Structural Drivers of Supply Chain Resilience in Chain Restaurant Enterprises: Evidence from Cotti Coffee

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Abstract. Against the backdrop of increasing global supply chain uncertainty and frequent disruptive events, this study takes Cotti Coffee (Enterprise A) as the research object and constructs a supply chain resilience evaluation system comprising four dimensions and 25 secondary indicators. An integrated IT2TrFN-DEMATEL-MMDE-ISM-MICMAC framework is employed to analyze causal relationships and hierarchical structures among influencing factors. Results indicate that supply concentration risk (C5) is the fundamental driving factor at the bottom level (L7) of the ISM hierarchy (Ci = 1.5539), and emergency response speed (C15) has the highest centrality (Mi = 2.9465). The MMDE method objectively determines the threshold (λ = 0.0910), and MICMAC analysis classifies the 25 factors into four strategic categories. The findings provide practical references for chain catering enterprises to identify key resilience drivers and formulate targeted management strategies.

Keywords: supply chain resilience; chain catering enterprises; influencing factors; DEMATEL-ISM method; Cotti Coffee

1 Introduction

Against the backdrop of increasing global supply chain uncertainty, supply chain resilience (SCR) has become essential for enterprises to maintain stable operations and cope with disruptions such as pandemics [1], geopolitical conflicts, and extreme climate events [2]. For chain catering enterprises, which rely heavily on raw materials, logistics efficiency, and extensive store networks, disruptions in key supply links may easily trigger cascading operational impacts [3].

Cotti Coffee (Enterprise A), founded in 2022, has rapidly expanded to more than 18,000 stores across 33 countries and regions by 2025. However, the enterprise relies heavily on a limited number of suppliers for core raw materials, leading to high supply concentration and potential interruption risks [4]. Meanwhile, its cross-regional resource allocation and digital supply chain management system are still developing, posing challenges in responding to sudden disruptions.

Although previous studies have explored supply chain resilience using methods such as system dynamics[5], fuzzy theory, and multi-criteria decision-making, limitations

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remain in handling uncertainty in expert evaluations and in objectively determining DEMATEL thresholds [6, 7].

To address these issues, this study constructs a supply chain resilience influencing factor system including resistance, adaptability, recovery capability, and network structural characteristics. By integrating IT2TrFN, DEMATEL, MMDE, ISM, and MICMAC, the causal relationships and hierarchical structure among the factors are analyzed to identify key drivers and provide references for improving resilience in chain catering enterprises.

2 Theoretical Foundation and Research Design

Supply chain resilience (SCR) has evolved from emphasizing resistance capability (safety stock, supplier diversification) to encompassing adaptability and recovery capability, with recent studies further highlighting network structural factors such as inter-organizational collaboration and organizational learning [8]. Accordingly, this study constructs a four-dimension SCR influencing factor system---resistance capability, adaptability capability, recovery capability, and network structural characteristics---comprising 25 secondary indicators, developed through literature analysis and expert consultation in light of Enterprise A's operational characteristics.

To analyze factor relationships, an integrated IT2TrFN–DEMATEL–MMDE–ISM–MICMAC framework is employed and implemented in Python 3.10 (NumPy/SciPy). IT2TrFN defuzzification uses upper and lower membership heights H_1=1 and H_2=0.9 [9]; DEMATEL normalization applies the row-maximum method; MMDE entropy is computed in base-10 logarithm; ISM reachability is derived via Boolean matrix power iteration until stabilization; and MICMAC quadrant boundaries are set at mean DP and Dep values [10].

3 Data Collection and Expert Evaluation

Seven experts with at least seven years of supply chain management experience were selected via purposive sampling from five types of institutions, consistent with prior DEMATEL-ISM studies where panels of 5 – 15 qualified experts are considered sufficient. Three robustness checks were conducted: threshold variation (λ=0.08–0.11) consistently retained C5 at L7; leave-one-out validation showed removal of any single expert affected at most two secondary rankings; and practitioner-weighted aggregation yielded results consistent with the equal-weight baseline (Spearman ρ=0.94).

