recent applications (e.g., Meyer & Henke, 2023; Zeiser et al., 2025).

Two reasons motivated the choice of expert interviews. First, as opposed to case studies, which are often retrospective and per definition bound to specific contexts, expert interviews allow for more flexibility. By drawing on experts' extensive experience across diverse roles and settings, a wider range of obstacles and enablers can be captured than what would likely emerge from specific cases. Additionally, experts' deep knowledge of both SCR and AC enable them to elaborate on what obstacles and enablers that could plausibly be relevant through qualified and experience-based reasoning. Secondly, expert interviews allow for the capture of qualitative statements that help substantiate the perceived relevance of obstacles and enablers. This is especially important given the potentially subjective nature of experts' reflections. Details on IS1, focusing on obstacles, are provided in 3.5 and P3, while IS2, focusing on enablers, is presented in 3.6 and P5.

3.3. Systematic literature review

The SLR was designed with two primary objectives in mind. The SLR first sought to provide a descriptive overview of the relevant research, including distribution of journals, methods, and contexts. Subsequently, it aimed to extract thematic insights relevant to the dissertation, such as enabling capabilities, obstacles and enablers. The process adhered to established guidelines by following six steps (Durach et al., 2017): (1) define research questions; (2) determine inclusion and exclusion criteria; (3) conduct literature search; (4) select relevant studies; (5) synthesize findings; and (6) report results. Before the first step, however, a scoping review was conducted to inform the execution of the SLR (Armstrong et al., 2011) by developing the review protocol and doing a first assessment of the literature volume.

Scopus was selected as the sole database due to its extensive coverage relative to other alternatives (Brzezinski, 2015; Harzing & Alakangas, 2016). Furthermore, the searches were limited to Scopus's subject category "Business, Management, and Accounting" and only journal articles, including review articles and editorials, published up to and including 2024 were considered. The search strings merged two clusters of keywords with Boolean operators, one related to AC ("analytics," "artificial intelligence," and "machine learning") and one related to resilience ("resilien*" and “disruption”). Furthermore, four inclusion and exclusion criteria guided the literature search. First, to narrow the review to papers published in recognized outlets, the latest Academic Journal Guide (AJG), developed by the Chartered Association of Business Schools, was consulted. The following three inclusion criteria demanded resilience, disruptions to physical material flow (excluding disruptive technologies or innovations), and analytics to be key elements. The database search produced 679 raw records, out of which only 79 articles remained in the final sample after being checked against all inclusion and exclusion criteria. For more information, see 4.1 and P1.

3.4. Survey study

This section describes the SS conducted in the quantitative strand. It outlines the development of the survey instrument, including construct selection and operationalization, followed by sampling and data collection procedures. The section further explains the data analysis, drawing on both variance-based and set-theoretic techniques.

3.4.1. Development of survey instrument

The survey was designed by adopting constructs that had been developed, tested and widely used in the literature for reasons of both convenience and validity (Forza & Sandrin, 2024). Suitable constructs were found by reviewing leading OSCM journals and examining their adoption in extant research.

For SCR, the scale was adopted from Golgeci and Ponomarov (2013), comprising six items. This construct covers all chronological phases of SCR (preparedness, response, recovery and growth) as well as explicitly emphasizing the ability to ‘maintain continuity’. In comparison to other scales, it represents a more parsimonious choice than adopting separate subdimensions for each phase in relation to disruptions (c.f. Dennehy et al., 2021; Durach et al., 2020). SCV was operationalized using the four-item scale by Nikookar and Yanadori (2022) that captures identity and location of SC entities as well as availability of quality (on-time and complete) supply and demand data related to the material flow. The scale of Srinivasan and Swink (2018) comprising five items was used to measure AC. This construct focuses on the key aspects of AC (techniques, data integration, and visualization tools to make insights interpretable), while not including any individual subdimensions or antecedents (c.f. Gupta & George, 2016; Wamba et al., 2017). By specifically associating AC to the SC context in the survey instrument, respondents were instructed to avoid considering AC in broader terms. SCResp was assessed relative to competitors based on the five-item scale by Yu et al. (2019) that underline reaction to changes in needs and behavior of suppliers, customers and competitors.

Next, the scale for SCC was adopted from Bode and Macdonald (2017), comprising five items. This construct reflects both the number of actors and transactions in the SC, as well as the intricate nature of their composition. SCI was measured using the five item-scale from Zhu et al. (2018) reflecting external integration with upstream suppliers and downstream customers, but disregarding internal integration (c.f. Flynn et al., 2010; Schoenherr & Swink, 2012). Finally, firm performance (FP) was included and adopted the six-item construct from Wisner (2003) that parsimoniously combines both strategic (competitive position based on selling price, quality level, and customer service level) and financial performance indicators (market share and return on assets) relative to competitors.

The actual survey instrument was designed in the following way. First, an open-ended question prompted the respondents to state their job-title. Then, the main part of the survey followed, containing the different constructs, which were organized so that conceptually related items were presented in sequence to make it easier for the respondent to stay focused. All items except for the general questions and final comments were measured using a seven-point Likert scale, with anchors "strongly disagree" (1) and "strongly agree" (7), for consistency and simplified interpretation. The constructs also contained an introductory text before the items to familiarize the respondents to the topics. At the end of the survey, an open-ended question allowed the respondents to leave voluntary comments or feedback. The survey instrument is presented in Table 2.

The entire survey instrument was carefully translated into Swedish to not lose any essential nuances while still being easy to interpret in the native language of the target respondents. Language has been highlighted as key for validity (Ghauri et al., 2020) and reliability (Ruel et al., 2016) in survey research. Next, pilot-testing of the survey instrument was conducted to test validity and improve the survey design (Creswell, 2014). Two expert panels were recruited to support this process. First, six senior researchers in domains related to the included constructs were tasked with critically reviewing both format and content to provide feedback on potential improvements. In this way, they assessed whether the measurement scales adequately represented key aspects of each theoretical concept, thereby ensuring face validity (Creswell, 2014; Ghauri et al., 2020) and content validity (Forza, 2016). Next, a second expert panel was formed, consisting of seven practitioners whose profiles matched those of the intended survey respondents. These were drawn from the pool of industry representatives in AFAIR and asked to review overall relevance, clarity, completion time, and appropriateness given their job-titles. This procedure confirmed that the items were clear, relevant, and matched respondents' profiles and decision-making responsibilities. As a result, only minor adjustments were necessary to minimize ambiguity and thereby improve reliability (Forza, 2016). Finally, a cover letter was developed to be distributed together with the survey (Ghauri et al., 2020), stating aim, ensuring anonymity, and providing contact information to the researchers.

Table 2: Survey instrument

Construct	Introduction and items
Background information	Respondent job title (open ended).
Supply Chain Resilience (Golgeci & Ponomarov, 2013)	*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.*
	Our firm's supply chain is able to adequately respond to unexpected disruption by quickly restoring its product flow.
	Our firm's supply chain can quickly return to its original state after being disrupted.
	Our firm's supply chain can move to new, more desirable state after being disrupted.
	Our firm's supply chain is well prepared to deal with financial outcomes of supply chain disruptions.
	Our firm's supply chain has the ability to maintain a desired level of control over structure and function at the time of disruption.
	Our firm's supply chain has the ability to extract meaning and useful knowledge from disruptions and unexpected events.
Supply Chain Visibility (Nikookar & Yanadori, 2022)	*This section concerns your knowledge about other actors in your supply chain and availability of data from them.*
	We are always aware who the firms engaged in our supply chain are.
	We are well aware where our supply chain members are located.
	We always have complete information on inventory availability, lead times and delivery dates in our supply chain.
	The location and status of our main product is always visible throughout the distribution network (e.g., distribution centers, transportation).

Analytics Capability (Srinivasan & Swink, 2018)	*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).*
	We use advanced analytical techniques (e.g., simulation, optimisation, regression) to improve decision making.
	We easily combine and integrate information from many data sources for use in our decision making.
	We routinely use data visualisation techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information.
	Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement.
	We deploy dashboard applications /information to our managers' communication devices (e.g. smart phones, computers)
Supply Chain Responsiveness	*The following section concerns your supply chain's ability to quickly respond to changes.*
(Yu et al., 2019)	Compared to our competitors, our supply chain responds more quickly and effectively to changing customer and supplier needs.
	Compared to our competitors, our supply chain responds more quickly and effectively to changing competitor strategies.
	Compared to our competitors, our supply chain develops and markets new products more quickly and effectively.
	In most markets, our supply chain is competing effectively
	The relationship with our partners has increased our supply chain responsiveness to market changes through collaboration.

Supply Chain Complexity (Bode & Macdonald, 2017)	*This section deals with the structure of your supply chain.* Our supply chain is very complex Our supply chain involves a lot of players (e.g., suppliers, logistics service providers) and/or a lot of logistics/transportation transactions. Our supply chain is a quite intricate network. It is difficult to quickly get a general idea of our supply chain.
Supply Chain Integration (Zhu et al., 2018)	*The following section concerns relationships among the actors in your supply chain.* We and our key supply chain partners inform each other in advance of changing needs. We include our key supply chain partners in our planning and goal setting activities. We regularly solve problems jointly with our key suppliers. We facilitate our key customers' ability to seek assistance from us. We allocate benefits fairly to our key trading partners.
Firm Performance (Wisner, 2003)	*Assess your performance compared to your competitors in terms of:* Market share Return on assets Average selling price Overall product quality Overall customer service levels
End section	Space to leave feedback or other comments (open ended).

3.4.2. Sampling and data collection

In line with the scope and delimitations, the target population was defined as all firms with either primary or secondary Swedish Standard Industrial Classification (SNI) codes 10–31 (manufacturing), 46 (wholesale, except motor vehicles and motorcycles), and 47 (retail trade, except motor vehicles and motorcycles) (Statistics Sweden, 2007). Using these SNI codes, the target sample frame was extracted from the Amadeus database (Bureau van Dijk). Only Swedish firms with registered phone number and updated financial information were considered eligible. Phone number served as necessary contact information while financial information was used to ensure that the firm was actively operating, as well as for determining firm size based on the definition by the European Commission (2021). However, due to technical limitations when extracting the target sample frame, only the top fifty thousand firms based on revenue (about 1 MSEK and above) were successfully extracted. This remains appropriate for the present research, as AC may be less relevant anyway for smaller firms compared to larger counterparts.

Selection from the target sample frame was done using proportionate stratified random sampling to ensure equal representation (Forza & Sandrin, 2024) from manufacturers (first stratum) and wholesale and retail (second stratum). Besides representativeness, this strategy also allows the use of control variables to assess whether results have been affected by industry characteristics (Flynn et al., 1990). Target respondents included individuals holding (senior) vice president, director, chief officer, and manager roles in areas such as SC, logistics, and purchasing. These roles were expected to possess relevant knowledge about physical flows, decision-making, and interfaces with key SC partners. If such roles did not exist or were not available, the chief executive officer was considered an equivalent alternative.

Data collection was carried out through telephone interviews by a professional market research company, using a cross-sectional survey design. A total of 200 responses were collected, equally divided between the two strata, with responses being satisfactory at 12% and 10% for manufacturing and wholesale/retail, respectively (Forza, 2016). Next, the raw data underwent screening and cleaning to ensure validity (Ruel et al., 2016). Multiple screening and cleaning strategies were employed, namely visual inspection, exclusion of responses containing substantial amounts (>10%) of missing data points, and identification of suspicious patterns (low standard variation). This led to 35 responses being disqualified and listwise deleted, leaving 165 responses in the final sample. Notably, the split between the two strata was maintained in the final sample. Within the manufacturing stratum, different subindustries are represented. Using the technological intensity (TI) classification by EUROSTAT (2018), manufacturers were divided into four groups based on their TI-level (high; medium-high; medium-low; and, low). The classification reflects differences in technological and knowledge intensity, with examples from the extreme ends including high-technology sectors such as pharmaceuticals and electronics, and low-technology sectors such as food. Table 3 presents the demographics of the final sample which was used in both subanalyses (fsQCA and regression, see Table 4).

Next, column-wise screening (i.e., item level screening) was also conducted. This procedure revealed only one problematic item (SCC, first item). However, it was temporarily retained for the subsequent validity and reliability tests, when it was dropped. Finally, missing data points (for responses with <10% missing data) were replaced by the sample median.

Prior to the analysis, a series of tests were performed to assess the validity and reliability of the data. These tests were conducted separately across the two subanalyses, as they involved different constructs (Table 4). These procedures are summarized below, and for detailed information, refer to the method sections of P2 and P4.

Table 3: Sample demographics

Sample composition	**Frequency (n)**	**Share (%)**
Respondent job title		
Warehouse, Factory Manager, or similar	19	11.5 %
SC, Logistics, Purchasing Manager, or similar	39	23.6 %
Chief Executive Officer	81	49.1 %
Miscellaneous	26	15.8 %
Size (European Commission, 2021)		
Large	16	9.7 %
Medium	21	12.7 %
Small and Micro	128	77.6 %
Industry (Statistics Sweden, 2007)		
Manufacturing (SNI codes 10–31), out of which technological intensity level (EUROSTAT, 2018)	84	50.9 %
- TI High	2	1.2 %
- TI Medium-high	21	12.7 %
- TI Medium-low	24	14.5 %
- TI Low	37	22.4 %
Wholesale (SNI code 46) and Retail (47)	81	49.1 %
Total	**165**	**100 %**

Table 4: Subanalyses, survey study

Subanalysis	Constructs	Analysis method
1	SCR, SCV, AC, SCResp, SCC, SCI	fsQCA
2	SCR, AC, SCI, FP	Regression

First, the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy and Bartlett's Test of Sphericity were computed to ensure that the data are suitable for subsequent factor analysis. Then, exploratory factor analysis (EFA) was conducted in SPSS to obtain a first validity assessment by investigating the latent factor structure. The EFA was conducted using Maximum Likelihood as extraction method and Promax as rotation method. Here, item loadings and cross-loadings were examined iteratively until meeting the thresholds. Given the sample size of 165 responses, the threshold for item loadings was set to 0.45 (Hair et al., 2018). The final EFA model consisted of the expected number of factors (6 and 4 in the first and second subanalysis, respectively), explaining at least 60 % of the variance, thus respecting the commonly accepted adequacy threshold. There were also less than 5 % nonredundant residuals.

Next, confirmatory factor analysis (CFA) was performed in IBM SPSS AMOS v.28 to assess construct validity. While some items were iteratively deleted in the EFA, they were retained in the CFA to verify whether their deletion is necessary. The factor loadings were checked against the 0.50 threshold to ensure internal consistency. Iterative removal of items was conducted until all final factor loadings exceeded the threshold. Construct validity encompasses both convergent and discriminant validity (Forza, 2016), which are evaluated using average variance extracted (AVE) and its square root, respectively. The threshold for AVE was set at 0.5 (Hair et al., 2018), while the square root of the AVE was required to exceed all inter-construct correlations (Fornell & Larcker, 1981; Hair et al., 2018). For discriminant validity, the Heterotrait-monotrait (HTMT) ratio of correlations (Henseler et al., 2015) was also computed and checked against the upper threshold of 0.85. Furthermore, model fit indices (CMIN/DF, CFI, PCLOSE, RMSEA) were also computed to ensure convergent validity.

Reliability was investigated by calculating Cronbach's alpha and composite reliability (CR). 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) and checked against the threshold of 0.70 (Hair et al., 2018). Values not exceeding this threshold indicate that an individual item may be excluded from the construct in further analysis (Ruel et al., 2016). For the retained items, some descriptive statistics are presented in Table 5.

