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Design of an analytical model based on fuzzy data envelopment analysis approach for evaluating the sustainability capability of supply chain systems against various risks

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Abstract In today's competitive business environment, the supply chain plays a crucial role in maintaining an organization's competitive advantage. However, environmental uncertainties, unpredictable delays, and various risks pose significant challenges to the sustainability of these systems. This study aims to present an analytical model based on Fuzzy Data Envelopment Analysis (FDEA) to assess the supply chain system's sustainability capabilities against different types of risks. The proposed model seeks to enhance supply chain flexibility and resilience under dynamic environmental conditions by utilizing fuzzy data. To achieve this goal, supply chain risks were initially identified and categorized into three levels: strategic, tactical, and operational. Subsequently, FDEA was employed to evaluate the impact of these risks on supply chain performance. The research findings indicate that increasing environmental uncertainties, over reliance on specific suppliers, reduced inventory levels, and inefficiencies in demand forecasting are key factors contributing to decreased supply chain sustainability. The results further suggest that adopting multidimensional risk management approaches and leveraging strategic management theories such as the resource based view (RBV) and dynamic capabilities can effectively mitigate risks and enhance supply chain flexibility. Additionally, a comparative analysis of the proposed model with traditional risk management approaches demonstrated that applying FDEA improves risk assessment accuracy and enhances decision making efficiency within organizations. Ultimately, this study underscores the importance of utilizing advanced decision making tools in supply chain management and recommends that organizations continuously evaluate their current status and adopt advanced analytical methods for managing potential risks. The proposed model not only provides a systematic, data driven approach for assessing supply chain sustainability but also serves as a practical tool for managers in developing risk mitigation strategies and optimizing supply chain processes.

Keyword: Fuzzy Data Envelopment Analysis (FDEA), Sustainability Assessment, Supply Chain Risk.

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1 Introduction

In today's highly competitive business environment, an efficient and effective supply chain plays a crucial role in enabling a company to remain competitive within its respective industry [1, 2]. As Mobin et al. [3] emphasized, the prevailing conditions of the business environment impose uncertainty, unpredictability, and delays on supply chain networks. These challenges increase the likelihood of production line disruptions and hinder the timely fulfillment of customer needs and preferences [4]. Such adverse outcomes stem from factors such as globalization, the growing dependence on external resources, the reduction in the number of suppliers, increased performance demands, and a significant decrease in inventory levels [5]. Consequently, both the severity and likelihood of disruptions tend to rise. Simultaneously, supply chains become more vulnerable and prone to interruptions [6].

As noted by Schmitt and Singh [7], adopting a systematic and structured approach is essential for managing and mitigating supply chain disruptions. They also identified other critical components such as inventory, capacity, and environmental impacts that pose high risk effects on the resilience and flexibility of supply chains. There are numerous meaningful causes of supply chain disruptions, which may be categorized as follows: unfavorable environmental conditions, failures in telecommunications and information networks, transportation related environmental issues, earthquake risks, and failures in allocating external resources to operations. Moreover, the manifestation of different risk dimensions can significantly impact organizations. These components underscore the need for organizations to develop and enhance robust and acceptable capabilities to confront various incidents and risks [8].

Previous risk management approaches, such as multidimensional risk management [9] have shown limitations that reduce their effectiveness and efficiency as tools for organizing supply chain disruptions [10]. Therefore, there is a growing need to implement applied management theories, such as the resource based view and the dynamic capabilities perspective, in supply chain management [11]. In many cases, these incidents have been analyzed and criticized primarily from a negative perspective.

Nevertheless, previous research suggests that successful organizations are those capable of adapting to challenging conditions [12]. Perhaps the most critical issue lies in how to motivate top level managers to proactively monitor and assess the sustainability status of their organizations, especially when no immediate threats or visible errors are present [13]. Identifying and evaluating the current status of the organization can be considered the first step in conducting a risk analysis.

Accordingly, managers must utilize reliable and acceptable tools to enhance the sustainability of their supply chain systems against environmental risks including strategic, tactical, and operational risks. By evaluating and analyzing the organization's technical conditions, such tools can provide a clear perspective on its future status. Therefore, identifying the key risks affecting the organization is a strategic necessity for analyzing both current and future organizational performance. Table 1 presents the classification of risks at different organizational levels:

Table 1 Classification of Risk Types at the Organizational Level

Operational Level	Tactical Level	Strategic Level
Labor cost per hour	Accuracy of forecasting methods	Total supply chain cycle time

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Information transfer cost	Product development cycle time	Total cash flow cycle time
Capacity utilization	Order receiving methods	Customer inquiry response time
Input stock level	Effectiveness of billing delivery methods	Customer perceived value of the product
Work in progress (WIP)	Purchase order cycle time	Profit to productivity ratio
Waste level	Planning process cycle time	Return on investment (ROI)
Amount of finished goods in transit	Effectiveness of production planning	Range of products and services
Supplier rejection level	Supplier involvement in problem solving	Budget variance ratio
Document delivery quality	Supplier responsiveness to issues	Order acquisition lead time
Productivity during purchase order cycle	Supplier cost saving initiatives	Flexibility of service policies in responding to customer needs
Number of deliveries	Supplier reservation methods	Buyer seller collaboration level
Confidence in operator performance	Delivery reliability	Supplier delivery time vs. industry benchmark
Product delivery quality	Responsiveness to urgent deliveries	Supplier defect rate
	Distribution planning effectiveness	Delivery lead time
	Delivery evaluation	

On the other hand, in the traditional and conventional perspective, supply chain management was primarily focused on integrating and coordinating all members of the supply chain with the aim of improving performance, increasing productivity, and maximizing profits. Supply chain managers prioritized faster delivery of goods and services, cost reduction, and quality enhancement, while aspects such as sustainability, social costs, and environmental degradation were largely overlooked [14]. Growing concerns about environmental warnings have compelled manufacturers to adopt sustainable management practices [15].

Given that environmental impacts occur throughout all stages of a product's life cycle and environmental programs and operations are not confined within organizational boundaries the concept of Sustainable Supply Chain Management (SSCM) has attracted significant attention as a comprehensive approach that encompasses all flows from suppliers to manufacturers and ultimately to consumers [16]. Increasing concerns regarding environmental, economic, and social issues have pushed producers to seek solutions for managing their environmental responsibilities. Approaches such as SSCM, economic sustainability, cleaner production, and environmental management systems have been implemented in distribution activities [17].

Since environmental impacts occur at all stages of a product's life cycle and managing environmental activities cannot be limited to within the organization, SSCM has emerged as a comprehensive perspective covering the entire process from suppliers and manufacturers to consumers and, ultimately, waste disposal and recycling [18].

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Considering the growing emphasis within organizations on productivity, aimed at the efficient and effective use of resources to achieve organizational goals, and in response to regulatory requirements and customer demands regarding sustainability in the supply chain, a meaningful compromise has emerged between the dual objectives of economic growth and environmental protection. This integration of economic and social dimensions into supply chain operations has led to the recognition of sustainable supply chains as a strategic weapon for gaining long term competitive advantage [19].

Accordingly, the necessity of designing a model for estimating the cost function in multi echelon inventory systems can be explained in light of the aforementioned discussions. As previously mentioned, supply chains typically have a multi level structure. The emphasis on collaboration and coordination in supply chain management arises due to conflicting interests between different segments of the chain, as well as the undesirable bullwhip effect resulting from poor synchronization among its various stages. Evaluating the sustainability of supply chains in the face of risks and unexpected events is a critical issue that has been widely acknowledged by numerous researchers. A comprehensive assessment involves evaluating both the overall supply chain system and its individual components. This is important because, according to recent supply chain theories, performance is not limited to overall system evaluation alone each component plays a vital role. To date, a thorough and comprehensive study on developing a localized and distinctive model for assessing the resilience of supply chains against sustainability related risks has been lacking, particularly considering the inherent complexity of this domain. Therefore, this research proposes a novel model based on the Network Data Envelopment Analysis (NDEA) method to assess and analyze the impact of risk factors on supply chain sustainability, as well as evaluate the efficiency of organizations in managing sustainable supply chains. In this study, a fuzzy network DEA modeling approach is employed with the aim of evaluating the sustainability of supply chains in the food manufacturing sector in response to various risks. Given that existing network models have not yet addressed improvement directions for the evaluated decision making units (DMUs), the current research introduces an innovative approach by incorporating shortage based models and considering undesirable outputs to determine the optimal levels of each input, output, and intermediate variable. This constitutes a key novelty of the present study.