Each expert independently completed a 25×25 influence matrix using the seven-level IT2TrFN linguistic scale (diagonal elements set to "Extremely Low"), without inter-expert communication. Ratings were defuzzified and aggregated via arithmetic mean to obtain the comprehensive direct influence matrix [11]. Kendall's W = 0.712 ($p < 0.01$) confirms strong inter-expert agreement.

4 Empirical Analysis Results

4.1 DEMATEL Causal Analysis and MMDE Threshold Determination

After IT2TrFN defuzzification, the linguistic evaluations of seven experts were converted into crisp values to construct the 25×25 direct influence matrix D, in which stronger influence relationships are mainly concentrated within the resistance capability dimension (B1) and between B1 and B4, indicating relatively close interactions among these indicators.

Matrix D was normalized using the factor s = 10.0370 to obtain matrix N, which removes dimensional differences and ensures the convergence of matrix operations. The results show that most relationships exhibit low to medium influence intensity, while only a limited number dominate system evolution.

Based on N, the comprehensive influence matrix T was calculated to derive the influence degree (D), affected degree (R), centrality (M), and cause degree (C) of each indicator. Among the 25 indicators, 14 are cause factors and 11 are result factors. The highest cause degrees are observed for C5 (supply concentration risk, C = 1.5539), C22 (supply chain learning capability, C = 0.7652), and C25 (cross-organizational collaborative innovation capability, C = 0.7385), indicating that these factors play key driving roles in the resilience system. In contrast, C15 (emergency response speed), C17 (cross-level recovery efficiency), and C16 (recovery time compression capability) show the most negative cause degrees, suggesting that recovery capability indicators are mainly influenced by upstream factors. From the perspective of centrality, C15, C5, and C9 exhibit the highest values, reflecting their strong connectivity in the system. The causal relationships among indicators are illustrated in Figure 1.

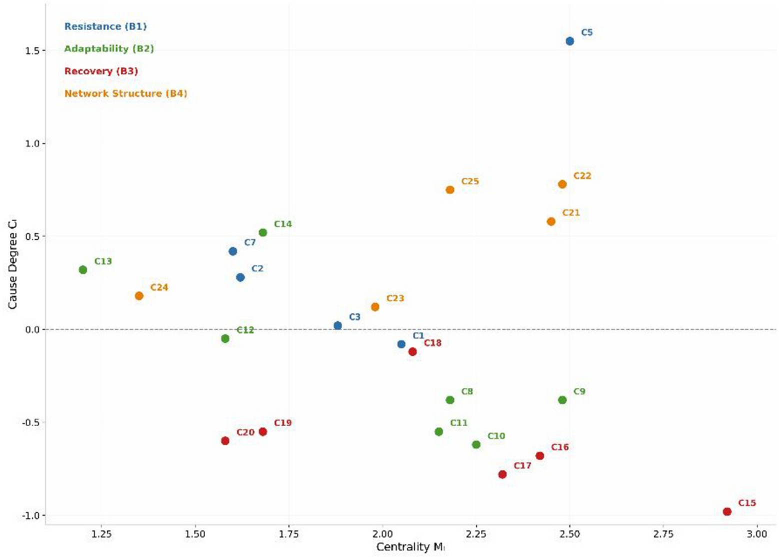

Fig. 1. DEMATEL causal diagram

To determine the binarization threshold objectively, the Maximum Mean De-Entropy (MMDE) method was applied. The optimal threshold was obtained as λ = 0.0910, and 72 effective influence relationships were retained among the 600 non-diagonal elements, accounting for 12% of all relationships. This process filters out weak influence noise while preserving the most structurally significant relationships for subsequent analysis.

4.2 ISM Hierarchical Structure and MICMAC Analysis

Using the threshold λ = 0.0910, the adjacency matrix was converted into the reachability matrix K, which reflects the accessibility relationships among indicators. According to the ISM hierarchical decomposition rule, the 25 indicators are divided into seven hierarchical levels. The results show that C5 (supply concentration risk) is located at the bottom level (L7) and serves as the fundamental driving factor influencing the entire system. The structural foundation layer (L6) includes network structural redundancy (C21), supply chain learning capability (C22), and cross-organizational collaborative innovation capability (C25), while higher levels mainly represent operational capability and outcome indicators.

