

A Hybrid Multi-Criteria Decision-Making Framework for Prioritizing Supply Chain Risks in Perishable Food Manufacturing

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Abstract

Food-processing supply chains are severely threatened by interruptions in procurement, storage and transport due to the perishability of products and the strict delivery demands. Conventional risk models rank the importance of the factors, but do not differentiate the root causes from the downstream consequences. The study proposes a multi-method framework for assessing ten critical disruption factors with the use of expert judgments. RII used to Quantifies perceived factor importance for Maps structural dependencies and hierarchy ISM is used. Fuzzy DEMATEL Identifies direct or indirect causal drivers despite expert ambiguity. AHP Establishes priority weights for strategic intervention. (F6) was perceived as the most important (RII) = 0.9857, but (F10) was the key root-cause driver (D - R = 1.574). AHP validated F10 as the highest priority for intervention (weight: 0.2189), followed by storage violations (F7) and demand spikes (F8). Highly visible disruptions are often symptoms not root causes. Focusing interventions on underlying causal drivers such as traceability significantly enhances overall food supply-chain resilience.

Keywords: Food-processing supply chain, Supply-chain resilience, Interpretive Structural Modeling, Analytic Hierarchy Process, Multi-criteria decision-making.

1. Introduction

Food processing supply chains are complex interdependent systems connecting agricultural producers, suppliers of raw materials, processors, packaging plants, warehouses, logistics providers, distributors, retailers, and consumers (Pradeepa et al., 2025; Worley & Caniato, 2016; Yun et al., 2020). Compared to traditional manufacturing supply chains, food processing systems have more constraints such as perishability, quality degradation, food safety, environmental sensitivity, seasonal availability, demand volatility and time-dependent delivery requirements (Osman et al., 2023; Szymonik & Chudzik, 2019). Disruptions can cascade down and upstream operations, affecting production continuity, inventory availability, product quality, customer service and financial performance. Recent reviews identify climatic, biological and environmental, logistics and infrastructure and supply related disruptions as vulnerability categories emphasizing the multidimensional nature of resilience challenges in food systems (Hobbs, 2025; Mu et al., 2021).

The globalization and interdependence of our food supply chains have only made this vulnerability worse. Modern food-processing organizations often depend on geographically dispersed suppliers, transportation networks, temperature-controlled storage, synchronized production schedules, and information exchange across organizational boundaries (Chen et al., 2019; Dharni & Sharma, 2015). Although such integration can improve efficiency and market responsiveness, it also increases disruption propagation. A delay in raw-material delivery may interrupt production; interruptions may then affect inventory availability; shortages can increase emergency transportation requirements; and transportation pressure may increase the probability of product damage or delivery failure (Ding, 2023; Siswanto et al., 2018). Thus, disruption in a food-processing supply chain should not be interpreted as isolated problems. Rather, it should be understood as a network of interdependent risk factors generating cascading effects (Hobbs, 2025).

The resilience perspective has become important in food-supply-chain research. Recent reviews emphasize the need to strengthen food-supply-chain resilience through better preparedness, adaptive capacity, technological integration, and sustainability-oriented strategies (Hobbs & Hadachek, 2024; Mu et al., 2021). Resilience is not only about recovering from a disruption, it is also about foreseeing vulnerabilities, absorbing disturbances, keeping essential functions running, being able to respond quickly and adapt the underlying system so that disruptions can be better managed (Vargas Florez et al., 2015). This challenge is relevant when organizations attempt to prioritize resilience investments. In environments, managers first identify critical disruption factors and rank them in terms of importance (Farinha & Pina, 2025). Such ranking is useful because organizational resources are limited and decision-makers must identify areas requiring attention. However, an importance ranking does not necessarily reveal why a factor is important or whether it is a fundamental driver of other disruptions. For example, Transit Damage and Breakage can be given an importance score as the consequences are visible. Damaged products return as a loss, customer complaints, returns, waste and expense (Faires et al., 2025).

Damage in transit can be influenced by factors upstream of transit such as packaging, storage, handling, pressure of production and lack of information. Investment in damage reduction without addressing root

causes may therefore lead to partial improvements (K & P, 2026). A factor might have systemic influence but be perceived as only moderately important as its effects are indirect or difficult to observe. This disconnects perceived importance from systemic influence. The Lack of End-to-End Batch Traceability is an illustration. Traceability gaps can reduce supply chain transparency even when they do not cause tangible losses, and they can also delay the detection of disturbances, complicate product recalls, worsen coordination and limit the opportunity to establish the source and location of affected batches (Kros et al., 2019; Razak et al., 2021; Wang et al., 2025). Traceability has been recognized in previous research as a component of supply chain transparency and resilience. The literature has examined digital traceability as a mechanism to improve visibility, efficiency, and sustainability (Kros et al., 2019; Razak et al., 2021).

This distinction reveals a methodological challenge. An important factor is not necessarily the one that should receive highest intervention priority. Resilience planning effectiveness requires the identification of structural relationships among the factors, their causal positions and prioritizing interventions based on the potential systemic impact (Cimellaro et al., 2014; Herrera & Kopainsky, 2018). Several analytical techniques address parts of this problem. The Relative Importance Index (RII) is a useful method for ranking factors in terms of their importance as perceived by experts (Elango, 2020). Interpretive Structural Modeling (ISM) can convert complex relationships into a hierarchical structure and identify the driving factors versus the dependent factors (Koh, 2015; Luchman et al., 2020). Decision-Making Trial and Evaluation Laboratory (DEMATEL) provides a mechanism for quantifying causal influence among factors (Taherdoost & Madanchian, 2023). However, expert judgments regarding causal influence are inherently uncertain and linguistic; consequently, integrating fuzzy logic with DEMATEL can represent ambiguity in expert assessments (Komleva & Antoshchuk, 2025). Finally, the Analytic Hierarchy Process AHP is used to provide a mechanism for the assignment of relative priorities on the basis of pairwise comparisons and consistency assessment (Khazaii, 2016). Despite the strengths of these techniques, their independent application creates a limitation. RII highlights importance, not causation. ISM helps understanding the structure hierarchical relationships, not strongly informative on influence magnitude (Thakkar, 2021). DEMATEL provides the causality relationships, but cannot be the sole management prioritization technique on its own (Taherdoost & Madanchian, 2023). AHP does establish priorities but may not differentiate root cause from effects if used in Isolation (Felice & Petrillo, 2024). Therefore, this study proposes an integrated framework:

RII→ISM→Fuzzy DEMATEL→AHP

Structure of logic for the framework: RII selects relevant factors, then ISM shows how those factors are structurally related. DEMATEL identifies the strength and direction of causal influence and distinguishes cause factors from effect factors. Finally, AHP prioritizes interventions. The central proposition of the study is therefore that supply-chain resilience decisions should move beyond conventional risk ranking toward causal and intervention-oriented analysis. Accordingly, the study addresses the following research questions:

RQ1: Which disruption factors are perceived as the most important in food-processing supply chains?
 RQ2: How are the identified disruption factors structurally interconnected?
 RQ3: Which factors act as fundamental causal drivers and which primarily represent downstream effects?
 RQ4: Which factors should receive the greatest managerial intervention priority?
 RQ5: To what extent do perceive importance, causal influence, and intervention priority produce different rankings?

To answer questions, the study develops a decision-support framework based on ten disruption factors covering procurement, production, storage, transportation, demand management, downstream coordination, and information visibility. First, it contributes a multi-dimensional perspective on food-processing supply-chain disruption by distinguishing importance, structural position, causal influence, and intervention priority. Secondly, it illustrates how RII, ISM, Fuzzy DEMATEL, and AHP can be used in tandem, rather than separately. Thirdly, it shows how least important elements based on importance analysis may well be top prioritized interventions when looking at systemic causal impact. Fourthly, the framework offers a method for shifting resilience investments from the symptoms of the problem back towards leverage points.

