Article

Not peer-reviewed version

Immune-Inspired Dynamic Modeling of Supply Chain Resilience: Organizational Memory, Adaptation, and System Recovery under Disruptions

Andrés Polo *

Posted Date: 16 March 2026

doi: 10.20944/preprints202603.1187.v1

Keywords: supply chain resilience; immune system analogy; organizational memory; agro-industrial chains; dynamic modeling; disruption management; system dynamics

Article

Immune-Inspired Dynamic Modeling of Supply Chain Resilience: Organizational Memory, Adaptation, and System Recovery under Disruptions

Andrés Polo

Department of Industrial Engineering, Universidad de Cundinamarca, Chía, 250008, Colombia, Colombia; andrespolo@ucundinamarca.edu.co

Abstract

Persistent and systemic disruptions—such as pandemics, geopolitical crises, and climate-related events—have exposed critical vulnerabilities in global supply chains, highlighting the urgent need for dynamic and adaptive resilience strategies. This paper proposes a novel immune system-inspired dynamic model for designing resilient, adaptive, and financially viable supply chains under severe disruptions. The model integrates innate and adaptive response mechanisms, including organizational memory as a dynamic capability that enables supply chains to learn from past disruptions and improve future responses. Unlike traditional models focused solely on structural redundancy or flexibility, this framework combines operational, financial, and learning dimensions within a unified system modeled through nonlinear differential equations. To validate the model, we conducted a scenario-based analysis, simulating three configurations: (1) a Total System Collapse without adaptation or learning, (2) a Baseline Resilience scenario with innate responses only, and (3) an advanced scenario with active organizational memory and adaptive mechanisms. Results demonstrate that the presence of learning and adaptive capacities significantly enhances both operational and financial resilience, reducing disruption intensity and accelerating recovery. Furthermore, a comprehensive sensitivity analysis was performed on three critical parameters: rate of active adaptation, organizational memory accumulation rate, and supply chain vulnerability. Findings reveal that higher adaptation rates and stronger organizational memory dramatically improve supply chain resilience, while higher structural vulnerability leads to systemic failures that cannot be mitigated by reactive measures alone. This study offers a quantitative and interdisciplinary contribution to supply chain resilience theory and provides practical guidelines for managers and policymakers to invest in adaptive capabilities, institutionalize learning processes, and reinforce structural robustness. The proposed model serves as a foundation for designing next-generation resilient supply chains, capable of surviving and thriving under persistent global uncertainty.

Keywords: supply chain resilience; immune system analogy; organizational memory; agro-industrial chains; dynamic modeling; disruption management; system dynamics

---

1. Introduction

The increasing frequency and intensity of global disruptions, such as pandemics, natural disasters, geopolitical conflicts, and financial crises, have exposed critical vulnerabilities in modern supply chains. In recent years, supply chains have faced unprecedented challenges that have not only interrupted production and logistics flows but also severely affected organizational financial viability and long-term sustainability. These disruptions have underscored the urgent need for supply chains to evolve from static, efficiency-driven models toward dynamic, resilient, and adaptive systems capable of surviving and thriving under uncertainty [1,2].

While the concept of supply chain resilience (SCR) has been widely studied, most existing models focus on structural redundancies, flexibility, and short-term risk mitigation strategies [3–5].

Although these mechanisms provide a degree of protection, they often fail to ensure full recovery and sustained viability under prolonged or complex disruptions [5,6]. More critically, the role of organizational learning and memory—key components in biological adaptive systems—remains underexplored in supply chain literature. This gap is particularly relevant considering that supply chains must not only recover from disruptions but also learn and adapt to emerging threats to improve their future responses.

In this context, biological systems, particularly the human immune system, offer a powerful analogy to understand and design resilient and adaptive supply chains. The immune system is a multi-layered defense system that operates with both innate and adaptive responses, including a memory mechanism that allows for quicker and more efficient responses to recurrent threats [7,8]. Unlike traditional supply chain models, which rarely incorporate learning, the immune system evolves through exposure, enhancing its resilience over time—a principle that can be translated into supply chain management to develop systems capable of learning, adapting, and evolving in response to dynamic environments [9–11].

1.1. Research Gap and Motivation

Despite the growing attention to resilience in supply chain management, few models incorporate formal mechanisms for organizational memory and adaptive learning as part of resilience strategies [12]. Existing frameworks often address supply chain disruptions through static responses, lacking a dynamic perspective that captures the evolution of supply chain capabilities in the face of recurring risks[13,14]. Furthermore, while bio-inspired models (e.g., swarm intelligence, neural networks) have been occasionally applied in logistics and supply chain contexts, the analogy with the immune system—characterized by proactive defense, learning, and memory—remains largely unexplored in supply chain resilience research [15].

1.2. Research Aim and Objectives

To address these gaps, this paper proposes a novel immune system-inspired dynamic model for designing resilient, agile, and financially viable supply chains, focusing on the integration of organizational memory as a core mechanism for adaptive response. The specific objectives of this research are:

- To develop a dynamic model inspired by the human immune system, incorporating both innate and adaptive responses, including organizational memory mechanisms, to address supply chain disruptions.
- To simulate and analyze the behavior of supply chains under different disruption scenarios, evaluating the role of organizational memory and adaptation in enhancing supply chain resilience, viability, agility, and sustainability.
- To provide a quantitative and theoretical contribution to the supply chain resilience literature, demonstrating how biological analogies can inform the design of supply chains capable of learning and evolving over time.

1.3. Contribution and Novelty

This study makes several key contributions to the field of supply chain resilience and management science:

1. Interdisciplinary Innovation: By applying concepts from immunology to supply chain design, this paper introduces a novel interdisciplinary approach that extends beyond traditional engineering or operational models, offering a biologically grounded understanding of resilience, adaptation, and learning.
2. Formal Dynamic Modeling: The research develops a set of nonlinear differential equations that capture the dynamic interactions between supply capacity, financial performance, disruption

Preprints.org (www.preprints.org) | NOT PEER-REVIEWED | Posted: 16 March 2026 doi:10.20944/preprints202603.1187.v1

intensity, adaptation, and organizational memory—quantifying how supply chains evolve under stress.

3. Organizational Memory as a Core Mechanism: The model explicitly integrates organizational memory, enabling supply chains to not only respond to disruptions but to learn and improve their response over time, thus closing a critical gap in existing resilience frameworks.
4. Application to Agro-industrial Supply Chains: The model is applied to a realistic case of a global agro-industrial supply chain (panela industry), demonstrating its relevance and transferability to sectors highly exposed to supply and demand disruptions, including agriculture, food, and pharmaceuticals.

The remainder of this paper is structured as follows. Section 2 reviews the literature on supply chain resilience and bio-inspired models, highlighting the theoretical foundations of the proposed approach. Section 3 details the methodology and the development of the immune system-inspired dynamic model. Section 4 presents the case study and simulation setup, followed by Section 5, which discusses the results of various disruption scenarios. Finally, Section 6 concludes the paper, outlining theoretical and managerial implications, as well as directions for future research.

2. Theoretical Background

2.1. Supply Chain Resilience: Definitions, Dimensions, and Gaps

Supply chain resilience (SCR) refers to the capacity of a supply chain to prepare for, respond to, and recover from disruptive events while maintaining its core functions and structure [16]. It encompasses not only the ability to absorb shocks but also to adapt to new realities and ensure long-term viability [5,17] .

Literature has identified several key dimensions of resilience, including redundancy, flexibility, collaboration, visibility, and adaptability [18,19]. However, the dominant focus has been on static or short-term mechanisms, such as increasing safety stock, dual sourcing, or flexible logistics [4]. Despite significant advances, existing resilience frameworks exhibit critical gaps:

- Limited integration of dynamic and systemic views of resilience, with most models focusing on individual capabilities rather than their interaction over time [6].
- Lack of explicit organizational learning and memory mechanisms, which are crucial for evolving resilience in the face of recurring or prolonged disruptions [20].
- Underrepresentation of models that integrate financial viability as part of resilience, often separating operational continuity from economic sustainability [21].

Thus, there is a clear need for models that not only ensure short-term responses but also enable supply chains to learn, adapt, and evolve, maintaining operational and financial viability under uncertainty.

2.2. Organizational Memory and Learning in Supply Chains

Organizational memory refers to the institutionalized knowledge that organizations accumulate from past experiences, enabling them to adapt more effectively to future challenges [20]. In supply chain contexts, organizational memory includes:

- Historical data on disruptions and responses.
- Lessons learned from crises and recovery processes.
- Institutionalized adaptive capabilities, such as flexible sourcing protocols or collaborative frameworks [22].

Although organizational learning has been explored in management science, its integration into supply chain resilience models remains underdeveloped [23]. Notably, most supply chain frameworks treat responses as static strategies, lacking mechanisms for adaptive improvement based on cumulative experience. This omission is critical since resilience should not be seen as a fixed capacity but as a dynamic capability that evolves over time [24].

