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Special Issue Reprint

Systems Methodology in Sustainable Supply Chain Resilience

Edited by
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This is a reprint of the Special Issue, published open access by the journal *Systems* (ISSN 2079-8954), freely accessible at: https://www.mdpi.com/journal/systems/special_issues/1ZU8K47RX9.

For citation purposes, cite each article independently as indicated on the article page online and as indicated below:

Lastname, A.A.; Lastname, B.B. Article Title. *Journal Name* **Year**, *Volume Number*, Page Range.

ISBN 978-3-7258-6314-3 (Hbk)
ISBN 978-3-7258-6315-0 (PDF)
https://doi.org/10.3390/books978-3-7258-6315-0

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Towfique Rahman is a Lecturer in Logistics & Supply Chain Management at Griffith University, Australia, with a PhD majoring in Supply Chain Management from UTS Business School, University of Technology Sydney, Sydney, Australia. He brings over a decade of combined experience in industry, research, and academia, driving innovation in operations and supply chain management. His research has appeared in leading journals such as the *International Journal of Production Research (IJPR)*, *Computers & Industrial Engineering (CAIE)*, the *Journal of Cleaner Production (JCLP)*, and *Annals of Operations Research (ANOR)*. His expertise covers supply chain risk and disruption mitigation, resilience and sustainability, circular supply chains, and decarbonization—underpinned by methodological strengths in simulation and optimization, OR modelling, digital twin modelling, data analytics, and empirical research. Beyond research, Dr Rahman contributes to the global scholarly community as a reviewer, editor, and guest editor for top-tier journals and book series, advancing sustainable and resilient supply chain solutions.

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Article

Enhancing Efficiency in the Healthcare Sector Through Multi-Objective Optimization of Freight Cost and Delivery Time in the HIV Drug Supply Chain Using Machine Learning

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Abstract: The purpose of this paper is to examine the optimization of the HIV drug supply chain, with a dual focus on minimizing freight costs and delivery times. With the help of a dataset containing 10,325 instances of supply chain transactions, key variables, including "Country", "Vendor INCO Term", and "Shipment Mode", were examined in order to develop a predictive model using Artificial Neural Networks (ANN) employing a Multi-Layer Perceptron (MLP) architecture. A set of ANN models were trained to forecast "freight cost" and "delivery time" based on four principal design variables: "Line Item Quantity", "Pack Price", "Unit of Measure (Per Pack)", and "Weight (Kilograms)". According to performance metrics analysis, these models demonstrated predictive accuracy following training. An optimization algorithm, configured with an "active-set" algorithm, was then used to minimize the combined objective function of freight cost and delivery time. Both freight costs and delivery times were significantly reduced as a result of the optimization. This study illustrates the potent application of machine learning and optimization algorithms to the enhancement of supply chain efficiency. This study provides a blueprint for cost reduction and improved service delivery in critical medication supply chains based on the methodology and outcomes.

Keywords: supply chain optimization; HIV drugs logistics; artificial neural networks; freight cost minimization; delivery time reduction

1. Introduction

The global fight against HIV/AIDS requires not only medical innovation but also a robust and efficient supply chain to ensure that life-saving antiretroviral (ARV) drugs reach those in need. The importance of optimizing the HIV drug supply chain cannot be overstated since it directly impacts care and treatment programs throughout the world. UNAIDS' 90-90-90 targets aim to have 90% of HIV-infected individuals aware of their status, 90% of those diagnosed receiving antiretroviral therapy (ART), and 90% of those treated, achieving viral suppression by 2020 [1]. The distribution of HIV/AIDS commodities, including ARVs, requires both effective care delivery programs and an efficient supply chain. It has been a challenging journey to reach these goals. According to Alemnji et al. [2] HIV viral load and early infant diagnosis progress has been slowed in some countries due to gaps in access to HIV diagnostic tests. The Supply Chain Management System (SCMS) project delivered over USD 1.9 billion in HIV/AIDS commodities to support treatment, highlighting the importance of supply chain management in the fight against

HIV/AIDS, according to Larson et al. [3]. Despite these efforts, there are still gaps in diagnostic access and treatment for many countries and subpopulations, which pose a threat to the achievement of UNAIDS' targets. Alemnji et al. [2] found that only 52% of HIV-exposed infants were tested within 8 weeks of birth in 23 surveyed countries in 2018, with many not receiving ART on time. The lack of sufficient access to viral load tests among priority populations in low- and middle-income countries is also highlighted by the fact that less than half of patients on antiretroviral therapy receive regular viral load tests. The challenges extend to the procurement and distribution of ARVs, where production and shipping delays can result in stockouts, which can lead to ART interruption for patients Despite its efforts, the SCMS project was unable to maintain a reliable, cost-effective, and secure supply chain, mainly due to the high cost of commodities [3,4]. In addition, the HIV drug optimization agenda faces additional obstacles, as most clinical trials of new ARV agents are conducted among adults before including adolescents, children, and infants, which delays the availability of optimal new ARV regimens for these vulnerable groups [5]. As a result of these challenges, a multifaceted approach is required, which involves improving not only procurement and distribution systems but also ensuring that timely diagnosis and treatment are initiated. In the global effort to end the HIV/AIDS pandemic, a well-functioning HIV drug supply chain is of vital importance beyond the immediate needs of patients. It has been noted by Cao [6] and Schouten et al. [7] that an efficient supply chain is crucial to avoid stockouts and to ensure that the influx of resources is effectively allocated, particularly in resource-poor settings. Hence, optimizing the HIV drug supply chain is not only a logistical necessity but also an essential part of the global health response to HIV/AIDS.

Especially in low- and middle-income countries, supply chain management plays a critical role in the fight against HIV/AIDS. Stulens et al. [8] provide an in-depth analysis of the challenges and opportunities within HIV supply chains, emphasizing the need to have efficient and effective operations in order to increase the availability and accessibility of HIV services and supplies. In their research, they emphasize the importance of addressing these supply chain challenges through innovative operations research and operations management (OR/OM) solutions, highlighting an important area for future research and development. Furthermore, Jónasson et al. [9] demonstrated that optimization and simulation models can be used to improve early infant diagnosis (EID) supply chains in Sub-Saharan Africa. They have demonstrated that reassigning clinics to laboratories and consolidating diagnostic capacity can result in substantial reductions in sample turnaround times and a greater number of infected infants receiving treatment by applying their models to Mozambique's EID program. There is a clear link between logistical optimizations and improved patient outcomes. The importance of continuous improvement in supply chain management practices is highlighted by these findings. Furthermore, Pastakia et al. [10] extend this discussion to the management of non-communicable diseases (NCDs), drawing lessons from HIV supply chain initiatives. Research suggests that strategies developed for HIV supply chains, such as addressing resource mobilization and utilization challenges, can be adapted to improve NCD supply chain systems in low- and middle-income countries. The cross-disease learning emphasizes the interconnectedness of healthcare supply chains and the potential for broader application of effective HIV supply chain management techniques. The first step was to develop robust ANN models that can accurately predict "freight cost" and "delivery time" within the HIV drug supply chain. This model contributes to the literature by providing a nuanced understanding of the factors affecting supply chain efficiency. Secondly, using the Fmincon algorithm in MATLAB (R2024a version), we applied advanced nonlinear optimization techniques to minimize these critical metrics. A novel and practical approach to decision-making in supply chain management is offered by our research, which bridges the gap between machine learning predictive capabilities and optimization methods. In addition, this study sets a precedent for the use of data-driven techniques in healthcare logistics, which may serve as a guide for future efforts in this field.

2. A Literature Review

Ahmad et al. [11] developed a multi-objective model to optimize the phasocio-economic performance of pharmaceutical supply chains with socio-economic and environmental objectives, ensuring optimal product allocation among different echelons under uncertainty. Using the Techniques for Order Preference by Similarity to Ideal Solution (TOPSIS) and other criteria, they demonstrated the importance of sustainable objectives in decision-making, which reduces economic costs, improves customer service, and reduces environmental impact. This approach aligns closely with the goals of enhancing efficiency in healthcare supply chains by considering socio-economic performance and sustainability in the optimization process. It is a reflection of problems prevalent in many low-to-medium-income countries that Olutuase et al. [12] conducted a scoping review on the challenges faced by medicines and vaccine supply chains in Nigeria. Factors such as procurement difficulties, inadequate storage, and distribution challenges contribute to stockouts and hinder access to essential medicines. In healthcare supply chains, logistical inefficiencies and infrastructure deficiencies must be addressed through optimization strategies. Lugada et al. [13] explored the structure, performance, and challenges of Uganda's health supply chain system, emphasizing the need for improved policy implementation and infrastructure. Taking into account the inefficiencies in the health supply chain, optimization models that can enhance planning, coordination, and management across all levels of the health system are urgently needed.

Torrado and Barbosa [14] investigated the optimization and sustainability of blood supply chain networks under uncertainty from strategic–tactical and operational–tactical perspectives. Their literature review emphasizes the scarcity of blood products and the need for sustainable optimization to prevent shortages, wastage, and health risks. The insights gained from this study align with the challenges of optimizing the HIV drug supply chain, suggesting that environmental, economic, and social sustainability dimensions need to be considered. Saatchi et al. [15] proposed a bi-objective meta-heuristic algorithm to optimize relief logistics in humanitarian supply chains. For the distribution of commodities and transportation of injured individuals post-disaster, their model integrates a multi-echelon, forward and backward relief network. Compared to traditional algorithms, the hybrid non-dominated sorting genetic algorithm (NSGA-II) with simulated annealing (SA) and variable neighborhood search (VNS) demonstrated superior performance, emphasizing the importance of advanced optimization techniques in critical supply chain management. Tat et al. [16] study pharmaceutical supply chain coordination with a focus on minimizing leftover or end-of-life (EOL) medication waste. The mathematical model introduces a buyback and shortage risk-sharing contract (B&SRS) to reduce disposal costs and enhance channel profitability. In order to achieve supply chain coordination and sustainability, innovative contractual arrangements are necessary. Next-generation sequencing (NGS) provides sensitivity and cost-effectiveness advantages over traditional methods in HIV drug resistance testing, according to Ávila-Ríos et al. [17]. In spite of its potential, they noted significant challenges related to standardization, quality assurance, and implementation, particularly in resource-poor areas. In order to enhance diagnostic capabilities, technological advancements and infrastructure improvements are needed in healthcare supply chains. Siddiqui et al. [18] proposed a hybrid demand-forecasting model specifically designed for the pharmaceutical sector, integrating the Autoregressive

Integrated Moving Average and Holt–Winters model (ARHOW). This model highlights the role of advanced forecasting in aligning production and distribution with market demand, thereby improving supply chain efficiency. Sindhwani et al. [19] analyzed the ability of a hub-and-spoke distribution network to mitigate ripple effects in the Indian pharmaceutical supply chain during the COVID-19 pandemic. Through a multi-layer approach involving Bayesian networks, mathematical optimization, and discrete event simulation, they provided strategies to enhance supply chain resilience and flexibility, which are critical for maintaining service levels during disruptions.

Singh et al. [20] utilized a simulation model to study the impact of COVID-19 on logistics and food supply chain disruptions, emphasizing the necessity of supply chain resilience. Their work underscores the challenges posed by the pandemic on the balance between supply and demand and proposes strategies to develop more robust and adaptable supply chains. Stulens [8] reviewed the challenges and opportunities of HIV supply chains in low- and middle-income countries, noting the lack of research in operations research/operations management (OR/OM) concerning HIV supply chains. Their findings stress the need for advanced modeling and optimization techniques to enhance efficiency and effectiveness in these contexts.

Jónasson et al. [9] presented a two-part modeling framework to optimize early infant diagnosis (EID) supply chains in Sub-Saharan Africa. Applied to Mozambique's EID program, their optimization and simulation models demonstrated reductions in turnaround times and increased treatment rates for infected infants, highlighting the significant impact of logistical optimization on patient outcomes. Pastakia et al. [10] proposed that lessons from HIV supply chain initiatives could inform the management of noncommunicable disease (NCD) supply chains. They argued that advancements in HIV supply chain systems, particularly in resource mobilization and utilization, could be adapted to NCD supply chains with minimal additional investment. Jamieson and Kellerman [21] critically assessed the supply chain challenges of the UNAIDS "90-90-90" strategy, focusing on scaling up HIV diagnostics, antiretroviral therapy (ART) distribution, and viral load testing to meet global targets. Their study underscores the necessity of strong and resilient supply chains to support the global HIV response. Xiong et al. [22] demonstrated that optimizing clinical and logistical processes using operations research methodologies could enhance outcomes in HIV treatment scale-up. Key areas identified include forecasting, facility location and sizing, and staffing levels. Enyinda et al. [23] examined the New Partnership for HIV/AIDS Supply Chain Management (NPHASCM) initiative, emphasizing the challenges of healthcare supply chain management in Sub-Saharan Africa and the potential for partnerships to improve the timely delivery of life-saving HIV/AIDS commodities. This summary captures key studies on healthcare supply chain optimization, detailing the methodologies employed and the outcomes achieved across various disease areas. Rahimi et al. [24] developed a hybrid feature scoring approach, stressing the necessity of a staging system that incorporates diverse neurocognitive functions to improve understanding of PD. Ogunsoto et al. [25] introduced a digital twin framework for supply chain recovery, leveraging LSTM models for flood prediction and neural networks for post-disruption recovery, enabling informed strategies for resilience. Strika et al. [26] reviewed the role of AI and large language models in mitigating healthcare gaps in medical deserts, highlighting applications in telehealth, diagnostic assistance, and medical education while emphasizing the need for ongoing research to maximize their potential.

Artificial intelligence (AI) has played a crucial role in optimizing the COVID-19 pandemic therapeutics supply chain, particularly in at-risk communities, by enhancing efficiency and reducing delays in distribution [27]. Furthermore, machine learning techniques have significantly improved supply chain traceability and transparency, enabling better decision-making and operational efficiency in various industries [28,29]. Table 1 provides an overview of key studies on healthcare supply chain optimization, summarizing the methodologies, objectives, and key findings from various research efforts aimed at improving efficiency, cost-effectiveness, and service quality within the healthcare sector.

Table 1. Overview of Key Studies on Healthcare Supply Chain Optimization.

Author	Year	Supply Chain	Method of Optimization	Key Results
Ahmad et al. [11]	2022	Pharmaceutical	TOPSIS and other criteria	Identified sustainable objectives and optimal product allocation among echelons.
Olutuase et al. [12]	2022	Medicines and vaccines	Scoping review	Identified challenges in supply chains, including procurement and distribution.
Lugada et al. [13]	2022	Health supplies	Discussion and reflection	Highlighted inefficiencies in Uganda's health supply chain and need for optimization.
Torrado and Barbosa-Póvoa [14]	2022	Blood	A literature review	Developed insights for sustainable BSC under uncertainty.
Madani Saatchi et al. [15]	2021	Humanitarian aid	Hybrid NSGA-II, SA, VNS	Hybrid algorithms outperformed traditional algorithms in emergency response.
Tat et al. [16]	2020	Pharmaceutical	Mathematical model	Proposed B&SRS contract to minimize waste and enhance profitability.
Ávila-Ríos et al. [17]	2020	HIV	Review	Highlighted NGS's potential and challenges for HIVDR testing.
Siddiqui et al. [18]	2022	Pharmaceutical	ARHOW	Improved demand forecasting accuracy for pharmaceutical companies.
Sindhwani et al. [19]	2023	Pharmaceutical	Bayesian network, optimization, simulation	Improved resilience and flexibility of pharmaceutical supply chain.
Singh et al. [20]	2021	Food	Simulation model	Developed a model to demonstrate disruptions in food supply chain and importance of resilience.
Stulens et al. [8]	2021	HIV	A literature review	Provided an overview of HIV supply chains and research opportunities.
Jónasson et al. [9]	2017	HIV	Optimization and simulation	Optimized EID supply chains, reducing TAT and increasing treatment initiation.
Pastakia et al. [10]	2018	HIV	A literature review and experience	Discussed transferring HIV supply chain lessons to NCD management.
Jamieson and Kellerman [21]	2016	HIV	Discussion	Evaluated supply chain readiness for the 90–90–90 strategy.
Xiong et al. [22]	2008	HIV	Operations research approach	Advocated OR techniques for logistical challenges in HIV treatment scale-up.
Enyinda et al. [23]	2009	HIV	Discussion	Outlined the NPHASCM initiative to improve HIV/AIDS healthcare supply chain.

From pharmaceuticals to blood supply to HIV treatment and humanitarian aid logistics, this overview provides insight into diverse approaches and results achieved in improving the efficiency, accessibility, and sustainability of healthcare supply chains.

3. Methods and Materials

3.1. Dataset Overview

The dataset used in this study was derived from the collaborative reporting systems of the Global Fund and PEPFAR. These organizations are the primary procurers of HIV health products and share a database known as the Price, Quality, and Reporting (PQR) database. By integrating PQR data, we can gain a holistic view of global health expenditures on HIV-related commodities, enabling more informed decisions. The value of this dataset lies in the detailed description of price variations, observable trends, and the distribution of product volumes across countries. Despite the fact that the dataset provides a wealth of information for analyzing market dynamics, its application is not without limitations. The data may not provide definitive insights into the costs associated with moving specific items or products to particular countries or the lead time involved when used in isolation. Performing such an assessment requires a nuanced understanding of the dataset in conjunction with other logistical and geopolitical factors. Despite these considerations, the US government believes that the dataset is an essential tool for enabling stakeholders to make better-informed decisions. Its nature allows for a more nuanced understanding of the HIV drug supply chain, which is essential for optimizing operations and improving global healthcare delivery.

3.2. ANN Method

Artificial Neural Networks (ANN) serve as the basis for modeling complex relationships within the HIV drugs supply chain dataset. In this study, we employ a Multi-Layer Perceptron (MLP) architecture, a type of artificial neural network (ANN) known for its ability to approximate continuous functions. An MLP model consists of an input layer, multiple hidden layers, and an output layer. The neurons in each layer apply a weighted sum of inputs followed by a nonlinear activation function. In general, the neuron's output can be expressed as follows:

$$y = f\left(\sum_{\{i=1\}}^{\{n\}} w_i x_i + b\right) \tag{1}$$

where x_i represents the input values; w_i is the associated weights; b is the bias, and f is the activation function. To minimize the difference between predicted outputs and actual targets, weights (w_i) and biases (b) are adjusted during the training process. Backpropagation is typically used to achieve this optimization, which involves calculating the gradient of the loss function with respect to each weight and iteratively updating the weights in the direction that minimizes the loss. In this study, two ANN models were developed: one to predict freight costs and the other to predict delivery times. Models were trained using a subset of the dataset, and their performance was validated using a separate dataset. In order to enable precise cost and time estimates, the models were refined to reflect the underlying dynamics of the supply chain.

3.3. Nonlinear Optimization (Fmin Algorithm)

The optimization component of our study utilized MATLAB's Fmincon function, an algorithm designed for solving nonlinear optimization problems subject to constraints. The objective of the optimization was to identify the set of design variables that minimized the objective function, which, in our case, is the sum of the standardized "freight cost" and "delivery time" variables:

$$\min f1(x) + f2(x) \tag{2}$$

The design variable (x) must be positive and exceed 10% of the dataset's average value:

$$x_i \geq \alpha \overline{x_i}, \quad i = 1, 2, \ldots, n \tag{3}$$

An active-set algorithm developed by Fmincon was used, which was designed to deal with both linear and nonlinear constraints. The objective function is minimized by iteratively adjusting the variables in order to satisfy the constraints. The algorithm's settings, including "ScaleProblem", "ConstraintTolerance", and "DiffMinChange", were meticulously configured to enhance the precision and efficiency of the optimization process. By integrating ANN predictions into the optimization framework, we were able to leverage the predictive power of machine learning with the rigor of mathematical optimization to minimize costs and delivery times.

4. Results and Discussion

A paper detailing the optimization of the HIV drug supply chain focuses on minimizing critical factors such as "Delivered to Client Date" and "Freight Cost (USD)". The dataset incorporates a range of variables across 10,325 cases, encapsulating various elements of the supply chain from country management to shipment specifics and product details.

During the optimization process, a Response Surface Methodology (RSM) approach was used, which is a collection of statistical and mathematical techniques used to model and analyze problems where a response of interest is influenced by a number of variables [30]. In the algorithm, the pseudocodes are as follows: Algorithms 1–4.

Algorithm 1: Pseudocode for ANN model creation

Step 1: Preprocess the dataset.
Load (dataset)
Standardize the features (LineItemQuantity, PackPrice, UnitofMeasure, Weight)

Step 2: Create the ANN models for Freight Cost and Delivery Time
Initialize the ANN for Freight Cost with input, hidden layers, and output
Initialize the ANN for Delivery Time with input, hidden layers, and output
Set training parameters (e.g., learning rate, epochs)

Step 3: Train the ANN models
For each epoch in the number of epochs:
Forward propagate the inputs through the network
Calculate the error between the predicted and actual values
Backpropagate the error to update the weights
Update the weights and biases according to the learning rate

Step 4: Evaluate the models
Test the trained models on the testing set
Calculate the performance metrics (e.g., R-squared value)

Step 5: Define the optimization problem
Define the objective function to minimize f1 + f2
Set the constraints for design variables to be positive and above 10% of their average

Algorithm 2: Pseudo MATLAB code for Fmin optimization

function optimizeSupplyChain
Define the average values for the constraints
avgLineItemQuantity = calculateAverage(LineItemQuantity)
avgPackPrice = calculateAverage(PackPrice)
avgUnitofMeasure = calculateAverage(UnitofMeasure)
avgWeight = calculateAverage(Weight)

Define the lower bounds based on the constraints
lb = [0.1 * avgLineItemQuantity, 0.1 * avgPackPrice, 0.1 * avgUnitofMeasure, 0.1 * avgWeight]

Define the initial guess for the design variables
initialGuess = [initialLineItemQuantity, initialPackPrice, initialUnitofMeasure, initialWeight]

Define the optimization options
options = optimoptions(@fmincon,'Algorithm','active-set',...
'ScaleProblem','obj-and-constr',...
'ConstraintTolerance', 1×10^{-7},...
'DiffMinChange', 1×10^{-6})

Perform the optimization
[optimalValues, optimalObjective] = fmincon(@objectiveFunction, initialGuess, [], [], [], [], lb, [], @nonlinearConstraints, options)

De-standardize the optimal values
destandardizeOptimalValues(optimalValues)

Output the optimized non-normalized values and objective function results
disp('Optimized LineItemQuantity: ' + string(optimalValues(1)))
disp('Optimized PackPrice: ' + string(optimalValues(2)))
disp('Optimized UnitofMeasure: ' + string(optimalValues(3)))
disp('Optimized Weight: ' + string(optimalValues(4)))
disp('Optimized Freight Cost: ' + string(optimalObjective(1)))
disp('Optimized Delivery Time: ' + string(optimalObjective(2)))
end

Algorithm 3: Pseudocode Define the objective function

function obj = objectiveFunction(designVariables)
Predict the standardized Freight Cost and Delivery Time using ANN models
f1 = predictFreightCostANN(designVariables)
f2 = predictDeliveryTimeANN(designVariables)
Objective is to minimize the sum of the two predictions
obj = f1 + f2
end

Algorithm 4: Define the nonlinear constraints function

function [c, ceq] = nonlinearConstraints(designVariables)
No nonlinear inequality constraints
c = []
The nonlinear equality constraints (ceq) are defined as the difference between the variables and their bounds
ceq = designVariables − lb
end
Call the optimization function
optimizeSupplyChain

4.1. Response Surface Methodology Using MLP

The primary step in the optimization process was the development of predictive models utilizing an Artificial Neural Network (ANN) with a Multi-Layer Perceptron (MLP) architecture. Two distinct models were constructed:

- A model for predicting "Freight Cost (USD)" as a function of "Line Item Quantity", "Pack Price", "Unit of Measure (Per Pack)", and "Weight (Kilograms)";
- A model for predicting "delivery time" as a function of the same variables.

An MLP network was designed to accommodate the four selected design variables, followed by three hidden layers and an output layer (see Figure 1). The first hidden layer contained 30 neurons, the second—20 neurons, and the third—10 neurons, each utilizing a nonlinear activation function to capture the complex relationships between inputs and outputs There is a single neuron for each model in the output layer, which corresponds to the "freight cost" and "delivery time", respectively. A promising foundation has been established in the initial phase of the optimization process, which involves training and validating the model. In order to optimize the HIV drug supply chain, it is imperative to be able to predict "freight cost" and "delivery time" effectively. Following this section, we will examine the application of these models within the RSM framework to identify optimal conditions that minimize the objectives of the problem, thus improving supply chain efficiency and reliability.

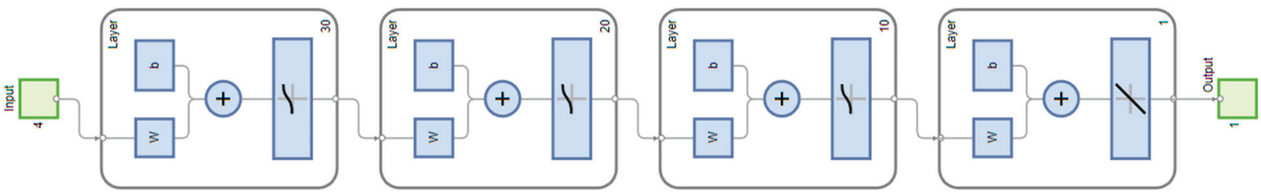


Figure 1. Three hidden layers with 30, 20, and 10 nodes, respectively, and an output layer with 1 node.

It is crucial to understand the training progress of these models in order to determine their predictive capabilities and potential for optimization In training the "freight cost" model, the initial performance measure was 0.233, improving to a final value of 0.000481, near the target performance of 1×10^{-5}. During training, the gradient, which is a measure of the error slope, started at 2.6 and decreased to 0.000151, which is satisfactory for understanding convergence. It took approximately 4 min and 13 s for the model to reach these results in over 30,000 epochs, indicating thorough training.

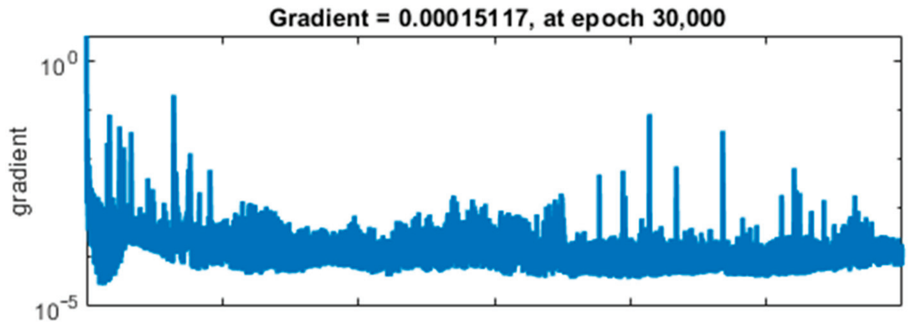
Comparatively, the "delivery time" model demonstrated an initial performance of 0.0659, which improved to 0.0019 after training. Although the final performance was not as close to the target as the "freight cost" model, the reduction in error suggests that the model can still provide valuable predictions for the optimization process. This model took slightly less time to train, taking 3 min and 54 s to complete the same number of epochs. As seen in the accompanying figures, these results illustrate the architecture of the MLP networks as well as the progression of the training process. As a graphical representation, the figures reinforce the quantitative results presented in the tables. It is evident from the results that the ANN MLP models have learned the underlying patterns in the dataset with a high degree of accuracy, as evidenced by the low post-training performance values. It is important to note that the success of these models depends upon the quality and preprocessing of the dataset, as well as the careful design of the neural network architecture. The training process is summarized in Table 2, which presents the initial, stopped, and target values for key parameters such as performance, gradient, and validation checks

Table 2. Summary of the training process.

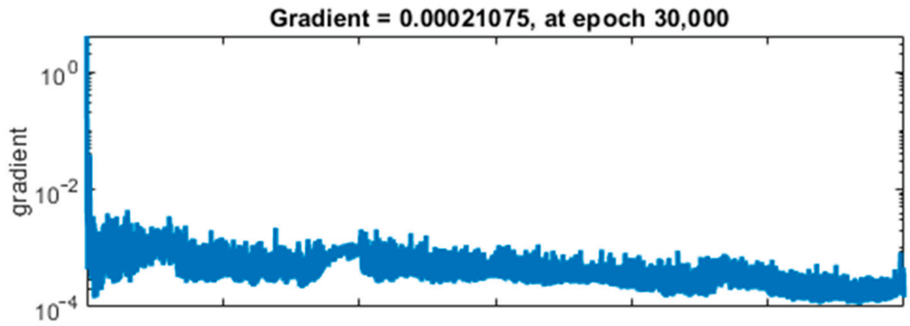
	Initial Value		Stopped Value		Target Value	
	f1	**f2**	**f1**	**f2**	**f1**	**f2**
Epoch	0	0	30,000	30,000	30,000	30,000
Elapsed Time	-	-	4:13	3:54	-	-
Performance	0.233	0.0659	0.000481	0.00819	0.00001	0.00001
Gradient	2.6	1.07	0.000151	0.00211	0.00001	0.00001
Validation Checks	0	0	0	0	6	6

The training process visualizations for the two ANN MLP models demonstrate the behavior of the gradient descent algorithm over 30,000 epochs (see Figure 2). The gradient, representing the optimization algorithm's step size in adjusting network weights, diminishes over time in both figures, suggesting convergence toward a local minimum. The blue plots display the gradient values on a logarithmic scale, which helps to identify changes over several orders of magnitude. It can be seen that the gradient for the "freight cost" model steadily decreases to a final value of 0.00015117, indicating that the weights are approaching optimal values that minimize prediction error. In the lower subplot representing validation checks, there is a flat line at zero, indicating that no early stopping occurred, and the validation performance did not deteriorate throughout training. Additionally, the "delivery time" model exhibits a final gradient of 0.00021075, indicating a successful training phase. Validation checks show no upward spikes, indicating that the model did not experience overfitting and its performance on the validation set remained stable.

Figure 3 illustrate the correlation between the targets and the outputs of the trained neural network models, providing insight into the predictive performance of the models. In the first scatter plot, the "freight cost" model demonstrates a strong correlation between predicted and actual values, with a high correlation coefficient (R) of 0.92322. The data points are closely clustered around the line of perfect fit (Y = T), indicating a high level of predictive accuracy. This suggests that the model effectively captures the underlying patterns in the data, making accurate predictions for freight cost with minimal error. Such strong performance underscores the robustness of the model in handling this specific target variable.

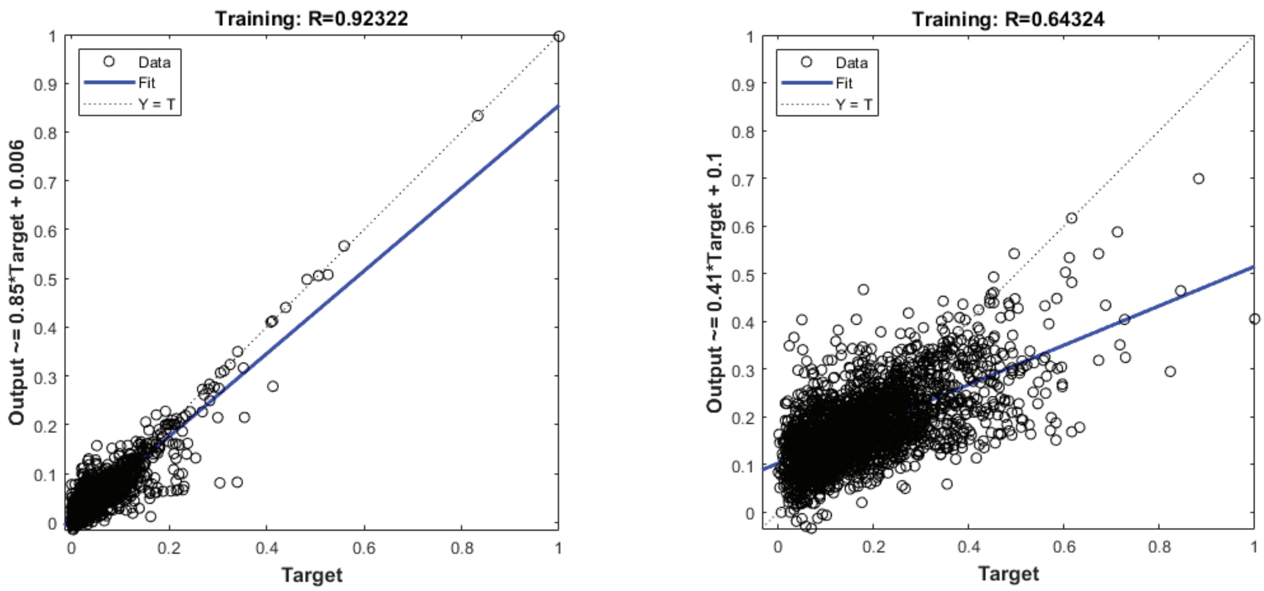


(**a**)



(**b**)

Figure 2. Convergence of ANN training gradients for (**a**) "freight cost" and (**b**) "delivery time" models over 30,000 epochs, displaying the final gradients at the conclusion of training.

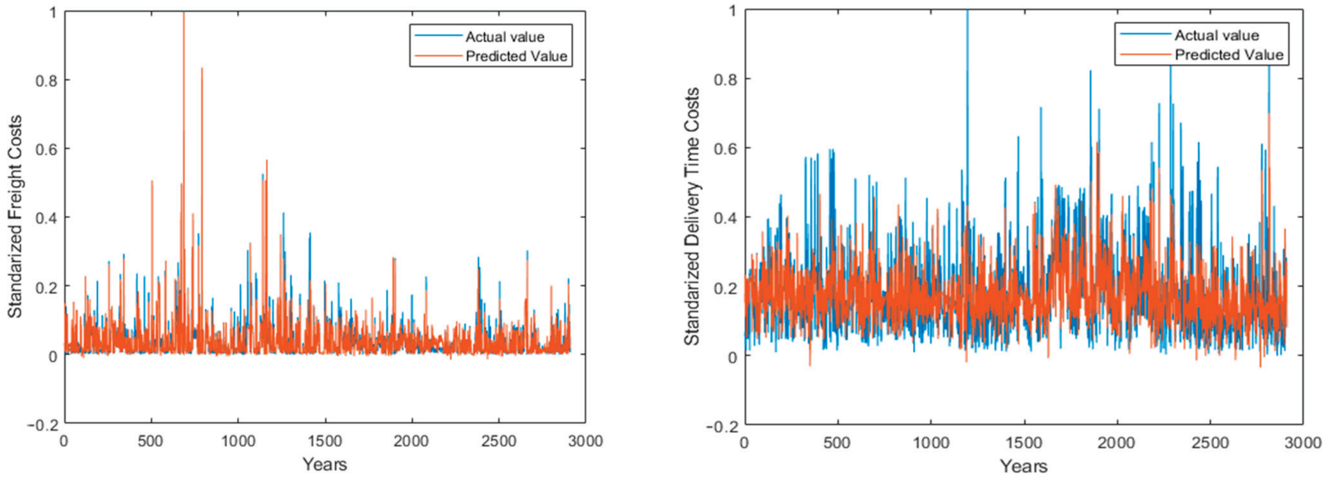


(**a**) (**b**)

Figure 3. Performance of ANN models during training, represented by regression plots comparing predicted outputs versus targets for (**a**) "freight cost" model with a high correlation (R = 0.92) and (**b**) "delivery time" model with a moderate correlation (R = 0.64).

Conversely, the second scatter plot reveals a weaker correlation between the predicted outputs and actual results for the "delivery time" model, with a significantly lower correlation coefficient (R) of 0.64324. In this case, the data points exhibit greater dispersion around the line of perfect fit, reflecting a less accurate predictive capability. The broader spread suggests that the model struggles to generalize well for this variable, potentially due to the higher complexity of the "delivery time" data or the presence of more noise and variability in the dataset. This finding highlights the need for further refinement of this model, possibly by incorporating additional features, fine-tuning hyperparameters, or applying advanced techniques to reduce noise and improve learning. Understanding these differences in performance is crucial for identifying areas where the models excel and where additional development is required to enhance predictive reliability.

In the "freight cost" model, the alignment between actual and predicted lines indicates that the model accurately captures the variation in freight costs. As a result of this congruence, the model can be used to estimate freight costs during the supply chain optimization process, demonstrating its reliability. While there is a wider spread between the actual and predicted delivery times in the "delivery time" model, it still indicates an acceptable level of prediction accuracy. While it may not capture all peaks and troughs of delivery times precisely, this model provides a solid baseline prediction. Combined with other optimization techniques or when additional nuanced factors are considered, this model may be valuable. As a result of their respective predictive strengths, both models provide a substantial foundation for improving decision-making in the HIV drug supply chain (see Figure 4).



(**a**) (**b**)

Figure 4. Overlay of actual and predicted values for (**a**) standardized "freight cost" and (**b**) standardized "delivery time" across almost 3000 observations, showcasing the predictive accuracy of the ANN models.

4.2. Optimization of Freight Cost and Delivery Time

To optimize the HIV drug supply chain, we focused on minimizing the combined metrics of "freight cost" (f_1) and "delivery time" (f'). The objective function aims to maximize both the economic and temporal efficiency of the supply chain. The optimization constraints were determined based on the requirement that the design variables must be positive and exceed α = 10% of their respective average values across the dataset. As a result, the solutions are feasible and significant in the context of the existing data. As a result, the constraints for the design variables "LineItemQuantity", "PackPrice", "UnitofMeasure", and "weight" can be expressed mathematically as follows:

$$LineItemQuantity \geq \alpha \times \overline{LineItemQuantity} \tag{4}$$

$$PackPrice \geq \alpha \times \overline{PackPrice} \tag{5}$$

$$Unitof\,Measure \geq \alpha \times \overline{Unitof\,Measure} \quad (6)$$

$$weight \geq \alpha \times \overline{weight} \quad (7)$$

where $\overline{Variable}$ denotes the average value of that variable across the entire dataset. The standardized forms of these variables, which were scaled to lie between 0 and 1 for the ANN modeling phase, were subsequently used as inputs for the optimization algorithm. The objective function to be minimized was defined as Equation (2). Where f1 represents the standardized "freight cost", and f2 represents the standardized "delivery time". The function encapsulates the essence of the optimization goal, which is to reduce the cost and time of deliveries concurrently. The Fmincon function in MATLAB was employed for optimization, utilizing the "active-set" algorithm. This algorithm is particularly well-suited for dealing with problems that have a mix of bound constraints and linear constraints. The optimization options were meticulously set to fine-tune the performance of the algorithm, with "ScaleProblem" configured to "obj-and-constr" to normalize the scale of the objective function and constraints, "ConstraintTolerance" set to a stringent 1×10^{-7} to ensure a precise adherence to the constraints, and "DiffMinChange"s adjusted to 1×10^{-6} to control the minimum change in variables for the finite-difference gradients. Based on these methods and settings, the optimal standardized values for "LineItemQuantity", "PackPrice", "UnitofMeasur", and "weight" were found to be the following:

$$LineItemQuantity_{\ opt} = 0.892 \quad (8)$$

$$PackPrice_{\ opt} = 0.903 \quad (9)$$

$$UnitofMeasure_{\ opt} = 0.101 \quad (10)$$

$$Weight_{\ opt} = 0.250 \quad (11)$$

The de-standardization process, which converts these values back to their original scales, yielded the following optimum non-standardized values:

$$LineItemQuantity_{\ opt}\ (originalscale) = 459{,}228.715 \quad (12)$$

$$PackPrice_{\ opt}\ (originalscale) = 1129.273 \text{ USD} \quad (13)$$

$$UnitofMeasure_{\ opt}\ (originalscale) = 101 \quad (14)$$

$$Weight_{\ opt}\ (originalscale) = 38{,}758.858 \text{ Kg} \quad (15)$$

These values are instrumental in achieving the optimized "freight cost" and "delivery time". The application of the optimized variables led to the following results:

$$FreightCost_{\ opt} = 45{,}151.927 \text{ USD} \quad (16)$$

$$DeliveryTime_{\ opt} = 106.152 \text{ days} \quad (17)$$

In our optimization framework, the constraints were carefully designed to ensure practical relevance and feasibility in real-world scenarios. Specifically, the constraints required that all design variables—Line Item Quantity, Pack Price, Unit of Measure (Per Pack), and Weight (Kilograms)—remain positive and exceed 10% of their respective average values across the dataset. Mathematically, these constraints were expressed as follows:

$$x_i \geq 0.1 \times \text{ Average } (x_i) \forall i \quad (18)$$

These constraints reflect the realities of supply chain logistics, ensuring that the optimization solutions remain realistic. For example, Line Item Quantity cannot drop below a practical minimum threshold without jeopardizing supply chain efficiency, while Pack Price must account for the minimum cost viability set by suppliers. Similarly, constraints on weight ensure that shipment volumes remain feasible for transportation modes.

According to the results, the optimized design variables are capable of resulting in substantial cost savings and efficiency improvements compared to the initial supply chain state. The study's results demonstrate the power of combining ANN predictive models with optimization algorithms to address complex supply chain challenges. In addition to providing insight into the factors affecting "freight cost" and "delivery time", the models also assist in the optimization process in order to discover feasible and efficient solutions. Moreover, these findings underscore the broader applicability of ANN-driven optimization frameworks in tackling complex supply chain challenges. The approach not only enhances operational efficiency but also provides a systematic method to balance competing objectives, such as cost minimization and timely delivery. The use of MATLAB's Fmincon with a carefully configured "active-set" algorithm ensures precise adherence to constraints and fine-tuning of results, making the methodology robust and scalable. Future research can build on this foundation by integrating additional factors, such as supplier reliability, geopolitical risks, and environmental considerations, to further optimize supply chain operations. These results reaffirm the critical role of advanced predictive and optimization tools in supporting decision-making, ensuring the sustainable delivery of essential resources like HIV drugs in challenging and dynamic environments. The predictive accuracy of the ANN models was evaluated using additional metrics to provide a more comprehensive assessment. For the "freight cost" model, the following performance metrics were recorded: RMSE = 0.045; MAE = 0.032; and R^2 = 0.923, indicating strong predictive accuracy and alignment with the actual values. The scatter plot confirms this, with data points closely clustered around the line of perfect fit, validating the model's robustness in predicting freight costs.