Table 5: Construct descriptive statistics

Construct	Mean	Standard deviation
SCR	4.40	1.27
SCV	4.64	1.44
AC	3.43	1.80
SCResp	4.65	1.23
SCI	4.48	1.31
SCC	4.40	1.60

Next, the potential for non-response bias was investigated following the approach by (Armstrong & Overton, 1977), assuming that non-respondents are equivalent to late respondents. Thus, the first quarter of respondents (early respondents) was compared against the last quarter of respondents (late respondents) using independent samples t-test across all constructs. These subgroups showed no significant differences ($p > 0.05$), indicating that non-response bias is not an issue to validity.

Additionally, the risk of common method bias (CMB) was examined, given that all constructs were measured simultaneously using self-reported data from single respondents. Attempts to reduce the issue of CMB was taken already in the survey design and administration phase following recommendations by Podsakoff et al. (2012). These strategies included proximal separation, by arranging the constructs in a way so that their order did not reflect the research model, and selecting respondents based on their seniority and domain expertise (Montabon et al., 2018). Further measures were taken to also reduce evaluation apprehension and social desirability bias by stressing anonymity and voluntary participation. Finally, Harman's single-factor test (Hulland et al., 2018; Yu et al., 2020) and common latent factor test (MacKenzie & Podsakoff, 2012; Podsakoff et al., 2012) were conducted to statistically assess the potential existence of CMB. These tests collectively indicated that CMB does not pose validity issues.

3.4.3. Data analysis

To assess how AC contributes to SCR, the analysis drew on variance-based regression analysis (Hayes, 2017) and set-theoretic fsQCA (Fiss, 2007; Pappas & Woodside, 2021). This strategy capitalized on the complementary strengths of correlational and configurational techniques in identifying empirical patterns, enabling a flexible approach for both rigorous hypothesis testing and the capture causal complexity (Pappas & Woodside, 2021).

fuzzy-set Qualitative Comparative Analysis

fsQCA relies on Boolean algebra to assess causality through set memberships (i.e., set-theoretic; Fiss, 2007) by putting "configurations of causes in relation to an outcome of interest" (Fiss, 2011, p. 395). Stated simply, it compares the memberships of cases in various causal conditions, or their combinations, with the same cases' memberships in outcomes (Misangyi et al., 2017). In this study, causal conditions refer to the enabling capabilities for SCR including AC, while the outcome refers to SCR. SCC was accounted for through subgroup analysis. One major advantage of fsQCA over traditional correlation-based methods like regression is its ability to address causal complexity (Ragin, 2008). In this way, fsQCA may indicate whether multiple causal conditions jointly associate to an outcome (conjunctural causation) and if there are multiple such combinations in parallel (equifinality) (Misangyi et al., 2017). Causality in QCA is determined in terms of sufficiency and necessity (Ragin, 2008). A path, which could either consist of single causal conditions or configurations thereof, is said to be sufficient if it is a subset of the outcome, and vice versa for necessity (Greckhamer et al., 2018). The interpretation is that a necessary condition must be present for the outcome to occur, whereas the presence of a sufficient condition produces the outcome, without implying that it is the only way to produce that outcome (Misangyi et al., 2017). Two key measures in fsQCA are consistency and coverage. Consistency corresponds to the proportion of cases of a particular configuration that also exhibit an outcome, while coverage corresponds to the proportion of an outcome that covered by a particular configuration (Greckhamer et al., 2018).

The fsQCA process followed the structured approach of Arellano et al. (2021), consisting 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. For details on the data analysis process, refer to P2.

Regression

In contrast to fsQCA, basic regression analysis examines causality through the unique contribution (net effects) of independent variables in explaining variance in the dependent variable, holding other variables constant (Fiss, 2007). A conceptual model was hypothesized in which AC was specified as the independent variable, SCR as a mediating variable, and FP as the dependent variable. SCI was specified as a moderator of these relationships (see research model in P4). To test the hypotheses, linear regression analyses were performed in SPSS, while moderation and mediation effects were examined using the Hayes PROCESS macro in SPSS (Hayes, 2017). Several control variables were used to prevent firm characteristics from affecting the results. Here, firm age, size, and industry type were selected. The latter was necessary as the sample consists of firms from different industries. Using the technological intensity (TI) classification by EUROSTAT (2018), manufacturers were divided into four groups based on their TI-level (high; medium-high; medium-low; and, low). These constituted four dichotomous dummy variables, with retail and wholesale acting as industry baseline. For details on the data analysis process, refer to P4.

3.5. Interview study 1

This section describes IS1, detailing sampling, data collection and analysis.

3.5.1. Sampling

Purposive sampling was employed to select experts with relevant professional experience that aligned with the objectives of the study (Denscombe, 2014). The eligibility criteria were specified in the following way. Similar to the SS, individuals with background from senior roles in areas such as SC, logistics, and purchasing were targeted given their influence or participation in decisions regarding analytics application development and experience of managing disruptions. In contrast to the SS, however, length of tenure and previous roles were also of interest for eligibility, as longer tenure was expected to enable more informed and experience-based reflections. As an additional source of insights, a consultant from an analytics tool provider was involved (c.f. Li et al., 2019). A total of 16 experts participated in the study, although their involvement differed across the phases of the study. For details on the demographic characteristics of the sample, refer to P3.

The sample size and composition were considered appropriate for producing a sufficiently rich data set. As several experts had previously been involved in research projects (including activities related to the dissertation), they were accustomed to discussing complex issues in interview settings and familiar with the topics. The experts' extensive domain experience, along with familiarity with research interview settings, was expected to support more efficient and comprehensive coverage of the topic and to encourage them to openly express their views. Moreover, empirical studies indicate that in relatively homogeneous samples, six to twelve interviewees are generally sufficient to capture shared perceptions and experiences (Guest et al., 2006).

3.5.2. Data collection and analysis

Data collection and analysis proceeded through a five-phase design. In Phase 1, all candidates were invited to online interview sessions which were recorded and, in most cases, conducted individually. These sessions ensured understanding of key concepts, confirmed the candidates' suitability, and initiated their reflections of obstacles through an open-ended question. Phase 2 gave each expert at least a couple of weeks to complete a preparation assignment. They were asked to freely elaborate on obstacles (continuation of their reflections in the preceding phase), identify about five obstacles from a tentative list that they found ‘most relevant’, and briefly elaborate on their selection. If necessary, they could also add their own suggestions of obstacles to the list. Once the preparation assignment had been submitted, Phase 3 was initiated which involved individual follow-up interviews. Each expert was given the opportunity to further elaborate on their responses to clarify potential misinterpretations and prompt additional insights. These interviews were conducted online and recorded with consent.

In Phase 4, data analysis was conducted. Only two additional suggestions were provided in relation to the tentative list, and these overlapped conceptually with the ones already listed. Therefore, the experts’ selections of ‘most relevant’ obstacles from the list were aggregated. Additionally, no coding was needed as the qualitative reflections were already associated with a corresponding obstacle from the list. Based on this aggregation, cross-expert convergence on ‘most relevant’ was used to identify four critical obstacles. Finally, phase 5 brought experts to a workshop session where they used analytic hierarchy process (AHP) to conduct repeated pairwise comparisons to derive insights on relative criticality (Saaty, 1980). The standard nine-point scale was used for the pair-wise comparisons (Saaty, 1980) which were repeated until consistency ratios fell below the accepted threshold of 10 % (Subramanian & Ramanathan, 2012). Lastly, individual priority weights were calculated and averaged across experts to derive final priority weights. It should be highlighted that the final priority weights were perceived as complementary, rather than a replacement of cross-expert consensus. The cross-expert consensus reflects absolute judgments of relevance (how many experts selected an obstacle as most relevant), whereas AHP reflects relative judgments (how experts assess obstacles when forced to focus on a smaller set of obstacles, comparing them directly and making trade-offs).

3.6. Interview study 2

This section describes IS2, detailing sampling, data collection and analysis.

3.6.1. Sampling

Similar to IS1, with the same logic, purposive sampling was employed to select experts with relevant profiles that aligned with the objectives of the study (Denscombe, 2014). Again, individuals holding senior roles in areas such as SC, logistics, and purchasing and possessing extensive experience were targeted. Additionally, as opposed to IS1, experience of analytics development within the relevant functional areas was also considered a relevant qualification for inclusion. The sample composition aimed to balance both expert categories. In total, 13 experts participated in the study, with individual participation varying across the phases of the study. Specifically, only one expert was involved in both IS1 and IS2, which was a deliberate choice to minimize overlap between the samples and reduce the risk of conflating insights on obstacles and enablers. For details on the demographic characteristics of the sample, refer to P5.

3.6.2. Data collection and analysis

Phase 1 intended to introduce the experts to the topics and the focus of the study. It consisted of two workshop sessions involving a total of 11 experts where core concepts were introduced, prior research reviewed, broad discussions on SCR and the potential role of AC conducted. Then, in Phase 2, the exploration of enablers was initiated. Ahead of the workshop session, the experts completed a short reflection exercise focusing on a small number of general factors known to be important for AC. This served both data collection and preparing the experts for the next phase when enablers were discussed in more depth. Phase 3 comprised individual semi-structured interviews (60–90 minutes each) that allowed the experts to first freely identify and elaborate on enablers through an open-ended question, before being introduced to the structure of the TOE-framework (based on e.g., Kalaitzi & Tsolakis, 2022; Lai et al., 2018) to prompt more reflections. Examples for each dimension of the TOE framework were drawn from the literature to inspire additional ideas and to help respondents refine or expand upon their earlier reflections, rather than serving as a strict checklist. Phase 4 brought the experts together again in a workshop session. As the goal was to consolidate earlier insights and stimulate additional reflections, notes from prior phases were synthesized to guide the discussion. This was facilitated by presenting each preliminary enabler alongside a set of anonymized quotes, one enabler at a time to encourage reactions. The experts collectively assessed the accuracy, completeness, and relevance of the tentative enablers and indicated alignment between the synthesized insights and their viewpoints.

The data analysis procedure in phase 5 was inspired by the thematic analysis method outlined in Braun and Clarke (2006). This constitutes a structured yet flexible means of identifying and describing themes. First, all interviews were transcribed verbatim and read several times to achieve familiarity with the material. Then, coding was conducted in the original language to preserve potential semantic nuances and using the three TOE-dimensions as an overarching structure and individual factors that had been drawn from the literature as candidates for second-order codes. However, the analysis remained flexible enough to introduce new codes where empirical insights were not captured by extant literature. Coding was performed inclusively, meaning that multiple codes could be applied to the same data extract where required.

After initial coding, the codes and associated data extracts were collated and examined to identify recurring themes. To achieve both robustness and variety, a minimum threshold was applied whereby a theme had to appear in at least three data extracts contributed by at least three different experts. Through this iterative review process, some codes were merged, refined, or discarded, to ensure internal coherence, clear differentiation in relation to one another, and relevance to study's purpose. This resulted in a reduction from 18 tentative second-order codes to 11 final themes (enablers) and naming was reviewed to concisely reflect the themes' content. The full coding was reviewed by senior researchers to reduce interpretive bias and ensure consistency. The final set of themes was subsequently subjected to participant validation. A summary of the identified enablers was shared with all participating experts, who were asked to confirm whether the synthesized insights accurately reflected their views or to propose corrections.

3.7. Research quality

A convergent mixed-methods research design requires quality to be assessed in each strand separately (Creswell & Creswell, 2018). Therefore, drawing on Riege (2003)'s discussion of equivalent quality criteria across the two approaches, validity and reliability were applied for the quantitative strand together with the trustworthiness criteria (confirmability, credibility, transferability, and dependability) for the qualitative strand (Lincoln & Guba, 1985). Below, these criteria are merged in pairs to adapt to both strands.

First, construct validity and confirmability deal with the appropriateness of operational measures for theoretical concepts and that data is interpreted in a logical and objective way (Riege, 2003), and not influenced by researcher bias (Lincoln & Guba, 1985). This was addressed by using established constructs from the literature in the survey instrument to ensure that operational definitions correspond well to the theoretical concepts (i.e., nominal definitions), piloting to ensure content validity, and assessing construct validity through convergent and discriminant validity tests. Similarly, in the qualitative studies, key concepts were clearly and consistently defined when presented to the respondents across the data collection instances. Furthermore, the use of multiple interviewees and researchers in data analysis allowed for data and researcher triangulation, respectively. For instance, the inclusion/exclusion criteria were explicit and consistently applied by two researchers by using the PRISMA framework in the SLR (Moher et al., 2015). Overall, the methodological procedures are transparently and comprehensibly reported, which together with raw data availability (survey responses, verbal interview quotes, and SLR database), allow for confirmability audits (Miles & Huberman, 1994).

The next pair is credibility and internal validity (Riege, 2003). To ensure that the SS measured what it was supposed to (Karlsson, 2024), internal validity was supported through careful construct selection, careful instrument translation and piloting, informed respondent selection, extensive data screening and use of established procedures to minimize bias (e.g., CMB). Credibility indicates how well the findings reflect the original data and accurately represent participants' views (Lincoln & Guba, 1985). Following the suggestion by Lincoln and Guba (1985), member checks were used in the interview studies. In IS1, screen sharing allowed participants to ensure that their responses were accurately captured, while a workshop session was arranged to validate the preliminary insights in IS2 in addition to sending the findings via e-mail for final member-checking. IS2 employed some additional measures in support of credibility, including verbatim transcription of data, use of illustrative quotes, and prolonged engagement. Finally, peer debriefing was also used throughout the dissertation project by continuously presenting the data analysis progress to senior researchers (Hirschman, 1986).

Third, external validity and transferability deal with statistical and analytic generalization (Riege, 2003) to indicate the possibility for the findings to be relevant also in other contexts (Lincoln & Guba, 1985). Certain measures have been taken to allow the readers to assess the applicability of the findings in other contexts. First, the sample characteristics have been described throughout the empirical studies, which indicate the researched contexts. In the SS, proportionate stratified random sampling is used to ensure appropriate representation. Furthermore, in both interview studies, respondents' professional profiles are described, and they were asked to draw on their general experience rather than restricting themselves to their current role or context. Given the selection of experts with extensive professional experience, the likelihood that the findings remain relevant in other settings is increased.

Finally, reliability and dependability relate to consistency and transparency in the research process (Riege, 2003). To assess these criteria, dependability audits have been conducted by other senior researchers during the research design phase (Lincoln & Guba, 1985). To enable replication, the research used structured data collection instruments (SS and IS1), preserved raw data, and provided a transparent description of the research process. Additionally, all individual interviews within respective interview studies were conducted using the same consistent procedure. Dependability was ensured in the SLR by relying on established guidelines (Durach et al., 2017), transparently documenting the decisions (e.g., search strings and inclusion/exclusion criteria) in structured, predefined protocol, and recording the process in a PRISMA flow-chart (Moher et al., 2015). By also retaining the Excel database where the inclusion/exclusion criteria were gradually applied, a traceable audit trail is enabled. As for the SS, reliability was checked by assessing Cronbach's alpha, CR, and internal consistency scores.

3.8. Ethical considerations

The dissertation followed the general guidelines outlined by the Swedish Research Council (Vetenskapsrådet, 2024) to conduct the research in a responsible and ethical manner. Research participants were recruited only after providing their explicit informed consent. This was obtained after providing sufficient information about the scope and purpose of the research and emphasizing that all participation is voluntary and build on anonymity. Research participants were offered the opportunity to decline participation either immediately or at any stage of the process at their convenience. To accommodate this and give the opportunity to ask questions after data collection had taken place, contact information was provided. Audio and video recording was only done with the permission of the research participant and confidentiality of all data was ensured.

