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Data analytics for supply chain resilience: a multiple case study analysis

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Abstract: Developing supply chain (SC) resilience through data analytics has emerged as an important area of research recently. However, the current literature offers a limited common understanding of the impact of data analytics enabling SC resilience across several phases of resilience development. Thus, this study aims to explore the role of data analytics in identifying potential supply chain disruptions, mitigating risks, and improving supply chain performance. We use a multiple-case study qualitative research approach to understand how firms successfully implement data analytics in their supply chain operations. The research data were collected through semi-structured interviews conducted with 7 supply chain experts from six different firms in Finland. The analysis includes investigating specific tools and techniques used, the data sources, and the types of data analyzed. In addition, this study explores the challenges firms face during the implementation of data analytics and how data analytics effectively builds supply chain resilience. The findings highlight that data analytics offers valuable insights into the supply chain and supports firms to proactively identify and mitigate risks. Furthermore, this study highlights the importance of data quality, data integration, and the need for new skills and capabilities in implementing data analytics in the supply chain. This study contributes to the emerging literature on data analytics' role in developing supply chain resilience and offers insights into the challenges and opportunities associated with its practical implementation. This study offers several theoretical and practical implications for supply chain research and managers.

1 Introduction

Supply chain (SC) resilience has emerged as an important point of discussion more than ever since COVID-19 hit as the pandemic's unexpected disruptions resulted in exposing the vulnerabilities of SCs and their effects on supply shortages. Thus, SC resilience is considered a firm's key capability which enables and sustains its competitive advantage in a fast-paced and uncertain business environment. However, effective SC resilience requires access to accurate and up-to-date information on SC operations. This, in turn, is driving companies to rely on data and use it as a tool in developing SC resilience. Data is considered a large and complex set of information generated by organizations. Emerging technologies such as artificial intelligence (AI) and the Internet of Things (IoT) have enabled the data revolution – a powerful tool for firms to access the information needed to enhance their SC operations. Therefore, data analytics can support firms in gathering, processing, and analyzing a large volume of data from different sources, enabling insights into their SC operations, which can help firms recognize any potential risks, offer real-time visibility, forecast demand, optimize inventory levels to enhance SC resilience [1,2]. Moreover, data analytics enables firms to enhance communication and collaboration with suppliers and customers [3]. It helps in predictive analytics, enabling firms not only to anticipate any possible disruptions but also to proactively deal with these potential disruptions [4,5].

The importance of using data analytics in developing SC resilience has been growing because of globalization and the increasing complexity of SCs. As SCs span multiple regions, countries, and continents, firms are required to tackle a variety of risks, including natural calamity, instability in geopolitical situations, and cyber-attacks. To overcome these challenges, data analytics support firms in developing SC operational views that are more comprehensive, enabling the identification of risks and developing mitigation strategies. This helps firms foresee and adjust to any disruptions and operate sustainably even when certain challenges are unforeseen [6]. The topic of SC resilience through data analytics has emerged as an important area of exploration in the literature. Several scholars have highlighted the importance of descriptive and predictive analytics within prescriptive models in modern SCM providing important parameters and insights that impact the performance of the models and SC operations [7,8]. However, there remains a limited amount of research investigating the impact of data analytics enabling SC resilience [9] and the progress across various phases of resilience development of SC has been inconsistent [10]. Thus, it is reasonable to argue that prior literature remained fragmented and has failed to explain how data-driven decision-making enhances the entire cycle of SC resilience. In the context of this research, the cycle of SC resilience refers to the stage model: identification and mitigation, response, recovery, and learning and improvement, as defined by [11]. Furthermore, the author highlights that there is a lack of a comprehensive understanding of SC resilience and its implementation strategies.

Therefore, the purpose of this research is to fill these gaps by exploring the impact that data analytics can have on developing SC resilience. This study offers practical knowledge by highlighting some key success factors for organizations that aim to enhance their SC resilience by utilizing data-driven decision-making. This research delves into the discussion of different ways where data can be used to enhance SC resilience – including managing risks, improved visibility, predictive analytics, quick decision-making, and enhanced cooperation between stakeholders. Thus, we ask the following research question, "How can data analytics be implemented for decision-making and optimizing the strategy to build SC resilience?" This research follows a multiple case study qualitative research approach and utilizes semi-structured interviews conducted with seven SC experts from six different firms in Finland. The study provides valuable insights into the emerging literature on data analytics and SC resilience by shedding light on the challenges in ensuring data quality and integration, new skills and capabilities, and opportunities related to the effective implementation of data analytics to enhance SC resilience.

2 Literature review

2.1 SC disruption and resilience

The SC concept has been studied with different angles and contexts for several decades. Since the SC involves networks, facilities, and distribution from upstream suppliers to downstream customers and end consumers, the SC plays an important role in business operations. However, there have been several SC disruptions, as SC needs to deal with several partners, stakeholders, information, and product flow throughout the whole chain. This makes the whole SC a complex process of moving products and information exposing organizations to unforeseen disruptions [12], thus affecting the operational performance of businesses through delays, shortages, and increased costs. Prior literature has defined SC disruption differently. For instance, [13] categorized SC disruptions into two types – internal and external. Internal disruptions are related to the organization's own procedures and controls, while external disruptions arise from the external environment and stakeholders, and issues related to demand and supply. Scholars such as [4] reported SC disruptions that deal with delays in delivery from suppliers, bankruptcy, and the quality of raw materials. The risk of supply disruptions can be attributed to several factors, such as the complexity of products, operational ineffectiveness of suppliers, catastrophic situations, and insufficient coordination among SC partners [14-16]. Furthermore, too much reliance on suppliers also enhances the risk of SC disruptions, particularly when buyers have limited flexibility or alternative sourcing options [17]. [18] argued that a complex SC network with a probability of human errors increases safety concerns, leading to SC disruption. [19] presented the eight stages disruption cycle and connected the degree of organizational performance over time.

Therefore, the SC risk management concept was introduced which depicts a systematic analysis of SC disruptions throughout in identifying and addressing any issues related to SCs [4]. Prior literature has identified two main approaches to handling SC disruptions: 1) the anticipating approach, which assesses vulnerabilities and takes preventative measures, and 2) the resisting approach, which reacts and adjusts post-disruption processes. Mitigation strategies aim to minimize negative implications by identifying risks and selecting appropriate responses [20]. [4] introduced some strategies including cooperation, flexibility, redundancy, and control. The preparation phase involves resource allocation, organization, and short-term proactive measures [4,5]. End-to-end visibility is crucial for identifying anomalies, achieved through information sharing, performance tracking, and employing alert systems. [21] emphasized real-time access to reliable data, disruption analytics, and decision-making support. An effective response to disruption involves rapid resource allocation, active communication, and collaboration [4,5]. The recovery phase aims to restore normal SC operations. [22] defined recovery capability as coordinating resources to return to planned product flow. Strategies should stabilize and modify operations quickly to minimize long-term impacts and maintain continuity [23]. Emergency purchases from unaffected suppliers and partial product type changes can help during prolonged disruptions [24].