Based on the reachability matrix K, the driving power (DP) and dependence (Dep) of each indicator were calculated, with mean values of 5.80. According to their positions in the driving–dependence coordinate system, the indicators were classified into four categories (Figure 2).

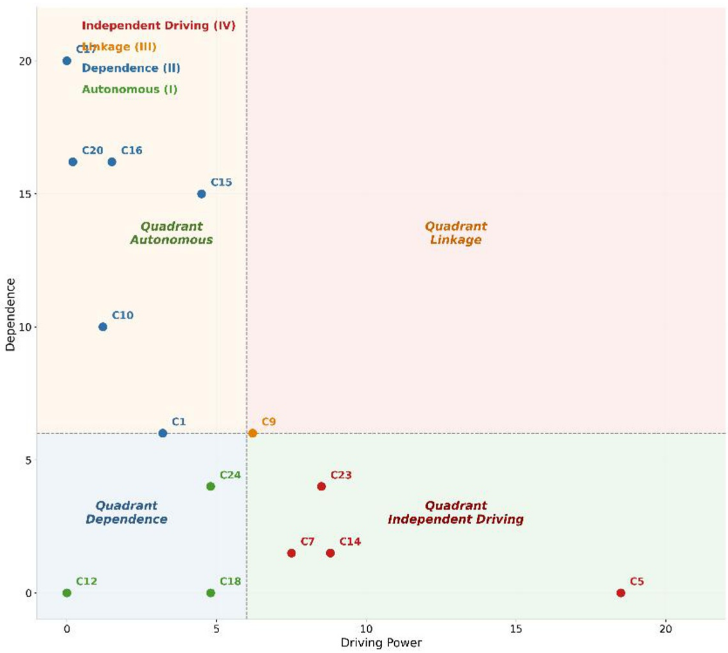

Fig. 2. MICMAC Driving–Dependence Quadrant Diagram

The independent driving factors include C5, C21, C22, C25, C14, C23, C6, and C7, which exhibit high driving power and low dependence and thus represent the core drivers of system evolution. C8 and C9 are linkage factors that play key intermediary roles in the network. Indicators such as C1, C10, C11, C15, and C16 belong to dependent factors, reflecting the final manifestation of supply chain resilience, while the remaining indicators function as autonomous factors with relatively weak system connections.

5 Discussion and Conclusion

Using the integrated IT2TrFN–DEMATEL–MMDE–ISM–MICMAC framework, this study explores the key driving mechanisms of supply chain resilience in chain catering enterprises. Results show that C5 (supply concentration risk) is the fundamental driving factor. Mechanistically, high supply concentration constrains network redundancy (C21) by limiting alternative sourcing options, undermines digital management (C14) due to insufficient multi-supplier data streams, and amplifies recovery time (C16) during disruptions. A feedback loop also exists: poor emergency response (C15) erodes supplier trust, further reinforcing concentration risk. C21, C22, and C25 serve as core structural drivers, while C14, C23, C8, and C9 function as transmission mechanisms linking structural foundations with operational performance. Recovery indicators C15, C16, and C17 mainly exhibit dependent characteristics.

Taking Cotti Coffee as the case study, the constructed four-dimension, 25-indicator system confirms that supply concentration risk is the core driver and emergency response speed has the highest network centrality. The ISM model reveals a seven-level hierarchical structure, and MICMAC analysis clarifies driving – dependence relationships among factors. The integrated framework effectively handles expert evaluation uncertainty and provides a systematic approach for analyzing complex resilience systems. Future research could expand beyond the single-enterprise case to further explore supply chain resilience across the catering industry. Table 1 summarizes prioritized interventions for key factors.

Table 1. Prioritized Interventions and Monitoring Indicators

Factor	Intervention	KPI / Target
C5	Supplier diversification	Core supplier share ≤ 40%; ≥ 3 regional sources
C21	Expand regional distribution centers	Alternative route activation ≤ 24h
C14/C23	Deploy SCV platform	Real-time inventory coverage ≥ 95%
C15	Quarterly BCP scenario drills	Emergency activation time ≤ 2h

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