2.3. Bio-Inspired Models in Supply Chain Management: Opportunities and Limitations

In recent years, bio-inspired models—drawing analogies from natural systems—have gained traction in supply chain management. Approaches based on swarm intelligence [15], neural networks, and genetic algorithms have been applied to optimize logistics, distribution, and inventory management Supply chain resilience[25,26].

However, most bio-inspired approaches focus on optimization and do not fully address resilience or adaptation to disruptions. Additionally:

- They lack multi-layered response structures that would allow different types of reactions (e.g., immediate vs. learned).
- They do not incorporate organizational memory as an evolving mechanism for future readiness.
- Their focus is primarily operational (e.g., routing, inventory levels), with limited integration of strategic and financial dimensions.

Thus, there remains significant untapped potential in leveraging biological systems that naturally deal with threats, such as the immune system, to inspire resilience and learning mechanisms in supply chains.

2.4. The Human Immune System as an Analogy for Resilient Supply Chains

The human immune system is a highly adaptive and resilient biological system, capable of detecting, neutralizing, and remembering threats [27]. It operates through two main subsystems:

- Innate immunity: Provides immediate, non-specific defense against pathogens, acting as the first line of response.
- Adaptive immunity: Develops targeted responses, including immune memory, enabling faster and more efficient reactions to recurring threats.

Key functional principles of the immune system relevant to supply chain resilience include:

- Rapid detection and response to external threats (analogous to disruption detection and immediate mitigation in supply chains).

Layered defense mechanisms are akin to combining proactive and reactive strategies in supply chains.

- Learning and memory creation (parallel to organizational memory and adaptive capability development).

Balancing responsiveness and sustainability to avoid overreaction (analogous to balancing operational and financial sustainability in supply chains) [28]. Despite its relevance, the analogy between the immune system and supply chain resilience has not been fully formalized or mathematically modeled in literature. By emulating the immune system's logic, supply chains could develop multi-layered responses combining immediate actions with long-term adaptation and memory.

2.5. Theoretical Contribution: Toward an Immune System-Inspired Supply Chain Resilience Model

Building on these insights, this paper proposes an immune system-inspired dynamic model for supply chain resilience, which:

- Integrates innate and adaptive responses, enabling both immediate reactions and long-term adaptation.
- Formalizes organizational memory as a dynamic, evolving capability, supporting faster responses to future disruptions.
- Captures the interactions between operational (supply capacity), strategic (adaptation), and financial (performance) dimensions.
- Provides a quantitative framework based on differential equations, simulating the temporal evolution of disruptions, responses, and learning processes.

This theoretical contribution aims to fill critical gaps in current supply chain resilience literature by offering a holistic, dynamic, and bio-inspired framework, extending beyond static and isolated risk management strategies.

3. Methodology

3.1. Research Approach

This study employs a quantitative modeling approach based on biological analogy and system dynamics to develop a resilient supply chain model inspired by the human immune system. The research follows a multi-phase methodology, including:

- Conceptual modeling: Establishing the analogy between the immune system and supply chain resilience.
- Mathematical formulation: Defining dynamic interactions using a system of nonlinear differential equations.
- Computational simulation: Implementing the model to evaluate resilience under different disruption scenarios.
- Comparative analysis: Assessing the impact of innate responses, adaptive mechanisms, and organizational memory on supply chain performance.

By integrating biological defense mechanisms into supply chain resilience strategies, this study proposes a novel adaptive framework capable of responding dynamically to disruptions.

3.2. Conceptual Model: Immune System Analogy for Supply Chains

The human immune system provides an effective defense mechanism against external threats, combining:

- Innate immunity: Immediate, non-specific defense mechanisms.
- Adaptive immunity: Specific, learned responses that improve over time through memory cells.

By analogy, resilient supply chains must:

- React immediately to disruptions (innate responses: redundancy, flexibility).
- Develop long-term strategies based on past disruptions (adaptive responses and memory).

As illustrated in Figure 1, the immune system-inspired supply chain model consists of:

1. Disruptions (external threats): Events affecting supply chain stability (e.g., geopolitical crises, pandemics).
2. Innate Response (immediate reaction): Includes redundant suppliers, safety stock, and flexible logistics.
3. Adaptive Response (learning-based mechanisms): Alternative sourcing strategies, financial risk management, and strategic alliances.
4. Organizational Memory (knowledge retention and initiative-taking adaptation): Enables faster and more efficient responses to future disruptions.
5. Resilient, agile, sustainable, and viable supply chain: The result of adopting immune-like responses.

The framework illustrates how external disruptions affect supply chain stability through the disruption intensity variable $Z(t)$. The supply chain reacts through two layers of response analogous to the human immune system. The first layer, the *innate response*, represents immediate operational mechanisms such as redundancy, safety stocks, and flexible logistics, which help maintain supply capacity $S(t)$. The second layer corresponds to the *adaptive response* $A(t)$, which emerges through strategic adjustments such as supplier reconfiguration and dynamic resource allocation. Over time, the system accumulates *organizational memory* $M(t)$, enabling faster and more efficient responses to future disruptions. The combined interaction of these mechanisms determines the evolution of financial performance $F(t)$and the overall resilience, agility, and sustainability of the supply chain.

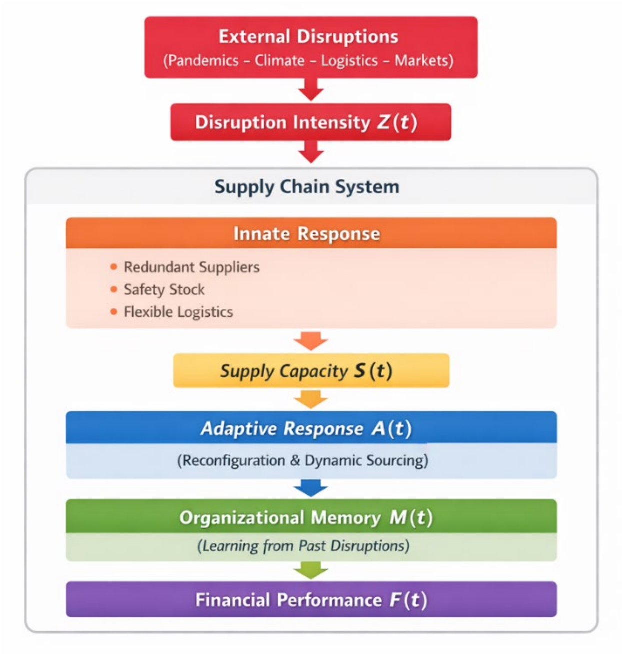

Figure 1. Immune system inspired dynamic framework for supply chain resilience.

3.3. Mathematical Model Formulation

The model likens supply chain disruptions to biological external threats and posits that the response relies on innate and adaptive mechanisms. Basic flexibility, redundancy, and safety stock help but are only partially effective against severe or long-term disruptions. Adaptive responses, such as reconfiguration of suppliers, dynamic inventory management, and strategic partnerships, require activation and development time, depending on the disruption intensity. Moreover, the model incorporates organizational memory as an accumulated knowledge mechanism, which enhances the efficiency and speed of future adaptive responses. Disruptions affect both operational capacity and financial viability of the supply chain over time. Finally, the model presumes that all these components—disruption level, supply capacity, inventory, adaptation, memory, and financial performance—are dynamically interrelated, evolving over time as feedback loops within the system. These assumptions align with the biological analogy of the immune system and provide a comprehensive foundation for modeling supply chain resilience as a dynamic and evolving capability.

The model compares supply chain disruptions to pathogenic threats, represented by the dynamic disruption level Z(t). The supply chain's response to disruptions depends on inherent and adaptive mechanisms, facilitated by a set of interacting variables and parameters. To simplify, we assume that:

i. $\boldsymbol{Z}(\boldsymbol{t})$: represents the intensity of disruption, analogous to the concentration of pathogens, which directly affects operational capacity and financial performance.
ii. $\boldsymbol{S}(\boldsymbol{t})$: denotes the available supply capacity, reflecting the ability of the supply chain to maintain product and service flows under stress.
iii. $\boldsymbol{P}(\boldsymbol{t})$: epresents finished-product availability or inventory level in the supply chain..
iv. $\boldsymbol{A}(\boldsymbol{t})$: represents active adaptation mechanisms, such as dynamic reconfiguration of sourcing, logistics, and production. These mechanisms respond to disruptions, increase with disruption levels, and decrease over time if not sustained.

 doi:10.20944/preprints202603.1187.v1

v. $Z_{mem}(t)$: represents the organizational memory, which accumulates as the supply chain learns from exposure to disruptions, enhancing the effectiveness and speed of future adaptive responses.

vi. $\boldsymbol{F(t)}$: measures financial performance, directly affected by disruptions and enhanced by adaptation mechanisms and organizational memory.