Scholars such as [25] described supply chain resilience (SCR) as the ability to handle unexpected disruptions, emphasizing proactive measures over reactive ones. Several scholars have noted that resilience in SCs involves adapting to disruptions and quickly resuming performance [3,4]. [26] formalized resilience as the capacity to anticipate, respond to, and recover from disruptions while maintaining operational continuity and control. Prior literature has defined SC resilience in different ways. For instance, [27] explained that SC resilience encompasses the ability to continue, recover, and restart operations after a disruption. It refers to the capacity of complex industrial systems to endure, grow, and adapt in the face of adversity. SC resilience involves a proactive, organized, and integrated approach to managing SC capabilities for unforeseen events, not just recovery from accidents [28]. SCR ensures the SC can respond to adverse consequences and uphold its goals [26]. Resilience involves a multi-stage process with two key phases: resistance and recovery, each with distinct strategies and procedures. In the resistance stage of the SC, the goal is to proactively prevent disruptions or minimize their impact. This begins with utilizing risk analytics and preventative measures to identify vulnerabilities and potential threats [29]. This phase is crucial for reducing the negative impacts of disruptions and protecting operations, reputation, and client relationships. The recovery phase follows, focusing on restoring normalcy and optimizing operations. Stabilization is the first step, aiming to restore functionality and ensure SC activities regain their footing. Flexibility and adaptability are key during this phase, allowing supply networks to recover from shocks. The return stage prioritizes maximizing operations and recovering lost ground. Efficient data analytics and technology use are essential here [30]. By leveraging data-driven insights and technical capabilities, companies can swiftly restore full operational capacity. This requires assessing performance, identifying problem areas, and applying lessons learned from past disruptions. Prior research highlighted the importance of a proactive approach to risk mitigation through avoidance and containment, rapid detection and damage control, adaptation and flexibility, evidence-based decision-making, and the strategic use of technology. A holistic strategy that covers all these phases ensures the continuous flow of goods and services and maintains market competitiveness in an increasingly complex and unpredictable business environment.

2.2 Data analytics as a driver of SC resilience

Data analytics involves gathering, processing, and analyzing large sets of data to uncover meaningful insights using advanced tools like machine learning, data mining, and predictive modeling. It identifies patterns, trends, and relationships within the data. SC data analytics uses these techniques to enhance SC operations and decision-making. By analyzing data from suppliers, customers, logistics providers, and internal systems, companies gain valuable insights into performance, uncover risks and opportunities, and streamline processes. This improves visibility, agility, and resilience, enabling better responses to disruptions and market changes. Data analytics functions are categorized into four types: descriptive, diagnostic, predictive, and prescriptive. [31] stated that descriptive analytics helps infer lessons from past events, identifying issues and opportunities in processes. It extracts information from large datasets to determine “what is happening?” in project management contexts. Predictive analytics answers “what will happen” by forecasting demand using historical data [31]. It uses mathematical methods and programming techniques to predict future events and explain why they might occur. Prescriptive analytics, based on descriptive, predictive, and optimization models, generates decision recommendations, answering “what is expected to happen?” [32]. It assesses possible decisions using mathematical models and advanced statistical methods [33]. Similarly, diagnostic analytics answers “what caused this to happen?” [32]. It identifies underlying causes of issues or patterns in both historical and current data, offering insights to inform future decisions, such as why SC shipments were delayed, or sales targets were unmet.

The integration of data analytics into SCs is proving to be transformative in today's corporate landscape. Given the complexity and unpredictability of global SCs, risk management has always remained a central concern across the discipline. Building trust within supply networks, as highlighted by [34], involves a company's ability to forecast, manage, and recover from operational disturbances. This concept serves as the foundation for the connection between data analytics and SCR. Improved SC visibility is crucial for resilience. Data analytics enables organizations to monitor, evaluate, and predict disruptions in real time, making anticipation a key stage of resilience. Beyond predictions, data analytics enhances scenario planning, a risk management technique that involves creating and examining possible situations. Organizations can thrive in an unstable world by making data-driven decisions, predicting disruptions, and responding effectively. Data creates value by enabling transparency, fostering experimentation, supporting customization, driving automated decision-making, and promoting innovation in business models, products, and services. The interpretation of business data enhances the value of analytics, and its timely presentation to decision-makers is crucial for effective decision-making [35]. The true potential of big data is realized when it informs decision-making. Predictive analytics is needed for short-term demand forecasting, considering patterns and seasonality [36]. Improved forecasting enhances risk management, benefiting supply risk management through data collection, analysis, and risk identification [37]. Both predictive and prescriptive analytics aid strategic decision-making [38]. Data analytics addresses issues in SC structure, organizational culture, sourcing decisions, and product/service design and development [36]. Using data analytics enhances the discovery of insights, leading to improved risk management and better corporate performance.

2.3 Descriptive analytics as a tool for proactive resistance in SC resilience

The Resistance Phase is crucial for maintaining uninterrupted operations during disruptions. Its main goals are to prevent, mitigate, and manage risks and vulnerabilities. Descriptive analytics enhances SCR by using real-time and historical data to inform decisions, helping companies manage obstacles during this phase. Descriptive analytics is vital for risk assessment, as it identifies potential weaknesses and risks in the SC. This information allows companies to proactively address and mitigate these risks. It also plays a key role in resource allocation, enabling informed decisions based on past performance data [39]. By optimizing resource allocation, businesses can ensure operational continuity during disruptions. By using past and present data, organizations can mitigate risks and strengthen SCR, ensuring the smooth flow of goods and services while enhancing market competitiveness. In an era of ongoing SC disruptions, descriptive analytics is essential for proactive resilience, enabling companies to overcome challenges and meet consumer needs sustainably.