The remainder of the paper is organized as follows. Section 2 reviews the literature on food-processing supply-chain disruptions, resilience, critical risk factors, traceability, and multi-criteria decision-making approaches. Section 3 presents the research methodology and the integrated RII–ISM–Fuzzy DEMATEL–AHP framework. Section 4 reports the empirical findings. Section 5 presents the results and their theoretical and managerial implications. Section 6 presents the contributions, limitations and future research directions of the study, followed by the conclusions.

2. Literature Review

2.1. Supply Chains in Food Processing and Systemic Vulnerability

Food processing supply chains are complex, interconnected systems that connect agricultural producers, raw-material suppliers, processors, packaging activities, warehouses, logistics providers, distributors, retailers, and consumers. Their performance is driven by synchronized flows of materials, products, information, and financial resources across organizational boundaries (Pradeepa et al., 2025; Yun et al., 2020). Food processing systems differ from traditional manufacturing supply chains in that they are subject to additional constraints such as perishability, limited shelf life, quality deterioration, food-safety requirements, seasonal availability, environmental sensitivity, and time-critical distribution. These features make them vulnerable to disruption and increase disruption propagation across interlinked activities (Hobbs, 2025; Osman et al., 2023).

Resilience studies in food supply chains emphasize that food systems must address disruption, sustainability, and technological transformation simultaneously rather than separately (Mu et al., 2021; Sutar et al., 2024). As it pertains to food-processing supply chains, the more complex the network, the

more vulnerable it becomes. Processors depend on suppliers from various geographic regions, specialist logistics providers, temperature-controlled storage, coordinated production schedules and distribution networks to the consumer. Integration may lead to efficiency benefits, as well as increased market awareness and a more reactive market response. Nevertheless, the integration of activities can also cause a range of interdependent risks that have the potential to result in the disruption cascading through several operations, such as if a delay in raw material delivery has the potential to impede planned activities and result in loss of capacity; stock outs that result in the requirement for special transportation with increases in the number of disruptions that may occur during handling and delivery (Lam & Yin, 2021). Study on perishable food supply chains identifies operational failures, equipment breakdowns, demand–supply variation, transportation delays, labor constraints, and external shocks as interconnected disruption sources (Org P A G E et al., 2024); short shelf life and cold-chain dependence amplify consequences, therefore identifying risks alone cannot replace understanding interrelationships (Mu et al., 2021; Osman et al., 2023).

2.2. Supply-Chain Disruption and Resilience in Food Systems

Supply-chain disruption can be understood as an event or condition that interrupts the normal flow of materials, products, information, or financial resources across a supply network. In food-processing environments, the consequences can extend beyond conventional operational losses because disruption may also affect product quality, food safety, shelf life, waste generation, and consumer confidence (Akkerman & Cruijsen, 2024; Beshara et al., 2023). Consequently, resilience has become an increasingly important research perspective for food-supply-chain management (Mu et al., 2021).

Supply-chain resilience extends beyond the ability to recover after a disruption. It encompasses the capability to anticipate potential disturbances, absorb their effects, maintain essential operations, respond effectively, recover performance, and adapt the system to future uncertainty (Luong & Putthakosa, 2023). A recent systematic review of food-supply-chain resilience identifies resilience, sustainability and technological adoption as increasingly intertwined research themes, indicating that digital technologies and enhanced information capabilities may result in more adaptive food-supply-chain systems (Iskandar, 2025). The literature also indicates that major disruptions can expose structural weaknesses that are hidden during normal operating conditions. Research examining food-supply-chain resilience during major disruptions emphasizes the need to understand not only immediate responses but also the structural vulnerabilities that determine the ability of food systems to withstand future shocks (Hobbs, 2025). This perspective is particularly relevant to the present study because resilience cannot be represented adequately by a single risk score. A supply chain may perform well under normal conditions while remaining highly vulnerable to a particular combination of demand volatility, transportation disruption, storage failure, or information deficiency. Therefore, resilience assessment requires identification of both critical factors and the relationships among those factors (X. Chen et al., 2016; Zhao et al., 2023).

2.3. Critical Disruption Factors in Food-Processing Supply Chain

Disruption in food-processing supply chains originates across multiple functional domains ([Sezer et al., 2024](#)). For the present study, the factors are organized into five interconnected dimensions: procurement, production, logistics and storage, demand and downstream coordination, and information visibility. Lead-Time Fluctuations (F1) represent uncertainty in the timing of raw-material and component arrivals, disrupting production planning, increasing safety-stock requirements, and reducing processors' ability to synchronize procurement with production schedules ([Dey et al., 2023](#); [Islam et al., 2025](#)). Raw Material Price Volatility (F2) is the financial uncertainty that arises from fluctuations in the prices of inputs, affecting supplier selection, purchase volume, inventory decisions, production cost, and pricing of the final product ([Dey et al., 2023](#)). Raw Material Quality Variability (F3) is a major issue in food processing, with the variability of incoming material affecting process parameters, product consistency, yield and overall product quality ([Azizur & Assistant Manager, 2018](#)). Procurement reliability is a combination of availability, price and quality attributes. Packaging Machine Downtime (F4) measures downtime of equipment causing bottlenecks in processing and packaging operations. In synchronized systems, such a failure at the packaging stage can stop the movement of finished product into storage or distribution, even when upstream production continues. Unflexible Production Batch Sizing (F5) is the limited ability to adjust production quantities, leading to excess inventory during periods of low demand and shortages during demand peaks. Production flexibility is closely related to a processor's capacity to react to market uncertainty.

F6 Transit Damage and Breakage: This category covers the loss of physical product in transit and handling resulting in waste, returns, customer dissatisfaction and financial loss. F7 Temperature/Humidity Storage Violations: This category covers the failure to provide suitable environmental conditions in storage which is critical to temperature and humidity sensitive food products ([Swarna et al., 2023](#)), in particular those dependent on the cold-chain. F8 Inaccurate Demand during spikes in events: this includes over/under forecasts during high rates of demand spikes – for new releases or Seasonal demand, which can also impact on the production schedule, the right place at the right time inventory, the logistics and the store inventory levels.

Payment and Order Processing Lag by Distributor (F9) indicates coordination problems in the downstream, affecting lead times at the replenishment layer and creating supply-demand misalignment. End-to-End Batch Traceability (F10) indicates lacking information visibility on product batches along several levels in the supply chain ([Anam et al., 2023](#)). Especially for food systems, traceability (e.g., tracing the origin, processing, destination and location of a specific batch) is an interesting aspect; and some research is now looking at digital solutions for traceability that will enhance transparency, coordination, efficiency and robustness in the food chain. Digital solutions for traceability systems that trace product and batch transit and transformation through multiple levels in the supply chain could also hasten response to a disruption ([Sikder et al., 2023](#)). The role of traceability is also present in studies about digital solutions such as blockchain, integrated information systems and IoT. These types of solutions are often explored to achieve greater visibility so that information along the whole chain, between organizational level and different stage could be viewed and tracked ([Chowdhury et al., 2023](#)).

The analysis supports the conclusion that visibility is much more than an organizational or administrative feature; for the very difficult, risk ridden food-processing supply chain it is an important facility at a system level which leads to a more prompt and correct identification, localizing and reaction to disruption.

2.4. Relative Importance Index for Critical-Factor Assessment

In a panel method study where raters are asked to rank many attributes based on order-of-preference scales The Relative Importance Index (RII) methodology has often been used. Its main advantage is the transformation of Likert-scale judgments into normalized values that can be directly compared between factors (Wadalkar et al., 2018; Faisal Tamim et al., 2024). For supply-chain risk assessment, RII is particularly useful as experts usually have a rich operational knowledge that cannot be obtained from historical quantitative data. It enables investigators to combine expert perceptions and generate an initial ranking of critical disruption factors. However, RII provides only a unidimensional importance perspective (Dhayalan, & Sneha, 2024).