2 Literature Review

Today, due to the increasing uncertainty within supply chains and the emergence of factors such as political issues, demand fluctuations, technological changes, financial instabilities, and natural disasters, organizations are compelled to allocate resources toward predicting demand, securing supply, and managing internal uncertainties. These uncertainties and the factors that generate risks have led to the emergence of supply chain risk management as a significant concern [20]. The presence of risk and the potential for supply chain disruptions can significantly impact short term performance and have long term negative effects on an organization's financial outcomes. Therefore, managing supply chain risk is essential to mitigating failures caused by various uncertainties such as unstable economic cycles, unpredictable customer demand, and unforeseen natural or human made disasters [21].

The occurrence of events that disrupt the flow of materials even if these events happen far from the core operations can result in large scale disruptions. Such disturbances may spread throughout the supply chain, leading to considerable negative consequences. In many cases, affected companies may no longer be able to maintain their productivity levels, ultimately

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losing their competitive advantage [22]. From this perspective, the assessment of supply chain resilience focuses on enhancing the system's ability to prepare for, respond to, and recover from the impacts of identified risks[23].

Considering the fact that it is not always possible to eliminate all sources of risk and that data on the frequency and recurrence of risks is often lacking or insufficient [24] it can be argued that the traditional supply chain management approach, which emphasizes identifying and proactively responding to risks [25], may only partially prevent destructive supply chain risks. Furthermore, issues related to supply chain risk indicate a direct relationship between supply chain resilience and the capabilities of organizations that structure their supply chains to assess existing risks and recover from their impacts. Hezam et al. [26] proposed a novel digital twin and fuzzy-based framework for assessing sustainability-related risks in supply chain systems, specifically within the supplier selection context. Their model integrates spherical fuzzy sets with multicriteria decision-making to capture uncertainty in evaluating alternative suppliers. The results highlight how digital and fuzzy techniques can substantially enhance the precision of sustainability assessments, especially under volatile market and environmental conditions. Tavassoli and Saen [27] introduced an advanced fuzzy network Data Envelopment Analysis (DEA) model to evaluate both sustainability and resilience within supply chains. By decomposing the Most Productive Scale Size (MPSS) and performing sensitivity analyses, their framework enables a more granular understanding of performance under fuzzy environments. This approach offers significant methodological innovation in measuring the operational and structural robustness of supply chain configurations. A study published in the [28] presented a hybrid fuzzy-rough network DEA model tailored for sustainability assessment in supply chains. The integration of fuzzy logic and rough set theory allows for handling incomplete and imprecise data while maintaining high discriminatory power across multiple decision-making units. This contributes to more informed and robust sustainability benchmarking. A recent investigation (2025) in China's iron and steel sector applied a fuzzy DEMATEL–ISM methodology to assess and structure sustainability risk factors [29]. The study emphasized the complex interrelations between logistical delays, raw material volatility, regulatory compliance, and environmental impact. Its strategic insights underscore the importance of adopting systemic approaches for risk mitigation in heavy industrial supply chains. In another notable contribution, Tavassoli and Saen [30] developed a fuzzy network DEA framework for measuring sustainability in combined-cycle power plants. The model reflects a three-stage input-process-output structure, enabling more realistic evaluation under uncertainty. Their empirical analysis showed that plants utilizing cleaner energy sources demonstrated superior sustainability performance. Zahedi-Seresht et al. [31] explored sustainable and robust supplier selection in the post-pandemic era using DEA. The study underscored the need for resilience-oriented criteria such as adaptability, crisis response, and environmental compliance when assessing suppliers. It effectively illustrated the limitations of conventional DEA in capturing disruption-related dynamics without sustainability augmentation. Nasri et al. [32] integrated Fuzzy DEMATEL, Analytic Network Process (ANP), and DEA to develop a multi-criteria model for sustainable supplier evaluation in the petroleum industry. Their approach considers interdependencies among qualitative and quantitative factors and provides a robust prioritization mechanism under conditions of uncertainty. The model's versatility enhances its practical relevance for complex industrial supply chains. Pérez-Pérez et al. [33] conducted an empirical study on climate transition risks in Colombia's processed food sector using fuzzy logic and multicriteria decision-making tools. Their model helps companies quantify and respond to environmental vulnerabilities. It further illustrates the increasing necessity for supply chains, particularly in climate-sensitive industries, to integrate adaptive risk assessment frameworks aligned with sustainability objectives.

Mardani [34] presented a framework integrating the core elements of sustainable supply chain management in global supply chains. The overall configurations, which involve stronger relationships between focal firms and multi tier suppliers either directly or through third parties are increasingly being adopted to enhance sustainability and open new areas for future research.

Gómez [35] advocated for implementing sustainable supply chains in developing countries. His study encourages managers and policymakers to align food supply chain performance with environmental protection while meeting social expectations. The paper concludes by highlighting research limitations and offering recommendations for future investigations regarding both practical and theoretical implications.

A summary of the reviewed literature is presented in Table 2.

Table 2 Summary of the Literature Review

No.	Author / Year	Strategic Risk	Tactical Risk	Operational Risk	Traditional Data	Fuzzy	Grey	Green SC	Sustainable SC	Resilient SC	MCDM	Network DEA	DEA AP	Super Efficiency
1	Mardani [34]	*			*			*		*		*		*
2	Gomez [35]	*			*			*		*		*		*
3	Rifki [23]	*			*									*
4	Barbosa [36]	*			*			*		*		*		*
5	Esqueri [37]	*			*							*		
6	Halati [38]	*			*							*		
7	Vargas [39]		*		*			*		*		*		*
8	Tseng [40]	*			*			*		*		*		*
9	Matietuana [41]	*			*			*		*		*		*
10	Mokhtader [42]		*		*			*		*		*		*
11	Zhang [43]	*			*			*		*		*		*
12	Baidinejad [44]	*	*		*			*		*		*		*
13	Present Study	*	*	*		*		*		*		*		*
14	Hezam et al. [26]	*		*		*			*	*	*			
15	Tavassoli & Saen [27]	*	*			*			*	*		*		
16	IJFS Study [28]	*				*	*		*			*		
17	Chinese Steel Sector [29]	*	*	*		*			*	*	*			
18	Tavassoli & Saen [30]	*				*			*	*		*		
19	Zahedi-Seresht et al. [31]	*	*					*	*	*	*			
20	Nasri et al. [32]	*	*			*		*	*	*	*	*		
21	Pérez-Pérez et al. [33]	*	*			*		*	*	*	*			

Based on the review of the existing literature both at the global and national levels it is evident that most studies have focused on the development of multi criteria and multi objective decision making approaches in the context of supply chain sustainability. These studies have proposed various decision making, statistical, and adaptive models. However, to date, no comprehensive research has specifically addressed the issue of operational risks related to sustainable supply chains within organizations.

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Another key innovation of the present study is the development of a mathematical model based on a three stage series Network Data Envelopment Analysis (NDEA) framework, in which the input data are considered as non dominated fuzzy variables. This provides a novel perspective in the evaluation of supply chain sustainability performance under uncertainty and risk.

3 Data Envelopment Analysis (DEA) Modeling

To achieve the objective of this study, a multi method approach has been adopted to enable the design and testing of an analytical model for evaluating the sustainability capability of supply chains in the face of various risks. Initially, in order to develop an analytical model for risk and sustainability assessment within a three stage supply chain, Data Envelopment Analysis (DEA) and fuzzy theory have been employed.

As will be elaborated in the following sections, DEA in this study allows for the integration of criteria as data inputs and outputs of the supply chain system, and it also facilitates the comparison between the current level of sustainability capability under different supply chain risks and the desired levels set by decision makers.

