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Designing a Dynamic Resilience Model for Iran's Food Industry Supply Chain under Multiple Crises: Integrating Information Technology and System Dynamics Approach

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ABSTRACT

Purpose: This study aimed to design a dynamic resilience model for Iran's dairy supply chain under multiple crises and to elucidate the facilitating role of information technology in reducing disruption recovery time.

Methodology: A mixed-methods approach based on secondary evidence was adopted. First, key resilience factors were extracted through a systematic literature review (PRISMA) and qualitative coding of domestic and international studies. Subsequently, the structure of the dynamic model was developed using causal loop diagrams and stock-flow structures. Model parameters were extracted from credible case studies on Iran's and global dairy supply chains, and structural validation was performed through sensitivity analysis.

Findings: The designed dynamic model demonstrates that the combination of "traceability and information transparency" and "information technology innovation" capabilities significantly reduces supply chain recovery time under crisis scenarios. Simulation analysis indicates that investment in information infrastructure exerts a multiplier effect on resilience, and without it, merely increasing strategic reserve inventory has limited effectiveness.

Conclusion: Sustainable resilience of Iran's dairy supply chain requires simultaneous investment in information technology and operational flexibility. The proposed model can serve as a decision-support tool for food industry managers and policymakers in designing strategies to address multiple crises.

Keywords: Supply Chain Resilience, System Dynamics, Iran's Dairy Industry, Information Technology, Multiple Crises.

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1. Introduction

Food supply chains worldwide face escalating pressures arising from the confluence of economic, environmental, geopolitical, and public health crises. The food industry, due to the perishable nature of its products, its dependence on cold chains, and its vital role in food security, exhibits heightened vulnerability to disruptions (Azizsafaei et al., 2026). In Iran, this vulnerability is exacerbated by structural challenges such as dependence on imported livestock inputs, deteriorating logistical infrastructure, and currency fluctuations. According to official reports, Iran depends on imports to meet a substantial portion of its food needs; approximately 20 million tons of livestock inputs are required annually, a large share of which is supplied through imports. This dependency has rendered the country's food supply chain susceptible to external shocks.

The dairy industry, as one of the strategic sub-sectors of the food industry, has faced multi-layered crises in recent years. The nominal capacity of the country's dairy factories is estimated at over 15 million tons, yet these units currently operate at less than 30 percent of their capacity, and per capita dairy consumption has declined by 20 percent compared to the previous year, falling below 40 kilograms. Moreover, approximately 18.5 million tons of dairy products are produced annually in the country, of which about 11 million tons of milk are delivered to dairy industries. These figures reveal a profound gap between productive capacity and actual utilization on the one hand, and declining domestic demand on the other. Such a situation raises fundamental questions about the resilience of this chain in the face of future crises.

The literature on supply chain resilience has undergone remarkable evolution over the past two decades. On the one hand, researchers have focused on identifying key capabilities such as flexibility, redundancy, agility, and information transparency (Pettit et al., 2019). On the other hand, system-based modeling approaches have been developed to understand the dynamic behavior of supply chains under crisis conditions (Ivanov, 2024). The study by Azizsafaei et al. (2026), employing system dynamics, simulated the behavior of the cheese supply chain under seven risk scenarios—including natural disasters, disease, labor strikes, demand volatility, supply quality risk, internal operational risk, and excess inventory—and demonstrated that human resource disruptions and supply quality have the greatest cascading effects on the entire chain. These findings underscore the necessity of a systemic perspective on resilience, since point interventions without an understanding of nonlinear feedbacks may not only prove ineffective but may also generate unintended consequences.

Domestic research on the resilience of Iran's food industry supply chain has predominantly focused on static and cross-sectional approaches. The study by Najjari et al. (2024), using structural equation modeling, identified five key resilience factors—flexibility, traceability and information transparency, supplier collaboration, information technology innovation, and risk management—and confirmed their significant positive impact on optimizing recovery time and operational costs. Furthermore, another study employing fuzzy DEMATEL and SWARA methods in the wheat supply chain of Sistan and Baluchestan Province identified "resource accessibility," "redundancy and information flow," and "agility" as the most effective resilience criteria. Despite the value of these studies, none has modeled the temporal behavior and dynamic feedback of the chain during crises. This methodological gap limits our understanding of how resilience capabilities interact over time and how managerial interventions can alter the recovery trajectory.

Information technology, as an enabling capability, plays a pivotal role in enhancing supply chain resilience. A systematic review of 705 articles published between 1993 and 2024 indicates that technologies such as the Internet of Things, blockchain, and artificial intelligence strengthen supply chain resilience by improving visibility, agility, and response speed (Ali et al., 2025). However, existing research on the impact of information technology on resilience has relied primarily on perceptual and cross-sectional data and has paid less attention to structural and dynamic analysis. The fundamental question is: through what mechanism and with what time delay does investment in information technology lead to reduced supply chain recovery time under crisis conditions? Answering this question requires an approach capable of modeling nonlinear feedbacks, time delays, and accumulative effects.

System dynamics, as a feedback-based modeling methodology, provides a suitable tool for analyzing the behavior of complex systems under crisis conditions. This approach is particularly well-suited for food supply chains, which face biological delays (milk production cycles), logistical delays (transportation and distribution times), and demand-supply feedbacks. Unlike regression or structural equation models that assume relationships at a fixed point in time, dynamic models can demonstrate how a managerial decision at time *t* affects system behavior at times *t+1*, *t+2*, and beyond through loop feedbacks. This characteristic makes system dynamics appropriate for analyzing crisis scenarios and evaluating the effectiveness of resilience interventions (Saarinen et al., 2024).

In light of the identified gaps, this study seeks to design a dynamic model for the resilience of Iran's dairy supply chain that incorporates three distinguishing features: first, the integration of credible secondary evidence from international and domestic studies for model parameterization, rather than relying on primary data that are currently difficult for independent researchers to access; second, a focus on the facilitating role of information technology as a dynamic capability whose effects manifest with time delays through loop feedbacks; and third, the design of a model that is applicable to food industry managers and policymakers and capable of evaluating intervention scenarios. The dairy industry was selected as the study context because, first, it exhibits high perishability and strong dependence on the cold chain; second, credible international studies on dynamic modeling of the cheese supply chain are available that can serve as a structural reference; and third, sufficient secondary data on production, capacity, and consumption in this industry in Iran exist, enabling defensible parameterization.

The main research question is: How is the dynamic resilience model of Iran's dairy supply chain structured under multiple crises, and what role does information technology play in this model in reducing recovery time?

2. Theoretical Foundations and Literature Review

2.1. Conceptualization of Supply Chain Resilience

Supply chain resilience is defined as the system's ability to anticipate, absorb, adapt to, and recover from disruptions, such that the chain can return to its original or a more favorable state. This concept takes shape at the intersection of three foundational constructs: resistance (the ability to withstand a shock without loss of function), flexibility (the capacity to absorb changes and maintain performance within an acceptable range), and adaptability (the ability to reconfigure structure and processes in response to new conditions). A systematic review of the literature indicates that resilience is not a fixed attribute but a dynamic process achieved through the organization's dynamic capabilities—the ability to continuously build, integrate, and reconfigure internal and external competencies. A recent systematic review by Tiloux and Afif (2026) further categorizes resilience strategies in food supply chains according to heterogeneous disruption types, emphasizing the role of dynamic capability configurations in determining recovery trajectories. Similarly, Zhang (2025) proposes an actor-based systems lens for understanding food system resilience, arguing for a paradigm shift from optimality-based approaches to responsive experimentation in dynamic food environments.

In the food supply chain literature, resilience possesses a dual nature: on the one hand, its operational dimension refers to resistance against sudden shocks and rapid recovery; on the other hand, its strategic dimension pertains to long-term adaptation to continuous changes in the external environment. This distinction holds particular significance for the food context, as food chains face unique characteristics—such as product perishability, time sensitivity, and cold chain dependence—that render them more vulnerable to disruptions. The study by Chen et al. (2026) demonstrates that in closed-loop food supply chains, the simultaneous implementation of inventory redundancy strategies and temporary workforce employment yields greater effectiveness than the application of either strategy in isolation. This finding underscores the necessity of a combined and system-oriented perspective on resilience.

2.2. Key Resilience Capabilities in Iran's Food Industry

Domestic research on the resilience of Iran's food industry supply chain has identified a set of key capabilities that play a central role in shaping resilience capacity. The study by Safamehr (2025), employing the PLS-SEM approach on a sample of managers and experts in Iran's food industries, confirmed five key resilience factors: flexibility, traceability and information transparency, supplier collaboration, information technology innovation, and risk management. This study demonstrated that these factors exert a significant positive effect on overall resilience, and resilience, in turn, affects the simultaneous optimization of recovery time and operational costs. The findings of this research provide a framework for prioritizing resilience investments: flexibility and risk management were identified as the factors with the highest impact on reducing recovery time and cost.