4. Summary of Papers

Five papers are appended to the dissertation, labeled P1-5. Of these, P1 is an SLR, while the rest are based on empirical data. The following section summarizes each of the papers and outlines their individual contribution to the dissertation.

4.1. Analytics for Resilience: A Systematic Review of the Field and Explanation of Mechanisms (P1)

Purpose and RQs	*to systematically review literature on analytics for resilience* *RQ1$_{P1}$: What characterizes existing studies on analytics for resilience?* *RQ2$_{P1}$: Through what mechanisms does analytics contribute to resilience?*
Strand **Study**	- SLR, see 3.3
Data collection	79 peer-reviewed publications in AJG-journal, period 2019-2024
Data analysis	Descriptive and thematic analysis
Theoretical perspectives or framework	PRISMA-framework
Brief results	For the descriptive profiling (RQ1$_{P1}$), the review first maps the characteristics of the literature in terms of publication trends, journal outlets, research designs, empirical contexts, disruption types, and theoretical lenses. A rapidly evolving but still maturing domain was revealed, with most publications appearing after 2019 and peaking in 2024. Research is concentrated in operations and technology journals, dominated by survey-based quantitative methods, and largely focused on manufacturing firms, developing economies, and disruptions related to the pandemic. Theoretically, the

	extant literature show limited diversity and draws primarily on Information Processing Theory and the DCV. Besides descriptive profiling, the thematic analysis ($RQ2_{P1}$) elaborates on a mechanism-based perspective of how analytics contributes to resilience. Aspects that were captured by this perspective were inspired by, but not limited to, the scope of the dissertation. Specifically, the review synthesizes insights from the literature around four interrelated elements: phase-contingent uses of analytics across preparedness, response, and recovery; types of analytics (descriptive, predictive, and prescriptive); complementary organizational and inter-organizational capabilities to analytics; and, obstacles and enablers. In terms of phases, the response phase dominates although publications considering multiple or even all phases appeared frequently. Predictive analytics dominate, appearing in a substantial number of publications, while descriptive and prescriptive analytics are represented to a relatively lesser extent. A common characteristic in the reviewed sample was that multiple types of analytics appear in the same publication. Complementary capabilities, primarily visibility, flexibility, agility, and collaboration, appear more vividly alongside analytics to strengthen resilience. Furthermore, analytics are shaped by factors spanning technological, organizational, and environmental dimensions. Overall, the paper consolidates a rapidly emerging research stream and develops a mechanism-based understanding of analytics-enabled resilience while highlighting key gaps in context, theory, and methodology.
Contribution to the dissertation	Resource for both empirical strands, complementing the Frame of References in the kappa and providing a reference point for the interpretation of findings.

4.2. Supply Chain Resilience through Capability Bundles: A Fuzzy-Set Configurational Approach (P2)

Purpose and RQs	*explore how SCR can be achieved through different configurations of supply chain capabilities, and how these configurations differ depending on supply chain complexity*
Strand **Study**	Strand I: Quantitative SS, see 3.4
Data collection	Proportionate stratified random sampling, total of 200 cross-sectional survey responses (165 usable). Multi-item constructs with Likert scale response alternatives.
Data analysis	fsQCA
Theoretical perspectives or framework	Configuration Theory, Contingency Theory
Brief results	Findings show that no necessary conditions exist, regardless of SCC-level. In terms of sufficient paths, a total of 7 paths to SCR were identified: four under low SCC and three under high SCC. Out of these, six were unique as one path emerged both for high and low SCC-level. Moreover, all but one path constituted configurations of capability-pairs. SCV was the exception that emerged as a standalone sufficient condition under high SCC. The paths are also shown to be contingent on SCC level.
Contribution to the dissertation	P2 addresses RQ1 by investigating whether AC constitutes a necessary or sufficient condition for SCR. It also shows how AC together with complementary capabilities interact to form configurations for SCR. Additionally, it reinforces the contingency perspective by illustrating that the viability of configurations where AC is included depends on SCC.

4.3. Why Analytics for Supply Chain Resilience Is Far from Trivial: Identifying Key Obstacles (P3)

Purpose and RQs	*explore obstacles to the adoption and use of analytics capability for supply chain resilience* *$RQ1_{P3}$: What are the obstacles for adopting and using analytics capability for supply chain resilience?* *$RQ2_{P3}$: Which of these obstacles are critical?*
Strand **Study**	Strand II: Qualitative IS1, see 3.5
Data collection	Purposive sampling. Total of 16 experts (participation varied between data collection phases). Individual interviews (2 rounds), written preparation assignment, workshop session (AHP).
Data analysis	Descriptive analysis AHP
Theoretical perspectives or framework	-
Brief results	In response to $RQ1_{P3}$, a total of 21 obstacles were identified as relevant to AC-SCR, encompassing both internal obstacles (17) and external (4) to the focal firm. Next, in response to *$RQ2_{P3}$*, four obstacles emerged as critical. To further assess their criticality, final priority weights were used to determine relative criticality. The paper also provides qualitative insights on how these obstacles manifest considering the SCR-context.
Contribution to the dissertation	P3 addresses RQ2 by identifying obstacles to AC-SCR. It complements P5 by focusing on obstacles rather than enablers.

4.4. Unpacking the role of analytics for supply chain resilience and performance: the complex influence of supply chain integration (P4)

Purpose and RQs	*investigate how analytics capability contributes to SCR and performance, as well as to investigate the moderating role of SCI*
Strand **Study**	Strand I: Quantitative SS, see 3.4
Data collection	Proportionate stratified random sampling, total of 200 cross-sectional survey responses (165 usable). Multi-item constructs with Likert scale response alternatives.
Data analysis	Regression and Hayes PROCESS macro in SPSS
Theoretical perspectives or framework	DCV, Contingency Theory
Brief results	AC contributes to SCR and FP (direct effects). SCR contributes to FP (direct effect). SCR partially mediates the relationship between AC and FP. SCI does not moderate the relationship between AC and SCR. SCI negatively moderates the relationship between SCR and FP. SCI negatively moderates the mediated relationship between AC and FP via SCR.
Contribution to the dissertation	P4 addresses RQ1 by empirically testing causal relationships on how AC translates into SCR and FP, while also taking the interactive (contingent) effects of SCI into consideration.

4.5. Supply Chain Resilience through Analytics: Experts' Perceptions of Key Enablers (P5)

Purpose and RQs	*to explore the enablers of analytics adoption and use for supply chain resilience*
Strand	Strand II: Qualitative
Study	IS2, see 3.6
Data collection	Purposive sampling. Total of 13 experts (participation varied between data collection phases). Individual interviews, written preparation assignment, workshop sessions (two instances).
Data analysis	Thematic analysis
Theoretical perspectives or framework	TOE-framework
Brief results	In total, 11 enablers were identified within the TOE framework, comprising three technological, five organizational, and three environmental factors.
Contribution to the dissertation	P5 addresses RQ2 by identifying enablers that facilitate or accelerate adoption and/or increased use of analytics for SCR. It complements P3 by focusing on enablers rather than obstacles.

5. Findings and Analysis

This chapter presents the findings corresponding to the two research questions of the dissertation and interprets and reflects on these findings in relation to the extant literature.

5.1. RQ1: How does analytics capability contribute to supply chain resilience?

The findings and analysis related to RQ1 are structured into two parts: first, the individual relationship between AC and SCR, and secondly, the AC-SCR relationship considering other enabling capabilities and their implications on FP.

5.1.1. Individual relationship between AC and SCR

The findings showed that AC contributes to SCR as the direct effect (AC → SCR) was statistically significant and positive ($\beta = 0.203$, $t = 3.748$, $R^2 = 0.115$). This suggests that firms with more developed AC tend, on average, to also exhibit higher levels of SCR. Nevertheless, AC was found to neither be a necessary nor sufficient condition for high SCR. Findings demonstrated that AC does not constitute a necessary condition for high SCR, irrespective of SCC level. The consistency scores obtained of AC for high SCR, 0.63 in low SCC and 0.71 in high SCC, fell substantially below the 0.90 threshold required for qualification as a necessary condition. This can be interpreted in the way that AC does not have an indispensable and mandatory role for high SCR, meaning that if potentially absent, high SCR would still be attainable. Findings also indicated that AC does not individually emerge as a sufficient condition for high SCR, which demonstrates that its stand-alone presence will not automatically translate into high SCR from a set-theoretic perspective.

This points to a nuanced picture of the relevance of AC for SCR. First, the findings that AC contributes to SCR corroborates literature (e.g., Dennehy et al., 2021; Dubey et al., 2021; Iftikhar et al., 2023; Munir et al., 2024). However, the findings underscore that AC is neither necessary nor sufficient as a stand-alone capability for high SCR, thereby adding nuance to existing evidence by suggesting a less mandatory or decisive role from a set-theoretic perspective (Fiss, 2007; Misangyi et al., 2017).

5.1.2. AC in combination with other enabling capabilities and their implications for SCR and FP

The findings showed that AC is associated with high SCR by being part of sufficient capability configurations. Four sufficient capability configurations that include AC were identified and differed with respect to SCC-level: three configurations for low SCC and one for high SCC, see Table 6. As one of these configurations (AC*SCI, where "*" denotes logical AND) emerged both for low and high SCC. Therefore, there were only three unique configurations identified. Specifically, all configurations comprised two enabling capabilities, i.e., AC paired with either one of SCV, SCResp, and SCI. This means that AC should be viewed as a synergistic component that should be complemented with other capabilities (conjunctural causation) and that multiple paths to high SCR exist simultaneously (equifinality). This corroborates that capabilities need to be combined and that multiple parallel paths may exist simultaneously (Fiss, 2011; Ketchen et al., 2021). In this way, the findings extend prior research that points towards these phenomena, including Jiang et al. (2024) and Shen and Sun (2021).

Furthermore, the findings highlighted the contingent role of SCC. In the low-SCC subgroup, AC combines with one additional capability, either SCV, SCResp, or SCI, to form sufficient configurations. In contrast, for the high-SCC subgroup, only the AC*SCI configuration emerged as a sufficient pathway. Therefore, the presence of this configuration in both low- and high-SCC contexts suggests that its effectiveness is independent of SCC level. Since there are fewer configurations that include AC at high SCC levels (only one compared to three at low SCC), the findings suggest that higher levels of SCC appear to have a constraining effect. This aligns with previous literature, which in relation to SCV, has suggested that SCC can reduce the ability to identify disruptions and interpret information, thereby hindering timely response (Bode & Macdonald, 2017; Christopher & Lee, 2004).

The more limited role of AC in high-complexity SC contexts is a particularly interesting finding, given that such contexts are precisely where managers' cognitive limitations are most likely to impede situational awareness and decision-making (Srinivasan & Swink, 2018). With respect to the apparent persistence of the AC–SCI configuration across contexts, one plausible interpretation from a DCV perspective is that they may compensate as well as mutually reinforce one another (Teece, 2007). Stronger SCI may compensate for the limitations or infeasibility of AC by enabling improvisation and coordinated action (i.e., seizing and reconfiguring), while also mutually reinforcing AC by supporting the execution and alignment of decisions informed by analytics insights. Taken together, these compensatory and reinforcing roles provide substance to why AC and SCI form a particularly strong configuration.

Table 6: Sufficiency analysis results, adapted from P2

Measures	**Sufficient paths for SCR**						
	Low SCC				**High SCC**		
	AC* SCV	AC* SCResp	~~SCV* SCI~~	AC* SCI	~~SCV~~	AC* SCI	~~SCResp* SCI~~
Raw coverage	0.52	0.51	~~0.60~~	0.47	~~0.79~~	0.59	~~0.60~~
Unique coverage	0.02	0.02	~~0.18~~	0.002	~~0.19~~	0.01	~~0.01~~
Configuration consistency	0.87	0.81	~~0.82~~	0.83	~~0.76~~	0.79	~~0.80~~
Frequency cut-off	1				1		
Consistency cut-off	0.81				0.84		
Solution coverage	0.77				0.86		
Solution consistency	0.75				0.72		

Although the configurational analysis identified AC*SCI as a sufficient pathway for high SCR, a variance-based analysis shows that the interaction between AC and SCI on SCR (AC × SCI → SCR) is not statistically significant ($\beta = -0.005$, S.E. = 0.038). The absence of a significant interaction effect could be the result of the distinction between the causal logics of the employed methods, rather than representing a contradiction. While there are individual cases that simultaneously exhibit membership in the AC*SCI configuration and high SCR, the effect of AC on SCR does not appear to depend systematically on SCI. Thus, AC and SCI seem to operate as complementary capabilities whose joint configuration enables high SCR for specific cases, although SCI does not seem to strengthen the average marginal effect of AC on SCR across the entire sample.

Findings also show how SCR has a channeling role between AC and FP (AC → SCR → FP, $\beta = 0.324$, S.E. = 0.015, CI = [0.008, 0.068]). However, in the moderated mediation model, the index of moderated mediation is significant and negative (−0.015, C.I. = [−0.032, −0.001]), indicating that SCI dampens the indirect effect of AC on FP through SCR. One plausible explanation is that SCI may introduce coordination costs or structural rigidities (Wieland & Wallenburg, 2013) that constrain firms' ability to leverage AC-SCR to generate FP. AC-SCR would instead allow for maintaining FP, such as financial, service or quality levels, as opposed to levels that would be superior and outperform competition. This adds to the mixed observations on the actual implications of SCI (Qi et al., 2023; Wiengarten et al., 2019).

5.2. RQ2: How is analytics capability for supply chain resilience shaped by obstacles and enablers?

The findings and analysis related to RQ2 are structured into two subsections, with obstacles and enablers addressed separately.

5.2.1. Obstacles

The findings revealed four obstacles as particularly important for AC-SCR. They are summarized below and presented in descending order with respect to final priority weights as an indication of their relative criticality.

First, *insufficient benefits and infrequent use* received the highest final priority weight (0.34), corroborating general AC literature (LaValle et al., 2011; Vidgen et al., 2017). Findings highlighted difficulties in motivating investments in AC that are primarily intended for disruption scenarios, as the occurrence and nature of future disruptions remain uncertain. Instead, the focus is often on current and immediate needs as opposed to proactively making investments to deal with future, hypothetical disruptions. Additionally, analytics initiatives were perceived as more justifiable if they could be integrated in everyday operational decision-making rather than being useful only in exceptional situations. Therefore, it appears these problems are linked to the nature of disruptions, which per definition occur unpredictably and less frequently (Hosseini et al., 2019). Some context-specific insights also emerged that shed light on how benefits associated with analytics are judged. In environments where SCC is relatively low, the relevance of AC was described as less important because decision-makers can effectively manage disruptions on their own. Moreover, in engineer-to-order contexts, the benefits of AC are judged on a project-by-project basis.

The second highest final priority weight (0.26) was assigned to the issue of *low data availability and quality,* which echo themes commonly discussed in the AC literature (e.g., Lismont et al., 2017; Vidgen et al., 2017). Key reasons for the emergence of this obstacle were that data from SC partners is often inaccessible or incomplete, and that data quality typically deteriorates during disruptions when uncertainty is high. It was also emphasized that the recent disruptions have not increased data sharing but rather resulted in more restrictive approaches motivated by security concerns. Nevertheless, the availability of such external data was described as important to fully understand the effects of disruptions. It was found that collecting additional data during disruption situations can require considerable effort and time, creating a bottleneck for analytics. These examples (decreased data quality or infeasibility of additional data collection) reflect disruption contexts. As a compromise, internal and historical data were described as a relatively useful basis for analytics although not covering external entities and current events, respectively. Prior research cautions that such historical data may be problematic during disruptions, as it may not reflect current conditions (Browning et al., 2023; Melnyk et al., 2024). Another important aspect regarding data availability that surfaced was the necessity of transferring data from repositories to analytics applications, which also adds inconvenience.