2.4 Descriptive and diagnostic analytics for effective response to SC disruptions

The Containment stage within the Resistance Phase of a robust SC focuses on controlling and mitigating disruptions. It aims to prevent disruptions from escalating and to minimize their impact. Descriptive Analytics forms the basis for containment strategies by analyzing past and present data to highlight SC vulnerabilities and emerging disruptive trends [40]. Identified vulnerabilities are further examined using Diagnostic Analytics to uncover the root causes of disruptions. By analyzing historical and current data, diagnostic analytics can pinpoint the fundamental factors behind disturbances. Understanding this, firms can develop containment strategies, such as collaborating with suppliers to increase production or diversifying supply sources [40]. Together, Descriptive and Diagnostic Analytics offer a comprehensive view of SC vulnerabilities and their underlying causes. This enables proactive, accurate, and effective containment strategies to mitigate disruptions during the Resistance Phase.

2.5 Diagnostic and predictive analytics in response and recovery phases: enabling stabilization

The Stabilization step in the Recovery Phase is crucial for resuming normal operations on track and ensuring overall organizational stability after a disruption. During this period, diagnostic analytics proves its efficiency by examining historical and real-time data to uncover the root causes of disruptions. These insights enable companies to make informed decisions to swiftly resolve and mitigate long-term risks, enhancing SCR and reducing future disruptions. When combined with diagnostic analytics, predictive analytics add value by focusing on future outcomes. It uses historical and real-time data to forecast potential disturbances and their impacts, allowing proactive measures to prevent or mitigate disruptions. The true power lies in the synergy between diagnostic and predictive analytics. Diagnostic analytics identifies and analyzes the root causes of problems, while predictive analytics forecasts potential future issues. This combination significantly supports SC recovery and safeguarding operations against future disruptions [19]. Together, diagnostic and predictive analytics ensure SC stability during the Response and Recovery stages. Predictive analytics provides insights to support proactive decision-making, while diagnostic analytics retrospectively examines disruptions for improvement [41].

2.6 Prescriptive analytics: enhancing SC resilience through data-driven approaches

The Return stage in the Recovery Phase marks the final step in overcoming a disruption and resuming normal operations. Prescriptive analytics, the most advanced form of data-driven SCR, enables strategic planning and enhancement of operations. It goes beyond descriptive and diagnostic analytics by providing actionable insights and recommending optimal strategies to improve resilience. Using historical and real-time data, prescriptive analytics enables informed decision-making, helping businesses to proactively respond to disruptions. Prescriptive analytics is crucial for quick reactions to disturbances, assessing various scenarios, and determining the best recovery strategies. It helps reduce the impact of disruptions by rerouting shipments, adjusting production schedules, and reassessing relationships with suppliers. Additionally, it fosters a culture of continuous improvement, constantly refining plans, and processes, and learning from past disruptions. In a dynamic SC environment, prescriptive analytics offers real-time decision support, enabling flexible, data-driven choices as conditions evolve. During the Recovery Phase, prescriptive analytics optimizes resource allocation, leverages technology, and provides adaptive solutions to effectively restore full operational capabilities [41].

We aim to illustrate the complex relationship between data analytics methodologies and the key stages of an effective SC. Figure 1 serves as a roadmap, guiding us through the strategic use of descriptive, diagnostic, prescriptive, and predictive analytics at each step of building a resilient SC process. The analysis will explore how analytics technologies help firms effectively manage disruptions and enhance their SCs in a complex and rapidly changing business environment.

3 Methodology

This research employs a qualitative multi-case study approach. Qualitative research explores social phenomena by exploring prevailing viewpoints, and their application in everyday activities. Case study, a form of qualitative research, provides realistic, dynamic, and personal insights to a deeper understanding of complex business problems. Case studies not only provide an in-depth understanding but can also generate hypotheses and be conducted either once or multiple times, examining phenomena from the perspective of the participants [42].

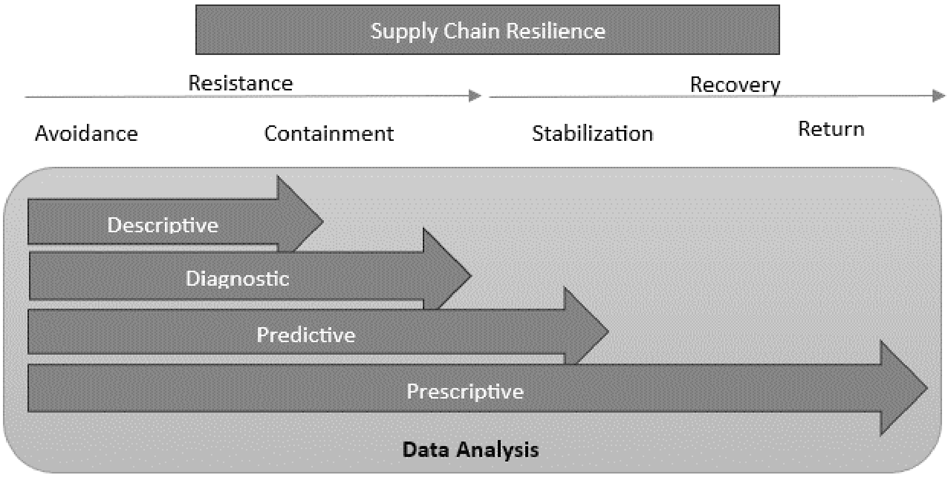

Figure 1 Conceptual framework of data-driven SC management

3.1 Data collection

The study aims to examine how businesses integrate data analytics into various phases of SCR. Purposive sampling principles were used to select the study's sample, allowing for the exploration of research themes while maintaining diversity for comparative analysis. The selection criteria are influenced by the study's goals, existing knowledge, theories, potential hypotheses, or knowledge gaps [43]. Case companies were selected based on their product offerings and business models, specifically involving electronic products and components in their SC operations. Interviewees were chosen based on their experience with data-driven processes and their roles related to SC operations. Six case companies with seven SC experts participated in semi-structured interviews in 2023. These interviews lasted between 35-57 minutes. These case companies belong to various sectors, ranging from medium to large sizes. To maintain confidentiality, each company is assigned an identity reflecting their specialty or industry. Purposive sampling guided the selection of these organizations, representing different degrees of data-driven execution and various industries. To ensure a broad range of viewpoints, we selected firms that vary in both industry type and size, as shown in Table 1.

