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Bridging the Gap Between Managerial Perceptions and Resilience Performance in Supply Chains: A Mixed-Methods Analysis

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ABSTRACT: Supply chain disruptions have become increasingly structural, driven by geopolitical tensions, pandemics, and climate-related events. This study investigates how managerial perceptions influence the selection and effectiveness of resilience strategies in the face of such disruptions. The objective is to assess whether perceptions align with actual performance outcomes of key resilience strategies. Using a mixed-methods approach, the study combines survey data from 214 supply chain managers with performance metrics from 180 companies. Five common strategies AI dynamic routing, digital integration, multi-sourcing, nearshoring, and inventory buffering were evaluated for cost, recovery speed, and resilience score. Quantitative analysis was supported by qualitative synthesis to understand behavioral influences on strategy adoption. The results show that AI-enabled strategies, particularly dynamic routing and digital integration, align strongly with managerial perceptions and deliver the highest resilience scores. Conversely, inventory buffering, while highly regarded by managers, underperforms in practice. This discrepancy suggests a cognitive bias influenced by traditional practices. Barriers such as risk aversion, overconfidence, and limited digital maturity hinder the adoption of effective strategies. The study identifies Protection Motivation Theory and Dynamic Capabilities Theory as key frameworks to understand how cognition shapes strategic choices. In conclusion, aligning managerial perceptions with data-driven insights is crucial for effective resilience strategy implementation. Investment in digital infrastructure, decision support systems, and a culture of adaptive learning are necessary to bridge perception-performance gaps. The findings contribute a behavioral-operational framework to guide resilience planning in modern supply chains.

Keywords: Supply Chain Resilience, Managerial Perception, AI Dynamic Routing, Strategic Alignment, Operational Disruption, Decision Support Systems, Digital Maturity.

INTRODUCTION

The global supply chain landscape has undergone a profound transformation in recent years due to a series of persistent and high-impact disruptions. From the widespread operational paralysis induced by the COVID-19 pandemic to the escalating effects of geopolitical conflicts and climate change, organizations now face an environment in which uncertainty and volatility are structurally embedded rather than sporadic anomalies. These disruptions have not only exposed critical vulnerabilities in the design and execution of global supply chains but have also challenged long-held assumptions about the efficacy of traditional, efficiency-focused operational models.

The characteristics of structural disruptions in global supply chains have been extensively studied and can be categorized into several critical aspects. Chief among these is the severity and reach of operational impact, which often depends on the type of disruption whether supply-oriented, process-related, or demand-driven. Disruptions caused by natural disasters or pandemics are particularly severe, due to their unpredictability and the cascading effects they trigger across interdependent supply networks (Duoming & Chin, 2022). Furthermore, the tightly woven nature of contemporary supply chains means that a disturbance in one region can quickly escalate into a systemic crisis with global ramifications (Herold & Marzantowicz, 2023).

The COVID-19 pandemic marked a turning point in how resilience is conceptualized within supply chain management. Prior to the pandemic, resilience was predominantly framed in terms of risk mitigation largely reactive measures aimed at minimizing cost and maximizing efficiency (Katsaliaki et al., 2021). However, the scale and duration of the pandemic underscored the limitations of such approaches, highlighting the need for a more dynamic framework. Resilience today is increasingly defined not only by an organization's capacity to absorb shocks but also by its ability to recover swiftly and adapt strategically. This has led to a growing emphasis on transformation-oriented resilience, where disruptions are viewed as catalysts for structural innovation (Craighead et al., 2020). The integration of advanced technologies such as artificial intelligence (AI) into supply chain planning and operations further reflects this shift, acknowledging the need for strategic, rather than purely operational, resilience (Atadoga et al., 2024).