In addition, Network DEA provides three levels of comparison at the process level (e.g., firms that are part of the supply chain) and the system level (the supply chain as a whole entity). DEA, originally introduced by Charnes et al. [45], measures the relative efficiency of *n* Decision Making Units (DMUs), each of which uses *m* inputs to produce *s* outputs. The fractional programming model for evaluating the efficiency of a particular DMU (denoted as DMU_k), as proposed by Charnes, Cooper, and Rhodes (CCR model, 1978), is formulated as follows:

$$
\begin{aligned}
&E_k = max \sum_{r=1}^{s} u_r Y_{r\mathrm{k}} \Big/ \sum_{i=1}^{m} v_i X_{i\mathrm{k}} \\
&\quad \text{s.t.} \\
&\sum_{r=1}^{s} u_r Y_{rj} \Big/ \sum_{i=1}^{m} v_i X_{ij} \leq 1, j = 1,2,\dots,n \\
&u_r \geq \varepsilon > 0, r = 1,2,\dots,s \\
&v_i \geq \varepsilon > 0, i = 1,2,\dots,m,
\end{aligned}
\tag{1}
$$

In this model:

- s = number of output variables
- m = number of input variables
- r = index of output variables ($r = 1, 2, \dots, s$)
- i = index of input variables ($i = 1, 2, \dots, m$)
- j = index of decision making units ($j = 1, 2, \dots, n$)
- Y_{rk} = amount of output r produced by decision making unit k
- X_{ik} = amount of input i used by decision making unit k
- u_r = weight (multiplier) assigned to output r in evaluating the efficiency of DMU k
- v_i = weight (multiplier) assigned to input i in evaluating the efficiency of DMU k
- ε = a non Archimedean infinitesimal (a very small positive number)

Using the Charnes and Cooper transformation method, the fractional CCR model (Model 1) is converted into a linear programming model, as shown in Equation (2) [46]:

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$$
\begin{aligned}
& E_k = max \sum_{r=1}^{s} u_r Y_{rk} \\
& \quad \text{s.t.} \\
& \sum_{i=1}^{m} v_i X_{ik} = 1 \\
& \sum_{r=1}^{s} u_r Y_{rj} - \sum_{i=1}^{m} v_i X_{ij} \le 0, j = 1,2,\dots,n \\
& u_r \ge \varepsilon > 0, r = 1,2,\dots,s \\
& v_i \ge \varepsilon > 0, i = 1,2,\dots,m
\end{aligned} \tag{2}
$$

This model, which is considered the first Data Envelopment Analysis (DEA) model, is known as the input oriented multiplier model. Essentially, it provides a non parametric estimation of the production function, assuming that the production possibility set is convex and exhibits constant returns to scale. Since the introduction of this model, various extensions and modifications of DEA models have been proposed by different researchers.

The present study introduces a proposed model for evaluating sustainability capability in a three stage supply chain, as illustrated in the figure below. Given the networked nature of the problem under investigation, it is necessary to use network based DEA models.

By extending Model (2) to a Network Data Envelopment Analysis (NDEA) framework following the developments by Kao [47] and Kao & Hwang [48, 49] it becomes possible to evaluate risk and reliability variables within a three stage supply chain. Furthermore, it has been shown that network DEA models, when compared with traditional non network DEA models [50], offer greater analytical power and lead to more accurate and reliable results.

While multi component models are related to the internal structure of an organization comprising various interconnected sections, such structures can be configured in series, parallel, or hybrid forms. Consider the three stage process illustrated in Figure 2. Suppose we are evaluating a Decision Making Unit (DMU), and each DMUj (for *j = 1, 2, ..., n*) has *m* input variables (x_{ij}) and produces output variables (z_{pj}) in the first stage.

The outputs of the first stage serve as the inputs to the second stage $\theta_j^1 = \sum_{d=1}^{D} \eta_d^1 z_{dj} \Big/ \sum_{i=1}^{m} v_i x_{ij}$, and $\theta_j^2 = \sum_{r=1}^{s} u_r y_{rj} \Big/ \sum_{d=1}^{D} \eta_d^2 z_{dj}$ are referred to as intermediate products or intermediate measures. The outputs of the second stage are denoted as (y_{rj}).

The efficiencies of DMU_j in the first and second stages are respectively denoted as θ_{1j} and θ_{2j}, where:

- v_i and u_p represent the input and output weights in the first stage;
- u_p and w_r represent the input and output weights in the second stage.

Based on the efficiency values θ_{1j} and θ_{2j} in each of the two stages, the overall efficiency θ_j of the entire process can be defined in several ways.

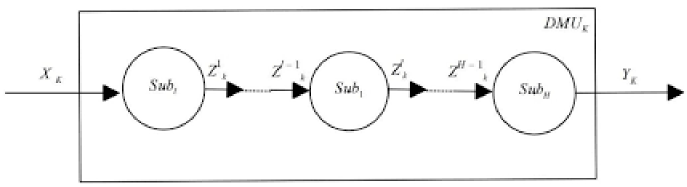

Fig. 1 Two-stage process

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Chen et al. [51] defined the overall efficiency of a two stage process as follows:

$$w_1 \cdot \frac{\sum_{d=1}^{D} \eta_d z_{do}}{\sum_{i=1}^{m} v_i x_{io}} + w_2 \cdot \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{d=1}^{D} \eta_d z_{do}} \tag{3}$$

Due to the sequential relationship between the two stages, they assumed that the intermediate outputs of the first stage are equal to the inputs of the second stage $\eta_d^1 = \eta_d^2$) .($d = 1,\dots,D$. In Equation (1), w_1 w_2 the weights α\alpha and w are user specified parameters such that $w_1 + w_2 = 1$. These weights are not optimization variables themselves, but rather functions of the optimization variables.

Chen et al. [51] proposed DEA Model (4) to calculate the overall efficiency in a two stage process:

$$\begin{aligned}
\max \quad & w_1 \cdot \frac{\sum_{d=1}^{D} \eta_d z_{do}}{\sum_{i=1}^{m} v_i x_{io}} + w_2 \cdot \frac{\sum_{r=1}^{s} u_r y_{ro}}{\sum_{d=1}^{D} \eta_d z_{do}} \\
\text{s.t.} \quad & \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1,\dots,n, \\
& \frac{\sum_{d=1}^{D} \eta_d z_{dj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad j = 1,\dots,n, \\
& \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{d=1}^{D} \eta_d z_{dj}} \le 1, \quad j = 1,\dots,n, \\
& \eta_d, v_i, u_r \ge 0, \quad d = 1,\dots,D; \quad r = 1,\dots,s; \quad i = 1,\dots,m.
\end{aligned} \tag{4}$$

The three sets of constraints essentially correspond to the definitions of system efficiency, efficiency of process 1, and efficiency of process 2, respectively. Note that the parameters $\sum_{d=1}^{D} \eta_d z_{dj} / \sum_{i=1}^{m} v_i x_{ij} \le 1$ and $\sum_{r=1}^{s} u_r y_{rj} / \sum_{d=1}^{D} \eta_d z_{dj} \le 1$ imply that $\sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \le 1$. Therefore, the redundant constraint $\sum_{r=1}^{s} u_r y_{rj} / \sum_{i=1}^{m} v_i x_{ij} \le 1$ is not included in Chen et al.'s model.

The parameters w1 and w2 respectively represent the relative importance or contribution of the performance of stages 1 and 2 to the overall performance of the DMU. To determine the relative importance of each stage, Chen et al. [51] assumed that:

- $\sum_{i=1}^{m} v_i x_{io} + \sum_{d=1}^{D} \eta_d z_{do}$ represents the overall size of the two stage process,
- $\sum_{i=1}^{m} v_i x_{io}$ and $\sum_{d=1}^{D} \eta_d z_{do}$ represent the sizes of stages 1 and 2, respectively.