Disruptions change over time, influenced by the supply chain's ability to adapt and learn. The model suggests that feedback loops define the system, where higher disruption leads to adaptation and learning, and accumulated memory enhances future resilience. Finally, financial performance is not only a result of operational capacity but also a determinant of the long-term viability of the system, reflecting the systemic nature of supply chain resilience.

These assumptions form the basis for the system of nonlinear differential equations described in the next section, where each variable interacts dynamically, capturing the evolving relationship between disruption intensity, operational responses, and organizational learning. The core equations governing the system dynamics are:

1. **Disruption Dynamics:** The disruption (or "infection") within the supply chain evolves in response to the intensity of external stressors, including climatic events, governmental interventions, and transportation failures, as well as the magnitude of the initial disruption event.

$$\frac{dZ(t)}{dt} = \alpha_1 \cdot \big(1 - Z(t)\big) - \beta_1 \cdot S(t) \cdot Z(t) \tag{1}$$

- α_1: Rate of disruption expansion (analogous to pathogen replication).
- β_1: Rate of disruption mitigation through supplier interventions or capacity adaptations.
- The term$(1 - Z(t))$ indicates that as the disruption approaches its maximum level (value 1), it becomes increasingly difficult for it to propagate further.

2. **Innate Immune Response (recognition and absorption of the disruption):** The monitoring and prompt response capabilities of the supply chain's immune system—such as early warning systems or disruption detection mechanisms—act to limit the spread of the disruption.

$$\frac{dS(t)}{dt} = \gamma_1 \cdot \big(1 - S(t)\big) - \delta_1 \cdot Z(t) \cdot S(t) \tag{2}$$

- γ_1: Rate of capacity expansion in response to a disruption, such as increasing supplier capacity or redirecting resources.
- δ_1: Rate of supply capacity reduction due to the disruption itself.

3. **Production processes and disruptions impact product inventory**: As disruptions intensify, the supply chain's ability to transform operational capacity into available products is reduced, while dispatches and disruption-related losses continue to deplete product availability. This dynamic is represented as:

$$\frac{dP(t)}{dt} = r_I \cdot S(t) - r_S \cdot P(t) - \delta_2 \cdot Z(t) \cdot P(t) \tag{3}$$

- r_I: Rate of conversion of inputs into finished products.
- r_S: Rate of product dispatch (sales).
- δ_2: Rate of product loss due to disruption in the supply chain.

4. **Adaptive Immune Response (Active Recovery and Adaptation):** The active response to a disruption involves actions taken by the firm—analogous to the role of cytotoxic T cells—to recover quickly from the effects of the disruption and restore the flow of products throughout the supply chain.

$$\frac{dA(t)}{dt} = \alpha_2 \cdot (S(t) - S_{lim}) + \beta_2 \cdot (P(t) - P_{min}) \cdot Z(t) \tag{4}$$

- α_2: Rate of adjustment of active adaptation capacity in response to the disruption.
- β_2: Rate of active recovery in response to the disruption.

 doi:10.20944/preprints202603.1187.v1

- S_{lim} y P_{min} represent the upper and lower bounds of supply capacity and product inventory, respectively.

5. **Organizational Memory Accumulation** (Passive Adaptive Immune Response - Absorption and Future Prevention**):** In the long term, memory B cells can mitigate the impact of future disruptions through passive adaptation strategies. This is evident in the adjustment of safety stock levels and the revision of contingency plans, which enable the supply chain to be more effectively prepared for similar events.

$$\frac{dZ_{mem}(t)}{dt} = \gamma_3 \cdot A(t) - \delta_3 \cdot Z_{mem}(t) \qquad (5)$$

- $Z_{mem}(t)$: Stores memory of the disruption for future use.
- γ_3: Rate of active memory formation that enables the firm to learn from the disruption.
- δ_3: Rate of disruption memory decay.

6. Financial Performance Impact:

$$\frac{dF(t)}{dt} = -k_F Z(t) \cdot F(t) + k_{Fm}(A(t) + Z_{mem}(t))(1 - F(t)) \qquad (6)$$

- k_F: Represents financial loss due to disruptions.
- k_{Fm}: Is financial resilience improvement from adaptation.

This system captures **the dynamic feedback between disruption impact, adaptation, and long-term resilience**, quantifying the role of **organizational memory as a critical enabler of supply chain recovery**.

3.4. Simulation Setup

The model is simulated under three distinct scenarios to evaluate the effects of adaptive and memory-based resilience strategies:

Scenario	**Description**
Total System Collapse	No adaptation, no memory. Disruptions escalate without containment.
Baseline Resilience	Innate responses only (flexibility, redundancy), but no memory.
Organizational Memory	Adaptive learning enables faster responses and improved resilience.

3.4.1. Empirical Plausibility Check and Case Study Alignment

Second, an empirical plausibility check is conducted to align the model's dynamics and outcomes with observed behaviors in real supply chains during major disruptions, such as:

- Global supply chain failures during the COVID-19 pandemic, including shortages of essential goods, transportation collapses, and financial strain [1,29].
- Agricultural supply chain disruptions faced by agro-industrial sectors (e.g., panela industry), where climatic events and market restrictions cause sudden drops in supply capacity and require adaptive responses.

By comparing simulation results with real-world cases, we ensure that the model's behavior reflects plausible supply chain responses, such as:

- Delayed adaptation and partial recovery when learning mechanisms are absent.
- Rapid containment of disruption and financial stabilization when organizational memory and proactive strategies are present.

Thus, the model's simulated trajectories (e.g., supply capacity recovery, disruption intensity containment) are cross validated against historical patterns of known disruption scenarios.

To complement the empirical validation, expert judgment is employed to assess the relevance and completeness of the proposed mechanisms. This includes:

- Validation of whether the identified responses (innate, adaptive, memory) correspond to real practices and needs in modern supply chains.

 doi:10.20944/preprints202603.1187.v1

- Review of the feedback loops modeled (e.g., how learning from disruption enhances future adaptation).

This ensures that the model reflects not only theoretical analogies, but also actionable mechanisms recognized by practitioners.

1. Case study and simulation setup

To validate and apply the proposed immune system-inspired dynamic model for supply chain resilience, a case study was developed based on a real-world agro-industrial supply chain. This supply chain involves the production and distribution of panela (unrefined whole cane sugar), which is an essential commodity in several countries and is particularly relevant to rural economies and food security systems. The panela supply chain was chosen due to its exposure to recurrent systemic disruptions, including climate events, transportation failures, market volatility, and regulatory changes that frequently affect both the upstream and downstream segments of the supply network.

3.5. Description of the Supply Chain Case

The selected supply chain includes multiple interconnected actors, such as:

- Small and medium-scale sugarcane producers, often located in rural regions.
- Intermediate processors and panela production facilities, where sugarcane is transformed into panela blocks, granules, or other forms.
- Logistics providers, managing the transportation of raw materials and finished products.
- Distributors and retailers, responsible for domestic and international market placement.
- Final consumers, including households and industrial clients.

The supply chain operates in a context of high vulnerability, facing challenges such as:

- Weather variability (e.g., droughts, floods affecting sugarcane crops).
- Logistical disruptions, including road blockages and port congestion.
- Regulatory disruptions, such as changes in trade policies and sanitary restrictions.
- Demand volatility, influenced by price fluctuations in both local and export markets.

These factors create a complex environment that makes resilience a critical capability for ensuring continuous operation and financial viability.

3.6. Alignment of the Model with the Case Study

The immune system analogy maps directly onto the operational logic of the panela supply chain:

- Disruptions ($Z(t)$) represent external threats such as climatic shocks, market closures, or logistics interruptions.
- Supply capacity ($S(t)$) captures the ability to produce and deliver panela under disruption.
- Inventory ($P(t)$) represents available stocks of panela products.
- Active adaptation ($A(t)$) reflects mechanisms such as alternative sourcing, temporary contracts, and reallocation of production resources.
- Organizational memory ($Z_{mem}(t)$) accounts for learning from previous disruptions, including improved contingency plans and flexible sourcing strategies.
- Financial performance ($F(t)$) measures the economic viability of the chain under stress.

3.7. Parameterization for Simulation

To simulate the behavior of the panela supply chain under disruption, specific parameter values were assigned to each of the key processes modeled through nonlinear differential equations. These values were defined based on qualitative and quantitative assessments of historical data, expert consultations with supply chain managers, and review of secondary sources on agro-industrial supply chains under disruption.

Simulations run for 50 days using Runge-Kutta (RK45) numerical integration with these initial conditions:

Initial Disruption Level: $Z(0) = 0$ (system starts in stable condition).
Initial Supply Capacity: $S(0) = 0.8$ (80% of full capacity).
Initial Adaptation and Memory: $A(0) = 0$, $Z_{mem}(0) = 0$.
Initial Financial Performance: $F(t) = 1$ (100% financial health).