Nonetheless, achieving strategic resilience remains a complex endeavor. One of the most pressing challenges lies in aligning operational systems with comprehensive resilience strategies. Risk management frameworks often rely on historical data that fail to capture the volatile and multifaceted nature of modern disruptions (Revilla & Sáenz, 2017). Moreover, there is a persistent gap between the theoretical insights emerging from academic research and their practical application within organizations (Odulaja et al., 2023). Resistance to change also poses a significant barrier. Many firms continue to prioritize cost minimization, a mindset that conflicts with the investments required to enhance adaptability and robustness (Ivanov, 2021).

Within this context, managerial perceptions become critically important. Leaders' interpretations of risk and resilience shaped by prior experiences, organizational norms, and cognitive biases directly influence which strategies are adopted or ignored. For example, an overemphasis on short-term cost control can discourage exploration of innovative or tech-enabled solutions, even when such measures promise greater long-term stability (Ye et al., 2022). Additionally, cognitive biases, such as optimism bias or the illusion of control, may lead managers to underestimate the likelihood or impact of certain risks, thereby skewing strategic priorities and undercutting resilience objectives (Nikookar et al., 2024).

Over the past decade, numerous frameworks have emerged to classify and assess supply chain disruptions. These frameworks typically distinguish between different disruption types natural, technological, or human-induced and evaluate their impact across multiple dimensions of supply chain performance (Zavala et al., 2018). Some advanced methodologies employ topological and network-based analyses to pinpoint vulnerable nodes within supply networks (Finck & Tillmann, 2023). Others incorporate a combination of quantitative metrics and qualitative assessments to evaluate resilience maturity at the firm level (Singh et al., 2019).

Artificial intelligence (AI) has emerged as a transformative force in supply chain disruption management. AI technologies enhance predictive analytics, offering early warning systems that help organizations anticipate potential threats and plan proactive responses (Baryannis et al., 2019). Beyond predictive capabilities, AI enables real-time monitoring of logistics flows, facilitating rapid adaptation when disruptions occur. By automating key decision-making processes, AI significantly reduces the latency between disruption identification and response, thereby improving overall agility and resilience (Nayal et al., 2021). AI's contribution also extends to strategic reconfiguration, allowing organizations to reoptimize supplier networks or transportation routes dynamically in response to changing risk landscapes (Pelegrina-Romero et al., 2024).

Despite the growing recognition of these innovations, a critical disconnect persists between perception and implementation. Managerial perceptions though increasingly oriented toward technological and hybrid resilience strategies do not always align with objective performance metrics. This misalignment can lead to suboptimal strategy adoption, undermining organizational resilience efforts.

The purpose of this study is to investigate the extent to which managerial perceptions align with the actual performance of various resilience strategies in high-disruption environments. Specifically, it examines five commonly used strategies AI-based dynamic routing, digital integration, multi-sourcing, nearshoring, and inventory buffering and compares how managers perceive their effectiveness versus how these strategies perform empirically. By analyzing perception-performance alignment, the study aims to provide insights into the behavioral drivers of strategic decision-making and offer recommendations for more effective resilience planning.

The novelty of this study lies in its integration of behavioral and operational perspectives, combining quantitative performance data from over 180 firms with qualitative survey insights from 214 supply chain managers. In doing so, it contributes a multidimensional framework that bridges the cognitive and empirical aspects of resilience strategy selection. Ultimately, the study seeks to inform both academic debates and managerial practice by highlighting the importance of aligning perception with evidence in order to build future-ready, disruption-resilient supply chains.

METHOD

This chapter outlines the research methodology employed to examine the alignment between managerial perceptions and the actual performance of supply chain resilience strategies. Given the behavioral and operational dimensions involved in the study, a mixed-methods research design was adopted. This approach allowed for the integration of numerical data from structured surveys and performance metrics with qualitative insights that deepen the understanding of strategic decision-making under conditions of persistent disruption.