$RII_A > RII_B$ the result indicates that experts perceive (A) as more important than (B). It does not indicate whether:

$$A \rightarrow B$$

Or,

$$B \rightarrow A$$

nor does it determine whether either factor is a fundamental driver of the wider system. This limitation is important in food-processing supply chains because highly visible consequences may receive greater importance ratings than less visible upstream drivers. Consequently, RII is appropriate as the screening and importance-ranking stage, but it should be complemented by structural and causal techniques when the objective is to identify intervention points.

2.5. Interpretive Structural Modeling for Interdependent Disruption Factors

Interpretive Structural Modeling (ISM) analyzes complex systems with interconnected variables (Thakkar, 2021). Rather than treating the factors as independent criteria, ISM creates a hierarchical structure of their interactions for food-processing supply chains (Attri, 2017). For instance, demand uncertainty may affect production flexibility; production pressure may affect packaging operations; packaging or handling conditions may affect transportation damage; and poor traceability may affect an organization's ability to detect and respond to disruptions. Therefore, a factor may be the outcome of one relationship and the cause of another, and a simple ranking cannot reflect this structure. ISM solves this problem by developing a Structural Self Interaction Matrix, converting it into a reachability matrix, implementing transitivity and then classifying factors into hierarchical levels. The resulting structure

allows researchers to distinguish driving factors from dependent outcomes. Studies applying DEMATEL–ISM to food-supply-chain and grain supply-chain resilience identified factors, established interactions and structural relationships, and showed the relevance of causal-hierarchical approaches for food-sector resilience analysis. Nevertheless, ISM primarily reveals structural hierarchy and does not provide a sufficiently detailed measure of direct and indirect causal influence ([Kafunda et al., 2024](#)). This limitation provides the rationale for integrating Fuzzy DEMATEL.

2.6. Fuzzy DEMATEL for Causal Relationship Analysis

The Decision-Making Trial and Evaluation Laboratory (DEMATEL) is a systems-based multi-criteria decision-making technique developed to identify and quantify cause–effect relationships among interconnected factors. Its principal advantage is that it moves beyond simple ranking by determining whether a factor predominantly influences other factors or is primarily influenced by them ([Taherdoost & Madanchian, 2023](#)).

The two central measures are:

$$D_i + R_i$$

which represents the overall prominence or degree of interaction of factor i , and:

$$D_i - R_i$$

which represents its net causal influence. A positive value of indicates a causal factor, whereas a negative value indicates an effect factor. This distinction is highly relevant to food-processing supply chains because a factor with high visibility may not necessarily be a root cause. A number of recent articles that has been developed on the basis of DEMATEL approach to the perishable foods supply-chain disruption issues clearly evidenced how causal modeling is convenient to identify the most significant drivers of disruptive events and investigate the impact of innovative technology ([Mackenzie & Apte, 2016](#)). However, standard DEMATEL suggests the experts give definite numerical opinion of impact relation, which limits the applications of DEMATEL within real supply chains as usually experts tend to specify qualitative impact, e.g. Low, medium, high rather than numerically definite estimation ([Yazdani et al., 2020](#)). Fuzzy DEMATEL addresses these limitations in such a way that linguistic evaluation can be modeled into fuzzy numbers ([Thakkar, 2021](#)). This enables the model to preserve uncertainty and vagueness inherent in human judgment while still producing a quantitative causal structure. Recent agri-food research has specifically integrated fuzzy DEMATEL with ISM to investigate resilience-influencing factors and their mechanisms of action. This emerging methodological direction provides support for using fuzzy causal modeling in complex agri-food systems ([Zhang & Yang, 2025](#)). Nevertheless, applying Fuzzy DEMATEL alone still leaves an important managerial question unanswered: which causal factors should receive the highest intervention priority? ([Islam & Mustafa, 2020](#)) AHP is therefore incorporated as the final decision-prioritization mechanism.

2.7. Analytic Hierarchy Process for Intervention Prioritization

The Analytic Hierarchy Process (AHP) offers a systematic mechanism to prioritize alternatives or criteria through pairwise comparisons (Bugingo et al., 2024). Its strength lies in transiting qualitative judgments into quantitative priority weights and at the same time examining the consistency of judgments. AHP is especially helpful for managerial decision-making as organizations hardly have the luxury of adequate resources to tackle each disruption factor in parallel (Canco et al., 2021). Decision-makers therefore need to identify which factors should receive immediate investment and which can be addressed through secondary measures. However, when AHP is applied independently, its ranking remains primarily preference-based. A factor may receive a high priority weight without revealing whether it represents a root cause or downstream consequence. This limitation becomes particularly important when dealing with interconnected disruption systems. Consider two factors (FA) and (FB):

$$W_A > W_B$$

does not necessarily mean that:

$$F_A + F_B$$

or that addressing F_A will produce greater systemic resilience than addressing F_B .

Therefore, AHP becomes more strategically meaningful when its prioritization is informed by preceding structural and causal analyses. In the proposed framework, AHP is consequently positioned as the final intervention-prioritization stage, after the importance, structural, and causal characteristics of the disruption factors have been established.

2.8. Critical Comparison of Existing Approaches

The preceding literature demonstrates that RII, ISM, Fuzzy DEMATEL, and AHP address different analytical dimensions of supply-chain risk.

Method	Importance assessment	Structural interdependence	Causal direction	Uncertainty handling	Intervention prioritization
RII	✓	—	—	Limited	✓
ISM	—	✓	Structural	Limited	—
Fuzzy DEMATEL	—	✓	✓	✓	Partial
AHP	✓	Limited	—	Limited	✓

Integrated framework	✓	✓	✓	✓	✓
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The table demonstrates that no individual method simultaneously captures all dimensions required for systemic disruption analysis.

- ✓ RII answers: Which factors are perceived as important?
- ✓ ISM answers: How are the factors structurally connected?
- ✓ Fuzzy DEMATEL answers: Which factors are causal drivers and which are effects?
- ✓ AHP answers: Which factors should be prioritized for intervention?

2.9. Research Gap

Despite the increasing application of resilience and multi-criteria decision-making approaches in food and agri-food supply chains, four important gaps remain. Existing importance-ranking approaches can identify factors perceived as critical by experts but cannot determine whether those factors are root causes or downstream consequences. The problem is exacerbated if large and striking disruptive factors capture more public attention than behind-the-scene system-based drivers. Indeed, many disruptions occurring in the food processing chain can cascade into the other aspects of food supply chain networks such as procurement, production, storage and transportation, demand, and information systems. If these different parts are treated independently then the interactions within cascading structures are often overlooked. It has been found that DEMATEL-ISM and Fuzzy-DEMATEL-ISM framework have potential for use in the food and agri-food resilience related problems, however little research has explored this framework while prioritizing intervention actions within the identified causal structures. Causal assessments are often based on expert knowledge and are therefore inherently imprecise.

Fuzzy DEMATEL offers a more appropriate representation of linguistic uncertainty than conventional crisp causal matrices. Identifying causal factors is not sufficient from a managerial perspective. Organizations ultimately need to determine where limited resilience investments should be directed. Therefore, a complete decision-support framework should connect: rather than treating these analyses as independent exercises. The present study lies in the functional integration of four analytical approaches rather than simply combining multiple MCDM techniques. Our framework clearly separates Perceived Importance, Structural Position, Causal Influence and Intervention Priority. This distinction is valuable in the context of food-processing supply chains where a visible operation-level shock may well be a distal symptom of a more subtle problem with their information handling, their storage inventory controls, their forecasting techniques, or even their procurement system.