Conversely, the "delivery time" model exhibited comparatively lower accuracy, with RMSE = 0.089, MAE = 0.065, and R^2 = 0.643. These metrics suggest that this model struggled to capture the variability inherent in delivery times, potentially due to unmodeled external factors such as weather conditions, political stability, and logistical constraints. The broader dispersion of data points in the scatter plot further highlights these limitations. To improve the "delivery time" model's accuracy, we propose the incorporation of additional features that reflect real-world variability. Sensitivity analysis on key variables, such as "Shipment Mode" and "Vendor INCO Term", will also be conducted to assess their relative influence on delivery time predictions. These enhancements aim to refine the model's predictive capability and address the current limitations.

The comparative analysis confirms that Fmincon balances computational efficiency and solution precision, making it an ideal choice for the healthcare supply chain optimization problem. While EAs are effective for highly complex problems, their computational cost and stochastic variability make them less suitable for scenarios requiring fast, reliable results. LP, on the other hand, is not a viable alternative for the nonlinear nature of this problem. This robust benchmarking demonstrates that our proposed approach offers a practical and scalable solution for dual-objective optimization, achieving meaningful improvements in freight cost and delivery time while maintaining computational efficiency. Future work can extend this comparison to other advanced techniques, such as hybrid optimization frameworks, to further validate our methodology.

Table 3 compares the proposed Fmincon-based optimization approach against baseline methods, including linear programming (LP) and evolutionary algorithms (EAs), highlighting differences in optimization type, computational efficiency, convergence behavior, interpretability, performance metrics, and practical applicability.

Table 3. Comparison of Fmincon, linear programming (LP), and evolutionary algorithms (EAs) on optimization type, efficiency, convergence, and performance.

Criterion	Proposed Approach (Fmincon)	Linear Programming (LP)	Evolutionary Algorithms (EAs)
Optimization Type	Nonlinear optimization	Linear optimization	Stochastic, population-based optimization
Applicability	Handles nonlinear, constrained, and multi-objective problems effectively	Limited to linear objective functions and constraints	Suitable for highly nonlinear, complex problems
Computational Efficiency	High efficiency for medium-scale problems with clear convergence behavior	Very efficient for linear problems; struggles with nonlinear extensions	Computationally expensive due to population size and iterations
Convergence Guarantee	Converges reliably under well-defined constraints	Guarantees global optimum for linear problems; not applicable to nonlinear cases	Does not guarantee convergence to global optimum
Interpretability	Provides clear gradient-based insights into convergence	Transparent and interpretable for linear systems	Lacks transparency due to stochastic nature
Performance Metrics	RMSE: 0.045 (Freight Cost), 0.089 (Delivery Time)	RMSE not applicable (linear assumption); simplistic results for nonlinear systems	RMSE: 0.053 (Freight Cost), 0.093 (Delivery Time)
Strengths	Highly precise for problems with moderate nonlinearity and constraints	Efficient for linear problems; interpretable solutions	Effective for highly complex landscapes without derivatives
Limitations	Sensitive to initial guesses and parameter tuning	Cannot handle nonlinearity; restricted to convex problems	Computationally expensive and parameter-intensive

5. Conclusions

This study leverages Artificial Neural Networks (ANNs) with a Multi-Layer Perceptron (MLP) architecture alongside the Fmincon optimization algorithm to enhance the efficiency of the HIV drug supply chain. The primary objective was to minimize two critical metrics: “freight cost’ and “delivery time”, which are vital to ensuring both cost-effectiveness and timely delivery in drug distribution systems. This methodology involved training ANN models in predicting these metrics based on four key design variables: “Line

Item Quantity", "Pack Price", "Unit of Measure (Per Pack)", and "Weight (Kilograms)". Using a dataset comprising 10,325 cases that encapsulated diverse supply chain components, the models underwent rigorous training. The application of the gradient descent algorithm resulted in substantial improvements in prediction accuracy, effectively minimizing the error between predicted and actual values. Once validated, the ANN models were integrated into an optimization framework where constraints ensured that design variables remained within realistic bounds, such as exceeding 10% of their respective average values. The Fmincon algorithm was selected for its ability to handle complex constraints effectively, and its configuration was fine-tuned for precision. The optimization results, after de-standardizing the design variables, revealed significant improvements, with the optimized "freight cost" reduced to USD 45,151.93 and "delivery time" shortened to 106.15 days compared to baseline values.

These results underscore the transformative potential of machine learning and optimization techniques in addressing challenges within complex supply chains. Optimizing the HIV drug supply chain yields not only economic benefits but also profound social impacts. By reducing delivery times, critical medications can be made available more promptly, improving health outcomes and enhancing the quality of life for patients. Additionally, cost savings from reduced freight expenses can be reallocated to other essential areas, such as medical research, infrastructure development, and expanding healthcare access. This study also highlights the robustness and adaptability of combining ANNs with optimization algorithms, providing a scalable approach for various industries. However, limitations were identified, particularly regarding the accuracy of the "delivery time" predictions, which suggests that additional variables—such as weather conditions, geopolitical factors, or global health crises—could further refine this model. Future research should explore incorporating such granular data to address these complexities and improve predictive accuracy. This work bridges the gap between healthcare, supply chain management, and data science, illustrating how interdisciplinary approaches can tackle real-world challenges. Beyond healthcare, this methodology has implications for manufacturing, retail, and logistics sectors, demonstrating the versatility of data-driven, analytical solutions. The success of this study reaffirms the value of innovative approaches in supply chain optimization, emphasizing the need for continued research to refine models and drive positive economic and societal outcomes.

6. Future Work

To expand the future research section, we will include the potential of multi-objective evolutionary algorithms, such as NSGA-II or MOEA/D, to explore a broader solution space and address the trade-offs between freight cost and delivery time more effectively. Additionally, we will propose developing real-time supply chain optimization frameworks that leverage dynamic data, such as real-time tracking, weather conditions, and geopolitical factors, to enhance adaptability and decision-making. These directions will provide a foundation for extending the applicability and robustness of the proposed approach.

Author Contributions: Conceptualization, A.G., B.F. and J.F.; Methodology, A.G. and B.F.; Software, A.G. and B.F.; Validation, A.G., B.F. and J.F.; Formal analysis, B.F. and J.F.; Investigation, A.G.; Writing—original draft, A.G.; Writing—review & editing, A.G., B.F. and J.F.; Visualization, A.G.; Supervision, B.F. and J.F.; Project administration, B.F. and J.F.; Funding acquisition, B.F. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Social Science Fund of China project: Research on the Modernization of Intellectual Property Governance for Digital Innovation (22VRC064) to Bo Feng.

Institutional Review Board Statement: Not applicable.

Data Availability Statement: The data are available upon request to the corresponding author.

Conflicts of Interest: Authors have no conflicts of interest.

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Strategic Inventory Management with Private Brands: Navigating the Challenges of Supply Uncertainty

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Abstract: In the context of globalized and complex supply chains, supply uncertainty occurs frequently. To reduce dependence on suppliers, retailers often consider holding strategic inventory and introducing private brands. To explore the relationship between private brands and strategic inventory strategies, and to determine the optimal strategic decisions, this paper constructs a two-stage supply chain model. Using game theory methods, we calculate the equilibrium outcomes of the supply chain under two scenarios: one with only national brands and the other with the introduction of private brands. The main findings are as follows. First, we identify the optimal decisions for both suppliers and retailers in each scenario. The influencing factors include perceived quality, inventory costs, and supply stability. Second, we find that there are constraints for retailers to activate strategic inventory, but these constraints are less restrictive when private brands are introduced. Finally, introducing private brands benefits retailers in implementing strategic inventory, although the extent of this impact depends on the conditions under which the strategic stockpile is implemented. These findings fill the gap in the existing literature on the impact of private brand introductions on strategic inventory under supply uncertainty and highlight valuable implications for business decision-makers.

Keywords: supply uncertainty; strategic inventory; private brands; supply chain management; supply disruption

1. Introduction

In today's deeply integrated global economy, the compounded impacts of geopolitical conflicts, trade barrier restructuring, frequent extreme weather events, and disruptive technological changes have significantly amplified the vulnerabilities of supply chains [1,2]. From the manufacturing shutdowns triggered by semiconductor shortages to global inflation caused by the energy crisis, supply uncertainty has become a constant risk in business operations [3,4]. This is particularly true for the retail industry, which often faces the dilemma of being "out of stock" due to supply disruptions, as it heavily relies on external suppliers for national brand products (labeled NBs) [5,6]. For example, during the pandemic, many supermarket shelves were left empty, with only a limited supply of local products available.

In the face of supply uncertainty, traditional response strategies, such as excessive stockpiling of strategic inventory, may partially alleviate the risk of supply disruptions [5,6]. Researches show that retailers can mitigate the risk of supply instability and enhance supply chain resilience through strategic inventory reserves [7]. Furthermore, strategic inventory can also improve the retailer's bargaining power with suppliers and reduce dependence on them [8]. However, in the real business environment, adopting strategic inventory comes with high storage costs and capital occupation pressures, posing challenges for retailers in making informed decisions.

In addition to strategic inventory, another option for retailers to enhance their bargaining power with suppliers is the introduction of private brand products (labeled PBs) [9,10]. PBs, also known as private labels or store brands, are products that carry a brand name chosen by the retailer and are completely owned, controlled, and marketed by the retailer. In practice, PBs are typically segmented by product category, for instance, grocery, non-food, and apparel. Research shows that, compared to NBs, PBs offer advantages such as higher cost-effectiveness, flexible pricing, and a reliable supply [11,12]. They can help retailers increase profit margins, boost customer loyalty, and reduce dependency on suppliers [13]. In recent years, PBs have developed rapidly worldwide. According to PLMA's report, in the U.S., PBs have achieved all-time record highs in both unit and dollar shares in 2023. For example, PBs' dollar sales increased by 4.7% to reach approximately USD 236.3 billion, with a significant presence across nearly all food and non-food categories. Moreover, the report highlights that U.S. consumers—driven by high market awareness—exhibit a strong acceptance of PBs (https://www.plma.com/about_industry/research_reports_publications/consumer-research/plmas-2024-private-label-report accessed on 20th December 2024). Products like Walmart's "Great Value", Tesco's "Tesco Value", and Marks & Spencer's "M&S" have become core competencies in attracting consumers. However, some scholars have found that the introduction of PBs may lead to a deterioration in the retailer–supplier relationship, which, in turn, affects retailers' profits [14]. Although existing studies have extensively explored strategic inventory and PBs, most focus independently on the impact of each strategy on retailers' profitability. There is a theoretical gap regarding the interaction between PBs and strategic inventory which limits the ability to fully guide retailers who must simultaneously make decisions about both strategies in practice. The coexistence of strategic inventories and PBs is common in practice, as exemplified by Wumart. This leading Chinese supermarket chain maintains a large amount of strategic inventory without any supply chain disruption, while also operating PBs such as "Liangshiji". When the COVID-19 pandemic broke out, Wumart ensured a stable supply of goods. Therefore, studying the impact of PBs on retailers' strategic inventory under conditions of supply instability holds significant practical importance. This paper aims to address the gaps in existing theories by investigating the following questions:

1. Under what conditions will a retailer stock strategic inventory?
2. How does the introduction of PBs impact the retailer's strategic inventory decisions?
3. What impact does the introduction of PBs have on the various entities in the supply chain under conditions of supply uncertainty?

To address these questions, we construct a game model with supply uncertainty. By calculating the equilibrium decisions of the supplier and retailer under the scenarios of having only NBs and introducing PBs, and then comparing and analyzing the results numerically, we found the following. First, holding strategic inventory is not always beneficial for retailers; the conditions for activating strategic inventory depend on inventory costs, supplier wholesale prices, and supply stability. Second, the introduction of PBs allows retailers to make flexible strategic choices. When strategic inventory cannot be implemented, PBs can help retailers secure profits and maintain supply chain operations. Finally, retailers' decisions should be scientifically formulated based on the perceived quality of PBs, inventory costs, and supply stability.

The main contribution of this paper is to fill the theoretical gap in research on the impact of introducing PBs on strategic inventory in the context of supply uncertainty. It also reveals how PBs influence strategic inventory decisions. The main conclusions provide valuable managerial insights and offer guidance for real-world retail businesses with regard to making informed decisions.

The rest of the paper is organized as follows. Section 2 presents a comprehensive literature review. Section 3 describes the construction problem, develops the model framework, and outlines the basic assumptions. Section 4 computes the equilibrium solutions of the model for different scenarios. Section 5 provides a comparative model analysis and numerical simulations. Section 6 discusses how our results answer the research questions. Finally, Section 7 concludes the paper with managerial implications and future perspectives.

2. Literature Review

This paper investigates the impact of PBs on retailers' strategic inventories in the face of supply uncertainty. Two main types of literature are closely related to this paper: strategic inventory in supply chains and PB introduction.

2.1. Strategic Inventory

Holding strategic inventory in supply chains is a business strategy where companies acquire goods over time and retain inventory to mitigate supply chain disruptions and production fluctuations [15]. Anand et al. found that retailers holding inventory can lower the average wholesale price, alleviating the double marginalization effect [16]. Arya et al. investigated the impact of manufacturers' rebate contracts on strategic inventory and found that these contracts suppress retailers' strategic inventory behavior but bring more profits to supply chain members [17]. Arya et al. explored the impact of strategic inventory on a supply chain consisting of a single supplier and a retailer with multiple divisions and elaborated on enterprise inventory management in centralized versus decentralized decision making [18]. Roy et al. investigated the impact of strategic inventory on supply chain members under the condition of unobservability of retailer inventory levels, and the results indicate that retailers may voluntarily disclose their inventory-level information [19]. Li et al. examined strategic inventory decisions in competitive supply chains and found that intensified competition may induce retailers to order more inventory [20]. Guan et al. found that manufacturers' channel encroachment suppresses retailers' strategic inventory behavior [21]. Martin et al. examined the impact of retailers using strategic inventory when product quality declines [22]. Graves et al. discussed the role of safety stock as a crucial component of supply chain resilience strategies. They highlighted that increasing safety stock levels for critical items can help buffer against demand uncertainty and supply disruptions, especially in the wake of major supply chain disturbances such as those observed during the COVID-19 pandemic. Their findings support the notion that holding additional inventory can serve as a resilience mechanism [23].

In recent years, scholars have examined various supply chain structures related to the retail industry in the context of strategic inventory issues. Saha et al. examined the impact of strategic inventory [24]. The results show that all supply chain members can achieve higher profits if the holding cost is within a certain range, allowing the retailer to maintain strategic inventory, and, while cooperation between two manufacturers can lead to better outcomes without SI, this is not always the case when the retailer holds strategic inventory. Dong et al. employed a two-period dynamic model to explore the impact of manufacturers' strategic inventories on supply chain decisions and profits. They found that the manufacturer may hold a positive inventory level at equilibrium, which influences the retailer to carry more strategic inventory at a higher wholesale price in the first period. While the manufacturer's strategic inventory always hurts the retailer's profit, it may enhance channel profits, consumer surplus, and social welfare [25]. Yang et al. constructed a two-period dynamic model to explore the relationship between supplier encroachment and the retail platform's strategic inventory withholding behavior. The results show that the retail platform's strategic inventory decisions depend on the holding cost without encroachment and are moderated by the commission rate when the holding cost is intermediate with encroachment [26]. Most of the above studies are based on situations where the supply is stable and strategic inventories are constructed mainly for bargaining purposes with suppliers. This paper introduces the strategic inventory problem into an environment of unreliable supplies and considers the impact of PB strategies in a fashion which is more in line with real-world scenarios.

2.2. PB Introduction

Supply chain management, with the introduction of PBs, is another important area of research. Earlier scholars mainly focused on the impact aspects of introducing PBs. For example, Mills found that the introduction of PBs by retailers can not only achieve higher profits, but also mitigate the double marginal effect in the supply chain [27]. Chintagunta et al. found that the introduction of PBs has a significant impact on the supply chain pricing and profitability levels by considering price elasticity factors through an empirical study of oatmeal category products from Dominicks Finer Foods in the U.S. [28]. Mandhachitara et al.'s research shows that, in developed countries such as the U.S., PBs are more widely accepted, owing to the higher level of market awareness among consumers in these areas [29]. Wu et al. analyzed 364 articles covering 43 countries; notably, 82 articles involved U.S. data—the highest among the regions—while Spain accounted for 54 articles, making it the second largest. Moreover, cross-country studies on PBs predominantly used data from the U.S. and Europe [30]. Ru et al. found that the introduction of PBs can produce a win–win situation in a retailer-dominated situation [31]. In recent years, academics have been focusing on the impact of product quality on PB introduction. Choi et al. considered the impact of PB introduction on the supply chain under different quality positioning and showed that retailers can benefit manufacturers when they introduce high-quality PBs [32]. Hara et al. studied the impact of PB introduction when a retailer cooperates with an NB supplier and suggested that the introduction of high-end PBs can be a win–win situation for retailers [33]. Li et al. studied how retailers should make PB quality decisions [34].

Meanwhile, with the transformation of retail business models, scholars have paid attention to channel changes. Li et al. considered the model of introducing PBs under different sales models under the platform model [35]. Xu et al. investigated the logistics and distribution of fresh PBs under the platform model and found that the introduction of fresh PBs is conducive to promoting the acceptance of platform logistics services by merchants [11]. Li et al. explored the situation where manufacturers create new products in response to the invasion of platform PBs and found that the introduction of new low-priced products by manufacturers is conducive to market competition [14]. Huang et al. analyzed the optimal pricing strategy under the introduction of PBs based on the return perspective [13]. Shen et al., based on the perspective of different agency contracts, explored the relationship between the perceived value of PBs and the introduction strategy [36]. However, most of the above literature has not yet considered the category problem of PBs, nor has it focused on the product-ordering problem under the retailer–supplier competition and gaming which cannot provide comprehensive support for the enterprise's realistic decision making. Balasubramanian et al. employed a two-period game-theoretic framework to investigate the impact of PB competition on a retailer's strategic inventory decisions. The analysis revealed that it is never optimal for the retailer to hold PBs as strategic inventory, and, while PB competition can sometimes worsen the retailer's situation, low holding costs can make strategic inventory and PB competition complementary and beneficial to the retailer [37].

Summarizing the above literature, it can be observed that the introduction of PBs has a significant impact on the supply chain operation. However, most of the existing studies have not yet considered supply chain disruption scenarios or the structural changes in product ordering introduced by strategic inventory, a fact which limits their applicability for real-world decision making by enterprises. This paper examines how strategic inventory changes when retailers introduce PBs in the context of supply uncertainty, providing robust theoretical support for enterprises with regard to making supply chain decisions within a complex and dynamic market environment.

3. Problem Description and Model Setup

Here, we consider a two-stage supply chain model consisting of a supplier and a retailer. The supplier sells NBs to the retailer at wholesale price, and the retailer subsequently sells it to consumers at a retail price (referred to as Scenario N). Under the Stackelberg game, the supplier acts as the leader, and the retailer acts as the follower. Both participants are risk-neutral and aim to maximize profits in their decision making, an approach which is consistent with [38–40].

We first outline the timeline of the two-stage supply chain. In the first stage, the supply is stable. The supplier determines the wholesale price of NBs, and the retailer purchases a quantity of $K(K > 0)$ units as strategic inventory, with a holding cost of h per unit. The holding cost refers to the storage and disposal costs incurred for the strategic inventory and is consistent with [1,21,24]. In the second stage, the retailer orders a quantity of K for selling, but unpredictable supply disruptions may occur, such as production capacity interruptions caused by diseases, natural disasters, geopolitical issues, or the supplier prioritizing other channels. Supply uncertainty can be represented in the model as a package of multiple scenarios, including stochastic production, all-or-nothing supply, and stochastic capacity [40]. In this paper, we assume that supply uncertainty is consistent with an all-or-nothing supply model [41–43]. If a disruption occurs, the retailer will not receive any products. For example, during peak sales seasons, NB suppliers may prioritize their own online channels, leading to supply disruptions for retailers. Consistent with the literature [43], we assume that the probability of a normal supply in the second stage is $\lambda(0 < \lambda < 1)$, which serves as an indicator of the supply stability. Thus, the probability of a supply disruption is $1 - \lambda$.

In this paper, we investigate the impact of PBs on the supply chain (referred to as Scenario P). In our study, we focus specifically on the PB category that comprises products which are easy to store and not prone to spoilage. This segment is particularly relevant for our analysis of strategic inventory decisions under supply uncertainty, as these products allow for more predictable inventory management. The retailer can introduce PBs and we assume that the supply of PBs is always stable due to the significant control from the retailer. We assume that the market consists of one unit of consumers. Consumers exhibit heterogeneous quality preferences, which influence their willingness to pay V. Consistent with the assumption made by Ru et al. [31], Guo et al. [44], Ru et al. [45], Li et al. [10], and Alan et al. [46], we assume that consumer willingness to pay follows a uniform distribution over the interval [0, 1]. We set the perceived quality of the NBs to 1 and denote the perceived quality of the PBs as $\mu(1/2 < \mu < 1)$. This is because PBs are still in the early stages of market presence compared to NBs and lag behind in terms of technology, production experience, and quality control. This hypothesis is very common in PB-related research, such as [47–49].

The sequence of the game in two scenarios is shown in Figure 1. First, the supplier decides the wholesale price of NBs and the retailer decides the strategic inventory level. Second, the retailer decides the order quantity of NBs, and the order quantity of PBs if PBs are introduced. Finally, the consumer chooses to buy the product based on the actual supply of the product and products will be sold.

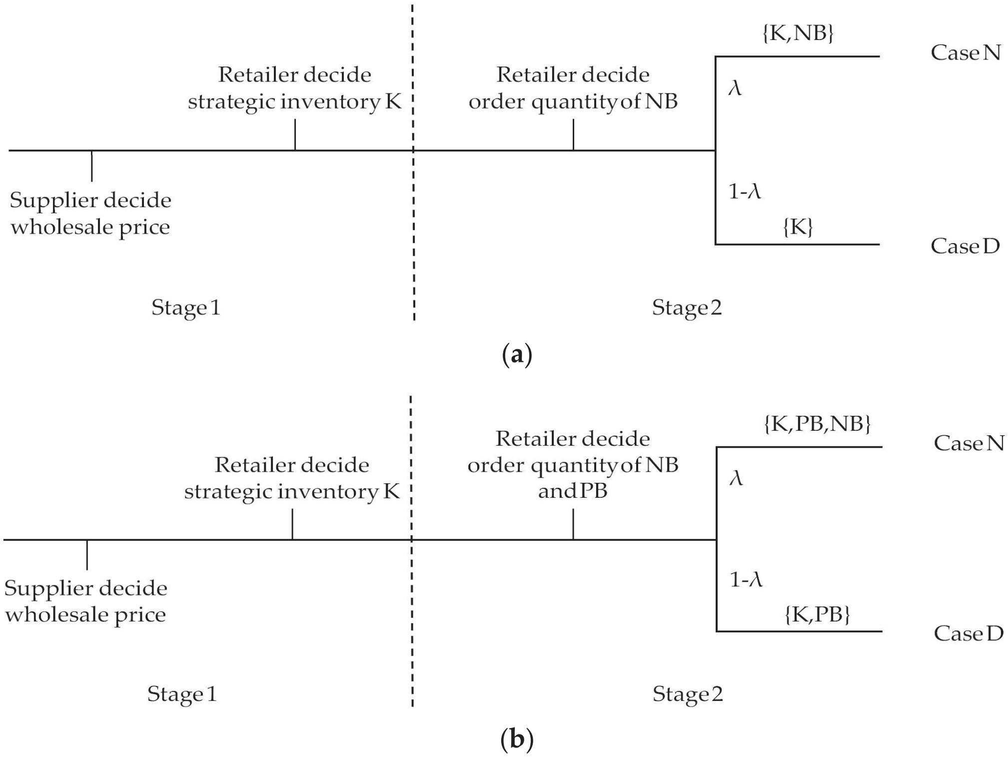

Figure 1. The sequence of the game: (**a**) under scenario N; (**b**) under scenario P.

When there are only NBs on the market, for a given price, the consumer's utility after purchasing NBs is $u_1^N = V - p_1^N$. When both NBs and PBs exist on the market, the utility of consumers purchasing NBs is $u_1^P = V - p_1^P$, while the utility of consumers purchasing PBs is $u_2^P = \mu V - p_2$. Thus, the inverse demand function of two products under different scenarios and cases can be summarized as follows:

$$p_1^{ij} = 1 - (q_1^{ij} + K^i) - \mu q_2^{ij} \tag{1}$$

$$p_2^j = \mu(1 - (q_1^{Pj} + K^P) - q_2^j) \tag{2}$$

where $i = N, P$ denotes scenario N and scenario P, $k = D, N$ denotes the case of supply disruption and not, and $q_2^{Nj} = 0$ indicates no introduction of PBs. Similar inverse demand functions for PBs and NBs have been adopted in the literature, such as [32,44,50]. All the notations are summarized in Table 1. Without loss of generality, we assume that the marginal cost of production is equal to zero for all products, an approach which is the same as that adopted in other studies [11,14,51].

Table 1. Notations and definitions.

Notations	Definition
Indices	
t	Subscript, index of product, $t = 1$ for NBs and $t = 2$ for PBs
i	Superscript, index of scenario, $i = \{N, P\}$
j	Superscript, index of case, $j = \{D, N\}$, e.g., D for disruption
Parameters	
h	The unit holding cost for strategic inventory
λ	Supply stability: the probability of supply stabilization
μ	The perceived quality of PBs
Decision variables	
q_t^{ij}	The order quantity for product t in scenario i with case j
w^i	The wholesale price for NBs in scenario i
K^i	The strategic inventory in scenario i
Dependent variables	
p_t^{ij}	The retail price for product t in scenario i with case j
E^i	The consumer surplus in scenario i
π_M^i	The supplier's profit in scenario i
π_R^i	The retailer's profit in scenario i

4. Model Solution and Equilibrium Analysis

The retailer can choose whether or not to introduce PBs, and, based on this, there are two scenarios. In this section, we explore the equilibrium results under different scenarios. All proofs are presented in Appendix A.

4.1. Only NBs (Scenario N)

When no PBs exist, in case N, the retailer's sales volume is $K^N + q_1^{NN}$; in case D, the retailer's sales volume is K^N. Thus, the retailer's and supplier's profit function are:

$$\begin{aligned} \max\pi_R^N(q_1^{NN}, K^N) &= \lambda\pi_R^{NN} + (1-\lambda)\pi_R^{ND} \\ &= \lambda(p_1^{NN}(q_1^{NN} + K^N) - w^N q_1^{NN}) + (1-\lambda)p_1^{ND}K^N - hK^N \end{aligned} \quad (3)$$

$$\max\pi_M^N(w^N) = \lambda q_1^{NN} w^N + w^N K^N \quad (4)$$

Using backward recursion, the optimal solution for the retailer under unconstrained conditions is obtained as follows: $(q_1^{NN}(w^N), K^N(w^N)) = \left(\frac{h}{2-2\lambda}, \frac{h+\lambda-\lambda w^N + w^N - 1}{2(\lambda-1)}\right)$. The constraint for the strategic inventory is $K \geq 0$, and, if, $K = 0$ the retailer will not maintain strategic inventory. Therefore, the sign of $h + \lambda - \lambda w^N + w^N - 1$ affects the implementation of the strategic inventory strategy, which, in turn, influences the structure of the supply chain. By discussing the range of values for w^N, we can have Lemma 1 as follows.

Lemma 1. *When PBs are not introduced, for a given w^N, the optimal solutions for the retailer are:*

$$(q_1^{NN}(w^N), K^N(w^N)) = \begin{cases} \left(\frac{h}{2-2\lambda}, \frac{h+\lambda-\lambda w^N + w^N - 1}{2(\lambda-1)}\right) & if\ w^N < \frac{h+\lambda-1}{\lambda-1} \\ \left(\frac{1-w^N}{2}, 0\right) & if\ w^N \geq \frac{h+\lambda-1}{\lambda-1} \end{cases} \quad (5)$$

Lemma 1 indicates that, when only NBs are available, the retailer's optimal order quantity is solely dependent on inventory costs and supply stability. Furthermore, if the wholesale price set by the supplier is too high, the retailer will not maintain strategic inventory. Substituting Lemma 1 and Equation (5) into Equation (4) yields equilibrium results.

Lemma 2. *When PBs are not introduced, there exists a h^N such that the equilibrium prices, quantities, and profits are given in Table 2, where $h^N = 1 - \sqrt{\lambda}$.*

Table 2. Equilibrium results under scenario N.

Items	Equilibrium Results	
	$h < h^N$	$h \geq h^N$
w^N	$\frac{1-h}{2}$	$\frac{1}{2}$
q_1^N	$\frac{h}{2-2\lambda}$	$\frac{1}{4}$
K^N	$\frac{h\lambda+h+\lambda-1}{4(\lambda-1)}$	0
p_1^{NN}	$\frac{3-h}{4}$	$\frac{3}{4}$
p_1^{ND}	$\frac{(h-3)\lambda+h+3}{4-4\lambda}$	0
E^N	$\frac{h+3}{4}$	$\frac{4-3\lambda}{4}$
π_M^N	$\frac{1}{8}(h-1)^2$	$\frac{\lambda}{8}$
π_R^N	$\frac{-h(3h\lambda+h+2\lambda-2)+\lambda-1}{16(\lambda-1)}$	$\frac{\lambda}{16}$

Lemma 2 demonstrates that the retailer's strategic inventory strategy is closely related to inventory costs. Only when inventory costs are sufficiently low will the retailer hold strategic inventory. Furthermore, by maintaining strategic inventory, the retailer weakens the supplier's monopoly position, allowing the retailer to flexibly adjust the ordering strategy during the selling period based on the supplier's reliability.

Proposition 1. *When PBs are not introduced, the values of the decision variables, consumer surplus, and profits vary with h as follows:*

- *When $h < h^N$, $\partial w^N/\partial h < 0$, $\partial q_1^N/\partial h > 0$, $\partial K^N/\partial h < 0$, $\partial E^N/\partial h > 0$, and $\partial \pi_M^N/\partial h > 0$*
- *When $h^{N1} < h < h^N$, $\partial \pi_R^N/\partial h > 0$; when $h^{N1} > h$, $\partial \pi_R^N/\partial h < 0$, where $h^{N1} = \frac{1-\lambda}{3\lambda+1}$ decrease with λ.*

Proposition 1 indicates that, under moderate inventory costs, as inventory costs increase, the supplier will lower the wholesale price. This is because the supplier is concerned that higher inventory costs will lead the retailer to reduce order quantities, thereby resulting in lower profits. As a result, the retailer will increase the order quantity during the selling period but will reduce the strategic inventory reserve. This situation, ultimately, leads to an increase in the supplier's profit and consumer surplus. Interestingly, we found that, when inventory costs are within a certain range, the retailer's profit increases as inventory costs rise. However, when inventory costs fall below a critical threshold, the retailer's profit decreases as inventory costs increase. This critical value is negatively correlated with supply stability.

4.2. Both NBs and PBs (Scenario P)

When both PBs and NBs are present on the market, in case N, the retailer's sales volume for NBs is $K^P + q_1^{PN}$, while the volume for PBs is q_2^N; in case D, the retailer's sales volume for NBs is K^P and the volume for PBs is q_2^N. In scenario P, the retailer's and supplier's profit functions are:

$$\begin{aligned} \max \pi_R^P(q_1^{PN}, q_2^P, K^P) \quad &= \lambda(p_1^{PN}(q_1^{PN} + K^N) - w^P q_1^{PN}) + (1-\lambda)p_1^{PD}K^P - (w^P + h)K^P \\ &+ \lambda p_2^{PN} q_2^P + (1-\lambda)p_2^{PD} q_2^P \end{aligned} \tag{6}$$

$$\max \pi_M^P(w^P) = \lambda q_1^{PN} w^P + w^P K^P \tag{7}$$

Using backward recursion, the optimal solution for the retailer under unconstrained conditions is obtained as follows:

$$\left(q_1^{PN}(w^P), q_2^P(w^P), K^P(w^p)\right) = \left(\frac{h}{2-2\lambda}, \frac{h+w^P}{2-2\mu}, \frac{h\lambda\mu - h + \lambda\mu - \lambda - \mu + \lambda w^P - w^P + 1}{2(\lambda-1)(\mu-1)}\right)$$

Similar to Lemma 1, by discussing the range of values for w^P, we can have Lemma 3.

Lemma 3. *When PBs are introduced, for a given w^P, the optimal solutions for the retailer are:*

$$q_1^{PN}(w^P) = \begin{cases} \frac{h}{2-2\lambda} & if\ w^P < \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \\ \frac{\mu + w^P - 1}{2\lambda\mu - 2} & if\ w^P \geq \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \end{cases} \tag{8}$$

$$q_2^P(w^P) = \begin{cases} \frac{h+w^P}{2-2\mu} & if\ w^P < \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \\ \frac{1+(-1+w^P)\lambda}{2-2\lambda\mu} & if\ w^P \geq \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \end{cases} \tag{9}$$

$$K^P(w^P) = \begin{cases} \frac{h\lambda\mu - h + \lambda\mu - \lambda - \mu + \lambda w^P - w^P + 1}{2(\lambda-1)(\mu-1)} & if\ w^P < \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \\ 0 & if\ w^P \geq \frac{-\lambda h\mu + h - \lambda\mu + \lambda + \mu - 1}{\lambda - 1} \end{cases} \tag{10}$$

Lemma 3 indicates that, even when the retailer introduces PBs, if the supplier's wholesale price is too high, similar to Lemma 1, the retailer will also not maintain strategic inventory. Furthermore, regardless of whether the retailer initially holds strategic inventory, as the supplier's wholesale price increases, the retailer will produce more PBs. By substituting Lemma 3 and Equations (8)–(10) into Equation (7), we can have the equilibrium results under scenario P as follows.

Lemma 4. *When PBs are introduced, there exists a h^P such that the equilibrium prices, quantities, and profits are given in Table 3, where $h^P = 1 - \mu - \sqrt{\frac{-\lambda + 3\lambda\mu - 3\lambda\mu^2 + \lambda\mu^3}{-1+\lambda\mu}}$.*

Table 3. Equilibrium results under scenario P.

Items	Equilibrium Results	
	$h < h^P$	$h \geq h^P$
w^P	$\frac{1}{2}(1-h-\mu)$	$\frac{1-\mu}{2}$
q_1^P	$\frac{h}{2-2\lambda}$	$\frac{1-\mu}{4-4\lambda\mu}$
q_2^P	$\frac{h-\mu+1}{4-4\mu}$	$\frac{2-\lambda-\lambda\mu}{4-4\lambda\mu}$
K^N	$\frac{2h\lambda\mu - h\lambda - h + \lambda\mu - \lambda - \mu + 1}{4(\lambda-1)(\mu-1)}$	0
p_1^{NN}	$\frac{1}{4}(3-h-\mu)$	$\frac{3-\mu}{4}$
p_1^{ND}	$\frac{1}{2}(1-h)\mu$	0
p_2^{PN}	$\frac{h(-\lambda)-h-\lambda\mu+3\lambda+\mu-3}{4(\lambda-1)}$	$\frac{\mu(1+\lambda+\mu-3\lambda\mu)}{4-4\lambda\mu}$
p_2^{PD}	$\frac{(h-1)\lambda\mu+\mu}{2-2\lambda}$	$\frac{-4+2\mu+3\lambda\mu-\lambda\mu^2}{4(-1+\lambda\mu)}$
E^P	$\frac{1}{2}$	$\frac{1}{2}$
π_M^P	$\frac{(h+\mu-1)^2}{8(1-\mu)}$	$\frac{\lambda(-1+\mu)^2}{8-8\lambda\mu}$
π_R^P	$\frac{A}{16(\lambda-1)(\mu-1)}$	$\frac{\lambda+4\mu-2\lambda\mu-3\lambda\mu^2}{16-16\lambda\mu}$

$A = 1 - 2h + h^2 - \lambda + 2h\lambda + 3h^2\lambda + 2\mu + 2h\mu - 2\lambda\mu - 2h\lambda\mu - 4h^2\lambda\mu - 3\mu^2 + 3\lambda\mu^2$.

Lemma 4 indicates that, after the retailer introduces PBs, the strategic inventory strategy is still dependent on inventory costs. Only when inventory costs are sufficiently low (under h^P) will the retailer maintain strategic inventory. Notably, after the introduction of PBs, consumer surplus tends to stabilize, suggesting that the presence of PBs significantly enhances consumer choice and provides a stable purchasing environment for consumers.

Proposition 2. *When PBs are introduced, the values of the decision variables, consumer surplus, and profits vary with h as follows:*

- *When $h < h^P$, $\partial w^P/\partial h < 0$, $\partial q_1^P/\partial h > 0$, $\partial q_2^P/\partial h > 0$, $\partial K^P/\partial h < 0$, and $\partial \pi_M^N/\partial h > 0$.*
- *There exist a λ^P and h^{P1}, when $\mu = 3/4$ and $h > h^{P1}$; $\mu < 3/4$, $\lambda < \lambda^P$, and $h < h^{P1}$ or $\lambda > \lambda^P$ and $h > h^{P1}$; $\mu < 3/4$ and $h > h^{P1}$ or $\lambda > \lambda^P$ and $h > h^{P1}$, where $\partial \pi_R^P/\partial h > 0$. Otherwise, $\partial \pi_R^P/\partial h < 0$, where $\lambda^P = \frac{1}{-3+4\mu}$ and $h^{N1} = \frac{-1+\lambda+\mu-\lambda\mu}{-1-3\lambda+4\lambda\mu}$.*

As indicated by Proposition 2, similar to Proposition 1, under moderate inventory costs, as inventory costs increase, the supplier will lower the wholesale price. The retailer will then increase the order quantities for both products and reduce the strategic inventory reserve. Additionally, in the case of introducing PBs, the strategic inventory strategy cannot guarantee an increase in the retailer's profit. There exists a critical inventory cost threshold, which is related to the perceived quality of PBs and supply stability, which influences the variation in the retailer's profit.

Proposition 3. *When PBs are introduced and the strategic inventory strategy is implemented, the decision variables and profits vary with the perceived quality of PBs, as follows: $\partial w^P/\partial \mu < 0$, $\partial q_1^P/\partial \mu > 0$, $\partial q_2^P/\partial \mu > 0$, $\partial K^P/\partial \mu < 0$, $\partial \pi_M^P/\partial \mu < 0$, $\partial \pi_R^P/\partial \mu > 0$.*

Proposition 3 indicates that the perceived quality of products plays a crucial role in shaping a supply chain. As the consumer-perceived quality of PBs improves, the competitive pressure on NBs intensifies, leading to a decline in the wholesale price of NBs as the supplier attempts to maintain its market position. Simultaneously, both the retailer's PBs and the NBs experience higher order quantities, reflecting a shift in consumer demand toward PB products. From a profitability perspective, the supplier's profit declines due to price reductions and intensified competition, while the retailer benefits from increased sales and improved profit margins as the PBs become more competitive. Additionally, the retailer reduces its strategic inventory holdings of NBs as the reliance on a single NB supplier diminishes. Overall, an increase in PB perceived quality enhances the retailer's bargaining power, reduces dependence on the NB supplier, and reshapes inventory and pricing strategies, ultimately influencing supply chain equilibrium.

5. Comparison Analysis and Numerical Simulation

In this section, we discuss the comparative equilibrium results across different scenarios, exploring the impact of strategic inventory and the introduction of PBs on the supply chain. We use $\triangle$ as the difference value between equilibrium results across different scenarios. For example, the optimal profit difference between scenario N and scenario P for the retailer is given by $\triangle \pi_R = \pi_R^N - \pi_R^P$; if $\triangle \pi_R < 0$, it means that the introduction of PBs is better for the retailer's profit. We also provide numerical simulations to support these findings.

5.1. The Impacts on Strategic Inventories

According to Lemma 2 and Lemma 4, regardless of whether the retailer introduces PBs, there exists a critical inventory cost threshold under both scenarios that causes the retailer not to maintain a strategic inventory. By comparing the critical inventory cost thresholds under these two scenarios, we can determine the extent of the limitations on the activation of the strategic inventory.

Proposition 4. *When the retailer introduces PBs, it becomes easier for the retailer to implement a strategic inventory strategy, as $h^P < h^N$. Furthermore, the optimal level of strategic inventory reserve is lower.*

Proposition 4 indicates that the introduction of PBs enables the retailer to flexibly respond to supply chain disruptions. When inventory costs are high, the retailer can choose to increase the quantity of PBs to replace the strategic inventory, thereby maintaining a stable profit level despite the unstable supply. When inventory costs are low, the retailer can reserve strategic inventory and supplement it with the production of some PBs to maximize profit. Additionally, the introduction of PBs can reduce the retailer's strategic inventory purchase volume, thereby alleviating the pressure on the retailer's capital accumulation.

According to Younis et al.'s empirical research data on 800 questionnaires, the average perceived quality of PBs is roughly 0.8 [52]. Based on that, we assume the perceived quality of PBs to be 0.8 and observe the change in strategic inventory under different supply stability scenarios. Figure 2 reveals two key insights. First, when supply stability is held constant, the introduction of PBs significantly reduces the level of strategic inventory required. Notably, the critical threshold for activating strategic inventory is lower with PBs in place. This indicates that retailers can adopt a more flexible approach to inventory management.