Table 1 Overview of case interviews

Number	Industry	Interview's position	Experience (years)	Interview duration
1	Telecommunication	Delivery Manager	6	52 minutes
2	Automobile Factory	Logistics Director	12	46 minutes
3	Electronics Manufacturing	Manager in Operational and Supply Chain	8	53 minutes
4	Health Care Devices and Applications	Procurement Manager	8	57 minutes
5		Planning Manager	6	51 minutes
6	Retail in Spare Parts and Accessories to Home and Leisure Products	Commodity Manager	11	49 minutes
7	Digital Appliance Device Manufacturer	Head of Procurement	20	35 minutes

3.2 Data analysis

This study utilizes thematic analysis in conjunction with [44]'s five-step qualitative data analysis framework to rigorously analyse empirical data. This approach facilitates the identification of key themes within large qualitative datasets, enabling effective communication of important findings. The analysis process begins by organizing data into a structured database. Notes and recorded material are carefully arranged for easy access and organization. Interview audio is transcribed and systematically categorized in Excel, using a matrix format, where each column represents a firm case, and each row corresponds to emerging themes or codes. The second stage involves breaking down the material into smaller, manageable chunks and exploring new labels or "codes" to these segments for deeper analysis. Thematic analysis relies on coding as a means to systematically index the data and identify important topics. [45] suggest template analysis as a coding strategy, which involves creating a flexible coding template from a subset of data, which can be refined iteratively to reflect the complexity of the entire dataset. The study applies deductive coding and investigates themes derived from the conceptual framework that guided the formulation of interview questions. [42] suggest that codes emerging from empirical data enhance the objectivity of qualitative analysis. [45] recommend using priori themes sparingly with ongoing re-evaluation and removal as needed.

Next, the data is rearranged and recombined to reveal underlying patterns and connections after the initial identification of recurring themes and codes. By employing this technique, disruption management strategies across firms can be effectively compared. Excel provides an effective platform for organizing interview quotes according to thematic categories. [44] recommends using two-dimensional matrices, a method well-suited to this analytical approach. The final steps involve interpreting the data and drawing conclusions based on the identified patterns. The data is evaluated to identify the most significant analytical insights, and results may be rechecked for completeness and accuracy. The findings are compared against existing theories to assess their practical applicability. These findings are organized into key topics in the subsequent sections of the paper. The synthesis of conceptual insights, empirical evidence, and answers to research questions leads to conclusions that summarize the study and offer meaningful insights.

4 Results and discussion

4.1 Data analytics enabling SC resilience

4.1.1 Avoidance

SC analytics are systematically applied during the Avoidance stage to build a resilient SC. The process typically begins with descriptive analytics, which involves examining historical data to understand past patterns and disruptions. This early detection plays a crucial role in timely and proactive preparation against potential shortages or disasters. For example, in the Automobile case, the respondent mentioned that they use data analysis to investigate recurring issues, often caused by transportation routes or customs procedures. Similarly, the Healthcare case highlighted how past inventory and shortage records help in understanding why certain products are consistently unavailable, enabling them to confidently address and resolve the issue.

Identifying and mitigating shortages involves coordination among various SC stakeholders, including suppliers and subcontractors. Most firms receive regular updates on component availability and purchase order status from their manufacturing partners and suppliers, often weekly. Staying updated and devising alternative strategies is essential. A comparison analysis is conducted to align findings with actual needs and priorities. This approach is reflected in the Electronics Manufacturing case, where the respondent stated “We have weekly reviews with our supplier to ensure our needs, and their supply are aligned. Instant updates allow us to respond quickly and minimize potential disruptions.” Together, these cases highlight how proactive data use and close supplier collaboration enhance SC resilience during the Avoidance stage. To further support this point, Table 2 provides an overview of the typical benefits firms gain from using data analytics to mitigate disruptions, with sample quotations from various firms.

Table 2 Advantages and illustrative quotes

Advantage	Illustrative quotes
Alignment	*“Keeping our information up to date is important for both us and the supplier. It allows us to ensure that we are aligned with each other's needs and abilities.”* (Case - Retails) *“Making sure that everyone understands the same information is important because it reduces the chances of miscommunication or misunderstandings.”* (Case - Digital Appliance)
Responsiveness	*“Having instant updates allows us to promptly respond to any changes or unexpected events that may occur in the supply chain.”* (Case - Automobile) “*Being flexible is really important when it comes to dealing with disruptions quickly*.” (Case - Electronics Manufacturing)
Disruption Mitigation	“*Visualizing vendor capacity and scheduling help us anticipate and minimize disruptions, lowering their effect on operations*.” (Case - Retails)
Prioritization	“*The supplier’s capacity and schedule in their coverage table allows us to alter our priorities depending on, ensuring most important demands are covered even with limits*.” (Case - Automobile)
Efficiency	“*Current information helps us to improve decision-making. Based on current data, we may allocate resources and change production plans*.” (Case - Electronics Manufacturing) “*We use data analytics tools to analyze historical sales data and customer demand patterns. Based on this analysis, it appears that certain products tend to be more popular during times of the year*.” (Case - Automobile)
Relationship Building	“*Maintaining open and honest communication, as well as sharing data regularly, can help foster a stronger relationship between your company and the supplier. Fostering trust and collaboration is important because it can greatly benefit long-term partnerships*.” (Case - Healthcare)

Thus, it is reasonable to say that data analytics serves as both an investigative and anticipatory tool for optimizing SC operations. It helps identify and proactively analyze potential disruptions, provides insights into supplier performance during crises and enables informed decision-making for resource allocation and emergency response measures.

4.1.2 Containment

Containment is an alternative strategy to avoidance, crucial for mitigating the spread of disruptions and minimizing their impacts. This capability enables companies to respond promptly and decisively, reducing negative effects on operational efficiency, reputation, and customer relationships. Data pipelines and reporting systems provide real-time visibility, enabling companies to quickly adjust their strategies in response to emerging issues. For example, in the Automobile case, the respondent shared, "*One thing we're currently working on is using technology to enhance visibility and transparency throughout SCs. It's all about finding ways to make things clearer and easier to understand. This can really help us identify and address risks faster and more effectively*." In the Electronics Manufacturing case, real-time monitoring played a key role during a disruption, with the respondent highlighting its importance by stating, "*During the disruption, we kept a close eye on real-time data, including online sales, customer inquiries, and social media sentiment. We also monitored the progress of component shipments from the supplier*." Similarly, in the Healthcare case, automation supported early intervention, with the respondent explaining, "*We have developed a system that automatically sends alerts whenever inventory levels of important components or finished products fall below a specific threshold. These alerts notify inventory managers and procurement teams to take necessary actions to avoid stockouts or production disruptions*."