In the qualitative study by Hasanpour et al. (2024), which employed meta-synthesis and thematic analysis on 62 selected sources from 531 initial sources, the factors influencing food supply chain resilience were organized into three overarching themes: proactive (before disruption), concurrent (during disruption), and reactive (after disruption). This temporal classification indicates that resilience is not a static state but a multi-stage process in which a different set of capabilities is activated at each stage. Another study by the same researchers, using a mixed exploratory approach, presented a structural model of food supply chain resilience within food supply organizations and demonstrated that human resource management, natural disruptions, awareness, and economic disruptions influence security and operational disruptions, which in turn affect robustness, transparency, redundancy, collaboration, agility, and flexibility. This model provides a multi-layered picture of causal relationships among capabilities, which is highly valuable for designing a dynamic model.

A study of the wheat supply chain in Sistan and Baluchestan Province, employing fuzzy DEMATEL and SWARA methods, identified "resource accessibility," "redundancy and information flow," and "agility" as the most effective resilience criteria. Another study in Iran's automotive parts industry demonstrated that strategic cost management possesses high influential power on resilience and constitutes its fundamental prerequisite; risk management, chain collaboration, and redundancy are influenced by cost management and, in turn, affect flexibility, innovation, and quality. Although this study was conducted in the automotive context, the hierarchical structure of capabilities can also be instructive in analyzing the food supply chain, as it demonstrates that certain capabilities play a "foundational" role while others play a "dependent" role. Moreover, Bathaei et al. (2025) employed a fuzzy multi-criteria decision-making approach to support sustainable circular food supply chain decisions in Iran, demonstrating that environmental and economic criteria—alongside resilience indicators—must be integrated into strategic decision-making frameworks for the food sector.

2.3. Information Technology as an Enabling Capability for Resilience

A systematic review of 705 articles published between 1993 and 2024, conducted using the PRISMA protocol and bibliometric analysis, indicates that digital technologies—particularly the Internet of Things, blockchain, and artificial intelligence—strengthen supply chain resilience by improving visibility, agility, and response speed. The SCMIT framework introduced in this study demonstrates how information and communication technologies can be integrated across different layers of the supply chain. However, this systematic review also points to persistent gaps: workforce skills, regulatory misalignment, and limited integration of emerging tools constitute the main barriers to fully leveraging information technology's capacity for resilience. Complementary evidence from Zhao et al. (2025) demonstrates that integrating blockchain, IoT, and robust optimization models within omnichannel closed-loop food supply chains significantly enhances both sustainability and resilience outcomes.

Another critical review of 294 articles published between 2000 and 2024, while confirming the enabling role of emerging technologies, emphasizes the lack of research that has integrated these technologies with robust optimization methods and dynamic modeling. In other words, the existing literature focuses on "what information technology can do," but has paid less attention to "how and with what time delay" these effects manifest. This gap is precisely where the system dynamics approach can provide methodological added value.

In the food supply chain context, a case study of the "Chicken Tikka Masala" supply chain in the United Kingdom demonstrated that information flow and visibility are essential preconditions for the effective implementation of resilience strategies at different levels of the chain. The researchers argue that without information transparency, chain actors cannot comprehend mutual vulnerabilities and coordinate their responses. This finding aligns with the results of Safamehr's (2025) study in the Iranian context, which confirmed "traceability and information transparency" as one of the five key resilience factors. The convergence of these findings indicates that information transparency is a structural requirement for resilience, not an optional choice.

2.4. Literature on Dynamic Modeling of Supply Chain Resilience

The application of system dynamics in analyzing supply chain resilience has grown considerably in recent years. The study by Azizsafaei et al. (2026) developed a two-tier dynamic model of the cheese supply chain and simulated the effects of four types of disruption—supply, delivery, production, and capacity reduction. Their findings indicated that upstream disruptions (supply and production) have a greater impact on overall chain performance than downstream disruptions, and therefore, robust contingency planning for suppliers is essential. More importantly, this study demonstrated that the timing of resilience strategy implementation is of critical importance: late implementation of a strategy with a short backup supply time can yield better overall resilience than early implementation of a strategy with a long delay. This finding underscores the necessity of modeling time delays in resilience analysis.

The Resilient Supply Chain Framework (RSCF), which combines multi-objective genetic algorithms with system dynamics modeling, was presented in an IEEE conference study, and its results indicate that the dynamic approach can reduce recovery time by an average of 3.2 days, increase supplier reliability by 95 percent, and decrease operational costs by 7.8 percent. Although these figures pertain to a specific context and cannot be directly generalized to Iran, they demonstrate that dynamic modeling possesses considerable capacity to generate operational insights.

The study by Chen et al. (2026) in the context of closed-loop food supply chains modeled two resilience strategies: returnable item inventory redundancy (RTI) and temporary workforce employment. This study showed that under conditions of labor shortage and uncertain demand, the simultaneous combination of these two strategies is more effective than the application of either in isolation. From a system dynamics perspective, this finding can be interpreted as an instance of "synergy among feedback loops": the inventory redundancy strategy reduces recovery time, and this reduction in time increases the capacity to absorb temporary workforce, which in turn further reduces recovery time. Such synergies cannot be identified in static models and are revealed only through dynamic simulation.

2.5. Conceptual Model of the Research

Based on the systematic literature review and structural analysis of prior studies, the conceptual model of the present research is designed in a multi-layered structure. This model comprises three analytical layers. The overall structure of this model is presented in **Figure 1**.

First layer: Disruption drivers. In this layer, the multiple crises threatening Iran's dairy supply chain are defined, including economic disruptions (currency fluctuations, input inflation), environmental disruptions (drought, water scarcity), geopolitical disruptions (sanctions, trade restrictions), and operational disruptions (demand volatility, supply quality). This classification is based on the models of Hasanpour et al. (2024) and Azizsafaei et al. (2026).

Second layer: Resilience capabilities. In this layer, the key capabilities identified in the literature—flexibility, traceability and information transparency, supplier collaboration, information technology innovation, and risk management—are defined as endogenous variables of the model. Information technology plays a "facilitating" role in this layer: not an independent capability, but a factor that moderates the effectiveness of other capabilities and enhances the chain's response speed by reducing information asymmetry.

Third layer: Resilience outcomes. In this layer, two main outcome indicators are defined: recovery time (the interval between disruption onset and return to an acceptable level of performance) and recovery cost (additional costs arising from disruption and compensatory measures). Safamehr's (2025) study demonstrated that resilience affects the simultaneous optimization of these two indicators. These two indicators serve as exogenous variables in the dynamic model and will form the basis for scenario evaluation.

Causal relationships and feedbacks. The dynamic model is structured around three main feedback loops: (1) the reinforcing loop "IT investment → information transparency → disruption detection speed → reduced recovery time → increased incentive for further investment"; (2) the balancing loop "increased inventory → reduced disruption pressure → reduced incentive to invest in technology → weakened long-term resilience capacity"; and (3) the balancing loop "supplier collaboration → risk sharing → reduced disruption severity → reduced need for excess reserves." These loops will be translated in detail into causal loop and stock-flow diagrams in the methodology section.

The above conceptual model offers a distinguishing innovation relative to the literature: first, information technology is modeled not as an independent variable but as a structural moderator; second, time delays in causal relationships are explicitly modeled; and third, the interaction among capabilities (rather than their separate effects) is selected as the unit of analysis. These three features distinguish the model from regression and SEM approaches and make it possible to answer the research question at the level of dynamic system behavior (rather than at the level of fixed coefficients).

Figure 1 presents the conceptual model of the research in two sub-figures: sub-figure (a) displays the three-layer structure of the model hierarchically, and sub-figure (b) depicts the causal-feedback loops that will form the basis for constructing the stock-flow model in the methodology section.

