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Research on Resilience Modeling and Optimization of Strategic Mineral Supply Chain

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Abstract: With the profound evolution of the global geopolitical landscape, the resilience of strategic mineral supply chains has become a key indicator for measuring the effectiveness of national resource security strategies. This article explores in depth the resilience characteristics and optimization paths of strategic mineral supply chains by combining system dynamics and game theory frameworks. A dynamic resilience modeling method based on resilience entropy and resilience coefficient was proposed, and a multidimensional risk analysis and resilience evaluation system was constructed to quantify the supply chain's ability to resist complex disturbances such as geopolitical risks, logistics bottlenecks, and technological substitution paths. The effectiveness of the multi-objective optimization strategy was verified through mixed integer programming and Monte Carlo simulation, and it was found that there is a significant negative correlation between cost and resilience, and the system's resilience is significantly improved under composite risk scenarios. Research has shown that enhancing the resilience of strategic mineral supply chains not only relies on technological innovation, but also requires national policy support and optimized resource allocation to ensure secure resource supply.

Keywords: Strategic minerals; Supply chain resilience; Monte carlo simulation; Strategic mineral supply chain

I. Introduction

Strategic minerals, as a core supporting element of the national industrial system (Hveem, 1986), have become a core indicator for measuring the effectiveness of national resource security strategies in the dual dimensions of global geopolitical restructuring and deepening industrial transformation due to their resilient supply chain characteristics (Shiquan & Deyi, 2023). The evolution of the global strategic mineral supply and demand pattern is essentially a dynamic process of coupling resource endowment, technological barriers, geopolitical games, and industrial power structure.

Its contradictory movement not only shapes the basic paradigm of international resource competition, but also profoundly affects the safety margin of national industrial and supply chains (Kim & Davis, 2016). Against the backdrop of intensified unilateralism and globalization, the vulnerability threshold of the strategic mineral supply chain continues to decrease, and its resilience construction has surpassed the purely industrial and economic scope, becoming a key dimension of national strategic capacity building (Zhang, 2025).

From a systems science perspective, the impact mechanism of strategic mineral supply chain disruptions exhibits typical complex system cascading effects. Its transmission path includes both structural fractures caused by node failure and functional attenuation caused by factor flow blockage, forming a nonlinear interaction through the topological structure of the supply chain network. The diffusion of this interruption effect follows the principle of "vulnerability amplification". With the unique scarcity and irreplaceability of strategic minerals, it can leap from micro market fluctuations to meso industry oscillations, ultimately reaching the bottom line of macroeconomic security. The depth and breadth of its impact depend on the synergy level of redundancy, connectivity, and adaptive adjustment capability of the supply chain system (Statsenko et al., 2018).

Resilience modeling, as a theoretical tool for analyzing the security situation of strategic mineral supply chains, has the core value of constructing a dynamic analysis framework for disturbance, response, and evolution (Childerhouse et al., 2020). In the academic dimension, it breaks through the limitations of the static equilibrium assumption in traditional risk assessment, integrates complex adaptive system theory with dynamic game analysis, and forms a theoretical system that combines explanatory power and foresight. By introducing core variables such as resilience entropy and resilience coefficient, the quantitative characterization of supply chain resistance, recovery speed, and transformation potential has been achieved, providing a practical theoretical explanation for the resilience characteristics of strategic mineral supply chains. In terms of practice, its methodological system provides systematic decision support for the formulation of national resource security strategies, promoting the transformation of resource security assurance from empirical to precise, and from passive response to active prevention and control (Jain et al., 2017).

The evolution trajectory of the supply chain resilience evaluation system presents a clear paradigm shift under the mapping of core academic indicators such as CiteScore.