During containment, data interpretation is crucial for scenario planning. Examining historical data provides significant contextual information, helping companies identify trends, patterns, and past events that could influence future situations. For example, in the Electronics Manufacturing case, the respondent explained, "*Historical and real-time shipping data helps us analyze shipping trends and risks. We assess routes, logistics vendors, and transportation methods, which might include establishing alternate shipment paths, backup logistics partners, and stockpiling finished goods in crucial locations*." Similarly, the respondent from the Telecommunication case highlighted how trade tensions disrupted semiconductor SCs, mentioning, "*Due to trade tensions between two important suppliers, semiconductor SCs are disrupted. We record their component SC, discovering alternate vendors and storage options. Our analysts use data analytics models to study the impact of a component supply disruptions, including manufacturing delays and potential price increases*." In the Digital Appliance case, scenario analysis was used as a proactive planning tool, as reflected in the respondent's statement, "*We have been exploring hypothetical situations for our business, which we refer to as scenario analysis. This tool helps us prepare for unexpected circumstances by examining various scenarios and their potential impact on our SC*."

These examples illustrate how, during the containment stage, combining historical and real-time data with scenario planning enables firms to anticipate disruptions and develop robust containment strategies. Table 3 presents a comprehensive analysis of the benefits associated with using data analytics in the SC, focusing on enhancing resilience during the containment phase.

Table 3 Empirical findings: Data-driven benefits in Containment Stage

Advantage	Illustrative quotes
Rapid Detection	"*As soon as the system notices a significant decrease in stock for a popular product, it promptly sends out alerts to restock the inventory. Rapid detection is beneficial because it helps prevent situations where there is a shortage of stock and customers are left unsatisfied.*" (Case - Digital appliance)
Precise Isolation	"*We can isolate and recall a batch of items if a manufacturer's quality control data analytics find errors. This accuracy avoids mass recall, saving time and money*." (Case - Digital Appliance)
Visibility	"*Delivery records such as delivery date and time helps identifying delays and route deviations early, enabling quick reactions to disturbances*." (Case - Electronics Manufacturing)
Robustness	"*We use past data to identify providers with late delivery or quality concerns. Data analytics may help a corporation diversify its supplier base for a more dependable supply of goods*." (Case - Retails)
Agility	"*Data-driven demand forecasting methods can predict seasonal demand surges. With this knowledge, we can immediately alter production and inventories to suit client demands without delays or shortages*." (Case - Digital appliance)
Velocity	"*Integrating data analytics into inventory management systems enables real-time stock and order changes*." (Case - Retails) "*This information speeds up our order processing and delivery, ensuring things flow quickly through the SC*." (Case - Automobile)

Case firms leverage SC data analytics to build resilient networks that ensure the continuation flow of products and services. Historical descriptive analytics improve visibility and robustness, diagnostic analytics enhance resilience and agility by identifying root causes, predictive analytics forecast disruptions, and prescriptive analytics provide effective solutions. This multifaceted approach enables organizations to develop resilient supply networks, boost performance, and minimize disruptions.

4.1.3 Recovery

Stabilization is the initial phase within the Recovery Phase of SCR. Following the disturbance, the primary objective is to restore stability and reinstate regular operations. Reconfiguration may play a crucial role in this process, including adjustments to supplier relationships, transportation networks, or industrial infrastructure to efficiently recover from the impact and re-establish operational continuity. In the Stabilization phase, addressing disruptions through redundancy measures in key components of the SC is advisable. Redundancy measures serve as a safeguard in the event of primary system failure, thereby enhancing overall operational stability.

Predictive analytics is crucial for supporting supplier diversification, providing valuable insights and forward-looking projections. These tools help firms make well-informed decisions about supplier selection and diversification plans, as noted in the Automobile case, "*When customized components are important and expensive to replicate, predictive analytics can evaluate risks of relying on a single supplier. By anticipating disruptions and understanding their impact, we can create backup plans and ensure we have essential components in reserve*."

Flexibility and adaptability are fundamental attributes of a resilient SC, especially during the Stabilization phase. This phase aims to restore normal operations after disruptions. Data analytics, when combined with a data-driven methodology, plays a significant role in enhancing these attributes. These capabilities enable organizations to adjust operations in real-time, reassess priorities, and reconfigure SC components as needed to respond effectively to changing post-disruption conditions. Table 4 summarizes how data analytics contributes to improving SC stability during the Stabilization phase, outlining key benefits and illustrating how various analytics approaches support flexibility, adaptability, and recovery.

Table 4 Data analytics improving SC stability

Attribute	Illustrative quotes
Real-time Demand Forecasting	"*Data analytics allows us to accurately predict and stay updated on demand, ensuring that SC activities align with changing consumer needs*." (Case Retails) "*Having flexibility helps to reduce the chances of having too many inventory or not enough inventory*." (Case - Automobile)
Inventory Optimization	"*When it comes to predictive analytics, we have developed a Bayesian method that helps us determine the best inventory levels. We do this by analyzing past data and current market trends. Being flexible in this way allows for the ability to maintain low inventory levels while still making sure that products are easily accessible*." (Case - Automobile)
Supplier Performance Monitoring	"*Using data analytics, we can constantly monitor the performance of our suppliers. When there are disruptions, being adaptable helps us find other sources or change our procurement strategies so that our SC keeps running smoothly*." (Case - Healthcare)
Efficient Production	"*Predictive analytics is a tool that allows us to make better production schedules by using up-to-date data and predictions of customer demand. The ability to adapt ensures that manufacturing processes can stay efficient, even when unexpected disruptions occur*." (Case - Electronics distributor)
Scenario Analysis	"*Data analytics helps us analyze different scenarios to understand the potential effects of various strategies. We can use this adaptability to assess and execute the most effective plan of action by utilizing real-time data*." (Case - Automobile)
Customer Insights	"*Using a data-driven approach allows us to gain a thorough understanding of what customers want and expect. We can enhance customer satisfaction by adjusting our products, services, and delivery methods to meet the changing needs of our customers*." (Case - Digital appliance)
Risk Mitigation	"*Predictive analytics helps to identify possible risks and disruptions in the SC, allowing companies to take proactive measures to mitigate these risks. Our ability to adapt allows us to respond swiftly to new threats and take proactive steps to prevent them*." (Case - Healthcare)
Resource Allocation	"*Predictive analytics helps in making resource allocation more efficient by ensuring that resources are allocated effectively to meet the changing demand, while also minimizing any unnecessary waste. The ability to adapt helps to lower the costs of operations*." (Case - Healthcare)

4.1.4 Return

The "Return" phase in SCR is crucial for enterprises, focusing on the rapid restoration of full operating capacity following a disruption. During this phase, prescriptive analytics plays a vital role in enhancing SC robustness. Analytics guide the recovery stage using diverse techniques. Diagnostic analytics are particularly useful for in-depth analysis of disruptions, helping identify root causes, and providing recovery guidance. This analysis framework improves readiness and recovery from future disruptions. For example, in the Health case, the respondent explained, "*Next year's sales margin estimate is determined using prescriptive analytics. We analyze market trends, competition intelligence, and historical sales data. Operational business units set sales and profitability objectives for product groups. Monitoring progress allows timely strategy adjustments*."