Then, the weights w1 and w2 were defined as follows:

$$w_1 = \frac{\sum_{i=1}^{m} v_i x_{io}}{\sum_{i=1}^{m} v_i x_{io} + \sum_{d=1}^{D} \eta_d z_{do}} \quad \textbf{and} \quad w_2 = \frac{\sum_{d=1}^{D} \eta_d z_{do}}{\sum_{i=1}^{m} v_i x_{io} + \sum_{d=1}^{D} \eta_d z_{do}} \tag{5}$$

Then, Chen et al. [51] transformed Model (4) into Model (6):

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$$
\begin{aligned}
&\max \frac{\sum_{d=1}^{D}\eta_d z_{do}+\sum_{r=1}^{s}u_r y_{ro}}{\sum_{i=1}^{m}v_i x_{io}+\sum_{d=1}^{D}\eta_d z_{do}} \\
&\text{s.t.}\quad \frac{\sum_{d=1}^{D}\eta_d z_{dj}}{\sum_{i=1}^{m}v_i x_{ij}}\le 1,\quad j=1,\dots,n, \\
&\quad \frac{\sum_{r=1}^{s}u_r y_{rj}}{\sum_{d=1}^{D}\eta_d z_{dj}}\le 1,\quad j=1,\dots,n, \\
&\eta_d, v_i, u_r \ge 0,\quad d=1,\mathrm{K}\ ,D;\quad r=1,\mathrm{K}\ ,s;\quad i=1,\mathrm{K}\ ,m.
\end{aligned}
\tag{6}
$$

3.1 DEA Model of the Present Study

The network DEA model for evaluating the sustainability capability of the supply chain in response to various risks is presented in the structure of a three stage supply chain model, which includes economic, social, and environmental processes, the risks associated with them, and the levels of sustainability capability (considered as inputs and outputs of inter and intra organizational processes).

Accordingly, the sustainability levels of the economic layer of the supply chain are considered as outputs, which may also serve as inputs to the social or environmental layers. As illustrated, economic risks ($\tilde{X}_{11}$), external risks ($\tilde{X}_{12}$), and network risks ($\tilde{X}_{13}$) are treated as inputs, while the sustainability capability of the supplier ($\tilde{Z}_1$) is regarded as the intermediate output of the economic process, which influences supplier operations.

Similarly, social risks ($\tilde{X}_{51}$), external risks ($\tilde{X}_{22}$), and network risks ($\tilde{X}_{23}$) are considered as inputs to the social process, and the sustainability capability of the manufacturer ($\tilde{Z}_2$) is treated as its intermediate output.

Finally, environmental risks ($\tilde{X}_{31}$), external risks ($\tilde{X}_{32}$), and network risks ($\tilde{X}_{33}$) serve as inputs to the environmental process, and the sustainability capability of the distributor ($\tilde{Y}_3$) is considered its final output.

The tilde symbol (~) indicates fuzzy values representing the levels of risk and sustainability capability.

3.2. Notation of the Data Envelopment Analysis Model

To develop the network DEA model for evaluating supply chain sustainability capability in response to risks, this section introduces the notations used throughout the modeling process in the remainder of the chapter.

Parameters

- $\tilde{X}_{11}^{j}$ Fuzzy assessed value of economic risks in the economic sustainability processes for the *j th* Decision Making Unit (DMU) (i.e., food manufacturing company)
- $\tilde{X}_{12}^{j}$: Fuzzy assessed value of external risks in the economic sustainability processes for the *j th* DMU

[DOI: 10.71885/ijorlu-2025-2-695]

- $\tilde{X}_{13}^{j}$: Fuzzy assessed value of network risks in the economic sustainability processes for the *j th* DMU
- $\tilde{X}_{21}^{j}$: Fuzzy assessed value of social risks in the social sustainability processes for the *j th* DMU
- $\tilde{X}_{22}^{j}$: Fuzzy assessed value of external risks in the social sustainability processes for the *j th* DMU
- $\tilde{X}_{23}^{j}$: Fuzzy assessed value of network risks in the social sustainability processes for the *j th* DMU
- $\tilde{X}_{31}^{j}$: Fuzzy assessed value of environmental risks in the environmental sustainability processes for the *j th* DMU
- $\tilde{X}_{32}^{j}$: Fuzzy assessed value of external risks in the environmental sustainability processes for the *j th* DMU
- $\tilde{X}_{33}^{j}$: Fuzzy assessed value of network risks in the environmental sustainability processes for the *j th* DMU
- $\tilde{Z}_{1}^{j}$: Fuzzy assessed value of supplier sustainability capability in economic processes for the *j th* DMU
- $\tilde{Z}_{2}^{j}$: Fuzzy assessed value of supplier sustainability capability in social processes for the *j th* DMU (e.g., petrochemical company)
- $\tilde{Y}_{3}^{j}$: Fuzzy assessed value of supplier sustainability capability in environmental processes for the *j th* DMU (e.g., food manufacturing company)

Variables

- v_{1i}: Weight of economic risks (i = 1), external risks (i = 2), and network risks (i = 3) in evaluating sustainability in economic processes
- v_{2i}: Weight of social risks (i = 1), external risks (i = 2), and network risks (i = 3) in evaluating sustainability in social processes
- v_{1i}: Weight of environmental risks (i = 1), external risks (i = 2), and network risks (i = 3) in evaluating sustainability in environmental processes
- w1: Weight of supplier sustainability in economic processes in sustainability evaluation
- w2: Weight of supplier sustainability in social processes in sustainability evaluation
- u3: Weight of supplier sustainability in environmental processes in sustainability evaluation

According to Kao and Hwang [48], the overall efficiency of the supply chain system for DMUk is formulated as follows:

$$\tilde{E}_k = max \frac{u_3\tilde{Y}_3^k}{\sum_{t=1}^{3}\sum_{i=1}^{3} v_{ti}\tilde{X}_{ti}^k}$$

$$\text{s.t. } \frac{u_3\tilde{Y}_3^j}{(\sum_{t=1}^{3}\sum_{i=1}^{3} v_{ti}\tilde{X}_{ti}^j)} \leq 0, j = 1,2,\dots,n \qquad (7)$$

$$v_{ti}, u_3, \geq \varepsilon, i = 1,2,3;\ t = 1,2,3$$

In the above model, the objective function aims to maximize the overall efficiency of DMUk, while the constraints ensure that the efficiency of all decision making units does not exceed one. This formulation corresponds to the fractional input oriented CCR multiplier model.

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By applying the Charnes and Cooper variable transformation, the linearized version of the model is formulated as follows:

$$\begin{aligned}
&\tilde{E}_k = max\ u_3\tilde{Y}_3^k \\
&\text{s.t. } \textstyle\sum_{t=1}^3\sum_{i=1}^3 v_{ti}\tilde{X}_{ti}^k = 1 \\
&u_3\tilde{Y}_3^j - (\textstyle\sum_{t=1}^3\sum_{i=1}^3 v_{ti}\tilde{X}_{ti}^j) \leq 0, \qquad j = 1,2,\dots,n \\
&v_{ti}, u_3, \geq \varepsilon, i = 1,2,3;\ t = 1,2,3
\end{aligned} \tag{8}$$

Using a similar logic, the sustainability capability of each of the economic, social, and environmental processes can also be evaluated based on the associated input risks and output sustainability indicators. Suppose that $\tilde{E}_k^1$ ‹$\tilde{E}_k^2$ and $\tilde{E}_k^3$ represent the sustainability capabilities of the economic, social, and environmental processes, respectively, for the *k th* food manufacturing company under evaluation.