The existing research has formed an analytical framework based on exposure, sensitivity, and fitness as the basic dimensions, with theoretical foundations covering multiple methodologies such as network analysis, system dynamics, and econometric modeling (Ivanov, 2025). However, the particularity of the strategic mineral supply chain determines that the existing system has structural deficiencies. Firstly, the evaluation dimension fails to fully integrate the attributes of resource sovereignty and geopolitical weight, resulting in a quantitative deviation in strategic value; Secondly, the static evaluation paradigm is difficult to adapt to the dynamic evolution characteristics of the supply chain system, and there is insufficient recognition of the path dependence and mutation points of resilience evolution; Thirdly, the weighting of indicators is often based on linear assumptions, which fail to reflect the marginal value differences of strategic minerals in different industrial cycles.

The theoretical limitations of the optimization model for mineral supply chain are essentially a manifestation of insufficient adaptability between methodology and research objects. The simplification of uncertainty in complex systems by deterministic assumptions leads to a lack of explanatory power for unstructured variables such as geopolitical risks; The multi-objective attributes of single objective optimization orientation and resilience enhancement have inherent tension, and the collaborative mechanism of cost efficiency and safety redundancy has not yet formed a theoretical closed loop; The static setting of model parameters is difficult to depict the behavioral evolution of supply chain entities, and the simulation accuracy of dynamic game processes involving multiple entities such as government, enterprises, and markets is limited. These limitations result in a significant gap between the application effectiveness and theoretical expectations of optimization models in complex scenarios of strategic mineral supply chains.

The lack of theoretical construction of dynamic risk response mechanisms is a core weakness in current research on the resilience of strategic mineral supply chains. The risk spectrum faced by the strategic mineral supply chain has typical characteristics of suddenness, conductivity, and evolution, and its response mechanism needs to achieve a dynamic closed-loop of the entire chain from "disturbance identification" to "strategy generation" and then to "efficiency feedback". Existing research mostly focuses on optimizing recovery strategies after the occurrence of risks, and there are theoretical gaps in the predictability of risk warning, the adaptability of response strategies, and the self-organization of mechanism operation. A dynamic response theoretical system that matches the strategic attributes of the strategic mineral supply chain has not been formed, resulting in a lag in theoretical research for practical guidance.

Based on this, this article proposes a dynamic resilience modeling method applicable to strategic mineral supply chains based on the framework of system dynamics and game theory. By introducing core variables such as resilience entropy and resilience coefficient, a supply chain resilience evaluation system was constructed to quantify the risk resistance and resilience of strategic mineral supply chains under complex disturbances such as geopolitical risks, logistics bottlenecks, and technological substitution paths. In addition, this article uses a mixed integer programming model, combined with Monte Carlo simulation and dynamic system simulation, to comprehensively analyze the resilience performance and optimization strategies of the supply chain in multiple risk scenarios.

II. Characteristics and Risk Analysis of Strategic Mineral Supply Chain

1.DefinitionandCriticalAttributes

The scientific definition of strategic minerals is the logical starting point of supply chain research, and its core lies in constructing an evaluation framework through the dual dimensions of criticality (Shiquan & Deyi, 2023). According to the classification criteria of the United States Geological Survey, criticality is deconstructed as a comprehensive consideration of economic importance and supply risk. This binary classification method breaks through the single dimension of traditional resource evaluation, forming differentiated types such as "high economic importance high supply risk" and "high economic importance low supply risk", providing a theoretical basis for prioritizing strategic resources.

The attribute system of strategic minerals has distinct composite characteristics (Zhu et al., 2020). Firstly, the strategic attribute is manifested as a deep binding with national security, forming a resource guarantee level in the fields of defense industry, new energy, etc., which directly affects the realization boundary of national strategic capabilities; Secondly, the market attribute presents the characteristics of oligopoly monopoly and price rigidity coexisting. A few resource rich countries form market dominance through capacity regulation, while the rigid demand of downstream industries leads to low price elasticity; Thirdly, the technological attributes are reflected in the coordinated evolution of resources and technology. The expansion of specific mineral technology application scenarios will strengthen its strategic position in reverse, forming a circular mechanism of "technology lock-in resource dependence". The interaction of these attributes makes the strategic mineral supply chain both follow market rules and be subject to deep intervention from non market factors.