Research Design

The study followed a mixed-method design with an embedded sequential explanatory strategy. Quantitative data were collected first, providing a foundational understanding of perception patterns and strategy effectiveness. This was followed by qualitative thematic synthesis to contextualize and interpret the quantitative findings. Such an approach facilitates a comprehensive evaluation of both behavioral and empirical dimensions of resilience strategies, allowing for triangulation of data sources and enhancement of the study's internal validity (Widodo & Sundari, 2024).

Data Collection

Managerial Perception Survey

A structured survey was administered to 214 supply chain managers across a range of industries. The instrument was designed to assess perceptions regarding the structural nature of supply chain disruptions, the perceived effectiveness of various resilience strategies, and perceived barriers to implementation such as data integration. Survey items employed Likert-scale ratings and open-ended questions to capture both quantitative agreement levels and qualitative insights. This combination enabled the collection of rich, contextualized data regarding managerial cognition and attitudes (Roberts et al., 2024).

Strategy Performance Dataset

A second dataset was compiled using resilience performance data from 180 companies. The dataset captured metrics across five commonly implemented resilience strategies: AI dynamic routing, supplier digital integration, multi-sourcing, nearshoring, and inventory buffering. The performance of each strategy was evaluated across three dimensions: cost impact, recovery speed, and resilience score. Quantitative data points such as time to recovery (TTR) and service level retention during disruptions were incorporated as standard resilience indicators (Shalini & Varghese, 2024).

Variables and Operational Definitions

Independent Variables

- Managerial Perceptions: Agreement levels with statements regarding disruption typology, AI adoption, hybrid resilience, and operational barriers.
- Strategy Type: The specific resilience strategy employed (e.g., AI routing, buffering).

Dependent Variables

- Performance Metrics: Quantitative indicators such as TTR, recovery speed, resilience score, and cost impact.
- Alignment Index: A derived variable representing the degree of congruence between perceived and actual effectiveness.

Analytical Framework

Quantitative Analysis

Descriptive statistics were used to analyze survey responses and to determine prevailing trends in managerial perceptions. Cross-tabulations were applied to compare perceived strategy effectiveness against empirical performance outcomes. To further test the relationship between perception and performance, correlation analysis and regression modeling were considered. Structural equation modeling (SEM) was used to identify latent relationships between strategic perceptions and resilience outcomes, drawing on frameworks validated in resilience and operations literature (Azar et al., 2024).

Qualitative Synthesis

Open-ended survey responses were thematically coded to identify key perception drivers and underlying cognitive frameworks. The integration of these qualitative findings helped interpret quantitative misalignments and refine the theoretical framing of behavioral influences on resilience strategy choices (Roberts et al., 2024).

Mixed-Method Integration

The sequential explanatory strategy supported deeper inquiry into discrepancies observed in the quantitative data. For example, high perceived effectiveness of inventory buffering, despite its relatively poor resilience score, was explored through the lens of organizational inertia and cost-based decision heuristics. The study also incorporated elements of the convergent parallel design by comparing qualitative insights from the perception survey with resilience outcomes recorded independently from organizational databases (Iskandar & Putri, 2020).

Validity and Reliability

Instrument validity was ensured through expert review and pretesting of the survey questionnaire. Reliability was assessed using Cronbach's alpha for internal consistency, with all major perception constructs exceeding the 0.70 threshold. The triangulation of data sources (survey and performance metrics) further enhanced the study's credibility.

Ethical Considerations

Respondents were assured confidentiality, and informed consent was obtained prior to data collection. Data handling adhered to GDPR standards, ensuring secure storage and anonymization of sensitive organizational performance information.

Limitations of Methodology

While the mixed-method approach provided robust insights, certain limitations exist. The reliance on self-reported data introduces the potential for bias in perception responses. Additionally, strategy performance data may be influenced by industry-specific conditions not fully accounted for in the model. Future studies could expand the dataset to include time-series analysis or sector-specific segmentation for greater granularity.