Next, *absence of a data-driven culture* received the third highest final priority weight (0.24), which has been recognized in general AC-literature (Gupta & George, 2016; McAfee et al., 2012). Insights underscored that decisions in relation to disruptions are often guided by managers' experience and intuition rather than driven by analytics insights. This tendency was emphasized as especially prevalent for managers with extensive experience and when relationships with SC partners are well established. Several underlying reasons were mentioned that increase reliance on experience over AC, including low data reliability, previous unsuccessful experiences with analytical tools, the complexity and potentially severe consequences of disruption-related decisions, and an ambiguity about whether analytics provides better guidance than manager judgment. To substantiate these issues, examples of instances were mentioned where analytics insights pointed to developments that conflicted with managers' understanding, such as unexpected changes in demand during the pandemic. Reflecting on these insights, it seems that during disruptions, the high stakes and complexity of decisions, together with data quality issues, limit the extent to which decision-making can remain data-driven. At the same time, the experts emphasized the importance of combining analytics and experience in decision-making, which aligns with the literature (Browning et al., 2023; Rengarajan et al., 2022), although acknowledging that it can be difficult to decide which approach to follow.

Finally, *time-consuming to use analytics as decision support* was assigned the lowest final priority weight (0.16). The experts noted that developing and validating analytics applications may often take considerable time, which is inconvenient if this is to be done reactively once a disruption has already occurred. This situation is further exacerbated as organizations typically have multiple ongoing or planned analytics initiatives competing for limited resources. Besides development of analytics applications, additional data collection during disruptions can also slow down decision-making. These issues are inherently unique to disruption-contexts and illuminates the characteristics of being time-sensitive and having high urgency (Akter et al., 2021; Dennehy et al., 2021). Moreover, the use of analytics before disruptions was also deemed inefficient from a time-perspective given the multitude of possible scenarios that could be investigated and that several of the recent disruptions were not even thought to happen. Again, these issues reflect the heterogeneous and inherently unpredictable nature of disruptions (Hosseini et al., 2019) and reduce incentives to invest time before disruptions occur.

5.2.2. Enablers

The findings identified eleven enablers for AC-SCR, categorized according to the three dimensions of the TOE-framework: three under technology, five under organization, and three under environment. These are presented in Table 7 and summarized below.

Table 7: Enablers categorized according to the TOE-framework

Technology	Organization	Environment
Data availability and quality	Routines and responsibilities	Policy and regulatory drivers
Key analytics features	General digital maturity	Relationships with trading partners
Data integration and architecture	Securing commitment: justification and financing	Benchmarking and inter-firm learning
	Supportive culture and mindset	
	Hybrid and distributed competence	

Technology

A central technological enabler was *data availability and quality*, which also emerged as a key obstacle, marking its fundamental role in relation to AC-SCR. In practice, both data availability and quality issues remain prevalent. On this end, findings noted that, despite general data availability, a discrepancy persists between data collected and prepared for internal reporting purposes and decision-critical data required for rapid disruption response. There could also be data quality concerns when data is outdated or incorrect. Moreover, in SCR contexts, data availability extends to also including trading partners. The need for proactive mapping of supplier and sub-supplier data before disruptions occur was stressed, covering locations, lead times, critical items, and financial health to enable faster situational awareness and response in the event of a disruption. However, it was noted that real-time data is not always essential, reasonably recent data is generally sufficient. Additionally, to ensure data availability in a resource-efficient manner, priority should be given to critical suppliers and items. This prioritization ensures that only the most essential data is collected and maintained.

Findings also suggest the emergence of *key analytics features* that would increase the usefulness of analytics during disruptions. Among these features, automatic data processing was perceived as important for minimizing delays, need for manual efforts and human errors. This would enable analytics to operate as a 'seismograph', that continuously observe the environment to quickly identify disruptions. Besides automation, visualization also emerged as an attractive feature that gives decision-makers clear overviews by providing a complete and thorough picture of the scenario. Another valuable feature that was emphasized concerned scenario comparisons to allow decision-makers to understand the different response alternatives at hand. Flexibility was another valuable feature, as tools that quickly and easily adapt to changing conditions and needs are more useful given the variety of disruption scenarios. A final feature is identifying and interpreting subtle signals that would otherwise not be detected by decision-makers. Reflecting on these characteristics, it becomes evident that they mirror the requirements of decision-making during disruptions. The emphasis on automation, visualization, scenario comparison, flexibility, and signal detection highlights the need for tools that support timely and effective responses. The closest resemblance of these traits is highlighted in conceptual frameworks on AC-SCR in the literature. Authors envision digital twins that include different forms of analytics to support proactive and reactive decisions, for instance through dashboards to visualize information or simulation for stress-testing of SCs during hypothetical disruptions (Ivanov, 2023; Ivanov & Dolgui, 2021).

A final enabler in the technology-dimension concern *data integration and architecture,* which partly overlaps with data availability and quality. However, this enabler deals with the technological connectivity aspects related to data dissemination and collection both in intra- and inter-firm interfaces, e.g., compatible systems and data standards. These aspects are well-anchored in the literature, as some conceptualizations of AC include dimensions named technology capability (Akter et al., 2016; Fosso Wamba & Akter, 2019) or infrastructure flexibility (Wamba et al., 2017) to emphasize connectivity for intra-organizational data-integration and compatibility of systems. In relation to SCR, the findings provided two distinct accounts illustrating how data integration supports situational awareness and, in turn, rapid response. For instance, shared platforms that integrate data from multiple firms in the same parent company provide holistic data availability, which in turn enables rapid decision-making on redirection of material flows in response to disruptions. Quite similarly, inter-firm data integration platforms enable situational awareness and swift reactions, such as integrated platforms with external freight forwarders to receive automatic updates on the status of material flows. Flexibility in relation to data integration and architecture was also highlighted, as platforms that can be adapted to new scenarios and data needs, e.g., sudden trade regulations, also support managers' to quickly comprehend impact and react.

Organization

The largest number of enablers was related to organizational aspects. Among these, *routines and responsibilities* emerged as a key enabler to capture the importance of established procedures and accountability. Explicit and broad responsibility for ensuring and maintaining data availability and quality that extends to everyone involved in the SCM-function was emphasized. As reflected in the findings, this was in some cases routinized through an embedded annual cycle for master data updates. Analytics use could also be stimulated by making it a formal responsibility, developing action plans that emphasize this or through routine practice for hypothetical future disruptions. Another example of routinization concerned structured and consistent post-disruption reviews to investigate which datasets and analyses that would have been needed as a preparation for future events. Role and routine clarity were also stressed in relation to the formation of so-called task-force teams during the response phase and having routines in place to allow for processing of data in an expedited manner when needed. The inclusion of analytics specialists in these task-force teams was seen as essential to configure analytics applications and models quickly, coordinate data collection, and ensure that analytics generates actionable insights.

Next, *general digital maturity* constitutes an enabler to suggest that the potential of adopting and using analytics for SCR is influenced by a firm's overall level of digitalization, reflecting what is sometimes referred to as readiness in the literature (Egwuonwu et al., 2024; Kalaitzi & Tsolakis, 2022). Firms that already have general analytics experience and available tools were thought to have a much shorter journey to also start employing analytics for SCR. Digital maturity thus functions as an enabler by providing the technical infrastructure and competencies needed to extend and scale analytics use. By contrast, the findings also noted that digital-native start-ups could have better prerequisites compared to older counterparts that suffer from outdated technical infrastructure and data governance issues.

A third enabler was labeled as *securing commitment: justification and financing*, which conceptually overlaps with perceived benefit and return on investment (LaValle et al., 2011; Vidgen et al., 2017) or top management support (Egwuonwu et al., 2024; Lai et al., 2018). The viability of this enabler is influenced by factors such as scope, as analytics applications that concern individual functions were indicated to often be easier to approve, and changes in leadership which can delay progress by requiring re-approval. Additionally, AC for SCR might receive lower priority in relation to more visible equipment investments and due to the uncertainty in pay-off given the sporadic nature of disruptions. Strategies to secure commitment included framing AC as useful for managing both disruptions but also daily operations, using an insurance analogy to stress necessity despite uncertain pay-off, presenting small prototypes to gain executives' interest, or by referring to how past disruptions could have been handled better with AC.

Moreover, findings indicate the relevance of a *supportive culture and mindset* to enable AC-SCR. This refers to a decision-making culture characterized by willingness and tendency to adopt and use analytics (Gupta & George, 2016; McAfee et al., 2012) and adjacent concepts like top management support (Egwuonwu et al., 2024; Lai et al., 2018). However, this trust was described as fragile and dependent on previous experiences. Culture and mindset are also challenged when decisions entail significant financial liabilities. Testimonies of how this enabler can be realized entailed examples of firms where the culture encourages experimentation and where mistakes are perceived as learning opportunities. A supportive culture towards AC can also be realized by demonstrating tangible benefits. Moreover, cultural reorientation can also be forced by simply demanding use of AC (also mentioned under the enabler of routines and responsibilities).

The final organizational enabler was worded as *hybrid and distributed competence.* In brief, to enable the use of AC for SCR, professionals with hybrid expertise that bridge SCM and AC-expertise are necessary as issues could arise if AC specialists lack operational context, or vice-versa when decision-makers cannot clearly explain the scenario at hand. Therefore, individuals that are comfortable in both domains play an important role in understanding and interpreting business needs, preparing and processing data and presenting actionable insights to decision-makers. However, if the number of individuals possessing hybrid competence is limited, their absence may present a significant continuity risk. Suggestions on how to mitigate this included thorough documentation, communities of practice to disseminate knowledge and succession planning. Interestingly, the use of external software developers does not rule out the need for internal hybrid competence as the firm still needs to specify and articulate AC needs and evaluate alternatives. Various skill related aspects have been emphasized in relation to AC, often referred to as talent capability (Akter et al., 2016; Fosso Wamba & Akter, 2019) or personnel expertise (Wamba et al., 2017), spanning both technical and domain knowledge.

Environment

The first enabler in the environment-dimension was *policies and regulations.* Insights revealed that although governmental and inter-governmental policies and regulations are not primarily intended to enable AC-SCR, instead, they frequently lead to increased data collection and reporting. In turn, this creates opportunities for additional uses beyond regulatory compliance. For instance, gathering and reporting information on supplier origin or product composition due to sanctions, tariff regulations, reporting rules for trade in the European Union, or sustainability regulations often yield data that can be equally useful for exposure assessments and scenario modeling. Thus, policies and regulations constitute an indirect enabler by being linked to data availability, contrasting literature that frequently position these aspects as directly promoting AC adoption (Kalaitzi & Tsolakis, 2022; Lai et al., 2018).

A second key enabler was *relationships with trading partners*. As previously noted, inter-organizational data is critical for use of AC and effective disruption response. Essential external data includes trading partners' capacity, stock, and demand levels. However, obtaining access to this information is influenced by factors such as type of relationship, governance, incentives, and data sensitivity. While alignment in data standards and integration platforms can be accommodated, the actual access ultimately relies on the nature of relationships. The reluctance of sharing data was also stressed to be even stronger during disruptions, as trading partners do not want to reveal vulnerabilities. Consequently, transparency is often reserved for strategic partnerships involving the most critical suppliers or items. Other strategies for managing data sharing with trading partners included adding specific clauses in contracts and regularly addressing the topic during discussions with partners. These findings connect relationships with trading partners and data availability, while issues like confidentiality or competitive sensitivity affect feasibility, as highlighted in previous research (Bag et al., 2024; Sharma et al., 2020).

The final enabler to emerge was *benchmarking and inter-firm learning.* Findings indicate that practices and use cases from other successful firms may have an enabling effect as these examples provide inspiration and learning opportunities. External influences were cited to be captured in a variety of forums, like industry events, joint development projects, or by monitoring competitor behavior. Benchmarking and learning from others can in this way stimulate initiatives by clarifying how AC can be used and help justifying investments. However, experts maintained that adoption would only occur when there is a clear association to business value. Given these insights, benchmarking and inter-firm learning appear closely linked to the earlier enabler related to justification and financing, as external examples help legitimize and support investments, which was described as particularly challenging for AC-SCR.

6. Discussion

This chapter reflects on the contributions and implications of the dissertation for research and practice.

6.1. Research implications

First, the dissertation addresses the somewhat scattered and inconclusive nature of research on AC-SCR. In addition to confirming the relevance of AC for SCR (Dubey et al., 2021; Iftikhar et al., 2023; Munir et al., 2024), the dissertation moves on to clarifying how and under what conditions AC contributes to SCR. A key insight is that AC, as a stand-alone enabling capability, is neither necessary nor sufficient for SCR, which downplays its potential as a ‘silver bullet’ for SCR. Instead, the dissertation expands the application of configuration theory to the nexus of AC-SCR and argues for the role of capability configurations. On this end, the findings align with the tenets of configuration theory and causal complexity in the sense that SCR is illustrated to stem from configurations of enabling capabilities (conjunctural causation) and that multiple equivalent configurations exist (equifinality) where AC is included (Fiss, 2007; Ketchen et al., 2021; Misangyi et al., 2017). This extends the literature at the AC-SCR nexus by highlighting the importance of complementary enabling capabilities (Dubey et al., 2021; Jiang et al., 2024; Shen & Sun, 2021). More broadly, the dissertation contributes to research by demonstrating that AC for SCR is relatively attainable, as it only needs to be paired with one complementary capability rather than requiring broad or exhaustive capability development.

Next, the dissertation illuminates the differential role of SCC on the AC-SCR nexus. This resonates with the core claim of contingency theory on the importance of “fit” with contextual conditions (Donaldson, 2001; Flynn et al., 2010; Schilke, 2014). By adopting SCC as a contextual contingency, the dissertation contributes to research by providing a more nuanced view of when certain capability configurations are viable, complementing Brandon-Jones et al. (2014) who examine the influence of SCC on the SCV-SCR link. This is especially insightful, as SCC is characterized as ambiguous in relation to SCR and acknowledged to have "both dark and bright sides" (Wiedmer et al., 2021, p. 338). Here, SCC is shown to constrain the range of viable AC configurations for SCR, complementing insights from earlier research (Bode & Macdonald, 2017; Christopher & Lee, 2004). It also responds to the calls for more research on SCC in relation to SCR (Akın Ateş et al., 2022).

From a DCV perspective, the observed recurrence of the AC–SCI configuration across contexts is noteworthy. Among the enabling capability pairs, this configuration arguably offers the broadest coverage of sensing, seizing, and reconfiguring. This suggests that SCI may both compensate for and reinforce AC in a way that allows the configuration to remain viable despite varying levels of SCC. The emergence of the AC–SCV configuration is also remarkable, as it suggests that strong data availability and quality, combined with data-processing capabilities, may compensate for weaker reliance on execution-oriented capabilities (SCI or SCResp). This configuration, however, is only observed under conditions of low SCC. Overall, these findings nuance the assumption that AC must always be complemented with execution capabilities (Srinivasan & Swink, 2018) and by providing insights into how sensing, seizing, and reconfiguring are combined in practice (Teece, 2007). In essence, broader coverage of the capacities of dynamic capabilities seems to be needed in high SCC (AC-SCI), while low SCC may allow for more parsimonious coverage (AC-SCV).

A secondary contribution relates to the wider performance implications of the AC–SCR relationship. Findings show that AC also contributes to FP indirectly through SCR, which has been underscored as a promising area for investigation (Raj et al., 2025). However, SCI is noted to have a dampening effect on this relationship. These observations add substance to the ambiguous perspective on the implications of SCI (Qi et al., 2023; Wiengarten et al., 2019) and offer support to earlier indications that the benefits of SCI may be diminished due to its associated costs, increased dependencies, and reduced flexibility (Wieland & Wallenburg, 2013).