Similarly, the Electronics Distributor case highlights, "*Data-driven pricing models help determine effective prices for products and services, maintaining profitability even in difficult circumstances. Increased revenue streams create a stable and resilient financial situation*."

Predictive analytics offers actionable recommendations for decision-making and resource allocation, by considering various constraints, objectives, and historical data. These insights help accelerate recovery and mitigate the impact of disruptions. An effective learning and growth plan is essential during the Return phase to guide recovery and strengthen against potential disruptions. For example, in the Telecommunication case, the respondent explained, "*When reaching the Return phase, we use historical data to identify areas for strengthening resilience and implement innovative measures*." Similarly, in the Automobile case, the respondent highlights, "*We delve into what happened to identify weaknesses. Setting up classes or training events where people share their learnings fosters a mindset of continuous improvement*."

4.2 Risks in data-driven resilience

Case companies encounter various risks and complexities in building data-driven SCR. Risks related to data quality, unexpected results, SC complexity, and accessibility are explored here. For example, in the Retails case, the respondent mentioned that "*Retailers gather significant data from various sources, including point-of-sale systems, customer loyalty programs, and social media. However, this data can be fragmented and inconsistent, making it challenging to understand the SC comprehensively*."

Analytical outcomes are often met with within companies due to concerns about data accuracy and reliability. Low-quality data leads to uncertain conclusions, inefficient decision-making, and potential vulnerabilities in the SC. For example, in Retail's case respondent, mentioned that "*Retailers frequently work with numerous suppliers, making it challenging to gather all necessary data for a complete SC understanding*." Similarly, the respondent from the Electronics Distributor case pointed out "*Data gathered from sensors on machines, production lines, quality control systems, and customer feedback can be noisy and incomplete, making it difficult to spot trends and patterns*". Also, the respondent from the Healthcare case explained that "*Healthcare device SCs undergo extensive regulation and adhere to demanding quality standards. Regulatory changes or product recalls can disrupt operations and create vulnerabilities*."

A major barrier to establishing a data-driven culture in SCs is the lack of data integration, over-reliance on experience, and resistance to change. For example, the respondent from the Electronics Manufacturing case pointed out "*It's frustrating how departments work in silos, making decisions without considering data from other areas. They miss out on the bigger picture. It would be better if they had a broader viewpoint*". Similarly, the respondent from the Automobile case emphasized "*Decision-making power is often granted based on experience, leading employees to rely on past knowledge rather than analyzing current trends*". Resistance to change further complicates efforts, as described by respondent in Retail's case "*Employees hesitate to adopt new technologies or methodologies, feeling comfortable with current processes, even when data suggests changes could lead to improvements*."

4.3 Summary of findings

The empirical results of this investigation address the research issues presented in the study. Firstly, the use of analytics on large volumes of data enables interviewed companies to anticipate and prepare proactively for disruptions. In the research companies reported employing predictive analytics to assess the likelihood of operational disruptions, allowing them to implement preventive measures in advance. This data-driven approach to decision-making emphasizes that SCR involves proactive planning and risk mitigation, not just reactive responses to unexpected events.

Furthermore, diagnostic analytics during the resistance phase plays a critical role in identifying vulnerabilities within the SC. The case companies demonstrated their ability to implement targeted measures aimed at protecting vulnerable areas and mitigating the negative impacts of disruptions. By addressing potential weaknesses before they escalate, companies enhance their overall resilience and effectively reduce their operational risks. Additionally, prescriptive analytics during the recovery phase contribute to the development of effective recovery strategies, optimal resource allocation, and informed decision-making processes. By enhancing flexibility and optimizing resource allocation, it enables companies to recover more rapidly and efficiently from disruptions. The research demonstrates that data-driven recovery efforts can significantly strengthen SCR, minimizing downtime and facilitating a fast return to normal operations. The results also highlight the competitive advantage of adopting a data-driven and integrated approach to resilience. A corporation's ability to withstand disruptions and navigate complex business environments distinguishes it from its competitors. Consistent with previous research, the findings suggest that leveraging data analytics to enhance SCR can provide a significant competitive edge in today's dynamic and interconnected global economy.

4.4 Discussion

This research confirms previous findings that using all analytical tools significantly impacts SCR [46,47]. Data-driven strategies help organizations predict, manage, and recover from disruptions, thereby enhancing overall operational resilience. Descriptive analytics provides a comprehensive understanding of current SC operations, serving as a starting point for measuring performance and identifying areas for improvement. This step is critical for mapping operational complexities and inefficiencies, optimizing their effects, and providing a solid foundation for subsequent analytical processes and optimization efforts.

During the resistance phase, diagnostic analytics plays a key role in identifying vulnerabilities within the SC by thoroughly analyzing both historical and real-time data. This approach helps organizations to pinpoint weak points and sources of risk, allowing strategic resource allocation to strengthen these areas and reduce disruption impacts. Integrating descriptive and diagnostic analytics improves the identification process, with insights derived from the descriptive phase enhancing the accuracy and depth of vulnerability identification. According to [48], organizations must proactively scan the environment and adapt to both internal and external changes to maintain resilience and competitiveness. Predictive analytics builds proactive resilience by forecasting potential future events and their associated impacts. The case companies examined in the study use both historical and real-time data to forecast potential disruption, allowing them to either prevent or lessen disruptions effectively. Predicting and preparing for disruptions helps businesses maintain smooth operations and reduce problem likelihood [29,49]. The integration of predictive analytics with descriptive and diagnostic data creates a comprehensive understanding of past, present, and future challenges, facilitating more informed decision-making.