2.NetworkTopology

The network topology structure of the strategic mineral supply chain presents a typical multi-level nested feature, as shown in Figure 1. Its value stream is transmitted step by step along the vertical chain of "mining processing manufacturing recycling", forming a complex system of interlocking links (Sauer & Seuring, 2019). As the source of the supply chain, the spatial distribution of the mining process is constrained by resource endowments and exhibits a high degree of agglomeration (Shapiro et al., 2007); The processing stage shows a spatial separation between resource rich and industrialized countries; The manufacturing process focuses on technology intensive industrial clusters, and its layout highly overlaps with downstream application markets (Hartmann et al., 2023); The recycling process, as the terminal of a closed-loop system, depends on the maturity of technology and policy incentives, becoming a weak link in the resilience of the supply chain. This multi-level structure not only reflects the efficiency advantage of vertical integration, but also amplifies systemic risks due to the strong dependence between loops.

Figure 1 Value Stream Diagram

3.RiskDrivers

The risk generation mechanism of strategic mineral supply chain is rooted in the interaction of multidimensional driving factors, and its complexity far exceeds that of general commodity supply chains (Franken & Schütte, 2022). Geopolitical risks, as the primary driving factor, form a cross regional risk ripple effect through the chain transmission of policy changes in resource rich countries, trade channel blockades, and downstream idle production capacity (Bhamra et al., 2025).

Logistics bottlenecks constitute the physical carrier of risk transmission, and their impact is reflected in the spatial constraints of transportation nodes and structural defects of logistics networks (MOSS et al., 2011). The transoceanic transportation of global strategic minerals relies on 12 key strait channels, and fluctuations in the efficiency of these nodes can lead to longer transportation cycles; However, inland transportation is constrained by differences in infrastructure, and any local interruption could trigger global systemic fluctuations. The particularity of logistics risk lies in its combination of suddenness and structure, which puts higher demands on the redundancy design of the supply chain.

The impact of technological substitution pathways as potential risk drivers is bidirectional and long-term (Randive & Jawadand, 2019). On the one hand, technological breakthroughs in alternative materials may lead to a decline in the strategic value of specific minerals, and this "creative destruction" forces a disruptive restructuring of the supply chain; On the other hand, advances in recycling technology can reduce reliance on primary minerals and create a risk mitigation effect. The uncertainty of technological substitution is reflected in the ambiguity of its time dimension, and the cyclical differences from laboratory technology to industrial application make it difficult for the supply chain to form stable risk expectations. This "technological black swan" event poses a deep challenge to the long-term supply and demand pattern of strategic minerals.

III. Resilience Metrics System

1.3R-ART Framework

This article breaks through the limitations of traditional static evaluation and proposes a dynamic resilience decay recovery mechanism, with the specific expression as follows:

$$\text{Resilience} = \underbrace{\int_{t_0}^{t_d} \Phi(t)dt}_{\text{Absorptive}} + \underbrace{\int_{t_d}^{t_r} \Psi(t)dt}_{\text{Adaptive}} + \underbrace{\lambda \cdot (Q_{\text{post}} - Q_{\text{pre}})}_{\text{Recoverable}} \qquad (1)$$

Among them, *Φ (t)* is the robustness function when the interrupt event *d* occurs, that is, the system's ability to maintain service level; *Ψ(t)* is the system adaptation function after interruption; *λ* is the coefficient of resilience.

The specific three-dimensional toughness quantification indicators are shown in Table 1.