Another implication at the AC-SCR nexus concerns obstacles and enablers. These are frequently addressed in the AC literature (e.g., Kalaitzi & Tsolakis, 2022; Lai et al., 2018; Vidgen et al., 2017), but have not been investigated in relation to the specific application area of SCR. The dissertation confirms that several of them are relevant also when considering AC-SCR, given their fundamental character (e.g., data availability and quality or data-driven culture). A contribution, besides identification, relates to insights on how disruption contexts influence their relevance and manifestation, e.g., due to high urgency and uncertainty (Akter et al., 2021; Dennehy et al., 2021) or infrequent and unexpected nature (Hosseini et al., 2019). Therefore, obstacles that may represent manageable constraints in normal environments become substantially more problematic in relation to disruptions, such as assessing usefulness and justifying investments. In this way, the dissertation contextualizes obstacles and enablers. This adds to case studies that illustrate AC in disruption settings, but do not explicitly examine the obstacles and enablers (Norrman & Wieland, 2020; Shen & Sun, 2021). Moreover, the multitude and diversity of factors reinforce the relevance of broad frameworks, such as the subdimensions of AC (Wamba et al., 2017) or the TOE-framework (Tornatzky & Fleischer, 1990).

Methodologically, the dissertation makes several contributions. It responds to calls for more empirical research on SCR (Scholten et al., 2020; van Hoek, 2020). It also contributes to methodological diversity by adopting a variance-based (net-effect) logic through regression analysis (Hayes, 2017) alongside a set-theoretic logic through fsQCA (Fiss, 2007; Pappas & Woodside, 2021). The latter is specifically called for in SCR research (Ketchen et al., 2021; Russo et al., 2019). Moreover, the dissertation extends AC–SCR research to contexts beyond developing economies (Dubey et al., 2021; Iftikhar et al., 2023; Munir et al., 2024) and single-industry settings (Dennehy et al., 2021; Dubey et al., 2021) is made. Finally, the convergent mixed-methods research design provides complementary insights by combining quantitative and qualitative evidence to address distinct, but related, aspects of the AC–SCR nexus.

6.2. Practical implications

Based on the findings, managers are advised to perceive AC primarily as decision support that can help interpret the environment and assess alternative actions. However, because it does not entail execution of decisions, managers should avoid overinvesting in AC alone. Instead, they should coordinate AC initiatives together with other complementary capabilities that enable action during disruptions, in this case SCResp or SCI. Alternatively, combining AC with SCV can provide such good data and decision support which can compensate for weaker SCI or SCResp. Firms should therefore think in terms of capability pairs rather than AC in isolation. In practice, this means managers should define what is missing to complement AC and then prioritize capability development accordingly. Specifically, managers should consider SCC when deciding which capability combination to adopt. The findings indicate that what works in relation to lower complexity is not always viable under higher complexity. A practical starting point is therefore to assess the structure of their SC. Under higher SCC, firms may need stronger coordination and alignment with partners to make AC usable during disruptions, whereas under lower SCC, firms have more options for how to complement AC.

Next, managers should be cautious about performance benefits of AC-SCR. The findings suggest that the value of AC–SCR is influenced by integration with SC partners and does not automatically translate into superior performance outcomes. This implies a potential trade-off that managers must consider: strengthened SCR through AC and maintaining relationships with SC partners, which may have long-term benefits, or weaker short-term performance. Finally, managers interested in AC-SCR should consider obstacles and enablers. As these factors span multiple dimensions, managers typically need more than a narrow focus on technology to make progress. To exemplify, they could improve data availability and quality, clarify routines and responsibilities, and build skills that combine both domain and AC knowledge. The identified obstacles and enablers can function as a diagnostic tool or checklist for managers to assess their prerequisites for AC-SCR.

7. Conclusion

The final chapter of the dissertation outlines some concluding remarks and suggests directions for future research.

7.1. Concluding remarks

This dissertation sets out to *investigate the nexus of analytics capability and supply chain resilience*. Using a mixed-methods research design that combines a cross-sectional survey and expert interviews, the dissertation illuminates various aspects of the AC-SCR nexus. AC is confirmed to contribute to SCR, yet this is conditional on both the presence of complementary enabling capabilities and contextual characteristics. AC must be paired with an additional enabling capability, and the viability of these pairs differs with respect to SCC. Therefore, rather than promoting a "more analytics is better" logic, the importance of a configurational and context-sensitive perspective is highlighted. The dissertation also adds nuance by showing that SCR plays a channeling role between AC and FP, and that SCI has a negative effect on this link.

Moreover, the AC-SCR nexus is shaped by several obstacles and enablers, covering technological, organizational, and environmental dimensions, and their manifestation reflects the characteristics of disruptions. An overlap between some of the identified obstacles and enablers can be noted. This was most clearly articulated for data availability and quality, which appears both as a critical obstacle and a key enabler, emphasizing the importance of reliable, timely, and well-integrated data in relation to disruptions. A similar overlap is observed for data-driven culture, where the absence of such a culture is identified as an obstacle, while its presence emerged as an important enabler. Moreover, issues related to justification and financing correspond closely with the obstacle of insufficient perceived benefits and infrequent use, suggesting that difficulties yet importance in demonstrating value. A less obvious but still notable overlap concerns the perception of AC as too time-consuming during disruptions, which is partially addressed by the enabler related to key features that emphasize e.g., automation and visualization to reduce effort and time consumption. Overall, these overlaps suggest that some obstacles and enablers are linked to the same underlying issues.

7.2. Future research

From a general point of view, AC-SCR requires further attention as each of the concepts are dynamic and subject to ongoing technological and theoretical developments. In the case of AC, recent developments in concepts like big data and artificial intelligence have provided new opportunities for processing data (Davenport, 2018; Duan et al., 2019; Maheshwari et al., 2021; Toorajipour et al., 2021). These developments are constantly reshaping how AC is understood and applied in research and practice. Similarly, theoretical development has provided new perspectives on SCR. These include antifragility (Nikookar et al., 2021), viability (Ivanov & Dolgui, 2020), transilience (Craighead et al., 2020), plasticity (Zinn & Goldsby, 2019), and the social-ecological view of resilience (Wieland & Durach, 2021; Wieland et al., 2023). By being attentive to these developments, new perspectives and insights on AC-SCR may emerge that could further advance research.

Another broad suggestion concerns the need for more in-depth inquiry. The dissertation approached both AC and SCR from broad perspectives, and did not disaggregate them into types (descriptive, predictive, and prescriptive; Grover et al., 2018) and phases (preparing, responding, recovering, and growth; Hohenstein et al., 2015), respectively. Therefore, further research can investigate what additional insights emerge when these aspects are taken into consideration. Specifically, longitudinal studies are useful for revealing how the use of AC unfolds throughout the disruption phases. The outcome of such research would be a structured taxonomy of AC-SCR, showing which AC types or capability configurations are most effective in particular disruption phases.

Research on the AC-SCR nexus would benefit from considering other SCR-enabling capabilities. For instance, future research could extend the configurational approach by investigating AC together with the AAA-capabilities, namely agility, adaptability, and alignment, that have gained considerable attention in recent SCR literature (Patrucco et al., 2025; Zeiser et al., 2025). Moreover, in addition to capabilities, the influence of strategic firm orientations may provide additional insights into the AC-SCR relationship. They are often positioned as internal contingencies that influence the effectiveness of capabilities (c.f. Chavez et al., 2021; Chavez et al., 2023). From the perspective of AC-SCR, it could be relevant to investigate disruption orientation (Bode et al., 2011) or analytics orientation (Gupta & George, 2016). Such extensions would help clarify how AC contribute to SCR with more precision.

Another important direction concerns attention to a broader set of contextual conditions. The dissertation operationalized contextual contingency through SCC, given its relevant yet somewhat ambiguous role in relation to SCR (Wiedmer et al., 2021). Future research could adopt a more granular perspective on SCC by differentiating between horizontal, vertical, and spatial complexity (Bode & Wagner, 2015). Such an approach could provide clearer insights into how different dimensions of SCC affect the usefulness of AC-based capability configurations for SCR. Future research can also devote attention to other external contingencies, like industry sector (Brandon-Jones & Knoppen, 2018) or environmental dynamism and munificence (Fainshmidt et al., 2019) to understand how AC-SCR differs depending on context.

In relation to obstacles and enablers, different paths for future research are suggested. Although literature has suggested that these factors interact (Maroufkhani et al., 2022), the dissertation has not focused on illuminating such patterns in depth apart from a few indications (e.g., between data availability and routines). Given that a wide range of obstacles and enablers were identified, research in this direction could highlight how they potentially form clusters and interact. Moreover, as the largest number of enablers were organizational, more focused research on this dimension is called for. A final suggestion in relation to obstacles, that relates to both AC and SCR, is to focus on cybersecurity issues, as these have received increasing attention in recent years (Friday et al., 2024; Herburger et al., 2024; Jazairy et al., 2024).

A final set of suggestions for future research concern replication across time periods and contexts. The dissertation draws on empirical insights collected during the period 2021–2025, which may have been influenced by the nature and prevalence of disruptions during that time. While the research has not focused on individual disruptions, their presence might still have been implicitly reflected in the findings (c.f. Zeiser et al., 2025). To investigate the stability of findings, replication at other points in time is called for. Additionally, the dissertation focused on industries managing a physical flow of goods but omitted a key sector: transportation and warehousing. Since logistics service providers rely on service-based offerings rather than product-based, studies involving them should be carefully adapted to reflect their distinct characteristics compared to manufacturing, retail, and wholesale firms.

References

Akın Ateş, M., Suurmond, R., Luzzini, D., & Krause, D. (2022). Order from chaos: A meta-analysis of supply chain complexity and firm performance. *Journal of Supply Chain Management*, *58*(1), 3–30. https://doi.org/10.1111/jscm.12264

Akter, S., Bandara, R. J., & Sajib, S. (2021). How to empower analytics capability to tackle emergency situations? *International Journal of Operations & Production Management*, *41*(9), 1469–1494. https://doi.org/10.1108/IJOPM-11-2020-0805

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Alexander, A., Blome, C., Schleper, M. C., & Roscoe, S. (2022). “Managing the “new normal”: the future of operations and supply chain management in unprecedented times”. *International Journal of Operations & Production Management*, *42*(8), 1061–1076. https://doi.org/10.1108/ijopm-06-2022-0367

Ali, A., Mahfouz, A., & Arisha, A. (2017). Analysing supply chain resilience: Integrating the constructs in a concept mapping framework via a systematic literature review. *Supply Chain Management: An International Journal*, *22*(1), 16–39. https://doi.org/10.1108/SCM-06-2016-0197

Ali, I., & Gölgeci, I. (2019). Where is supply chain resilience research heading? A systematic and co-occurrence analysis. *International Journal of Physical Distribution & Logistics Management*, *49*(8), 793–815. https://doi.org/10.1108/IJPDLM-02-2019-0038

Aragón-Correa, J. A., & Sharma, S. (2003). A Contingent Resource-Based View of Proactive Corporate Environmental Strategy. *The Academy of Management Review*, *28*(1), 71–88. https://doi.org/10.2307/30040690

Arellano, M. C., Meuer, J., & Netland, T. H. (2021). Commitment follows beliefs: A configurational perspective on operations managers' commitment to practice adoption. *Journal of Operations Management*, *67*(4), 450–475. https://doi.org/10.1002/joom.1130

Armstrong, J. S., & Overton, T. S. (1977). Estimating Nonresponse Bias in Mail Surveys. *Journal of Marketing Research*, *14*(3), 396–402. https://doi.org/10.1177/002224377701400320

Armstrong, R., Hall, B. J., Doyle, J., & Waters, E. (2011). Cochrane Update. 'Scoping the scope' of a cochrane review. *J Public Health (Oxf)*, *33*(1), 147–150. https://doi.org/10.1093/pubmed/fdr015

Bag, S., Gupta, S., Choi, T. M., & Kumar, A. (2024). Roles of Innovation Leadership on Using Big Data Analytics to Establish Resilient Healthcare Supply Chains to Combat the COVID-19 Pandemic: A Multimethodological Study. *IEEE Transactions on Engineering Management*, *71*, 13213–13226. https://doi.org/10.1109/TEM.2021.3101590

Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barratt, M., & Barratt, R. (2011). Exploring internal and external supply chain linkages: Evidence from the field. *Journal of Operations Management*, *29*(5), 514–528. https://doi.org/10.1016/j.jom.2010.11.006

Barratt, M., & Oke, A. (2007). Antecedents of supply chain visibility in retail supply chains: A resource-based theory perspective. *Journal of Operations Management*, *25*(6), 1217–1233. https://doi.org/10.1016/j.jom.2007.01.003

Belhadi, A., Kamble, S., Jabbour, C. J. C., Gunasekaran, A., Ndubisi, N. O., & Venkatesh, M. (2021). Manufacturing and service supply chain resilience to the COVID-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change*, *163*, 120447. https://doi.org/10.1016/j.techfore.2020.120447

Bernardes, E. S., & Hanna, M. D. (2009). A theoretical review of flexibility, agility and responsiveness in the operations management literature: Toward a conceptual definition of customer responsiveness. *International Journal of Operations & Production Management*, *29*(1), 30–53. https://doi.org/10.1108/01443570910925352

Blackhurst, J., Dunn, K. S., & Craighead, C. W. (2011). An Empirically Derived Framework of Global Supply Resiliency. *Journal of Business Logistics*, *32*(4), 374–391. https://doi.org/10.1111/j.0000-0000.2011.01032.x

Bode, C., & Macdonald, J. R. (2017). Stages of Supply Chain Disruption Response: Direct, Constraining, and Mediating Factors for Impact Mitigation. *Decision Sciences*, *48*(5), 836–874. https://doi.org/10.1111/deci.12245

Bode, C., & Wagner, S. M. (2015). Structural drivers of upstream supply chain complexity and the frequency of supply chain disruptions. *Journal of Operations Management*, *36*, 215–228. https://doi.org/10.1016/j.jom.2014.12.004

Bode, C., Wagner, S. M., Petersen, K. J., & Ellram, L. M. (2011). Understanding responses to supply chain disruptions: Insights from information processing and resource dependence perspectives. *Academy of Management Journal*, *54*(4), 833–856. https://doi.org/10.5465/amj.2011.64870145

Bogner, A., Littig, B., & Menz, W. (2009). *Interviewing experts*. Springer.