Consider the economic processes. In these processes, three types of risks namely economic, organizational (external), and network risks are defined as inputs, and sustainability capability is defined as the output. Accordingly, the efficiency of this part of the system can be formulated as follows:

$$\tilde{E}_k^1 = w_1^*\tilde{Z}_1^k / \textstyle\sum_{i=1}^3 v_{1i}^*\tilde{X}_{1i}^k \tag{9}$$

Similarly, the organizational (social) processes receive the resilience of economic processes along with a set of social, external, and network risks as inputs, and produce sustainability capability as the output. Using the notations introduced in the previous section, the sustainability capability of the social processes is formulated as follows:

$$\tilde{E}_k^2 = w_2^*\tilde{Z}_2^k / w_1^*\tilde{Z}_1^k + \textstyle\sum_{i=1}^3 v_{2i}^*\tilde{X}_{2i}^k \tag{10}$$

A similar formulation can also be applied to the environmental processes. These processes receive the sustainability capability of the organizational (social) processes along with a set of economic, organizational, and network risks as inputs, and produce sustainability capability as the output. As a result, the sustainability efficiency of the environmental processes can be formulated as follows:

$$\tilde{E}_k^3 = u_3^*\tilde{Y}_3^k / w_2^*\tilde{Z}_2^k + \textstyle\sum_{i=1}^3 v_{3i}^*\tilde{X}_{3i}^k \tag{11}$$

Considering the constraint that efficiency values must be less than or equal to one, Relations (10) and (11) can be incorporated into the model as follows, in the form of model constraints:

$$\begin{aligned}
&w_1^*\tilde{Z}_1^k / \textstyle\sum_{i=1}^3 v_{1i}^*\tilde{X}_{1i}^k \leq 1 \\
&w_2^*\tilde{Z}_2^k / w_1^*\tilde{Z}_1^k + \textstyle\sum_{i=1}^3 v_{2i}^*\tilde{X}_{2i}^k \leq 1 \\
&u_3^*\tilde{Y}_3^k / w_2^*\tilde{Z}_2^k + \textstyle\sum_{i=1}^3 v_{3i}^*\tilde{X}_{3i}^k \leq 1
\end{aligned} \tag{12}$$

By linearizing the above constraints and incorporating them into Model (13), the final model for assessing the sustainability capability of the company's processes is formulated as follows:

$$\begin{aligned}
&\tilde{E}_k = max\, u_3\tilde{Y}_3^k \\
&\text{S.T. } \textstyle\sum_{t=1}^{3}\sum_{i=1}^{3} v_{ti}\tilde{X}_{ti}^k = 1 \\
&u_3\tilde{Y}_3^j - (\textstyle\sum_{t=1}^{3}\sum_{i=1}^{3} v_{ti}\tilde{X}_{ti}^j) \le 0, j = 1,2,\dots,n \\
&w_1\tilde{Z}_1^j - \textstyle\sum_{i=1}^{3} v_{1i}\tilde{X}_{1i}^j \le 0, j = 1,2,\dots,n \\
&w_2\tilde{Z}_2^j - (w_1\tilde{Z}_1^j + \textstyle\sum_{i=1}^{3} v_{2i}\tilde{X}_{2i}^j) \le 0, j = 1,2,\dots,n \\
&u_3\tilde{Y}_3^0 - (w_2\tilde{Z}_2^j + \textstyle\sum_{i=1}^{3} v_{3i}\tilde{X}_{3i}^j) \le 0, j = 1,2,\dots,n \\
&v_{ti}, u_3, w_1, w_2 \ge \varepsilon, i = 1,2,3;\ t = 1,2,3
\end{aligned} \tag{13}$$

Model (14) is a fuzzy linear programming model, the solution of which requires the development of specialized methods. In the present study, to solve the above fuzzy linear model, an alpha cut–based approach is employed, which will be explained in the following section.

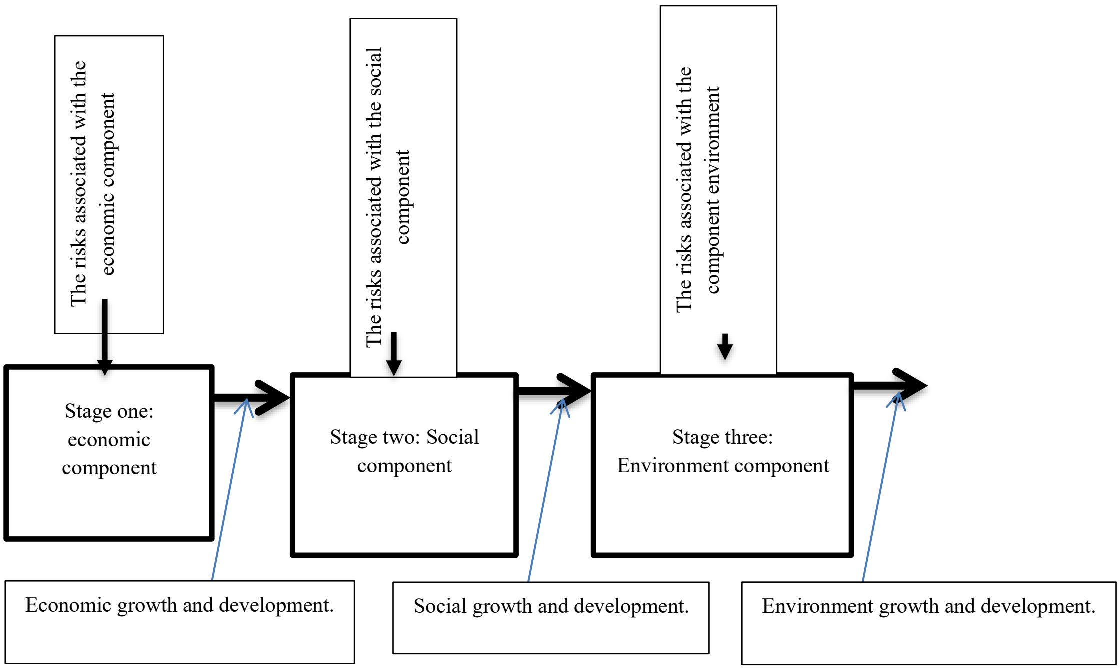

Fig. 2 Schematic diagram of the data envelopment analysis model for supply chain sustainability.

Since the fuzzy numbers used in this study for evaluating various risk types and resilience indicators are triangular fuzzy numbers, their α cuts are also specifically considered. For a triangular fuzzy number defined as (l,m,u)(l, m, u), the membership function is given in Equation (14).

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$$\mu = \begin{cases} 0, & x \leq l \\ \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & x \geq u \end{cases} \tag{14}$$

Based on the definition of the α cut for the above membership function, we have:

$$\frac{x-l}{m-l} \geq \alpha \rightarrow x \geq l(1-\alpha) + \alpha m \tag{15}$$

$$\frac{u-x}{u-m} \geq \alpha \rightarrow \leq u(1-\alpha) + \alpha m \tag{16}$$

As a result, the α cut of the above triangular fuzzy number includes all values within the interval:
$[l(1-\alpha) + \alpha m,\ u(1-\alpha) + \alpha m]$
By applying the above definition to the triangular fuzzy numbers representing the various types of risks and resilience indicators, the α cuts of these indicators are calculated as follows:

$$\begin{aligned}
(X_{11})_\alpha &= [(X_{11})_\alpha^L, (X_{11})_\alpha^U] = [(1-\alpha)X_{11}^1 + \alpha X_{11}^2, \alpha X_{11}^2 + (1-\alpha)X_{11}^3] \\
(X_{12})_\alpha &= [(X_{12})_\alpha^L, (X_{12})_\alpha^U] = [(1-\alpha)X_{12}^1 + \alpha X_{12}^2, \alpha X_{12}^2 + (1-\alpha)X_{12}^3] \\
(X_{13})_\alpha &= [(X_{13})_\alpha^L, (X_{13})_\alpha^U] = [(1-\alpha)X_{13}^1 + \alpha X_{13}^2, \alpha X_{13}^2 + (1-\alpha)X_{13}^3] \\
(X_{21})_\alpha &= [(X_{21})_\alpha^L, (X_{21})_\alpha^U] = [(1-\alpha)X_{21}^1 + \alpha X_{21}^2, \alpha X_{21}^2 + (1-\alpha)X_{21}^3] \\
(X_{22})_\alpha &= [(X_{22})_\alpha^L, (X_{22})_\alpha^U] = [(1-\alpha)X_{22}^1 + \alpha X_{22}^2, \alpha X_{22}^2 + (1-\alpha)X_{22}^3] \\
(X_{23})_\alpha &= [(X_{23})_\alpha^L, (X_{23})_\alpha^U] = [(1-\alpha)X_{23}^1 + \alpha X_{23}^2, \alpha X_{23}^2 + (1-\alpha)X_{23}^3] \\
(X_{31})_\alpha &= [(X_{31})_\alpha^L, (X_{31})_\alpha^U] = [(1-\alpha)X_{31}^1 + \alpha X_{31}^2, \alpha X_{31}^2 + (1-\alpha)X_{31}^3] \\
(X_{32})_\alpha &= [(X_{32})_\alpha^L, (X_{32})_\alpha^U] = [(1-\alpha)X_{32}^1 + \alpha X_{32}^2, \alpha X_{32}^2 + (1-\alpha)X_{32}^3] \\
(X_{33})_\alpha &= [(X_{33})_\alpha^L, (X_{33})_\alpha^U] = [(1-\alpha)X_{33}^1 + \alpha X_{33}^2, \alpha X_{33}^2 + (1-\alpha)X_{33}^3] \\
(Z_1)_\alpha &= [(Z_1)_\alpha^L, (Z_1)_\alpha^U] = [(1-\alpha)Z_1^1 + \alpha Z_1^2, \alpha Z_1^2 + (1-\alpha)Z_1^3] \\
(Z_2)_\alpha &= [(Z_2)_\alpha^L, (Z_2)_\alpha^U] = [(1-\alpha)Z_2^1 + \alpha Z_2^2, \alpha Z_2^2 + (1-\alpha)Z_2^3] \\
(Y_3)_\alpha &= [(Y_3)_\alpha^L, (Y_3)_\alpha^U] = [(1-\alpha)Y_3^1 + \alpha Y_3^2, \alpha Y_3^2 + (1-\alpha)Y_3^3],
\end{aligned} \tag{17}$$