RESULT AND DISCUSSION

This chapter presents the results of the study in three major subsections: the landscape of managerial perceptions, comparative performance of selected resilience strategies, and the alignment between perceived and actual performance. Each subsection integrates findings from empirical datasets with theoretical insights drawn from recent literature.

Managerial Perceptions of Supply Chain Disruptions

Survey responses from 214 managers revealed a widespread recognition of persistent and systemic risks in global supply chains. A strong majority (89%) agreed that supply chain disruptions are now structural rather than temporary, reflecting lessons drawn from the COVID-19 pandemic and related crises. These findings are consistent with broader trends in the field, where risks such as geopolitical tension, economic instability, and health emergencies are viewed as permanent threats to operational continuity (Guntuka et al., 2023).

Managers also acknowledged the strategic importance of technological solutions. Specifically, 77% of respondents expressed confidence in AI-based modeling for enhancing risk visibility, and 84% supported hybrid resilience frameworks that combine anticipation and adaptation. This growing support for advanced and integrated resilience strategies aligns with emerging evidence on the efficacy of AI in predicting disruptions and optimizing recovery processes (Abaku et al., 2024).

However, perceptions are not homogenous across sectors or regions. As noted in comparative studies, industries like healthcare tend to place higher emphasis on resilience due to the criticality of service delivery during crises (Okafor et al., 2021), whereas manufacturing sectors may prioritize cost efficiency over redundancy (Zhao et al., 2023). Similarly, geographical disparities influence perceptions: managers in less stable economic regions often express heightened sensitivity to supply disruptions due to higher dependency on international networks (Younis et al., 2021).

Cognitive biases were evident in perception-based responses. For instance, managers showed strong support for inventory buffering despite mixed performance outcomes, indicating a potential overestimation based on familiarity or previous experiences. Literature suggests that such biases can lead to over-reliance on known strategies while underappreciating the contextual limitations of their application (Esmaeilzadeh, 2020).

Table 1. Managerial Perception Survey (N = 214)

Statement	Agree (%)
Disruptions are now structural, not temporary.	89%
AI-based modeling improves our risk visibility.	77%
Hybrid resilience (anticipation + adaptation) is vital.	84%
Data integration is the biggest barrier.	69%
Supplier diversification should be mandatory.	71%

Strategy Effectiveness Comparison

This section presents performance data from 180 firms across five major resilience strategies. Each strategy was evaluated using three key indicators: cost impact, recovery speed, and a calculated resilience score.

Table 2. Strategy Performance Comparison (N = 180)

Strategy	Cost Impact	Recovery Speed	Resilience Score
AI dynamic routing	Low	Very High	0.91
Supplier digital integration	Medium	High	0.88
Multi-sourcing	Medium	High	0.86
Nearshoring	High	Medium	0.74
Inventory buffering	High	Low/Medium	0.63

AI dynamic routing proved to be the most effective across all dimensions, reducing delay times through real-time optimization and significantly enhancing operational continuity (Alnsour et al., 2023). Organizations using AI systems reported improved service levels and reduced cost overruns during high-impact disruptions. Supplier digital integration and multi-sourcing also performed well, offering both flexibility and robustness.

Conversely, inventory buffering, while perceived as reliable, scored the lowest. Despite providing immediate shock absorption, buffering incurred high storage costs and risks of obsolescence. The trade-offs observed among nearshoring, multi-sourcing, and buffering validate earlier findings that resilience strategies vary in applicability depending on organizational context and risk exposure.

Perception vs. Performance Alignment

To evaluate alignment, perception data were compared with actual strategy performance outcomes. This analysis highlights both congruencies and misalignments between belief and reality.