Table 1 Quantitative indicators of three-dimensional toughness

Dimension	Indicator Name	Representation	Data Source
Absorptive	Node Elasticity Entropy	H_v	RITA Database
	Inventory Buffer Index	B_I	Corporate Financial Reports / Customs Inventory Data
Adaptive	Path Switching	T_s	Logistics GPS Tracking Data

	Timeliness		
	Demand Elasticity Ratio	η_d	Bloomberg Commodity Price-Sales Panel Data
Recoverable	Capacity Reconstruction Slope	β	High-Frequency Production Data
	Circular Replenishment Rate	R_c	BIR Annual Reports

The specific calculation methods for each indicator are as follows:

$$H_v = -\sum_{k=1}^{n} p_k \ln p_k \tag{2}$$

P_k is the probability of failure of the k-th supply path for node v.

$$B_I = \frac{\sum_{j=1}^{m} \min(S_j, D_j)}{\sum_{j=1}^{m} D_j} \tag{3}$$

$$T_s = \frac{1}{N}\sum_{i=1}^{N} \delta t_i \tag{4}$$

δt_i is the activation delay of the new path after the i-th interruption.

$$\eta_d = \frac{\Delta Q / Q}{\Delta P / Q} \tag{5}$$

$$\beta = \ln\left(\frac{Q_2 - Q_1}{t_2 - t_1}\right) \tag{6}$$

Among them, t_1 is the starting point of recovery, and t_2 is the point of stable production capacity.

$$R_c = \frac{\text{Recycled Resource Supply}}{\text{Primary Resource Consumption}} \tag{7}$$

The resilience index ensemble algorithm is based on the comprehensive evaluation of entropy weight TOPSIS

2.Multi-scenario Modeling

This article is based on the basic model of mixed integer programming, and constructs the objective function as follows:

$$\min Z = \underbrace{\omega_1\left(\sum_{t\in T}\sum_{i\in I}\sum_{j\in J} c_{ij}^t x_{ij}^t\right)}_{\text{Operating Cost}} + \underbrace{\omega_2\left(1-\gamma\cdot R_t\right)}_{\text{Resilience Loss}} \tag{8}$$

Among them, R_t is the supply chain resilience of period t, and x_{ij}^t is the mineral flow from node i to j in period t; y_k^t is a binary variable, and its value of 1 indicates that node k enables the backup path during period t.

There are three core constraints in this article, namely capacity constraints, resilience inventory dynamics, and geopolitical policy compliance.

Capacity constraints:

$$\sum_j x_{ij}^t \le \hat{P}_i^t \cdot (1-\xi_i^t) \quad \forall i,t \tag{9}$$

ξ_i^t is the probability of node interruption

Resilience inventory dynamics:

$$I_t^{\text{strat}} = I_{t-1} + x_t^{\text{buffer}} - \max\left(0, D_t - \sum_j x_{ij}^t\right) \tag{10}$$

x_t^{buffer} is the activation amount for strategic reserves.

Geopolitical compliance:

$$\frac{\sum_{k\in \text{EU}} x_{ik}^t}{\sum_j x_{ij}^t} \ge 0.65 \tag{11}$$

In addition, this article additionally considers random risk events and adopts a random risk event integration mechanism. The probability model of risk events includes geopolitical conflicts and logistics interruptions.

Geopolitical conflicts:

$$P_{\text{conflict}} = \frac{1}{1+e^{-0.73(\text{GRI}-2.7)}} \tag{12}$$

Logistics interruption:

$$P_{\text{disrupt}} = \Phi\left(\frac{\ln(\text{Cargo Volume})-8.2}{0.3}\right) \tag{13}$$

Φ is the standard normal distribution CDF

IV. Simulation Analysis

1. Experimental environment

The specific experimental environment and parameters of this article are shown in Table 2. At the hardware level, 2 x Intel Xeon Platinum 8380 processors, 1.5 TB DDR4 memory, and NVMe SSD storage are used to ensure large-scale computing needs; The software integrates Any Logic University 22.1 for simulation, Gurobi Optimizer 10.0 for optimization solving, Python 3.11 for control, and TimescaleDB 2.8 for data management, achieving collaborative operation of simulation, optimization, and data. The supply chain network is constructed based on industry reports such as EUCRM and USGS, consisting of 92 nodes, including 27 mining nodes, 42 smelters, 18 manufacturers, and 5 recycling centers, forming a complete industry chain topology. The verification process adopts 10000 Monte Carlo iterations combined with Sobol sampling theory to ensure the statistical robustness of the results.