Key Parameter Values:

To model the impact of disruptions on the supply chain, the system of differential equations was assigned the following parameter values:

- α_1 = 0.3: Rate of disruption expansion.
- β_1 = 0.02: Rate of disruption mitigation through supply chain interventions.
- γ_1 = 0.1: Rate of supply capacity expansion.
- δ_1 = 0.4: Rate of supply capacity reduction due to disruption.
- r_I = 0.7: Rate of conversion of inputs into finished products.
- r_S = 0.6: Rate of product dispatch (sales).
- δ_2 = 0.05: Rate of product loss due to disruption.
- α_2 = 1.5: Rate of adjustment of active adaptation capacity in response to disruption.
- β_2 = 0.2: Rate of active supply chain recovery.
- S_{lim} = 0.5: Upper limit of supply capacity under critical conditions.
- P_{min} = 2000: Minimum level of product availability required for survival.
- γ_3 = 0.6: Rate of active memory formation for future adaptation.
- δ_3 = 0.02: Rate of disruption memory decay.
- k_F = 0.3: Financial loss due to disruptions

3.8. Validation Strategy

Validating the immune system-inspired supply chain resilience model is essential to confirm its theoretical soundness and practical applicability. A multi-tiered validation strategy is employed, combining conceptual, empirical, and sensitivity analysis approaches.

3.8.1. Theoretical and Structural Validation

The conceptual framework and dynamic interrelations of the model are substantiated through an extensive examination of literature on supply chain resilience and adaptive systems [5,30]. The relationship between the functions of the human immune system and the elements of supply chain resilience is carefully structured to maintain logical consistency and align with biological defense mechanisms, particularly:

- The correspondence between innate immune responses and operational flexibility/redundancy.
- The analogy between adaptive immune responses and organizational learning/adaptation mechanisms.
- The role of immune memory and organizational memory in enabling faster, more targeted responses to recurring threats.

This conceptual validation ensures that the proposed model reflects both biological principles and supply chain realities.

3.9. Simulation Design and Scenarios

To explore the dynamic behavior of the supply chain, three main scenarios were simulated:

Total System Collapse:

A critical scenario where neither adaptation mechanisms nor organizational memory are present. This represents a worst-case situation in which the disruption grows without containment, leading to total breakdown of supply and financial systems.

$$\alpha_2 = 0, \beta_2 = 0, \gamma_3 = 0$$

Baseline Resilience:

 doi:10.20944/preprints202603.1187.v1

A scenario where only innate responses such as basic flexibility and safety stock are available. Here, the system can react to disruptions but lacks learning and active adaptation, showing limited resilience.

$$\gamma_3 = 0$$

With Organizational Memory:

A scenario where adaptive mechanisms and organizational memory are fully operational. This represents a resilient and learning supply chain capable of responding dynamically and improving over time. Each simulation was conducted over a 50-day period, with disruptions introduced on day 10, simulating the sudden onset of a systemic shock. The Runge-Kutta (RK45) method was employed to solve the system of nonlinear differential equations, ensuring accurate time-based evolution of all variables.

In the proposed model, innate response mechanisms are not represented as an independent state variable. Instead, they are embedded in the dynamics of supply capacity $S(t)$, which captures the immediate operational reaction of the supply chain through flexibility, redundancy, and short-term absorption capacity.

4. Results and Discussion

This section presents the results of the immune system-inspired supply chain resilience model. First, we analyze the scenario-based simulations, evaluating the effects of different levels of organizational adaptation and learning. Second, a sensitivity analysis is conducted to identify the most influential parameters affecting resilience, agility, and viability. Finally, we discuss the practical implications of these findings for supply chain management.

4.1. Scenario-Based Analysis: The Role of Organizational Memory and Adaptation

To understand the impact of adaptive mechanisms and organizational learning on supply chain resilience, three distinct scenarios were simulated:

(1) Total System Collapse – representing a case with no adaptation or organizational memory,

(2) Baseline Resilience – incorporating innate response mechanisms (e.g., basic flexibility and redundancy) but lacking learning, and

(3) With Organizational Memory – combining both innate and adaptive responses, including accumulated organizational memory to enable faster and more efficient reactions.

These scenarios allow for the analysis of how different levels of organizational capabilities influence supply chain performance in the face of severe and prolonged disruptions. The analysis focuses on four critical dimensions of resilience: operational capacity (S), financial performance (F), disruption containment (Z), and adaptive response (A).

4.1.1. Supply Chain Resilience Across Scenarios

The evolution of supply capacity *(S)* over time under each scenario is presented in Figure 2. The results highlight significant differences in the ability to maintain and recover operational capacity depending on the level of adaptive and learning mechanisms available. Figure 2 illustrates the temporal evolution of key system variables following the onset of a disruption at day 10 (red dashed line). The upper panels show the response of supply capacity $S(t)$ and financial performance $F(t)$, both experiencing a short-term decline followed by gradual recovery. The lower panels present the dynamics of active adaptation $A(t)$ and organizational memory $Z_{mem}(t)$, which progressively increase as the system learns from the disruption, as well as the disruption intensity $Z(t)$ affecting the supply chain. Together, these trajectories illustrate how adaptive responses and learning mechanisms contribute to the recovery and stabilization of supply chain performance.

In the Total System Collapse scenario, supply capacity experiences an immediate and irreversible collapse, rapidly falling to nearly 0% after the disruption onset. This scenario illustrates the extreme vulnerability of supply chains that lack both innate and adaptive resilience capabilities, confirming findings in the literature on supply chain fragility when resilience is not proactively designed. In contrast, the Baseline Resilience scenario, which includes innate responses such as safety stock and alternative suppliers, slows down the collapse of capacity, but fails to fully recover even after 50 days. Supply capacity drops to approximately 50% and stabilizes at that level, demonstrating that innate mechanisms alone are insufficient to restore full operational performance under severe disruptions, aligning with arguments that resilience requires more than mere redundancy.

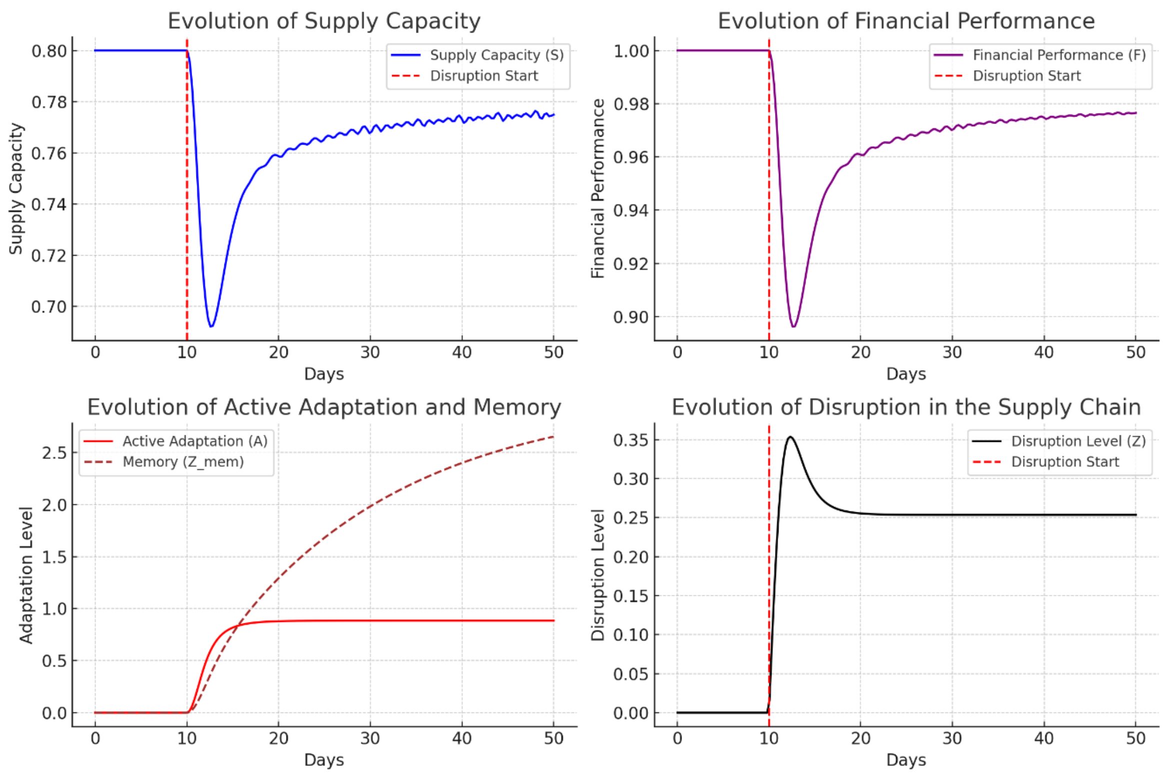

Figure 2. *Dynamic behavior of the immune-inspired supply chain model under disruption.*

4.1.2. Financial Viability and Disruption Containment

In the Total System Collapse scenario, financial performance deteriorates irreversibly, falling below 20% of pre-disruption levels, reflecting the compounded impact of operational failures on revenue and cost structures. This result aligns with studies that highlight the financial fragility of supply chains when resilience is absent [1]. In the Baseline Resilience scenario, although financial performance does not collapse entirely, it remains significantly compromised, stabilizing at around 50% of the initial value. This indicates that basic redundancy and safety stock mechanisms can only partially protect financial viability, and without learning and adaptive responses, prolonged disruptions continue to erode profitability and operational sustainability. Figures 3 and 4 illustrate the evolution of financial performance *(F)* and disruption intensity *(Z)* under each scenario.