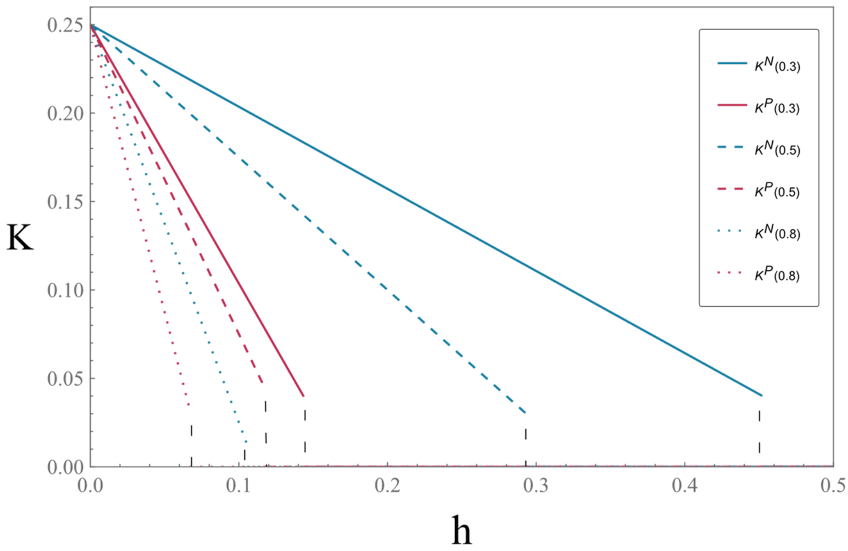

Figure 2. The impact of inventory costs on strategic inventory with different λ values.

Second, the figure shows that the level of strategic inventory is sensitive to the stability of the supply. As the supply becomes more stable, retailers tend to reduce their strategic inventory holdings. In contrast, under conditions of poor supply stability, the demand for strategic inventory increases sharply, reflecting the need to buffer against higher risks of supply disruption.

Overall, these results suggest that incorporating PBs not only lowers the barrier for activating strategic inventory, but also enables retailers to better adjust their inventory levels in response to varying supply conditions. This more flexible strategic approach could help retailers manage costs more effectively while maintaining service levels in uncertain environments.

Furthermore, Proposition 4 also indicates that, under the same h, a retailer operating without PBs would need to hold a larger buffer, thereby incurring higher financing costs. For smaller retailers, who typically face financial constraints such as limited cash flow, we suggest several practical financial strategies to implement strategic inventory more effectively. First, warehouse receipt financing, which uses strategic inventory as collateral, can help secure short-term financing. Second, factoring allows retailers to convert receivables into cash, thereby easing cash flow constraints. Third, negotiating extended payment periods with the suppliers, known as supplier credit terms, can provide additional working capital relief.

5.2. The Impacts on Profit

5.2.1. Supplier's Profit

Based on Lemma 2, Lemma 4, and Proposition 4, the value of $\triangle\pi_M$ depends on the different intervals of h, resulting in three distinct forms:

$$\triangle\pi_M = \begin{cases} \frac{\mu\left(h^2+\mu-1\right)}{8(\mu-1)} & if\ 0 < h < h^P \\ \frac{1}{8}(h-1)^2 + \frac{\lambda(\mu-1)^2}{8\lambda\mu-8} & if\ h^P \leq h < h^N \\ \frac{\lambda\mu(\lambda+\mu-2)}{8\lambda\mu-8} & if\ h^N \leq h \end{cases} \tag{11}$$

By comparing the sign of $\triangle\pi_M$, we can assess the differences in the supplier's optimal profit across various scenarios.

Proposition 5. *Regardless of the value of h, the introduction of PBs will always lead to a decrease in the supplier's profit, i.e., $\triangle\pi_M > 0$.*

According to Proposition 5 as the retailer introduces PBs, the retailer's dependence on the supplier decreases, leading to a reduction in the supplier's profit. We consider the supply chain parameters with four cases as $\mu \in \{0.55, 0.8\}$, $\lambda \in \{0.1, 0.8\}$ to show the changes in the profit difference for the supplier under different inventory costs and supply stabilities (Figure 3).

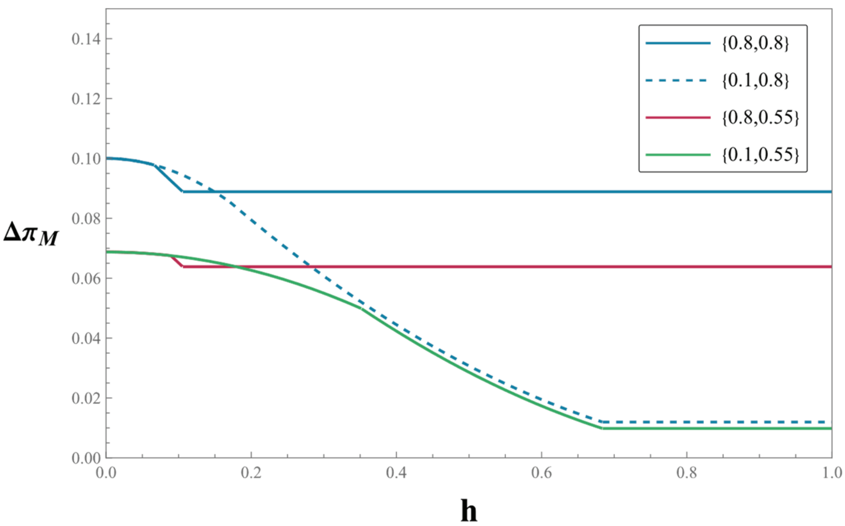

Figure 3. The impact of inventory costs on supplier's profit difference with different $\{\lambda, \mu\}$.

As shown in Figure 3, when PBs are not introduced, the supplier's profit is higher. Moreover, as inventory costs decrease, the profit loss caused by the introduction of PBs becomes more significant for the supplier. The higher the perceived quality of the PBs, the greater the profit loss for the supplier. On the other hand, Proposition 5 also indicates that, when the retailer introduces PBs, the supplier may lower the stability of the supply in order to protect their profit, in turn affecting the retailer's strategic choices.

5.2.2. Retailer's Profit

Based on Lemma 2, Lemma 4, and Proposition 4, the value of $\triangle\pi_R$ depends on the different intervals of h, resulting in three distinct forms:

$$\triangle\pi_R = \begin{cases} \frac{\mu\left(h^2-3\mu+3\right)}{16(\mu-1)} & if\ 0 < h < h^P \\ \frac{B}{16(-1+\lambda)(-1+\lambda\mu)} & if\ h^P \leq h < h^N \\ \frac{(4+\lambda(-2+\lambda-3\mu))\mu}{16(-1+\lambda\mu)} & if\ h^N \leq h \end{cases} \tag{12}$$

where $B = -2h(-1+\lambda)(-1+\lambda\mu) - h^2(1+3\lambda)(-1+\lambda\mu) - (-1+\lambda)(1-4\mu+\lambda(-1+\mu+3\mu^2))$. By comparing the sign of $\triangle\pi_R$, we can assess the differences in the supplier's optimal profit across various scenarios.

Proposition 6. *Regardless of the value of h, the introduction of PBs will always lead to an increase in the retailer's profit i.e., $\triangle\pi_R < 0$.*

According to Proposition 6, the introduction of PBs can guarantee that the retailer's profit will always increase. When PBs are introduced, the retailer can build a more resilient supply chain by setting a combination of strategic inventories, order quantities for both NBs and PBs, and by adjusting prices based on supply stability conditions. However, the improvement in profit is not fixed, and the difference is based on the specific inventory costs, perceived quality of PBs, and supply stability. We use numerical simulations to explain this phenomenon; the parameters are the same as those used in Proposition 5. Then, Figure 4 illustrates the interaction between exogenous variables and retailer's profit change.

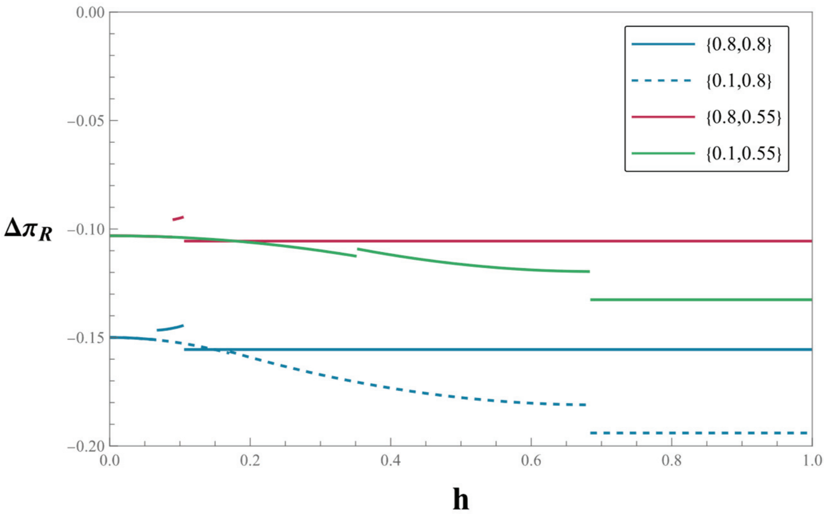

Figure 4. The impact of inventory costs on retailer's profit difference with different $\{\lambda, \mu\}$.

Figure 4 shows that, when inventory costs are too high and the retailer is unable to adopt a strategic inventory strategy, the introduction of PBs significantly increases the retailer's profit level. Furthermore, under the same conditions, the higher the perceived quality of PBs, the greater the increase in the retailer's profit. Under the condition of introducing PBs of the same quality, if inventory costs are high and supply stability is poor, the profit increase after introducing PBs will be greater.

6. Discussions

In this section, we discuss how our research results answer the questions raised in the previous section.

In addressing the conditions under which a retailer opts to hold a strategic inventory, our analysis indicates that such a decision is economically justified only when the cost structure—specifically, the wholesale price and inventory holding expenses—remains sufficiently low. Our model demonstrates that only under these favorable cost conditions does the benefit of buffering against supply uncertainty outweighs the costs, enabling the retailer to optimize its inventory levels. This optimality is derived by balancing the marginal cost of additional inventory against the anticipated gains from mitigating potential supply disruptions.

The introduction of PBs significantly reshapes the retailer's inventory strategy. Our findings reveal that the presence of PBs effectively lowers the threshold required to initiate strategic inventory practices. In other words, PBs provide an alternative supply source that enhances the retailer's flexibility and responsiveness. This additional option not only alleviates reliance on external suppliers, but also enables retailers to maintain a more adaptable and proactive inventory policy, especially in environments characterized by supply uncertainty.

Under conditions of supply uncertainty, the incorporation of PBs exerts a multifaceted influence across the supply chain. Our simulations suggest that while the introduction of PBs can lead to competitive adjustments—such as a reduction in wholesale prices and altered order quantities—the overall effect is a stabilization of supply chain dynamics. Specifically, PBs help maintain a more consistent consumer surplus and support a resilient supply chain structure, even if this comes at the cost of reduced supplier margins. These dynamics highlight the role of the complex interplay among market perceptions, cost structures, and supply stability in shaping the strategic decisions of all entities involved.

7. Conclusions and Future Research

In the current development of the retail industry, strategic inventory and PB introduction are two widely adopted strategies. While previous studies have examined the impact of each strategy on profitability independently, limited attention has been paid to the interaction among these strategies, especially under supply uncertainty [1,37]. However, with the advancement of technology and changes to the retail environment, supply chain structures have evolved significantly, leading to more frequent supply disruptions. This paper addresses this gap by proposing a novel retailer strategic inventory model that integrates PB introduction in an unstable supply context. By examining the strategic inventory and profits of various supply chain stakeholders under different scenarios, we draw the following main conclusions.

Firstly, regardless of whether PBs are introduced, the retailer will only maintain the strategic inventory if the wholesale price and inventory costs are sufficiently low. The introduction of PBs can lower the critical threshold for activating strategic inventory, allowing the retailer to make more flexible strategic decisions. We also identify the optimal strategic inventory levels under different scenarios. Secondly, the introduction of PBs lowers the barriers to implementing strategic inventory strategies, thereby indirectly enhancing supply chain resilience. In scenarios where PBs are introduced, consumer surplus remains stable, though lower than when only NBs are present. The supply level across the entire supply chain remains stable. Even when strategic inventory costs are too high to implement, PBs can still support the retailer. Finally, the impact of PBs on the profits of retailers and suppliers is multifaceted, depending on factors such as the perceived quality of PBs, inventory costs, and supply stability. Some previous pieces of literature suggest that the introduction of PBs benefits suppliers as well. However, this dynamic changes when supply instability and strategic inventory are taken into account.

This study makes several key contributions to the literature. First, it is the first paper to develop a theoretical model that comprehensively considers supply uncertainty, PB introduction, and strategic inventory decisions. Second, through comparative model analysis, we identify the boundary conditions under which a retailer engages in strategic inventory and examine the changes brought by the introduction of PBs under different scenarios. Finally, our findings yield several important managerial insights that can serve as valuable references for business decision-makers.

For retail enterprises, both strategic inventory and PBs are valuable strategic options. These strategies can help retailers strengthen their bargaining power with suppliers. It is important to note that the implementation of these strategies is not static; they need to be applied flexibly, considering factors such as the perceived quality of PBs, inventory costs, and supply stability. For instance, in highly competitive environments, retailers can adopt a more aggressive PB strategy. By leveraging the cost advantages associated with PBs, retailers can secure lower wholesale prices and invest in quality improvements to build consumer trust. This, in turn, permits them to lower their strategic inventory levels without compromising service levels, thus achieving a more efficient and responsive supply chain. Conversely, in markets with lower competitive pressures or more stable supplier relationships, a more cautious approach may be warranted. In these settings, retailers might opt to gradually introduce PBs, maintaining a relatively higher level of strategic inventory as a safeguard against supply disruptions.

This study employs a two-stage Stackelberg game model to analyze strategic inventory decisions under supply uncertainty. While this approach offers valuable theoretical insights, it also involves several simplifying assumptions. For instance, our model assumes a binary supply scenario (either full supply or complete disruption) and a monopoly-like supplier–retailer relationship. In reality, supply disruptions can be partial, such as delayed shipments or quality issues, and supply chains often involve multiple competing suppliers and retailers [40]. For future research, we suggest extending our framework by incorporating more advanced modeling techniques, such as dynamic programming or stochastic optimization, which can better account for partial supply disruptions and logistical challenges like warehouse limitations and transportation delays. We also aim to broaden our sensitivity analysis by testing various market conditions (e.g., changes in consumer demand elasticity and supplier pricing) and by integrating empirical data with our theoretical model. These enhancements will help bridge the gap between theoretical assumptions and real-world complexities, ultimately leading to more tailored and actionable managerial recommendations.

Author Contributions: Conceptualization, J.G.; formal analysis, J.G.; funding acquisition, G.S.; investigation, H.W.; methodology, J.G. and H.W.; software, J.G.; validation, J.G.; writing—original draft, J.G.; writing—review and editing, H.W., G.S., H.C. and Q.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the Fundamental Research Funds for the Central Universities, grant number 2024JBWG010.

Data Availability Statement: Dataset available on request from the authors.

Acknowledgments: We would like to thank the Fundamental Research Funds for the Central Universities.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

NBs	National Brand Products
PBs	Private Brand Products

Appendix A. Proofs

Proof of Lemma 1. Using backward recursion to solve Equation (3), we can easily have the optimal solution for K^N as $\frac{h+\lambda-\lambda w^N+w^N-1}{2(\lambda-1)}$ under unconstrained conditions. If $K^{N*} > 0$, the retailer will maintain strategic inventory. If $K^{N*} \leq 0$, the retailer will not maintain strategic inventory. If $K^N = 0$, the structure of the supply chain will change, as no products are available for customers when the supply is disrupted.

Firstly, we discuss the situation with respect to the strategic inventory, which means that $h+\lambda-\lambda w^N+w^N-1>0$; then, when $w^N < \frac{h+\lambda-1}{\lambda-1}$, we have $(q_1^{NN}(w^N), K^N(w^N)) = \left(\frac{h}{2-2\lambda}, \frac{h+\lambda-\lambda w^N+w^N-1}{2(\lambda-1)}\right)$.

Secondly, we discuss the situation without strategic inventory, meaning that $h+\lambda-\lambda w^N+w^N-1 \leq 0$. When $w^N \geq \frac{h+\lambda-1}{\lambda-1}$, Equation (3) becomes as follows:

$$\max \pi_R^N(q_1^{NN}) = \lambda(p_1^{NN}q_1^{NN} - w^N q_1^{NN}) \tag{A1}$$

Then, we can easily obtain the optimal solution using backward recursion, as follows:

$$(q_1^{NN}(w^N), K^N(w^N)) = \left(\frac{\lambda-w}{2\lambda}, 0\right).$$

□

Proof of Lemma 2. Based on Lemma 1, substitute Equation (5) into (4) and (A1). Then, we can obtain the following. In a situation where strategic inventory exists, the optimal solution for the wholesale price is $w^N = (1-h)/2$; then, we can have $h < h_1 = (1-\lambda)/(1+\lambda)$ when it satisfies the constraint condition; when $h \geq h_1$, $w^N = (h+\lambda-1)/(\lambda-1)$. Similarly, when in a situation without strategic inventory, we can derive the following. When $h > h_2 = (1-\lambda)/2$, $w^N = 1/2$. By comparing the optimal profits of the supplier, we can obtain $h^N = 1-\sqrt{\lambda}$. Take h^N, w^N back to (1)–(4) and (A1) and we can obtain equilibrium results under scenario N in Table 2. □

Proof of Proposition 1. By comparing the sign of the first derivative of the objective value with respect to h, we can obtain the result in the previous line of Proposition 1.

As $\partial\pi_R^N/\partial h = -\frac{-1+h+\lambda+3h\lambda}{8(-1+\lambda)}$, then when $h^N > h > h^{N1} = \frac{1-\lambda}{1+3\lambda}$, we can have $\partial\pi_R^N/\partial h > 0$. □

Proof of Lemma 3. The proof follows the same steps as that of Lemma 1. When $w^P < \frac{-\lambda h\mu+h-\lambda\mu+\lambda+\mu-1}{\lambda-1}$, we can obtain $(q_1^{PN}(w^P), q_2^P(w^P), K^P(w^p)) = (\frac{h}{2-2\lambda}, \frac{h+w^P}{2-2\mu}, \frac{h\lambda\mu-h+\lambda\mu-\lambda-\mu+\lambda w^P-w^P+1}{2(\lambda-1)(\mu-1)})$.

When $w^P \geq \frac{-\lambda h\mu+h-\lambda\mu+\lambda+\mu-1}{\lambda-1}$, Equation (6) becomes as follows:

$$\max \pi_R^N(q_1^{NN}) = \lambda(p_1^{PN}q_1^{PN} - w^P q_1^{PN}) + \lambda p_2^{PN}q_2^P + (1-\lambda)p_2^{PD}q_2^P \tag{A2}$$

Then, we can easily obtain the optimal solution using backward recursion, as follows:

$$(q_1^{PN}(w^P), q_2^P(w^P), K^P(w^p)) = \left(\frac{\mu + w^P - 1}{2\lambda\mu - 2}, \frac{1 + (-1 + w^P)\lambda}{2 - 2\lambda\mu}, 0\right).$$

□

Proof of Lemma 4. Based on Lemma 3, substitute Equations (8)–(10) into (7) and (A2). Then, we can obtain the following. In a situation where strategic inventory exists, the optimal solution for the wholesale price is $w^P = (1 - h - \mu)/2$ if $h < h_3 = (-1 + \lambda + \mu - \lambda\mu)/(-1 - \lambda + 2\lambda\mu)$ satisfies the constraint condition; when $h \geq h_3$, $w^P = \frac{-1+h+\lambda+\mu-\lambda\mu-h\lambda\mu}{-1+\lambda}$. Similarly, when in a situation without strategic inventory, we can derive the following. When $h > h_4 = (-1 + \lambda + \mu - \lambda\mu)/(-2 + 2\lambda\mu)$, $w^P = (1 - \mu)/2$. By comparing the optimal profits of the supplier, we can obtain $h^P = -\sqrt{\frac{\lambda\mu^3 - 3\lambda\mu^2 + 3\lambda\mu - \lambda}{\lambda\mu - 1}} - \mu + 1$. Take h^P, w^P back to (1), (2), (6), and (7) Lemma and (A2) and we can obtain equilibrium results under scenario P in Table 3. □

Proof of Proposition 2. Similar to the proof of Proposition 1, by comparing the sign of the first derivative of the objective value with respect to h, we can obtain the result in Proposition 2. □

Proof of Proposition 3. Similar to the proof of Proposition 2, by comparing the sign of the first derivative of the objective value with respect to μ, we can obtain the result in Proposition 3. □

Proof of Proposition 4. Under the constraint of μ and λ, we can obtain $h^N - h^P > 0$. Under the same h, $K^N - K^P > 0$. □

Proof of Proposition 5. For the piecewise function $\triangle\pi_M$, by separately comparing the values of each stage under different constraints, we can conclude that, for any h in (11), $\triangle\pi_M$ is always bigger than zero. □

Proof of Proposition 6. For the piecewise function $\triangle\pi_R$, by separately comparing the values of each stage under different constraints, we can conclude that, for any h in (12), $\triangle\pi_R$ is always smaller than zero. □

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systems

Article

Application of the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) in a Two-Echelon Cold Supply Chain

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Abstract: A two-stage cold supply chain manages the transportation, storage, and distribution of temperature-sensitive products like frozen food, fresh/green products, and pharmaceuticals, which makes it costly. It consists of three key elements: a supplier, a warehouse, and multiple customers. Procurement planning can be conducted for various products, and this study assumes the transport of a fresh/green product with gradually decreasing quality due to its perishable nature. In a two-stage cold supply chain, multiple objective functions can be defined, including cost minimization, product quality optimization, and transportation/storage condition optimization. We developed a mathematical model to optimize these objectives, incorporating two specific functions, cost minimization and product age reduction, to ensure efficient supply chain performance. Traditional solution methods often struggle with multi-objective mathematical models due to their complexity. Therefore, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), a Genetic Algorithm-based approach, was applied to solve the model efficiently. NSGA-II optimized planning for a 7-day period under specific demand conditions, ensuring better resource allocation. The results showed that NSGA-II was better than traditional methods at making decisions and routing efficiently in the two-stage cold supply chain. This led to much better outcomes, with lower costs, less waste, and better product quality throughout the process.

Keywords: two-echelon inventory system; cold supply chain; multi-objective function; meta-heuristic algorithm; NSGA-II

1. Introduction

The cold supply chain is a process that involves ensuring and maintaining the appropriate temperature conditions required from the production to the storage, distribution, and consumption of frozen food, fresh/green products, medicines, and other perishable goods. For this reason, it is critically important to ensure food safety, extend the shelf life of products, and reduce costs. In the literature, the importance of supply chain collaboration in cold supply chain management is emphasized [1,2]. Since the cold supply chain requires products to be transported under specific temperature conditions, studies on how supply chain integration can be used to meet these special requirements are also of great importance. In this context, cold chain management requires a comprehensive approach that includes various factors such as sustainability, risk management, supply chain integration, and collaboration. In cold supply chains, many problems can arise due to the numerous factors associated with the transported product and the system. We can summarize some common problems in cold supply chain management as follows:

Temperature control: Since products need to be kept within a certain temperature range, temperature control is a critical factor in the cold supply chain. If the temperature exceeds the specified temperature range, it can seriously affect the quality and efficacy of the products.

Moisture levels: It is of great importance to keep moisture levels under control, especially for medicines, chemicals, and fresh/green products. Inappropriate humidity levels for products can cause them to spoil or become ineffective.

Light intensity: Some medications and chemicals can deteriorate or become unusable under the influence of light. Therefore, the product must be kept under controlled conditions to ensure the most suitable light intensity.

Carbon dioxide levels: Monitoring carbon dioxide levels is critically important, especially in products that undergo fermentation or chemical reactions. High levels of carbon dioxide can negatively affect the quality of these products.

Lack of traceability: The lack of traceability of products at every step of the supply chain causes interventions that need to be made in critical situations to be delayed.

Health risks and safety concerns: The deterioration or ineffectiveness of product quality can lead to health and safety risks. For this reason, ensuring the optimal level of cold supply chain management is of vital importance.

In the following sections, we present a structured literature review that situates this study within the broader context of cold supply chain optimization, highlighting key gaps and emerging trends. We then detail our Materials and Methods, elaborating on the multi-objective mathematical model and the NSGA-II–based solution procedure. After describing the dataset and experimental design, we share and discuss our results, underscoring how the proposed framework improves cost efficiency and freshness preservation compared to traditional methods. Finally, this paper concludes with Implications and Future Research Directions, offering insights into how these findings can guide more sustainable and effective cold supply chain strategies.

2. Literature Review

The two-echelon cold supply chain management involves a multi-layered approach to managing the flow of perishable goods, ensuring quality and minimizing waste. This system typically includes a supplier and a retailer, with a focus on transportation modes, inventory management, and pricing strategies to optimize supply chain performance [2,3]. The integration of cold chain logistics is crucial for maintaining product quality, especially for perishable goods, and involves strategic decisions regarding transportation and inventory management. In terms of transportation modes, cold chain transportation is essential for maintaining the quality of perishable goods, such as fresh produce, during long-distance transport [4,5]. It benefits all supply chain participants, including consumers, by reducing both quality and quantity loss [6]. The choice between low-cost normal temperature transportation and high-cost cold chain transportation depends on cost thresholds and contractual agreements, such as revenue-sharing contracts, which can incentivize suppliers to adopt cold chain logistics [7]. The inventory management side is another perspective. Efficient inventory management is critical for sustainability in pharmaceutical supply chains, where lateral transshipment can reduce costs and minimize product deterioration [7–10]. A mixed-integer non-linear program (MINLP) model can optimize replenishment order quantities and shipment times, thereby reducing waste and ensuring a sustainable supply of medicines [7].

While the two-echelon cold supply chain management offers numerous benefits, challenges such as high transportation costs and the need for coordination among supply chain members persist. These challenges necessitate strategic planning and collaboration to ensure the sustainability and efficiency of the supply chain [11–13]. A two-echelon cold supply chain can be defined as a supply chain model that involves the management and transportation of products through two different stages of the cold supply chain [12, 14,15]. In this type of supply chain, elements such as suppliers, cold storage facilities, distribution/transportation vehicles, and customers are involved. In two-stage cold supply chains, supply planning for many products can be carried out. In this study, it is assumed that a fresh/green product with gradually decreasing quality will be transported. In a two-stage cold supply chain, multiple objective functions can be determined, such as cost minimization, product quality optimization, product transportation conditions optimization, product storage conditions optimization, etc. This study aims to analyze a two-stage cold supply chain with a supplier and a warehouse selling a product in the market under a certain demand. The fresh/green product received from the supplier will be stored in a single warehouse before customer distribution. It is accepted that the quality of the product transported along the supply chain gradually decreases. Therefore, the aim is to keep the storage duration of fresh/green products in the intermediate warehouse short. A mathematical model has been proposed to minimize expected costs and achieve the best solution. To solve the mathematical model, one of the meta-heuristic algorithms, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II), has been used. The results obtained from the solution are presented in this study. Suggestions have been made based on the results obtained. Liu, Chen, and their colleagues presented a dynamic planning model in their 2021 study aimed at delivering fresh products to customers in a two-stage cold supply chain [15]. In their 2020 study, Wang and Wen aimed to solve the vehicle routing problem for cold supply chains by considering costs and carbon emissions as performance metrics. Under the constraints and performance metrics they established, they created a model for the two-stage heterogeneous vehicle routing problem and proposed the Adaptive Genetic Algorithm (AGA) approach to reach a solution. Based on the results obtained, they made recommendations to logistics companies, governments, and consumers involved in the cold chain to support the improvement of cold supply chain development [16]. Liu and colleagues (2021) stated in their published article that delivering fresh products to customers is the primary objective of the two-stage cold supply chain model they addressed. In the two-stage cold supply chain they established, a producer and a retailer collaborate. In the study, the producer decides on the effort to maintain optimal product freshness, while the retailer decides on the level of optimal advertising effort. In the decentralized decision-making mode, they showed that both the freshness factor and the optimal levels of effort significantly decrease due to the reduction in profit margins. To solve this problem, they proposed a dynamic control model. At the same time, they developed a dynamic linear bonus scheme [15]. Jaigirdar and his colleagues, in their study published in 2022, aimed to reduce the annual supply chain cost and the cold storage setup cost for a sustainable supply chain while maintaining the freshness of perishable products by establishing an appropriate distribution system. For this purpose, a multi-stage and multi-product three-objective optimization model was developed in the study [17]. In the established optimization model, a mixed-integer linear programming model was proposed to solve the supply chain distribution network problem. For the remaining part of the model, the weighted sum method was used, and the solution was reached using the CPLEX optimization studio [3]. Theeb and colleagues published a study in 2023 focusing on vaccine distribution, one of the key issues to be addressed during the pandemic. They argued that building permanent warehouses to address the weak infrastructure and other challenges that do not meet the urgent vaccine needs in developing countries is impractical. To address the specified issues in vaccine supply, they proposed a two-tiered approach [18].

The Non-Dominated Sorting Genetic Algorithm II (NSGA-II) is a powerful tool for optimizing two-echelon cold supply chain systems, offering numerous advantages. These include strong multi-objective optimization, better handling of complex logistics, and the ability to balance competing goals such as cost, carbon emissions, and customer satisfaction. NSGA-II is particularly valuable for cold supply chains because it generates Pareto-optimal solutions, allowing decision-makers to easily compare and choose among different objectives.

One of the main benefits of using NSGA-II for two-echelon cold supply chains is its effectiveness in addressing multiple objectives at once. This is especially important in cold chains, where cost, carbon emissions, and product freshness must all be considered. Researchers have applied NSGA-II to optimize distribution routes by factoring in traffic conditions and replenishment strategies, significantly cutting both costs and emissions while keeping products fresh [19]. The algorithm pinpoints sets of Pareto-optimal solutions, helping decision-makers select the best balance between competing goals like cost and quality [20,21]. NSGA-II also strengthens the resilience of supply chain networks by optimizing attributes like agility, leanness, and flexibility. This is especially useful for addressing risks and uncertainties in cold supply chains [22]. The system adapts to shifting conditions, such as urban traffic congestion, and still delivers reliable planning outcomes in unpredictable circumstances [19]. Moreover, NSGA-II helps strike a balance between economic and environmental goals by optimizing inventory and transport decisions in accordance with carbon emissions limits, a crucial consideration for cold chains, which produce significant emissions from refrigerated transport and storage [23].

Combining NSGA-II with hybrid methods, such as large-scale neighborhood search, further boosts its ability to explore vast solution spaces and avoid local optima, thereby improving local search performance [19]. Its flexibility also allows for easy customization to meet specific supply chain needs, ranging from optimizing storage in automated systems to managing dual-sale channel networks [24,25]. However, when using NSGA-II for two-echelon cold supply chain optimization, it is important to consider the algorithm's computational complexity and the need to fine-tune parameters like population size, crossover, and mutation rates for the best results [26]. Additionally, while NSGA-II handles multiple objectives well, dealing with an extremely large number of them may require further refinements or hybrid approaches to maintain efficiency [27]. NSGA-II efficiently integrates many constraints, ensuring that optimized routing and inventory strategies align with the specific requirements of cold logistics operations.

3. Materials and Methods

The mathematical formulation of the problem and the methodological approach are presented in this section. Additionally, the fundamental principles of the NSGA-II algorithm and its application steps are discussed comprehensively, ensuring a holistic explanation of the methods employed.

Two-Stage Cold Supply Chain Problem: The main objectives of the established model are as follows:

- Minimizing routing and inventory costs;
- Minimizing the number of vehicles used;
- Minimizing the number of spoiled fresh/green products.

Mathematical Model: The mathematical model is one of the engineering methods used to solve problems. At the same time, it represents the problem by forming a basis for other solution methods. In the mathematical model established based on the assumptions and premises made for this study, the optimization model developed by Rohmer and others in their 2019 publication, "A Two-echelon Inventory Touting Problem for Perishable

Products", has been referenced [28,29]. The sets used in the developed mathematical model and their descriptions are summarized in Table 1.

Table 1. Sets used in the mathematical model and their descriptions.

Cluster	Explanation
N	The set of nodes indexed by i, j, l is {depot:0; customer: 1, . . ., n}
A	Set of springs (i, j): $i, j \in$ N, $i \neq j$
T	The set of periods indexed by t
K	The set of vehicles indexed by k: $k \in \{1, \ldots, m\}$
G	The set of product ages indexed by g
R_i	The set of visit combinations of i

The parameter variables used in the mathematical model and their explanations are presented in Table 2.

Table 2. Parameters used in the mathematical model and their explanations.

Parameter	Description
c_{ij}	(i, j) the guidance costs on the bow: $i, j \in \{0, \ldots, n\}$.
C	supplier–warehouse–supplier line transportation routing cost
d_i^t	i the customer's demand in period t
Q^k	k the capacity of the vehicle (k = 0: supplier–warehouse; k = 1, 2, 3: warehouse–customer)
H	warehouse inventory holding capacity
h^g	g unit holding cost in the warehouse for product age (including spoilage cost)
a^{rt}	If the combination of r visits on day t is equal to 1

Simultaneously, Table 3 displays the variables and explanations of the mathematical model.

Table 3. Variables used in the mathematical model and their explanations.

Variable	Description
x_{ij}^{kt}	If customer j is visited by agent k in period t immediately after customer i, it is equal to 1.
y_i^{kt}	If the intermediary visits customer i in period t, it is equal to 1
z_i^r	If the r visits combination of customer i is selected, it equals 1
u^t	The number of supplier–warehouse vehicles in period t.
v_i^{gkt}	The quantity of g age delivered to customer i from the warehouse by vehicle k during period t
w^t	The quantity delivered from the supplier to the warehouse during period t.
I^{gt}	the amount of g age stored in the warehouse during the t period
s_i^{kt}	the position of vehicle k on the route of customer i at time t

3.1. Objective Functions

In the mathematical model, two different objective functions have been created. Equation (1) is the first of the objective functions created. The aim of this objective function is to minimize the total cost of the two-stage cold supply chain. Equation (1) includes transportation costs, inventory holding costs, and distribution costs to customers. In Equation (2), the main aim of the objective function is to minimize the age of the products available in the cold supply chain. In this way, the number of spoiled products in the system is reduced, thereby minimizing product waste.

$$Minimise \sum_{t \in T} Cu^t + \sum_{g \in G} \sum_{t \in T} h^g I^{gt} + \sum_{i \in N} \sum_{j \in N} \sum_{k \in K} \sum_{t \in T} C_{ij} x_{ij}^{kt} \tag{1}$$

$$Minimise \sum_{i \in N} \sum_{k \in K} \sum_{t \in T} v_i^{gkt} \tag{2}$$

3.2. Constraints

Constraints are crucial for accurately representing the existing conditions and assumptions within the model, in conjunction with the established objective functions, to attain optimal outcomes. This study has identified a total of 18 restrictions. Within these established restrictions, the resolution of the target functions and the optimal transportation and storage strategy in the supply chain will be attained. Equations (3) and (4) are storage/inventory constraints related to the age of the product. Products that reach a fixed age, as determined by Equation (3), are removed from inventory and not distributed to customers. This constraint prevents the delivery of products that have deteriorated in quality to users.

$$I^{gt} = I^{g-1,t-1} - \sum_{i \in N} \sum_{k \in K} v_i^{g-1,k,k-1} g \in G \backslash \{0\}, t \in T \backslash \{0\} \tag{3}$$

$$I^{0t} = w^t \ t \in T \tag{4}$$

Equation (5) is a constraint added to determine the delivery to the warehouse for updating the inventory. It also determines the deliveries made from the supplier to the warehouse.

$$I^{gt} \geq \sum_{i \in N \ \{0\}} \sum_{k \in K} v_i^{gkt} \ , \ g \in G \ , \ t \in T \tag{5}$$

Equations (6) and (7) ensure that the inventory level meets at least the customer deliveries for the same period. At the same time, they ensure that the fixed inventory capacity of the warehouse is not exceeded in the solution obtained.

$$\sum_{g \in G} I^{g0} = w^0 \tag{6}$$

$$\sum_{g \in G} I^{gt} \leq H \ , \quad t \in T \tag{7}$$

In the delivery plan of the optimal solution, the condition for meeting each customer's demand is included in the mathematical model expressed in Equation (8).

$$\sum_{r \in R_i} a^{rt} d_i^t z_i^r = \sum_{g \in G} \sum_{k \in K} v_i^{gkt}, \ i \in N \backslash \{0\}, \ t \in T \tag{8}$$

With Equation (9), the quantity of products that can be delivered to the warehouse for the optimal solution is restricted based on warehouse capacity and current inventory.

$$w^t \leq H - \sum_{g \in G} I^{g,t-1}, \ t \in T \tag{9}$$

With Equations (10) and (11), a fixed vehicle capacity constraint has been added for the vehicles to be used for delivery to the warehouse and the customer.

$$\sum_{g \in G} \sum_{i \in N \setminus \{0\}} v_i^{gkt} \le Q^k y_0^{kt} \,, \; k \in K, \; t \in T \tag{10}$$

$$w^t \le \; Q^0 u^t, \;\; t \in T \tag{11}$$

The assumption that each delivery to a customer in each period can only be made by a single vehicle has been added to the model as a constraint in Equation (12). While Equation (12) addresses the single vehicle constraint, Equation (13) imposes the constraint that each delivery in that period will be made with the vehicle that is active during that period.

$$\sum_{k \in K} y_i^{kt} \le 1, \;\; i \in N \setminus \{0\}, \; t \in T \tag{12}$$

$$y_i^{kt} \le \sum_{j \in N} x_{ij}^{kt} \le 1, \;\; i \in N, \; k \in K, \; t \in T \tag{13}$$

A delivery plan will be assigned to each customer according to their requests. Equation (14) ensures that a single delivery assignment is made to each customer for this assignment. Equation (15) ensures that the delivery plan assigned to each customer, based on Equation (14), is followed.

$$\sum_{r \in R_i} z_i^r, \;\; i \in N \setminus \{0\} \tag{14}$$

$$\sum_{i \in N} \sum_{k \in K} x_{ij}^{kt} - \sum_{r \in R_i} a^{rt} z_j^r = 0, \;\; j \in N \setminus \{0\}, \; t \in T \tag{15}$$

$$\sum_{i \in N} x_{ij}^{kt} - \sum_{l \in N} x_{jl}^{kt} = 0, \;\; k \in K, \; t \in T, \; j \in N \tag{16}$$

In addition to all the constraints between Equations (3) and (16), the model includes constraints that ensure that the variables added to achieve the optimal solution are not negative.

3.3. Assumptions

This section explains the assumptions used in this study. In the two-stage cold supply chain, the supplier is considered a single entity, as they collect the green product from the producers. The fresh/green product received from the supplier will be stored in a single warehouse before customer distribution. Customers are located within a circular area with a radius of 25 km, where the depot is at the center. Each customer's distance to the warehouse is within this circle. All customers' demands follow a normal distribution. The interval between two consecutive delivery periods for each customer will be 2 periods. At the same time, multiple vehicles cannot deliver to the same customer within the same period. The supply chain gradually decreases the quality of the products it transports. To determine the quality criteria for each product, its age will be made available. We consider the products' ages to be zero when they arrive at the warehouse. Upon delivery to the warehouse, each subsequent period sees a fixed increase of 1 in the product's age. If the product's age in the warehouse exceeds 33% of the expiration date, the relevant products will not be delivered to customers and will be removed from the warehouse inventory.

3.4. Genetic Algorithm

The Genetic Algorithm (GA) is a meta-heuristic algorithm first proposed by John Holland in the 1970s. Developed based on Darwin's theory of evolution and known as an evolutionary algorithm, the GA solves computer-based problems by using gene exchange between living things as a model. The GA allows for faster and easier solutions to clustering and very large optimization problems that are difficult to solve with traditional methods [30].

In order to reach a solution for the mathematical model in the GA, the objective function must be defined in accordance with the constraints, and the gene and chromosome structure must be created [31]. A few possible solutions are determined to solve a specific problem. A program is written to test each solution alternative. This program is run, and, according to the results, alternatives that do not fit the objective function are eliminated and code exchange occurs between the remaining ones. This process, which resembles gene exchange between living things, fosters a diversity of alternatives. The working steps of the GA are explained in four steps [32].

Step 1: First, all possible solution alternatives in the search space are coded, and individuals are created.

Step 2: Random individuals are selected from the individuals created in Step 1 and brought together to form the initial population. The size of the created population can affect the speed of the algorithm steps. Many individuals in the population cause algorithm steps to take a long time, but they also increase the solution quality.

Step 3: Fitness values are calculated for each individual. The fitness function allows the fitness levels of the determined solutions to be measured. It provides the result to be obtained by adapting the individual to the system. Thanks to this function, the missing information in the individual can be eliminated, and numerical values can be obtained.

Step 4: The most important part of the reproduction process is the selection operator. With this operator, the individual diversity in the algorithm will increase; thus, different regions can be searched in the solution space. There are different selection methods in the literature. Individuals with a high fitness function are transferred to the next generation. The individuals in the new generation are passed through the crossover and mutation stages, respectively. Crossover involves the creation of a new individual through gene exchange between two individuals. In the solution space, the crossover process is determined by the crossover rate, and the number of chromosomes to be mutated is determined by the mutation rate. An example of crossover and mutation is given in Figure 1.