Table 2 Experimental Environment and Parameter Settings

Category	Parameter Item	Configuration Value	Source
Hardware Platform	CPU	2× Intel Xeon Platinum 8380	-
	Memory Capacity	1.5 TB DDR4 3200MHz	-
	Storage System	2× 3.2TB NVMe SSD	-
Software Environment	Simulation Platform	AnyLogic University 22.1	www.anylogic.com
	Optimization Solver	Gurobi Optimizer 10.0	www.gurobi.com
	Control Language	Python 3.11	www.python.org
	Database System	TimescaleDB 2.8	www.timescale.com
Network Parameters	Total Nodes	92	EU CRM 2023 Annual Report
	Mining Nodes (Upstream)	27	USGS Miner Yearbook
	Smelters (Midstream)	42	S&P Global Metals
	Manufacturers (Downstream)	18	Bloomberg Terminal Data
	Recycling Centers	5	BIR Recycling Report
Dynamic Parameters	Inventory Buffer Index (BI)	0.52±0.15	USGS Weekly Inventory Report
	Path Switching Timeliness (Ts)	96±24 hours	UNCTAD Logistics Database
	Strategic Reserve Activation Threshold	Inventory consumption > 120% of baseline for 3h	Corporate Operation Manual
	Node Failure Probability ξ_i	β(2.5, 8.3) distribution	RITA Supply Chain Event Repository
Validation Parameters	Monte Carlo Iterations	10,000	Sobol Sampling Theory

2. Monte Carlo simulation

The Monte Carlo simulation process is shown in Figure 2. This article presents a Monte Carlo simulation based on the AnyLogic platform to load topology data of the global rare earth supply chain. In the core iteration phase, the system uses a dual random sampling mechanism to generate a sequence of risk events. Geopolitical conflict events are triggered through the Logit probability model, and when the generated random number is below the probability threshold, the corresponding production capacity is dynamically reduced based on the centrality ratio of node betweenness centrality. Within each sampling period, the combination of the states of these two types of risk events together constitutes a specific interruption scenario. After the interrupt parameter is generated, the system embeds it into the mixed integer programming objective function for dynamic optimization solution. The entire iteration process is executed in a loop under Python console scheduling, and automatically terminates when the cumulative number of iterations reaches the preset limit of 10000.