Conversely, in the Organizational Memory scenario, financial performance recovers to approximately 95% of pre-disruption levels within 30 days, showing a robust capacity to regain financial health. This is primarily driven by adaptive responses *(A)* and organizational learning *(*Z_{mem}*)*, which allow the system to restore supply flows and re-establish customer relationships quickly, minimizing revenue losses and cost overruns. In terms of disruption intensity *(Z)*, Figure 3 shows that in the absence of adaptive mechanisms (Total System Collapse), disruption intensity peaks at near 80% and remains elevated, reflecting the inability to contain or neutralize the disruption. Even in the Baseline Resilience scenario, disruption intensity stabilizes around 60%, indicating that innate responses are insufficient to fully suppress the disruptive effects. Figure 3 compares the evolution of supply capacity $S(t)$across three scenarios following the disruption onset at day 10. In the Total System Collapse scenario (red dashed line), the absence of adaptive and learning mechanisms leads to a rapid and irreversible decline in operational capacity. In the Baseline Resilience scenario (blue dash–dot line), basic redundancy mechanisms partially stabilize the system, limiting the capacity drop but preventing full recovery. In contrast, the Organizational Memory scenario (green solid line) demonstrates a stronger recovery trajectory, as adaptive responses and accumulated learning allow the supply chain to restore operational capacity more effectively over time.

However, in the Organizational Memory scenario, disruption intensity is contained below 40% and rapidly decreases, confirming that learning from past disruptions and proactive adaptation are critical to minimizing the operational impact of future disruptions. These results reinforce the concept that resilience is an evolving capability, as argued by [14], and requires continuous development and investment in learning processes.

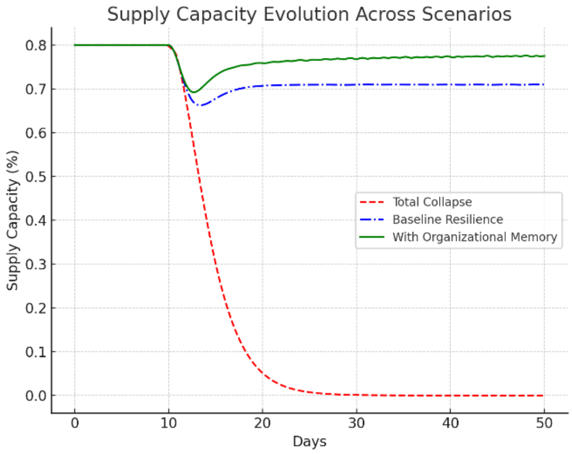

Figure 3. Supply capacity dynamics under different disruption-response scenarios.

The most favorable results are observed in the Organizational Memory scenario, where the supply chain limits the drop in capacity to 70% and recovers to 90% within 20 days. This scenario demonstrates that the integration of adaptive mechanisms and organizational memory enables faster and more effective responses, supporting the supply chain's capacity to dynamically adjust operations, reallocate resources, and resume production and distribution activities. These findings confirm that organizational learning and adaptation are essential components of resilient supply chains.

4.1.3. Adaptive Response and Learning Activation

A crucial insight from the scenario-based analysis is the central role that active adaptation *(A)* and organizational memory *(Z_{mem})* play in determining the supply chain's capacity to withstand and recover from disruptions. These two dynamic mechanisms are essential to explain how resilient supply chains develop both immediate and long-term responses to external shocks, shaping not only the trajectory of recovery but also the capacity to manage future disruptions more effectively.

In the Total System Collapse scenario, neither active adaptation nor memory mechanisms are activated, as expected in a system devoid of resilience capabilities. The absence of these mechanisms results in a complete collapse of supply capacity and financial performance, leaving the system highly vulnerable to the initial and ongoing effects of disruption. This scenario demonstrates that without any dynamic capability for adaptation or learning, supply chains are unable to contain, mitigate, or recover from adverse events, confirming theoretical insights from the literature that emphasize the necessity of dynamic resilience element.

 doi:10.20944/preprints202603.1187.v1

In the Baseline Resilience scenario, limited adaptive response *(A)* is observed. Although some degree of flexibility and operational adjustments are deployed — such as reallocating available inventory or shifting minor production resources — these actions are insufficient to restore full operational performance. More importantly, the system lacks any form of organizational memory (Z_{mem} remains null), meaning that no learning is accumulated to improve responses to future disruptions. This finding reflects the limitations of purely reactive strategies, which, while offering short-term containment, do not foster long-term resilience-building processes. Such findings align with prior research indicating that organizations relying solely on basic flexibility and redundancy remain vulnerable to recurrent and severe disruptions.

The most significant and positive outcomes are observed in the Organizational Memory scenario, where both active adaptation *(A)* and organizational memory (Z_{mem}) are fully operational and interact dynamically. Following the onset of disruption, adaptive responses *(A)* are rapidly activated, peaking shortly after the disruption reaches its critical level. These adaptive responses encompass diversifying suppliers, reallocating production capacity, engaging alternative logistics channels, and implementing emergency procurement. As a result, the supply chain successfully limits the operational damage and begins to recover supply capacity and financial performance much faster than in the other scenarios.

Importantly, the presence of organizational memory (Z_{mem}) allows the system to accumulate knowledge and experience during and after disruption. This accumulated memory enhances the efficiency of adaptation mechanisms and reduces the response time in subsequent periods. Z_{mem} continues to grow even after the disruption has been contained, indicating that the supply chain is actively learning and storing relevant knowledge that will improve its resilience to future shocks. This behavior parallels the biological immune system's adaptive immunity, where the body retains memory cells to mount a faster and more effective defense when exposed to the same pathogen again — a key inspiration for the proposed model.

Moreover, the interaction between A and Z_{mem} generates a virtuous feedback loop: as the supply chain adapts and deploys solutions during a crisis, it simultaneously enhances its memory, which in turn improves the effectiveness of future adaptation efforts. This co-evolutionary process is at the core of dynamic resilience development, demonstrating that resilience is not a static trait, but a continuously evolving capability, as suggested in modern resilience and complex adaptive system (CAS) literature [31].

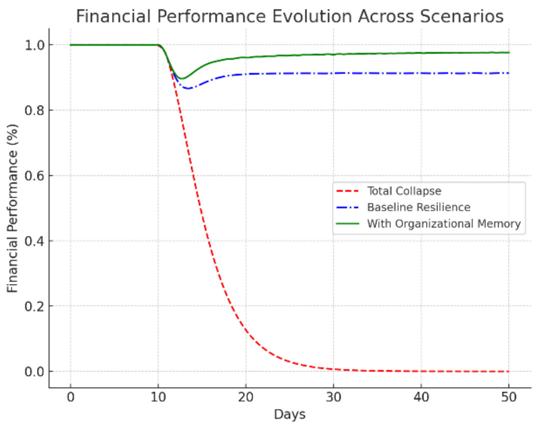

Figure 4. Financial performance dynamics under different disruption-response scenarios.

Figure 4 illustrates the evolution of financial performance $F(t)$ following the disruption event at day 10 under three supply chain response scenarios. In the Total System Collapse scenario (red dashed line), the absence of resilience mechanisms results in a rapid and irreversible deterioration of financial performance. In the Baseline Resilience scenario (blue dash–dot line), basic operational safeguards partially mitigate the impact, stabilizing financial performance at a reduced level. In contrast, the Organizational Memory scenario (green solid line) shows a stronger recovery trajectory, as adaptive responses and accumulated learning enable the supply chain to restore financial health and gradually approach pre-disruption performance levels.

From a managerial perspective, these results emphasize the need to design supply chains with embedded dynamic adaptation and learning mechanisms. This means that beyond preparing contingency plans, organizations must:

- Establish formal processes for capturing and institutionalizing lessons learned from disruptions, ensuring that knowledge is shared across all levels of the supply chain.
- Invest in technologies and tools that facilitate rapid detection of disruptions and support adaptive decision-making (e.g., AI-based supply chain risk analytics, real-time monitoring platforms).
- Develop cross-functional crisis response teams, capable of integrating operational, financial, and strategic responses dynamically during crises. Foster a culture of continuous improvement and knowledge sharing, where adaptive learning becomes part of the organizational DNA, enabling the supply chain to become increasingly resilient over time.