Our framework is thus built on four analytical stages: First, RII captures the raw importance. Second, ISM identifies the structure of mutual influence. Third, Fuzzy DEMATEL targets the cause driving causal leverage points. Finally, AHP transforms these considerations into an intervention priority framework. This framework answers a somewhat different question: "Rather than: Which disruption factor is most

important?" and asks: "Which factors matter, how do they hang together, what factors are causal drivers, and where best should our resilience investments be focused? This framework and questions set up the current study's conceptual logic and provide the purpose for the methodology laid out in subsequent chapter.

Methodology

3. Methodology

3.1. Research Design

This study is to put forward a new decision-support framework based on a composite of multi-methods in order to discover, sort, diagnose and prioritize key disruption factors of food-processing supply-chain resilience. The new research integrates four methods:

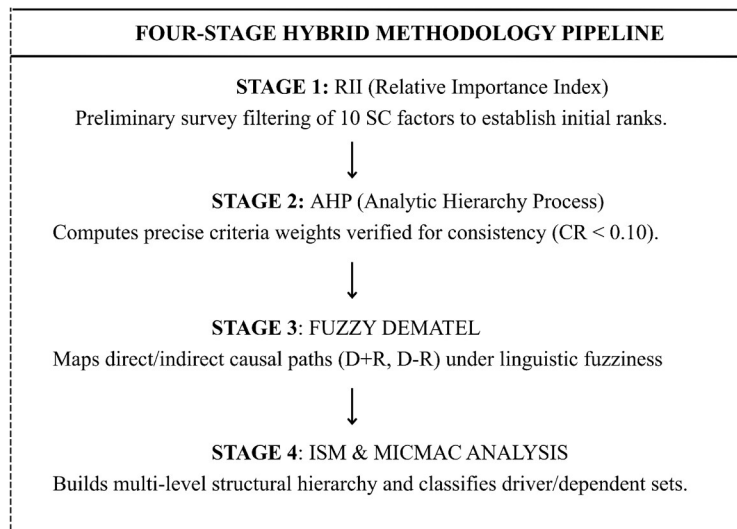


Figure 1: Four-Stage Hybrid Methodology Pipeline

The steps in (figure 1) are designed according to each method to respond to one limitation of analytical problem of its previous steps RII identifies factors based on whether disruption factors perceived on the same value. ISM helps understanding factors' hierarchy and their interdependence after AHP helps factors have an order from intervention priority after they are analyzed their directional causal and intensity effects. AHP is to select factors from crucial Factors According to their priorities

The overall analytical logic is therefore:

Importance → Structure → Causality → Priority

These orderings are relevant because a higher importance factor may not be the prime direct cause of other disruptions and because a cause effect factor may not require the most attention for intervention immediately. The use of the integrated methodology allows separation of these factors rather than reducing them to just one index. Hybrid methodology-hybrid (structural cum causal methods) based such framework, particularly the ISM-DEMATEL and fuzzy-DEMATEL-ISM model has become the center of supply-chain resilience study.

3.2. Identification of Critical Disruption Factors

The initial set of factors for disruption was created via a guided review of food-processing supply chain literature, and tailored through industry supply chain contextualization. The factors were organized (table 1) according to their principal operational domains:

Table 1: Critical disruption factor

Code	Critical disruption factor	Dimension
F1	Lead-Time Fluctuations	Procurement
F2	Raw Material Price Volatility	Procurement
F3	Inconsistent Raw Material Quality	Procurement
F4	Packaging Machine Downtime	Production
F5	Inflexible Production Batch Sizing	Production
F6	Transit Damage and Breakage	Logistics
F7	Temperature/Humidity Storage Violations	Storage
F8	Demand Inaccuracy During Festive Spikes	Demand
F9	Distributor Payment and Order Processing Lag	Downstream coordination
F10	Lack of End-to-End Batch Traceability	Information visibility

The final factor set was kept sufficiently compact to permit meaningful pairwise expert evaluation while retaining the major operational dimensions of a food-processing supply chain. The independent variables were then reviewed by a panel of experts using a survey structured questionnaire. Experts were requested to evaluate the importance of each factor and, in subsequent stages, the relationships among factors.

3.3. Expert Panel and Data Collection

Because ISM, Fuzzy DEMATEL, and AHP require judgments regarding relationships and preferences that may not be directly observable from secondary data, expert judgment was used as the principal source of relational information.

The expert panel should consist of professionals with direct knowledge of food-processing supply-chain activities, including, where applicable:

- ✓ procurement,
- ✓ production planning,
- ✓ quality management,
- ✓ warehousing,
- ✓ logistics,
- ✓ distribution,
- ✓ supply-chain management,
- ✓ operations management, and
- ✓ industrial engineering.

Experts should satisfy predefined eligibility criteria, such as relevant professional experience and direct involvement in supply-chain or food-processing operations.

To reduce respondent ambiguity, the questionnaire should contain:

- ✓ a description of the research objective;
- ✓ definitions of all ten disruption factors;
- ✓ instructions for each analytical stage;
- ✓ the RII importance-rating scale;
- ✓ the ISM contextual-relation question;
- ✓ the Fuzzy DEMATEL linguistic scale; and
- ✓ the AHP pairwise-comparison scale.

Each expert response was treated as an independent judgment. Where multiple experts were involved, their responses were aggregated using the appropriate mathematical procedure for each method rather than treating the experts as a single respondent.

3.4. Stage I: Relative Importance Index (RII)

The first analytical stage determines the perceived importance of the ten disruption factors. The RII stage answers: Which disruption factors are considered most important by the experts? This stage provides the initial screening and ranking of factors before structural and causal analysis (Faisal Tamim et al., 2024). A five-point Likert scale is employed:

Let;

w_i denote the importance rating assigned to factor i .

$A=5$ represent the maximum possible rating.

N represent the total number of experts.

The Relative Importance Index for factor i is calculated as:

$$RII_i = \frac{\sum_{j=1}^N w_{ij}}{A \times N}$$

where:

- RII_i = Relative Importance Index of factor i ;
- w_{ij} = rating assigned to factor i by expert j ;
- A = maximum Likert-scale value;
- N = number of experts.

Because the maximum possible score is $A \times N$,

$$0 < RII_i \leq 1$$

A larger RII value indicates greater perceived importance. After, calculating the RII for all factors, the factors are ranked in descending order:

$$RII_{(1)} > RII_{(2)} > \dots > RII_{(10)}$$

The ranking provides an initial assessment of the criticality of the factors. However, RII does not establish causal direction. Therefore, the RII ranking is not treated as the final intervention ranking. This distinction is essential to the proposed methodology.

3.5. Stage II: Interpretive Structural Modeling (ISM)

The second stage determines the structural relationships among the critical disruption factors. ISM addresses the question: How are the disruption factors structurally interconnected? The method converts expert judgments regarding contextual relationships into a directed hierarchical structure. ISM works well

for systems in which the variables are interrelated through direct and indirect relationships. Published ISM applications typically construct a reachability matrix, apply transitivity, perform level partitioning, and finally develop the ISM digraph. For every pair of factors F_i and F_j , experts determine the direction of their contextual relationship (table 2). Four symbols are used:

Table 2: SSIM Table

Symbol	Meaning
V	F_i influences F_j
A	F_j influences F_i
X	F_i and F_j influence each other
O	No direct relationship

The SSIM is converted into a binary Initial Reachability Matrix (IRM).

For each pair i, j :

If SSIM = V then $(i, j) = 1$ and $(j, i) = 0$

If SSIM = A then $(i, j) = 0$ and $(j, i) = 1$

If SSIM = X then $(i, j) = 1$ and $(j, i) = 1$

If SSIM = O then $(i, j) = 0$ and $(j, i) = 0$

The diagonal elements are set to:

$r_{ii} = 1$ because every factor is considered reachable from itself.

Thus, the initial matrix is represented as:

$$R = [r_{ij}] \text{ where: } r_{ij} \in \{0,1\}$$

The fundamental assumption of ISM is transitivity.