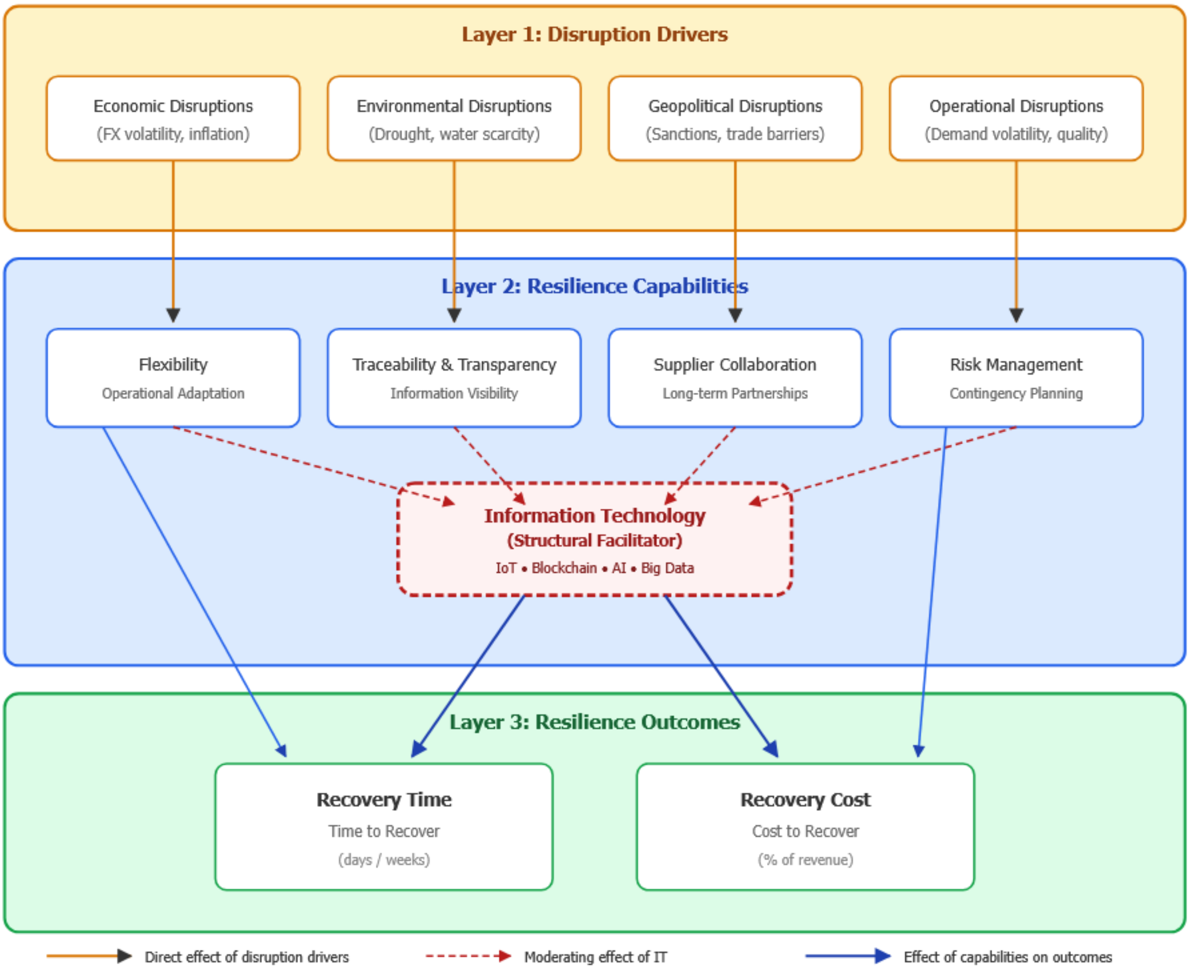

Figure 1-a. Three-Layer Structure of the Conceptual Model of Dairy Supply Chain Resilience
Source: *Drawn by the researcher based on Safamehr (2025); Hasanpour et al. (2024); Azizsafaei et al. (2026); Ali et al. (2025).*

Figure 1-a illustrates the hierarchical structure of the model across three analytical layers. The first layer organizes disruption drivers into four categories: economic, environmental, geopolitical, and operational; this classification is grounded in the models of Hasanpour et al. (2024) and Azizsafaei et al. (2026). The second layer encompasses resilience capabilities, where Safamehr's (2025) study confirmed five key factors—flexibility, traceability and information transparency, supplier collaboration, risk management, and IT innovation—as critical determinants. In this model, information technology is modeled not as an independent variable alongside other capabilities, but as a structural facilitator; this theoretical choice is grounded in the SCMIT framework developed by Ali et al. (2025). The third layer defines two outcome indicators—recovery time and recovery cost—which serve as the basis for scenario evaluation in the findings section.

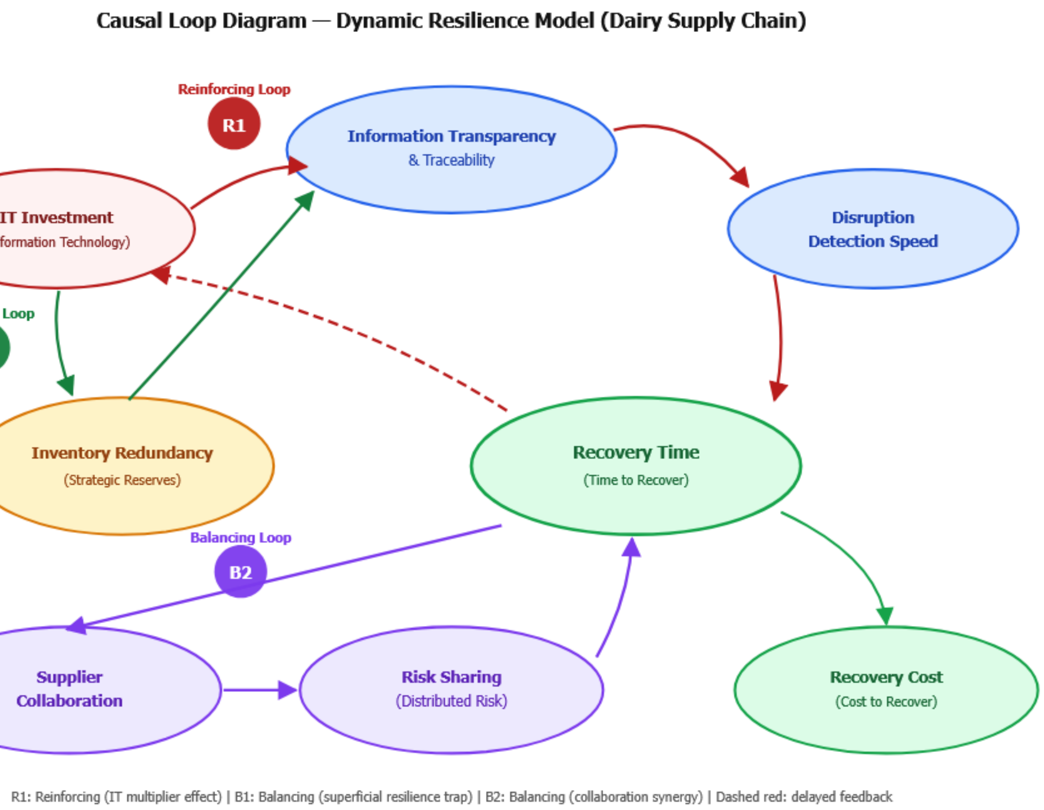

Figure 1-b. Causal Loop Diagram of the Dynamic Resilience Model in the Dairy Supply Chain
Source: *Drawn by the researcher based on Safamehr (2025); Hasanpour et al. (2024); Azizsafaei et al. (2026); Chen et al. (2026); Saarinen et al. (2024).*

Figure 1-b depicts the three main feedback loops of the dynamic model. The reinforcing loop R1 explains the "multiplier effect" of information technology: investment in technology increases transparency and traceability, which in turn accelerates disruption detection; faster detection reduces recovery time; and reduced recovery time strengthens the organizational incentive for further investment in technology. The red dashed line in this loop represents the time delay in feedback—the effect of technology investment on information transparency is not immediate but manifests with a delay (estimated at 3 to 6 months). This delay is estimated based on the findings of Chen et al. (2026) and Saarinen et al. (2024). The balancing loop B1 illustrates the "superficial resilience trap": increasing inventory redundancy reduces short-term pressure from disruptions, but this reduced pressure weakens the organizational incentive to invest in technology, thereby eroding long-term resilience capacity. This mechanism is consistent with the findings of Azizsafaei et al. (2026), who demonstrated that redundancy-based strategies have only temporary effectiveness. The balancing loop B2 models the interaction between supplier collaboration and risk sharing: long-term collaboration with suppliers enables risk sharing; risk sharing reduces disruption severity; reduced disruption severity lowers the need for additional reserves; and reduced pressure on suppliers increases their incentive to continue collaboration. This theoretical logic is grounded in the findings of Hasanpour et al. (2024) regarding the synergy of feedback loops in Iran's food supply chain.