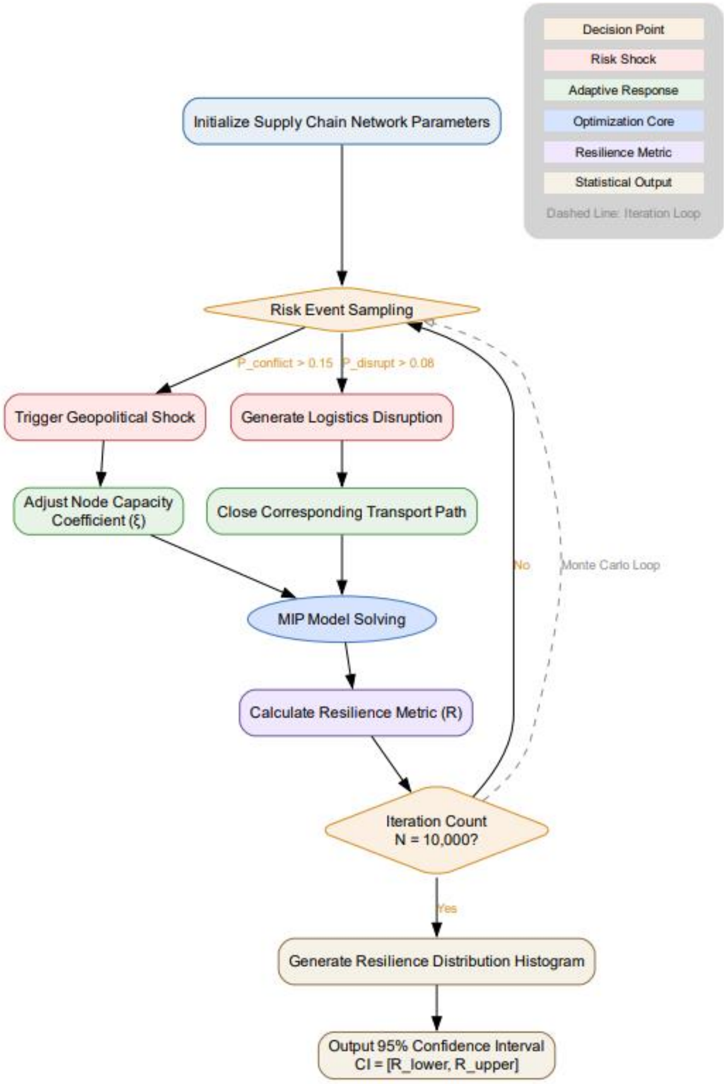
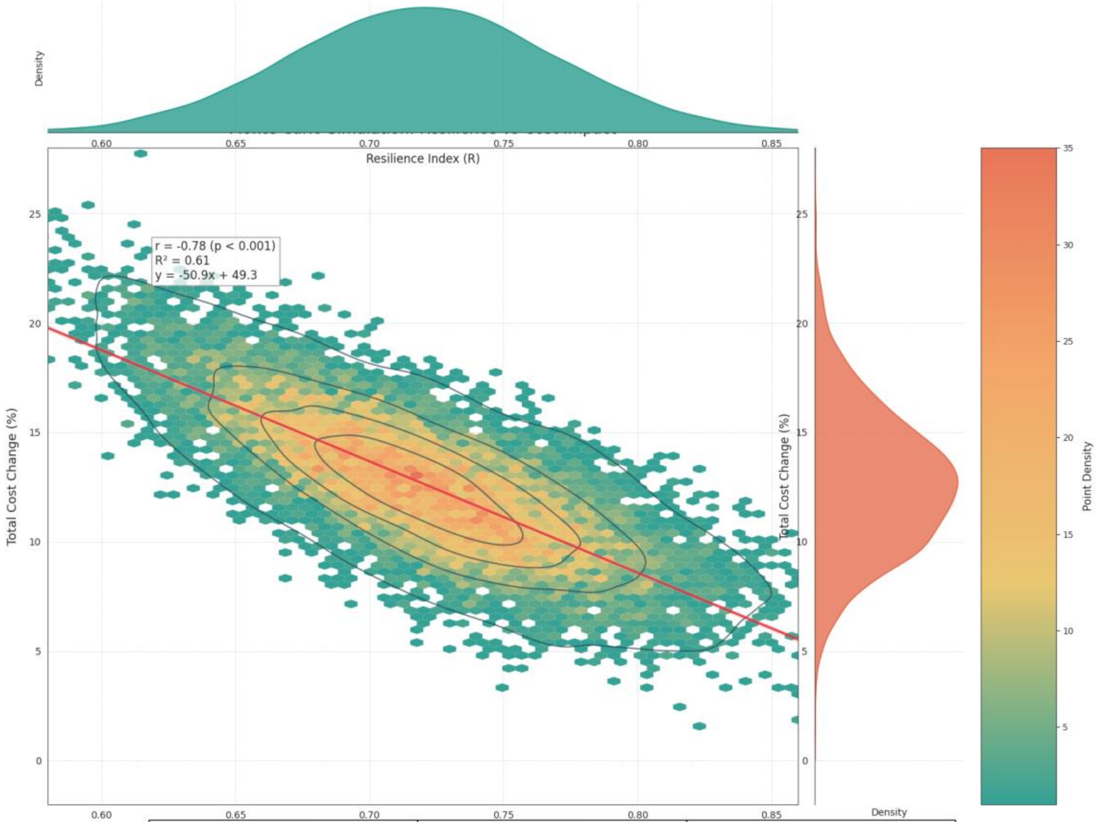