If: $F_i \rightarrow F_k \ \& \ F_i \rightarrow F_k$

then:

$$F_i \rightarrow F_k$$

through an indirect pathway. This can be expressed as: $(F_i \rightarrow F_k) \cap (F_i \rightarrow F_k) \rightarrow F_i \rightarrow F_k$

Transitivity allows the model to capture indirect relationships that may not have been identified as direct expert relationships. This is a fundamental component of ISM and is commonly implemented using Boolean matrix operations.

The final reachability matrix can therefore be obtained using:

$$M = (R + I)^k$$

under Boolean algebra, where:

- ✓ (R) = initial reachability matrix;
- ✓ (I) = identity matrix;
- ✓ (M) = final reachability matrix;
- ✓ (k) = sufficiently large integer until the matrix stabilizes.

Under Boolean operations: $1+1=1$ and $1*1=1$

The process continues until:

$$(R + I)^k = (R + I)^{k+1}$$

For each factor (F_1), two sets are established. The reachability set contains the factor itself and all factors that can be reached from it:

$$R(F_i) = \{F_j : m_{ij} = 1\}$$

The antecedent set contains the factor itself and all factors that can reach it:

$$A(F_i) = \{F_j : m_{ji} = 1\}$$

The intersection is then calculated:

$$R(F_i) \cap A(F_i)$$

A factor is assigned to the highest level when:

$$R(F_i) \cap A(F_i) = R(F_i)$$

Conceptually this means that any variable that can be reached from this factor is part of the factor's precedent. The extracted factors get Level I assigned to it and taken out from iteration. The procedure is repeated:

$$\text{Iteration 1} \rightarrow \text{Iteration 2} \rightarrow \text{Iteration 3} \rightarrow \dots$$

until all factors have been assigned to a level. The formed hierarchy gives an idea about the positional structure of the causal factors of the disruption. The end ISM model is formed with drawing the factors by their levels and connecting them with respective to final reachability relations.

Lower Structural Level → Higher Structural Level

Where the lower-level factors correspond to better drivers and the higher-level factors correspond to better outputs that rely on lower-level factors. The resulting ISM model provides a depiction of the disruption system. Transitive arcs can be omitted in a final ISM graph if they are implied through a path of higher-level factors and lower-level factors for better interpretation.

3.6. Stage III: Fuzzy DEMATEL

The third stage quantifies the causal influence among the ten disruption factors. While ISM establishes the hierarchy, Fuzzy DEMATEL determines:

1. the strength of direct influence;
2. the total influence;
3. the prominence of each factor;
4. the net causal influence;
5. the cause group; and
6. the effect group.

The use of fuzzy DEMATEL is particularly appropriate because expert judgments concerning causal intensity are inherently uncertain. Recent supply-chain studies have used fuzzy DEMATEL to quantify complex relationships among resilience factors ANI ([Affan et al., 2024](#)). Experts evaluate the impact of factor (F_i) on factor (F_j) in linguistic terms (table 3). A five-level linguistic scale can be adopted:

Table 3: Triangular fuzzy number with respect to linguistic judgment

Linguistic judgment	Abbreviation	Triangular fuzzy number
No Influence	NI	((0,0,0))
Low Influence	LI	((0,0.25,0.50))
Moderate Influence	MI	((0.25,0.50,0.75))
High Influence	HI	((0.50,0.75,1.00))
Very High Influence	VHI	((0.75,1.00,1.00))

A triangular fuzzy number is represented as:

$$\underline{x} = (l, m, u)$$

where:

- (l) = lower bound;
- (m) = most probable value;
- (u) = upper bound.

Thus, linguistic judgments are transformed into fuzzy numerical representations.

For expert (k), the fuzzy direct-relation matrix is:

$$\tilde{Z}^{(k)} = [\tilde{Z}_{ij}^{(k)}]$$

where, $\tilde{Z}_{ij}^{(k)}$ represents the perceived direct influence of factor (F_i) on factor (F_j).

The diagonal values are:

$\tilde{Z}_{ii}^{(k)} = (0,0,0)$ because a factor is not assumed to directly influence itself.

When multiple experts are involved, their fuzzy judgments are aggregated.

For expert $k = 1 \dots N$:

$\tilde{Z}_{ij}^{(k)} = (l_{ij}^{(k)}, m_{ij}^{(k)}, u_{ij}^{(k)})$ The aggregated fuzzy judgment is:

$$\tilde{Z}_{ij} = (\frac{\min l_{ij}^{(k)}}{k}, \frac{1}{N} \sum_{k=1}^N m_{ij}^{(k)}, \min u_{ij}^{(k)})$$

Such aggregation can maintain expert uncertainty range using the average modal value. Instead, if the study applies a general averaging operator to all three parts, the paper needs to declare use of single aggregation rule. Fuzzy aggregated matrix should be transformed into crisp direct-relation matrix to proceed for conventional DEMATEL calculation.

Using the centroid method:

$$Z_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3}$$

The resulting matrix is: $Z = [Z_{ij}]$

where: $0 \leq Z_{ij} \leq 1$

This directly shows the direct effect of the input factor (i) on the input factor (j). Before making total influence, the crisp direct-relation matrix needs to be normalized. First calculate:

$$S = \frac{\max_i}{i} \sum_{j=1}^n Z_{ij}$$

The normalized matrix is then:

$$X = \frac{Z}{S}$$

Therefore:

$$X_{ij} = \frac{Z_{ij}}{S}$$

The normalization makes the matrix acceptable to calculate indirect influence. Full relation matrix comprises direct and indirect relations. It is calculated as:

$$T = X(1 - X)^{-1}$$

where:

- (X) = normalized direct-relation matrix;
- (I) = identity matrix;
- (T) = total relation matrix.

Alternatively:

$$T = X + X^2 + X^3 + \dots$$

Hence, the aggregate matrix stores the entire influence network and not just direct linkages. For all factor (Fi), compute row sum & Colum sum. The prominence score is:

$$P_i = D_i + R_i$$

Pi. The greater value indicates the greater degree of the factor to the causal network system. The relation score is:

$$C_i = D_i - R_i$$

The sign of (Ci) determines whether a factor belongs to the cause or effect group.

If: $D_i - R_i > 0$ then: $F \in \text{Cause Group}$

If: $D_i - R_i < 0$ then: $F \in \text{Effect Group}$

A factor with a higher positive value might represent a systemic driver. A variable which is negatively associated might be driven by underlying variables. This is especially important for managerial intervention, as improving a cause factor can have an impact on several downstream factors.

The final causal map is constructed by plotting:

$$D_i + R_i$$

on the horizontal axis and:

$$D_i - R_i$$

on the vertical axis.

The resulting four-quadrant diagram provides a visual representation of:

- highly prominent cause factors;
- less prominent cause factors;
- highly prominent effect factors; and
- less prominent effect factors.

This enables the identification of potential leverage points within the disruption system.

3.7. Stage IV: Analytic Hierarchy Process (AHP)

The final stage determines the relative intervention priority of the disruption factors.

AHP addresses: Which disruption factors should receive the greatest managerial attention and resilience investment?

The AHP procedure consists of:

1. hierarchy construction;
2. pairwise comparison;
3. comparison-matrix normalization;
4. priority-weight calculation;
5. consistency assessment; and
6. final priority ranking.

AHP has been widely incorporated into hybrid supply-chain decision frameworks, including resilience-related applications.