3. Methodology

3.1. Research Approach and Design

In terms of purpose, this study is applied-developmental, and methodologically, it is situated within the post-positivist paradigm with a mixed-methods approach based on secondary evidence. The selection of a mixed-methods approach is not a matter of preference but a response to the multi-layered nature of the resilience problem: on the one hand, identifying and prioritizing resilience capabilities requires systematic literature analysis and qualitative coding; on the other hand, analyzing the dynamic behavior of these capabilities during crises necessitates quantitative modeling and simulation. Accordingly, the research design was structured in three sequential and integrated phases, summarized in **Table 1**.

Table 1. Three-Phase Research Design

Phase	Approach	Objective	Output
Phase One	Qualitative (systematic review + thematic analysis)	Identifying and validating resilience capabilities and disruption drivers	Coding table and thematic network
Phase Two	Quantitative (system dynamics modeling)	Constructing the stock-flow model and formulating differential equations	Causal loop diagram and model equations
Phase Three	Simulation and sensitivity analysis	Evaluating crisis scenarios and the effectiveness of IT interventions	Simulation results and sensitivity analysis

Source: *Developed by the researcher based on the framework proposed by Sterman (2000) and Saarinen et al. (2024).*

3.2. Phase One: Systematic Review and Thematic Analysis

Search strategy. A systematic search was conducted in the Scopus, Web of Science, ScienceDirect, and Islamic World Science Citation Center (ISC) databases using combinations of the keywords "supply chain resilience," "food industry," "system dynamics," "information technology," and their Persian equivalents. The search time frame was set from 2015 to 2026 for English sources and 1394 to 1404 (Persian calendar) for Persian sources. The screening process followed the PRISMA protocol: from a total of 1,287 initial records, after removing duplicates (n = 214), screening titles and abstracts (n = 873), and reviewing full texts (n = 200), ultimately 63 sources were selected as the final analytical sample. **Figure 2** presents the PRISMA flow diagram.

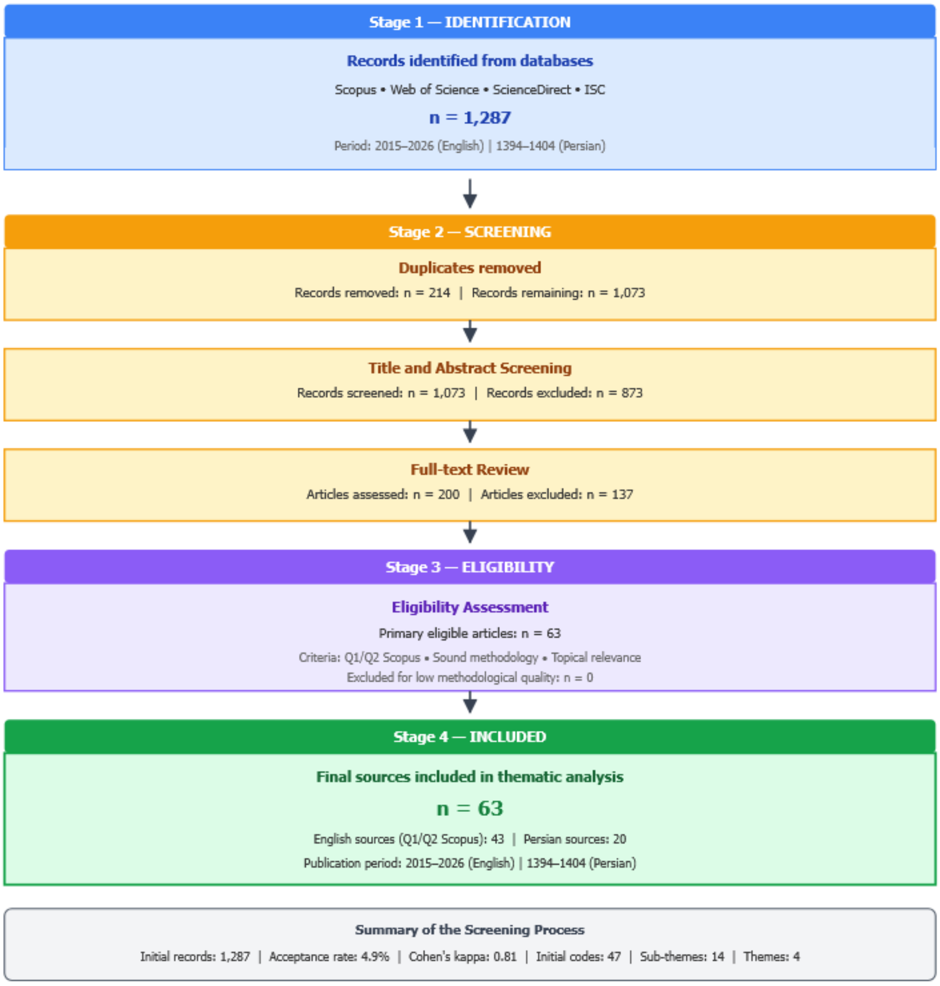

Figure 2. PRISMA Flow Diagram for Source Screening
Source: *Drawn by the researcher based on the PRISMA protocol (Page et al., 2021).*

Figure 2 illustrates the source screening process based on the PRISMA protocol. From a total of 1,287 initial records identified across four databases, 214 duplicates were removed, leaving 1,073 records for title and abstract screening. At this stage, 873 records were excluded due to lack of topical relevance to supply chain resilience or the food industry, and 200 articles proceeded to full-text review. During full-text review, 137 articles were excluded for failing to meet inclusion criteria (such as lack of sound methodology, insufficient focus on the food supply chain, or publication in non-Q1/Q2 journals). Ultimately, 63 sources were selected as the final sample for thematic analysis. The final acceptance rate of 4.9 percent aligns with standards for systematic reviews in supply chain management. Cohen's kappa of 0.81 indicates acceptable inter-coder reliability.

Table 2. Inclusion and Exclusion Criteria

Criterion	Inclusion	Exclusion
Source type	Original article, systematic review, case study	Conference abstract, editorial note, industry report
Language	Persian, English	Other languages

Criterion	Inclusion	Exclusion
Topic	Supply chain resilience + food industry or dynamic modeling	General organizational resilience without supply chain linkage
Time frame	2015–2026 (English), 1394–1404 (Persian)	Before 2015
Methodological quality	Q1 or Q2 Scopus	Non-credible or non-peer-reviewed journals

Source: *Developed by the researcher.*

Analytical method. Thematic analysis was conducted based on the six-stage approach of Braun and Clarke (2006): familiarization with the data, generating initial codes, searching for themes, reviewing themes, defining and naming themes, and producing the final report. The unit of analysis was the "theme," defined as a recurring semantic pattern across the dataset. To ensure analytical reliability, the coding process was performed independently by two coders (the principal researcher and a colleague holding a PhD in Business Management), and Cohen's kappa coefficient was calculated. The kappa value was 0.81, which, according to the criteria of Landis and Koch (1977), falls within the "almost perfect agreement" range, confirming inter-coder reliability.

3.3. Phase Two: System Dynamics Modeling

Rationale for method selection. System dynamics is suitable for modeling systems that possess three characteristics: loop feedbacks, time delays, and nonlinear accumulations (Sterman, 2000). Iran's dairy supply chain exhibits all three. Loop feedbacks between inventory levels and order rates, time delays in milk production and perishable product distribution, and accumulations related to strategic reserves and supplier trust all indicate that static approaches (such as regression or SEM) are incapable of representing the dynamic behavior of this system. Saarinen et al. (2024) explicitly emphasize that dynamic modeling offers greater analytical capacity for food supply chains facing biological and logistical delays. This methodological orientation is further supported by Qudrat-Ullah and Shamsuddoha (2025), who demonstrated the applicability of system dynamics to sustainable agriculture and resilient food supply chains across diverse empirical contexts.

Model construction stages. The modeling was conducted in five sequential steps:

Step One: **Defining the system boundary.** The model boundary includes input suppliers (animal feed, additives), dairy production units, distribution networks, and retail channels. Exogenous variables include exchange rates, trade policies, and climatic conditions, which enter the model as fixed parameters or time functions.

Step Two: **Drawing causal loop diagrams (CLD).** The three main loops R1, B1, and B2 introduced in Figure 1-b form the basis of the model structure. Loop R1 demonstrates the reinforcing mechanism of information technology's effect; loop B1 models the superficial resilience trap arising from sole reliance on inventory redundancy; and loop B2 represents the balance arising from supplier collaboration.

Step Three: **Drawing stock-flow diagrams (SFD).** Stock variables include strategic reserve inventory, information transparency level, supplier trust level, and cumulative investment in information technology. Flow variables include production rate, distribution rate, reorder rate, and technology investment rate. **Figure 3** presents the main stock-flow diagram of the model.