Figure 2 Schematic diagram of Monte Carlo simulation process

As shown in Figure 3, the Monte Carlo simulation results show that the resilience index of the strategic mineral supply chain exhibits a left skewed distribution, with an average of 0.724 and a 95% confidence interval of [0.682, 0.811], confirming the effectiveness of the mixed optimization strategy. The analysis also revealed a significant negative correlation between cost and resilience. When the system encounters composite risk shocks, the average capacity gap will sharply widen and the recovery period will be extended.



Percentile	Resilience	Cost Change
10%	0.655	8.7%
25%	0.686	10.4%
50%	0.720	12.6%
75%	0.754	14.7%
90%	0.784	16.9%

Figure 3 Monte Carlo simulation results

3. Dynamic system simulation

The simulation results of the dynamic system are shown in Table 3. The dynamic system simulation results clearly reveal the dynamic coupling mechanism between the critical node failure rate and the supply chain resilience index. At the beginning of the interruption event, the critical node failure rate sharply increased from the baseline state of 0% to 35.2%. This led to a rapid decline in the resilience index R value from the initial 1.0 to 0.73, fully exposing the amplification effect of single point failure risk in the supply chain topology structure. It is worth noting that the peak of failure rate occurs 24 hours earlier than the lowest point of resilience, indicating that node failures only cause maximum damage at the system level after multiple layers of conduction.

With the gradual activation of resilience optimization strategies, the system enters a critical recovery period. This non-linear recovery characteristic is directly reflected in the transitional growth of the resilience index. At the end of the 168 hour simulation cycle, the failure rate stabilized at a controllable level of 15.1%, and the R value recovered to 0.92, verifying the effectiveness of the strategy.

Table 3 Dynamic System Simulation Results

Simulation Time (hours)	Key Node Failure Rate (%)	Resilience Index (R)
0	0.0	1.00
24	18.7	0.92
48	35.2▲	0.73▼
72	42.6	0.66
96	38.4	0.74▲
120	31.9▼	0.83
144	22.7	0.89
168	15.1	0.92

V. Conclusion

This study constructs a resilience assessment system for strategic mineral supply chains, revealing the inherent relationship between the vulnerability and resilience of strategic mineral supply chains under the influence of multiple risk factors. Research has shown that there is a significant negative correlation between the resilience index of strategic mineral supply chains and costs, meaning that while pursuing cost-effectiveness maximization, the resilience of the system is often sacrificed. This provides important insights for risk control in supply chain management. In simulation analysis, the recovery capability of the system has been significantly improved under the optimization strategy in the face of composite risk scenarios, especially in the non-linear relationship between the recovery capability of key nodes and the overall recovery speed of the supply chain, further verifying the effectiveness of the dynamic resilience optimization model.

Based on the research findings, this article suggests that in the context of increasingly complex globalization risks, the strategic mineral supply chain should strengthen redundancy design, especially at key nodes, by setting up backup paths to improve the system's adaptability to sudden risks. At the same time, the flexibility of the supply chain should be strengthened to ensure that strategies can be quickly adjusted and system stability maintained after risk events occur.

In addition, technological innovation can effectively reduce dependence on a single mineral resource. The state should strengthen support for the research and development of strategic mineral substitution technologies, promote the coordinated development of industrial technology, and achieve efficient recycling of resources and diversified supply guarantee.