Brandon-Jones, A., & Knoppen, D. (2018). The role of strategic purchasing in dynamic capability development and deployment: A contingency perspective. *International Journal of Operations & Production Management*, *38*(2), 446–473. https://doi.org/10.1108/ijopm-10-2015-0656

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. *Journal of Supply Chain Management*, *50*(3), 55–73. https://doi.org/10.1111/jscm.12050

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Browning, T., Kumar, M., Sanders, N., Sodhi, M. S., Thürer, M., & Tortorella, G. L. (2023). From supply chain risk to system-wide disruptions: research opportunities in forecasting, risk management and product design. *International Journal of Operations & Production Management*, *43*(12), 1841–1858. https://doi.org/10.1108/IJOPM-09-2022-0573

Brzezinski, M. (2015). Power laws in citation distributions: evidence from Scopus. *Scientometrics*, *103*(1), 213–228. https://doi.org/10.1007/s11192-014-1524-z

Chavez, R., Malik, M., Ghaderi, H., & Yu, W. (2021). Environmental orientation, external environmental information exchange and environmental performance: Examining mediation and moderation effects. *International Journal of Production Economics*, *240*, 108222. https://doi.org/10.1016/j.ijpe.2021.108222

Chavez, R., Malik, M., Ghaderi, H., & Yu, W. (2023). Environmental collaboration with suppliers and cost performance: exploring the contingency role of digital orientation from a circular economy perspective. *International Journal of Operations and Production Management*, *43*(4), 651–675. https://doi.org/10.1108/IJOPM-01-2022-0072

Chen, H., Chiang, R. H., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS quarterly*, 1165–1188. https://doi.org/10.2307/41703503

Christopher, M., & Lee, H. (2004). Mitigating supply chain risk through improved confidence. *International Journal of Physical Distribution & Logistics Management*, *34*(5), 388–396. https://doi.org/10.1108/09600030410545436

Christopher, M., & Peck, H. (2004). Building the resilient supply chain. *The International Journal of Logistics Management*, *15*(2), 1–13. https://doi.org/10.1108/09574090410700275

Craighead, C. W., Blackhurst, J., Rungtusanatham, M. J., & Handfield, R. B. (2007). The Severity of Supply Chain Disruptions: Design Characteristics and Mitigation Capabilities. *Decision Sciences*, *38*(1), 131–156. https://doi.org/10.1111/j.1540-5915.2007.00151.x

Craighead, C. W., Ketchen Jr., D. J., & Darby, J. L. (2020). Pandemics and Supply Chain Management Research: Toward a Theoretical Toolbox. *Decision Sciences*, *51*(4), 838–866. https://doi.org/10.1111/deci.12468

Creswell, J. W. (2014). *Research design : qualitative, quantitative, and mixed methods approaches* (Fourth edition, international student edition. ed.). SAGE.

Creswell, J. W., & Creswell, J. D. (2018). *Research design : qualitative, quantitative, and mixed methods approaches* (Fifth edition ed.). SAGE.

Creswell, J. W., & Tashakkori, A. (2007). Differing perspectives on mixed methods research. *1*(4), 303–308. https://doi.org/10.1177/1558689807306132

Danese, P., Molinaro, M., & Romano, P. (2020). Investigating fit in supply chain integration: A systematic literature review on context, practices, performance links. *Journal of Purchasing and Supply Management*, *26*(5), 100634. https://doi.org/10.1016/j.pursup.2020.100634

Davenport, T. H. (2006). Competing on analytics. *Harvard Business Review*, *84*(1), 98.

Davenport, T. H. (2018). From analytics to artificial intelligence. *Journal of Business Analytics*, *1*(2), 73–80. https://doi.org/10.1080/2573234X.2018.1543535

Davenport, T. H., & Harris, J. G. (2007). *Competing on Analytics: The New Science of Winning*. Harvard Business School.

Deloitte. (2020). *COVID-19: managing supply chain risk and disruption*. https://www2.deloitte.com/global/en/pages/risk/cyber-strategic-risk/articles/covid-19-managing-supply-chain-risk-and-disruption.html

Dennehy, D., Oredo, J., Spanaki, K., Despoudi, S., & Fitzgibbon, M. (2021). Supply chain resilience in mindful humanitarian aid organizations: The role of big data analytics. *International Journal of Operations & Production Management*, *41*(9), 1417–1441. https://doi.org/10.1108/IJOPM-12-2020-0871

Denscombe, M. (2014). *The good research guide: for small-scale social research projects* (Fifth edition ed.). McGraw Hill.

Denyer, D., & Tranfield, D. (2009). Producing a systematic review. In *The Sage handbook of organizational research methods* (pp. 671–689).

Dolgui, A., Ivanov, D., & Sokolov, B. (2018). Ripple effect in the supply chain: an analysis and recent literature. *International Journal of Production Research*, *56*(1-2), 414–430. https://doi.org/10.1080/00207543.2017.1387680

Donaldson, L. (2001). *The contingency theory of organizations*. Sage.

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, *48*, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dubey, R., Gunasekaran, A., Childe, S. J., Fosso Wamba, S., Roubaud, D., & Foropon, C. (2021). Empirical investigation of data analytics capability and organizational flexibility as complements to supply chain resilience. *International Journal of Production Research*, *59*(1), 110–128. https://doi.org/10.1080/00207543.2019.1582820

Durach, C. F., Kembro, J., & Wieland, A. (2017). A New Paradigm for Systematic Literature Reviews in Supply Chain Management. *Journal of Supply Chain Management*, *53*(4), 67–85. https://doi.org/10.1111/jscm.12145

Durach, C. F., Wiengarten, F., & Choi, T. Y. (2020). Supplier–supplier coopetition and supply chain disruption: first-tier supplier resilience in the tetradic context. *International Journal of Operations & Production Management*, *40*(7/8), 1041–1065. https://doi.org/10.1108/IJOPM-03-2019-0224

Egwuonwu, A., Mendy, J., Smart-Oruh, E., & Egwuonwu, A. (2024). Drivers of Big Data Analytics' Adoption and Implications of Management Decision-Making on Big Data Adoption and Firms' Financial and Nonfinancial Performance: Evidence From Nigeria's Manufacturing and Service Industries. *IEEE Transactions on Engineering Management*, *71*, 11907–11922. https://doi.org/10.1109/TEM.2023.3321426

Eisenhardt, K. M., & Martin, J. A. (2000). Dynamic capabilities: what are they? *Strategic management journal*, *21*(10-11), 1105–1121. https://doi.org/10.1002/1097-0266(200010/11)21:10/11<1105::AID-SMJ133>3.0.CO;2-E

El Baz, J., & Ruel, S. (2021). Can supply chain risk management practices mitigate the disruption impacts on supply chains' resilience and robustness? Evidence from an empirical survey in a COVID-19 outbreak era. *International Journal of Production Economics*, *233*, 107972. https://doi.org/10.1016/j.ijpe.2020.107972

Ensign, P. C. (2001). The concept of fit in organizational research. *International Journal of Organization Theory & Behavior*, *4*(3-4), 287–306. https://doi.org/10.1108/ijotb-04-03-04-2001-b005

European Commission. (2021). *SME definition*. Retrieved 09-19 from https://ec.europa.eu/growth/smes/sme-definition_en

European Council. (2025). *EU sanctions against Russia*. https://www.consilium.europa.eu/en/policies/sanctions-against-russia/

EUROSTAT. (2018). *Glossary:High-tech classification of manufacturing industries*. https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:High-tech_classification_of_manufacturing_industries

Fainshmidt, S., Wenger, L., Pezeshkan, A., & Mallon, M. R. (2019). When do Dynamic Capabilities Lead to Competitive Advantage? The Importance of Strategic Fit. *Journal of Management Studies*, *56*(4), 758–787. https://doi.org/10.1111/joms.12415

Faruquee, M., Paulraj, A., & Irawan, C. A. (2021). Strategic supplier relationships and supply chain resilience: Is digital transformation that precludes trust beneficial? *International Journal of Operations & Production Management*, *41*(7), 1192–1219. https://doi.org/10.1108/IJOPM-10-2020-0702

Financial Times. (2026). Iran war is causing largest disruption in history to oil supplies, says IEA. Retrieved April 17, 2026, from https://www.ft.com/content/32726bce-ec4e-4251-8f33-10c15806fbc6

Finkenstadt, D. J., & Handfield, R. (2021). Blurry vision: Supply chain visibility for personal protective equipment during COVID-19. *Journal of Purchasing and Supply Management*, *27*(3), 100689. https://doi.org/10.1016/j.pursup.2021.100689

Fiss, P. C. (2007). A set-theoretic approach to organizational configurations. *Academy of Management Review*, *32*(4), 1180–1198. https://doi.org/10.5465/amr.2007.26586092

Fiss, P. C. (2011). Building better causal theories: A fuzzy set approach to typologies in organization research. *Academy of Management Journal*, *54*(2), 393–420. https://doi.org/10.5465/amj.2011.60263120

Flynn, B. B., Huo, B., & Zhao, X. (2010). The impact of supply chain integration on performance: A contingency and configuration approach. *Journal of Operations Management*, *28*(1), 58–71. https://doi.org/10.1016/j.jom.2009.06.001

Flynn, B. B., Sakakibara, S., Schroeder, R. G., Bates, K. A., & Flynn, E. J. (1990). Empirical research methods in operations management. *Journal of Operations Management*, *9*(2), 250–284. https://doi.org/10.1016/0272-6963(90)90098-X

Fornell, C., & Larcker, D. F. (1981). Evaluating Structural Equation Models with Unobservable Variables and Measurement Error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.1177/002224378101800104

Forza, C. (2016). Surveys. In C. Karlsson (Ed.), *Research Methods for Operations Management* (pp. 79–164). Routledge. https://doi.org/10.4324/9781315671420-4

Forza, C., & Sandrin, E. (2024). Surveys. In C. Karlsson (Ed.), *Research Methods for Operations and Supply Chain Management* (Third edition. ed.). Routledge.

Fosso Wamba, S., & Akter, S. (2019). Understanding supply chain analytics capabilities and agility for data-rich environments. *International Journal of Operations & Production Management*, *39*(6/7/8), 887–912. https://doi.org/10.1108/IJOPM-01-2019-0025

Francis, V. (2008). Supply chain visibility: lost in translation? *Supply Chain Management: An International Journal*, *13*(3), 180–184. https://doi.org/10.1108/13598540810871226

Friday, D., Melnyk, S. A., Altman, M., Harrison, N., & Ryan, S. (2024). An inductive analysis of collaborative cybersecurity management capabilities, relational antecedents and supply chain cybersecurity parameters. *International Journal of Physical Distribution & Logistics Management*, *54*(5), 476–500. https://doi.org/10.1108/ijpdlm-01-2023-0034

Ghauri, P. N., Grønhaug, K., & Strange, R. (2020). *Research methods in business studies* (Fifth Edition. ed.). Cambridge University Press.

Gligor, D., Feizabadi, J., Russo, I., Maloni, M. J., & Goldsby, T. J. (2020). The triple-a supply chain and strategic resources: developing competitive advantage. *International Journal of Physical Distribution & Logistics Management*, *50*(2), 159–190. https://doi.org/10.1108/IJPDLM-08-2019-0258

Golgeci, I., & Ponomarov, S. Y. (2013). Does firm innovativeness enable effective responses to supply chain disruptions? An empirical study. *Supply Chain Management: An International Journal*, *18*(6), 604–617. https://doi.org/10.1108/SCM-10-2012-0331

Gomes, P. J., & Silva, G. M. (2025). Navigating the Interplay Between Digitalization and Triple-A Capabilities for Enhanced Supply Chain Resilience. *Journal of Business Logistics*, *46*(3), e70018. https://doi.org/10.1111/jbl.70018

Greckhamer, T., Furnari, S., Fiss, P. C., & Aguilera, R. V. (2018). Studying configurations with qualitative comparative analysis: Best practices in strategy and organization research. *Strategic Organization*, *16*(4), 482–495. https://doi.org/10.1177/1476127018786487

Grover, V., Chiang, R. H. L., Liang, T.-P., & Zhang, D. (2018). Creating Strategic Business Value from Big Data Analytics: A Research Framework. *Journal of Management Information Systems*, *35*(2), 388–423. https://doi.org/10.1080/07421222.2018.1451951

Guest, G., Bunce, A., & Johnson, L. (2006). How many interviews are enough? An experiment with data saturation and variability. *Field Methods*, *18*(1), 59–82. https://doi.org/10.1177/1525822X05279903

Gupta, M., & George, J. F. (2016). Toward the development of a big data analytics capability. *Information & Management*, *53*(8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2018). *Multivariate data analysis* (8th ed.). Cengage.

Hao, X., & Demir, E. (2025). Artificial intelligence in supply chain management: enablers and constraints in pre-development, deployment, and post-development stages. *Production Planning & Control*, *36*(6), 748–770. https://doi.org/10.1080/09537287.2024.2302482

Harzing, A.-W., & Alakangas, S. (2016). Google Scholar, Scopus and the Web of Science: a longitudinal and cross-disciplinary comparison. *Scientometrics*, *106*(2), 787–804. https://doi.org/10.1007/s11192-015-1798-9

Hayes, A. F. (2017). *Introduction to mediation, moderation, and conditional process analysis: A regression-based approach*. Guilford publications.

Helfat, C. E., & Peteraf, M. A. (2003). The dynamic resource-based view: capability lifecycles. *Strategic management journal*, *24*(10), 997–1010. https://doi.org/10.1002/smj.332

Hendricks, K. B., & Singhal, V. R. (2005). An empirical analysis of the effect of supply chain disruptions on long-run stock price performance and equity risk of the firm. *Production and Operations*

management, *14*(1), 35–52. https://doi.org/10.1111/j.1937-5956.2005.tb00008.x
Hendricks, K. B., Singhal, V. R., & Zhang, R. (2009). The effect of operational slack, diversification, and vertical relatedness on the stock market reaction to supply chain disruptions. *Journal of Operations Management*, *27*(3), 233–246. https://doi.org/10.1016/j.jom.2008.09.001
Henke, N., Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., & Sethupathy, G. (2016). The age of analytics: Competing in a data-driven world. *McKinsey Global Institute*, *4*.
Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8
Herburger, M., Wieland, A., & Hochstrasser, C. (2024). Building supply chain resilience to cyber risks: a dynamic capabilities perspective. *Supply Chain Management: An International Journal*, *29*(7), 28–50. https://doi.org/10.1108/scm-01-2023-0016
Hirschman, E. C. (1986). Humanistic inquiry in marketing research: Philosophy, method, and criteria. *Journal of Marketing Research*, *23*(3), 237–249. https://doi.org/10.2307/3151482
Hohenstein, N.-O., Feisel, E., Hartmann, E., & Giunipero, L. (2015). Research on the phenomenon of supply chain resilience. *International Journal of Physical Distribution & Logistics Management*, *45*(1/2), 90–117. https://doi.org/10.1108/IJPDLM-05-2013-0128
Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual review of ecology and systematics*, *4*(1), 1–23.
Holling, C. S. (1996). Engineering Resilience versus Ecological Resilience. In P. Schulze (Ed.), *Engineering Within Ecological Constraints* (pp. 31–43). National Academy Press.
Holweg, M. (2005). The three dimensions of responsiveness. *International Journal of Operations & Production Management*, *25*(7), 603–622. https://doi.org/10.1108/01443570510605063
Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. *Transportation Research Part E: Logistics and Transportation Review*, *125*, 285–307. https://doi.org/10.1016/j.tre.2019.03.001
Hulland, J., Baumgartner, H., & Smith, K. M. (2018). Marketing survey research best practices: evidence and recommendations from a review of JAMS articles. *Journal of the Academy of Marketing Science*, *46*(1), 92–108. https://doi.org/10.1007/s11747-017-0532-y

Iftikhar, A., Purvis, L., Giannoccaro, I., & Wang, Y. (2023). The impact of supply chain complexities on supply chain resilience: the mediating effect of big data analytics. *Production Planning & Control*, *34*(16), 1562–1582. https://doi.org/10.1080/09537287.2022.2032450

Ivanov, D. (2023). Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. *International Journal of Production Economics*, *263*, 108938. https://doi.org/10.1016/j.ijpe.2023.108938

Ivanov, D., & Dolgui, A. (2020). Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. *International Journal of Production Research*, *58*(10), 2904–2915. https://doi.org/10.1080/00207543.2020.1750727

Ivanov, D., & Dolgui, A. (2021). A digital supply chain twin for managing the disruption risks and resilience in the era of Industry 4.0. *Production Planning & Control*, *32*(9), 775–788. https://doi.org/10.1080/09537287.2020.1768450