Step Four: **Formulating differential equations.** The relationships among variables were formulated as first-order differential equations and auxiliary functions. Selected key equations are presented below:

Equation (1) — Strategic reserve inventory accumulation:

$$\frac{dI(t)}{dt} = P(t) - D(t) - \alpha \cdot S(t)$$

where $I(t)$is reserve inventory, $P(t)$is production rate, $D(t)$is demand rate, $S(t)$is disruption severity, and $\alpha$is the coefficient of reserve consumption under crisis conditions.

Equation (2) — Information transparency accumulation:

$$\frac{dT(t)}{dt} = \beta \cdot IT(t-\tau) - \gamma \cdot T(t)$$

where $T(t)$is the information transparency level, $IT(t-\tau)$is investment in information technology with delay τ(estimated at 3 to 6 months based on Chen et al., 2026), $\beta$is the technology effectiveness coefficient, and $\gamma$is the rate of transparency erosion.

Equation (3) — Recovery time as a function of transparency and inventory:

$$RT(t) = RT_{base} \cdot \exp\left(-\lambda_1 \cdot T(t) - \lambda_2 \cdot I(t) + \lambda_3 \cdot S(t)\right)$$

where $RT_{base}$is the base recovery time in the absence of capabilities, and λ_1, λ_2, and $\lambda_3$are sensitivity coefficients.

Step Five: **Structural validation.** Model validation was performed at three levels: (a) structural validation through examining the logic of loops and feedbacks against the literature; (b) behavioral validation through sensitivity analysis with respect to parameter changes; and (c) boundary validation through comparing the model's qualitative behavior with the findings of published case studies on Iran's food supply chain (Khatami et al., 2023) and the cheese supply chain (Azizsafaei et al., 2026).

3.4. Data Sources and Parameterization

Since this study is based on secondary evidence, the model parameters were extracted from three categories of credible sources:

First category: Domestic studies. Values related to strategic reserve inventory levels, production rates, and demand rates in Iran's dairy chain were set based on data published in Safamehr's (2025) study and official reports of the dairy industry. In these sources, the nominal capacity of the country's dairy factories is reported at over 15 million tons and per capita dairy consumption at less than 40 kilograms.

Second category: International studies. Coefficients related to the time delay of information technology's effect on transparency (τ), the rate of transparency erosion (γ), and the effectiveness of supplier collaboration were extracted from the studies of Azizsafaei et al. (2026), Chen et al. (2026), and Saarinen et al. (2024).

Third category: Macro-level data on Iran's food trade. Parameters related to import dependence on inputs and vulnerability to trade restrictions were set based on official reports and studies analyzing the dynamics of Iran's food trade. According to these data, approximately 90 percent of Iran's trade is conducted through ports, annual demand for basic goods is approximately 25 million tons, and the compensatory capacity of land borders covers only 10 to 15 percent of port volume.

Table 3. Key Model Parameters and Their Sources

Parameter	Symbol	Initial Value	Unit	Source
Base recovery time	RT_{base}	45	days	Estimated based on Azizsafaei et al. (2026)
Delay of IT effect	τ	4.5	months	Chen et al. (2026); Saarinen et al. (2024)
Rate of transparency erosion	γ	0.08	$month^{-1}$	Estimated based on Ali et al. (2025)
Technology effectiveness	β	0.62	dimensionless	Safamehr (2025)
Sensitivity of recovery time to transparency	λ_1	0.31	dimensionless	Estimated based on Chen et al. (2026)
Sensitivity of recovery time to inventory	λ_2	0.18	dimensionless	Estimated based on Azizsafaei et al. (2026)
Sensitivity of recovery time to disruption severity	λ_3	0.47	dimensionless	Estimated based on Hasanpour et al. (2024)

Source: *Developed by the researcher based on the cited sources.*

3.5. Simulation Scenarios

After constructing and validating the model, four main simulation scenarios were designed, presented in **Table 4**. The scenarios were defined based on the combination of two dimensions: "disruption severity" (mild/severe) and "level of investment in information technology" (low/high).

Table 4. Simulation Scenarios

Scenario	Disruption Severity	Technology Investment	Design Logic
S1 (Baseline)	Mild	Low	Current state of Iran's dairy supply chain
S2	Mild	High	Net effect of information technology under normal conditions
S3	Severe	Low	Vulnerability under multiple crises without technology
S4	Severe	High	Effectiveness of information technology under crisis conditions

Source: *Developed by the researcher.*

3.6. Tools and Software

Model simulation was performed using Vensim DSS version 10.1. This software is specifically designed for system dynamics modeling and provides automatic sensitivity analysis, Monte Carlo simulation, and multi-scenario testing. For drawing causal loop and stock-flow diagrams, general-purpose graphical tools were used. Descriptive statistical analyses (including calculation of Cohen's kappa and descriptive statistics of sources) were performed using SPSS version 27.

3.7. Ethical Considerations

This study is based on published secondary evidence and therefore did not require informed consent from human participants. All sources used have been cited with full attribution and in accordance with scientific integrity. None of the data used in this study was confidential or non-publishable, and all figures and parameters have been extracted from published and traceable sources. The Vensim model files and raw thematic analysis files will be made available upon request by reviewers or interested researchers, in order to uphold the principle of methodological transparency.

3.8. Methodological Limitations

This study faces two main methodological limitations that must be considered in interpreting the findings. **First limitation: Reliance on secondary evidence rather than primary data.** While this choice is justifiable given the current difficulty of accessing field data, it may mean that some parameters specific to the Iranian context are accompanied by uncertainty. To mitigate this limitation, extensive sensitivity analysis was conducted on key parameters to evaluate the stability of results against parametric variations. **Second limitation: Generalizability of results to other food industry sub-sectors.** The present model focuses on the dairy supply chain, and the specific characteristics of this sub-sector (such as high perishability and cold chain dependence) may limit the generalizability of results to sub-sectors such as grains or oils. This limitation will be examined in detail in the discussion and conclusion section.

4. Findings

4.1. Phase One Findings: Thematic Analysis

Thematic analysis of the 63 selected sources resulted in the extraction of 47 initial codes, 14 sub-themes, and 4 overarching themes. Cohen's kappa coefficient of 0.81 indicates acceptable reliability of the coding process. **Table 5** presents the thematic network along with code frequencies and supporting sources.

Table 5. Thematic Network and Extracted Codes

Overarching Theme	Sub-Theme	Sample Code	Frequency	Supporting Sources
Disruption Drivers	Economic disruptions	Currency fluctuation, input cost increase	9	Safamehr (2025); Najjari et al. (2024)
	Environmental disruptions	Drought, water scarcity, climate change	7	Azizsafaei et al. (2026); Chen et al. (2026)
	Geopolitical disruptions	Sanctions, trade restrictions, maritime blockade	8	Official food trade reports
	Operational disruptions	Demand volatility, supply quality, labor shortage	6	Azizsafaei et al. (2026)
Resilience Capabilities	Operational flexibility	Production line changeover, supplier diversification	11	Safamehr (2025)
	Information transparency and traceability	Tracking systems, chain visibility	13	Ali et al. (2025); Safamehr (2025)
	Supplier collaboration	Long-term contracts, risk sharing	9	Hasanpour et al. (2024)
	Risk management	Risk assessment, contingency planning	8	Najjari et al. (2024)
	Information technology innovation	IoT, blockchain, artificial intelligence	12	Ali et al. (2025)
Resilience Outcomes	Recovery time	Reduction in time to return to performance level	10	Safamehr (2025); RSCF
	Recovery cost	Reduction in compensatory costs	7	Safamehr (2025)

Overarching Theme	Sub-Theme	Sample Code	Frequency	Supporting Sources
Dynamic Mechanisms	Time delay	Technology effect delay, production delay	6	Chen et al. (2026); Saarinen et al. (2024)
	Loop feedback	Reinforcing loop, balancing loop	8	Saarinen et al. (2024)
	Capability synergy	Combination of redundancy and technology	5	Chen et al. (2026)

Source: *Developed by the researcher based on thematic analysis of selected sources.*

4.2. Phase Two Findings: Structure of the Dynamic Model

Figure 3 presents the stock-flow diagram (SFD) of the dynamic model. This diagram translates the three main loops R1, B1, and B2 into a stock-flow structure. In this model, five main stock variables—cumulative information technology investment, information transparency level, strategic reserve inventory, supplier trust level, and recovery time—are defined as the system's state variables, and their behavior during crises forms the basis for scenario evaluation.