In sum, adaptive responses and organizational memory are interdependent and mutually reinforcing pillars of supply chain resilience. Supply chains that lack either of these elements remain exposed to both immediate and future risks. Conversely, systems that effectively combine dynamic adaptation and learning are not only able to recover more quickly from disruptions but are also able to anticipate and mitigate future risks proactively, moving beyond reactive crisis management toward a model of proactive and sustainable resilience.

4.1.4. Implications for Supply Chain Resilience Design

The scenario-based analysis provides critical insights into the strategic design of resilient supply chains, emphasizing the multidimensional nature of resilience and the need for integrated, dynamic capabilities that go beyond static measures such as redundancy or safety stocks.

First, the results highlight that resilience cannot depend solely on innate mechanisms, such as holding safety stock, redundant suppliers, or basic flexibility in logistics. While these elements provide a first line of defense, they are insufficient when facing prolonged, systemic disruptions. The Baseline Resilience scenario, although incorporating innate responses, fails to fully restore operational and financial performance, demonstrating that static solutions cannot cope with evolving and complex disruption scenarios. This reinforces prior findings in the literature, such as those by Christopher and Peck (2004), which argue that resilience must include dynamic capabilities that evolve with the environment.

Second, the model emphasizes the critical role of organizational memory in enhancing resilience. Supply chains that are capable of learning from disruptions, codifying responses, and integrating those lessons into operational strategies recover more rapidly and more completely. Organizational memory, as represented in the model by $Z_{mem}(t)$, enables the system to avoid past mistakes, deploy pre-tested contingency plans, and implement faster adaptive measures. This aligns with research that highlights the role of organizational learning as a key enabler of resilience [9]. Therefore, building and maintaining organizational memory through systematic after-action reviews, scenario simulations, and adaptive playbooks is a critical investment for long-term supply chain viability.

Third, the interaction between active adaptation (A) and organizational memory (Z_{mem}) creates a positive feedback loop that enhances resilience over time. As the system responds to a disruption, it not only deploys immediate adaptations but also learns from the event, improving its response capacity for future disruptions. This process reflects the biological analogy of the immune system, where adaptive immunity and memory cells allow the organism to respond more effectively to future threats. In supply chains, this translates to evolving risk management strategies, flexible contracts, and dynamic sourcing models that improve over time. This dynamic view of resilience is consistent with the perspective of supply chains as complex adaptive systems [32], which require constant learning and evolution to survive in volatile environments.

Moreover, the results show that resilience design must integrate structural robustness as a foundational element, upon which adaptation and learning mechanisms can operate effectively. Structural robustness refers to the inherent ability of the supply chain to absorb shocks without complete breakdown, achieved through supplier diversification, geographical dispersion, flexible production facilities, and redundancy in critical nodes. Without this foundation, even sophisticated adaptive mechanisms may fail to prevent systemic collapse, as demonstrated in the Total System Collapse scenario. This finding supports the argument by Ivanov and Dolgui [1] that resilience must balance efficiency with redundancy and flexibility to mitigate the risks of cascading failures.

Furthermore, the scenario analysis implies that resilience must be understood as a dynamic and systemic capability, rather than a set of isolated practices. The interplay of disruption intensity, supply capacity, adaptation, memory, and financial performance illustrates that disruptions affect multiple layers of the supply chain simultaneously, and responses must be coordinated across operational, strategic, and financial dimensions. Therefore, resilience strategies should be embedded in the governance of the supply chain, involving all relevant stakeholders — including suppliers, logistics partners, customers, and regulatory bodies — to ensure coordinated and effective responses.

From a managerial perspective, these insights highlight several actionable recommendations:

- Invest in dynamic adaptation mechanisms, such as real-time supply chain monitoring, AI-based demand sensing, and agile production systems, to enable rapid responses to emerging disruptions.
- Institutionalize organizational learning by creating formal processes for capturing and codifying lessons from past disruptions and ensure that these lessons inform contingency planning and strategic decisions.
- Design structurally robust supply chains, avoiding over-reliance on single suppliers or production sites, and ensuring alternative pathways for supply and distribution.
- Develop collaborative risk-sharing frameworks with key partners, including joint contingency plans and mutual aid agreements, to address disruptions that exceed the capacity of individual firms.
- Balance efficiency with resilience, recognizing that while lean operations are economically attractive, they must be tempered with sufficient buffers and redundancies to ensure survival under crisis conditions.

Finally, from a theoretical standpoint, these findings contribute to advancing the conceptualization of supply chain resilience by demonstrating that resilience emerges from the interaction of structural, adaptive, and learning capabilities, rather than from any single factor. This supports an integrated, systemic view of resilience that aligns with complex systems theory and offers a richer understanding of how supply chains can survive and thrive in environments characterized by persistent uncertainty and risk.

These findings confirm that supply chains that integrate both immediate adaptation and long-term learning are not only more resilient but also better positioned to anticipate and respond to future disruptions, moving toward a model of proactive resilience rather than reactive crisis management.

4.5. Sensitivity Analysis: Identifying Key Resilience Factors

The sensitivity analysis was performed to examine how changes in three key parameters affect the system's recovery trajectory: the adaptation rate k_A, the organizational memory accumulation rate k_{Zmem}, and the supply chain vulnerability parameter k_{Sm}. The results reveal that each parameter influences the system differently, highlighting distinct resilience mechanisms within the model.

4.5.1. Sensitivity to the Adaptation Rate $\boldsymbol{k_A}$

Figure 5 presents the sensitivity analysis of the adaptation rate parameter k_A. Increasing k_A improves the overall response of the system in several dimensions. A higher adaptation rate reduces the depth of the shock in supply capacity, improves the recovery path of financial performance, lowers the peak disruption level, and accelerates the buildup of active adaptation. Conversely, a lower value of k_A leads to deeper operational deterioration, worse financial losses, and a higher disruption peak.

Among the parameters analyzed, k_A shows the clearest system-wide effect. This suggests that the speed with which the supply chain activates adaptive responses is a decisive determinant of resilience. Faster adaptation not only improves operational recovery but also reduces the severity of the disruption itself.

From a managerial perspective, this implies that investments in agile sourcing, dynamic reconfiguration, responsive coordination mechanisms, and rapid decision protocols can significantly strengthen resilience performance.

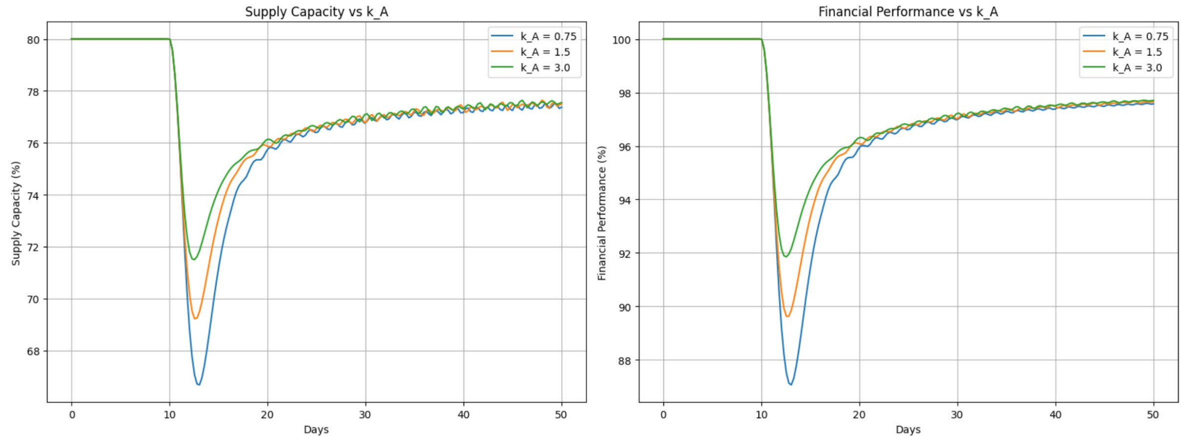

Figure 5. Sensitivity analysis of the adaptation rate parameter k_A.

4.5.2. Sensitivity to Organizational Memory $\boldsymbol{k_{Zmem}}$

Figure 6 shows the effect of varying the organizational memory accumulation parameter k_{Zmem}. The most visible effect appears in the trajectories of supply capacity and financial performance. When k_{Zmem} is higher, the system experiences a less pronounced operational decline and recovers toward a better long-run level. Financial performance also improves more steadily. However, the disruption level and active adaptation curves remain comparatively similar across parameter values.

This finding suggests that organizational memory acts primarily as a recovery enhancer rather than as an immediate disruption suppressor. In other words, memory does not strongly change the initial shock dynamics, but it improves how the system stabilizes and recovers once the disruption has taken place. This is consistent with the idea that learning mechanisms strengthen future responsiveness and improve recovery quality over time.