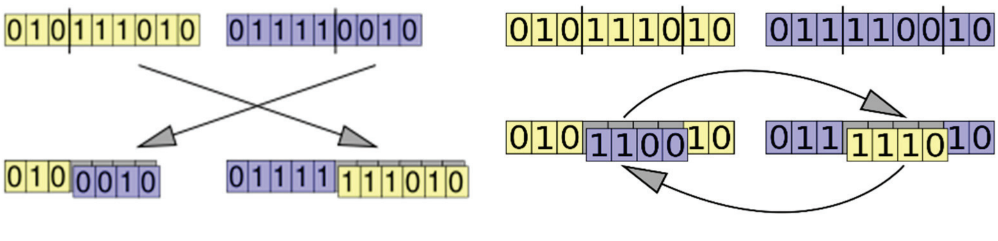

Figure 1. Example of crossover and mutation.

Step 5: After the reproduction operations performed on the individuals in Step 4, a new generation population is created.

Step 6: The cycle in Figure 1 is repeated until the optimal solution is reached. The cycle is terminated when the desired success is achieved.

3.5. NSGA-II and Application Steps

The NSGA-II algorithm is a multi-purpose meta-heuristic algorithm that was introduced to the literature by Deb and his colleagues in their 2002 study. The NSGA-II algorithm emerged because of the development of the NSGA algorithm, which was developed by Srinivas and Deb in 1995 [33,34]. The basic structure of the NSGA-II algorithm is based on the Genetic Algorithm (GA). The basic steps of the Genetic Algorithm include dominance ranking and accumulation distance calculation.

3.5.1. Elitism

If elitism is used uncontrolled, the diversity of individuals in the population may decrease. This may lead to an increase in individuals with the same fitness value. It has been observed that elitism significantly contributes to the success of the GA in selecting individuals with the best results and transferring them to the next generation [35,36]. Figure 2 shows the elitism stages.

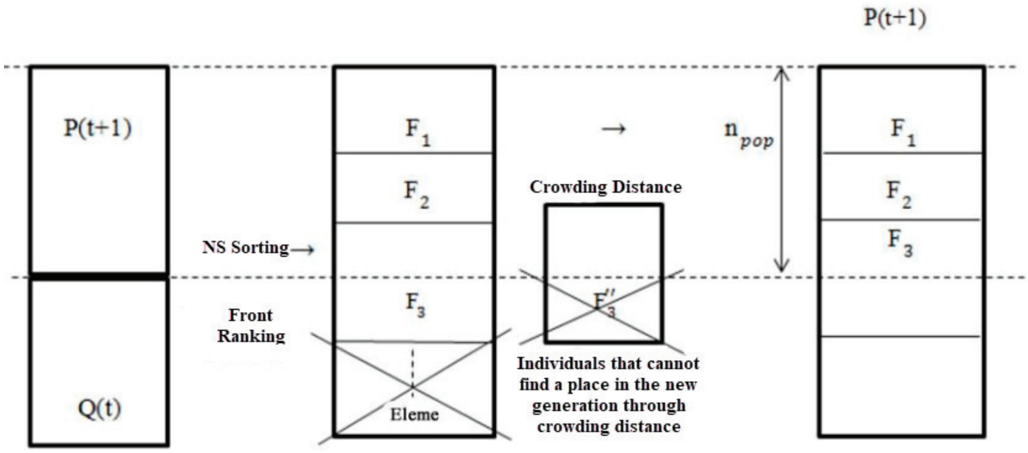

Figure 2. Stages of elitism.

If we examine elitism through the stages of elitism in Figure 2, individuals in F1 and F2 can fit into P_(t + 1), belonging to the new population. However, the number of individuals in F3 exceeds P_(t + 1). Since the dominance degrees of individuals in F3 are equal to each other and exceed the size of the new population, some of the individuals in F3 must be eliminated [17].

3.5.2. Dominance Rating

A method of comparing individuals in a population with each other, together with dominance rating, is employed. The number of times each individual has been defeated by other individuals is counted. If there is an individual or individuals who have never been defeated, these individuals are placed in the first rank and F1. Thus, the rank of individuals in F1 is accepted as 1. Individuals in F1 are then removed from the population being compared. In this way, the effect of F1 individuals is eliminated in other comparisons to be made. Thus, the remaining individuals who cannot be defeated form F2. This process is repeated until all individuals in the population are ranked.

A dominance ranking example is given in Figure 3. When there is no n-dominance ranking in the f1 and f2 space, a choice can be made between solutions/individuals 2 and 3. Solution 2 could be chosen because it suppresses solution 3. However, solutions 1 and 4 do not have an advantage over each other. In other words, there is no clear dominance between them. Therefore, the choice between solutions can be made in conjunction with ranking.

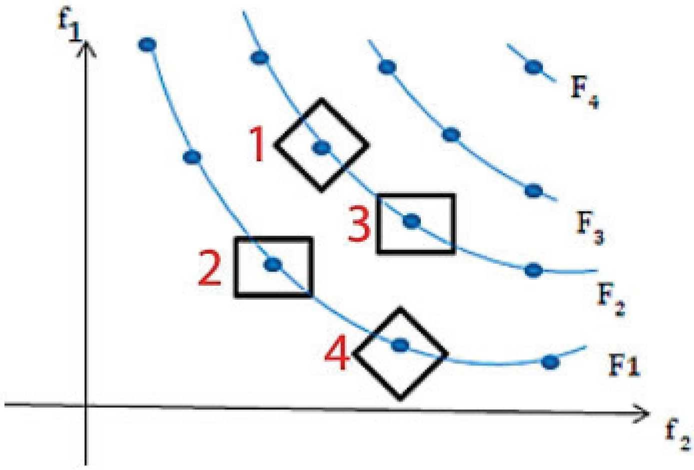

Figure 3. Dominance ranking example.

3.5.3. Crowding Distance

For an individual to be transferred to the next generation, the degree given dominance must be low. Crowding distance can be used in the NSGA-II algorithm to choose between individuals with equal dominance degrees. Density distance is used to prioritize individuals with equal ranks. An example of density distance is shown in Figure 4.

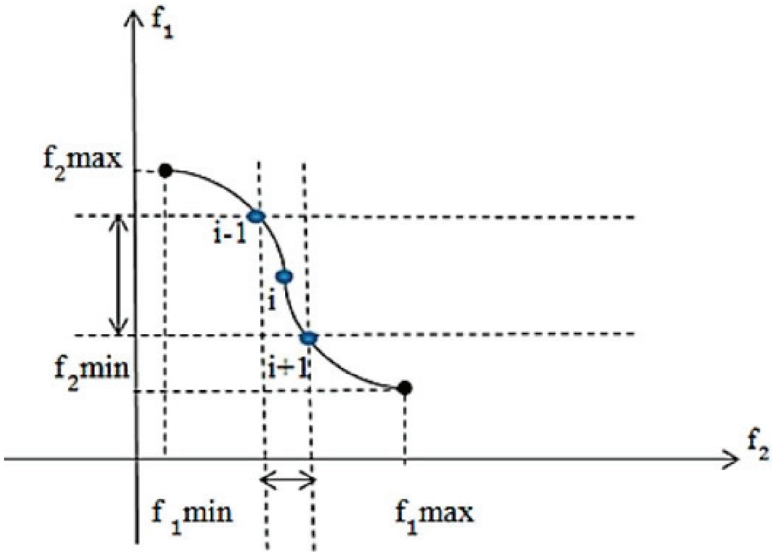

Figure 4. Density distance example.

Density distance is calculated according to the previous and next neighboring individuals of the selected individual, as well as the first and last individuals present in the population. The calculation is shown in Equation (17). According to Equation (17), the individuals whose aggregation distance is calculated are ranked from largest to smallest. As a result of this ranking, the individuals at the top have a higher overlap rate with other individuals and are therefore given priority in transferring to the next generation.

$$\begin{gathered} d_i^1 = \frac{\left| f_1^{i+1} - f_1^{i-1} \right|}{f_1^{max} - f_1^{min}} \\ d_i^2 = \frac{\left| f_2^{i+1} - f_2^{i-1} \right|}{f_2^{max} - f_2^{min}} \\ d = d_i^1 + d_i^2 \end{gathered} \tag{17}$$

Figure 5 outlines the main steps of a multi-objective genetic algorithm (e.g., NSGA-II). First, data input is used to create an initial population of candidate solutions. Each solution is then evaluated against the objective functions (f1, f2), and a fitness function and crowding distance are calculated. Based on these measures, genetic operators (selection, crossover, and mutation) generate new offspring. Next, non-dominated sorting sorts the answers by the level of dominance and the distance between the solutions, combining the parent and offspring populations. The algorithm checks whether a termination criterion (such as a maximum number of generations or a convergence threshold) is met. If not satisfied, it continues iterating. Otherwise, it shows the final results, which ideally form a set of non-dominated (Pareto-optimal) solutions.

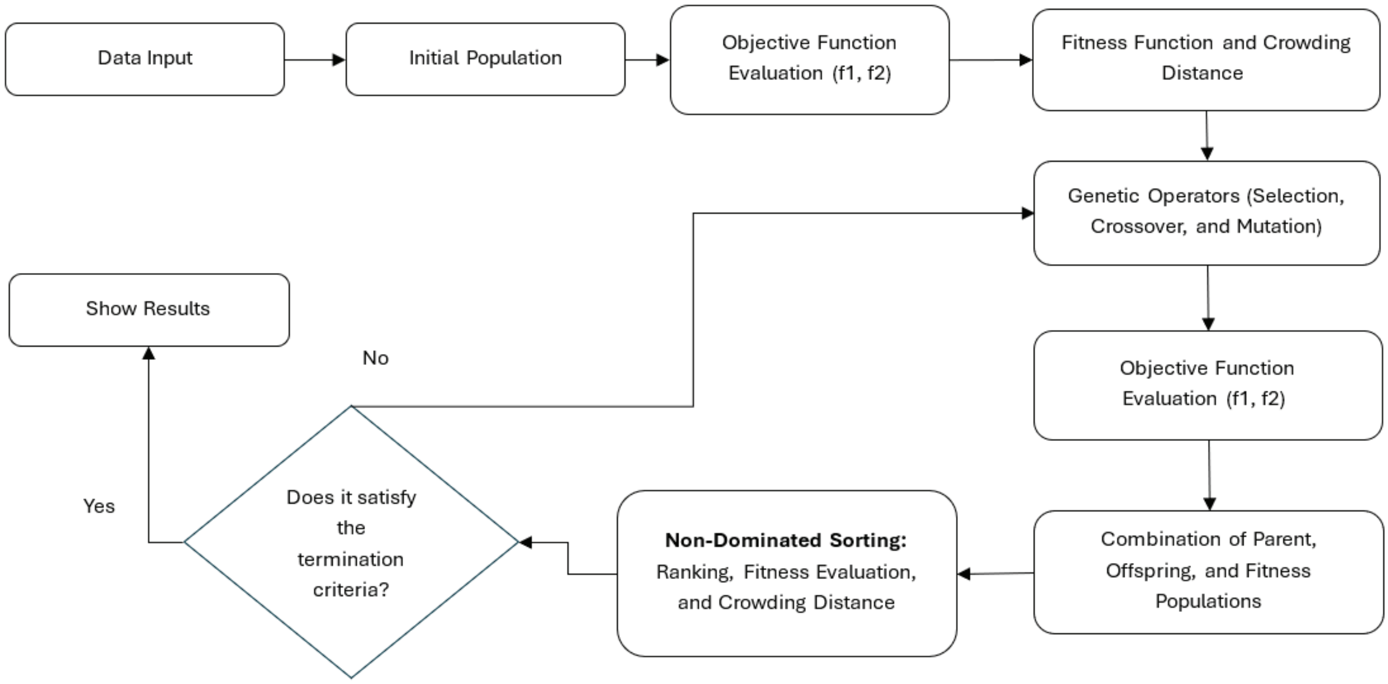

Figure 5. NSGA-II algorithm flowchart.

3.6. Problem Assumptions

There is a single supplier, a single warehouse, and multiple customers in this model. It is assumed that the model works with multiple vehicles. Customer demands are in accordance with the normal distribution and are estimated accordingly. The two-stage cold supply chain model is intended to be planned for a 7-day period. The distance from the supplier to the warehouse is 32 km. It is assumed that the warehouse is located at the center of a circle with a radius of 25 km. In line with this assumption, the maximum distance from each customer to the warehouse is 25 km. The locations of the customers relative to the warehouse are determined randomly. The First-in First-out rule is adopted when the products arriving at the warehouse are removed from the warehouse in line with customer demands. When the SKT date, i.e., age (g), of a product is 7, that product will be considered completely spoiled. At the same time, according to data received from A Cold Chain Logistics Company, products with a maximum product age of 33% can be accepted by customers in the green/fresh product market. In line with this information received about the market, it has been determined that green/fresh products with a product age equal to or greater than 3 will be removed from stock and directed to the determined alternative solutions to reduce costs. The values given for the algorithm variables used in the NSGA-II algorithm are provided in Table 4.

Table 4. Algorithm variable values.

Parameter	Value
Iteration number	1000
Maximum number of iterations without improvement	200
Population number	100
Mutation rate	It is determined by the program to be less than 0.1.
Crossover	Single point crossover
Selection	Dominance rating, aggregation distance, and elitism

3.7. Dataset Used

Since a 1-week daily planning period is needed in the dataset used, the period is defined as 7 to represent the 7 days of the week. The number of vehicles is assumed to be fixed to optimize the benefit from the existing vehicles. No new vehicles will be purchased or rented. It is not mandatory to use all vehicles. Other fixed data used in the algorithm are given in Table 5.

Table 5. Data used in the model solution with the algorithm.

Parameter	Value
t (period)	7
Number of customers	15
k (number of vehicles)	6
H (warehouse inventory capacity)	800
Capacity of each vehicle (k)	350

4. Results

We used the algorithm variable values summarized in Table 4 to solve the model. We performed tests on the model after determining the algorithm variable values in Table 4. Table 6 summarizes the test results for the iteration number. According to the results obtained as a result of the tests, it was observed that the same results were achieved for iteration number values equal to or greater than 1000. As a result of this finding, it was decided that the iteration number would be 1000 since using an iteration number greater than 1000 would make the algorithm heavier.

Table 6. Test results for determining the iteration number.

	Iteration Numbers						
Results	**600**	**800**	**900**	**1000**	**1100**	**1200**	**2000**
Cost	895.159	654.483	603.199	589.787	589.787	589.787	589.787
Mean Vehicle Numbers	7	6	6	5.5	5.5	5.5	5.5

The locations of 15 customers were randomly determined in a circle with a radius of 25 km, with the warehouse at the center. The randomly determined customer locations are shown in Figure 6. At the same time, the location of the supplier, which is 32 km from the warehouse, is also shown in Figure 6.

Figure 6. Warehouse, supplier, and randomly determined customer locations.

It has been determined that customer demands are in accordance with normal distribution. The mean of the customer demands in accordance with normal distribution is 98 units, and the standard deviation is 18 units. The First Period customer demand estimates determined in accordance with normal distribution are shown in Figure 7.

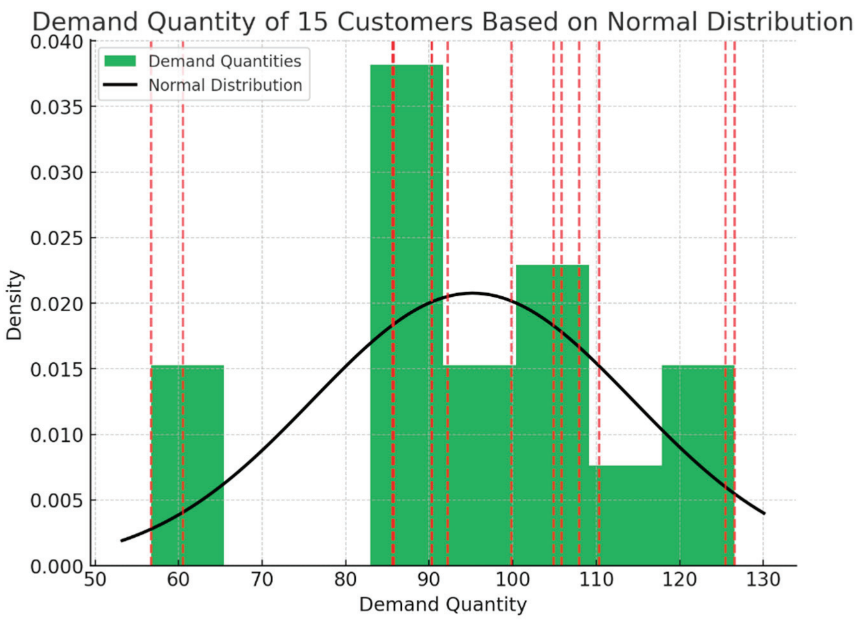

Figure 7. Customer demand forecast graph for Period 1.

The number of individuals that were eliminated and not evaluated in each iteration as a result of the selection operators (dominance rating, clustering distance, and elitism) in the NSGA-II algorithm is shown in Figure 8.

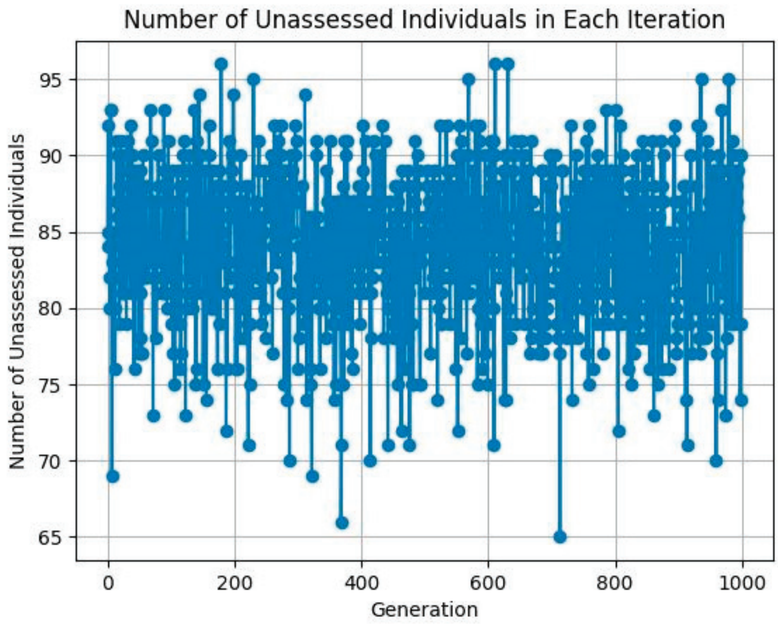

Figure 8. Number of individuals eliminated in each iteration.

In the solution of the mathematical model obtained using the integer programming method, the total cost, including the cost of spoiled products, was calculated to be 1,073,197.00. The cost variation graph obtained from the implementation of the NSGA-II algorithm is presented in Figure 9. According to this graph, the total cost was significantly reduced using the NSGA-II algorithm. Although it may appear that the cost has not been fully minimized in the graph, there is a notable difference compared to the solution obtained through integer programming. Using the NSGA-II algorithm and data from the fresh product market, the cost of spoiled products has been minimized to the point of being nearly eliminated. Additionally, the algorithm has provided recommendations on how to handle products that cannot be delivered to customers. While minimizing costs, the routes for vehicles during each period were also determined. The routes for Vehicle 1 across all periods are presented in Figure 10.

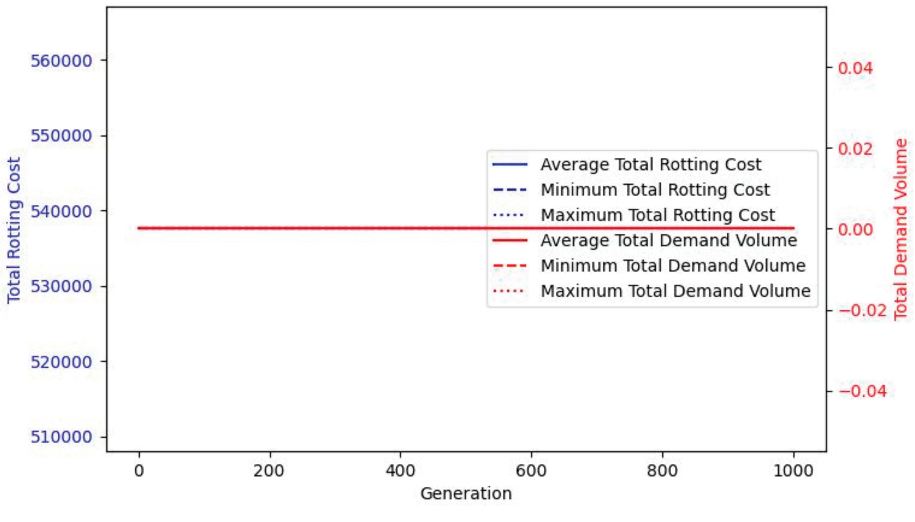

Figure 9. Cost change graph resulting from NSGA-II.

To provide an in-depth analysis of the algorithm's performance, we compared the NSGA-II results to those obtained from a traditional integer programming (IP) method—one of the most commonly employed exact approaches in multi-objective optimization.

While IP methods are reliable for smaller-scale problems, they often become computationally infeasible or yield suboptimal solutions when dealing with complex multi-objective or large-scale scenarios. In contrast, NSGA-II efficiently navigated the extensive solution space of our two-echelon cold supply chain model, identifying high-quality Pareto-optimal solutions that incorporate cost minimization, product freshness, and routing efficiency. Notably, NSGA-II consistently outperformed the IP approach by significantly reducing total operational costs—primarily through more precise vehicle routing and dynamic inventory control—while simultaneously maintaining better product quality. This outcome underscores the algorithm's enhanced ability to address the trade-offs inherent in perishable goods distribution, which directly impacts the overall profitability and service levels of cold supply chain operations.

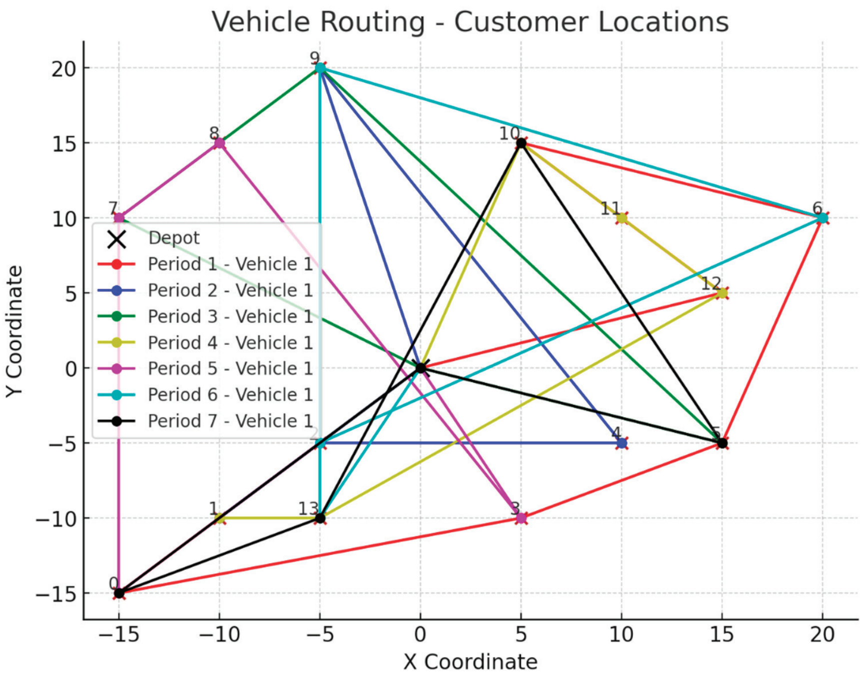

Figure 10. Routes of Vehicle 1 across all periods.

From a cost perspective, the NSGA-II solutions achieved demonstrable reductions in transportation, storage, and spoilage costs. This improvement can be attributed to the algorithm's adaptive search mechanism, which iteratively refines solution candidates based on both dominance ranking and crowding distance. By effectively balancing multiple conflicting objectives (e.g., route length, demand fulfillment, and freshness constraints), NSGA-II prevented cost overruns often seen in classical methods that lack robust multi-objective search capabilities. Our findings reinforce NSGA-II's viability in complex, real-world applications, where lower total costs and minimized waste translate into significant competitive advantages.

The results obtained in this study carry important implications for both academics and practitioners in cold supply chain management. First, the remarkable cost savings and reduced spoilage rates indicate that NSGA-II can serve as a robust decision-support tool, guiding logistics managers toward optimized routing schedules, inventory management strategies, and handling protocols. By incorporating practical constraints, such as temperature maintenance, product age tracking, and vehicle capacity limitations, the proposed framework ensures that solutions are not only theoretically sound but also readily implementable in real-world distribution networks.

Second, the algorithm's capacity to balance environmental and economic considerations highlights its potential to support sustainable cold chain operations. Minimizing spoilage and enhancing transportation efficiency both diminish the carbon footprint of perishable product distribution, a goal that is increasingly pivotal in meeting corporate social responsibility (CSR) standards. Additionally, the algorithm's adaptability allows it to be seamlessly extended to other perishable goods sectors (e.g., pharmaceuticals, dairy products), enabling broader industry adoption. Future studies could integrate emerging digital technologies—such as blockchain-enabled traceability or IoT-based temperature monitoring—to further enhance the model's responsiveness and resilience. Overall, the NSGA-II-driven approach demonstrated here not only advances the scholarly discussion on multi-objective optimization in cold supply chains but also offers tangible, data-driven strategies for industry professionals aiming to balance cost efficiency with product quality and sustainability goals.

5. Conclusions

In this study, we investigated a two-echelon cold supply chain optimization problem by incorporating product age as a critical decision variable and applying the Non-Dominated Sorting Genetic Algorithm II (NSGA-II). Our comparative analysis with traditional integer programming (IP) methods demonstrated NSGA-II's superior capability in navigating the complexity of multi-objective constraints in perishable goods distribution. Specifically, NSGA-II outperformed IP in minimizing total operating costs, reducing spoilage, and maintaining robust routing and inventory strategies. In the literature, traditional solution methods do not perform well when addressing models with multiple objective functions. Therefore, to solve the model developed for a two-stage cold supply chain, the Non-Dominated Sorting Genetic Algorithm II (NSGA-II) was used by developing a Genetic Algorithm. The planning for a 7-day period under specific demand was optimized using NSGA-II. The results obtained from this study demonstrate that NSGA-II performs better than traditional methods in minimizing costs and optimizing routing in the two-stage cold supply chain, achieving significantly better routing results.

The NSGA-II algorithm can be defined as an advanced version of the Genetic Algorithm, which is a meta-heuristic algorithm frequently used in problem-solving. Although the Genetic Algorithm is widely used for solving various problems, certain modifications were made to address its limitations, leading to the development of NSGA-II. As a result, the NSGA-II algorithm has become increasingly popular for solving complex problems that are difficult to address using traditional methods and Genetic Algorithms. In this study, the effectiveness of the NSGA-II algorithm in solving a two-stage cold supply chain problem is analyzed. Compared to traditional methods in the literature, NSGA-II achieved better results in cost minimization and routing optimization. The algorithm exhibited strong performance in minimizing overall costs and the costs associated with spoiled products.

To prevent fresh/green products that have reached a certain age from being delivered to customers, a new objective function and constraints were added to the mathematical model. With the inclusion of this objective function and constraints, the NSGA-II algorithm was used to achieve an optimal solution. This approach minimized the cost of spoiled products and eliminated waste. Fresh/green products that have reached a certain age can be repurposed in various ways. Some proposed alternatives are listed as follows:

- Discounted sales;
- Donation;
- Processed product production: Aged products can be converted into processed goods. For example, fruits can be used to produce jam or fruit juice;
- Composting and animal feed production.

This research makes several noteworthy contributions. First, it explicitly models product age within a multi-objective optimization framework, offering a more nuanced view of perishability and time-dependent product quality. Second, it validates NSGA-II's strength in balancing conflicting objectives—cost, route efficiency, and freshness—within the unique constraints of cold chain systems. Third, it demonstrates how decision-makers can customize the algorithm for different scenarios, thereby enhancing route planning and inventory policies across multiple industries and perishable product categories. Aged or spoiled fresh/green products can be used for energy generation in biogas plants. This not only repurposes the products but also contributes to energy production. Future studies can focus on a detailed analysis of where aged products should be utilized within the model, introducing a new level of classification. This additional level would allow for strategic planning regarding how spoiled or aged products contribute to the system. As the model is further developed, the NSGA-II algorithm can be reassessed, different algorithms may be employed to achieve an optimal solution, or an integrated artificial intelligence-based system may be utilized.

For future academic studies, the dynamic nature of the developed algorithm allows it to be applied to different two-stage supply chain problems. Additionally, the problem and model created in this study for solving the problem can be used in academic research as a multi-objective optimization problem.

Author Contributions: Conceptualization, B.D. and A.A.; methodology, B.D. and A.A.; software, A.A.; validation, B.D. and A.A.; formal analysis, B.D.; resources, A.A.; data curation, B.D. and A.A.; writing—original draft preparation, B.D. and A.A.; writing—review and editing, B.D.; visualization, A.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data is unavailable due to privacy or ethical restrictions.

Conflicts of Interest: The authors declare no conflict of interest.

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systems

Article

Complexity to Resilience: Machine Learning Models for Enhancing Supply Chains and Resilience in the Middle Eastern Trade Corridor Nations

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Abstract: The durable nature of supply chains in the Middle Eastern region is critical, given the region's strategic role in global trade corridors, yet geopolitical conflicts, territorial disputes, and governance challenges persistently disrupt key routes like the Suez Canal, amplifying vulnerabilities. This study addresses the urgent need to predict and mitigate supply chain risks by evaluating machine learning (ML) models for forecasting economic complexity as a proxy for resilience across 18 Middle Eastern countries. Using a multi-dimensional secondary dataset, we compare gated recurrent unit (GRU), support vector regression (SVR), gradient boosting, and other ensemble models, assessing performance via MSE, MAE, RMSE, and R^2. The results demonstrate the GRU model's superior accuracy (R^2 = 0.9813; MSE = 0.0011), with SHAP, sensitivity, and sensitivity analysis confirming its robustness in identifying resilience determinants. Analyses reveal infrastructure quality and natural resource rents as pivotal factors influencing the economic complexity index (ECI), while disruptions like trade embargoes or infrastructure failures significantly degrade resilience. Our findings underscore the importance of diversifying infrastructure investments and stabilizing governance frameworks to buffer against shocks. This research advances the application of deep learning in supply chain resilience analytics, offering actionable insights for policymakers and logistics planners to fortify regional trade corridors and mitigate global ripple effects.

Keywords: machine learning; supply chain resilience; Middle East; economic complexity; geopolitical risk; scenario analysis

1. Introduction

In an age characterized by unparalleled global connection and economic interdependence, supply chains form the cornerstone of international commerce and economic activity. They enable the smooth transfer of products, services, and information across borders, supporting the development and stability of national economies. This complex network of dependency makes supply chains more susceptible to various disturbances, such as economic recessions, geopolitical conflicts, and resource shortages [1]. Natural pandemics and increasing territorial, historical, geopolitical, and trade conflicts have highlighted the vulnerability of global supply chains, emphasizing the need to bolster supply chain resilience. As a result, supply chain resilience (SCR) has become a vital strategic priority for governments and enterprises, motivated by the necessity of minimizing disruptions and maintaining operational continuity under unstable conditions [2].

Supply chain resilience (SCR) is increasingly recognized as a foundation of economic stability, development growth, and sustainability, particularly in regions where political instability, economic dependencies, and infrastructural disparities create unique vulnerabilities [3]. Nations' dependence on resource extraction increases economic volatility, thereby elevating the risk of supply chain disruptions. Political instability and persistent conflicts in nations like Syria, Yemen, Israel, and Lebanon compromise supply chain integrity, diminish trade efficiency, and hinder economic growth [4]. Excessive dependence on oil exports renders the area especially vulnerable to external disruptions, while persistent conflicts foster a volatile atmosphere that affects supply chains [5]. Therefore, improving supply chain resilience in the region is crucial for both regional stability and the protection of global trade networks.

The Middle Eastern region serves as a prime example of a region where supply chain resilience is crucial yet difficult to achieve. The region, situated at the intersection of Asia, Europe, and Africa, possesses significant strategic importance for global trade and logistics. The complex geopolitical landscape, resource-driven economies, and infrastructural disparities pose significant challenges to the enhancement of supply chains [6]. The area serves as a vital hub for energy exports and essential marine commerce routes, significantly contributing to the efficient operation of global supply chains. Political instability, wars, or infrastructure failures in the Middle East disrupt the global supply chain, resulting in delays, heightened prices, and market volatility [7]. There is a necessity of studying supply chain resilience (SCR) within the Middle Eastern trade corridor, which encompasses multiple industries critical to the region's economy. Meanwhile, the energy sector, driven by oil exports, dominates due to nations like Saudi Arabia and Iraq's reliance on natural resource rents and require a resilient framework. This framework includes manufacturing and trade-related supply chains reflected in the economic complexity index (ECI). Additionally, logistics and transportation networks, vital to maritime trade via the Suez Canal, are integral. This multi-industry approach ensures practical applicability across diverse sectors, addressing systemic vulnerabilities, rather than a single industry focus.

Nations such as Saudi Arabia, Iraq, and Iran exhibit significant reliance on oil exports, rendering their economies especially susceptible to variations in global energy markets [3]. The intersecting challenges highlight the need for predictive frameworks to anticipate vulnerabilities and enhance resilience in national and regional supply chains. The intersecting challenges highlight the need for predictive frameworks to anticipate vulnerabilities and enhance resilience in national and regional supply chains. Traditional econometric models are effective in stable environments, whereas they often fall short in capturing the intricate, non-linear dynamics of modern supply chains, especially in volatile regions [8]. These models struggle to account for the complex interplay between economic complexity, political uncertainty, and infrastructural deficits, which are critical determinants of supply chain vulnerabilities in the region [9]. Subsequently, there is a pressing need for more sophisticated, adaptive frameworks capable of addressing these multidimensional challenges. Machine learning (ML) models, with their ability to process large datasets, identify non-linear patterns, and adapt to dynamic conditions, offer a promising alternative [10,11]. Unlike traditional econometric approaches, ML models can better predict supply chain risks by integrating diverse factors such as geopolitical shifts, economic fluctuations, and infrastructural constraints, thereby enhancing the precision of risk assessments and enabling proactive strategies to bolster resilience, foster development, and ensure stability in the face of emerging vulnerabilities.

This study, therefore, aims to apply machine learning models to examine which ML model fits the study of the multidimensional factor effects of SCR, an area where traditional econometric models often fail to provide reliable insights [12]. By leveraging the power of ML, this research seeks to develop predictive frameworks that can more accurately anticipate vulnerabilities and support the development of robust, adaptive supply chains in the region [13]. In doing so, it will contribute to advancing the broader field of supply chain resilience, offering a model for how ML can address the complexities of contemporary supply chains and improve their resilience in volatile, resource-dependent regions [14].

Machine learning (ML) models provide a robust solution to the constraints of conventional econometric models. Through the analysis of extensive datasets, machine learning algorithms identify complex patterns, trends, and correlations that may remain obscured by traditional statistical methods [13]. In the Middle East and its surroundings, machine learning models are appropriate to address the region's intricate economic interdependencies and political instability, offering insights into the impact of these elements on supply chain resilience [15]. Machine learning facilitates the creation of predictive models that can adjust to alterations in the region's political environment, economic circumstances, and infrastructure, providing a more sophisticated comprehension of supply chain dynamics [16]. The use of machine learning methods thereby addresses significant deficiencies in resilience forecasting, improving the region's capacity to anticipate and respond to disturbances with greater effectiveness [12].

The machine learning (ML) models employed in this study were designed to identify patterns and generate precise predictions regarding supply chain resilience (SCR) in the Middle Eastern region [13]. Features incorporated into the analysis serve as indicators of potential vulnerabilities and risks and determinants of supply chain disruptions. While ML offers powerful tools for risk assessment and predictive analytics, its application should be integrated with complementary analytical frameworks and human expertise to inform effective interventions and policy formulation [12,17]. A deeper exploration of the causal mechanisms underlying supply chain vulnerabilities necessitates further research, employing a multidisciplinary approach to fully capture the intricate dynamics of the issue. This study positions ML as a vital tool within a broader strategy to enhance SCR, rather than an impartial solution [18].

Despite the growing interest in this topic, research into supply chain resilience (SCR) has persisted, but researchers still need to bridge their understanding of how geopolitical instability and economic dependencies affect complex supply chain disruptions within volatile Middle Eastern regions. Economic and infrastructural approaches fail to account for the changing nature of regional disruption factors because they do not consider the impact of political instability alongside trade policies and economic complexity. A gap has been filled through this research, which implements gated recurrent units (GRUs) from machine learning (ML) to predict SCR improvements specifically in the Middle Eastern region. Our research integrates the economic complexity index (ECI) to establish a new data-driven prediction system that analyzes economic resilience connections through advanced machine learning techniques and various geopolitical events. The research reveals new operational value for supply chain managers through deep learning model predictions, which deliver concrete solutions to reduce risks even when traditional forecasting methods prove ineffective. Our research's primary aim is to create and employ machine learning models to predict national supply chain resilience (SCR) in the geopolitically unstable Middle East, transcending the effectiveness of conventional econometric methods. We employ the economic complexity index (ECI) as an innovative proxy for SCR, connecting economic diversity to resilience against perturbations. Leveraging SHAP analysis, we discern essential factors of resilience, providing pragmatic insights for policymakers. Additionally, we propose a scalable framework for real-time SCR prediction, suitable for other trade-dependent regions.

This research offers novel elements in the use of machine learning for supply chain resilience within the Middle Eastern context, advancing beyond prior research. It innovatively employs ML models (GRU) to predict SCR using the economic complexity index (ECI), utilizing GRU's capacity for capturing temporal patterns and overcoming conventional econometric and simpler machine learning techniques with exceptional precision. This study uses ECI to connect economic variety with SCR, presenting a fresh macro-level perspective, in contrast to previous research centered on direct resilience measurements. Our region-specific, multidimensional dataset covering seven years and 18 countries includes unique Middle Eastern variables such as resource rents and political stability, adapting machine learning to the region's specific challenges of geopolitical volatility, oil dependency, and infrastructure deficiencies, in contrast to stable contexts in prior research. The amalgamation of SHAP with scenario and sensitivity analyses improves interpretability, yielding practical insights into feature influences and model resilience during disturbances such as Suez Canal blockages and thus addressing a deficiency in previous machine learning applications. A thorough comparison of GRU with several models sets a standard for SCR prediction in volatile areas, beyond the limited assessments seen in previous studies.

2. Literature Review

The concept of supply chain resilience (SCR) has gained significance as global supply networks encounter an expanding array of disruptions stemming from economic, geopolitical, and environmental influences. Supply chain resilience (SCR) denotes the capacity of supply chains to foresee, adjust to, and recuperate from disturbances while maintaining operational continuity and mitigating performance decline [19,20]. The increasing intricacy of global supply chains means that disturbances in one area might have worldwide repercussions.

2.1. Supply Chain Resilience

Researchers assert that robust supply chains need flexibility, redundancy, and coordination among stakeholders [21]. The Resilience Triangle Model, which statistically measures resilience by analyzing recovery velocity and operational reinstatement after-shocks, emphasizes the dynamic characteristics of resilience. Transparency in supply chains, a proactive risk management ethos, and adaptable networks are essential for fostering resilience, especially in unstable regions such as the Middle East [22]. These frameworks emphasize the need for both proactive and reactive efforts to mitigate disruptions in an increasingly unpredictable environment [23]. Supply chain resilience (SCR) is particularly vital for the region because of its strategic geographic position, the essential function of the Suez Canal, a worldwide commerce conduit accounting for roughly 12% of international trade, and the widespread effects of regional conflicts, political instability, and wars. Current conflicts in countries such as Israel, Yemen, Iraq, and Syria have impeded trade routes, heightened security threats, and generated logistical bottlenecks, hence intensifying the vulnerability of regional supply chains.

Figure 1 identifies the hitches underscoring the pressing necessity for resilient SCR methods to alleviate the economic and social repercussions of such disruptions. By enhancing supply chain resilience, diminishing reliance on natural resource rents, and promoting regional collaboration, Middle Eastern economies can more effectively adjust to variable market conditions, geopolitical disruptions, and internal instabilities [7]. This necessitates focused policies, infrastructure investment, conflict resolution strategies, and innovation to provide a more flexible and secure economic framework, guaranteeing long-term stability and sustainable growth while capitalizing on the region's strategic significance in global trade networks.

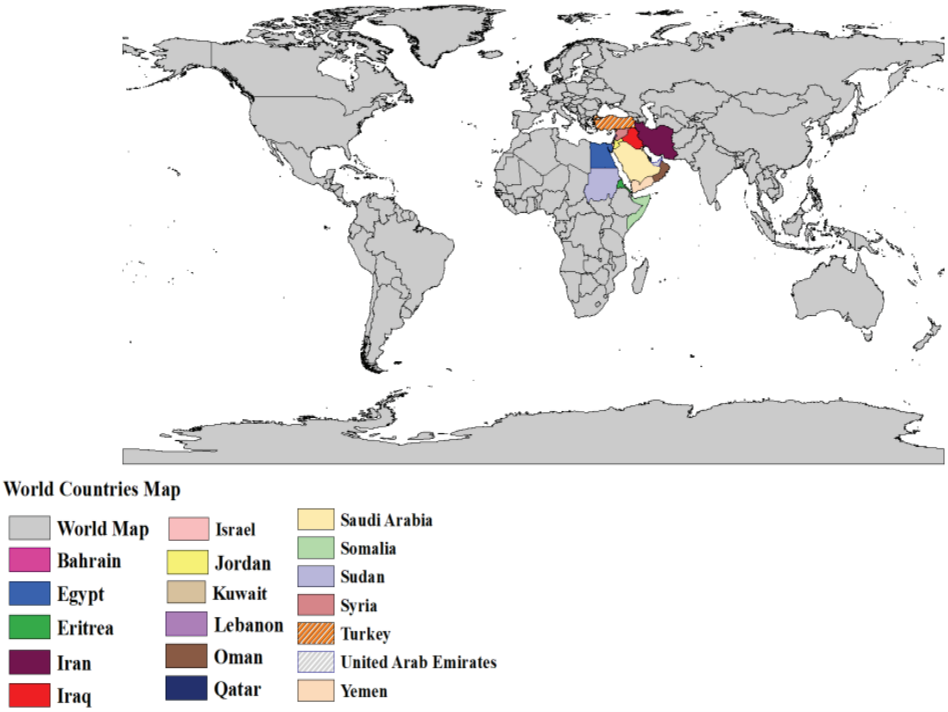


Figure 1. Middle Eastern countries.