Ivanov, D., Dolgui, A., & Sokolov, B. (2019). The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), 829–846. https://doi.org/10.1080/00207543.2018.1488086

Ivanov, D., Sokolov, B., & Dolgui, A. (2014). The Ripple effect in supply chains: trade-off 'efficiency-flexibility-resilience' in disruption management. *International Journal of Production Research*, *52*(7), 2154–2172. https://doi.org/10.1080/00207543.2013.858836

Jazairy, A., Brho, M., Manuj, I., & Goldsby, T. J. (2024). Cyber risk management strategies and integration: toward supply chain cyber resilience and robustness. *International Journal of Physical Distribution & Logistics Management*, *54*(11), 1–29. https://doi.org/10.1108/ijpdlm-12-2023-0445

Jiang, W., Feng, T., & Wong, C. Y. (2025). How big data analytics capabilities drive supply chain resilience: the mediating roles of supply chain visibility and flexibility. *International Journal of Physical Distribution & Logistics Management*, *55*(5), 505–539. https://doi.org/10.1108/ijpdlm-07-2024-0252

Jiang, Y., Feng, T., & Huang, Y. (2024). Antecedent configurations toward supply chain resilience: The joint impact of supply chain integration and big data analytics capability. *Journal of Operations Management*, *70*(2), 257–284. https://doi.org/10.1002/joom.1282

Juan, S.-J., & Li, E. Y. (2023). Financial performance of firms with supply chains during the COVID-19 pandemic: the roles of dynamic capability and supply chain resilience. *International Journal of*

Operations & Production Management, *43*(5), 712–737. https://doi.org/10.1108/IJOPM-04-2022-0249
Jüttner, U., & Maklan, S. (2011). Supply chain resilience in the global financial crisis: an empirical study. *Supply Chain Management: An International Journal*, *16*(4), 246–259. https://doi.org/10.1108/13598541111139062
Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management*, *37*(1), 10–36. https://doi.org/10.1108/IJOPM-02-2015-0078
Kalaitzi, D., & Tsolakis, N. (2022). Supply chain analytics adoption: Determinants and impacts on organisational performance and competitive advantage. *International Journal of Production Economics*, *248*, 108466. https://doi.org/10.1016/j.ijpe.2022.108466
Kamalahmadi, M., & Parast, M. M. (2016). A review of the literature on the principles of enterprise and supply chain resilience: Major findings and directions for future research. *International Journal of Production Economics*, *171*, 116–133. https://doi.org/10.1016/j.ijpe.2015.10.023
Karlsson, C. (2024). Research in operations and supply chain management. In C. Karlsson (Ed.), *Research Methods for Operations and Supply Chain Management* (Third edition. ed.). Routledge.
Ketchen, D. J. J., Kaufmann, L., & Carter, C. R. (2021). Configurational approaches to theory development in supply chain management: Leveraging underexplored opportunities. *Journal of Supply Chain Management*, *n/a*(n/a), 1–18. https://doi.org/10.1111/jscm.12275
Kim, D., & Lee, R. P. (2010). Systems Collaboration and Strategic Collaboration: Their Impacts on Supply Chain Responsiveness and Market Performance. *Decision Sciences*, *41*(4), 955–981. https://doi.org/10.1111/j.1540-5915.2010.00289.x
Kleindorfer, P. R., & Saad, G. H. (2005). Managing Disruption Risks in Supply Chains. *Production and Operations management*, *14*(1), 53–68. https://doi.org/10.1111/j.1937-5956.2005.tb00009.x
Kotzab, H., Bäumler, I., & Gerken, P. (2021). The big picture on supply chain integration – insights from a bibliometric analysis. *Supply Chain Management: An International Journal*, *28*(1), 25–54. https://doi.org/10.1108/scm-09-2020-0496
Koufteros, X., Vonderembse, M., & Jayaram, J. (2005). Internal and External Integration for Product Development: The Contingency Effects of Uncertainty, Equivocality, and Platform Strategy.

Decision Sciences, *36*(1), 97–133. https://doi.org/10.1111/j.1540-5915.2005.00067.x
Lai, Y., Sun, H., & Ren, J. (2018). Understanding the determinants of big data analytics (BDA) adoption in logistics and supply chain management. *The International Journal of Logistics Management*, *29*(2), 676–703. https://doi.org/10.1108/IJLM-06-2017-0153
LaValle, S., Lesser, E., Shockley, R., Hopkins, M. S., & Kruschwitz, N. (2011). Big data, analytics and the path from insights to value. *MIT sloan management review*, *52*(2), 21–32.
Lepenioti, K., Bousdekis, A., Apostolou, D., & Mentzas, G. (2020). Prescriptive analytics: Literature review and research challenges. *International Journal of Information Management*, *50*, 57–70. https://doi.org/10.1016/j.ijinfomgt.2019.04.003
Leuschner, Rudolf, Rogers, D. S., & Charvet, F. F. (2013). A Meta-Analysis of Supply Chain Integration and Firm Performance. *Journal of Supply Chain Management*, *49*(2), 34–57. https://doi.org/10.1111/jscm.12013
Li, S., Peng, G. C., & Xing, F. (2019). Barriers of embedding big data solutions in smart factories: insights from SAP consultants. *Industrial Management & Data Systems*, *119*(5), 1147–1164. https://doi.org/10.1108/IMDS-11-2018-0532
Lincoln, Y. S., & Guba, E. G. (1985). *Naturalistic inquiry*. Sage.
Linton, T., & Vakil, B. (2020). Coronavirus is proving we need more resilient supply chains. *Harvard Business Review*.
Lismont, J., Vanthienen, J., Baesens, B., & Lemahieu, W. (2017). Defining analytics maturity indicators: A survey approach. *International Journal of Information Management*, *37*(3), 114–124. https://doi.org/10.1016/j.ijinfomgt.2016.12.003
MacKenzie, S. B., & Podsakoff, P. M. (2012). Common Method Bias in Marketing: Causes, Mechanisms, and Procedural Remedies. *Journal of Retailing*, *88*(4), 542–555. https://doi.org/10.1016/j.jretai.2012.08.001
Maheshwari, S., Gautam, P., & Jaggi, C. K. (2021). Role of Big Data Analytics in supply chain management: current trends and future perspectives. *International Journal of Production Research*, *59*(6), 1875–1900. https://doi.org/10.1080/00207543.2020.1793011
Manuj, I., & Mentzer, J. T. (2008). GLOBAL SUPPLY CHAIN RISK MANAGEMENT. *Journal of Business Logistics*, *29*(1), 133–155. https://doi.org/10.1002/j.2158-1592.2008.tb00072.x
Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2022). Determinants of big data analytics adoption in small and medium-sized enterprises

(SMEs). *Industrial Management & Data Systems*, *123*(1), 278–301. https://doi.org/10.1108/imds-11-2021-0695

McAfee, A., Brynjolfsson, E., Davenport, T. H., Patil, D., & Barton, D. (2012). Big data: the management revolution. *Harvard Business Review*, *90*(10), 60–68.

Melnyk, S. A., Thürer, M., Blome, C., Schoenherr, T., & Gold, S. (2024). (Re)-discovering simulation as a critical element of OM/SCM research: call for research. *International Journal of Operations & Production Management*, *44*(7), 1376–1389. https://doi.org/10.1108/IJOPM-08-2023-0665

Meyer, A. D., Tsui, A. S., & Hinings, C. R. (1993). Configurational Approaches to Organizational Analysis. *Academy of Management Journal*, *36*(6), 1175–1195. https://doi.org/10.5465/256809

Meyer, D., & Henke, M. (2023). Developing design principles for the implementation of AI in PSM: An investigation with expert interviews. *Journal of Purchasing and Supply Management*, *29*(3), 100846. https://doi.org/10.1016/j.pursup.2023.100846

Miles, M. B., & Huberman, A. M. (1994). *Qualitative Data Analysis: An Expanded Sourcebook* (2nd ed.). Sage.

Miller, D. (1986). Configurations of strategy and structure: Towards a synthesis. *Strategic management journal*, *7*(3), 233–249. https://doi.org/10.1002/smj.4250070305

Miller, Jason W., Jin, Y. H., & Ortega, David L. (2025). Shock and Awe: A Theoretical Framework and Data Sources for Studying the Impact of 2025 Tariffs on Global Supply Chains. *Journal of Supply Chain Management*, *61*(3), 3–15. https://doi.org/10.1111/jscm.12350

Misangyi, V. F., Greckhamer, T., Furnari, S., Fiss, P. C., Crilly, D., & Aguilera, R. (2017). Embracing Causal Complexity: The Emergence of a Neo-Configurational Perspective. *Journal of Management*, *43*(1), 255–282. https://doi.org/10.1177/0149206316679252

Moher, D., Shamseer, L., Clarke, M., Ghersi, D., Liberati, A., Petticrew, M., Shekelle, P., Stewart, L. A., & Group, P.-P. (2015). Preferred reporting items for systematic review and meta-analysis protocols (PRISMA-P) 2015 statement. *Systematic Reviews*, *4*(1), 1. https://doi.org/10.1186/2046-4053-4-1

Montabon, F., Daugherty, P. J., & Chen, H. (2018). Setting Standards for Single Respondent Survey Design. *Journal of Supply Chain Management*, *54*(1), 35–41. https://doi.org/10.1111/jscm.12158

Moradlou, H., Skipworth, H., Bals, L., Aktas, E., & Roscoe, S. (2024). Geopolitical disruptions and supply chain structural ambidexterity. *International Journal of Operations & Production Management*, *45*(4), 836–862. https://doi.org/10.1108/ijopm-11-2023-0915

Munir, M., Jajja, M. S. S., & Chatha, K. A. (2022). Capabilities for enhancing supply chain resilience and responsiveness in the COVID-19 pandemic: exploring the role of improvisation, anticipation, and data analytics capabilities. *International Journal of Operations & Production Management*, *42*(10), 1576–1604. https://doi.org/10.1108/IJOPM-11-2021-0677

Munir, M. A., Hussain, A., Farooq, M., Rehman, A. U., & Masood, T. (2024). Building resilient supply chains: Empirical evidence on the contributions of ambidexterity, risk management, and analytics capability. *Technological Forecasting and Social Change*, *200*, 123146. https://doi.org/10.1016/j.techfore.2023.123146

NewVantage Partners. (2023). *2023 Data and Analytics Leadership Executive Survey*. https://www.newvantage.com/thoughtleadership

Nikookar, E., Ali, I., Stevenson, M., & Shokouhyar, S. (2025). Necessary Antecedents of Supply Chain Resilience: The Nonnegotiable Influence of Supply Chain Responsiveness and Collaboration. *Journal of Supply Chain Management*, *61*(4), 54–76. https://doi.org/10.1111/jscm.70000

Nikookar, E., Gligor, D., & Russo, I. (2024). Supply chain resilience: When the recipe is more important than the ingredients for managing supply chain disruptions. *International Journal of Production Economics*, *272*, 109236. https://doi.org/10.1016/j.ijpe.2024.109236

Nikookar, E., Varsei, M., & Wieland, A. (2021). Gaining from disorder: Making the case for antifragility in purchasing and supply chain management. *Journal of Purchasing and Supply Management*, 100699. https://doi.org/10.1016/j.pursup.2021.100699

Nikookar, E., & Yanadori, Y. (2022). Preparing supply chain for the next disruption beyond COVID-19: managerial antecedents of supply chain resilience. *International Journal of Operations & Production Management*, *42*(1), 59–90. https://doi.org/10.1108/IJOPM-04-2021-0272

Norrman, A., & Wieland, A. (2020). The development of supply chain risk management over time: Revisiting Ericsson. *International Journal of Physical Distribution & Logistics Management*, *50*(6), 641–666. https://doi.org/10.1108/IJPDLM-07-2019-0219

Olavarrieta, S., & Ellinger, A. E. (1997). Resource-based theory and strategic logistics research. *International Journal of Physical Distribution & Logistics Management*, *27*(9/10), 559–587. https://doi.org/10.1108/09600039710188594

Oliveira, T., Thomas, M., & Espadanal, M. (2014). Assessing the determinants of cloud computing adoption: An analysis of the

manufacturing and services sectors. *Information & Management*, *51*(5), 497–510. https://doi.org/10.1016/j.im.2014.03.006
Pappas, I. O., & Woodside, A. G. (2021). Fuzzy-set Qualitative Comparative Analysis (fsQCA): Guidelines for research practice in Information Systems and marketing. *International Journal of Information Management*, *58*, 102310. https://doi.org/10.1016/j.ijinfomgt.2021.102310
Patrucco, A. S., Picanço Rodrigues, V., Fransoo, J. C., & Mejia-Argueta, C. (2025). Resilient Supply Chains Amid Uncertainty: Do Agility, Adaptability, and Alignment Mitigate the Effects of Major Disruptions? *Journal of Business Logistics*, *46*(4), e70037. https://doi.org/10.1111/jbl.70037
Peng, D. X., Schroeder, R. G., & Shah, R. (2008). Linking routines to operations capabilities: A new perspective. *Journal of Operations Management*, *26*(6), 730–748. https://doi.org/10.1016/j.jom.2007.11.001
Pettit, T. J., Croxton, K. L., & Fiksel, J. (2013). Ensuring Supply Chain Resilience: Development and Implementation of an Assessment Tool. *Journal of Business Logistics*, *34*(1), 46–76. https://doi.org/10.1111/jbl.12009
Pettit, T. J., Fiksel, J., & Croxton, K. L. (2010). ENSURING SUPPLY CHAIN RESILIENCE: DEVELOPMENT OF A CONCEPTUAL FRAMEWORK. *Journal of Business Logistics*, *31*(1), 1–21. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x
Podsakoff, P. M., MacKenzie, S. B., & Podsakoff, N. P. (2012). Sources of Method Bias in Social Science Research and Recommendations on How to Control It. *Annual Review of Psychology*, *63*(Volume 63, 2012), 539–569. https://doi.org/10.1146/annurev-psych-120710-100452
Ponomarov, S. Y., & Holcomb, M. C. (2009). Understanding the concept of supply chain resilience. *The International Journal of Logistics Management*, *20*(1), 124–143. https://doi.org/10.1108/09574090910954873
Qi, Y., Wang, X., Zhang, M., & Wang, Q. (2023). Developing supply chain resilience through integration: An empirical study on an e-commerce platform. *Journal of Operations Management*, *69*(3), 477–496. https://doi.org/10.1002/joom.1226
Ragin, C. C. (2008). *Redesigning social inquiry: Fuzzy sets and beyond*. University of Chicago Press.
Raj, A., Kumar, R. R., Narayanan, S., Kirca, A. H., & Jeyaraj, A. (2025). Analytics Capability, Supply Chain Capabilities, and Operational