Table 3. Perception vs. Performance Alignment

Strategy	Perceived Effectiveness	Actual Score	Alignment
AI dynamic routing	High	0.91	Strong
Supplier digital integration	Medium–High	0.88	Strong
Inventory buffering	High	0.63	Weak
Nearshoring	Medium	0.74	Moderate
Multi-sourcing	High	0.86	Moderate–Strong

The strongest alignment was observed in AI-based strategies, confirming that managerial confidence in these tools is well-founded. However, the significant overestimation of buffering effectiveness points to perception biases driven by legacy practices. These biases can hinder the adoption of more adaptive and cost-effective strategies.

Literature supports the notion that such misalignments are often rooted in limited data access, cognitive inertia, and overconfidence in outdated systems. Additionally, the allure of cutting-edge technology sometimes overshadows basic, underappreciated strategies like cross-functional communication or collaborative partnerships (Sodiya et al., 2024).

Organizations seeking to improve perception-performance alignment can benefit from implementing decision support systems (DSS). These tools offer real-time analytics and performance tracking, enabling managers to make evidence-based decisions (Adenuga et al., 2024). By visualizing gaps between expectations and actual results, DSS help recalibrate strategic preferences and ensure more effective resilience outcomes.

The findings presented in this study reinforce a critical shift in the managerial understanding of supply chain risk and resilience. The recognition that disruptions are structural rather than transient is consistent with recent scholarly consensus and real-world observations. This change in perception represents an essential precursor to more strategic and future-oriented resilience planning. However, despite this evolving awareness, psychological and organizational barriers continue to hinder the full-scale adoption of high-performing resilience strategies.

Psychologically, managerial decision-making is frequently shaped by cognitive biases that affect both risk appraisal and strategic preference. Overconfidence in existing systems, for example, may lead managers to underestimate their organization's vulnerability to large-scale disruptions (Arianpoor & Zaidan, 2023). Risk aversion further impedes proactive resilience planning, as leaders may delay necessary investments in adaptive infrastructure due to perceived uncertainty or fear of failure (Bode et al., 2021). These behavioral patterns can result in reactive responses, where significant disruptions become catalysts for change only after damage has occurred.

Organizational barriers compound these psychological limitations. Many firms prioritize short-term financial performance, driven by shareholder expectations or competitive pressures, and thus deprioritize long-term resilience planning (Tu, 2018). Furthermore, organizational silos can obstruct the integration of resilience strategies across functional departments. In such environments, the fragmented flow of information and limited cross-functional collaboration undermine cohesive strategy execution (Manuj et al., 2024). Without a culture that values learning, innovation, and proactive risk management, even technically sound strategies may fail to gain traction (Keller et al., 2020).

Digital maturity has emerged as a pivotal determinant of resilience strategy effectiveness. Organizations with advanced digital capabilities are significantly better positioned to gather, analyze, and act upon operational data. Digital maturity facilitates the use of predictive analytics and real-time monitoring systems, enabling rapid adjustments to supply chain operations during disruptions (Li et al., 2022). Empirical evidence shows that such capabilities correlate with reduced recovery times and enhanced continuity of operations (Arcidiacono et al., 2022). In contrast, firms with low digital readiness often lack the infrastructure and human capital needed to implement or sustain resilient practices. These organizations struggle with fragmented data systems and limited visibility, which hampers both situational awareness and response coordination (Heikkinen, 2024).

The interaction between cognition and operational choices can be framed through established theoretical models. Protection Motivation Theory (PMT), for instance, suggests that decisions to adopt resilience measures are rooted in the cognitive appraisal of both threats and the perceived efficacy of available responses (Bode et al., 2021). Within the context of supply chains, managers who perceive high disruption risk and believe in the effectiveness of certain tools such as AI modeling or multi-sourcing are more likely to invest in them. However, when perceived threats are low or tools are misunderstood, investment is less likely regardless of objective need.

Dynamic Capabilities Theory (DCT) further supports the findings by positing that organizations must continuously integrate and reconfigure internal competencies to respond to volatile environments (Kessler et al., 2023). Managerial cognition plays a central role in this dynamic process, guiding strategic adaptations and resource allocation. Firms that develop strong sensing, seizing, and transforming capabilities are better able to navigate disruptions and gain competitive advantages through resilience.