The above equations represent the α cuts of the input, output, and intermediate indicators in the resilience evaluation model. By applying these α cuts to the resilience assessment model, and in order to determine the membership function of the overall network efficiency of DMUk, it is necessary to compute the lower and upper bounds of the α cut for the fuzzy efficiency value$\widetilde{E}_k$, i.e.:

$$(E_k)_\alpha = [(E_k)_\alpha^L, (E_k)_\alpha^U]$$

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According to the models proposed by Kao and Liu [52], Kao [53], and Kao and Liu [54], the upper bound of the efficiency function is calculated using Model (16), and the lower bound is determined using Model (28).

$$
\begin{aligned}
&(E_k)_\alpha^U = max\, u_3 (Y_3^k)_\alpha^U \\
&\text{s.t. } \textstyle\sum_{t=1}^3 \sum_{i=1}^3 v_{ti} (X_{ti}^k)_\alpha^L = 1 \\
&u_3 (Y_3^k)_\alpha^L - \left(\textstyle\sum_{t=1}^3 \sum_{i=1}^3 v_{ti} (X_{ti}^k)_\alpha^U\right) \le 0 \\
&u_3 (Y_3^j)_\alpha^L - \left(\textstyle\sum_{t=1}^3 \sum_{i=1}^3 v_{ti} (X_{ti}^j)_\alpha^U\right) \le 0, j = 1,2,\dots,n, j \ne k \\
&\hat{z}_1^k - \textstyle\sum_{i=1}^3 v_{1i} (X_{1i}^k)_\alpha^L \le 0 \\
&\hat{z}_1^j - (\textstyle\sum_{i=1}^3 v_{1i} (X_{1i}^j)_\alpha^U) \le 0, j = 1,2,\dots,n, j \ne k \\
&\hat{z}_2^k - (\hat{z}_1^k + \textstyle\sum_{i=1}^3 v_{1i} (X_{2i}^k)_\alpha^L) \le 0 \\
&\hat{z}_2^j - (\hat{z}_1^j + \textstyle\sum_{i=1}^3 v_{1i} (X_{2i}^j)_\alpha^U) \le 0, j = 1,2,\dots,n, j \ne k \\
&u_3 (Y_3^k)_\alpha^U - (\hat{z}_2^k + \textstyle\sum_{i=1}^3 v_{1i} (X_{3i}^k)_\alpha^L) \le 0 \\
&u_3 (Y_3^j)_\alpha^L - (\hat{z}_2^j + \textstyle\sum_{i=1}^3 v_{1i} (X_{3i}^j)_\alpha^U) \le 0, j = 1,2,\dots,n, j \ne k \\
&w_1 (Z_1^j)_\alpha^L \le \hat{z}_1^j \le w_1 (Z_1^j)_\alpha^U, j = 1,2,\dots,n \\
&w_2 (Z_2^j)_\alpha^L \le \hat{z}_2^j \le w_2 (Z_2^j)_\alpha^U, j = 1,2,\dots,n \\
&v_{ti}, u_3, w_1, w_2 \ge \varepsilon, \quad i = 1,2,3; t = 1,2,3
\end{aligned}
\tag{18}
$$

After computing the optimal values for v_{ti}^*, u_3^*, w_1^*, w_2^*, $\hat{z}_1^*$ and $\hat{z}_2^*$, Model (19) calculates the efficiency scores for the entire network as well as for the three individual process levels, as expressed by the following formula:

$$
\begin{aligned}
&(E_k)_\alpha^U = u_3^* (Y_3^k)_\alpha^U / \textstyle\sum_{t=1}^3 \sum_{i=1}^3 v_{ti}^* (X_{ti}^k)_\alpha^L \\
&(E_k^1)_\alpha^U = \hat{z}_1^{*k} / \textstyle\sum_{i=1}^3 v_{1i}^* (X_{1i}^k)_\alpha^L \\
&(E_k^2)_\alpha^U = \hat{z}_2^{*k} / (\hat{z}_1^{*k} + \textstyle\sum_{i=1}^3 v_{2i}^* (X_{2i}^k)_\alpha^L) \\
&(E_k^3)_\alpha^U = u_3^* (Y_3^k)_\alpha^U / (\hat{z}_2^{*k} + \textstyle\sum_{i=1}^3 v_{3i}^* (X_{3i}^k)_\alpha^L)
\end{aligned}
\tag{19}
$$

Formulating the lower bound of the α cut for the efficiency scores of the proposed model (as shown in Figure 2) requires a bi objective function derived from Model (28) to be transformed into its fuzzy representation. Accordingly, a bi objective reformulation of Model (28) is developed, and the lower bound of the α cut for overall efficiency, along with the efficiency scores of the three process levels upstream, organizational, and downstream is calculated.

The bi objective version of Model (20) for the overall Decision Making Units (DMUs) is computed as follows, based on the formulation by Kao and Hwang [48]:

$$
\begin{aligned}
&\tilde{E}_k = \min \theta - \varepsilon((\sum_{t=1}^{3}\sum_{i=1}^{3} s_{ti}^{v}) + s_1^{w} + s_2^{w} + s_3^{u})\\
&\text{s.t.}\\
&\theta \tilde{X}_{1i}^{k} - \sum_{j=1}^{n} \alpha_j \tilde{X}_{1i}^{j} - \sum_{j=1}^{n} \beta_j \tilde{X}_{1i}^{j} - s_{1i}^{v} = 0, i = 1,2,3\\
&\theta \tilde{X}_{2i}^{k} - \sum_{j=1}^{n} \alpha_j \tilde{X}_{2i}^{j} - \sum_{j=1}^{n} \gamma_j \tilde{X}_{2i}^{j} - s_{2i}^{v} = 0, i = 1,2,3\\
&\theta \tilde{X}_{3i}^{k} - \sum_{j=1}^{n} \alpha_j \tilde{X}_{3i}^{j} - \sum_{j=1}^{n} \delta_j \tilde{X}_{3i}^{j} - s_{3i}^{v} = 0, i = 1,2,3\\
&\sum_{j=1}^{n} \beta_j \tilde{Z}_1^{j} - \sum_{j=1}^{n} \gamma_j \tilde{Z}_1^{j} - s_1^{w} = 0\\
&\sum_{j=1}^{n} \gamma_j \tilde{Z}_2^{j} - \sum_{j=1}^{n} \delta_j \tilde{Z}_2^{j} - s_2^{w} = 0\\
&\sum_{j=1}^{n} \alpha_j \tilde{Y}_3^{j} + \sum_{j=1}^{n} \delta_j \tilde{Y}_3^{j} - s_3^{u} = \tilde{Y}_3^{k}\\
&\alpha_j, \beta_j, \gamma_j, \delta_j, s_{ti}^{v}, s_1^{w}, s_2^{w}, s_3^{u} \geq 0, j = 1,2,\dots,n; i = 1,2,3; t = 1,2,3
\end{aligned} \tag{20}
$$