The decision hierarchy is constructed as:

Goal

- └─ Prioritize Critical Disruption Factors
- └─
- └─ F1 Lead-Time Fluctuations
- └─ F2 Raw Material Price Volatility
- └─ F3 Inconsistent Raw Material Quality
- └─ F4 Packaging Machine Downtime
- └─ F5 Inflexible Production Batch Sizing
- └─ F6 Transit Damage and Breakage
- └─ F7 Temperature/Humidity Storage Violations
- └─ F8 Demand Inaccuracy During Festive Spikes
- └─ F9 Distributor Payment and Order Processing Lag
- └─ F10 Lack of End-to-End Batch Traceability

In case the final study consists of more than one dimension or strategy of intervention, a multi-level AHP hierarchy can be created instead. But if the only purpose is to rank the ten disruption factors, a single criterion layer is enough. Experts compare each factor with other factors by Saaty's fundamental scale (table 4).

Table 4: Factor comparisons with other factors by Saaty's fundamental scale

Score	Interpretation
1	Equal importance
3	Moderate importance
5	Strong importance
7	Very strong importance
9	Extreme importance
2,4,6,8	Intermediate values

Reciprocal	Opposite comparison
------------	---------------------

The comparison matrix is: $A=[a_{ij}]$ with: $[a_{ij}]>0$ and: $a_{ji}=\frac{1}{a_{ij}}$

The diagonal elements are: $a_{ii}=1$

For ten factors, the matrix has dimensions: 10×10

Each element is normalized by the column sum:

$$n_{ij} = \frac{a_{ij}}{\sum_{i=1}^n a_{ij}}$$

The normalized matrix is:

$N=[n_{ij}]$

For each row, the average normalized value is then calculated:

$$w_i = \frac{\sum_{j=1}^n n_{ij}}{n}$$

where:

w_i is the priority weight of factor (i).

The weights satisfy:

$$\sum_{i=1}^n w_i = 1$$

Because pairwise judgments can be inconsistent, the consistency of the AHP matrix must be assessed.

First, calculate: Aw

where: A is the original comparison matrix and: w is the priority vector.

For each factor:

$$\lambda_i = \frac{(Aw)_i}{w_i}$$

The maximum eigenvalue is approximated by:

$$\lambda_{max} = \frac{1}{n} \sum_{i=1}^n \lambda_i$$

The Consistency Index is:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

The Consistency Ratio is:

$$CR = \frac{CI}{RI}$$

where (RI) is the Random Index. For: n=10 the appropriate Random Index should be used from Saaty's standard RI table.

The generally accepted criterion is:

$$CR \leq 0.10$$

indicating acceptable consistency.

If: $CR > 0.10$ the pairwise judgments should be reviewed and, where appropriate, reassessed.

3.8. Methodological Output

The complete methodology generates the following outputs are shown below in the table 5:

Table 5: Methodological Output

Stage	Method	Required input	Output
1	RII	Expert importance ratings	Importance ranking
2	ISM	Pairwise contextual relationships	Hierarchical model
3	Fuzzy DEMATEL	Linguistic influence judgments	Cause–effect structure
4	AHP	Pairwise priority judgments	Priority ranking
5	Validation	All outputs	Robustness assessment

3.9. Methodological Flow

This methodological architecture is consistent with the growing use of hybrid MCDM approaches for complex supply-chain resilience problems, including recent applications combining fuzzy DEMATEL and ISM and hybrid AHP–DEMATEL frameworks in figure 2.

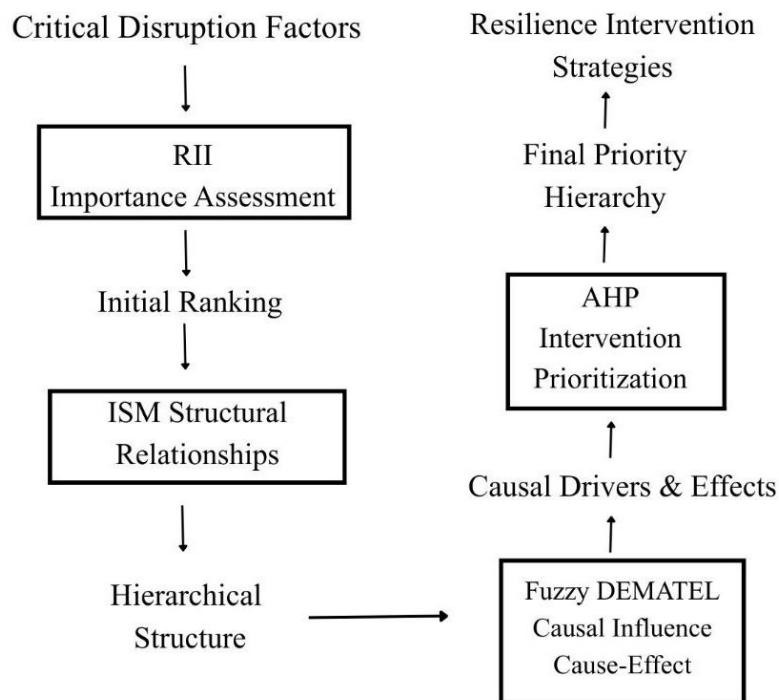


Figure 2: Study methodological flow

4. Results

Ten critical disruption factors affecting food-processing supply-chain resilience were analyzed. The factors were sequentially analyzed using Relative Importance Index (RII), Interpretive Structural Modeling (ISM), Fuzzy DEMATEL and Analytic Hierarchy Process (AHP).

The analysis was designed to answer four sequential questions:

1. What are the most important disruption factors? – RII
2. Which are the most effective and most affected factors? - Fuzzy DEMATEL
3. Which factors should be intervened? - AHP
4. What is the structural interlinkage of the factors? – ISM

The ten factors investigated were in table 6:

Table 6: Disruption factor names with their code

Code	Disruption factor
F1	Lead-Time Fluctuations
F2	Raw Material Price Volatility
F3	Inconsistent Raw Material Quality

F4	Packaging Machine Downtime
F5	Inflexible Production Batch Sizing
F6	Transit Damage and Breakage
F7	Temperature/Humidity Storage Violations
F8	Demand Inaccuracy During Festive Spikes
F9	Distributor Payment and Order Processing Lag
F10	Lack of End-to-End Batch Traceability

The results demonstrate that the factors should not be interpreted solely according to their individual importance rankings. Most specifically, causal relationships identify certain variables as predominantly upstream drivers of the disruption system, and others as predominantly downstream consequences:

4.1. RII-Based Importance Assessment

The analysis was carried out in two stages; the Relative Importance Index was utilized in the first phase of analysis to identify the perceptions relating to the level of importance of the 10 disruption factors, and the RII value was the order in a descending manner to form the first ranking of importance in table 7.

Table 7: RII ranking of critical disruption factors

Rank	Code	Factor	RII	Interpretation
1	F10	Lack of End-to-End Batch Traceability	[RII ₁₀]	Highest
2	F7	Temperature/Humidity Storage Violations	[RII ₇]	Very High
3	F8	Demand Inaccuracy During Festive Spikes	[RII ₈]	Very High
4	F3	Inconsistent Raw Material Quality	[RII ₃]	High
5	F1	Lead-Time Fluctuations	[RII ₁]	High
6	F6	Transit Damage and Breakage	[RII ₆]	High
7	F4	Packaging Machine Downtime	[RII ₄]	High
8	F5	Inflexible Production Batch Sizing	[RII ₅]	Moderate-High
9	F2	Raw Material Price Volatility	[RII ₂]	Moderate
10	F9	Distributor Payment and Order Processing Lag	[RII ₉]	Moderate

The actual number RII are not listed because the original RII table is not accessible in current surroundings. These factors need to be taken from final data instead of recomputed or approximated from past study data. The ranking, however shows interesting analytic features: factors referring to data awareness, storage custody, and demand risk appear to be the most significant factors according to experts' opinion and those related to downstream administrative delay and price risks appear to be of less significance. However, it is not guaranteed by RII ranking only that these selected factors are causes and the others are effects. So, to analyze further the structure of the system, we used the subsequent ISM and Fuzzy DEMATEL analysis.