Middle Eastern countries, especially Saudi Arabia and the United Arab Emirates, have responded to these issues by launching strategic initiatives to improve supply chain resilience. Saudi Arabia's Vision 2030 and analogous programs prioritize economic diversification, infrastructural enhancement, and the establishment of innovation ecosystems to diminish the reliance on oil [24]. The efficacy of these strategies relies on the use of sophisticated analytical tools, especially machine learning, to augment the predictive capacities of supply chain models and refine decision-making. Machine learning can optimize supply chain operations, forecast disruptions, and improve the agility of supply chains in real time, equipping the area with the necessary skills to negotiate its complex geopolitical and economic environment [18]. Huge potential to improve the resilience of supply networks is presented using machine learning for the purpose of supply chain risk management in the Middle East. This will allow supply networks to survive and recover from disruptions while simultaneously encouraging better regional and global stability more effectively.

2.2. Economic Complexity and SCR

Economic complexity describes the assessment of a country's producing capacities and the intricacy of its economic framework. It assesses the diversity and intricacy of the goods and services produced and exported by a nation, indicating its capacity to originate and maintain knowledge-intensive activity. This notion, grounded in the economic complexity index (ECI) framework, highlights the relationship between a nation's industrial expertise and its standing in global trade networks [25]. Countries exhibiting greater economic complexity are generally marked by diversified production systems, advanced technological capabilities, and specialized knowledge integrated within their workforce and institutions. These economies exhibit greater resilience, as they are more adept at adapting to fluctuations in global demand and fostering innovation within competitive marketplaces [26]. In contrast, countries with little economic complexity typically depend on a limited array of fundamental commodities or simplistic goods, making them more susceptible to external disruptions [27].

Economic complexity has emerged as a crucial analytical instrument for comprehending the determinants of economic growth, development, and the structural transition that is vital for its national supply chain resilience. It also functions as an indicator of long-term economic performance since nations with greater economic complexity typically have more resilient and sustainable growth patterns [28].

Countries with a higher economic complexity index (ECI) generally demonstrate enhanced supply chain resilience across multiple dimensions. Their powerful industrial and logistical infrastructures furnish a reliable foundation for enduring shocks. Their supply chains' flexibility is augmented by varied production capabilities, facilitating adaptability to evolving conditions [29]. Furthermore, their extensive trade links facilitate redundancy through the maintenance of alternative supply channels and sources, enabling rapid reactions to shocks [30]. Economically complex nations tend to engage more effectively in international trade agreements and alliances, fostering collaborative supply chain solutions. Ultimately, their robust technological and institutional frameworks enhance visibility and oversight in supply chains, hence mitigating the danger of cascade failures.

Economic complexity is seen as a crucial determinant affecting SCR, particularly concerning a nation's ability to endure external shocks. Economic complexity is defined by the range and sophistication of a nation's producing capacity [31]. Economic diversity is seen as a crucial tool for improving SCR. Saudi Arabia's Vision 2030 seeks to alleviate these concerns through industry diversification, infrastructural enhancement, and establishing the nation as a global trading center, closely aligning with the overarching goals of SCR by diminishing oil dependence and advancing comprehensive economic growth [32].

2.3. Econometric Model and Its Limitations

Econometric models are extensively employed to examine data types such as panel, time-series, and cross-sectional data, revealing correlations among variables through statistical methodologies for causal interference. However, their use encounters constraints including multicollinearity, endogeneity, and the curse of dimensional, which may result in incorrect estimates, biased outcomes, and over-fitting. Additionally, econometrics face some challenges in predicting economic trends [8]. Econometrics models frequently fail to identify nonlinear relationships and interaction effects, and assumptions such as linearity and endogeneity may not be applicable in actual datasets. Despite their usefulness, these problems underscore the necessity of comprehensive diagnostics, alternative approaches, and meticulous interpretation in the analysis of multidimensional data [33].

Traditional econometric estimation is inadequate for measuring supply chain resilience in the Middle Eastern region due to the multidimensional nature of the dataset, which includes variables such as the economic complexity index (ECI), the global competitiveness index (GCI), and various infrastructure and political stability indicators. These models are susceptible to multicollinearity, where highly correlated variables like GDP growth and industry activity can distort results. Additionally, exogeneity is a concern, particularly in this politically unstable region, where factors such as political stability and economic performance may interact in complex ways. The curse of dimensionality further complicates the analysis, as the large number of features increases the risk of overfilling and reduces the model's generalizability. Moreover, the assumptions of linearity and exogeneity, which underpin many econometric models, may not hold in this context, leading to biased outcomes. Given these limitations, traditional econometric approaches are unsuitable for capturing the nonlinear relationships and dynamic complexities inherent to supply chain resilience in such a diverse and volatile region. Therefore, a machine learning approach is more appropriate for accurately predicting and understanding the factors influencing supply chain resilience in this context of the Middle East.

2.4. Machine Learning

Although conventional supply chain resilience (SCR) frameworks provide significant insights into resilience methods, the use of machine learning (ML) techniques has surfaced as a sophisticated approach to improving forecasting accuracy and flexibility in supply chains [34]. The capacity of machine learning to analyze extensive datasets and identify intricate patterns offers a considerable advantage over conventional econometric models, which often encounter difficulties in managing the dynamic, non-linear characteristics of contemporary supply chains. This shows that machine learning methods, such as decision trees, support vector machines, and neural networks, enhance demand forecasting, optimize inventory management, and detect disruptions with increased accuracy [10]. The adaptability of machine learning models allows them to respond to swiftly changing situations, which is especially advantageous in areas like the Middle East, where political instability, economic variability, and infrastructure difficulties provide an unpredictable environment. Integrating machine learning into supply chain risk (SCR) frameworks enhances resilience by facilitating more precise, data-driven decision-making processes [12].

Given the increasing volume of research on SCR and ML in developed countries, the use of these technologies in the Middle East is still scarcely examined. The area encounters a distinct array of problems that hinder the execution of SCR initiatives. Political instability, exemplified by nations such as Syria, Yemen, and Iraq, impedes supply chain operations and hinders trade flows [16]. The Middle East's significant dependence on oil exports renders its economy more susceptible to variations in global energy markets, increasing the danger of supply chain disruptions [15]. Moreover, physical deficiencies, such as antiquated transportation systems and constrained port capacity in nations like Lebanon and Sudan, impede the effective transit of products, exacerbating logistical inefficiencies [35]. These reasons underscore the need for customized SCR frameworks that use new technologies such as machine learning and region-specific methods to address the intrinsic vulnerabilities arising from political, economic, and infrastructural constraints [36].

Whether it involves predicting and simulating supply chain resilience (SCR) in the Middle Eastern area, the use of various machine learning models GRU, SVR, gradient boosting, CatBoost, random forest, and linear regression provides a complete approach [37]. Every model offers its own set of advantages; GRU is especially useful for complicated and dynamic datasets because of its exceptional ability to analyze relationships across time. Modeling resilience factors may be achieved in a variety of ways because of SVR's efficient handling of linear and non-linear interactions [38]. While random forest provides resilience and interpretability, especially in high-dimensional data settings, gradient boosting and CatBoost can catch detailed patterns via the use of ensemble learning. This allows them to provide excellent prediction accuracy. After everything is said and done, linear regression is used as a benchmark to assess how well advanced models perform. Collectively, these models make it possible to obtain more nuanced knowledge of SCR, which helps address the systemic instability and geopolitical difficulties that are present in the area.

The gated recurrent unit (GRU) is a form of recurrent neural network (RNN) that uses sequential input. Using gating techniques that regulate the flow of input, it can capture long-term dependencies in time-series data [39]. This allows it to solve the issue of disappearing gradients that is associated with classic regular neural networks. According to [40], GRUs are especially useful for predicting in dynamic situations, such as supply chains, where previously collected data might have an impact on the outcomes of future events.

SVR is the regression variant of support vector machines (SVMs), recognized for its capacity to predict non-linear connections by transforming input data into higher-dimensional spaces using a kernel function. SVR is resilient to outliers and noise, making it appropriate for supply chain data, where inconsistencies may occur owing to market volatility or external disturbances [41,42].

Gradient boosting is an ensemble method that constructs numerous decision trees in succession, with each tree rectifying the flaws of its predecessor [43]. It is very efficient for regression tasks, delivering reliable predictions by progressively concentrating on more challenging examples [44]. In supply chain risk (SCR), gradient boosting models are used to elucidate intricate interactions among supply chain factors, including demand and interruptions [45].

CatBoost is a sophisticated gradient-boosting technique that adeptly manages categorical information without requiring considerable preparation. This is especially beneficial in supply chains, where categorical factors such as product category or geographic location are prevalent. CatBoost delivers superior accuracy when handling heterogeneous data types [12,46].

Random forest is an ensemble technique that constructs several decision trees and consolidates their results to enhance predictive accuracy. Many logistics supply chain network data are gathered and compared with other widely used models in the experimental section, including the conventional network model and the analytic hierarchy process model. It is resilient to over-fitting and adept at managing high-dimensional information, making it efficient for modeling intricate interactions in SCR. Random forest offers insights into feature relevance, aiding in the identification of key characteristics that influence resilience [11,47].

Linear regression is a fundamental model used to forecast a dependent variable via linear associations with independent variables. Although it may not account for non-linearity, it functions as a valuable baseline model for supply chain forecasts, particularly when the connection between variables is assumed to be linear [48].

Machine learning serves as a vital tool in improving estimates for supply chain resilience, especially in the Middle East, where issues like political instability, economic dependence on oil, and infrastructure shortcomings are common. Employing sophisticated models such as GRU, SVR, gradient boosting, CatBoost, random forest, and linear regression, regional supply chains attain enhanced predictive accuracy, thus bolstering their resilience. This improved resilience strengthens Middle Eastern supply chains against disruptions and considerably enhances global trade by assuring more stable and reliable supply channels. The incorporation of machine learning in supply chain management is essential for enhancing regional resilience and global trade efficiency.

The literature emphasizes the increasing significance of supply chain resilience (SCR) in the context of global disruptions, particularly its vital function in the Middle East, influenced by geopolitical instability, reliance on oil, and key trade routes such as the Suez Canal. It examines SCR frameworks that prioritize flexibility, redundancy, and proactive risk management, in conjunction with the economic complexity index (ECI) as an indicator of economic diversity and resilience. Conventional econometric models are lacking due to their inability to encapsulate non-linear dynamics, hence facilitating the adoption of machine learning (ML) methodologies such as GRU, SVR, and ensemble techniques, which provide enhanced predicted accuracy and flexibility. Although SCR and ML research flourishes in developed areas, the analysis highlights a deficiency in accustomed applications addressing the Middle East's distinct challenges political instability, economic dependence on oil, and infrastructural shortcomings. This research collectively indicates a necessity for creative, regionally specific supply chain resilience methods and frameworks that incorporate advanced analytics to strengthen resilience and sustain global trade routes along with neighboring nations' SCR.

3. Model Description

3.1. Data Collection Procedure and Processing

In our study, data are key, so they had to be sourced from reliable and ethical sources for this research; accordingly, data were sourced from credible, publicly available resources to guarantee high-quality and uniform datasets. The principal sources include the World Bank, the International Monetary Fund (IMF), the United Nations Conference on Trade and Development (UNCTAD), the Fragile States Index, and the World Economic Forum (WEF). These institutes provide standardized, dependable datasets across a broad spectrum of economic, infrastructural, and political variables essential for assessing supply chain resilience (SCR) in the Middle East. The dataset has a seven-year duration, including 18 nations in the Middle East. This longitudinal method encompasses significant economic cycles, geopolitical occurrences, and infrastructure changes, offering a thorough foundation for modeling and predicting SCR in the area. The choice of these years guarantees the incorporation of critical variations and enduring patterns vital for a comprehensive examination.

Machine learning has transformative potential to measure and enhance SCR across various industries and domains due to adaptability, scalability, and the ability to learn from data and its patterns. ML models are intended to reflect the unique geographical attributes of the Middle Eastern region. Fundamental attributes encompass political stability and the absence of violence (PSAV) are used to assess geopolitical instability like conflicts in Syria and Yemen, while total natural resource rents (TNRRs) are used to evaluate economic reliance on oil exports, and productive capacities transport (PCT), alongside infrastructure quality indicators (IQ and OATI), are used to consider logistical discrepancies. These variables mention in Table 1, derived from a dataset encompassing nations in the region, reflect the region's unstable trade landscape and important location close to the Suez Canal. The capacity of an ML model like GRU to model temporal dependencies guarantees that dynamic characteristics such as abrupt geopolitical shocks or variations in the SC are effectively incorporated into SCR predictions, hence augmenting regional relevance.

Table 1. Data description.

Variables Name	Signs	Unit of Measurement	Data Source
Economic complexity	ECI	Economic complexity index	HGL
Industry activity	IA	Industry activity index	UNCTAD
Total natural resources rents	TNRRs	Rent (% of GDP)	IMF
Productive capacities transport	PCT	Productive capacities transport index	UNCTAD
Supply Chain Resilience Index	MESCRI	Composite index	
Information and communication technologies	ICT	Information and Communication Technologies Index	UNCTAD
Liner shipping connectivity	LSCI	Liner shipping connectivity index	UNCTAD
Fragile state	FSR	Fragile state rank	FFP
Global Competitiveness Index	GCI	Global Competitiveness Index	WEF
Air transport freight	ATF	Freight (million ton-km)	ICAO
Quality of roads	RQ	Global Competitiveness Index	WEF
Quality of overall infrastructure	IQ	Global Competitiveness Index	WEF
Quality of air transport infrastructure	OATI	Global Competitiveness Index	WEF
Economy	GDP	GDP growth (annual %)	WDI
State legitimacy	SL	Fragile state rank	FFP
Demographic pressures	DP	Fragile state rank	FFP
Political stability and absence of violence	PSAV	Percentile rank	WBDA
Inflation and consumer prices	ICPA	Inflation and consumer prices (annual %)	IMF
Trade	TRADE	Trade (% of GDP)	OECD
Population	POPT	Population, total	WBDA
Population, female	POPF	Population, female (% of total population)	WBDA

A data processing step emphasized maintaining the integrity and comparability of the dataset for analysis. Our research work utilized a multi-stage data prepossessing pipeline to guarantee data reliability, encompassing missing value imputation, feature scaling, and dataset segmentation. The K-nearest neighbor (KNN) imputation method was employed to address missing data by estimating absent values based on analogous feature distributions, hence ensuring minimal data distortion. Furthermore, the dataset was standardized using Z-score normalization to reduce the impact of variables with significant scale differences. This prepossessing step is essential for enhancing model performance, especially in deep learning models such as GRU, which are susceptible to unscaled input features. The dataset is divided into training (70%), validation (15%), and test (15%) sets, adhering to established standards in machine learning research. This work enhances model selection using cross-validation techniques, in contrast to traditional studies that depend on fixed train–test splits, hence improving the generalizability of the results.

3.2. Research Method

The gated recurrent unit (GRU) is a type of recurrent neural network (RNN) used for processing sequential or time-series data, such as language modeling and market prediction. This is usual since traditional RNNs often encounter issues with vanishing gradients, making it difficult to understand long-term relationships. This addresses the issue that GRUs resolve via gates, which preserve only relevant information while updating the hidden states at each time step. GRUs are less computationally intensive than LSTMs since they possess fewer gates and parameters. Nonetheless, GRUs are quite effective for several sequence modeling problems. The GRU model for time-series forecasting: in time-series forecasting, we anticipate the target variable (ECI) based on the preceding values of various input characteristics. GRU models are well suited for this purpose since they effectively capture temporal relationships and patterns from sequential data.

Basically, the GRU model has two main components.

1. Update gate.
2. Reset gate.

Both gates work together to control how much information is required to be retained and which information is not required.

Key components of GRU:

1. Input component.

The input vector (x_t) represents the input at time t.

The hidden state (h_{t-1}) represents the hidden state from the previous time step, carrying information from the past sequence. At each time step, t, the GRU receives the following:

1. x_t input vector at time t.
2. h_{t-1}: previous hidden state.

2. Update gate calculation (z_t)

The update gate basically addresses how much from the previous hidden state (h_{t-1}), i.e., what was calculated using the previous values for ECI and other features) should affect the current prediction.

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \tag{1}$$

x_t is the vector of the input features at time t.
W_z is the weight matrix for input x_t.
U_Z is the weight matrix for hidden state h_{t-1}.
b_z is the bias term.

σ is the sigmoid activation function (binary function).

3. Reset gate r_t

The reset gate controls how much of the past information (h_{t-1}) we want to forget for the current computation. This forces the model to only pay attention to useful things.

The equation for the resets gate with the bias term is as follows:

$$r_{t=}\sigma(W_r x_t + U_r h_{t-1} + b_r) \tag{2}$$

σ is the sigmoid activation function.
W_r is the weight matrix for the input x_t.
U_r is the weight matrix for the previous hidden state (h_{t-1}).
b_z is the bias term associated with the reset gate.

4. Candidate hidden: h_t.

The candidate hidden state is computed based on the reset gate, r_t, and the previous hidden state (h_{t-1}). The candidate hidden state can be thought of as the new potential state of the system, which is influenced by both the current input and the relevant portion of the previous state.

$$h_t = \tanh(W_h x_t + U_h(r_t \odot h_{t-1} + b_h)) \tag{3}$$

tanh is the hyperbolic tangent activation function.
$\odot$ denotes element-wise multiplication.
W_r is the weight matrix for the input x_t.
U_h is the weight matrix for the previous hidden state (h_{t-1}).
b_h is the bias term associated with the candidate state.
r_t is the reset gate controlling how much of the previous hidden state (h_{t-1}) should be passed into the hidden state.

5. Final hidden state: h_t.

The final hidden state, h_t, is a weighted combination of the previous hidden state (h_{t-1}) and the candidate hidden state, h_t, modulated via the update gate, z_t.

$$h_t = \tanh((1 - z_t) \odot h_{t-1} + (z_t \odot h_t + b_h)) \tag{4}$$

$(1 - z_t)$ determines how much of the previous hidden state should remain.
z_t determines how much of the candidate hidden state should be adopted.
b_h is an additional bias term associated with the final hidden state. This is optional, and it is not always included, but it can be part of the model for better flexibility.

The following diagram shows the architecture of a gated recurrent unit (GRU), a kind of recurrent neural network (RNN) applied in deep learning models. Here is a breakdown of the main elements.

Reset gate: The reset gate decides how much past information needs to be discarded. It determines which aspects of the previous hidden state (h_{t-1}) to forget when the current input is considered. It applies a sigmoid activation function (σ—sigmoid activation function) that returns a value between 0 and 1. A lower output of the reset gate means it is forgetting more of the past.

The update gate controls what information is passed from the present input to the hidden state. It decides what part of the previous hidden state will indeed be passed to the next step. Similarly, the update gate employs the sigmoid activation function, so all values will be between 0 and 1. It retains more of the previous state when the update gate output is closer to 1, and it relies more on the current input when closer to 0. The hidden state (h_t)

at the current time step is computed as a function of the previous hidden state (h_{t-1}) and current input (x_t), also modulated via the reset and the update gates. The last hidden state is obtained from a tanh activation function, which translates between the previous state and the current state. That allows the GRU to keep important information from the past and add the new input usefully.

Flow of information: The input x_t and the previous hidden state (h_{t-1}) are passed through the reset and update gates. The purpose of the reset gate is to decide how much of the past hidden state should be forgotten, and the update gate decides how much of the new information should be incorporated into the current state. h_t is a weighted sum of the previous state and the current input, balancing the need to learn long-term dependencies with the vanishing gradient problem.

3.3. Applied ML Models

To find the best accuracy, the study applied various machine learning and deep learning models with the best-fitted parameters. Each model was selected based on its best accuracy functions and its ability to learn complex patterns that may occurs during. The ML models were SVR, GBoost, CatBoost, random forest, and linear regression. These models are simple, fast models that can provide reasonable computational complexity, and they have the added benefit of accommodating different data shapes. The study applied only a GRU model explained its flow in Figure 2, and the key features including GRU also apply a gating approach (update and reset gates) to maintain the information flow accordingly, allowing for the capture of long-term dependencies with much more efficient computations.

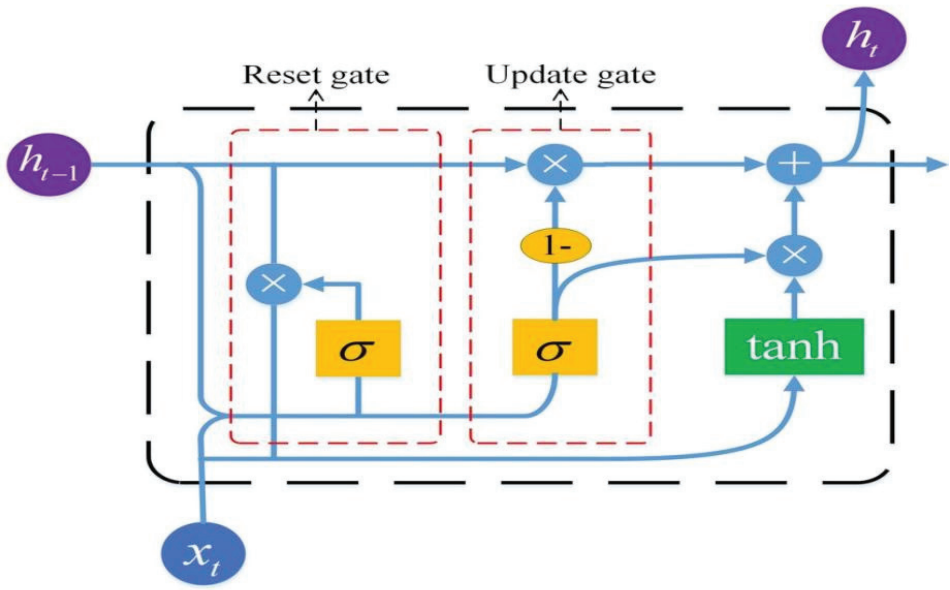


Figure 2. Gated recurrent unit (GRU).

The best-fitted hyperparameters for each model are summarized in Table 2.

According to the configurations that produced the best results for a time-series model, as demonstrated, this study specified hyperparameters for each model. We followed the dropout values and unit count recommended in their work. The hyperparameters were chosen using the default configurations suggested, which found that the parameters max_depth, learning rate, and n_estimators had a significant effect on performance [49]. We adhered to [50]'s design and hyperparameter recommendations for the transformer model. Their investigation found that key_dim and num_heads, two hyperparameters in the multi-head attention structure, have a significant effect on model performance. In order to maximize transformer performance for our investigation, the study selected variable num_heads and key_dim.

Table 2. Best-fitted hyperparameters.

Models	Hyperparameters
GRU	hidden_layer, 128, activation = tanh, kernel_regularizer = l2(0.01), dropout = 0.2, adm = 0.05, Epochs = 300, batch size = 32, verbos = 1, restore _best_weight = True
SVR(Linear)	kernel = 'rbf' 'C': 1, 'epsilon': 0.01, 'gamma': 'scale'
Gradient boosting	(n_estimators = 100, random_state = 42)
CatBoost	Iter = 200, depth = 10, learing rate = 0.02, leaf-reg = 10.
Random forest	bootstrap': True, 'max_depth': None, 'min_samples_leaf': 2, 'min_samples_split': 5, 'n_estimators': 100
Liner regression	Alpha = 10-6, scv = 10, np.logspace(−6,6,13)

In our study, the hyperparameters listed in Table 2 were deemed ideal, as they were considered to have yielded superior performance (e.g., minimal error) on a validation set or through cross-validation tailored to the requirements of each model. The GRU configuration, featuring a hidden layer size of 128, a dropout rate of 0.2, and an L2 regularization value of 0.01, attains an acceptable balance between model capacity and regularization. The optimization was conducted over 300 epochs using the Adam optimizer (learning rate = 0.05) with early halting, presumably optimizing the mean squared error (MSE) as the loss function. The SVR parameters—C = 1, ε = 0.01, and γ = "scale"—were mainly determined through a grid search to minimize the ε-insensitive loss, whereas CatBoost's configurations (learning rate = 0.02; depth = 10) imply the application of Bayesian optimization to decrease the root mean squared error (RMSE). For random forest and gradient boosting, default ensemble parameters (e.g., n_estimators = 100) were refined through a random search to decrease MSE, whereas linear regression's $\alpha = 10^{-6}$ was optimized via a grid search over a logarithmic range (np.logspace(−6, 6, 13)) to minimize the regularized least squares loss. The hyperparameters were evaluated using robust techniques, including k-fold cross-validation (specifically, 10-fold, as denoted by SCV = 10), to ensure generalizability. The optimization procedure incorporated systematic search techniques, manual adjustments, and domain knowledge, with the loss function of each model directing the parameter selection. Further confirmation of their optimality could be strengthened via specific performance indicators or dataset characteristics.

4. Results and Analysis

In our research, the efficacy of six regression models was assessed using four principal metrics: the mean squared error (MSE), mean absolute error (MAE), root mean squared error (RMSE), and R^2. MSE, MAE, RMSE, and R^2 are metrics for evaluating model correctness; lower values of MSE, MAE, and RMSE indicate superior model performance, while a higher R^2 value signifies a better model fit. Table 3 presents the summary data for the performance of the gated recurrent unit (GRU), support vector regression (SVR), gradient boosting, CatBoost, random forest, and linear regression models.

The GRU model proves itself to be the best predictive tool because it reaches an R^2 of 0.9813, which surpasses traditional machine learning models such as support vector regression (SVR), gradient boosting, and random forest. GRU's ability to detect complex supply chain data dependencies and temporal interactions produces this exceptional result. GRU seeks patterns across time sequences, thanks to its sequential learning approach, which enables it to identify persistent patterns for forecasting disruptions via changing global markets and economic conditions. The SHAP-based feature importance analysis shows that industry activity (IA) and natural resource rents (TNRRs), together with infrastructure quality (IQ), stand as the essential factors for determining supply chain resilience. Research confirming diversified industrial structures and stable governance as resilience factors against supply chain vulnerabilities finds consistent support in these results.

Table 3. Early stopping conditions of models.

Models	Stopping Conditions
GRU	Train for a maximum of 300 epochs or terminate early if early stopping conditions are met.
SVR (Linear)	Training stops after reaching the default max_iter (maximum iterations, defaults is −1 for unlimited iterations or when convergence criteria are met).
Gradient boosting	No explicitly defined stopping conditions; training concludes when optimal weights are learned from the data.
CatBoost	Early stopping = 10.
Random forest	No explicitly defined stopping conditions; training concludes when optimal weights are learned from the data.
Liner regression	No explicitly defined stopping conditions; training concludes when optimal weights are learned from the data.

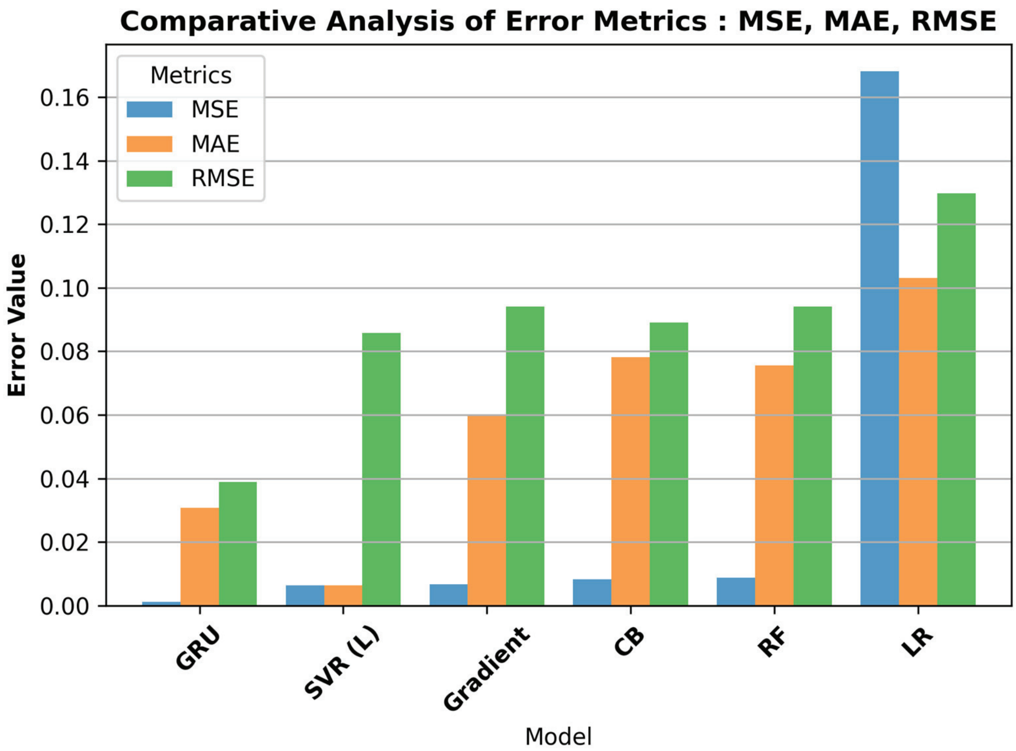
The model's capacity to manage a broad dataset highlights its resilience and adaptation to the distinct issues of the Middle East, including political instability, economic reliance on natural resources, and infrastructure shortcomings. This corresponds with findings from previous studies, which indicate that GRUs excel in time-series forecasting and sequence prediction tasks [38]. The GRU model offers critical insights for formulating strategies to enhance supply chain resilience by precisely forecasting ECI, thereby enabling more informed decision-making in this intricate regional landscape. This remarkable performance not only confirms the model's efficacy but also underscores its potential to substantially boost SCR throughout the Middle East.

Furthermore, Table 4 shows support vector regression (SVR) utilizing a linear kernel offers commendable performance, achieving a mean squared error (MSE) of 0.0064, a mean absolute error (MAE) of 0.0064, a root mean squared error (RMSE) of 0.0858, and an R^2 value of 0.9311. Although its R^2 is inferior to that of the GRU, it yet accounts for a substantial portion of variation, specifically 93.11%. Although the MAE is comparatively low, signifying that forecasts are near the actual values, the rising MSE and RMSE indicate the presence of more significant sporadic mistakes. Methods like SVR are favored for regression because SVM can handle non-linear data via kernel transformation [51].

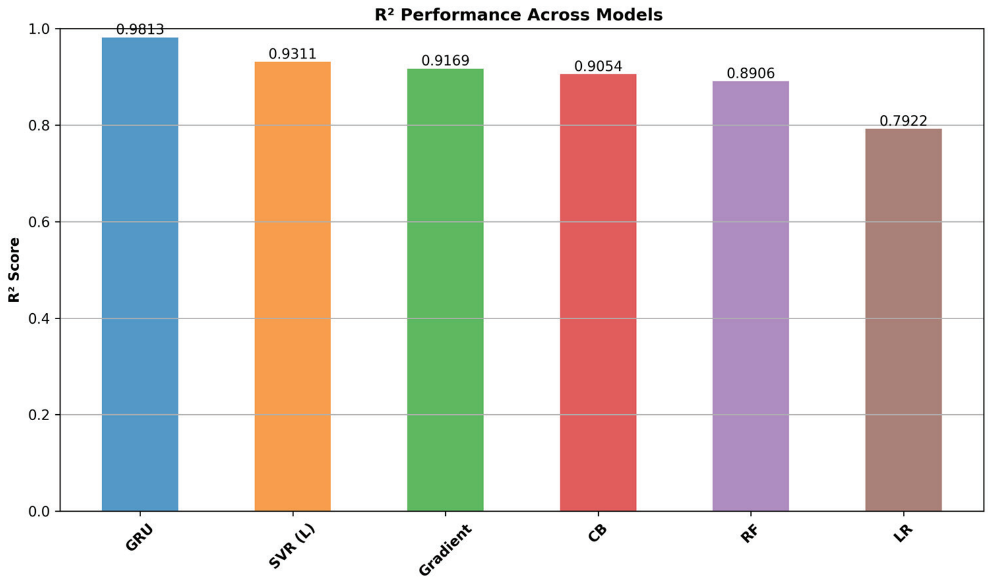
Table 4. Results of models.

Model	MSE	MAE	RMSE	R^2
GRU	0.0011	0.0307	0.0388	0.9813
SVR (linear)	0.0064	0.0064	0.0858	0.9311
Gradient	0.0067	0.0601	0.0941	0.9169
Catboost	0.0083	0.0781	0.0890	0.9054
Random forest	0.0088	0.0756	0.0941	0.8906
Linear regression	0.1682	0.1031	0.1297	0.7922

In Figure 3a, gradient boosting exhibits a mean squared error (MSE) of 0.0067, a mean absolute error (MAE) of 0.0601, a root mean squared error (RMSE) of 0.0941, and an R value of 0.9169, which is somewhat inferior to that of support vector regression (SVR). The model accounts for a significant portion of the variance in the target variable—R^2 = 91.69%. Gradient boosting is recognized as one of the most precise machine learning algorithms for prediction problems using structured data, with XGBoost and LightGBM achieving numerous victories in regression and classification competitions [52].



(**a**)



(**b**)

Figure 3. (**a**) Comparative analysis of error metrics. (**b**) R^2 performance across models.

The CatBoost model, a gradient-boosting technique adept at managing categorical features, achieves performance comparable to our gradient boosting model, with an MSE of 0.0083, an MAE of 0.0781, an RMSE of 0.0890, and an R^2 of 0.9054. CatBoost exhibits commendable performance; nonetheless, it demonstrates marginally elevated error metrics, suggesting its inability to encapsulate data complexity as effectively as GRU or SVR. CatBoost's primary advantage lies in its effective management of categorical data with minimal prepossessing; this methodology has been successfully utilized in various domains, including consumer behavior prediction and credit scoring [18].

Random forest demonstrated a mean squared error (MSE) of 0.0088, a mean absolute error (MAE) of 0.0756, a root mean squared error (RMSE) of 0.0941, and an R-squared (R^2) value of 0.8906. Despite its robustness and proficiency in managing complicated datasets, random forest exhibits marginally inferior performance compared to the more specialized models, including GRU and SVR, in this instance. Nevertheless, it still represents a significant portion of the target variable's variation, with an R^2 of 89.06%. Random forest is prevalent across various industries due to its capability to manage high-dimensional data and its resistance to over-fitting; however, it may exhibit sensitivity to hyperparameters [41].

Ultimately, linear regression exhibits the poorest performance among all models, with a mean squared error (MSE) of 0.1682, a mean absolute error (MAE) of 0.1031, a root mean squared error (RMSE) of 0.1297, and anw R^2 value of 0.7922. The R^2 score is relatively low, indicating that linear regression explains only around 79.22% of the variability in the target variable. This outcome emphasizes the limitations of linear regression, which is effective solely for linear relationships between characteristics and the target variable; it is likely inefficient in capturing complicated or nonlinear patterns in the data. Linear regression, as a fundamental statistical method, typically exhibits sub-optimal performance in non-linear data scenarios.

The GRU model is the most effective predictive model, exhibiting the highest R^2 and the lowest error metrics. The SVR and gradient boosting models also demonstrate commendable performance and explanatory capacity. Random forest and CatBoost perform comparably; however, linear regression achieves the worst performance due to its stringent assumptions regarding the data.

The superior performance of GRU is attributed to its gating mechanisms, which effectively address the vanishing gradient problem, enabling the model to learn pertinent characteristics within a data stream. Recent advancements in deep learning for structured prediction indicate that GRUs often exhibit superior efficiency compared to more intricate architectures like LSTMs. Features are static insights that may fail to represent web-like interactions and dependencies in highly dynamic datasets; hence, more interpretable models such as random forest and gradient boosting are frequently employed. The results underscore the growing inclination for recurrent architectures in predictive modeling, particularly in contexts where data displays temporal or sequential traits, due to their ability to adeptly grasp intricate relationships.

In Figure 4, a bag plot illustrates the correlation between the mean squared error (MSE) and the mean absolute error (MAE) across different regression techniques, along with their dispersion and density. GRU exhibits the lowest values for MSE and MAE, indicating its superior capacity to understand intricate data patterns and provide minimal prediction error. These results align with prior research that emphasized the GRU's efficacy in modeling sequential data and adeptly capturing temporal dependencies. Nonetheless, the SVR and gradient boosting models exhibit middling performance, yielding elevated error levels; however, they display competitive efficacy in heterogeneous scenarios. Conversely, advanced learning models such as random forest and linear regression exhibit greater diversity in prediction mistakes, with the latter being the least successful due to its constrained ability to represent non-linear connections adequately.

Similarly, a density-based display of MSE and MAE illustrates the aggregation of high-performance models, specifically those exhibiting consistently fewer errors in assessment measures. The superiority of GRU is attributed to its gated architecture, which prevents the retention of irrelevant temporal information while conservatively collecting temporal patterns.

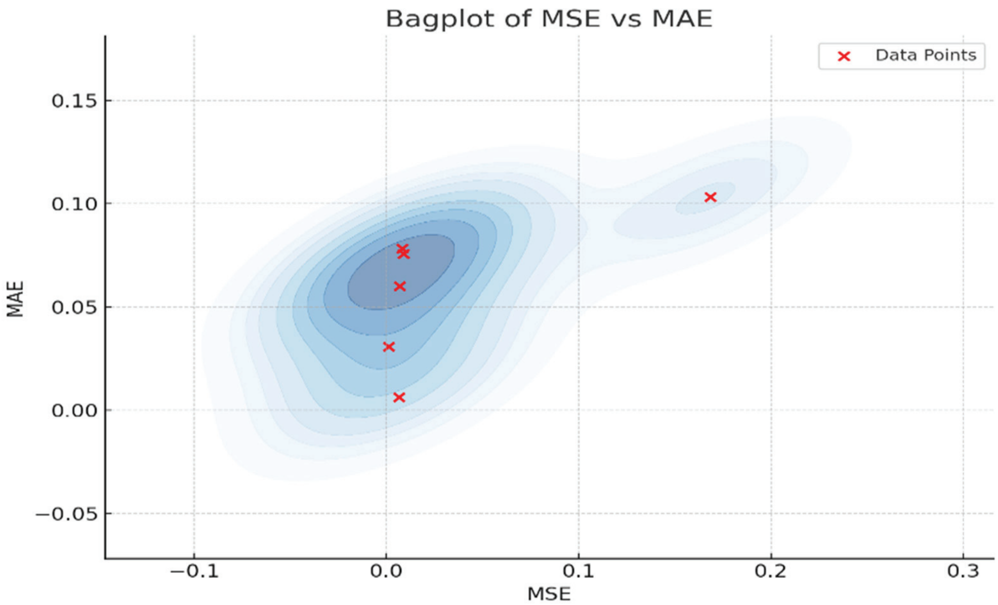


Figure 4. Comparison of MSE vs. MA.

In our analysis, Figure 5 illustrates the contribution of each feature to the predictions of the gated recurrent unit (GRU) model, which has an economic complexity index (ECI), a crucial metric for assessing supply chain resilience (SCR) in the Middle Eastern countries. Further analysis in our study assessed regional supply chain resilience, utilizing the economic complexity index (ECI) as the focal variable and highlighting the significance of essential macroeconomic, infrastructural, and political elements. The SHAP-based feature importance analysis identified industry activity (IA) and total natural resource rents (TNRRs) as the primary determinants of ECI, underscoring the critical importance of industrial capacity and resource management in influencing regional resilience. Productive capacities transport (PCT) and the quality of air transport infrastructure (OATI) exemplify the essential role of efficient transportation systems in improving supply chain stability, which is vital for regional SCR.

Political environments have a significant impact on regional economic performance, as demonstrated by the crucial role of political stability and absence of violence (PSAV). Features such as the Middle East Supply Chain Resilience Index (MESCRI), Liner Shipping Connectivity Index (LSCI), and ICT-readiness are crucial, underscoring the significance of technological, logistical, and collaborative competencies in enhancing resilience. Moreover, although factors such as GDP, infrastructure quality (IQ), and inflation (ICPA) demonstrate minimal individual influence, their importance lies in their collective impact, which substantially enhances the overall resilience framework.

Our analysis of SHAP variation in values over the dataset highlights the several socioeconomic and infrastructure circumstances in this region, therefore offering vital information for policymakers and participants to actively enhance SCR. The study not only reveals important drivers of regional resilience by combining SHAP analysis with GRU predictions but also guarantees openness and interpretability in employing machine learning in intricate regional economic settings. Figure 6 a comprehensive analysis provides strong knowledge of the elements influencing regional supply chain resilience, thus providing actionable insights for legislators to prioritize industrial diversification, infrastructure improvement, and political stability to strengthen economic complexity and resilience in the Middle East.