Accordingly, the lower bound of the α cut for the overall efficiency model (Model (21)) is given as follows:

$$
\begin{aligned}
&(E_k)_\alpha^L = \min \varepsilon((\sum_{t=1}^{3}\sum_{i=1}^{3} s_{ti}^{v}) + s_1^{w} + s_2^{w} + s_3^{u})\\
&\text{s.t.}\\
&\theta (X_{1i}^{k})_\alpha^U - \left[\alpha_k \left(X_{1i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \alpha_j \left(X_{1i}^{j}\right)_\alpha^L\right] - \left[\beta_k \left(X_{1i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \beta_j \left(X_{1i}^{j}\right)_\alpha^L\right] - s_{1i}^{v} = 0, i = 1,2,3\\
&\theta (X_{2i}^{k})_\alpha^U - \left[\alpha_k \left(X_{2i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \alpha_j \left(X_{2i}^{j}\right)_\alpha^L\right] - \left[\gamma_k \left(X_{2i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \gamma_j \left(X_{2i}^{j}\right)_\alpha^L\right] - s_{2i}^{v} = 0, i = 1,2,3\\
&\theta (X_{3i}^{k})_\alpha^U - \left[\alpha_k \left(X_{3i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \alpha_j \left(X_{3i}^{j}\right)_\alpha^L\right] - \left[\delta_k \left(X_{3i}^{k}\right)_\alpha^U + \sum_{j=1,j\neq k}^{n} \delta_j \left(X_{3i}^{j}\right)_\alpha^L\right] - s_{3i}^{v} = 0, i = 1,2,3\\
&\sum_{j=1}^{n} \beta_j z_1^{j} - \sum_{j=1}^{n} \gamma_j z_1^{j} - s_1^{w} = 0\\
&\sum_{j=1}^{n} \gamma_j z_2^{j} - \sum_{j=1}^{n} \delta_j z_2^{j} - s_2^{w} = 0\\
&\left[\alpha_k (Y_3^{k})_\alpha^L + \sum_{j=1,j\neq k}^{n} \alpha_j (Y_3^{j})_\alpha^U\right] + \left[\delta_k (Y_3^{k})_\alpha^L + \sum_{j=1,j\neq k}^{n} \delta_j (Y_3^{j})_\alpha^U\right] - s_3^{u} = (Y_3^{k})_\alpha^L\\
&(Z_1^{j})_\alpha^L \leq z_1^{j} \leq \left(Z_1^{j}\right)_\alpha^U, j = 1,2,\dots,n\\
&(Z_2^{j})_\alpha^L \leq z_2^{j} \leq \left(Z_2^{j}\right)_\alpha^U, j = 1,2,\dots,n\\
&\alpha_j, \beta_j, \gamma_j, \delta_j, s_{ti}^{v}, s_1^{w}, s_2^{w}, s_3^{u} \geq 0, j = 1,2,\dots,n; i = 1,2,3; t = 1,2,3
\end{aligned} \tag{21}
$$

Upon obtaining the optimal solution from Model (21), the values $s_{ti}^{*v}, s_1^{*w}, s_2^{*w}, s_3^{*u}$, are respectively assigned v_{ti}^{*}, w_1^{*}, w_2^{*}, u_3^{*}. Consequently, the lower bounds of the system efficiency and the lower bounds of the efficiency scores for the upstream, organizational, and downstream processes at the α cut level are calculated as described in Equation (22).

$$(E_k)_\alpha^L = u_3^{*}(Y_3^{k})_\alpha^L / \sum_{t=1}^{3}\sum_{i=1}^{3} v_{ti}^{*}(X_{ti}^{k})_\alpha^U \tag{22}$$

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$$(E_k^1)_\alpha^L = w_1^* z_1^{*k} / \sum_{i=1}^{3} v_{1i}^* (X_{1i}^k)_\alpha^U$$

$$(E_k^2)_\alpha^L = w_2^* z_2^{*k} / (w_1^* z_1^{*k} + \sum_{i=1}^{3} v_{2i}^* (X_{2i}^k)_\alpha^U)$$

$$(E_k^3)_\alpha^L = u_3^* (Y_3^k)_\alpha^L / (w_2^* z_2^{*k} + \sum_{i=1}^{3} v_{3i}^* (X_{3i}^k)_\alpha^U)$$

The α values in Models (18) and (22) are set to 0 and 1, respectively. These values are significant and are used to provide a comprehensive report on the final results of the two models.

When α = 0, the range of all possible efficiency scores for different alpha levels is determined. Additionally, when α = 1, the most likely efficiency scores for the decision making units (DMUs) are obtained.

Therefore, by using efficiency scores at different alpha levels and linking the lower and upper bounds of these scores, the membership function of the fuzzy resilience levels of supply chain risks is determined.

This process leads to the calculation of risk and systemic resilience (i.e., the resilience of the entire supply chain), the evaluation of supply chain layers, and ultimately the assessment of risk to resilience ratios across decision making units and various supply chain processes.

4 Research Findings

Despite the unique investment opportunities that Iran's major industries offer to foreign investors, these investors face certain constraints in the Iranian market and, therefore, approach investment in Iran with greater caution. In recent years, Iran's main foreign investors primarily from the European Union and the United States have gained the opportunity to participate in the country's key industrial sectors [55, 56].

To improve the investment climate and enhance the transparency of investment opportunities in Iran, one of the critical factors is the assessment of risk and resilience in the supply chains of the country's core industries.

All industries examined in this study source their raw materials from both domestic and international suppliers. After converting raw materials into final products, they primarily offer their products to customers operating within Iran.

The research instrument used to enable respondents to assess supply chain risk is based on the model developed by Wagner and Bode [57]. In this study, the instrument was updated according to a revised risk categorization. Moreover, the items related to supply chain resilience assessment were defined based on the following five resilience performance criteria, which were applied equally to all three processes:

- Robustness performance,
- Redundancy performance,
- Resourcefulness performance,
- Responsiveness performance, and
- Recovery performance.

To test the model, 50 senior and middle managers from 30 Iranian companies participated in the assessment. They were asked to rank the resilience of risks within their companies and to score the risk and resilience of upstream, organizational, and downstream processes within their supply chains.

The respondents were selected through coordination with targeted food production companies, and participation was arranged through in person visits to their workplaces. During

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these visits, the overall purpose of the study was explained, and the participants were provided with guidance on how to complete the questionnaire. This process took place over a period of three months.

Finally, based on the evaluations conducted, the efficiency results of the companies are presented as follows:

Table 3 Evaluation of Network Data Envelopment Analysis (DEA)

DMU	TET(L)1J	TET(L)2J	TET(L)3J	TET(U)2J	TET(U)1J	TET(U)3J	E1	E2	E3	TETA
1	1	1	1	1	1	1	1	1	1	1
2	0.9786	1	1	0.8975	1	1	0.8979	1	1	0.9850
3	1	1	1	1	1	1	1	1	1	1
4	1	1	1	1	1	1	1	1	1	1
5	1	1	1	1	1	1	1	1	1	1
6	1	1	1	1	1	1	1	1	1	1
7	1	1	1	1	1	1	1	1	1	1
8	0.95069	0.466		0.495	0.00019	0.659	0.7284	0.1375	0.34566	0.9398
9	0.87367	1	1	0.944	1	1	0.75772	1	1	0.71182
10	0.52849	1	1	0.728	1	1	0.51255	1	1	0.2784
11	0.3641	1	1	1	1	1	0.3641	1	1	0.34525
12	0.78364	1	1	0.405	1	1	0.68214	1	1	0.27369
13	0.95069	1	1	0.495	1	1	0.7284	1	1	0.10016
14	0.93782	1	1	0.591	1	1	0.66762	1	1	0.09317
15	0.48224	1	1	1	1	1	0.48224	1	1	0.14745
16	0.69129	0.533	0.69129	0.659	0.10123	0.606	0.54512	0.24152	0.894	0.9775
17	0.23269	0.501	0.23269	0.606	0.00034	0.917	0.23269	0.55404	0.463	0.9395
18	1	1	1	1	1	1	1	1	1	1
19	0.55255	0.765		1	0.12703		0.46595	0.38535	0.54512	0.9948
20	1	1	1	1	1	1	1	1	1	1
21	1	1	1	1	1	1	1	1	1	1
22	1	0.754		0.894	0.00062		0.89288	0.34566	0.894	0.9939
23	1	1	1	1	1	1	1	1	0.463	1
24	1	1	1	1	1	1	1	1	0.785	1
25	0.45128	0.966	0.765	0.967	0.00006	0.34566	0.43649	0.4248	1	0.7986
26	1	1	1	1	1	1	1	1	1	1
27	1	1	1	1	1	1	1	1	1	1
28	1	1	1	1	1	1	1	1	1	1
29	1	1	1	1	1	1	1	1	1	1
30	1	1	1	1	1	1	1	1	1	1