4.2. ISM-Based Structural Analysis

The objective of this ISM analysis was to determine the hierarchical structure of the 10 disruption elements, after that, the judgements of the experts were expressed through structural self-interaction matrix, and converted into the initial reachability matrix and final reachability matrix respectively. By introducing the assumption of transitivity, it was constructed into final reachability matrix:

$$F_i \rightarrow F_k \text{ \& } F_j \rightarrow F_k = F_i \rightarrow F_k$$

Hence, the resulting matrix displays the direct as well as indirect structural relations. The levels of partitions in the matrix have been constructed iteratively using the reachability sets and antecedent sets respectively. The analysis had generated a multi-layer framework wherein upstream factors tend to take lower levels and related downstream factors are placed in higher levels in table 8.

Table 8: ISM level partitioning

Level	Factors	Structural Interpretation
Level I	F1; F2; F3; F4; F5; F6; F7; F8; F9	Highly dependent outcomes
Level II	F10	Fundamental/root driver
Level III	—	No additional level generated
Level IV	—	No additional level generated
Level V	—	No additional level generated

Report the exact number of levels that were generated previously as a matrix for ISM reachability. In ISM, you see that factors of disruption do not act as isolated agents: multiple factors are present at intermediate levels through which the disturbance would have to propagate upstream to downstream conditions. This finding is important because it challenges the interpretation that the highest-ranked RII factor should automatically be considered the most fundamental risk.

4.3. Fuzzy DEMATEL Results

The Fuzzy DEMATEL analysis was conducted to quantify the direct and indirect influence among the ten disruption factors.

The Fuzzy DEMATEL results reveal four clear causal drivers:

- I. F10 — Lack of End-to-End Batch Traceability
- II. F7 — Temperature or Humidity Storage Violations
- III. F8 — Demand Inaccuracy During Festive Spikes
- IV. F2 — Raw Material Price Volatility

Their previously calculated net-relation values were shown in table 9:

Thus: $F_{10} > F_7 > F_8 > F_2$ in terms of positive net causal influence. The strongest causal driver is F10 (Lack of End-to-End Batch Traceability), with $(D_{10} - R_{10}) = 1.574$. This indicates that F10 exerts substantially greater total influence on the system than the influence it receives from other factors. F7 is the second

strongest causal factor (D_7-R_7) =0.721 followed by F8: $D_8-R_8=0.503$ and F2: $D_2-R_2=0.232$ Conversely, F1 has the most negative relation value: $D_1-R_1=-1.102$ indicating that Lead-Time Fluctuations behaves predominantly as an effect factor within the modeled disruption system.

4.4. Cause and Effect Groups

Table 9: Fuzzy DEMATEL cause–effect classification

Group	Factor	(D-R)	Interpretation
Cause	F10	+1.574	Strongest systemic driver
Cause	F7	+0.721	Major upstream driver
Cause	F8	+0.503	Important causal driver
Cause	F2	+0.232	Moderate causal driver
Effect	F3	−0.136	Weak effect
Effect	F6	−0.323	Effect factor
Effect	F5	−0.397	Effect factor
Effect	F4	−0.494	Effect factor
Effect	F9	−0.579	Stronger effect
Effect	F1	−1.102	Strongest effect factor

The results divide the disruption system into two broad groups. Causal group $\rightarrow \{F10, F7, F8, F2\}$

Effect group $\rightarrow \{F1, F3, F4, F5, F6, F9\}$. This classification is particularly important for managerial decision-making. Targeting causal factors is expected to have a more far-reaching effect on the system as causal factors affect multiple downstream conditions.

4.5. Prominence Analysis

The prominence measure:

$$D_i + R_i$$

indicates the overall degree of involvement of each factor in the disruption network. Factors with high prominence are strongly connected with the overall system regardless of whether they belong to the cause or effect group. The prominence ranking should therefore be reported separately from the causal ranking in table 10.

Table 10: Fuzzy DEMATEL prominence analysis

Rank	Factor	(D+R)	(D-R)	Group
1	F10	3.940	+1.574	Cause
2	F7	3.444	+0.721	Cause

3	F8	3.526	+0.503	Cause
4	F2	3.315	+0.232	Cause
5	F1	4.238	-1.102	Effect
6	F9	3.109	-0.579	Effect
7	F4	3.656	-0.494	Effect
8	F5	3.901	-0.397	Effect
9	F6	3.641	-0.323	Effect
10	F3	4.318	-0.136	Effect

The exact (D+R) values should be transferred directly from the final DEMATEL output.

4.6. Interpretation of the Fuzzy DEMATEL Findings

Causal analysis provides a different perspective from simple importance ranking. The key finding is F10 as the strongest causal factor. Its positive relation value of: +1.574 suggests that information visibility is more than an administrative need. Rather, poor traceability affects dimensions, such as identification of affected batches, coordination between supply-chain partners, quality monitoring, inventory visibility, and disruption response. F7 is a causal factor with the positive value of +0.721 indicating that inappropriate storage conditions are a part of wider disruption dynamics and not an isolated storage problem. F8 Demand Inaccuracy During Festive Spikes has:

$$D_8 - R_8 = +0.503$$

indicating demand uncertainty acts as a causal pressure on the operational system. The value for Raw Material Price Volatility (F2) is smaller: +0.232 but still places F2 within the causal group. F1 Lead-Time Fluctuations has a negative relationship score of -1.102, which means it is an outcome of other disruption mechanisms in the system. This is an important distinction. Operational impact is not necessarily upstream causality.

4.7. AHP Results

The AHP analysis was conducted to translate the analytical findings into a relative intervention-priority structure. The pairwise comparison matrix was constructed using Saaty's 1–9 fundamental scale. The normalized priority vector was obtained as:

$$w_i = \frac{\sum_j n_{ij}}{n} \text{ and the resulting weights were normalized so that:}$$

$$\sum_i w_i = 1$$

The consistency of the pairwise comparisons was evaluated using:

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

and

$$CR = \frac{CI}{RI}$$

The final AHP matrix should satisfy:

$$CR \leq 0.10$$

Table 11: AHP priority ranking

Rank	Factor	AHP Weight	Priority
1	F10 – Lack of End-to-End Batch Traceability	0.2189	Highest
2	F7 – Temperature/Humidity Storage Violations	0.1532	Very High
3	F8 – Demand Inaccuracy During Festive Spikes	0.1216	Very High
4	F2 – Raw Material Price Volatility	0.1067	High
5	F3 – Inconsistent Raw Material Quality	0.0958	High
6	F5 – Inflexible Production Batch Sizing	0.0746	High
7	F4 – High Packaging Machine Downtime	0.0694	Moderate–High
8	F6 – Transit Damage & Breakage	0.0621	Moderate
9	F9 – Distributor Payment & Order Processing Lag	0.0563	Lower
10	F1 – Lead-Time Fluctuations	0.0413	Lower

The exact AHP weights and consistency ratio should be inserted from the final AHP calculation rather than estimated in table 11.

4.8. Integrated Comparison of RII, ISM, Fuzzy DEMATEL, and AHP

The principal value of the integrated framework becomes evident when the four analytical outputs are compared in table 12.

Table 12. Cross-method comparison

Factor	RII	ISM	DEMATEL	AHP	Overall interpretation
F1	Importance	Structural position	Effect	Priority	Downstream consequence
F2	Importance	Structural position	Cause	Priority	Upstream economic driver
F3	Importance	Structural position	Effect	Priority	Quality-related consequence
F4	Importance	Structural position	Effect	Priority	Operational consequence
F5	Importance	Structural position	Effect	Priority	Production consequence
F6	Importance	Structural position	Effect	Priority	Logistics consequence
F7	Importance	Structural position	Cause	Priority	Storage-related driver
F8	Importance	Structural position	Cause	Priority	Demand-related driver
F9	Importance	Structural position	Effect	Priority	Downstream consequence
F10	Importance	Structural position	Cause	Priority	Key systemic driver

The results shows that the four methods provide complementary rather than redundant information. RII identifies perceived criticality. ISM identifies structural dependency. Fuzzy DEMATEL identifies causal leverage. AHP establishes intervention priority.