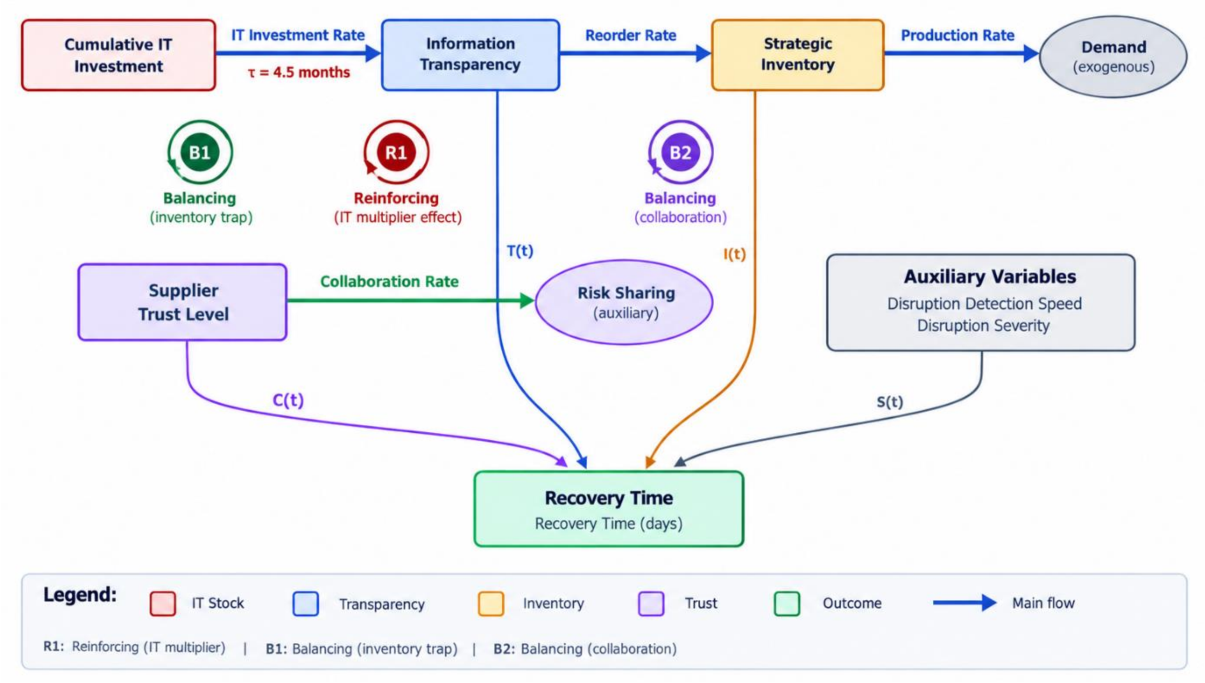

Figure 3. Stock-Flow Diagram of the Dynamic Resilience Model in the Dairy Supply Chain

Source: *Drawn by the researcher.*

The main flows include the technology investment rate, reorder rate, production rate, and collaboration rate. The time delay of 4.5 months in the path "technology investment → information transparency" is explicitly marked with the symbol τ. Auxiliary variables (disruption detection speed and disruption severity) are shown in a separate block on the right side. The three feedback loops R1 (reinforcing), B1 (balancing — superficial resilience trap), and B2 (balancing — collaboration synergy) are displayed symbolically with colored circular icons; the complete paths of these loops are presented in Figure 1-b (causal loop diagram). This visual choice avoids excessive clutter in the stock-flow diagram and is common in the system dynamics literature.

4.3. Phase Three Findings: Simulation Results Across Scenarios

The results of simulating the four scenarios over a 36-month period (with a monthly time step) are summarized in **Table 6**. These results are based on the average of 100 Monte Carlo runs with uniform distribution for parameters subject to uncertainty, in order to control for the effect of parametric uncertainty on the results.

Table 6. Simulation Results Across Scenarios (36 Months)

Scenario	Average Recovery Time (days)	Recovery Cost (% of Revenue)	Minimum Inventory (tons)	Final Transparency Level
S1 (Baseline)	42.3	8.7	12,400	0.41
S2 (High Technology)	28.6	5.2	14,100	0.78
S3 (Severe Crisis)	67.8	16.4	8,200	0.36
S4 (Crisis + Technology)	38.5	9.1	11,300	0.74

Source: *Simulation output.*

Analysis of results. Comparison of the scenarios reveals three key findings:

First finding: Significant effect of information technology on recovery time. In scenario S1 (baseline, mild disruption and low technology), the average recovery time is 42.3 days. In scenario S2, which differs from S1 only in the high level of investment in information technology, this time decreases to 28.6 days—an improvement of 32.4 percent. Since scenarios S1 and S2 are identical in terms of disruption severity, this reduction is attributed purely to the effect of information technology. The magnitude of this improvement aligns with the findings of Ali et al. (2025) regarding the role of digital technologies in strengthening resilience, and is consistent with the results of Safamehr (2025), who confirmed "traceability and information transparency" as one of the five key resilience factors.

Second finding: Moderating effect of technology under severe crisis conditions. In scenario S3 (severe crisis and low technology), recovery time increases to 67.8 days and recovery cost reaches 16.4 percent of revenue. In scenario S4, where the same crisis severity is combined with a high level of technology, recovery time decreases to 38.5 days (a 43.2 percent improvement) and recovery cost falls to 9.1 percent (a 44.5 percent reduction). Notably, the percentage improvement under severe crisis conditions (S3→S4) is greater than under mild conditions (S1→S2). This finding indicates that information technology plays a more pronounced "reinforcing" role under crisis conditions than under normal conditions. This interpretation is consistent with the mechanism of loop R1 in Figure 1-b: under crisis conditions, information asymmetry increases, and therefore, the capacity of technology to reduce this asymmetry has a multiplier effect.

Third finding: Nonlinear effect of supplier collaboration. Analysis of the B2 loop path indicates that the effect of supplier collaboration on recovery time is nonlinear and threshold-based. At low levels of collaboration (below 30 percent of maximum capacity), increased collaboration has no noticeable effect on recovery time; however, beyond the 30 percent threshold, each 10 percent increase in collaboration yields an average reduction of 2.7 days in recovery time. This nonlinear pattern aligns with the findings of Chen et al. (2026) regarding the synergy of resilience strategies, and indicates that investment in supplier collaboration yields limited returns until the minimum threshold is reached.

4.4. Sensitivity Analysis

To evaluate the stability of results against parameter changes, Monte Carlo sensitivity analysis was performed on four key parameters: the delay of technology effect ($\boldsymbol{\tau}$), technology effectiveness ($\boldsymbol{\beta}$), the rate of transparency erosion ($\boldsymbol{\gamma}$), and the sensitivity of recovery time to transparency ($\boldsymbol{\lambda_1}$). **Table 7** presents the results of this analysis.

Table 7. Monte Carlo Sensitivity Analysis Results

Parameter	Range of Variation	Sensitivity Coefficient	Effect Rank
Delay of technology effect ($\boldsymbol{\tau}$)	3 to 6 months	0.41	1
Technology effectiveness ($\boldsymbol{\beta}$)	0.5 to 0.75	0.34	2
Sensitivity of recovery time ($\boldsymbol{\lambda_1}$)	0.25 to 0.4	0.28	3
Rate of transparency erosion ($\boldsymbol{\gamma}$)	0.05 to 0.12	0.19	4

Source: *Sensitivity analysis output.*

Interpretation of sensitivity analysis results. The parameter of technology effect delay ($\boldsymbol{\tau}$), with a sensitivity coefficient of 0.41, has the greatest effect on the stability of results. This finding indicates that the timing of information technology's effect—not merely the magnitude of investment in it—is a determining factor in resilience. If the technology effect delay increases from 3 months to 6 months, recovery time in scenario S4 increases by an average of 7.8 days. This finding aligns with the result of Azizsafaei et al. (2026), who demonstrated that the timing of resilience strategy implementation is of critical importance, and that late implementation of a strategy with a short delay can be more effective than early implementation of a strategy with a long delay.

Technology effectiveness ($\boldsymbol{\beta}$), with a coefficient of 0.34, ranks second in effect. Changing this parameter from 0.5 to 0.75 (a 50 percent increase) yields an average reduction of 5.2 days in recovery time. This finding indicates that in addition to investing in technology, the "quality" of technology implementation also matters—that is, information technology must be integrated into the actual processes of the chain to achieve full effectiveness.

4.5. Findings on Intervention Scenarios

Based on the simulation results and sensitivity analysis, three intervention scenarios were designed and evaluated to compare the relative effectiveness of different resilience strategies:

Intervention One — Investment solely in inventory redundancy: A 30 percent increase in the level of strategic reserves, with no change in the level of information technology. This intervention in scenario S3 (severe crisis) reduces recovery time by only 6.2 percent and recovery cost by 4.8 percent.