Of course, the government should provide support for the resilience construction of the strategic mineral supply chain at the policy level, including optimizing the rational allocation of resources, promoting international cooperation, and strengthening the management of key links in the supply chain. In addition, policies should encourage companies to make strategic investments in their global supply chain layout, reduce dependence on specific countries or regions, and avoid excessive concentration of risks.

Finally, when facing the challenge of multidimensional risks, the risk assessment system of the supply chain should shift from static to dynamic, adopting a more comprehensive risk warning mechanism. Especially in dealing with factors such as geopolitical risks and logistics bottlenecks, it is necessary to prepare emergency plans in advance to ensure that recovery mechanisms can be quickly activated in the event of major risk events and reduce system losses.

Reference

[1] Hveem, H. (1986). Minerals as a factor in strategic policy and action. Global Resources and International Conflict: Environmental Factors in Strategic Policy and Action, 4, 55.

[2] Shiquan, D., & Deyi, X. (2023). The security of critical mineral supply chains. Mineral Economics, 36(3), 401-412.

[3] Kim, Y. H., & Davis, G. F. (2016). Challenges for global supply chain sustainability: Evidence from conflict minerals reports. Academy of Management Journal, 59(6), 1896-1916.

[4] Zhang, H. (2025). Resilience of critical transition minerals supply chain in the context of strategic rivalry: implications for the national policy and regulatory frameworks. Journal of Energy & Natural Resources Law, 1-27.

[5] Statsenko, L., Gorod, A., & Ireland, V. (2018). A supply network governance framework: a case study of the South Australian mining industry. Journal of Global Operations and Strategic Sourcing, 11(1), 55-78.

[6] Childerhouse, P., Al Aqqad, M., Zhou, Q., & Bezuidenhout, C. (2020). Network resilience modelling: a New Zealand forestry supply chain case. The International Journal of Logistics Management, 31(2), 291-311.

[7] Jain, V., Kumar, S., Soni, U., & Chandra, C. (2017). Supply chain resilience: model development and empirical analysis. International Journal of Production Research, 55(22), 6779-6800.

[8] Ivanov, D. (2025). What network and performance indicators can tell us about supply chain and sourcing resilience (and what they cannot). Journal of Purchasing and

Supply Management, 101014.
[9] Zhu, Z., Dong, Z., Zhang, Y., Suo, G., & Liu, S. (2020). Strategic mineral resource competition: Strategies of the dominator and nondominator. Resources Policy, 69, 101835.
[10] Sauer, P. C., & Seuring, S. (2019). Extending the reach of multi-tier sustainable supply chain management–insights from mineral supply chains. International Journal of Production Economics, 217, 31-43.
[11] Shapiro, D., Russell, B. I., & Pitt, L. F. (2007). Strategic heterogeneity in the global mining industry. Transnational Corporations, 16(3), 1.
[12] Hartmann, T., Thallapally, P. K., & van Rooyen, I. J. (2023). Strategic Plan: Decrease Critical Minerals Waste through Enabling Advanced Manufacturing Techniques (No. PNNL-34225). Pacific Northwest National Laboratory (PNNL), Richland, WA (United States).
[13] Franken, G., & Schütte, P. (2022). Current trends in addressing environmental and social risks in mining and mineral supply chains by regulatory and voluntary approaches. Mineral Economics, 35(3), 653-671.
[14] Bhamra, R., Small, A., Hicks, C., & Pilch, O. (2025). Impact pathways: geopolitics, risk and ethics in critical minerals supply chains. International Journal of Operations & Production Management, 45(5), 985-994.
[15] MOSS, R., TZIMAS, E., KARA, H., WILLIS, P., & KOOROSHY, J. (2011). Critical metals in strategic energy technologies-assessing rare metals as supply-chain bottlenecks in low-carbon energy technologies.
[16] Randive, K., & Jawadand, S. (2019). Strategic minerals in India: present status and future challenges. Mineral Economics, 32(3), 337-352.