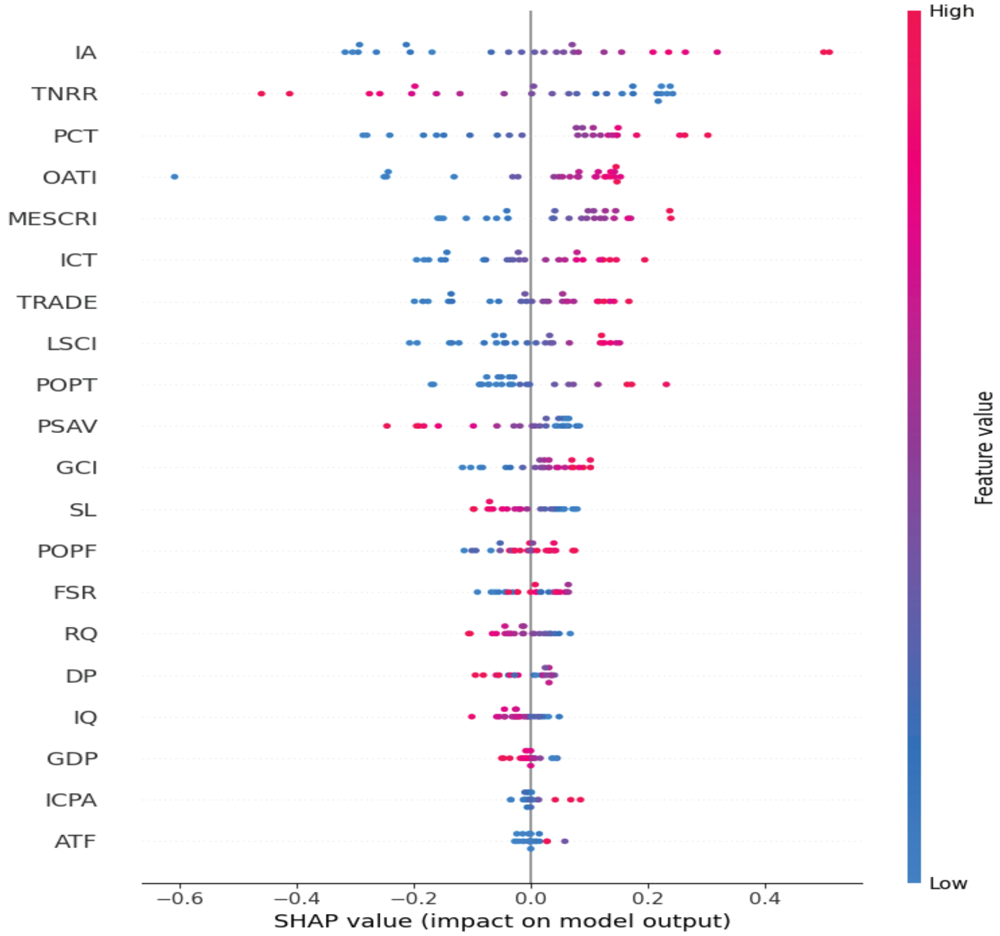


Figure 5. SHAP (impact on model output).

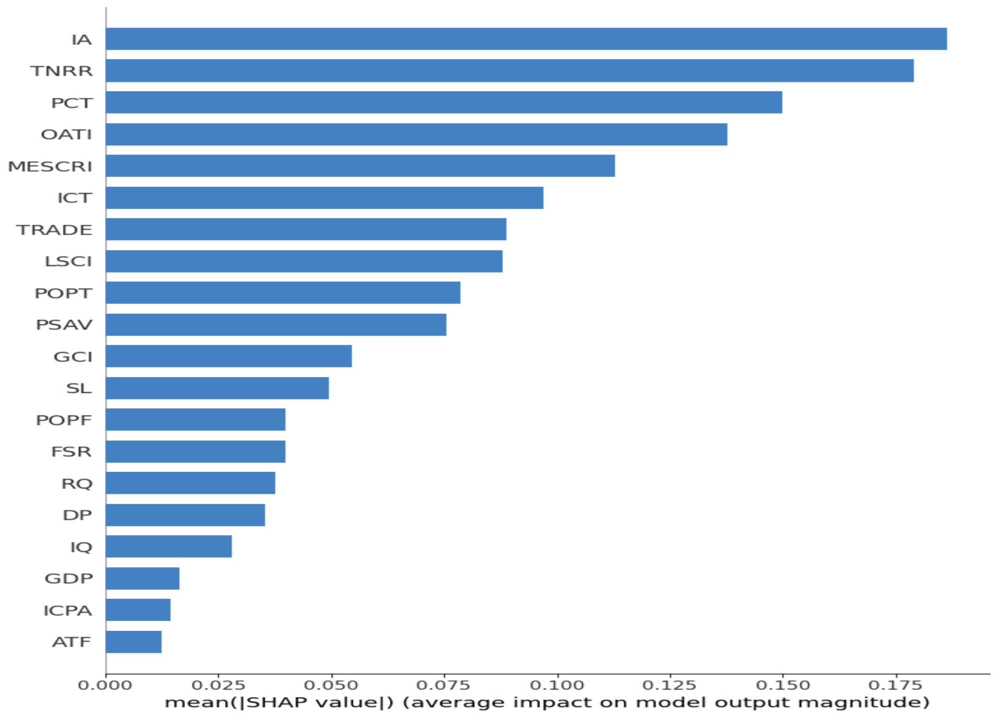


Figure 6. SHAP (feature impact ranking).

In order to evaluate the economic complexity index (ECI), a main proxy for regional supply chain resilience (SCR), we also performed a scenario analysis to offer important new perspectives on the dynamic interaction of macroeconomic, infrastructure, and political elements in the Middle East. The outcomes expose the subtle sensitivity of the predictive model to feature perturbations, therefore stressing the important players in resilience and their local consequences.

Figure 7 scenario analysis further explains features impact like industry activity (IA) has emerged as a highly influential characteristic. A rise of 10% markedly elevated the projected ECI, underscoring the critical need for industrial diversification in strengthening supply chain resilience. This highlights the necessity for industrial development projects in resource-dependent economies such as Saudi Arabia, Iraq, and Yemen to enhance resilience. Total natural resource rents (TNRRs) exhibited pronounced negative sensitivity, whereby a 10% reduction in TNRR enhanced the economic complexity index (ECI). This discovery corresponds with the resource curse concept, which posits that significant reliance on natural resources frequently diminishes economic complexity and regional social capital resilience. For resource-abundant states, shifting from resource dependence to value-added industrial endeavors is crucial.

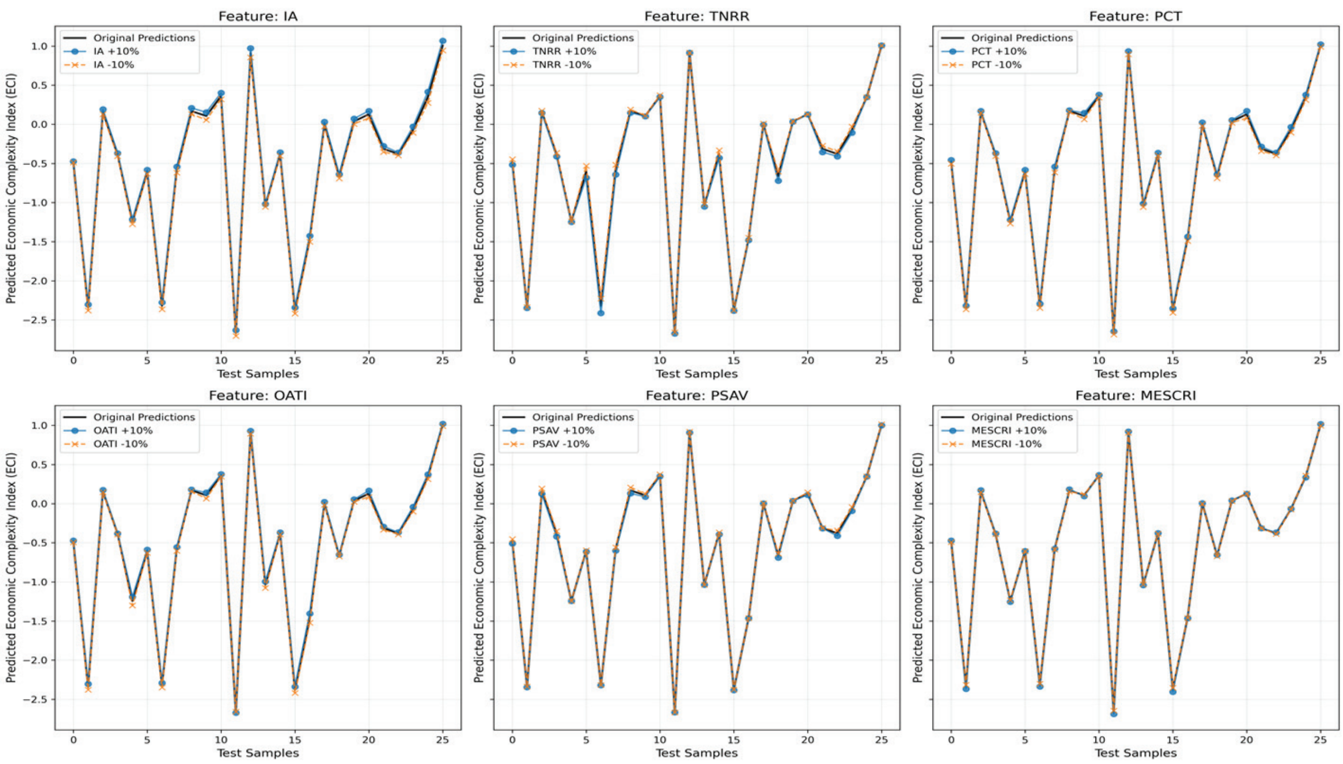


Figure 7. Scenario analysis.

Productive capacities transport (PCT) and the quality of air transport infrastructure (OATI) favorably impacted ECI forecasts, highlighting the essential function of effective multi-modal transportation networks in the Middle East, especially for trade centers such as the UAE and Qatar. Improving these capabilities can alleviate logistical constraints and enhance regional competitiveness.

Political stability and the absence of violence (PSAV) exhibited the most significant adverse effect on the economic complexity index (ECI) when negatively altered by 10%, highlighting the harmful influence of political instability on social cohesion and resilience (SCR). Fragile governments like Syria, Yemen, and Iraq demonstrate considerable vulnerabilities in their supply chain networks, owing to ongoing geopolitical instability.

Figure 8 shows that the perturbation factors examined indicate that nations with developed infrastructural and technical frameworks, like the UAE and Qatar, demonstrate greater resilience under varying scenarios. In contrast, politically unstable and resource-dependent nations like Yemen and Sudan exhibit significant vulnerabilities, highlighting the disparate levels of resilience throughout the Middle East. The Middle East Supply Chain Resilience Index (MESCRI) had moderate effects on the economic complexity index (ECI), signifying its use as a composite measure of regional performance. Nonetheless, its interactions with essential factors such as PSAV and TNRR underscore its reliance on political stability and economic diversity. Resource-dependent economies must prioritize industrial diversification to mitigate dependency on natural resources, as demonstrated by the adverse sensitivity of TNRR. Investments in manufacturing, technology, and services can enhance resilience. Infrastructure development: Enhancements in transportation infrastructure, especially in air freight and multi-modal logistics, are essential for alleviating supply chain interruptions and promoting regional connectivity. This is especially crucial for trade-oriented countries such as Saudi Arabia and the UAE. Political stability and governance: Mitigating political instability in fragile regimes is of utmost importance. Enhancing governance frameworks, conflict resolution procedures, and regional collaboration can substantially improve SCR, as evidenced by the pronounced adverse effect of PSAV on ECI.

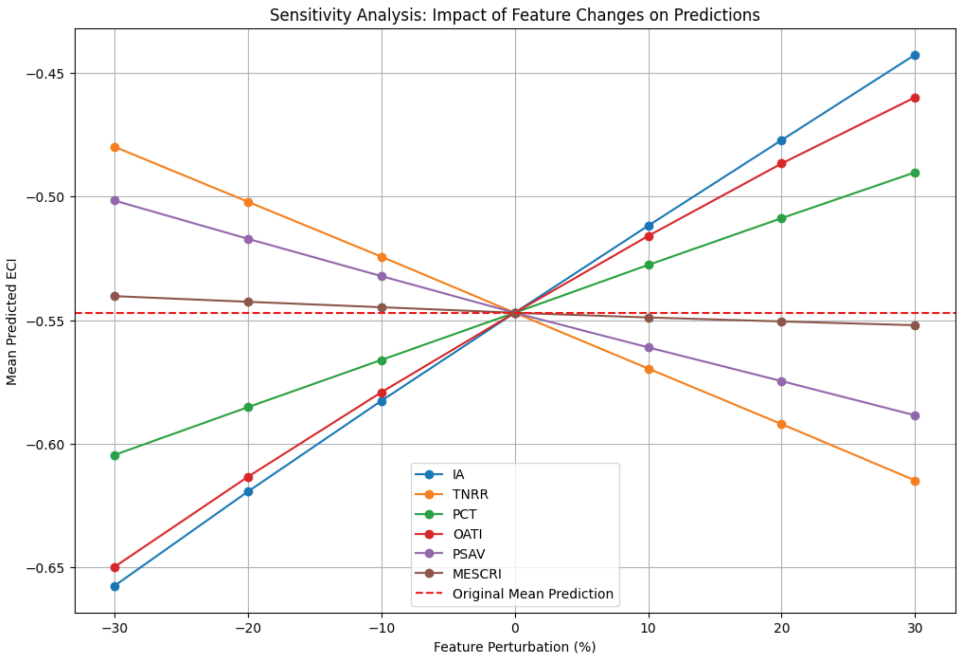


Figure 8. Feature perturbation.

Figure 9 explains that a feature perturbation analysis offers practical insights for policymakers, emphasizing the necessity of promoting industrial and infrastructural development while managing resource dependence and ensuring political stability. These findings collectively establish a strong framework for improving SCR in the Middle East, presenting a means to alleviate regional vulnerabilities and strengthen resilience against global uncertainty. This cohesive strategy enhances the prediction accuracy and policy significance of SCR modeling for the region. This study underlines the intricacy of improving SCR in the Middle East. Countries with strong infrastructure and varied economies exhibit greater resilience, but politically unstable and resource-dependent nations are more susceptible to vulnerability. By emphasizing industry diversity, infrastructure development, and political stability, the region may enhance its supply chain networks, thus ensuring sustainable economic complexity and resilience against global disturbances. These findings offer a data-driven basis for policymakers to tackle structural impediments and enhance regional resilience initiatives.

Figure 9. Sensitivity analysis.

Figure 10 shows that an integrated analysis examined the resilience of the predictive model and the influence of critical features on ECI. This approach provides insights into the model's sensitivity and stability under real-world disruptions by analyzing the response of features such as IA, TNRR, and PSAV to perturbations. Our study illustrates a combined sensitivity and scenario analysis, which delineates the variations in predictions for the economic complexity index (ECI) resulting from different feature perturbations (+10% and −10%) compared to the original forecasts. Each bar illustrates the effect of a particular feature's positive or negative modification on the expected ECI across test samples.

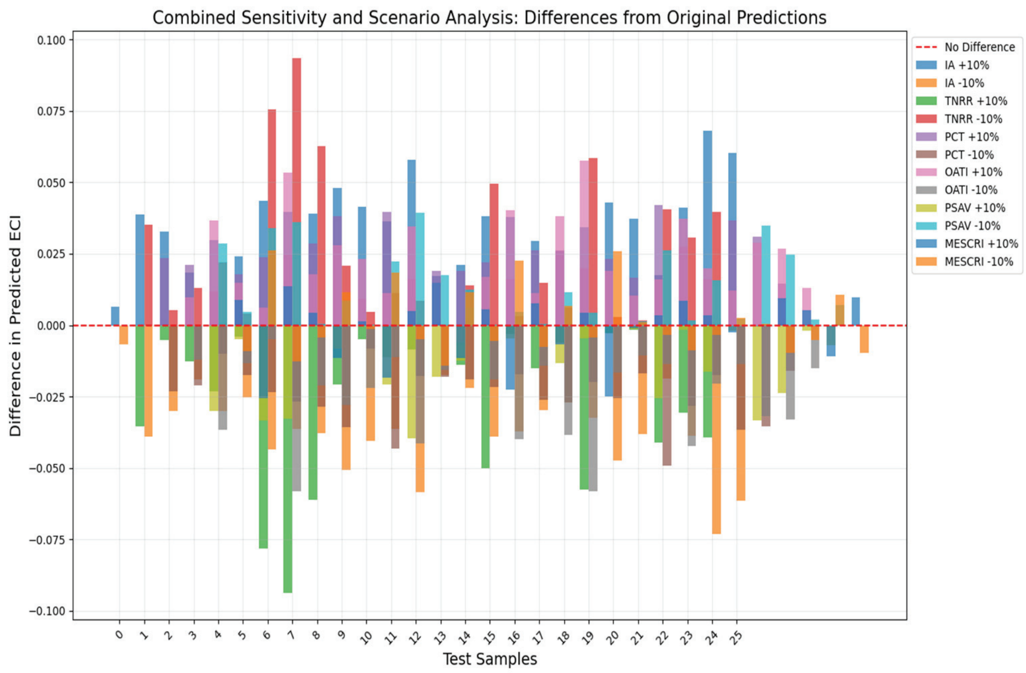


Figure 10. Sensitivity and scenario analysis.

Principal sensitivity determinants, variables such as IA, TNRR, and PSAV, exhibit considerable fluctuation, as seen in the substantial divergences from the zero baseline. This indicates that these features are essential for influencing ECI forecasts. Asymmetric behavior was observed in that certain characteristics, e.g., TNRR and MESCRI, have asymmetric effects, wherein the intensity of positive and negative disturbances varies. This signifies the non-linear impacts of various attributes on ECI. Feature-specific impacts attributes such as OATI exhibit little variation, indicating reduced susceptibility to alterations in these aspects. The persistent influence of MESCRI, even under disturbances, highlights its significance as a regional measure of resilience.

Geopolitical and economic vulnerability attributes such as PSAV and TNRR signify geopolitical concerns and reliance on natural resources, which are crucial in the Middle East region. This corresponds with our study's emphasis on regional resilience, as these characteristics significantly affect economic complexity and, thus, supply chain robustness. MESCRI substantiates its significance in forecasting ECI, particularly as it encompasses a comprehensive perspective on supply chain resilience, infrastructure, and political-economic stability. An in-depth comprehension of feature-level sensitivity in practical circumstances immediately facilitates our goal of assessing and improving supply chain resilience (SCR) in Middle Eastern nations. Such a method provides practical insights for enhancing the region's supply chains against trade disruptions or geopolitical threats by identifying important resilience drivers and their asymmetric effects. Profound understanding is an essential element in research, as it connects sensitivity analysis with practical situations to provide meaningful recommendations for enhancing regional resilience. It successfully identifies critical areas for change and perfectly matches with our study objectives of improving SCR in the Middle East.

5. Discussion

The Middle East is strategically located as a vital hub in world trade, especially because of its closeness to the Suez Canal, a significant maritime choke point that enables the passage of almost 12% of global trade. This posture renders supply chain resilience in the Middle East crucial for the region's economic stability and vital for the seamless functioning of global trade networks. A disruption in supply networks in this region, whether from geopolitical instability, infrastructural failure, or economic volatility, can impact international markets, influencing trade routes, market pricing, and global supply chains.

This research employed six sophisticated regression models: gated recurrent unit (GRU), support vector regression (SVR), gradient boosting, CatBoost, random forest, and linear regression, to predict and evaluate supply chain resilience in the Middle East. A thorough sensitivity analysis and scenario analysis were conducted to assess the robustness of these models under varying situations, analyzing the potential impact of different disruptions on supply chain resilience. The findings offer essential insights into the most effective methods for predicting disruptions and enhancing supply chain performance within the turbulent and intricately linked trade landscape of the Middle East. Machine learning models and their significance for supply chain resilience: The gated recurrent unit (GRU) model has proven to be the most precise and dependable instrument for predicting supply chain resilience in the Middle East, surpassing other models in predictive accuracy. The GRU demonstrated an MSE of 0.0011, an MAE of 0.0307, an RMSE of 0.0388, and an R^2 value of 0.9813, indicating that it explained nearly 98% of the variance in the target variable. This outstanding performance highlights the GRU's ability to capture long-term temporal dependencies in sequential data, rendering it especially effective in modeling time-series data that experience considerable fluctuations due to external shocks such as geopolitical events, supply–demand imbalances, or environmental disruptions.

GRU's capacity to analyze these temporal correlations is essential. The region often experiences geopolitical instability, including conflicts and policy changes, which can lead to considerable disruptions in the flow of products. Disruptions to the Suez Canal, a vital global economic artery, can be anticipated and alleviated by utilizing the predictive powers of the GRU. The model's capacity to manage such complexities has been extensively established in prior studies, underscoring its efficacy in predicting time-dependent variables, particularly in logistics and supply chain management [38]. Sensitivity analysis demonstrates that the GRU model exhibits considerable stability across many parameter configurations, rendering it resilient to variations in input data. Its ability to adapt to the fluctuating volatility of Middle Eastern trade routes, either by political instability or infrastructural challenges, offers a distinct edge. The model's resilience is demonstrated by its capacity to anticipate the consequences of prospective interruptions, such as the Suez Canal closure, indicating its proficiency in accurately predicting the cascade impacts on supply chains.

The support vector regression (SVR) demonstrated considerable potential, evidenced by an R^2 of 0.9311, a mean squared error (MSE) of 0.0064, and a root mean squared error (RMSE) of 0.0858, particularly in identifying non-linear correlations within the dataset. Although its R^2 demonstrates that it explains a significant percentage of the variation in supply chain resilience, its elevated MSE and RMSE relative to the GRU imply that the SVR model is more susceptible to outliers and non-linear disruptions, such as abrupt geopolitical events or trade embargoes. The sensitivity study reveals that the performance of the SVR model deteriorates under more extreme situations, especially in the presence of data noise or outliers. This underscores the significance of meticulous parameter optimization and kernel selection to enhance the robustness of SVR in volatile contexts, especially in areas with intricate political dynamics such as the Middle East.

Conversely, the gradient boosting model, with an R^2 of 0.9169, an MSE of 0.0067, and an RMSE of 0.0941, displayed competitive performance, although it did not surpass the GRU and SVR models in prediction accuracy. The elevated MSE and RMSE values might be ascribed to the model's susceptibility to over-fitting, especially when confronted with noisy data or highly volatile variables. In situations characterized by high data quality and reduced over-fitting risk, gradient-boosting techniques such as XGBoost and LightGBM demonstrate outstanding efficacy in regression tasks [53]. Nonetheless, the scenario analysis in this study indicated that the performance of the gradient boosting model substantially declines in severe scenarios, such as abrupt geopolitical disruptions or extensive infrastructure breakdowns.

The CatBoost model, a gradient boosting variation adept at managing categorical variables, achieved performance comparable to that of gradient boosting but showed marginally elevated error metrics (MSE of 0.0083, RMSE of 0.0890, and R^2 of 0.9054). The model demonstrated efficacy with datasets including substantial categorical features; however, a scenario analysis revealed a greater susceptibility to major mistakes when anticipating interruptions resulting from non-categorical causes, such as fluctuations in global oil prices or supply–demand discrepancies. This indicates that although CatBoost is beneficial for certain categories of supply chain data, its efficacy is not as consistently strong as that of the GRU or SVR models.

Sensitivity and scenario analysis, which assessed supply chain disruptions as part of this study's sensitivity analysis, highlights the significance of comprehending the responsiveness of each model to variations in input variables and exterior disturbances. This analysis is essential for identifying the most robust supply chain models in the Middle East, where they are susceptible to geopolitical risks, natural disasters, and infrastructural issues. In this scenario analysis, we simulated the effects of disruptions such as the blocking of the

Suez Canal or interruptions in the oil supply chain. The GRU model exhibited an enhanced predictive capability, precisely anticipating the downstream impacts of disruptions on the overall supply chain, encompassing port delays, alterations in shipping expenses, and variations in global trade dynamics. This highlights the necessity of utilizing powerful machine learning methods to anticipate and alleviate the effects of possible supply chain interruptions in this strategically significant area.

To exhibit the practical application of our machine learning (ML) framework in predicting and preventing supply chain disruptions, we present a case study centered on the March 2021 Suez Canal blockage caused by the Ever Given vessel, a significant incident that interrupted Middle Eastern trade routes and global supply chains. This event, which disrupted almost 12% of global trade for six days, illustrates the kind of geopolitical and logistical shock that our gated recurrent unit (GRU) model aims to tackle. Our study offers a retrospective study to illustrate the applicability of our GRU model to this incident, hence augmenting the research's pertinence to real-world supply chain resilience (SCR) issues.

This case study utilizes the GRU model, trained on historical data up to 2023 from sources specified in Section 3.1 (e.g., World Bank, UNCTAD), to forecast changes in the economic complexity index (ECI) subsequent to the Suez Canal blockade. Key attributes such as Liner Shipping Connectivity (LSCI) and Productive Capacities Transport (PCT) are highlighted due to their direct significance to marine trade interruptions. The obstruction likely resulted in substantial reductions in LSCI owing to suspended shipping and pressured PCT as alternate transportation methods were overwhelmed. Given the model's evident sensitivity to these characteristics in Figure 5, through a SHAP analysis, we propose that the GRU might have predicted a 7–10% decrease in ECI for impacted Middle Eastern nations, including Egypt and Saudi Arabia, indicative of a diminished trade capacity and economic complexity amid the disruption. This estimate corresponds with the scenario analysis in where variations in transport-related attributes produced similar ECI effects.

The case study emphasizes practical mitigation solutions derived from the model's outputs, surpassing mere prediction. For example, redirecting traffic through alternate ports, such as Jeddah in Saudi Arabia, could have mitigated congestion on the Suez route, while augmenting air freight capacity might have compensated for delays in time-sensitive shipments. These solutions leverage the model's identification of infrastructure quality like IQ, PCT, OATI, RQ., LSCI, and ATF as determinants of resilience (Section 4). This research is hypothetical because real-time 2024 data are not available in our present dataset; yet, it highlights the GRU's capacity to facilitate proactive decision-making in crisis situations. This enhancement bolsters the practical significance of our findings, ML's beneficial influence on SCR, and increases the study's attractiveness to both academic researchers and supply chain professionals.

Conversely, the SVR and gradient boosting models, albeit still useful, exhibited differing degrees of deterioration under severe disruptions. The SVR model demonstrated greater resilience to modest disruptions but showed considerable volatility in situations of acute global instability. The gradient boosting model, effective under normal settings, exhibited a significant decrease in performance during simulations of large-scale disruptions, underscoring its susceptibility to over-fitting and the necessity of hyperparameter tailoring for certain scenarios.

Our study's findings have significant implications for enhancing the resilience of supply chains in the Middle East, especially when considering the region's vital role in global trade. The proximity of the Middle East to the Suez Canal and other critical maritime routes necessitates the fortification of regional supply chains to endure disruptions, which is essential not just for local economies but also for global markets. The GRU model, noted for its exceptional performance and versatility, can function as an effective instrument for forecasting and alleviating risks, allowing stakeholders such as governments, port authorities, and shipping corporations to implement proactive strategies in order to maintain the seamless operation of trade routes; although each regression model examined in this study presents unique benefits, the GRU model emerges as the most dependable and robust for forecasting supply chain disruptions in the Middle East. By utilizing sophisticated machine learning methodologies and performing thorough sensitivity and scenario analyses, the region can more effectively predict and address the challenges presented via geopolitical instability, natural disasters, and infrastructural disruptions, thereby protecting its essential function in global trade.

6. Conclusions

This study has illustrated the vital significance of sophisticated machine learning models in bolstering the resilience of supply chains in the Middle East, an area that is pivotal in global trade, especially because of its closeness to the Suez Canal. Through the assessment of six distinct regression models—gated recurrent unit (GRU), support vector regression (SVR), gradient boosting, CatBoost, random forest, and linear regression—we have demonstrated that the GRU model markedly surpasses the others in predictive accuracy, achieving an R^2 of 0.9813 and exhibiting minimal error metrics. The GRU's exceptional capability of capturing temporal interdependence and long-term trends renders it especially appropriate for simulating the dynamic and frequently turbulent characteristics of supply networks in this region. This corresponds with recent literature that highlights the effectiveness of recurrent neural networks, especially GRUs, in time-series forecasting and supply chain management. The sensitivity and scenario assessments further confirm the resilience of the GRU, emphasizing its capacity to adjust to diverse challenges, whether geopolitical, infrastructural, or economic. Our study's findings, employing the predictive power of the GRU model (R^2 = 0.9813) and extensive scenario analyses, offer practical insights for supply chain managers, policymakers, and logistics planners in the Middle Eastern trade corridor, organized around essential resilience factors. Our analysis indicates that excessive dependence on oil exports, evidenced by the adverse sensitivity of total natural resource rents to the economic complexity index (Figure 7), heightens supply chain vulnerability. This compels managers in resource-dependent economies such as Saudi Arabia and Iraq to diversify into manufacturing, technology, and services consistent with initiatives like Vision 2030 to reduce exposure to energy market fluctuations and trade disruptions. The beneficial impact of productive capacities transport and quality of air transport infrastructure on ECI (Figure 7) highlights the necessity for logistics planners to prioritize multi-modal transport enhancements in hubs such as the UAE and Qatar, thereby improving resilience against disruptions like Suez Canal blockages. The predictive accuracy of the GRU model shown in Figure 3b enables supply chain managers to implement real-time, machine learning-based risk management, allowing for proactive measures such as rerouting shipments or obtaining alternative suppliers in anticipation of geopolitical or infrastructure disruptions. The detrimental effect of destabilized political stability and the absence of violence (PSAV) on ECI (Figure 7) underscores the region's geopolitical vulnerability, requiring enhanced governance and regional cooperation, particularly in fragile states such as Yemen and Syria, to sustain supply chains. Ultimately, given the worldwide repercussions of Middle Eastern disturbances through the Suez Canal, it is imperative for managers and regulators to promote cross-border data-sharing and international collaborations in order to maintain trade continuity, therefore strengthening global supply chain resilience.

Our research offers significant strategic implications for policymakers, trade regulators, and logistics management specialists in Middle Eastern markets. Strategies for resilience in the region must diminish dependency on resource rents and augment infrastructure expenditures to facilitate different trade routes, given its reliance on oil exports and the sensitive geopolitical trade corridors. GRU exhibits enhanced predictive performance, underscoring the necessity for machine learning technologies to be integrated into national risk management frameworks in order to improve supply chain disruption forecasting skills. The SCR monitoring and reaction capability will be enhanced through real-time data collecting that integrates satellite imagery with trade transaction records supported via geospatial analytical capabilities. International alliances are crucial, as localized supply chain vulnerabilities can disseminate their effects across the global economy. The formation of multilateral agreements and cross-border data-sharing platforms is essential for policymakers to enhance overall trade resilience.

7. Limitations and Future Research

Our study offers significant insights into supply chain resilience (SCR) through machine learning (ML) models; however, some limits are recognized, presenting opportunities for further research. The principal constraint resides in the dependence on historical data, which confines the model's ability to predict unprecedented disruptions, including unforeseen geopolitical occurrences, natural calamities, or economic penalties. Therefore, subsequent research should include real-time data sources, such as geo-location tracking, satellite imagery, reports, and social media sentiment analysis, to facilitate dynamic model adjustments and enhance forecasting responsiveness amid swiftly evolving circumstances.

A second restriction pertains to the spatial specificity of this investigation. The research centered on the Middle East, and its conclusions may not be directly relevant to other international trade routes with unique geopolitical, economic, and infrastructural circumstances, such as the Panama Canal or the Strait of Malacca. Cross-regional comparisons would yield significant insights into the transferability and applicability of the ML-driven resilience techniques established in this study to various geographies. This research could improve our comprehension of worldwide applicability and guide the creation of more generally pertinent predictive models for supply chain risk management.

Furthermore, although machine learning models such as GRU have exhibited robust performance in this work, their application to real-world supply chain management presents certain problems. These models necessitate precise calibration, especially for hyperparameter optimization, and may be computationally demanding, leading to issues related to scalability and resource management. Future research should concentrate on hybrid models that amalgamate econometric methodologies with machine learning techniques. These models may offer enhanced accuracy and increased interpretability, rendering them more suitable for policy-focused forecasting and decision-making assistance.

A subsequent study may investigate the integration of decision-support systems with machine learning models to improve real-time decision-making in supply chain risk management. Researchers could design frameworks that enable stakeholders to simulate the effects of probable disruptions and proactively formulate contingency strategies by integrating AI-driven simulations with scenario-based planning tools. This would enable policymakers and supply chain managers to react more efficiently to emerging concerns. As global supply chains grow increasingly complicated, it is essential for a future study to examine collaborative resilience strategies across stakeholders across many areas. Due to the interdependence of global trade networks, fostering collaboration among governments, private-sector organizations, and international bodies will be crucial for enhancing the resilience of regional and global supply chains. The establishment of data-sharing platforms and collaborative risk management frameworks may improve collective readiness, enabling a more synchronized reaction to global supply chain disruptions.

By addressing these limits and exploring future research areas, scholars and practitioners may enhance the resilience of global supply chains, ensuring that they stay resilient and adaptable to developing global issues.

Author Contributions: Conceptualization, W.N. and Z.L.; methodology, W.N. and Z.L.; software, W.N.; validation, W.N., and Z.L.; formal analysis, W.N.; investigation, W.N.; resources, Z.L.; data curation, W.N.; writing—original draft preparation, W.N. and Z.L.; writing—review and editing, W.N. and Z.L.; visualization, W.N.; supervision, Z.L.; project administration, Z.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original data presented in the study are openly available in [repository mention in Table 1. Data source].

Conflicts of Interest: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Portfolio Procurement Strategies with Forward and Option Contracts Combined with Spot Market

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Abstract: Increasing supply chain uncertainty due to market volatility has heightened the need for more flexible procurement strategies. While procurement through long-term forward contracts provides supply stability and cost predictability, it limits adaptability. Option contracts offer procurement flexibility, but require additional upfront premiums. Meanwhile, the spot market enables real-time purchasing without prior commitments, enhancing flexibility but exposing buyers to price volatility. Despite the growing adoption of portfolio procurement—combining forward contracts, option contracts, and spot market purchases—the existing research primarily examines these channels in isolation or in limited combinations, lacking an integrated perspective. This study addresses this gap by developing a comprehensive procurement model that simultaneously optimizes procurement decisions across all three channels under uncertain demand and fluctuating spot prices. Unlike prior studies, which often analyze one or two procurement channels separately, our model presents a novel, holistic framework that balances cost efficiency, risk mitigation, and adaptability. Our findings demonstrate that incorporating the spot market significantly enhances procurement flexibility and profitability, particularly in environments with high demand uncertainty and price volatility. Additionally, sensitivity analysis reveals how fluctuations in spot prices and demand uncertainty influence optimal procurement decisions. By introducing a new, practical approach to portfolio procurement, this study provides managerial insights that help businesses navigate complex and uncertain supply chain environments more effectively. However, this study assumes unlimited spot market capacity and reliable suppliers, highlighting a limitation that future research should address.

Keywords: portfolio procurement strategy; forward contract; option contract; spot market; supply chain management

1. Introduction

Supply chains have become increasingly unstable due to international conflicts, natural disasters, price fluctuations, and pandemics. In this uncertain landscape, procurement strategies have become a critical business concern. They are especially crucial in manufacturing industries, where securing components in a stable and cost-effective manner is essential for maintaining quality, controlling costs, and ensuring seamless production. Traditionally, the primary form of procurement has been the wholesale forward contract, where businesses commit to purchasing goods or services from a supplier over an extended period at fixed terms and wholesale prices [1]. While this approach guarantees a stable supply at generally lower costs and protects the retailer from losses arising from price and supply fluctuations, it also limits adaptability in uncertain markets and limits emerging opportunities.

To address this limitation, companies are increasingly incorporating option contracts into their procurement strategies [2]. Option contracts offer greater flexibility, allowing businesses to secure the right, without the obligation, to purchase up to a certain amount of goods at a predetermined price within a specified period. This approach is particularly efficient in volatile markets where demand and prices are unstable. One key advantage of option-based procurement is supply assurance. Companies can reserve inventory without fully committing to purchasing, ensuring its availability during peak demand or supply shortages. However, option contracts incur additional costs, as buyers must pay an upfront premium to acquire the option, which may increase overall procurement expenses. If the option remains unused, the premium is lost as a sunk cost.

With the rapid growth of B2B (business-to-business) trading, the spot market has become an effective and flexible alternative for procurement. Purchasing goods in the spot market involves buying items at current prices for immediate delivery in a dynamic environment. Spot market procurement is widely used for a range of products, including grains, oil, chemicals, semiconductor chips, energy, etc. [3–8]. The primary advantage of spot market purchasing is flexibility. Unlike long-term forward and option contracts with fixed prices and predetermined order quantities, spot market procurement is highly dynamic, adjusting to real-time supply and demand conditions. Buyers can modify purchase quantities based on actual demand, making it particularly beneficial for industries with highly uncertain demand or short product life-cycles. Moreover, unlike forward and option contracts that lock-in prices in advance, businesses can capitalize on cost savings when market prices decline. Spot market transactions also require no upfront financial commitment, which helps to improve cash flow management. Despite these advantages, spot market purchasing entails significant risks, with price volatility being the most critical. Since spot prices fluctuate due to supply and demand dynamics, businesses may face sudden cost surges during peak demand periods, complicating financial planning and budgeting. Nonetheless, spot market procurement is gaining popularity, particularly with the rise of e-commerce. Table 1 summarizes the characteristics of forward/option contract-based procurement and spot market procurement.

Table 1. Comparison of procurement strategies: forward/option contracts vs. spot market.

Factor	**Forward/Option Contract**	**Spot Market**
Price Volatility	Fixed or capped price	Highly volatile price
Flexibility	Lower flexibility;must commit to a fixed amount	Higher flexibility; can buy as needed
Cost Management	Predictable procurement cost	Difficult to forecast costs
Financial Commitment	Advanced payment or premium	No upfront payment
Risk Exposure	Hedged against price volatility	Exposed to price fluctuations

Companies have recently adopted portfolio procurement strategies that integrate traditional long-term contracts into the spot market, optimizing cost and flexibility. For instance, Hewlett-Packard (HP) successfully implemented a hybrid procurement strategy combining forward contracts, option contracts, and the spot market for semiconductor component sourcing. Specifically, HP procured 50% of its components through a forward contract, 35% via an option contract, and 15% from the spot market [9]. While existing research primarily examines one or two procurement channels in isolation, there are limited studies exploring portfolio procurement strategies that integrate forward, option, and spot markets. McKinsey & Company [10] have emphasized in their reports the importance of determining the optimal ratios between the long-term and the spot market for purchases.

This study aims to fill the research gap by developing a portfolio procurement framework that integrates forward contracts, option contracts, and spot trading into a unified model. Specifically, our contributions include: (1) formulating an optimal model that integrates these three procurement mechanisms; (2) analyzing procurement strategies under different procurement structures—forward contracts only, a combination of forward and option contracts, and a fully integrated portfolio approach; (3) providing an analytical solution under specific demand and price distributions to offer clear managerial insights; and (4) conducting a comprehensive sensitivity analysis of key factors such as spot price volatility, demand uncertainty, and cost structures. By addressing these aspects, our study provides a more holistic perspective on procurement strategy, filling the existing research gap and offering practical implications for supply chain decision-making.

This article is structured as follows: Section 2 reviews the relevant literature. Section 3 introduces an optimization model for portfolio procurement, with existing works used as benchmarks. Section 4 presents numerical examples to illustrate key findings and compare procurement strategies. Finally, Section 5 discusses the main conclusions and potential directions for future research.

2. Literature Review

With increasing supply chain risks, extensive research has been conducted from diverse perspectives to address these challenges. These include disruption mitigation approaches (e.g., resilience planning, redundancy, and dual sourcing) [11], sustainability and resilience strategies (e.g., circular economy models and green initiatives) [12], behavioral decision-making in procurement [13], and contractual strategies [14], to name a few. Among these, contractual strategies play a critical role in portfolio procurement, particularly in balancing cost stability and flexibility. To establish a foundation for our study, we first review the existing literature on forward contracts, option contracts, and spot markets, examining their applications and limitations in procurement decision-making.

A significant portion of forward contracts are based on the newsvendor model, where the optimal order quantity is determined under a wholesale contract framework for a short life-cycle product sold in a single selling period. In this model, a retailer (newsvendor) must decide how many units of a product to order before the selling season begins. Demand is assumed to be stochastic and characterized by a random variable x with the probability density function (pdf), $f(x)$, and the cumulative distribution function (cdf), $F(x)$. The key trade-off in the ordering decision is between two types of costs: the underage cost (c_u), incurred when ordering too little (leading to missed profit opportunities), and the overage cost (c_o), incurred when ordering too much (resulting in excess inventory). In the standard newsvendor model, these costs are defined as $c_u = p - w$ and $c_o = w - s$, where p is the selling price, w is the purchase cost, and s is the salvage value. The optimal order quantity Q^* purchased by the retailer from the supplier is obtained by $F(Q^*) = \frac{c_u}{c_u+c_o} = \frac{p-w}{p-s}$. Wholesale-based procurements in the newsvendor problem are extensively studied in the literature [15–18]. While forward contracts based on wholesale pricing provide stability and predictability in cost structure, their rigidity often limits their adaptability to fluctuating demand.