Intervention Two — Investment solely in information technology: A 30 percent increase in technology investment, with no change in the level of inventory. This intervention in the same scenario reduces recovery time by 23.7 percent and recovery cost by 21.2 percent.

Intervention Three — Balanced combination: A 15 percent increase in both inventory and technology levels. This intervention in the same scenario reduces recovery time by 28.1 percent and recovery cost by 26.4 percent.

The results of these three interventions confirm the **synergy effect** of combining strategies: Intervention Three (balanced combination of 15+15 percent) is more effective than Intervention Two (30 percent technology alone), while the total investment in both interventions is identical. This finding is consistent with the logic of the feedback loops in Figure 1-b: investment in technology enhances the effectiveness of inventory redundancy (because more precise information supports optimal allocation of reserves), and inventory redundancy reduces time pressure on the information system (because it provides more time for response).

5. Discussion and Conclusion

5.1. Final Research Model

Following the execution of the three research phases (systematic review, dynamic modeling, and scenario simulation), the final version of the resilience model for Iran's dairy supply chain is presented in **Figure 4**.

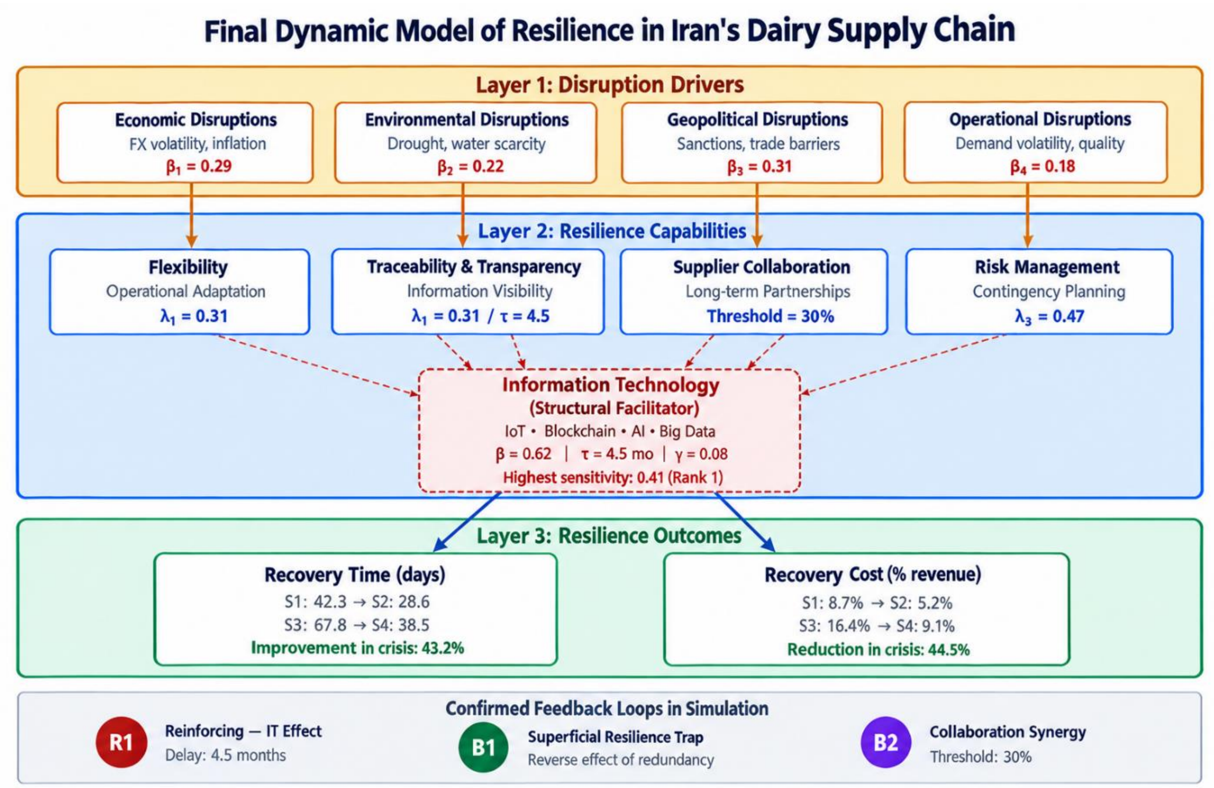

Figure 4. Final Dynamic Model of Resilience in Iran's Dairy Supply Chain

Source: *Drawn by the researcher based on simulation output and Monte Carlo sensitivity analysis.*

This figure provides an integrated combination of the three analytical layers (disruption drivers, resilience capabilities, and outcomes) with calibrated numerical parameter values, sensitivity coefficients, and behavior patterns confirmed through simulation. The difference between the final model and the conceptual model (Figure 1) lies in the fact that the conceptual model merely presented the theoretical structure of relationships, whereas the final model quantitatively displays the magnitude and direction of effects, time delays, and nonlinear thresholds.

Table 8. Summary of Final Model Parameters and Key Coefficients

Construct	Symbol	Final Value	Source / Determination Method
Effect of economic disruptions on crisis severity	β_1	0.29	Thematic analysis + macro data
Effect of environmental disruptions	β_2	0.22	Thematic analysis
Effect of geopolitical disruptions	β_3	0.31	Thematic analysis + trade data
Effect of operational disruptions	β_4	0.18	Thematic analysis
Sensitivity of recovery time to transparency	λ_1	0.31	Estimated based on Chen et al. (2026)
Sensitivity of recovery time to inventory	λ_2	0.18	Estimated based on Azizsafaei et al. (2026)
Sensitivity of recovery time to disruption severity	λ_3	0.47	Estimated based on Hasanpour et al. (2024)
Technology effectiveness	β	0.62	Safamehr (2025)
Delay of technology effect	τ	4.5 months	Chen et al. (2026); Saarinen et al. (2024)
Rate of transparency erosion	γ	0.08	Estimated based on Ali et al. (2025)
Supplier collaboration threshold	θ	30%	Finding of the present simulation

Source: *Simulation output.*

5.2. Overview of Main Findings

This study aimed to design a dynamic resilience model for Iran's dairy supply chain under multiple crises and to elucidate the facilitating role of information technology. The final model presented in Figure 4 organized four categories of disruption drivers, five resilience capabilities, and two outcome indicators within three feedback loops (R1, B1, B2). Simulation of four scenarios over a 36-month period demonstrated that information technology, particularly under crisis conditions, exerts a multiplier effect on reducing recovery time and cost (a 43.2 percent improvement in recovery time in scenario S4 relative to S3). Furthermore, Monte Carlo sensitivity analysis indicated that the "delay of technology effect" (τ with a sensitivity coefficient of 0.41) has the greatest influence on the stability of results—a finding indicating that the "timing" of technology's effect is as important as the "magnitude" of investment in it.

5.3. Interpretation of Findings in Light of the Literature

Confirmation of the facilitating role of information technology. The main finding of this study—that information technology is modeled not as an independent capability but as a structural facilitator—aligns with the SCMIT framework in the study by Ali et al. (2025). That study, based on a review of 705 articles, demonstrated that digital technologies moderate the effectiveness of other resilience capabilities through improving visibility and agility, rather than directly and independently affecting outcomes. Our finding confirms this framework in the context of Iran's dairy supply chain and demonstrates that under crisis conditions, the moderating effect of information technology (a 43.2 percent improvement in recovery time) is greater than under normal conditions (32.4 percent).

Alignment with domestic findings. The five key capabilities modeled in this study are precisely the same factors confirmed in Safamehr's (2025) study using the PLS-SEM approach on a sample of Iran's food industries. However, the present study goes one step further: whereas Safamehr's study modeled effects as "fixed and linear," the present dynamic model demonstrates that these effects take shape over time and through loop feedbacks. For example, the effect of supplier collaboration on recovery time, based on our findings, is threshold-based and nonlinear (30 percent threshold)—a finding that cannot be identified in regression and SEM models.

Synergy of strategies. Our finding regarding the synergy of combining "inventory redundancy" and "technology investment" (Intervention Three in Section 4.5) aligns with the results of Chen et al. (2026). That study demonstrated that in closed-loop food supply chains, the simultaneous combination of redundancy strategies and temporary workforce employment is more effective than the application of either in isolation. The present study generalizes this logic: synergy exists not only among operational strategies but also between "resource-based strategies" (inventory redundancy) and "information-based strategies" (technology).