Based on the evaluation and analysis conducted on 30 food manufacturing companies, using the defined input and output indicators, it was found that 16 companies were deemed efficient, while the remaining companies showed a significant gap from the efficiency frontier.

In the first stage evaluation, it was shown that 16 companies were efficient based on the first stage indicators, while the remaining companies were close to the efficiency frontier.

According to the second stage efficiency analysis, 25 companies achieved efficiency, whereas the remaining companies were separated from the efficiency frontier due to weak output performance and excessive input levels in their processes.

In the third stage evaluation, 23 companies were identified as efficient, while the rest did not fall on the efficiency frontier. It is therefore recommended that these companies implement continuous improvement practices (Kaizen approach) to enhance their operational performance and move closer to the efficiency frontier.

5 Conclusion

The necessity of the present study largely stems from the growing development of multi level systems, along with the increasing relevance of supply chain management and sustainable planning in advanced organizations. Today, many businesses are organized in the form of networks of producers and distributors that procure raw materials, transform them into final products, and distribute them to customers.

The term multi level production/distribution networks refers to such structures, which are commonly known as supply chains. These supply chains encompass the various stages that a product passes through before reaching the end customer [21]. A supply chain consists of entities such as customers, retailers, wholesalers/distributors, manufacturers, and suppliers of components/raw materials, all of whom are directly or indirectly involved in meeting customer demand.

Fundamentally, there are three major flows within a supply chain product flow, information flow, and financial flow that move bidirectionally across various stages. Effective supply chain management requires efficient handling of all three flows, considering that the supply chain is a dynamic system composed of a continuous flow of information, materials, and capital [22].

Making coordinated decisions across all levels of the supply chain while considering the needs and characteristics of each stage is of critical importance. This necessity can be understood in light of the bullwhip effect, one of the main factors resulting from misalignment between stages of the supply chain in adopting optimal policies. When each stage of the supply chain operates as a single level system, making decisions independently without coordination with other stages, it causes a chain reaction affecting the entire system.

Such a lack of coordination in decision making especially as it moves upstream from customer facing stages to raw material suppliers intensifies demand fluctuations, leading to the emergence of various types of risks throughout the supply chain. In essence, a small variation in customer demand can trigger large variability in decisions across other stages [58].

To put it more simply, in a multi level system, making improvements at individual stages does not necessarily lead to overall supply chain improvement. Achieving comprehensive development requires the application of models that simultaneously consider the goals and constraints of all levels within the supply chain [22].

In a supply chain, making coordinated decisions while taking into account the requirements and characteristics of various stages is of great importance. This significance can be understood in light of the bullwhip effect, a phenomenon primarily caused by a lack of coordination between different stages of the supply chain in adopting appropriate policies.

When each stage of the supply chain operates as a single level system, making decisions independently and without considering other stages, this leads to reactions and adjustments at other stages. Such misalignment in decision making, as it propagates from customer facing segments to upstream suppliers of raw materials and components, amplifies demand fluctuations, thereby giving rise to multiple types of risks across the supply chain. Even a minor fluctuation in customer demand can trigger significant variability in decisions made at upstream stages [58].

Simply put, in a multi level system, making improvements in individual stages does not necessarily lead to the improvement of the entire chain. Achieving comprehensive development requires the implementation of models that simultaneously consider the objectives and constraints of all levels of the supply chain [22].

Accordingly, organizations within the supply chain are becoming increasingly aware of the need for planning and decision making based on collaboration and coordination, taking into account both the specific characteristics of each stage and the requirements set by the overall supply chain. For example, the Collaborative Planning, Forecasting, and Replenishment (CPFR) model is one of the approaches used in supply chains to improve the planning process.

The necessity of designing a model to estimate the cost function in multi level systems can be explained in light of the points discussed above. As previously mentioned, supply chains have a multi tiered structure, and the emphasis on collaboration and participation in supply chain management is due both to the conflicting interests among different sections and the emergence of the bullwhip effect, which leads to operational and field level risks as a result of lack of coordination across various stages of the chain.

Based on the above discussions, the significance of the present study lies in the development of a framework and the design of a model for managing multi level systems in the context of supply chain sustainability under risk, specifically within food manufacturing companies. The importance of this research can be summarized as follows:

First, in today's competitive environment, companies seek to accelerate their operations and activities. Topics such as globalization and the expansion of networks like the internet significantly impact sourcing, marketing, and other business processes. As supply sources expand and distribution channels multiply, companies alone can no longer produce and distribute all necessary components and products. In such cases, raw materials and parts must be sourced from suppliers, transformed within the company, and then delivered to the customer through distribution channels. This requires the formation of a chain of collaborating companies to jointly produce and deliver products. Hence, the concept of the supply chain emerges. Companies increasingly prefer to be part of a supply chain and compete chain to chain, rather than company to company. A supply chain includes all activities related to the flow and transformation of goods, from the procurement of raw materials to the delivery of the final product to the end consumer [22].

Second, supply chains inherently consist of multi level systems, in which inventory is stored at different stages and is managed and owned by various units. Therefore, using single level models for such systems is inadequate. The unique features of multi level structures require the development and use of specialized models tailored to their characteristics.

Third, if a model is to be developed for managing multi level systems, it must be compatible with the features of such systems. Given that distribution networks vary in structure and configuration, multi level systems within supply chains also possess distinct characteristics that must be considered during model design. (This diversity in features and design is evident in the assumptions made by various researchers in their modeling of multi level systems, as discussed in detail in the literature review section.)

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Considering the above points, the study evaluated and analyzed the sustainability and risks arising from the bullwhip effect within the supply chains of 30 companies, of which 16 were found to have an acceptable level of efficiency.

Based on the mathematical model developed using the Data Envelopment Analysis (DEA) approach, it is recommended that the model be enhanced by incorporating robust optimization techniques to address uncertainty, and that the results be further examined using a fuzzy based model for comparative analysis.

5.1 Managerial Insights

The findings of this study offer critical insights for supply chain managers operating in complex, risk-prone environments. First, the integration of fuzzy Data Envelopment Analysis (DEA) within a multi-stage framework provides a robust decision-support tool for evaluating sustainability performance under uncertainty. Managers are advised to institutionalize continuous sustainability assessment mechanisms that incorporate not only financial and operational metrics but also social and environmental indicators. Second, the identification and classification of risks into strategic, tactical, and operational levels equip decision-makers with a structured lens for prioritizing resource allocation and contingency planning. This reinforces the need for proactive risk mitigation strategies that align with broader sustainability objectives.

Third, the study underscores the managerial value of adopting dynamic capabilities particularly agility, adaptability, and absorptive capacity in strengthening supply chain resilience. By embedding such capabilities into the organizational culture, firms can respond more effectively to disruptions and maintain competitiveness. Finally, the practical implementation of this model requires the collaboration of cross-functional teams across procurement, operations, and sustainability departments. Managers should champion the development of integrated performance dashboards that track sustainability efficiency in real time, thereby enabling informed, strategic decision-making across the supply chain.

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