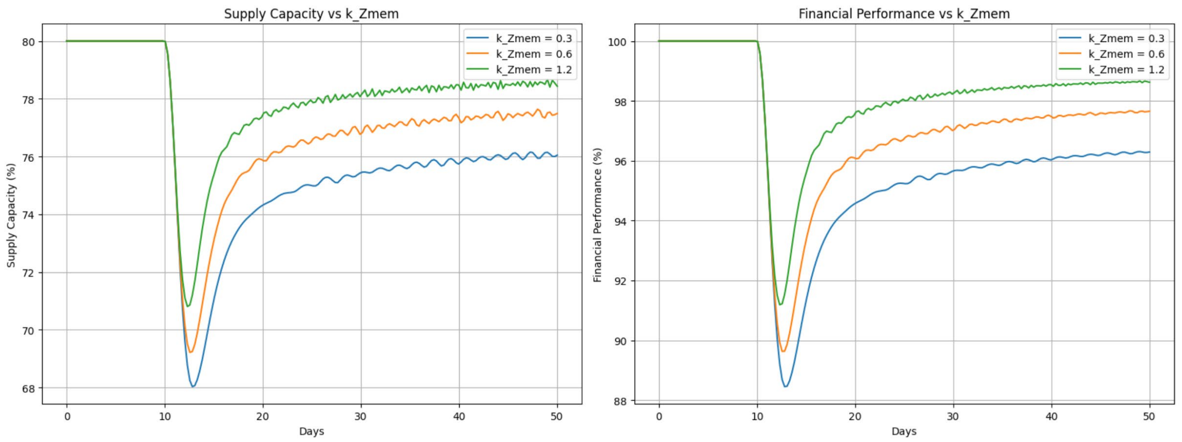

Figure 6. Sensitivity analysis of the organizational memory accumulation parameter k_{Zmem}.

Managerially, the result highlights the importance of post-disruption learning, documented contingency plans, knowledge repositories, and repeated training processes. These mechanisms do not eliminate disruptions directly, but they improve the system's ability to recover more effectively and sustain performance after the shock.

4.5.3. Sensitivity to Supply Chain Vulnerability $\boldsymbol{k_{Sm}}$

Figure 7 presents the sensitivity analysis for the supply chain vulnerability parameter k_{Sm}. In this case, the dominant effect is concentrated on supply capacity. Higher vulnerability leads to a much deeper decline in operational capacity and a lower long-run recovery level. By contrast, the effect on financial performance is relatively small, while disruption intensity and active adaptation remain almost unchanged across the tested values.

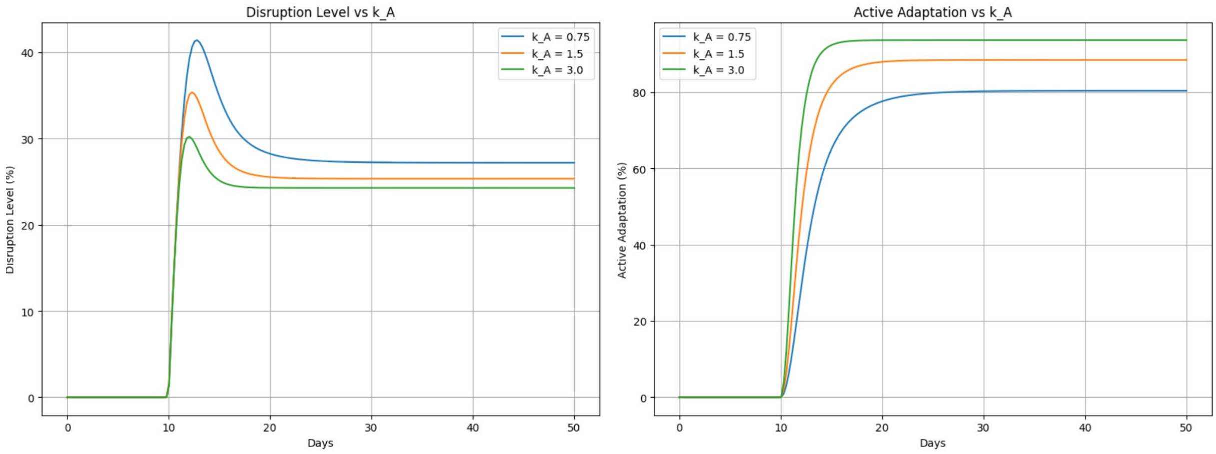

Figure 7. Dynamic interaction between disruption intensity and active adaptation.

This indicates that k_{Sm}captures a primarily structural weakness in the system. Vulnerability determines how strongly disruption translates into operational damage, but it does not substantially alter the generation of adaptive response or the shape of the disruption process itself. Thus, this parameter reflects the intrinsic fragility of the supply chain architecture.

From a managerial standpoint, this result underscores the value of structural resilience measures such as supplier diversification, redundancy in critical nodes, alternative logistics routes, and reduced dependency on single points of failure. These actions may not change the disruption event itself, but they substantially reduce its operational consequences.

4.6. Comparative Discussion

Taken together, the sensitivity analyses reveal three distinct resilience roles within the model. The adaptation rate k_A acts as the main driver of system-wide resilience, influencing operational recovery, financial recovery, adaptation buildup, and disruption containment. The organizational memory parameter k_{Zmem} mainly improves the quality and stability of post-disruption recovery, particularly in operational and financial terms. The vulnerability parameter k_{Sm}, in turn, controls the structural exposure of the system, primarily affecting the depth of the operational shock.

These results suggest that resilience in supply chains cannot be reduced to a single mechanism. Instead, resilient performance emerges from the interaction of rapid adaptation, accumulated learning, and reduced structural vulnerability. This reinforces the value of the immune system analogy adopted in this study: just as biological resilience depends on both immediate response and memory, supply chain resilience depends on combining adaptive action with learning and structural robustness.

The sensitivity analysis highlights that resilience in the proposed immune-inspired supply chain model arises from the interaction of adaptive response, organizational learning, and structural vulnerability. Rather than acting independently, these mechanisms shape different stages of the disruption–recovery trajectory observed in the simulations.

The parameter controlling the rate of active adaptation (k_A) exerts the strongest influence on the system's short-term response to disruption. As illustrated in Figure 5, higher values of this parameter reduce the depth of the operational shock and accelerate the recovery of both supply capacity and financial performance. When adaptive responses are activated more rapidly, the system reorganizes its operations sooner, allowing production flows and financial performance to stabilize more quickly. This pattern supports the view that agility and rapid response capabilities are central elements of supply chain resilience, particularly during the initial stages of disruption.

Organizational memory plays a different but complementary role in the recovery process. Variations in the parameter k_{Zmem}, shown in Figure 6, mainly affect the long-term stabilization of the system. Higher memory accumulation leads to stronger recovery levels for both operational capacity and financial performance, even though the immediate disruption dynamics remain relatively similar across scenarios. This suggests that learning mechanisms do not primarily suppress the initial shock but instead improve the quality and stability of the recovery trajectory. In practice, mechanisms such as knowledge sharing, post-disruption evaluations, and institutional learning can enhance the system's ability to regain stability after disturbances.

The interaction between disruption intensity and adaptive response further clarifies the internal dynamics of the model. As shown in Figure 7, higher adaptation rates lead to a faster increase in the active adaptation variable while simultaneously reducing the peak level of disruption intensity. This interaction indicates that disruptions are not only external shocks but also processes that can be progressively contained through internal system responses. The behavior resembles biological immune responses, where rapid activation of defense mechanisms limits the severity and duration of disturbances. These results suggest that resilient supply chains behave as adaptive systems in which response speed, accumulated learning, and structural robustness jointly determine recovery outcomes. Strengthening only one of these mechanisms is unlikely to produce sustained resilience; instead, effective recovery emerges from their coordinated interaction over time.

5. Conclusions

This study proposed a dynamic model of supply chain resilience inspired by the functioning of the human immune system. The model integrates disruption dynamics, operational capacity, financial performance, adaptive response, and organizational memory within a system of differential equations that captures the interaction between disruption propagation and recovery mechanisms over time. Through simulation experiments and sensitivity analyses, the study examined how key resilience parameters influence the behavior of supply chains under disruption.

The results show that resilience emerges from the interaction of several mechanisms rather than from a single protective capability. The rate of adaptive response plays a decisive role in shaping the immediate reaction of the system to disruption. Faster activation of adaptive mechanisms reduces the severity of operational shocks and accelerates the recovery of both supply capacity and financial performance. In contrast, slower adaptation allows disruptions to propagate more strongly before recovery begins. Organizational memory contributes primarily to the stability and quality of the recovery process. While learning mechanisms do not significantly alter the initial shock dynamics, they improve the long-term trajectory of operational and financial recovery. Supply chains with stronger learning capabilities are better able to stabilize their performance after disruption and regain operational capacity more effectively over time. The analysis also highlights the importance of structural vulnerability within supply chains. Systems with higher vulnerability parameters experience deeper operational losses and weaker recovery trajectories, emphasizing the role of network design, redundancy, and diversification in mitigating disruption impacts.