Our findings demonstrate that performance insights from historical descriptive analytics enhance both robustness and visibility in SC. In parallel, diagnostic analytics uncover underlying causes of disruptions, promoting resilience and agility. Predictive analytics increases velocity and agility by forecasting disruptions. Prescriptive analytics expedites decision-making with a data-driven methodology. Collectively, these insights enhance visibility, improve problem diagnosis, enable disruption prediction, and support the development of effective solutions, ultimately building resilient SC networks. A multimodal strategy further maximizes efficiency and reduces disruptions across SC. The ability to respond rapidly during emergencies is crucial for SCR [19]. Predictive analytics, which analyzes historical and real-time data, helps predict potential disruptions, allowing organizations to respond proactively. Prescriptive analytics goes beyond offering specific, data-driven recommendations to mitigate their impacts, providing timely and effective responses. Delayed reactions to disasters can lead to substantial financial losses for companies and supply channels [49]. Response and recovery capabilities are critical for developing SCR [19,26,36]. Key organizational capabilities include promptly responding to environmental forces, reconfiguring resources, and recovering from vulnerabilities. Recovery is assessed based on cost, recovery time, disruption absorption, and mitigation power [19,26,29]. Predictive analytics optimizes resource allocation through suggested actions, ensuring coordinated and effective responses. Diverse data analytics techniques enhance SC resilience, especially during recovery. Descriptive analytics provides insights into past performance, aiding recovery process comprehension and enhancement. Diagnostic analytics identifies disruption root causes, facilitating targeted recovery strategies. Predictive analytics enables organizations to take proactive measures that reduce recovery time and costs. Prescriptive analytics builds on this by using real-time data to recommend optimal recovery strategies, ensuring that response efforts are both efficient and effective. Combining these technologies allows businesses to develop a comprehensive data-driven recovery plan, enhancing their ability to navigate the complexities of today's dynamic business environment. This integrated approach not only strengthens an organization's capacity to manage disruptions but also underscores the critical role of data analytics in building resilience. This leads to the first proposition:

Proposition 1: By effectively integrating various analytical tools, a company can enhance its ability to anticipate future events, mitigate risks efficiently, and maximize recovery measures. Together, these efforts play a crucial role in strengthening SC resilience.

Organizations can enhance resilience and adaptability by learning from past disasters. Continuous knowledge acquisition is crucial for developing creativity, flexibility, and resilience. Collecting insights from previous experiences helps mitigate the risk of losses due to disruptions. Unexpected disruptions highlight the need for a flexible SCR plan that can adapt to evolving challenges and uncertainties. In this study, data analytics is extremely significant for case companies. By accumulating substantial data and drawing from past experiences, these companies enhance their strategic approaches. Understanding previous disruptions strengthens SCR through the implementation of effective risk mitigation strategies. The case companies have shown that ongoing learning and adaptation make them more proactive, flexible, and resilient in the face of ongoing and future challenges. For the Telecommunication and Machinery Manufacturers, using data on bottlenecks and recovery times helps streamline recovery procedures, enabling quicker resumption of operations and more flexible SC architectures after disruptions. Each disruption and recovery instance presents learning opportunities.

Businesses may implement technology development and training programs as part of their risk mitigation strategies [50]. Training and development programs, especially those focusing on technical proficiency, equip SC professionals with the skills needed to effectively identify, manage, and reduce risks [51]. Acquiring information, learning from experiences, and drawing lessons from past events are essential for identifying and mitigating vulnerabilities [48]. During disruptions and recovery phases, data analytics significantly facilitate the process. These measures not only restore regular operations but also provide valuable information for developing and improving avoidance strategies. This two-way flow of information ensures weak spots are identified and recovery steps' effectiveness is studied, leading to changes that prevent similar disruptions from recurrence. Enhancing the avoidance phase involves seamlessly transferring recovery phase outputs forward. The case Retails has shown how data analytics directly inform the development of avoidance tactics. Such learning is critical for building greater resilience, reducing risk, and greater flexibility within the SC [52].

Incorporating a continuous, cyclical resilience strategy requires a committed data-driven approach to decision-making at every stage of the SC. Within this framework, benchmarking and experience-based learning serve as critical components of SCR [49]. Learning is essential in crisis management [53], contributing to enhanced resilience within a business and its SC. Resilience is not a static condition, but rather an ongoing commitment to proactive, evidence-based strategies. Insights gained from one cycle serve as input for the next, enhancing avoidance strategies. In conclusion, SCR as a continuous, data-driven process is vital in a rapidly evolving business environment. Firms need agile and adaptable approaches to respond to unforeseen circumstances. By acquiring valuable information during each phase of disruption and recovery, organizations can continuously enhance their SCR, improving both resilience and operational effectiveness over time. This leads to the second proposition:

Proposition 2: SCR is not a one-time effort but an ongoing commitment, requiring data-driven adaptable policies at every stage of the SC.

While SC analytics improve resilience, they also have drawbacks. Success depends heavily on proficiency in Data Analytics, which requires active involvement from senior management. Factors affecting the impact of Business Data Analytics on SC effectiveness include strategic alignment [54], recognition stage [55], supplier base complexity [56], and supply uncertainty. Our findings from the cases in "Electronics manufacturing", "Automobile", and "Retail" reveal challenges in creating a data-driven culture, such as resistance to change, reliance on past experiences, and lack of data integration. Addressing these constraints is crucial for fostering a robust and efficient SC through effective data analytics. Experts must align their data analytics knowledge with the organization's strategic objectives. Adopting data-driven approaches requires a cultural transformation toward data-driven decision-making. This shift involves optimizing data analytics benefits, considering risk reduction strategies, and integrating analytics into the core business culture.

Traditionally, SC decisions relied on intuition, experience, or established norms. Transitioning to data-driven methods requires strong leadership commitment to support this shift. Organizations must foster a data-driven culture that enables informed decisions at all levels [56]. Comprehensive training programs are essential for closing the knowledge gap across all business functions, including SC management, procurement, and logistics. These programs should aim to equip individuals with skills to interpret data, analyze insights, and effectively use analytical tools to support informed decision-making. Overcoming resistance to change requires efficient change management techniques led by advocates of data-driven methodologies, fostering a collaborative and adaptable culture. To ensure a smooth transition to data-based decision-making, leaders must proactively address concerns, allocate necessary resources, and provide ongoing support. Ongoing development and learning are crucial in a data-driven culture. Organizations should include feedback loops in their decision-making process, enabling them to regularly evaluate outcomes and modify plans based on acquired knowledge. Extracting insights from past disruptions and integrating them into future decision-making is essential for developing SCR. This leads to the third proposition:

Proposition 3: Organizations must undergo a significant cultural transformation to fully adopt data-driven decision-making. By leveraging data analytics, they can effectively mitigate risks and strengthen SC resilience.