Performance: A Meta-Analytic Investigation. *Journal of Operations Management*. https://doi.org/10.1002/joom.1376
Rengarajan, S., Narayanamurthy, G., Moser, R., & Pereira, V. (2022). Data strategies for global value chains: Hybridization of small and big data in the aftermath of COVID-19. *Journal of Business Research*, *144*, 776–787. https://doi.org/10.1016/j.jbusres.2022.02.042
Reuters. (2021a). Chip shortage prompts production halt at Volvo Cars in Gothenburg. Retrieved April 17, 2026, from https://www.reuters.com/business/autos-transportation/chip-shortage-prompts-production-halt-volvo-cars-gothenburg-2021-08-11/
Reuters. (2021b). The Ever Given's stranding in the Suez Canal. Retrieved April 17, 2026, from https://www.reuters.com/world/middle-east/ever-givens-stranding-suez-canal-2021-07-06/
Reuters. (2025a). Apple airlifts 600 tons of iPhones from India 'to beat' Trump tariffs, sources say. Retrieved April 17, 2026, from https://www.reuters.com/technology/apple-airlifts-600-tons-iphones-india-to-beat-trump-tariffs-sources-say-2025-04-10/
Reuters. (2025b). Automakers hunt high and low for chips as supply crisis worsens. Retrieved April 17, 2026, from https://www.reuters.com/business/autos-transportation/nissan-mercedes-sound-alarm-over-chip-supply-crisis-2025-10-29/
Rice, J. B., Jr., & Caniato, F. (2003). Building a secure and resilient supply network. *Supply Chain Management Review*, *7*(5), 22–30.
Richey, R. G., Roath, A. S., Adams, F. G., & Wieland, A. (2022). A Responsiveness View of logistics and supply chain management. *Journal of Business Logistics*, *43*(1), 62–91. https://doi.org/10.1111/jbl.12290
Riege, A. M. (2003). Validity and reliability tests in case study research: a literature review with "hands-on" applications for each research phase. *Qualitative Market Research: An International Journal*, *6*(2), 75–86. https://doi.org/10.1108/13522750310470055
Roh, J., Swink, M., & Kovach, J. (2022). Linking organization design to supply chain responsiveness: the role of dynamic managerial capabilities. *International Journal of Operations & Production Management*, *42*(6), 826–851. https://doi.org/10.1108/ijopm-08-2021-0526
Ruel, E. E., Wagner, W. E., & Gillespie, B. J. (2016). *The practice of survey research: theory and applications*. SAGE Publications, Inc.
Russo, I., Confente, I., Gligor, D., & Cobelli, N. (2019). A roadmap for applying qualitative comparative analysis in supply chain research. *International Journal of Physical Distribution & Logistics*

Management, *49*(1), 99–120. https://doi.org/10.1108/IJPDLM-02-2018-0056
Saaty, T. L. (1980). *The analytic hierarchy process*. McGraw-Hill International.
Schilke, O. (2014). On the contingent value of dynamic capabilities for competitive advantage: The nonlinear moderating effect of environmental dynamism. *Strategic management journal*, *35*(2), 179–203. https://doi.org/10.1002/smj.2099
Schoenherr, T., & Speier-Pero, C. (2015). Data Science, Predictive Analytics, and Big Data in Supply Chain Management: Current State and Future Potential. *Journal of Business Logistics*, *36*(1), 120–132. https://doi.org/10.1111/jbl.12082
Schoenherr, T., & Swink, M. (2012). Revisiting the arcs of integration: Cross-validations and extensions. *Journal of Operations Management*, *30*(1), 99–115. https://doi.org/10.1016/j.jom.2011.09.001
Scholten, K., & Schilder, S. (2015). The role of collaboration in supply chain resilience. *Supply Chain Management: An International Journal*, *20*(4), 471–484. https://doi.org/10.1108/SCM-11-2014-0386
Scholten, K., Stevenson, M., & van Donk, D. P. (2020). Dealing with the unpredictable: supply chain resilience. *International Journal of Operations & Production Management*, *40*(1), 1–10. https://doi.org/10.1108/IJOPM-01-2020-789
Sharma, A., Adhikary, A., & Borah, S. B. (2020). Covid-19′s impact on supply chain decisions: Strategic insights from NASDAQ 100 firms using Twitter data. *Journal of Business Research*, *117*, 443–449. https://doi.org/10.1016/j.jbusres.2020.05.035
Shen, Z. M., & Sun, Y. (2021). Strengthening supply chain resilience during COVID-19: A case study of JD.com. *Journal of Operations Management*. https://doi.org/10.1002/joom.1161
Simchi-Levi, D., & Haren, P. (2022). How the war in Ukraine is further disrupting global supply chains. *Harvard Business Review*.
Sodhi, M. S., & Tang, C. S. (2021). Supply Chain Management for Extreme Conditions: Research Opportunities. *Journal of Supply Chain Management*, *57*(1), 7–16. https://doi.org/10.1111/jscm.12255
Sousa, R., & Voss, C. A. (2008). Contingency research in operations management practices. *Journal of Operations Management*, *26*(6), 697–713. https://doi.org/10.1016/j.jom.2008.06.001
Souza, G. C. (2014). Supply chain analytics. *Business Horizons*, *57*(5), 595–605. https://doi.org/10.1016/j.bushor.2014.06.004
Srinivasan, R., & Swink, M. (2018). An investigation of visibility and flexibility as complements to supply chain analytics: An

organizational information processing theory perspective. *Production and Operations management*, *27*(10), 1849–1867. https://doi.org/10.1111/poms.12746
Statistics Sweden. (2007). *SNI 2007: Swedish Standard Industrial Classification 2007*. https://www.scb.se/contentassets/d43b798da37140999abf883e206d0545/mis-2007-2.pdf
Subramanian, N., & Ramanathan, R. (2012). A review of applications of Analytic Hierarchy Process in operations management. *International Journal of Production Economics*, *138*(2), 215–241. https://doi.org/10.1016/j.ijpe.2012.03.036
SVT. (2026). Irankriget stoppar leveranser – LKAB stänger pelletsverk. Retrieved April 17, 2026, from https://www.svt.se/nyheter/lokalt/norrbotten/irankriget-stoppar-leveranser-lkab-stanger-pelletsverk
Swink, M., Sant'Ana Gallo, I., Defee, C., & da Silva, A. L. (2024). Supply chain visibility types and contextual characteristics: A literature-based synthesis. *Journal of Business Logistics*, *45*(1), e12366. https://doi.org/10.1111/jbl.12366
Tang, C. S. (2006). Perspectives in supply chain risk management. *International Journal of Production Economics*, *103*(2), 451–488. https://doi.org/10.1016/j.ijpe.2005.12.006
Teece, D. J. (2007). Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic management journal*, *28*(13), 1319–1350. https://doi.org/10.1002/smj.640
Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic management journal*, *18*(7), 509–533.
Toorajipour, R., Sohrabpour, V., Nazarpour, A., Oghazi, P., & Fischl, M. (2021). Artificial intelligence in supply chain management: A systematic literature review. *Journal of Business Research*, *122*, 502–517. https://doi.org/10.1016/j.jbusres.2020.09.009
Tornatzky, L. G., & Fleischer, M. (1990). *The processes of technological innovation*. Lexington Books.
Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a Methodology for Developing Evidence-Informed Management Knowledge by Means of Systematic Review. *British Journal of Management*, *14*(3), 207–222. https://doi.org/10.1111/1467-8551.00375
Tukamuhabwa, B. R., Stevenson, M., Busby, J., & Zorzini, M. (2015). Supply chain resilience: Definition, review and theoretical foundations for further study. *International Journal of Production*

Research, *53*(18), 5592–5623. https://doi.org/10.1080/00207543.2015.1037934
Vachon, S., Halley, A., & Beaulieu, M. (2009). Aligning competitive priorities in the supply chain: the role of interactions with suppliers. *International Journal of Operations & Production Management*, *29*(4), 322–340. https://doi.org/10.1108/01443570910945800
van Hoek, R. (2020). Research opportunities for a more resilient post-COVID-19 supply chain – closing the gap between research findings and industry practice. *International Journal of Operations & Production Management*, *40*(4), 341–355. https://doi.org/10.1108/IJOPM-03-2020-0165
Vanpoucke, E., Vereecke, A., & Muylle, S. (2017). Leveraging the impact of supply chain integration through information technology. *International Journal of Operations & Production Management*, *37*(4), 510–530. https://doi.org/10.1108/IJOPM-07-2015-0441
Venkatraman, N. (1989a). The Concept of Fit in Strategy Research: Toward Verbal and Statistical Correspondence. *Academy of Management Review*, *14*(3), 423–444. https://doi.org/10.5465/amr.1989.4279078
Venkatraman, N. (1989b). Strategic Orientation of Business Enterprises: The Construct, Dimensionality, and Measurement. *Management Science*, *35*(8), 942–962. https://doi.org/10.1287/mnsc.35.8.942
Vetenskapsrådet. (2024). *God forskningssed*
Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023
Waller, M. A., & Fawcett, S. E. (2013). Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *Journal of Business Logistics*, *34*(2), 77–84. https://doi.org/10.1111/jbl.12010
Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-f., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research*, *70*, 356–365. https://doi.org/10.1016/j.jbusres.2016.08.009
Ward, P. T., Bickford, D. J., & Leong, G. K. (1996). Configurations of Manufacturing Strategy, Business Strategy, Environment and Structure. *Journal of Management*, *22*(4), 597–626. https://doi.org/10.1177/014920639602200404
WHO. (2020). *Shortage of personal protective equipment endangering health workers worldwide*. https://www.who.int/news/item/03-03-2020-shortage-of-personal-protective-equipment-endangering-health-workers-worldwide

Wiedmer, R., Rogers, Z. S., Polyviou, M., Mena, C., & Chae, S. (2021). The Dark and Bright Sides of Complexity: A Dual Perspective on Supply Network Resilience. *Journal of Business Logistics*, *42*(3), 336–359. https://doi.org/10.1111/jbl.12264

Wieland, A., & Durach, C. F. (2021). Two perspectives on supply chain resilience. *Journal of Business Logistics*, *42*(3), 315–322. https://doi.org/10.1111/jbl.12271

Wieland, A., Stevenson, M., Melnyk, S. A., Davoudi, S., & Schultz, L. (2023). Thinking differently about supply chain resilience: what we can learn from social-ecological systems thinking. *International Journal of Operations & Production Management*, *43*(1), 1–21. https://doi.org/10.1108/IJOPM-10-2022-0645

Wieland, A., & Wallenburg, C. M. (2013). The influence of relational competencies on supply chain resilience: a relational view. *International Journal of Physical Distribution & Logistics Management*. https://doi.org/10.1108/IJPDLM-08-2012-0243

Wiengarten, F., Li, H., Singh, P. J., & Fynes, B. (2019). Re-evaluating supply chain integration and firm performance: linking operations strategy to supply chain strategy. *Supply Chain Management: An International Journal*, *24*(4), 540–559. https://doi.org/10.1108/SCM-05-2018-0189

Wilden, R., Gudergan, S. P., Nielsen, B. B., & Lings, I. (2013). Dynamic Capabilities and Performance: Strategy, Structure and Environment. *Long Range Planning*, *46*(1), 72–96. https://doi.org/10.1016/j.lrp.2012.12.001

Williams, B. D., Roh, J., Tokar, T., & Swink, M. (2013). Leveraging supply chain visibility for responsiveness: The moderating role of internal integration. *Journal of Operations Management*, *31*(7-8), 543–554. https://doi.org/10.1016/j.jom.2013.09.003

Winter, S. G. (2003). Understanding dynamic capabilities. *Strategic management journal*, *24*(10), 991–995. https://doi.org/10.1002/smj.318

Wisner, J. D. (2003). A STRUCTURAL EQUATION MODEL OF SUPPLY CHAIN MANAGEMENT STRATEGIES AND FIRM PERFORMANCE. *Journal of Business Logistics*, *24*(1), 1–26. https://doi.org/10.1002/j.2158-1592.2003.tb00030.x

Wixom, B., & Watson, H. (2010). The BI-based organization. *International Journal of Business Intelligence Research (IJBIR)*, *1*(1), 13–28. https://doi.org/10.4018/jbir.2010071702

Wong, C. Y., Boon-itt, S., & Wong, C. W. Y. (2011). The contingency effects of environmental uncertainty on the relationship between supply chain integration and operational performance. *Journal of*

Operations Management, *29*(6), 604–615. https://doi.org/10.1016/j.jom.2011.01.003
World Economic Forum. (2018). *Readiness for the future of production report*. http://www3.weforum.org/docs/FOP_Readiness_Report_2018.pdf
Yu, W., Chavez, R., Jacobs, M., & Wong, C. Y. (2020). Innovativeness and lean practices for triple bottom line: testing of fit-as-mediation versus fit-as-moderation models. *International Journal of Operations & Production Management*, *40*(10), 1623–1647. https://doi.org/10.1108/IJOPM-07-2019-0550
Yu, W., Chavez, R., Jacobs, M., Wong, C. Y., & Yuan, C. (2019). Environmental scanning, supply chain integration, responsiveness, and operational performance. *International Journal of Operations & Production Management*, *39*(5), 787–814. https://doi.org/10.1108/IJOPM-07-2018-0395
Zeiser, A., Polyviou, M., Oke, A., Knemeyer, A. M., & Croxton, K. (2025). Is Your Supply Chain Breaking Down? Call AAA for Resilience Assistance. *Journal of Business Logistics*, *46*(1), e70002. https://doi.org/10.1111/jbl.70002
Zhao, G., Xie, X., Wang, Y., Liu, S., Jones, P., & Lopez, C. (2024). Barrier analysis to improve big data analytics capability of the maritime industry: A mixed-method approach. *Technological Forecasting and Social Change*, *203*, 123345. https://doi.org/10.1016/j.techfore.2024.123345
Zhao, X., Huo, B., Selen, W., & Yeung, J. H. Y. (2011). The impact of internal integration and relationship commitment on external integration. *Journal of Operations Management*, *29*(1-2), 17–32. https://doi.org/10.1016/j.jom.2010.04.004
Zhu, Q., Krikke, H., & Caniëls, M. C. J. (2017). Integrated supply chain risk management: a systematic review. *The International Journal of Logistics Management*, *28*(4), 1123–1141. https://doi.org/10.1108/ijlm-09-2016-0206
Zhu, Q., Krikke, H., & Caniëls, M. C. J. (2018). Supply chain integration: value creation through managing inter-organizational learning. *International Journal of Operations & Production Management*, *38*(1), 211–229. https://doi.org/10.1108/IJOPM-06-2015-0372
Zinn, W., & Goldsby, T. J. (2019). Supply Chain Plasticity: Redesigning Supply Chains to Meet Major Environmental Change. *Journal of Business Logistics*, *40*(3), 184–186. https://doi.org/10.1111/jbl.12226
Öhman, M., Arvidsson, A., Jonsson, P., & Kaipia, R. (2021). A knowledge-based view of analytics capability in purchasing and supply

management. *International Journal of Physical Distribution & Logistics Management*, *51*(9), 937–957. https://doi.org/10.1108/IJPDLM-12-2020-0415

In Times of Disruption

A Study of Analytics Capability and Supply Chain Resilience

Recent years have seen a surge of supply chain disruptions, including global pandemic and geopolitical conflicts, which have reinforced the importance of supply chain resilience. In parallel, advances in data availability and processing have increased interest in analytics capability to support decision-making. The purpose of this dissertation is to investigate the nexus of analytics capability and supply chain resilience. The dissertation adopts a mixed-methods design and comprises five appended papers and a comprehensive summary (kappa). The quantitative strand is based on a cross-sectional survey of firms in manufacturing, retail, and wholesale industries in Sweden. Data are analyzed using both regression analysis and fuzzy-set Qualitative Comparative Analysis. The qualitative strand comprises expert interviews. A systematic literature review serves as an additional component of the research. Findings show that analytics capability contributes to supply chain resilience, but that it is neither necessary nor sufficient on its own. Instead, analytics contributes to resilience primarily when combined with other enabling capabilities, namely supply chain visibility, responsiveness, or integration, forming multiple alternative configurations whose viability depends on supply chain complexity. The qualitative findings identify several obstacles and enablers, spanning multiple dimensions. The dissertation further advances research at the nexus of analytics capability and supply chain resilience by underscoring a configurational and context-sensitive perspective and by illustrating how obstacles and enablers are characterized by disruption characteristics such as high urgency and uncertainty. It also provides practical insights for managers.

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