The observed alignment between managerial perceptions and strategy performance in some areas such as AI dynamic routing and digital integration suggests progress toward evidence-informed decision-making. However, discrepancies like the overestimation of inventory buffering indicate that cognitive biases and historical experiences continue to skew judgment. Addressing these perception-performance gaps is vital for effective strategy execution.

To bridge this gap, integrating operational data into executive-level decision-making is paramount. Unified data platforms that consolidate metrics across functions can improve the visibility of supply chain vulnerabilities and support informed strategy selection (Li et al., 2022). Moreover, cultivating a data-driven culture through executive training and cross-functional dialogues ensures that decision-making processes are not solely reliant on intuition or legacy approaches (Kessler et al., 2023).

Decision support systems (DSS) represent another best practice. By incorporating real-time data and scenario modeling, DSS tools allow managers to evaluate potential outcomes and proactively adjust strategies. These systems promote accountability and facilitate continuous learning by providing feedback loops between operational managers and executive leadership (Keller et al., 2020; Lima et al., 2024). Through such mechanisms, organizations can progressively align managerial perceptions with performance-based evidence.

In conclusion, while managerial awareness of structural disruptions and the value of AI-enhanced strategies is increasing, full alignment between perception and performance remains a work in progress. Cognitive biases, organizational silos, and low digital maturity continue to challenge the implementation of high-performing resilience strategies. Addressing these issues through enhanced digital infrastructure, theoretical grounding in decision-making models, and best practices for data integration can empower organizations to design and implement more effective and future-ready supply chain resilience frameworks.

CONCLUSION

This study investigated the intersection of managerial perceptions and the effectiveness of resilience strategies in supply chain management amidst persistent and structural disruptions. Drawing on data from 214 supply chain managers and performance metrics from 180 companies, the findings reveal both areas of alignment and misalignment between perceived and actual strategy performance.

One of the most significant insights is the growing recognition among managers that disruptions are no longer isolated events but structural realities. This shift has increased support for adaptive strategies, particularly those that integrate artificial intelligence (AI) and digital technologies. AI-based dynamic routing and supplier digital integration were not only perceived positively but also demonstrated high empirical effectiveness across key resilience metrics, such as recovery speed, operational continuity, and cost efficiency.

However, the research also uncovered notable gaps between perception and performance. Strategies like inventory buffering, though widely supported by managers, scored lowest in empirical resilience, indicating cognitive bias rooted in familiarity and traditional practices. These misalignments suggest the need for greater emphasis on evidence-based decision-making and continuous feedback mechanisms.

The study further identifies several psychological and organizational barriers that hinder the adoption of high-performing resilience strategies. These include overconfidence, risk aversion, resistance to change, and siloed communication structures. Overcoming these barriers requires organizations to cultivate a culture of learning, innovation, and cross-functional collaboration. In parallel, investment in digital maturity and decision support systems (DSS) is essential to enhance real-time visibility, scenario planning, and data-driven strategy formulation.

From a theoretical perspective, models such as Protection Motivation Theory and Dynamic Capabilities Theory provide valuable frameworks to understand how cognition influences operational choices. These models emphasize the role of perceived threats, strategic intentionality, and adaptive competencies in guiding resilience planning. Aligning these cognitive factors with operational data through integrated systems can significantly enhance strategic coherence and resilience outcomes.

In summary, this research contributes to both academic and managerial discourse by highlighting the importance of aligning perception with performance in the realm of supply chain resilience. By bridging behavioral insights with empirical evaluations, the study offers a multidimensional framework for selecting and implementing effective resilience strategies. The findings advocate for a future in which strategic decisions are informed by data, shaped by realistic threat appraisals, and supported by integrated technological infrastructures ultimately enabling organizations to thrive amidst ongoing disruption.

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