From a theoretical perspective, the study contributes to the literature on supply chain resilience by introducing an immune-system-inspired modeling framework that captures the dynamic interaction between disruption, adaptation, and learning. The model provides a conceptual bridge between biological resilience mechanisms and supply chain management, illustrating how adaptive response and memory can shape recovery trajectories in complex operational systems. Managerially, the findings suggest that improving supply chain resilience requires coordinated investment in rapid response capabilities, organizational learning processes, and structural robustness. Mechanisms such as agile decision-making, flexible sourcing strategies, and institutionalized learning from disruptions can significantly enhance the ability of supply chains to recover from shocks.

Several limitations of the study open avenues for future research. The model focuses on aggregated system dynamics and does not explicitly represent multi-echelon network structures or stochastic disruption processes. Future work could extend the framework to include network-level interactions, probabilistic disruption patterns, and empirical calibration using real supply chain data. Integrating the model with digital monitoring systems or machine learning-based disruption prediction tools may also provide valuable directions for advancing adaptive supply chain resilience modeling.

References

1. Ivanov D, Dolgui A. Viability of intertwined supply networks: extending the supply chain resilience angles towards survivability. A position paper motivated by COVID-19 outbreak. Int J Prod Res 2020;58:2904–15. https://doi.org/10.1080/00207543.2020.1750727.
2. Pettit TJ, Fiksel J, Croxton KL, Jackson R, Hellman T, Patel S, et al. Ensuring supply chain resilience: Development of a conceptual framework. JOURNAL OF BUSINESS LOGISTICS 2010;31. https://doi.org/10.1002/j.2158-1592.2010.tb00125.x.
3. Wagner SM, Bode C. An empirical investigation into supply chain vulnerability. Journal of Purchasing and Supply Management 2006;12:301–12. https://doi.org/10.1016/j.pursup.2007.01.004.
4. Sheffi Y, Rice JB. A Supply Chain View of the Resilient Enterprise. MIT Sloan Manag Rev 2005;47:41–8.
5. Christopher M, Peck H. BUILDING THE RESILIENT SUPPLY CHAIN. vol. 15. 2004. https://doi.org/10.1108/09574090410700275.
6. Ivanov D. Supply Chain Viability and the COVID-19 pandemic: a conceptual and formal generalisation of four major adaptation strategies. Int J Prod Res 2021;59:3535–52. https://doi.org/10.1080/00207543.2021.1890852.
7. Weng L, Xia M, Liu Q, Wang W. An immunology-inspired fault detection and identification system. Int J Adv Robot Syst 2012;9. https://doi.org/10.5772/51010.
8. Polo A, Morillo-Torres D, Escobar JW. An Immune-Structural Adaptive Response for Viability of Carbon Capture, Use, and Storage Supply Chains. Sustainability (Switzerland) 2025;17. https://doi.org/10.3390/su17219838.

9. Argote L, Miron-Spektor E. Organizational Learning: From Experience to Knowledge. Organization Science n.d.;22:1123–37.
10. Aslam H, ur Rehman A, Iftikhar A, ul Haq MZ, Akbar U, Kamal MM. Digital transformation: Unlocking supply chain resilience through adaptability and innovation. Technol Forecast Soc Change 2025;219. https://doi.org/10.1016/j.techfore.2025.124234.
11. Miller WB, Torday JS, Baluška F. Biological evolution as defense of 'self.' Prog Biophys Mol Biol 2019;142:54–74. https://doi.org/10.1016/j.pbiomolbio.2018.10.002.
12. Villar A, Abowitz S, Read R, Butler J. Maximizing Supply Chain Resilience: Viability of a Distributed Manufacturing Network Platform Using the Open Knowledge Resilience Framework. Operations Research Forum 2024;5. https://doi.org/10.1007/s43069-024-00303-1.
13. Najar T. Lean-Agile supply chain innovation performance; the mediating role of dynamic capability, innovation capacity, and relational embeddednes. Supply Chain Forum 2022;23:285–306. https://doi.org/10.1080/16258312.2022.2031276.
14. Han N, Um J. Risk management strategy for supply chain sustainability and resilience capability. Risk Management 2024;26. https://doi.org/10.1057/s41283-023-00138-w.
15. Liu B, Xu M, Gao L. Enhanced swarm intelligence optimization: Inspired by cellular coordination in immune systems. Knowl Based Syst 2024;290. https://doi.org/10.1016/j.knosys.2024.111557.
16. Ivanov D. Supply chain resilience: Conceptual and formal models drawing from immune system analogy. Omega (United Kingdom) 2024;127. https://doi.org/10.1016/j.omega.2024.103081.
17. Jia F, Hu S, Chen L. Does supply chain visibility improve firm resilience: An organizational information processing theory perspective. Transp Res E Logist Transp Rev 2025;204. https://doi.org/10.1016/j.tre.2025.104428.
18. Alhozaimy S, Menascé DA, Albanese M. Resilience and performance quantification of dynamic reconfiguration. Future Generation Computer Systems 2024;160:120–30. https://doi.org/10.1016/j.future.2024.05.040.
19. Ivanov D. Two views of supply chain resilience. Int J Prod Res 2024;62:4031–45. https://doi.org/10.1080/00207543.2023.2253328.
20. Alvarenga MZ, Oliveira MPV de, Oliveira T. Let's talk about bad experiences instead of forgetting them: An empirical study on the importance of memory for supply chain disruption management. Int J Prod Econ 2023;261. https://doi.org/10.1016/j.ijpe.2023.108872.
21. Tufan C, Çiğdem Ş, Kılıç Y, Sayar G. Agility and Resilience in Supply Chains: Investigating Their Roles in Enhancing Financial Performance. Sustainability 2024;16:7842. https://doi.org/10.3390/su16177842.
22. Blackhurst J, Rungtusanatham MJ, Scheibe K, Ambulkar S. Supply chain vulnerability assessment: A network based visualization and clustering analysis approach. Journal of Purchasing and Supply Management 2018;24:21–30. https://doi.org/10.1016/j.pursup.2017.10.004.
23. Wei S, Liu H, Chen X, Ke W. How does supplier integration influence supply chain robustness and resilience? The moderating roles of information technology agility and managerial ties. Information and Management 2024;61. https://doi.org/10.1016/j.im.2024.104028.
24. Alyasein OIY, Ojha D, Sadeghi R. K. Supply chain digitalization, innovation capability, and organizational agility: The moderating role of institutionalization and supply chain integration. Industrial Marketing Management 2025;125:215–25. https://doi.org/10.1016/j.indmarman.2025.01.008.
25. Pei H, Owari T, Tsuyuki S, Hiroshima T, Hong D. Combined gated graph convolution neural networks with multi-modal geospatial data for forest type classification. International Journal of Applied Earth Observation and Geoinformation 2025;136. https://doi.org/10.1016/j.jag.2025.104372.
26. Ivanov D. Intelligent digital twin (iDT) for supply chain stress-testing, resilience, and viability. Int J Prod Econ 2023;263. https://doi.org/10.1016/j.ijpe.2023.108938.
27. Yılmaz ÖF, Guan Y, Yılmaz BG. Designing a resilient humanitarian supply chain by considering viability under uncertainty: A machine learning embedded approach. Transp Res E Logist Transp Rev 2025;194. https://doi.org/10.1016/j.tre.2024.103943.

doi:10.20944/preprints202603.1187.v1

28. Khan ZA, Khan MT, Ul Haq I, Iqbal J, Tufail M. Human immune system inspired framework for disruption handling in manufacturing Process. Int J Comput Integr Manuf 2019;32:1081–97. https://doi.org/10.1080/0951192X.2019.1686174.
29. Huang A, Farboudi Jahromi M. Resilience building in service firms during and post COVID-19. Service Industries Journal 2021;41:138–67. https://doi.org/10.1080/02642069.2020.1862092.
30. Ruel S, El Baz J, Ivanov D, Das A. Supply chain viability: conceptualization, measurement, and nomological validation. Ann Oper Res 2021;335:1107–36. https://doi.org/10.1007/s10479-021-03974-9.
31. Wang J, Qin P, Chen L, Gu C, Yuan Y, Zhou H. Enhancing the topological robustness of supply chain networks against dynamic disruptions: A complex adaptive system perspective. Chaos Solitons Fractals 2025;199. https://doi.org/10.1016/j.chaos.2025.116767.
32. Ashby WR. Requisite Variety and Its Implications for the Control of Complex Systems. Cybernetica 1958;1:83–99. https://doi.org/10.1007/978-1-4899-0718-9_28.