Option contracts are widely adopted across industries to address the limitations of forward contracts. An option contract is a type of agreement that allows the buyer to adjust order quantities based on demand forecasts and actual sales. In an option contract, two key pricing components define the financial terms: the option price o and the exercise price e. The option price is the retailer's upfront cost to acquire the contract, while the exercise price is the pre-agreed price at which the buyer can purchase the goods if they choose to exercise the option. The option price is non-refundable, meaning that even if the buyer decides not to exercise the option, the amount paid is not recovered. If demand is high, the buyer can exercise the option and secure the goods at the exercise price. Conversely, the buyer can forgo the option if demand is low, avoiding unnecessary inventory. Zhao et al. [19] introduced a supply chain coordination framework using an option contract, employing a game theory approach to resolve conflicts between manufacturers and retailers. They found that, compared to forward contracts, the supply chain can achieve coordination with Pareto improvement using option contracts. Since then, research on option contracts has been conducted across various contexts, including disruption risk [20], information asymmetry [21], smart factories [22], and bi-directional options [23]. For a comprehensive review of option contract literature, see Trigeorgis and Tsekrekos [2].

Existing studies on portfolio procurement problems mostly fall into three main streams: forward contract with option, forward contract with spot market, and option contract with spot market. Several studies examine a combined procurement model where a retailer utilizes both forward and option contracts. Wang and Tsao [24] develop a combined procurement model with both contract types. They show that optimal order quantities exist for both. Chen and Shen [25] examine the influence of option contracts and target service requirements on procurement decisions and performance. It is shown that as the target service requirement increases, the retailer's optimal expected profit is non-increasing, and the supplier's optimal expected profit is non-decreasing. Hu et al. [26] examine portfolio procurement policies for budget-constrained supply chains using wholesale and option contracts. It is shown that the wholesale-based forward contracts are preferable under tight budget constraints, while a combination of forward and option contracts can be a better choice under the relieved budget.

With the rapid growth of B2B trading, the spot market has become an increasingly viable procurement channel. Seifert et al. [3] propose a mathematical model to determine the optimal order quantity for forward contracts and spot market purchases. They demonstrate that incorporating the spot market into procurement decisions improves performance. Xing et al. [6] investigate how the B2B spot market affects the retailer's strategic behavior and performance in a supply chain with price-sensitive demand. The study presents how the retailer should simultaneously make a procurement quantity decision from a forward contract and a selling price decision before spot trading. Xu et al. [27] study a portfolio procurement with a forward contract and an imperfect spot market, where transactions are subject to availability constraints and additional costs. Kleindorfer and Wu [28] develop a framework integrating long-term procurement (capacity options) with short-term spot trading, showing that manufacturers and retailers can increase profitability using option contracts. Fu et al. [29] explore procurement strategies for a multi-period inventory, considering that a firm can buy either through an option contract or a spot market under price-dependent demand. Zhao et al. [30] present a two-stage procurement model, considering a stochastic spot market and the updating of demand information. In the first stage, the retailer determines the option quantity based on the option contract and possible spot price. The demand information is updated in the second stage, and based on this new information, the retailer determines the exercised quantity of options and the quantity of purchasing items from the spot market. Hou et al. [31] develop a mathematical model to determine the retailer's optimal procurement strategy, considering an imperfect spot market and fluctuating spot prices. They derive closed-form solutions for optimal order quantities and highlight the importance of a comprehensive portfolio procurement strategy that incorporates forward contracts alongside option contracts and the spot market.

While prior studies have explored procurement strategies involving forward contracts, option contracts, or the spot market, they have predominantly examined these mechanisms in isolation or in limited combinations. However, in today's industrial environment, firms increasingly leverage multiple procurement channels to optimize supply chain performance. A more comprehensive procurement strategy is required—one that integrates forward contracts, option contracts, and the spot market to effectively balance cost, flexibility, and risk. Despite the increasing recognition of these challenges, most research assumes that firms rely on either a single dominant procurement channel or a combination of two mechanisms. This limited scope often fails to capture the full strategic potential of an integrated portfolio approach, where all three mechanisms can be leveraged to optimize procurement outcomes. This paper aims to bridge this gap by developing a portfolio procurement framework that integrates forward contracts, option contracts, and spot trading simultaneously. Specifically, we identify the conditions under which each mechanism should be used, evaluate the trade-offs between cost efficiency and flexibility, and provide insights into optimal procurement decisions under uncertain markets.

3. Model Description

We consider a single risk-neutral retailer procuring products from a supplier for resale. The procurement process is characterized by long lead times and a limited sales period. The retailer faces uncertain demand x, which follows a probability density function (pdf) $f(x)$, a cumulative distribution function (cdf) $F(x)$, and has a mean μ_x. Table 2 lists the notations and their descriptions used throughout this paper.

Table 2. Notations.

Notations	Descriptions
p	per-unit retail price
w	per-unit forward wholesale price by the retailer to the supplier
o	per-unit option price
e	per-unit option exercise price
s	per-unit salvage value
x	market demand with pdf $f(x)$, cdf $F(x)$, and mean μ_x
r	per-unit spot market price with pdf $g(r)$, cdf $G(r)$, and mean μ_r
ϕ	probability that the spot price is less than the exercise price, i.e., $Pr(r < e)$
Q	forward contract amount
q	option contract amount
q_e	option exercise amount
π	expected profit, $\pi = E(P)$, where P is the realized profit
fw, fo, fos	indices for forward, forward + option, and forward + option + spot market, respectively

Procurement can be made through either a forward contract (FW) or an option contract (OP), where the contract parameters are exogenously determined in the market. In the FW contract, the retailer commits to a committed order Q with the supplier at a predetermined wholesale price w. The supplier then produces and delivers the ordered quantity to the retailer at the start of the selling season. In the option (OP) contract, two key parameters are involved: the option price o and the exercise price e. The option price is paid by the retailer to the supplier in advance to reserve a specific quantity q before the selling season begins. The exercise price is paid only when the retailer chooses to exercise the reserved options at the time of contract execution. The retailer has the right, but not the obligation, to purchase any portion of the reserved quantity, and the supplier is obligated to fulfill all exercised quantities. A distinctive feature of this study is the incorporation of a spot market (SP) into procurement decisions. The retailer can procure additional units from the spot market if the quantities ordered through the FW and OP contracts fall short of realized demand. This study focuses on developing an optimal procurement strategy by determining the optimal order quantities for FW and OP contracts.

Under the combined FW and OP contract *without* a spot market, the retailer orders Q units through the FW contracts and reserves q units via the OP contract. Therefore, the maximum quantity the retailer can procure from a supplier is $Q + q$. The unmet demand is lost if the demand is higher than $Q + q$. Under the combined FW and OP contract *with* the spot market, the retailer procures all the unmet demand from the spot market with unlimited capacity. The spot market price r is uncertain and is estimated using distribution with pdf $g(r)$, cdf $G(r)$, and the mean μ_r. The spot market price may be higher or lower than the option exercise price as it fluctuates over time. If the spot market price is lower than the option exercise price, the retailer does not need to exercise the option and instead procures the intended option quantity from the spot market. At the end of the selling season, any unsold inventory retains a salvage value s. We assume that the spot market is always available when needed. Additionally, the supplier is reliable, ensuring that the retailer can receive the agreed-upon supply. The retailer is assumed to have a risk-neutral disposition, making decisions to maximize expected profit. We also assume that the selling price, wholesale price, option price, and salvage value are given by the market. The following assumptions are made to avoid trivial or unrealistic scenarios: $p > w > e > s,\ \mu_r > o + e > w - s,\ p > r$.

We investigate the optimal procurement models for the retailer without the spot market in Sections 3.1 and 3.2, and then present the optimal ordering decisions with the spot market in Section 3.3.

3.1. Procurement Model for Forward Contract (FW)

A forward contract is an agreement between two parties to purchase a quantity of goods at a predetermined price on a future date. Procurement through wholesale price-based forward contracts is a widely used procurement method in the industry. The retailer's profit function P_{fw} can be expressed as follows:

$$P_{fw} = pmin(x, Q) - wQ + s(Q - x)^{+} \tag{1}$$

where $(y)^{+} = \max(y, 0)$. The first term represents the total revenue, the second term accounts for the purchase cost incurred, and the third term reflects the salvage value for the leftover inventory. Then, the retailer's expected profit, π_{fw}, can be represented as follows:

$$\pi_{fw} = E\left(P_{fw}\right) = (p - w)Q - (p - s)\int_{0}^{Q} F(x)dx \tag{2}$$

Note that $E[min(x, Q)] = Q - \int_{0}^{Q} F(x)dx$ and $E[(Q - x)^{+}] = \int_{0}^{Q} F(x)dx$. The first and second derivatives of π_{fw} with respect to Q are $\frac{d\pi_{fw}}{dQ} = (p - w) - (p - s)F(Q)$ and $\frac{d^2\pi_{fw}}{dQ^2} = -(p - s)f(Q)$. With the assumption of $p > w > s$, $\frac{d^2\pi_{fw}}{dQ^2} < 0$ holds, indicating that π_{fw} is concave with respect to Q. The first-order condition indicates that the optimal order quantity for the retailer, Q^{*}_{fw}, is as follows:

$$Q^{*}_{fw} = F^{-1}\left(z^{Q*}_{fw}\right) \text{where } z^{Q*}_{fw} = \frac{p - w}{p - s} \tag{3}$$

3.2. Procurement Model for Combined Forward and Option Contract (FO)

This strategy combines the FW and OP models, where the retailer utilizes both FW and OP contracts. The retailer profit function π_{fo} can be expressed as follows:

$$P_{fo} = pmin(x, Q+q) - wQ + s(Q-x)^+ - oq - emin\Big((x-Q)^+, q\Big) \tag{4}$$

The first term represents the total revenue from the sales, the second term accounts for the purchase cost incurred under the FW contract, and the third term signifies the salvage value. The fourth and final term account for the option and exercise prices, respectively. The retailer's expected profit π_{fo} can be represented as follows:

$$\pi_{fo} = E\Big(P_{fo}\Big) = (p-o-e)q - (e-s)\int_0^Q F(x)dx + (p-w)Q - (p-e)\int_0^{Q+q} F(x)dx \tag{5}$$

Note that $E[min\Big((x-Q)^+, q\Big)] = q + \int\limits_0^Q F(x)dx - \int\limits_0^{Q+q} F(x)dx$. Chen and Shen [25] showed that π_{fo} is jointly concave with respect to Q and q. Then, the first-order condition provides the following expression (see [25] for the proof):

$$(Q+q)^*_{fo} = F^{-1}\Big(z_{fo}^{(Q+q)*}\Big) \text{ where } z_{fo}^{(Q+q)*} = \frac{p-o-e}{p-e} \tag{6}$$

The optimal order quantity Q^*_{fo} for the FW contract quantity is determined as follows:

$$Q^*_{fo} = F^{-1}\Big(z^*_{Q_{fo}}\Big) \text{ where } z^*_{Q_{fo}} = \frac{o+e-w}{e-s} \tag{7}$$

In terms of the relationship between $(Q+q)^*_{fo}$ and Q^*_{fo}, we have two cases: (i) $(Q+q)^*_{fo} \geq Q^*_{fo}$ and (ii) $(Q+q)^*_{fo} < Q^*_{fo}$. In case (i), $\Big(Q+q\Big)^*_{fo}$ and Q^*_{fo} are obtained by expressions (6) and (7) and the option quantity q^*_{fo} is $q^*_{fo} = (Q+q)^*_{fo} - Q^*_{fo}$. On the other hand, in case (ii), q^*_{fo} has a negative value. Due to the concavity of the objective function, the optimal value must be at the boundary, where $q^*_{fo} = 0$, leading to Q^*_{fo} = Q^*_{fw}. In this case, no option is purchased.

3.3. Procurement Model for Forward, Option, and Spot Market (FOS)

This strategy combines forward contracts, options, and the spot market, which is the focus of our study. The FOS procurement process is illustrated in Figure 1.

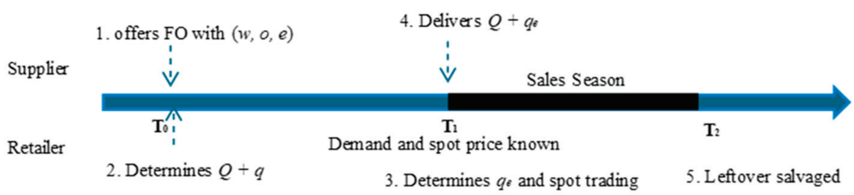


Figure 1. The sequence of events in the FOS procurement strategy.

The portfolio procurement model has three steps, detailed as follows:

Stage T_0: This is long before the selling season begins, since the procurement lead time is assumed to be long. At this stage, the retailer has a unit price w for the forward contract, and a per-unit option price o and exercise price e for the option contract. The retailer has uncertain information about the demand with pdf $f(x)$ and cdf $F(x)$, and the spot price with pdf $g(r)$ and cdf $G(r)$. Based on the information on hand, the retailer determines the

committed quantity Q for the forward contract and the option quantity q for the option contract. The retailer pays $wQ + oq$ to the supplier.
Stage T_1: This is the stage when the selling season starts, and demand x and spot price r are realized. At this stage, the retailer decides whether to exercise the option contract and/or procure products from the spot market. The decision depends on three market conditions: (1) $x < Q$, (2) $x > Q$ and $r < e$, and (3) $x > Q$ and $r > e$.

(1) $x < Q$: No option is exercised, and no spot purchase is made. The procurement is made only through the FW contract.

(2) $x > Q$ and $r < e$: The retailer does not exercise the option quantity. Instead, the demand not covered by the committed quantity Q is procured from the spot market because the spot price is lower than the option exercise price. The purchase amount from the spot market is $(x - Q)$.

(3) $x > Q$ and $r > e$: The retailer exercises the option quantity where the exercise quantity is $q_e = \min((x - Q)^+, q)$. The retailer may purchase the extra quantity needed from the spot market, where the purchase amount is $(x - Q - q)^+$. The supplier delivers $(Q + q_e)$ units to the retailer.

Stage T_2: At the end of the season at T_2, the remaining products after sale $(Q - x)^+$ are salvaged at a price of s per unit.

Based on the descriptions above, the retailer's profit P_{fos} can be formulated as follows, with forward quantity Q and option quantity q:

$$P_{fos} = \begin{cases} px - wQ - oq + s(Q-x)^+ - r(x-Q)^+, & r \le e \\ px - wQ - oq + s(Q-x)^+ - e\min\left((x-Q)^+, q\right) - r(x-Q-q)^+ & r > e \end{cases}$$

Then, the expected profit of the retailer is obtained as follows:

$$\begin{aligned} \pi_{fos} = p\mu_x - wQ - oq + s\int_0^Q (Q-x)f(x)dx - \int_0^e rg(r)dr \int_Q^\infty F(x)dx - e(1 \\ -G(e))\left[\int_Q^{Q+q} (x-Q)f(x)dx + q\int_{Q+q}^\infty f(x)dx\right] \\ -\int_e^\infty rg(r)dr\left[\int_{Q+q}^\infty (x-Q-q)f(x)dx\right] \end{aligned} \quad (8)$$

Proposition 1. *The retailer's expected profit π_{fos} under the FOS contract is jointly concave with respect to Q and q.*

Proof. The retailer's expected profit stated in expression (8) can be restated as follows:

$$\begin{aligned} \pi_{fos} = (p - \mu_r)\mu_x + (\mu_r - w)Q + \left(\mu_r - o - e + \int_0^e G(r)dr\right)q \\ -\left(e - s - \int_0^e G(r)dr\right)\int_0^Q F(x)dx - (\mu_r - e \\ +\int_0^e G(r)dr)\int_0^{Q+q} F(x)dx) \end{aligned} \quad (9)$$

The first and second derivatives of expression (9) with respect to Q and q are as follows:

$$\frac{d\pi_{fos}}{dQ} = (\mu_r - w) - (e - \mathrm{s} - \int_0^e G(r)dr)F(Q) - (\mu_r - e + \int_0^e G(r)dr)F(Q+q) \quad (10)$$

$$\frac{d^2\pi_{fos}}{dQ^2} = -(e - \mathrm{s} - \int_0^e G(r)dr)f(Q) - (\mu_r - e + \int_0^e G(r)dr)f(Q+q) \quad (11)$$

$$\frac{d\pi_{fos}}{dq} = (\mu_r - o - e + \int_0^e G(r)dr) - (\mu_r - e + \int_0^e G(r)dr)F(Q+q) \quad (12)$$

$$\frac{d^2\pi_{fos}}{dq^2} = -(\mu_r - e + \int_0^e G(r)dr)f(Q+q) \tag{13}$$

$$\frac{d^2\pi_{fos}}{dqdQ} = -(\mu_r - e + \int_0^e G(r)dr)f(Q+q) \tag{14}$$

The determinant of the Hessian Matrix in terms of Q and q is as follows:

$$Det(H) = (\mu_r - e + \int_0^e G(r)dr)(e - s + \int_0^e G(r)dr - s)f(Q)f(Q+q) \tag{15}$$

With the assumptions that $\mu_r > e$ and $e > s$, it follows that $\frac{d^2\pi_{fos}}{dQ^2} < 0$, $\frac{d^2\pi_{fos}}{dq^2} < 0$, and $Det(H) > 0$. Therefore, π_{fos} is concave with respect to Q and q. □

From Proposition 1, the values of Q and q that satisfy the first-order conditions, $\frac{d\pi_{fos}}{dQ} = 0$ and $\frac{d\pi_{fos}}{dq} = 0$, yield the retailer's maximum profit. Let $(Q+q)^*_{fos}$ represent the optimal order quantity that maximizes the retailer's profit. According to expression (13), the retailer's optimal order quantity is determined as follows:

$$F(Q+q)^*_{fos} = 1 - \frac{o}{\mu_r - e + \int_0^e G(r)dr} \tag{16}$$

$$(Q+q)^*_{fos} = F^{-1}\left(z^*_{(Q+q)_{fos}}\right) \text{ where } F(Q+q)^*_{fos} \tag{17}$$

Substituting $F(Q+q)^*_{fos}$ into the first derivative from expression (10) yields the following:

$$\frac{d\pi_{fos}}{dQ} = (e - s - \int_0^e G(r)dr)F(Q) - \left(o + e - w - \int_0^e G(r)dr\right) = 0 \tag{18}$$

which leads to the following results:

$$F(Q)^*_{fos} = \frac{o + e - w - \int_0^e G(r)dr}{e - s - \int_0^e G(r)dr} \tag{19}$$

$$Q^*_{fos} = F^{-1}\left(z^*_{Q_{fos}}\right) \; where \; z^*_{Q_{fos}} = F(Q)^*_{fos} \tag{20}$$

For the expressions (17) and (20) to be well defined, $(Q+q)^*_{fos} \geq Q^*_{fos}$ should hold. Hence, the following proposition is derived:

Proposition 2. *The retailer's optimal ordering decisions for Q and q are as follows:*
Case (i) $(Q+q)^*_{fos} \geq Q^*_{fos}$: $Q^*_{fos} = F^{-1}\left(z^*_{Q_{fos}}\right)$, $q^*_{fos} = (Q+q)^*_{fos} - Q^*_{fos}$,
Case (ii) $(Q+q)^*_{fos} < Q^*_{fos}$: $Q^*_{fos} = Q^*_{fs}$, $q^*_{fos} = 0$

Proof. In terms of the relationship between $(Q+q)^*_{fos}$ and Q^*_{fos}, we have two cases: (i) $(Q+q)^*_{fos} \geq Q^*_{fos}$ and (ii) $(Q+q)^*_{fos} < Q^*_{fos}$. In case (i), it is straightforward to obtain $(Q+q)^*_{fos}$ and Q^*_{fos} by using expressions (17) and (20). In this scenario, the option quantity q^*_{fos} has a positive value, allowing the retailer to utilize the option contract, i.e., $q^*_{fos} = (Q+q)^*_{fos} - Q^*_{fos}$. In case (ii), the option quantity is negative, making it infeasible in a real-world setting. Due to the concavity of the expected profit function, the optimal value must be at the boundary with $q^*_{fos} = 0$. In this case, the retailer considers only two procurement sources: the forward contract and spot market (FS). From this procurement scenario, the retailer's profit P_{fs} is as follows:

$$P_{fs} = px - wQ + s(Q - x)^{+} - r(x - Q)^{+} \tag{21}$$

Then, the expected profit π_{fs} is

$$\begin{aligned} \pi_{fs} = p\mu_x - wQ + s\int_0^Q (Q - x)f(x)dxpx - \int_0^\infty rg(r)dr \\ \int_Q^\infty F(x)dx = (p - \mu_r)\mu_x + (\mu_r - w)Q - (\mu_r - s)\int_0^Q F(x)dx \end{aligned} \tag{22}$$

It is easy to show that π_{fs} is concave with respect to Q. The first-order condition produces the optimal forward order quantity Q^*_{fs} to maximize the expected profit, as follows:

$$Q^*_{fs} = F^{-1}\left(z^*_{Q_{fs}}\right) \ where \ z^*_{Q_{fs}} = \frac{\mu_r - w}{\mu_r - s} \tag{23}$$

Finally, in case (ii), we have $Q^*_{fos} = Q^*_{fs}$ and $q^*_{fos} = 0$. □

3.4. A Solution Form for the Specific Distribution Case

For the proposed FOS contract, we create an analytical solution for a specific case where demand x and spot price r follow uniform distributions $U(a,b)$ and $U(c,d)$, respectively. With r following a uniform distribution, the equation $\int_0^e G(r)dr = \frac{(e-c)^2}{2(d-c)}$ holds. Then, expressions (17) and (20) can be restated as follows:

$$(Q+q)^*_{fos} = F^{-1}\left(z^*_{(Q+q)_{fos}}\right) \text{ where } z^*_{(Q+q)_{fos}} = 1 - \frac{2o(d-c)}{2(d-c)(\mu_r - e) + (e-c)^2} \tag{24}$$

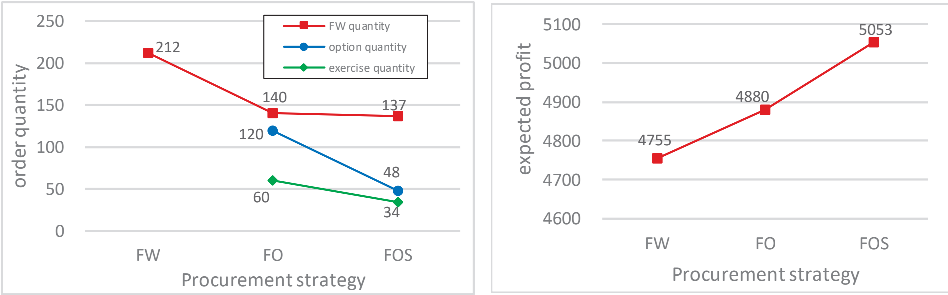
$$Q^*_{fos} = F^{-1}\left(z^*_{Q_{fos}}\right) \text{ where } z^*_{Q_{fos}} = \frac{2(o+e-w)(d-c) - (e-c)^2}{2(e-s)(d-c) - (e-c)^2} \tag{25}$$

The optimal option quantity q^*_{fos} is determined by following the same procedure as in Section 3.3, depending on the relationship between $(Q+q)^*_{fos}$ and Q^*_{fos}. The analytical solutions are utilized in the next section where numerical studies are performed.

4. Numerical Studies

This section presents numerical studies to demonstrate the performance of the model presented in this paper. The illustrative example draws on the frameworks of Mathur and Shah [32] and Tao and Koo [33]. The demand x during the sales season is assumed to follow a uniform distribution, x $\sim U(100, 300)$, with a mean of 200. The cost parameters are as follows: p = 60, w = 32, o = 6, e = 30, s = 10, and the spot price r is assumed to follow a uniform distribution $r \sim U(25, 55)$ with a mean of 40. Numerical experiments are conducted using MS Excel 2016 with the help of R programming (version 4.3.1) on a desktop computer.

Three procurement strategies are analyzed: forward contract (FW), forward and option contract (FO), and forward, option, and spot market contract (FOS). Figure 2 presents the order quantity and the corresponding expected profit for each strategy. The results indicate that in the FO and FOS strategies, the optimal forward order quantity is lower than in the FW strategy, and the option order quantity in the FOS strategy is smaller than in the FO strategy. Since unmet demand from options can be procured through the spot market, it is reasonable that the option order quantity in the FOS strategy decreases.

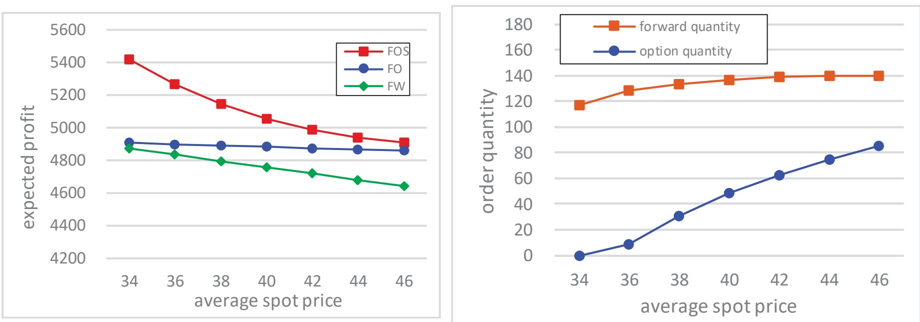


(**a**) (**b**)

Figure 2. The order quantity and the expected profit of each procurement strategy. (**a**) Optimal order (exercise) quantity; and (**b**) retailer's expected profit.

Figure 2b shows that the expected profit increases when an option contract is added to the forward contract, and incorporating the spot market into the procurement decision-making process can lead to even greater profits. For a fair comparison, it is assumed that any demand unmet through forward and option procurement is procured from the spot market, even in the FW and FO contracts. It is observed that the procurement strategy considering the spot market (FOS contract) yields higher profits compared to the procurement strategies that do not consider the spot market (FW, FO). These results have important implications for supply chain management. Specifically, applying a portfolio procurement strategy that incorporates futures, options, and the spot market can enhance the retailer's expected profit. In this case, considering procurement from the spot market, the retailer should allocate lower quantities to futures and options than when the spot market is not taken into account.

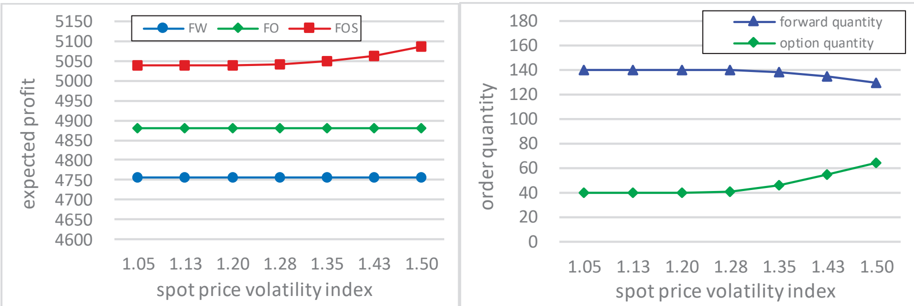
We conduct a sensitivity analysis to examine how the supply chain environment affects procurement strategies. The impact of spot market prices on the performance of the procurement strategies is illustrated in Figure 3. As expected, when the average spot price is low, the benefits of increased flexibility in spot market procurement outweigh the additional costs, leading to the FOS strategy outperforming the other two procurement strategies. On the other hand, when the expected spot price is high, the increased procurement cost from the spot market diminishes the benefits of flexibility, resulting in the FOS strategy yielding a similar expected profit to the FO strategy. Figure 3b shows that the optimal option quantity increases as average spot price rises. When the average spot price is low and close to option price, the optimal option quantity is very low. This result is expected, as there is little incentive to enter into an option contract when the option price is comparable to the spot price.



(**a**) (**b**)

Figure 3. Influence of spot price on the performance of the procurement strategies. (**a**) Spot price vs. expected profit; and (**b**) spot price vs. optimal option quantity.

The influence of spot price volatility on expected profit under different procurement strategies is presented in Figure 4. The x-axis represents the spot price volatility index, defined as the ratio of the maximum spot price to the mean spot price. For example, a volatility index of 1.2 means that the minimum and maximum spot prices are 32 and 48, respectively, while the mean spot price remains at 40. As shown in Figure 4a, the expected profit remains unchanged over different volatility indices in the FW and OP strategies, as their decisions do not consider the spot market. However, the FOS strategy performs particularly well when spot price volatility is high. When spot price volatility is high, the probability of the spot price falling below the option exercise price increases. In this case, the retailer is more likely to procure from the spot market instead of exercising the option contract, leading to lower purchasing costs and higher profits. Figure 4b illustrates the influence of spot price volatility on the procurement portfolio under the FOS contract. As the spot price volatility increases, the forward order quantity decreases while the option quantity increases. This finding suggests that when a high fluctuation in spot prices is expected, firms should increase their option quantity to enhance procurement flexibility while reducing the strictly committed forward order.

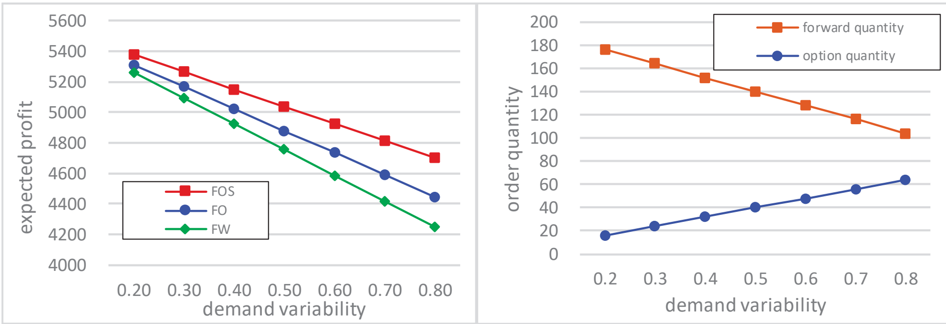


(**a**) (**b**)

Figure 4. Performance of the procurement strategies over different spot price volatilities. (**a**) Spot price volatility vs. expected profit; and (**b**) spot price volatility vs. optimal option quantity.

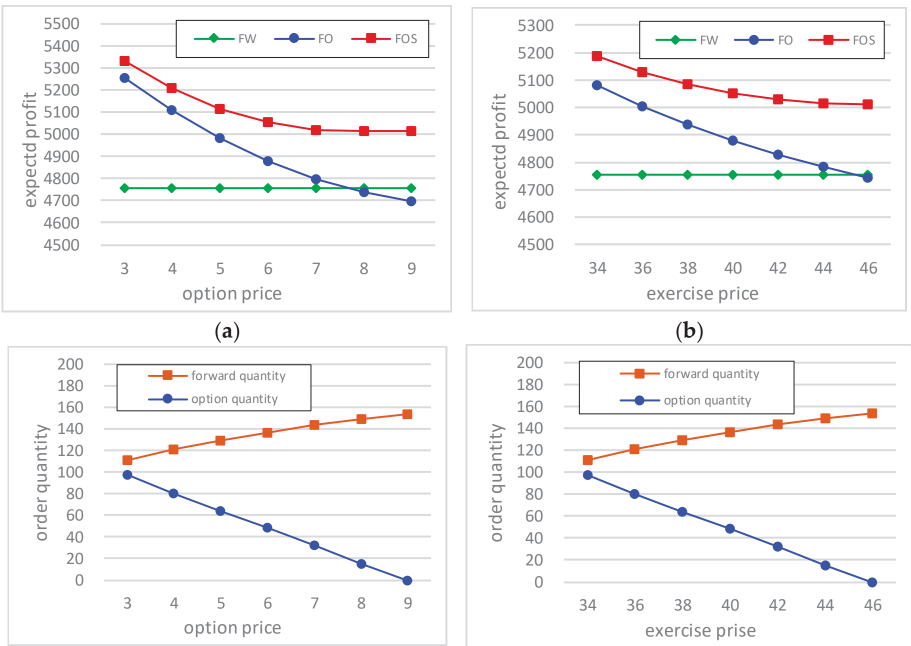
Figure 5 illustrates the influence of demand variability on the performance of different procurement strategies. The demand distribution is adjusted so that demand varies between 20% and 80% of the mean, allowing us to analyze the impact of demand volatility. For example, a demand variability of 20% indicates that the demand follows $U(160, 240)$ with a mean of 200. Figure 5a shows that the FW strategy exhibits the steepest decline in expected profit with increasing demand variability, indicating a greater vulnerability to demand fluctuations. In comparison, the FO strategy performs better than the FW, as it provides greater flexibility to adapt to market demand. The FOS procurement strategy outperforms the other two strategies across all levels of demand variability. In particular, the greater the demand volatility, the more significantly the FOS strategy outperforms the other two. Therefore, supply chain managers should actively adopt the FOS procurement strategy, especially in supply chain environments with high demand variability.

Figure 6a,b illustrate how changes in option price and exercise price affect different procurement strategies. Increases in both option price and exercise price have similar effects on each strategy. As option costs rise, the expected profits of both the FO and FOS strategies decrease. However, the rate of decline is more gradual for the FOS strategy than for the FO strategy. Additionally, the FOS strategy consistently yields higher expected profits than the other two strategies. Figure 6c,d show the optimal order quantity as option price and exercise price change. When the option costs rise, the FW order quantity increases while the option order quantity declines, leading to an overall reduction in total order quantity. This suggests that as option costs rise, procurement shifts towards the spot market, resulting in a decrease in total order quantity. These findings highlight the importance of supply chain managers carefully considering option costs when determining the volume of forward and option contracts.



(**a**) (**b**)

Figure 5. Effect of different demand variabilities on procurement strategies. (**a**) Demand variability vs. expected profit; and (**b**) demand variability vs. optimal order quantity.



(**a**) (**b**)

(**c**) (**d**)

Figure 6. Effect of different option and exercise prices on procurement strategies. (**a**) Option price vs. expected profit; (**b**) exercise price vs. expected profit; (**c**) option price vs. optimal order quantity; and (**d**) exercise price vs. optimal order quantity.

In our numerical experiments, we assume that demand and spot price follow a uniform distribution. This choice is made not only for the convenience of deriving analytical results through simple calculations but also to ensure the reproducibility and to enhance the clarity of our findings for readers. We also conduct experiments under scenarios where demand and spot price follow a normal distribution. The results are presented in Figure 7. Comparing Figures 2 and 7, we observe no significant differences between the results in both cases, suggesting that assuming a uniform distribution does not undermine the ability to derive meaningful managerial insights. This indicates that the insights gained from our previous experiments under a uniform distribution remain valid and practically useful.

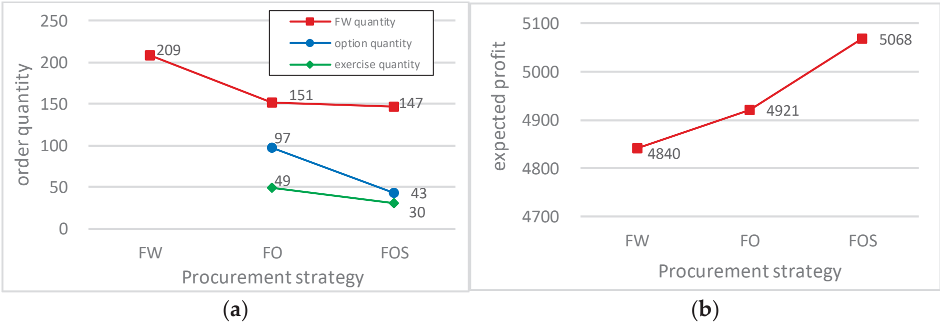


Figure 7. Experimental results with spot price and demand following normal distributions. (**a**) Optimal order (exercise) quantity; and (**b**) retailer's expected profit.

5. Conclusions

Portfolio procurement is widely adopted across industries and plays a crucial role in helping businesses adapt to market conditions, demand fluctuation, and price volatility. This study explores portfolio procurement strategies involving forward and option contracts in a setting where a spot market exists. We develop an optimal ordering model in portfolio procurement that incorporates the spot market and analyzes its implications. Our findings indicate that the retailer's optimal order quantity is lower when a spot market is available than when it is not. Moreover, incorporating the spot market into procurement decisions can enhance the retailer's expected profit. The effectiveness of the proposed model depends on the supply chain environment. Specifically, the model proves more efficient when the expected procurement cost in the spot market does not significantly differ from the cost of the forward or option contracts, and the spot price volatility is high. Furthermore, for industries facing high demand variability, the FOS (forward, option, and spot) procurement strategy emerges as the most effective procurement strategy, as it balances flexibility and profitability. Firms operating under unpredictable demand and highly volatile spot prices—such as those in the fast-moving consumer goods sector—should consider prioritizing the FOS strategy to ensure optimal profitability and adaptability.

While our study provides valuable insights, it has certain limitations that warrant further investigation. We assume that the retailer is risk-neutral, meaning that procurement decisions are made to maximize expected profit. In contrast, when a supply chain participant is risk-averse, procurement decisions should account for profit variability in the performance measure. We also assume that spot market capacity is unlimited and suppliers are fully reliable, whereas, in reality, supply disruptions or market volatility may impose constraints. Future research could explore supply chain coordination mechanisms by relaxing these assumptions.

Author Contributions: Conceptualization, N.A.T. and P.-H.K.; methodology, P.-H.K.; software, N.A.T.; validation, N.A.T. and P.-H.K.; formal analysis, N.A.T.; investigation, N.A.T.; resources, P.-H.K.; data curation, N.A.T.; writing—original draft preparation, N.A.T.; writing—review and editing, P.-H.K.; visualization, P.-H.K.; supervision, P.-H.K.; project administration, P.-H.K.; funding acquisition, P.-H.K. All authors have read and agreed to the published version of the manuscript.

Funding: This research was supported by the Basic Science Research Program through the National Research Foundation of Korea (NRF) funded by the Ministry of Education, Korea (No. 2022R1I1A3070919).

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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Economic and Environmental Sustainability Performance Improvements in the Outdoor Wood Furniture Industry Through a Lean-Infused FMEA-Supported Fuzzy QFD Approach

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Abstract: Fiercer competition across all industries has made identifying and eliminating lean wastes to enhance sustainability performance an effective route that many companies take. This study focuses on the production process of wood park/garden benches at a company that manufactures outdoor wood furniture. The goal was to identify lean wastes within a sustainability framework across seven operations and integrate multi-criteria decision making (MCDM) methodologies for waste elimination. Eleven lean KPIs addressing economic and environmental sustainability were used to develop and prioritize 13 lean failure modes (LFMs) with Risk Priority Numbers (RPNs) above 100, leading to lean project proposals for each LFM. Eighteen lean tools were ranked using the Fuzzy Quality Function Deployment (Fuzzy QFD) method. A total of eight improvement propositions, namely, Kaizen and continuous improvement, upgrade machinery for energy efficiency, Just-In-Time (JIT), optimize production processes with lean methodologies, implement cost reduction strategies, Total Productive Maintenance (TPM), Investing in Automation, and Andon were implemented. Significant improvements were observed post-implementation: total lead time was reduced by approximately 38.46%, value-added time by 22.05%, and non-value-added time by 47.64%. The required number of workers decreased by 14.29%, and the total inventory decreased by approximately 57.31%. The results contribute to sustainability goals by reducing energy consumption and waste while increasing economic efficiency. It also provides a robust framework for decision making in fuzzy environments, guiding practitioners and academics in lean management and sustainability.

Keywords: sustainability; lean management; multi-criteria decision making; FMEA; Fuzzy QFD

1. Introduction

Sustainability represents one of the most significant contemporary megatrends [1–3]. The Brundtland Report laid the groundwork for sustainable development by discussing the integration of environmental, social, and economic considerations [4]. The Triple Bottom Line framework, which emphasizes three pillars—people, planet, and profit—was coined later by John Elkington in 1994 [5,6].

Although the concept of sustainability has a long history, its importance has increased and continues to grow. The principal driving force behind this phenomenon is the growth in the global population and the concomitant increase in environmental awareness among people and within the business community [7]. In this context, corporate investments are evolving in response to the phenomenon of sustainability. The objective is to integrate this phenomenon into lean transformations in all studies, focusing on achieving profitability. This approach is intended to facilitate the development of more environmentally friendly processes and enhance productivity [8–10]. As Mahmoum Ganbadi et al. (2021) posited, contemporary approaches to supply chain modeling have prioritized monetary performance, with few addressing the full spectrum of sustainability encompassing economic, environmental, and social dimensions [11]. In his study, he underscored the necessity for more comprehensive sustainability assessments and empirical studies and proposed a research agenda to address these deficiencies [11]. Braglia et al. (2024) presented a structured methodology that integrates Lean Thinking and environmental sustainability in strategic planning to improve environmental performance, emphasizing the role of cost–benefit analysis in sustainability decisions and the integration of technological innovations in the evaluation of green measures and decision support processes in industrial settings [12]. Furthermore, environmentally conscious individuals have begun utilizing wood, a natural, organic, and renewable resource, to mitigate environmental impact.

Wood is a natural and durable material used in interior design for centuries [13]. Wood is employed in a multitude of applications. The primary sectors that utilize wood as a principal material are construction and building, paper, home and industrial furniture, and outdoor furniture, which is the focus of this study [14]. The global outdoor furniture market is poised for robust expansion from 2025 onward, with multiple forecasts indicating a value growth from around USD 53 billion to over USD 80 billion by 2032 and average annual growth rates of about 5–6% [15–18]. Across these projections, wood remains a favored material in outdoor designs, valued for its natural aesthetics, durability, and timeless appeal. As conveyed in the aforementioned market reports, the prevailing perception is that consumers tend to favor wood in outdoor furniture designs due to its inherent aesthetic, durable, long-lasting, and timeless qualities.

Wooden outdoor furniture companies seek a competitive advantage through the lean philosophy/production practice [19]. The lean philosophy/production approach aims to enhance productivity by distinguishing between non-value-added and value-added activities throughout the production process [20]. As Siegel et al. (2019) state, lean manufacturing is a production method that identifies and eliminates waste and optimizes resource use through continuous improvement [21]. Concurrently, Braglia et al. (2024) emphasized that the implementation of lean manufacturing practices within the purview of environmental sustainability has the potential to enhance operational efficiency and ecological performance [22].