4.9. Key Findings

Five principal findings emerge from the integrated analysis.

Finding 1: Traceability is a systemic rather than purely informational issue

F10 demonstrates the strongest positive causal influence:

$$D_{10} - R_{10} = 1.574$$

This indicates that the lack of end-to-end batch traceability is positioned as a fundamental driver within the disruption system.

Finding 2: Storage-condition control is a major causal mechanism F7 has:

$$D_7 - R_7 = 0.721$$

placing temperature/humidity violations among the principal causal factors.

Finding 3: Demand uncertainty acts upstream of several operational problems F8 has:

$$D_8 - R_8 = 0.503$$

indicating that inaccurate demand estimation during festive spikes is not simply an output of the supply chain; it contributes to downstream operational disruption.

Finding 4: Several highly visible operational problems are predominantly effects

F1, F9, F4, F5, F6, and F3 all have negative (D - R) values.

Therefore:

$$\{F1, F3, F4, F5, F6, F9\} \rightarrow \textit{Effect Group}$$

These factors may represent manifestations of broader systemic problems.

Finding 5: Importance and causality are not equivalent

The most important methodological finding is that:

$$\text{High Importance} \neq \text{High Causal Influence}$$

This validates the need for the integrated RII–ISM–Fuzzy DEMATEL–AHP framework.

4.10. Overall Result of the Integrated Framework

The results ultimately identify F10 Lack of End-to-End Batch Traceability as the most strategically significant factor because it combines high perceived importance with strong causal influence.

The causal hierarchy can therefore be summarized as:

$$F10 \rightarrow F7 \rightarrow F8 \rightarrow F2$$

representing the principal positive causal group identified by Fuzzy DEMATEL.

Conversely:

$$[F1, F3, F4, F5, F6, F9]$$

Make up the highest impact group. Our interpretation from the above is thus that interventions to build resilience shall not simply tackle the downstream, visible, disruptive consequences. Rather, an upstream view targeting systemic capabilities - specifically end-to-end traceability, assurance of proper storage conditions, accuracy of planning the demand, and uncertainty in relation to purchasing - would be more effective. The evidence supporting this claim form the basis for the following Discussion section, where the findings are related to existing literature and discussed in relation to their managerial and business consequences. One thing that I have not done before the submission to the journal: the bracketed RII value, ISM level, DEMATEL (D+R) and AHP value for the cells above shall be obtained from the exact final calculation worksheet. I did not guess such values intentionally; the available previous calculation results just provided the values for DEMATEL(D-R) shown above.

5. Discussion

The results of this study suggests that food processing supply chain disruptions are not only failures, but rather interconnected influences of factors that may be causally related among others. Organizations must therefore not develop resilience strategies through a reactive and individual-factor by individual-factor treatment for risks, but rather use the causality based systemic reasoning methodology to identify the main causes and build better strategies. Combined RII-ISM-Fuzzy DEMATEL-AHP framework provides a much deeper insight in the disruptions not just classifying them as perceived important or structurally significant but as causal influencers. Interpretive Structural Modeling (ISM) confirms that the factors are not independent, with upstream deficiencies cascading through the system to create downstream effects. Traceability is a strategic capability for resilience with the highest net influence value (1.574) and not a compliance task. Traceability enables early identification and precise localization of disruptions such that small quality defects do not cascade into systemic breakdowns. Violations of storage conditions are proactive drivers of disruption, suggesting that continuous environmental monitoring and automatic alerts are more effective than end-of-supply-chain quality inspections. The festive period is not constant, which causes instability in operations and implies that real-time market information has to be integrated into production and procurement planning. Effect factors were considered, e.g., Lead-Time Fluctuations (F1) and Inconsistent Raw Material Quality (F3). F1 had the largest negative impact, which is a consequence of other system failures and not a stand-alone logistics problem. Effect-based factors are performance measures that can be used to evaluate how successful past interventions in traceability or storage were in terms of achieving improved operational results. Managers should direct their resources to high-leverage leverage points that affect many downstream outcomes such as traceability, storage monitoring, and demand sensing. Digitalization should not be used to automate existing processes but should be designed

around the end-to-end visibility created by IoT, RFID, and centralized databases to enable proactive risk identification.

6. Conclusion

The study establishes that food-processing supply chain resilience calls for moving from simple risk ranking to systemic causal diagnosis through an integrated RII–ISM–Fuzzy DEMATEL–AHP framework. The major findings and implications are summarized as follows: a. Dominant Causal Drivers: The study identifies Lack of End-to-End Batch Traceability (F10) as the most dominant systemic driver of disruption, followed by storage violations (F7), demand inaccuracy (F8), and price volatility (F2). b. Symptoms vs. Causes: Lead-Time Fluctuations (F1), which have high visibility, are "effect-oriented" symptoms whose variation is driven largely by the causes upstream, not independent risk. c. Strategic Principle: Effectiveness must be achieved by progressing analytically.: Importance → Structure → Causality → Priority. d. Investment Focus: To maximize systemic impact, industrial practitioners should focus investments on digital traceability, environmental monitoring and demand intelligence to improve visibility and to prevent the propagation of disruptions. In the end, the framework offers a decision support mechanism for shifting from reactive risk identification to proactive strategic intervention at high-leverage points.

7. Limitations

The findings should be considered in the light of several limitations. First, the framework is highly dependent on expert judgment. Although expert knowledge is useful to identify relationships that cannot be directly observed from historical data, individual perceptions may introduce subjectivity and judgmental bias. The use of fuzzy numbers in DEMATEL reduces the rigidity of linguistic judgments, but does not fully remove this limitation. Second, the findings are context-dependent. The relative importance and causal relationships among disruption factors may vary according to the type of food product, organizational size, supply-chain configuration, geographical environment, technological capability, and market characteristics. Consequently, the results should be generalized to other food-processing sectors only after appropriate contextual validation. Third, the framework provides a primarily static representation of a dynamic supply chain. In fact, the causal relation between factors may vary across time depending on the season, the market, weather conditions, holidays/festivals, supplier impacts or the organization capabilities. No explicit time variations are modeled for the proposed study. Fourth, the proposed model is unable to make explicit estimation for the financial impact of each disruptive element given that only causal relationships and interventions priorities are assigned values. Some factor that is rated very high is not the one that has the biggest loss, as financial losses also rely on probability and severity and recuperation costs and vulnerability factors. Finally, the study focuses on the selected ten disruption factors. These are important aspects of the disruption in food-processing supply chains.

However, there may be other risks related to climate change, cyber security, energy shortages, labor constraints, geo-political instability, regulatory changes, and infrastructure failures that future studies may uncover.

8. Future Scope

Future research can explore these areas to develop a data-driven resilience system. Research needs to integrate expert analysis and data on lead times, temperature monitoring and inventory levels with visibility through IoT sensors and RFID. By integrating machine learning for disruption prediction and Fuzzy DEMATEL framework for explanation, an architecture with foresight and interpretability can be achieved. The researchers are able to use digital twins and system dynamics to simulate disruptions and to evaluate interventions. Connecting AHP results to optimization would help budget allocation for resilience investments. The framework should be further developed to include climate risks (e.g. extreme temperatures, water scarcity) and do comparative studies across sectors such as dairy, seafood and frozen foods to test generalizability across industries and regions. Then we need to integrate knowledge, data, AI and optimization into a system that can predict, explain and mitigate disruptions in real time.

Conflict of interest

The authors state that they do not have any conflict of interest in the publication of this paper.

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AI technology

(Grammarly and Paperpal) was used to correct the grammatical errors.

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