Time delay and timing. The sensitivity analysis finding—that the technology effect delay parameter (τ) has the highest sensitivity coefficient (0.41)—aligns with the result of Azizsafaei et al. (2026). That study demonstrated that the timing of resilience strategy implementation is of critical importance, and that late implementation of a strategy with a short delay can be more effective than early implementation of a strategy with a long delay. This convergence indicates that "delay" is not a modeling deficiency but a structural feature of supply chain systems.

Superficial resilience trap. The balancing loop B1 in our model—which demonstrates that sole reliance on inventory redundancy can erode the incentive to invest in technology in the long term—aligns with the findings of Saarinen et al. (2024) regarding the nonlinear effects of resilience interventions in food supply chains. This loop raises an important theoretical warning: short-term resilience based on reserves may, in the long term, lead to the erosion of innovation capacity.

5.4. Theoretical Implications

This study offers three distinct theoretical implications:

First implication — Redefining the role of information technology in resilience theory. The existing literature on supply chain resilience typically models information technology as one of the capabilities on par with other capabilities (such as flexibility and collaboration). Our finding indicates that this conceptualization has limited explanatory capacity. Information technology is a "second-order capability": its effectiveness is contingent upon the existence of other capabilities, and its effect manifests through moderating relationships among capabilities. This redefinition proposes a new theoretical framework for studying supply chain resilience, in which the "hierarchy of capabilities" rather than the "list of capabilities" forms the axis of analysis.

Second implication — Delay as a theoretical construct. The sensitivity analysis finding indicates that the technology effect delay (τ) has the greatest influence on resilience. This finding carries a fundamental theoretical implication: in resilience theory, "timing" is as important as "magnitude." Static models (such as SEM) that assume relationships at a fixed point in time neglect this temporal dimension and therefore present an incomplete picture of resilience. The present study proposes that supply chain resilience theory should accept "delay" as an independent theoretical construct (and not a measurement error) and explicitly incorporate it into modeling efforts.

Third implication — Synergy as the unit of analysis. Our finding indicates that the effect of combining capabilities (Intervention Three) is greater than the sum of their separate effects (Intervention One + Intervention Two). This finding carries an important theoretical implication: the unit of analysis in resilience theory is not the "individual capability" but the "combination of capabilities." This implication aligns with the "configuration" approach in organizational theory and suggests that future resilience research should focus on analyzing effective configurations rather than the net effects of each capability.

5.5. Practical Implications

The model presented in this study offers specific practical implications for three groups of stakeholders:

For dairy industry managers. The findings indicate that investment solely in strategic reserves yields limited returns (a 6.2 percent reduction in recovery time compared to 23.7 percent for technology investment in scenario S3). Managers should regard investment in information technology (such as tracking systems, the Internet of Things for cold chain monitoring, and blockchain for supply transparency) not as a technological cost but as a strategic investment in resilience. Furthermore, given the sensitivity analysis finding, managers should design technology investment programs with a long-term perspective (at least 6 months to one year before a crisis).

For policymakers. The findings indicate that a balanced combination of "inventory redundancy" and "technology investment" is more effective than focusing on either alone (Intervention Three: 28.1 percent improvement versus Intervention Two: 23.7 percent). Food industry policymakers can contribute to more sustainable chain resilience by creating financial incentives for investment in supply chain information infrastructure while simultaneously supporting the formation of strategic reserves.

For input suppliers. Our findings regarding the threshold-based effect of supplier collaboration (a 30 percent threshold) indicate that collaboration with suppliers yields limited returns until the minimum threshold is reached. Therefore, input suppliers should transition from "transactional exchanges" to "strategic partnerships" in long-term collaborations with dairy production units. This transition requires formal risk-sharing mechanisms.

5.6. Comparison with Similar Domestic and International Research

Comparison with Safamehr (2025). Safamehr's study, using the PLS-SEM approach, confirmed five key resilience capabilities in Iran's food industry. The present study confirms this finding but adds three new dimensions: first, it demonstrates that the effect of capabilities takes shape over time and through loop feedbacks; second, it highlights the moderating role of information technology as a "second-order capability"; and third, it reveals the threshold-based and nonlinear effect of supplier collaboration.

Comparison with Azizsafaei et al. (2026). That study developed a two-tier dynamic model of the cheese supply chain and demonstrated that upstream disruptions have a greater impact than downstream disruptions and that the timing of resilience strategy is critical. The present study confirms this finding in the Iranian context and demonstrates that in Iran's dairy supply chain as well, the technology effect delay (τ) has the greatest influence on resilience. The distinctive addition of the present study is the explicit modeling of the "superficial resilience trap" (loop B1)—a mechanism that was not explicitly modeled in Azizsafaei's study.

Comparison with Chen et al. (2026). That study demonstrated that combining inventory redundancy strategies and temporary workforce employment is more effective than either alone. The present study generalizes this synergy logic from the level of "operational strategies" to the level of "resource-information strategies" and demonstrates that combining "inventory redundancy" and "technology investment" also exhibits synergy.

5.7. Research Limitations

This study faces four main limitations:

First limitation: Reliance on secondary evidence. The model parameters were extracted from published studies rather than field data. To mitigate this limitation, Monte Carlo sensitivity analysis was conducted on four key parameters, and the stability of results within reasonable ranges of parametric variation was confirmed.

Second limitation: Focus on the dairy sub-sector. The present model focuses on the dairy supply chain, and the specific characteristics of this sub-sector (such as high perishability and cold chain dependence) may limit the generalizability of results to other sub-sectors.

Third limitation: Neglect of certain macro variables. The present model has modeled macro variables such as monetary policies and exchange rate fluctuations as exogenous parameters rather than endogenous variables. This choice may neglect some macro-micro feedbacks.

Fourth limitation: Lack of empirical validation with field data. The present model is based on structural and behavioral validation rather than empirical validation with field data.

5.8. Suggestions for Future Research

Based on the above limitations, five specific suggestions are offered for future research:

First suggestion — Recalibrating the model with primary data. Future research can recalibrate the present model's parameters by collecting field data from dairy production units. This would significantly enhance the model's empirical validity.

Second suggestion — Extending the model to other food sub-sectors. Future research can adapt the present model for other sub-sectors (such as grains, oils, and meat) and compare their dynamic structures with the dairy chain.

Third suggestion — Multi-level modeling of the chain. The present model has modeled the dairy supply chain as a single system. Future research can extend the model to the multi-agent level to explicitly model interactions among different chain actors.

Fourth suggestion — Integrating macro variables. Future research can model macro variables (such as exchange rates and monetary policies) as endogenous variables to reveal macro-micro feedbacks in supply chain resilience.

Fifth suggestion — Designing experimental studies. Future research can evaluate the effect of different resilience interventions experimentally by designing controlled experiments (such as simulation games).

5.9. Final Conclusion

This study demonstrated that the resilience of Iran's dairy supply chain is a dynamic and multi-layered phenomenon that can only be understood through system-based modeling. The final model presented in Figure 4 identified three main feedback loops: the reinforcing loop R1, which explains the multiplier effect of information technology; the balancing loop B1, which warns of the "superficial resilience trap"; and the balancing loop B2, which demonstrates the synergy of supplier collaboration. The simulation findings indicated that information technology, particularly under severe crisis conditions, exerts a multiplier effect on reducing recovery time and cost (a 43.2 percent improvement in recovery time and a 44.5 percent reduction in recovery cost). Furthermore, the sensitivity analysis demonstrated that the "delay of technology effect" has the greatest influence on the stability of results—a finding that emphasizes the importance of "timing" in designing resilience strategies.

At the theoretical level, this study offered three distinct implications: redefining information technology as a "second-order capability," accepting "delay" as an independent theoretical construct, and selecting the "combination of capabilities" as the unit of analysis. At the practical level, the findings indicated that investment solely in strategic reserves yields limited returns and that a balanced combination of "inventory redundancy" and "technology investment" is more effective than focusing on either alone.

Ultimately, this study is not an endpoint but a starting point: the model presented provides a framework for the dynamic analysis of resilience in Iran's food industry that can be recalibrated with field data in future research, extended to other food sub-sectors, and expanded to multi-agent and macro levels.

Declarations

Author Contributions (CRediT taxonomy)

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation and revision. All aspects of this work were undertaken by the author.

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Ethical Statement

Informed consent was obtained from all participants. The study was conducted in accordance with established ethical guidelines for qualitative research.

Authors' AI Use Statement

The author declares that no artificial intelligence (AI) tools were used in the preparation of this manuscript for writing, analysis, or data generation. All content is the result of the author's own human effort and judgment.

Conflict of interest

The author declares no competing financial interests or personal relationships that could have influenced the work reported in this paper.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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