4.5 Framework for data-driven SC management

The shift from traditional, linear SC analytics to a resilience-focused approach underscores the need for flexible, data-driven strategies at every stage of the SC. Resilience is now seen as a continuous commitment, requiring various data analytics methods (prescriptive, predictive, diagnostic, descriptive) to improve SC resilience. Firms with strong data analytics capabilities are better positioned to identify disruptions, reduce risks, and enhance recovery processes. Analytics should be applied comprehensively across all phases to ensure continuity and readiness. Proactive risk mitigation and continuous adaptation based on data insights are crucial for outperforming conventional, linear processes. Prescriptive analytics, the most advanced form of data analysis, offers significant advantages by recommending optimal actions. However, it remains underutilized due to its high demands on IT infrastructure, skilled human resources, and advanced modeling capabilities. To address these challenges, the study proposes a flexible framework (see Figure 2) that adapts to practical constraints by prioritizing alternative analytical methods more suitable for the specific needs of the investigated firms. This approach enhances the efficiency and feasibility of using data analytics in SCs while ensuring the integration of data-driven decision-making at every stage of the SC process.

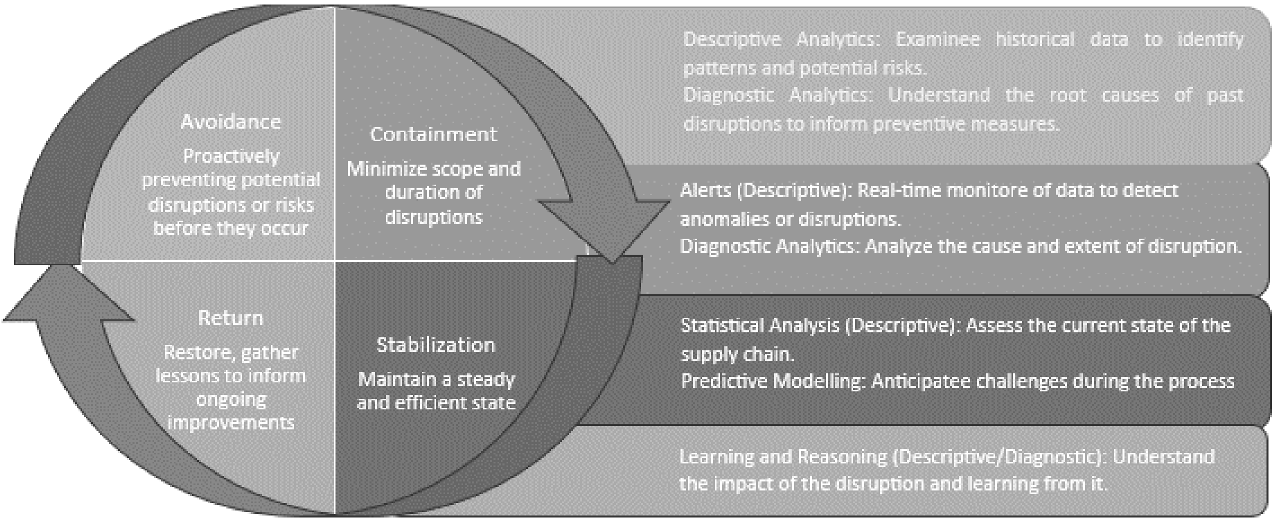

Figure 2 Modified and elaborated Conceptual framework for Data-Driven SC management

5 Conclusions

This research aimed to explore SC data analytics theories and their role in building resilience. It examined how resilience can manage supply disruptions and assist firms in dealing with them effectively. The research provided valuable insights into how data analytics strengthens SCR, drawing on real-life examples from various industries. It explored key areas like risk management, demand forecasting, and inventory optimization, demonstrating how data analytics make SCs more adaptable and resilient to disruptions. Additionally, the study examined methods for effectively implementing data analytics in SCs, considering theoretical frameworks and real-world case studies. It discussed the most effective approaches, identified key obstacles, and discussed strategies for successfully integrating data analytics into SC management systems.

5.1 Theoretical and managerial implications

This study addresses gaps in SCR by linking data analytics to every stage of the resilience cycle. It integrates data analytics throughout the SCR processes, outlining both the advantages and disadvantages of adopting data-driven SC approaches to resilience. The study examines the positive and negative aspects of incorporating data analytics at each stage of SC and offers practical recommendations for companies looking to enhance resilience through data-driven decision-making. The study fills gaps in the literature on data analytics and SC resilience, as noted by [7-10]. Previous studies have highlighted the importance of integrating descriptive and predictive analytics into prescriptive models. However, fully understanding the benefits of data-informed decision-making at each stage of the resilience cycle has remained challenging. By addressing these gaps, this research advances the field with a comprehensive analysis of practical data analytics at different stages of SCR. It provides an authoritative framework for utilizing data analytics to enhance SC operations effectively, closing gaps identified by [8]. The study offers a comprehensive data analytics framework for SCR, derived from empirical data and analysis. It provides a clearer understanding and actionable recommendations for organizations seeking to adopt a resilient, data-driven approach to strengthen their SCs.

The qualitative analysis of data analytics in enhancing SCR has significant managerial implications. Firstly, the research underscores the importance of data-driven decision-making, enabling managers to better navigate uncertainty more effectively, allocate resources strategically, and adjust their strategies to evolving conditions, thereby improving operational resilience. Secondly, the findings emphasize the importance of proactive risk mitigation. Data analytics enables managers to identify vulnerable areas within the SC, allowing for strategic resource allocation and proactive problem resolution, both of which are crucial in navigating a turbulent business environment. Lastly, the research highlights the need for organizational flexibility and continuous learning. Managers should foster a culture of ongoing learning, ensuring employees are equipped to effectively use data analytics tools, stay updated about technological advancements, and implement the industry's best practices. This commitment to learning and flexibility enhances overall resilience and competitiveness.

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5.2 Limitations and future research

This study has inherent limitations due to its qualitative approach. Qualitative methods, such as interviews and case studies, may be biased by the personal interpretations of a small, selected group, which could potentially limit the comprehensive evaluation of data analytics' impact. To gain more robust evidence, future research could benefit from quantitative analysis using a larger dataset. The study's generalizability is also limited by industry, location, and company-specific factors, which may not fully represent the broader landscape of SC scenarios. Additionally, the financial implications of implementing data-driven approaches are often overlooked. Assessing the costs of technology implementation, data procurement, training, and system maintenance is crucial, especially for smaller or medium-sized businesses. Future research should combine both quantitative and qualitative methods, including a wide range of industries, and perform comprehensive cost-benefit analyses. Continuous studies could capture the evolving impact of technology over time, and comparative analysis across companies can uncover effective strategies and challenges, further deepening our understanding of data analytics can strengthening SC resilience.

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