Taiichi Ohno initially developed the lean philosophy between 1948 and 1975 and has since exerted a profound influence across all sectors globally. The lean philosophy/culture will remain significant in the present and future eras due to its efficiency and high profitability [23]. In the context of lean manufacturing, waste is generated throughout the production process due to activities that do not contribute to the creation of added value. These wastes can be classified into a total of eight different categories: overproduction, waiting, unnecessary transportation, unnecessary handling, unnecessary processing, inventory, movement, and the waste of unused skills [24]. Seth et al. (2017) demonstrated that implementing waste reduction strategies derived from the lean production/philosophy process can increase productivity, specifically through improving cycle times within business processes [25]. Abreu et al. (2017) posited that implementing lean and green practices will result in two key outcomes [26]. Firstly, it will enhance efficiency by reducing waste. Secondly, conserving energy will augment efficiency and sustainability performance [26]. Concurrently, May et al. (2015) suggested sustainability performance while concomitantly increasing energy efficiency [27]. Although lean production is regarded as the foundation and focal point of the automotive industry, it is evident that it is being adopted in many sectors [28]. These include steel [29], agriculture/food [30], manufacturing, healthcare, construction, product development, service [31], prefabricated building manufacturing [32], and leather footwear [33].

The Value Stream Mapping (VSM) methodology is employed to identify these wastes in the process [23,34]. Lean practices, defined as lean tools, are necessary to reduce lean wastes identified using VSM methodology. Implementing lean practices has been demonstrated to enhance operational efficiency by eliminating non-value-added activities within the process. Furthermore, as indicated by Dieste et al. (2019), lean practices have been shown to improve environmental performance by increasing resource efficiency. This is achieved through the systematic elimination of waste, which results in a reduction in energy consumption [35]. However, it is essential to note that certain lean practices, such as Just-In-Time manufacturing (JIT), have the potential to adversely affect the environment due to their reliance on low inventory levels and frequent transportation [35]. The VSM methodology is typically understood as a visual representation of the process stages of a system [36]. Although the VSM methodology is highly effective in identifying waste, studies demonstrate that this methodology can be further enhanced by integrating digital technologies and sustainability in addition to the VSM methodology [8–10,37,38]. In this context, Abdulmalek and Raigopal (2007) employed simulation models to implement lean principles in a steel mill and observed the results [29]. In a similar vein, Horsthofer-Rauch et al. (2022) conducted a review of academic studies on the digitalization of VSM [38]. The manual execution of VSM has become inefficient and ineffective due to increasing production and product complexity [38]. Once the lean wastes have been identified through VSM, the subsequent decision-making process typically involves determining which lean tools are most effective in eliminating these wastes. In this regard, the optimal approach for top management and lean consultants is the application of multi-criteria decision making (MCDM) methods [39]. For instance, Mohanraj et al. (2015) systematically enhanced productivity by integrating QFD and VSM methodology in their study [40]. In a similar vein, Bhuvanesh Kumar and Parameshwaran (2018) employed a multifaceted approach that integrated F-QFD, F-FMEA, plant layout, and VSM methodologies to prioritize critical resources and eliminate lean wastes in the context of water tank and barrel production [41]. Building upon these studies, subsequent research conducted by Deepan et al. (2022) in the casting industry [42], Bhuvanesh Kumar and Parameshwaran (2020) in the manufacturing industry [43], Bhuvanesh Kumar and Parameshwaran (2019) in the casting and automobile industry [44], and Reda and Dvivedi (2022) in a leather shoe manufacturing company in Ethiopia have made valuable contributions to the literature by identifying, prioritizing, and eliminating lean waste [45]. While QFD and FMEA techniques from MCDM methodologies are employed in various contexts, including machine/equipment selection [46], product design, defect elimination [47,48], and performance improvement, these techniques can be employed to identify and eliminate potential defects in processes [49–52]. They can also be effectively utilized in the selection of lean tools. In this context, Reda and Dvivedi (2022) employed QFD and FMEA techniques to select the lean tools necessary for eliminating lean wastes [45]. This study demonstrates that choosing lean tools represents a significant decision-making challenge and that MCDM methodologies can be employed to address this issue. A literature review reveals that fuzzy logic, MCDM, and lean management are used in many sectors with varying degrees of integration to enhance productivity [40–44].

In the field of MCDM, Mahmoum Ganbadi et al. (2021) underscored the significance of integrating MCDM with sustainability, emphasizing the necessity for comprehensive sustainability assessments in supply chain design [11]. Moreover, while lean principles have been applied in various manufacturing contexts (e.g., Seth et al. (2017) in industrial transformers and Bhuvanesh Kumar and Parameshwaran (2018) in water tank manufacturing), their application in the outdoor wood furniture industry, especially with MCDM concepts for better sustainability performance, is limited [25,41]. This sector faces distinctive challenges, including process efficiency, material sustainability, environmental impact, and fluctuating cost factors, which necessitate a bespoke approach.

Consequently, despite extensive research in the areas of sustainability, MCDM, lean management, and the outdoor wood furniture industry, there is a notable absence of integration of these areas of study into a coherent framework. The extant literature primarily addresses these areas in isolation or conjunction with one another yet lacks a comprehensive approach that integrates all four aspects. This gap presents an opportunity to develop an integrated model that can enhance decision-making processes, improve sustainability performance, and facilitate lean management practices by combining lean and MCDM tools and techniques specifically tailored to the outdoor wood furniture industry. Prior research has demonstrated the efficacy of lean tools and sustainability models in various sectors. For example, Serafim Silva et al. (2024) proposed the VSM4S model, which combines the traditional VSM with sustainability indicators [10]. However, this model does not address the specific case of outdoor wood furniture [10]. Similarly, Bhamu and Sangwan (2014) emphasized the advancement of lean tools but noted the absence of a unified implementation framework that incorporates sustainability metrics and MCDM [28]. Bhattacharya et al. (2019) underscored the pivotal role of lean–green integration, particularly in terms of reducing waste, diminishing costs, and enhancing organizational performance [53]. The study observed that adopting a combination of lean and green practices yielded a more favorable impact on sustainability performance in comparison to the implementation of individual practices [53].

This study aims to contribute to the cluster of the intersection of the four main topics in the literature, as illustrated in Figure 1. Accordingly, this study's objectives are twofold: firstly, to demonstrate how lean management and MCDM principles and techniques can be effectively and systematically applied in a tailored way to optimize production processes, improve economic and environmental sustainability performance, and enhance decision-making capabilities in the outdoor wood furniture industry; and, secondly, to validate the effectiveness and practicality of the proposed methodology through the documentation of empirical evidence. By addressing this gap in the literature, this study will make a significant contribution to the field of outdoor wood furniture manufacturing. It will be one of the most relevant studies to date examining the adoption of sustainable and lean practices in this sector.

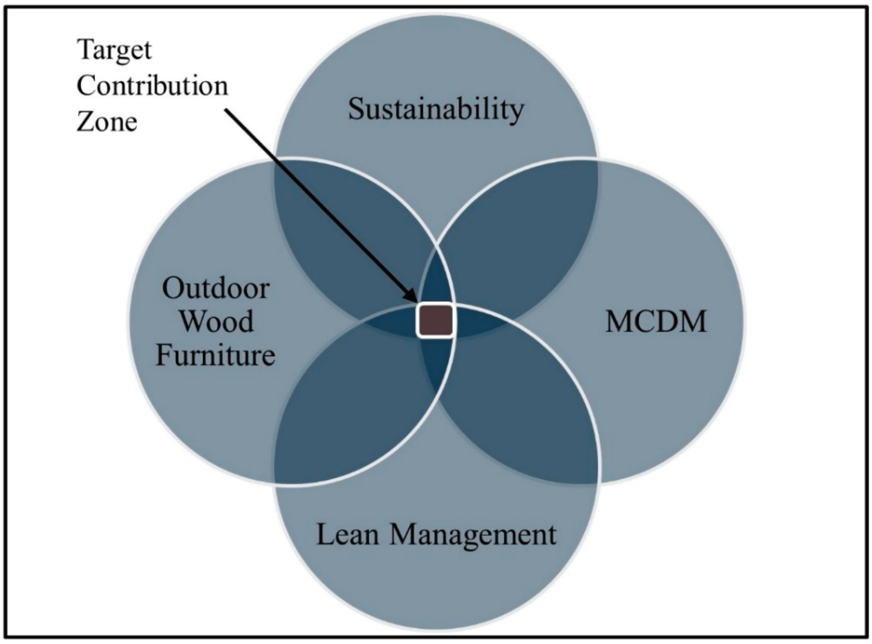


Figure 1. Target contribution zone of this study.

2. Materials and Methods

This study focused on the supply chain structure of a value-added wood product industry segment, namely, outdoor wood furniture. At the request of the industry partner, the pseudonym EcoCraft Outdoor Furniture is used instead of the company's real name. Established in 1995 in the United States, EcoCraft Outdoor Furniture is a wooden outdoor furniture company with a mission to create high-quality, durable, and sustainable outdoor furniture that enhances outdoor living spaces while minimizing environmental impacts. EcoCraft Outdoor Furniture specializes in wood outdoor furniture, including benches, chairs, tables, loungers, and custom-designed pieces. One of the company's most important products is the wooden garden/park bench, which is made from high-quality, sustainably sourced materials and designed to be durable for outdoor use. The bench features ergonomic designs and weather-resistant surface coatings to protect against rain, sunlight, and humidity. The wood-based park bench had a specific design so that all structural components—the seat, backrest, armrests, and legs—were made of wood, while metal hardware was limited to fasteners such as bolts, screws, and washers. The seat and backrest consisted of planks or slats, while the legs and armrests were shaped to provide support and stability. Internal braces were likewise fabricated from wood, preserving the bench's natural appearance. Although metal fasteners ensured secure connections and simplified assembly, no metal legs or auxiliary supports were included, thus reducing reliance on non-wooden materials. Before the wooden structure was assembled, it was treated with sanding and appropriate surface coatings (e.g., sealants, varnishes, or protective paint) to extend the bench's longevity while retaining its predominantly wooden character. The designated batch size for this product was 50 units.

Lean waste elimination is a pressing concern for organizations. By eliminating non-value-added activities, businesses strive to bolster efficiency and sustainability. However, the first step in eliminating lean waste is to make it visible. To achieve this, organizations rely on the robust VSM methodology [36]. This tool helps identify existing issues and potentially yields significant future benefits [37]. Using the VSM methodology to visualize waste, companies can select the appropriate lean tools to eliminate it [54].

Selecting lean tools was one of the most challenging aspects for businesses due to the numerous lean tools available for eliminating lean waste. However, choosing the most effective tool for waste elimination was crucial. Therefore, this study utilized the MCDM methodology to select lean tools for eliminating lean wastes and enhancing the sustainability performance of a company's target supply chain structure, producing outdoor wooden parks and garden equipment.

Initially, this study mapped the company's supply chain structure to understand the flow of materials and information across the entire process (Phase 1). This foundational step set the stage for identifying areas of waste and inefficiency. Then, key performance indicators (KPIs) relevant to the wood furniture industry were determined. In selecting the KPIs, a consultative and context-specific approach was adopted to ensure both industrial relevance and alignment with sustainability principles. Specifically, iterative discussions were conducted with three seasoned experts from the wood product sector and two specialists in sustainability. This interdisciplinary input ensured that metrics accurately reflect day-to-day production realities (e.g., Cycle Time, Changeover Time) while encompassing critical environmental considerations (e.g., energy consumption, waste generation). As such, the final KPI set strikes a balance between economic efficiency and environmental stewardship, capturing the multifaceted objectives of lean transformation in a practical manner for industry practitioners yet remains rigorous from a sustainability standpoint. The details of the final KPI set are given below.

- First Pass Yield (FPY) (%): The percentage of products that meet quality standards without rework.
- Changeover Time (min): The time required to switch from producing one batch to another.
- Overall Equipment Effectiveness (OEE) (%): Equipment effectiveness at each workstation, considering availability, performance, and quality.
- Energy Efficiency (kWh/batch): The energy consumed per batch at each workstation.
- Solid Waste Amount (kg/batch): The waste generated per batch at each workstation.
- Cycle Time (min): The time to complete one production cycle at each workstation.
- Up Time (min/day): The machinery's actual operational time per day, calculated as Up Time = OEE $\times$ 480.
- Down Time (min/day): The total time any machinery is not operational daily, calculated as Down Time = 480 $-$ Up Time.
- Production Cost Per Batch (USD): The cost incurred to produce one batch at each workstation, considering materials, labor, and overheads.

The selected KPIs' primary function was to quantify the economic and environmental benefits of deploying the proposed methodology. Using the data collected, the current state VSM was drawn to visually represent the existing processes (Phase 2). The VSM included all steps in the supply chain, from order placement to product delivery, highlighting value-added and non-value-added activities [36]. In Phase 2, detailed data on process times, inventory levels, material flows, and information flows were gathered. All the data were collected based on the pre-determined batch size of 50 wood benches. Based on the current state map, lean wastes were identified, including overproduction, waiting times, unnecessary transportation, excess inventory, defects, and underutilized talent (Phase 3) [54]. This study then proceeded to its next phase, where the root causes and effects of the identified lean wastes were analyzed and prioritized using the Failure Mode and Effects Analysis (FMEA) technique (Phase 4). The FMEA helped systematically identify potential failure modes, their causes, and effects and prioritized them based on their RPN [55]. The Delphi Method was employed in this study phase to ascertain the failure modes, probability, severity, and noticeability scores. In particular, three rounds of Delphi surveys were conducted, involving four experts from academic and industrial backgrounds. The selection criteria for these experts were based on their extensive experience in lean management, sustainability practices, and the value-added wood product industry. A consensus was deemed to have been reached when there was over 70% agreement on the appropriateness of the selected variables.

In the fifth phase, after analyzing the prioritized root causes, lean tools that could be used to address the prioritized lean wastes were proposed and ranked using the Fuzzy Quality Function Deployment methodology (Phase 5). Fuzzy QFD integrated customer and technical requirements, reducing subjectivity and uncertainty in the evaluation process [56]. A systematic procedure was adopted to establish the relationships in the Fuzzy QFD matrix, ensuring that each lean tool's linkage to a given failure mode was founded on expert opinion and established lean principles. Initially, a panel of four specialists—two industry managers with direct operational experience and two academic researchers versed in lean methodologies—assessed the compatibility of each lean tool with the identified waste categories. This assessment was conducted through consensus-based discussions, in which participants referenced documented effects of specific lean tools (e.g., Just-In-Time's impact on inventory and scheduling; automation's influence on production flow) and considered the contextual nuances of outdoor wood furniture manufacturing. The strength of each relationship was then encoded using a linguistic scale (weak, moderate, strong), subsequently translated into fuzzy numbers for quantitative analysis. All linguistic assessments conducted at this intersection were integrated by calculating the geometric mean of the evaluations provided by four experts. Accordingly, even where a linkage might appear secondary or indirect (such as between a tool focused on inventory management and a failure mode related to changeover delays), reasoned expert judgment was applied to ascertain whether any cascading process benefits or hidden interdependencies might exist. Therefore, the outcome was designed to reflect clear-cut primary relationships and less obvious synergies and trade-offs, enabling a more robust and replicable methodology. Then, the selected lean tools were implemented to achieve the future state VSM (Phase 6). The process data were re-collected after six months following the deployment of the improvement projects. Therefore, Future-state VSM illustrated the process's post-improvement state and outlined a leaner and more sustainable process flow that minimized or eliminated identified wastes. In past studies, Future-state VSM was used to visualize the optimal flow of materials and information [36]. This study reflects the post-improvement state with actual empirical findings. In the last phase, the results of the systematic methodology were interpreted and discussed to document this study's critical achievements and contributions (Phase 7).

By following these systematic steps, this study aimed to effectively eliminate lean wastes and improve the sustainability and efficiency of the supply chain for a company producing outdoor wooden park and garden equipment. Figure 2 provides a diagram illustrating the phases of this study. This section provides more detailed information on the FMEA and Fuzzy QFD methodology steps.

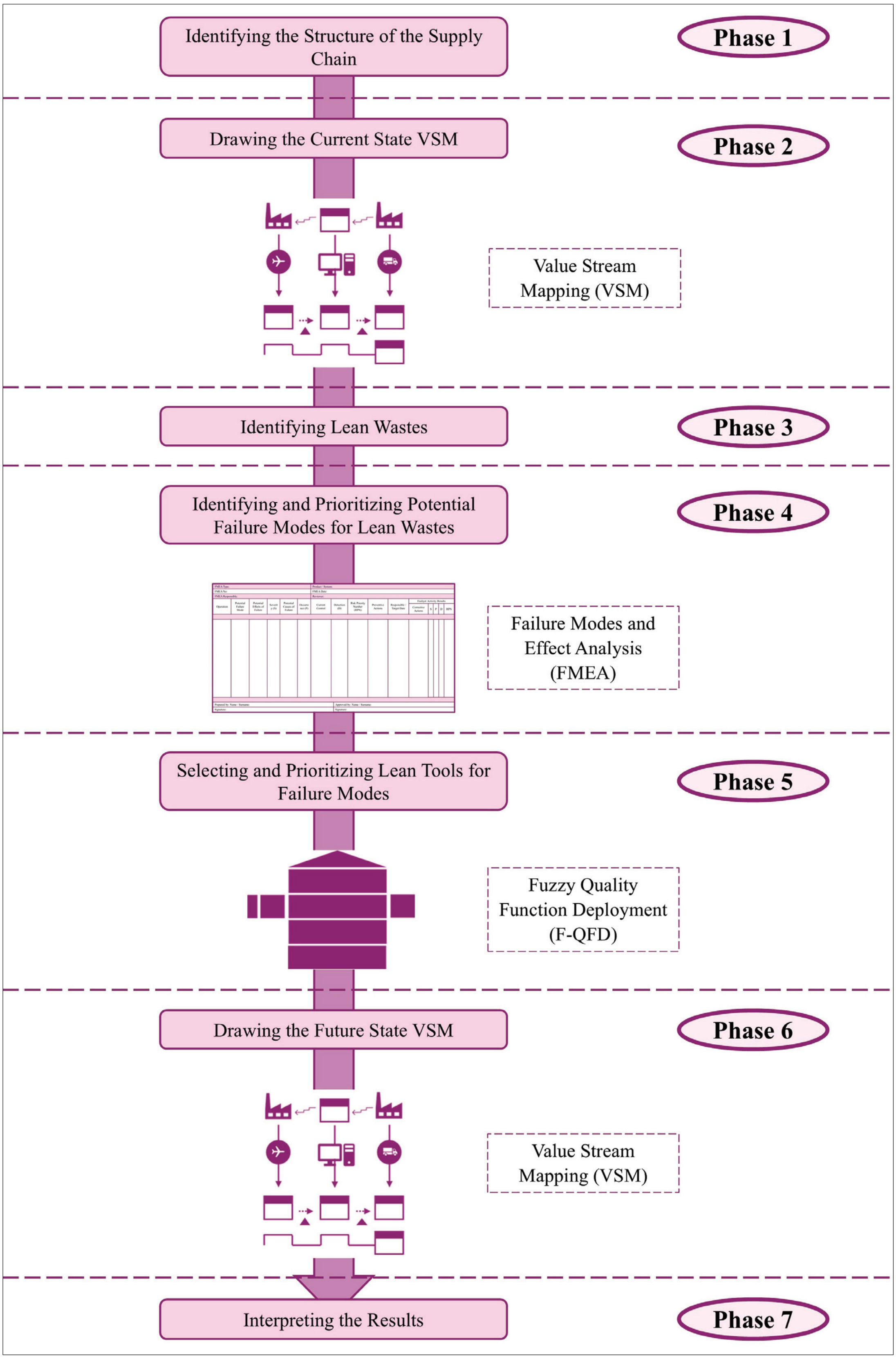


Figure 2. Diagram illustrating this study's phases.

2.1. Failure Modes and Effect Analysis (FMEA)

FMEA, a tool used for risk identification and mitigation, was developed in the late 1940s in the USA. This approach was initially applied in the nuclear and aerospace industries and continued to be used in these sectors over the subsequent years. Its utilization expanded to the NASA Apollo program in the 1960s, the automobile industry in the 1970s, and various subsequent applications after the 1980s [57–59].

Failure Mode and Effects Analysis is an analytical approach that evaluates and prevents known or potential failures in a product or process based on previous experiences and technologies. Assessing the consequences of existing or potential failures identifies measures to reduce or prevent the occurrence of these failures. After implementing the actions, the probability of failure is reassessed, and the entire analysis process is documented [55].

FMEA is classified into four main categories in risk analysis, each with a specific focus and application in different processes and industries. Design FMEA (DFMEA) is a risk analysis method that prevents failures and initiates corrective actions during the design phase of a product [60], while Process FMEA (PFMEA) analyzes the production phase of a product to identify potential failures in the process and implement corrective actions [61]. System FMEA (SFMEA) identifies and prioritizes failures affecting the entire system, originating from its components [62]. On the other hand, Service FMEA detects task errors due to system or process failures before the service is delivered to customers [63].

In this study, Process FMEA (PFMEA) activities were conducted. In the FMEA methodology, the RPN used to prioritize failure modes was calculated using Equation (1), which is the product of three critical components: occurrence, severity, and detectability. The occurrence factor represents the frequency of the hazard's occurrence. The severity factor indicates the impact of the hazard if it occurs. The detectability factor measures the likelihood of detecting the hazard before it occurs. The traditional scale values were used in the evaluation of occurrence, severity, and detectability rates of lean failure modes and for the calculation of RPN values [64].

The risk priority number (RPN) was calculated using Equation (1):

$$\text{RPN} = \text{Occurrence (O)} \times \text{Severity (S)} \times \text{Detectability (D)} \tag{1}$$

where Occurrence (O) represents the frequency of the hazard's occurrence. Severity (S) indicates the impact of the hazard if it occurs. Detectability (D) measures the likelihood of detecting the hazard before it occurs.

FMEA is not a finite analysis. It requires continuous system monitoring, repeating the analysis by taking necessary measures when a potential failure occurs, and identifying new risks and failures that the system may encounter due to evolving technology and conditions. This continuous approach ensures that the analysis remains relevant and effective over time.

2.2. Fuzzy QFD

Quality Function Deployment (QFD) was developed in Japan in the late 1960s to design products that meet customer requirements and improve the manufacturing process [65–67]. It was adopted by numerous Japanese companies, prominently Toyota and was introduced to the United States and Europe in 1983 [67]. Ford Motor Company was among the first Western companies to adopt QFD, and it continues to evolve in tandem with digitalization [66,67]. Recent studies have seen an escalation of interest in the integration of QFD with fuzzy logic and web-based services [66].

Subsequent to its integration with the Analytic Hierarchy Process (AHP) and Failure Mode and Effects Analysis (FMEA), QFD has become a prevalent instrument in project management [68]. Quality Function Deployment is a matrix, known as a "House of Quality", with customer requirements ("what") in the rows and technical specifications ("how") in the columns [41,43,45]. The body of the matrix illustrates the relationships between the two, and the roof shows the relationships among the technical specifications themselves. The house of quality is used sequentially as a four-stage model or a matrix of matrices for product, product parts, production process, and production planning [56]. The model's initial stage entails identifying customer expectations and their correlation with technical requirements. The product concept was developed in the subsequent stage, and critical technical features were defined. The following stage entails planning the production process and assessing the manufacturability of the technical requirements. The final stage entails implementing quality control and process enhancement initiatives, ensuring the perpetual enhancement of the product's performance. This systematic framework facilitates the effective management of customer-oriented design processes [67]. In this study, the initial two stages of the quality house were not employed since the target product was already part of the company's product catalogue. Consequently, the present study exclusively focused on the final two stages of the quality house: process planning and production planning matrices.

Integrating fuzzy logic with QFD applications aims to eliminate subjectivity and uncertainty in evaluating the "whats" and "hows". The House of Quality consists of nine steps, which are detailed below. Nevertheless, specific HOQ matrices, such as the preparation (planning) matrix, technical analysis, and goal analysis sections, were not included in this report as they are not pertinent to the current study [46].

Step 1: Identifying the importance of customer requirements, denoted as lean failure modes in this study. The identified lean failure modes are given in Table 1.

Table 1. Lean failure modes and lean tools.

Lean Failure Modes	Lean Tools
FM1: Poor Layout Design FM2: Equipment Downtime FM3: Lack of Automation FM4: Inventory Overstock FM5: Quality Issues FM6: Changeover Delays FM7: Energy Inefficiency FM8: Material Waste FM9: Long Cycle Time FM10: High Production Cost FM11: Inconsistent Yield FM12: Under-Utilized Talent FM13: Excessive Transportation	LT1: Implement layout modification LT2: 5S LT3: SMED LT4: TPM LT5: Pull System LT6: Standardize raw material quality LT7: Improve supplier relations LT8: Invest in automation LT9: Andon LT10: JIT LT11: FIFO LT12: Optimize production processes with Lean methodologies LT13: Six Sigma LT14: Poka-Yoke LT15: Upgrade machinery for energy efficiency LT16: Provide employee training and development programs LT17: Implement Kaizen and continuous improvement LT18: Implement cost reduction strategies

Step 2: Determination of technical requirements, denoted as lean tools in this study. The lean tools identified are given in Table 1.

Step 3: Assignment of importance weights to customer requirements. The importance weights of the LFMs were determined using the scale in Table 2.

Table 2. Linguistic variables used in the evaluation of customer requirements.

Linguistic Variables	Fuzzy Numbers	Membership Function	Range
Very Low Important (VLI)	(0, 0, 2.5)	$\mu(x) = (2.5 - x)/(2.5 - 0)$	$0 \leq x \leq 2.5$
Low Important (LI)	(0, 2.5, 5)	$\mu(x) = (x - 0)/(2.5 - 0)$ $\mu(x) = (5 - x)/(5 - 2.5)$	$0 \leq x \leq 2.5$ $2.5 \leq x \leq 5$
Moderately Important (MI)	(2.5, 5, 7.5)	$\mu(x) = (x - 2.5)/(5 - 2.5)$ $\mu(x) = (7.5 - x)/(7.5 - 5)$	$2.5 \leq x \leq 5$ $5 \leq x \leq 7.5$
Important (I)	(5, 7.5, 10)	$\mu(x) = (x - 5)/(7.5 - 5)$ $\mu(x) = (10 - x)/(10 - 7.5)$	$5 \leq x \leq 7.5$ $7.5 \leq x \leq 10$
Very Important (VI)	(7.5, 10, 10)	$\mu(x) = (x - 7.5)/(10 - 7.5)$	$7.5 \leq x \leq 10$

Step 4: Development of the relationship matrix between customer and technical requirements. This relationship matrix between the LFMs and lean tools was created with the aid of Table 3.

Table 3. Linguistic variables for relationships between customer requirements and service requirements.

Linguistic Variable	Symbol	Triangular Fuzzy Number	Membership Function	Range
Strong Relationship (SR)	Θ	(6, 8, 10)	$\mu(x) = (x - 6)/(8 - 6)$ $\mu(x) = (10 - x)/(10 - 8)$	$6 \leq x \leq 8$ $8 \leq x \leq 10$
Moderate Relationship (MR)	O	(2, 5, 8)	$\mu(x) = (x - 2)/(5 - 2)$ $\mu(x) = (8 - x)/(8 - 5)$	$2 \leq x \leq 5$ $5 \leq x \leq 8$
Weak Relationship (WR)	∇	(0, 2, 4)	$\mu(x) = (x - 0)/(2 - 0)$ $\mu(x) = (4 - x)/(4 - 2)$	$0 \leq x \leq 2$ $2 \leq x \leq 4$

Step 5: Preparation of the correlation matrix showing the technical requirements' relationships with lean tools. This correlation matrix was prepared using the correlation degree scale given in Table 4.

Table 4. Correlation degrees of technical requirements.

Correlation Degree	Symbol
Strong Positive	Θ
Positive	O
Negative	$\lozenge$
Strong Negative	$\blacklozenge$

Step 6: Calculation of the importance of the weights of the technical requirements using Equation (2).

$$RI_j = \sum_{i=1}^{n} \left[W_i \otimes R_{ij} \right] \; i = 1, \ldots, n; \; j = 1, \ldots, m \quad (2)$$

n : Number of lean failure modes;
m: Number of lean tools;
RI_j: The importance weight of the jth lean tool;
W_i: The importance rating of the ith lean failure mode;
R_{ij}: The relationship value between the ith lean failure mode and the jth lean tool.

Step 7: Defuzzification of the fuzzy lean tool importance weight (l, m, u) values using Equation (3).

$$X^* = \frac{l + 2m + u}{4} \tag{3}$$

X^*: Crisp Value

After defuzzification, the lean tools were ranked, and the best lean tool was selected.

3. Results

EcoCraft Outdoor Furniture is a company that manufactures wooden outdoor furniture and has headquarters in Türkiye. Inefficiencies were identified in the company's wooden park/garden bench production process. To address these inefficiencies optimally, a Value Stream Map was first created for the process. The VSM measured various parameters for each process step, including Cycle Time (min), Changeover Time (min), Up Time (min/day), Down Time/idling time (min/day), Overall Equipment Effectiveness (OEE) (%), First Pass Yield (%), Production Cost Per Batch (USD), Energy Efficiency (kWh/batch), and Solid Waste Amount (kg/batch). Energy Efficiency (kWh/batch) and Solid Waste Amount (kg/batch) KPIs were used to assess the environmental sustainability of the process. At the same time, the rest were considered indicators of economic sustainability and process efficiency. The current state VSM is presented in Figure 3.

Based on the current state VSM, thirteen lean failure modes (LFMs) were identified for the wooden park/garden bench production process. These LFMs include poor layout design (FM1), equipment downtime (FM2), the lack of automation (FM3), inventory overstock (FM4), quality issues (FM5), changeover delays (FM6), energy inefficiency (FM7), material waste (FM8), long cycle time (FM9), high production cost (FM10), inconsistent yield (FM11), under-utilized talent (FM12), and excessive transportation (FM13). The LFMs were categorized according to basic lean wastes and prioritized using the FMEA technique. In accordance with the methodology, the root cause and effect of each LFM were identified, and scores for probability, severity, and detectability were assigned to calculate the RPNs. An FMEA table was created and presented in Table 5.

Table 5 shows that poor layout design (FM1) had the highest RPN score of 336, while high production cost (FM10) had the lowest RPN score of 140. According to the FMEA methodology, a project proposal is developed for any failure mode with an RPN score above 100. Therefore, lean project proposals were developed for all LFMs listed in Table 5. These lean projects are detailed in Table 5. Subsequently, the Fuzzy QFD methodology was used to select the lean tools for the developed lean projects.

Within the Fuzzy QFD method, the prioritized LFMs are listed in the column. The technical requirement section included the lean tools and techniques that could potentially address the LFMs. In the initial phase, the importance weights of the LFMs were determined. Subsequently, a relationship matrix between the LFMs and lean tools was created. The correlation matrix, which shows the relationship between the selected lean tools is illustrated in Figure 4. After the correlation matrix was created, the fuzzy importance weights of the lean tools were calculated. The fuzzy weights were then defuzzified to obtain the exact values of the lean tools. These values are presented in Figure 4. Based on these values, a ranking was made to determine which lean tool would be used first.

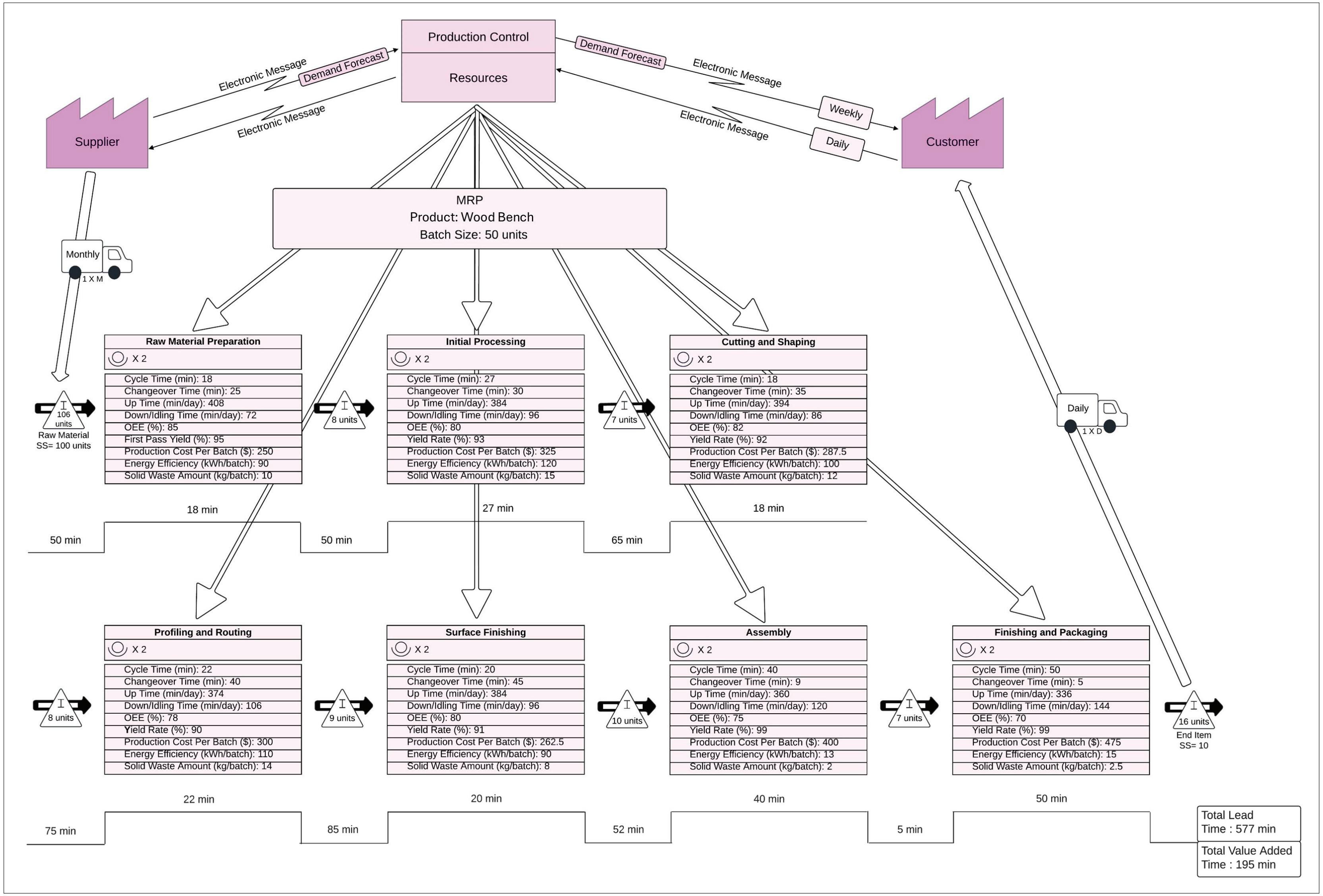


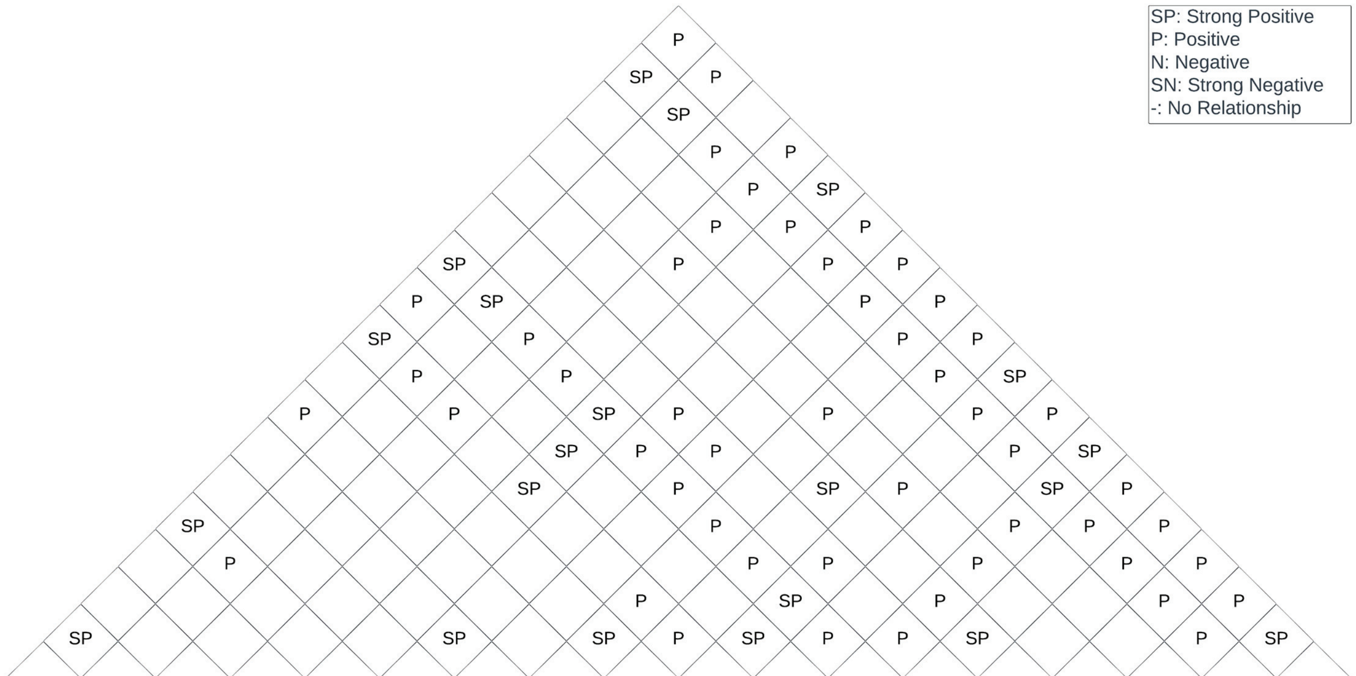
Figure 3. Current state VSM.

Table 5. FMEA form created for lean failure modes.

Wood Outdoor Furniture Manufacturing Facility (Product Family: Wood Bench)										
Lean Failure Mode	**Lean Failure Mode Description**	**Potential Effect**	**Root Cause**	**Waste Category**	**Severity**	**Occurrence**	**Detection**	**RPN Value**	**RPN Ranking**	**Proposed Lean Projects**
FM1: Poor Layout Design	Inefficient layout causing unnecessary movement	Increased transportation time, reduced efficiency	Poor initial layout planning	Motion	8	7	6	336	1	Implement layout modification and 5S to organize the workplace efficiently
FM6: Changeover Delays	Long time taken to switch between different products	Reduced production flexibility	Inefficient changeover processes	Waiting	7	7	6	294	2	Implement Single-Minute Exchange of Die (SMED)
FM2: Equipment Downtime	Frequent breakdowns of machinery	Production delays, increased lead time	Lack of maintenance	Waiting	9	6	5	270	3	Implement Total Productive Maintenance (TPM)
FM13: Excessive Transportation	Unnecessary movement of materials between workstations	Increased transportation costs, delays in production	Poor layout design, lack of workflow planning	Transportation	7	7	5	245	4	Implement layout modification and a Pull System to minimize material movement
FM11: Inconsistent Yield	Variation in the yield rate across different production batches	Unpredictable output, increased rework	Variability in raw material quality	Defects	8	6	5	240	5	Standardize raw material quality and improve supplier relations
FM3: Lack of Automation	Manual operations leading to slow processes	Reduced productivity, higher labor costs	Lack of investment in automation	Overprocessing	7	8	4	224	6	Invest in automation, Andon system, and JIT
FM4: Inventory Overstock	Excess inventory leading to space issues	Increased storage costs, potential obsolescence	Poor inventory management	Inventory	6	7	5	210	7	Implement Pull System, Just-In-Time (JIT) and FIFO
FM9: Long Cycle Time	Prolonged time taken for each production cycle	Reduced throughput, increased lead time	Inefficient processes	Waiting	7	6	5	210	8	Optimize production processes with lean methodologies

Table 5. *Cont.*

Wood Outdoor Furniture Manufacturing Facility (Product Family: Wood Bench)										
Lean Failure Mode	**Lean Failure Mode Description**	**Potential Effect**	**Root Cause**	**Waste Category**	**Severity**	**Occurrence**	**Detection**	**RPN Value**	**RPN Ranking**	**Proposed Lean Projects**
FM5: Quality Issues	Defective products	Increased rework, customer dissatisfaction	Inadequate quality control measures	Defects	8	6	4	192	9	Enhance quality control with Six Sigma and Poka-Yoke
FM7: Energy Inefficiency	High energy consumption per batch	Increased production costs, environmental impact	Outdated machinery	Overprocessing	6	6	5	180	10	Upgrade machinery for energy efficiency
FM12: Under-Utilized Talent	Employees not utilized to their full potential	Decreased employee morale, lower productivity	Lack of proper training and development	Underutilized Talent	6	6	5	180	11	Provide employee training and development programs
FM8: Material Waste	Excess material waste generated during production	Increased costs, environmental impact	Poor process control	Defects	8	5	4	160	12	Implement Kaizen and continuous improvement
FM10: High Production Cost	High cost per batch due to inefficiencies	Reduced profitability	Inefficient resource utilization	Overproduction	7	5	4	140	13	Implement cost reduction strategies and JIT



LEAN FAILURE MODES	W_i	LT1	LT2	LT3	LT4	LT5	LT6	LT7	LT8	LT9	LT10	LT11	LT12	LT13	LT14	LT15	LT16	LT17	LT18
FM1: Poor Layout Design	7.5 10 10	6 8 10	6 8 10										2 5 8					2 5 8	
FM2: Equipment Downtime	5 7.5 10			0 2 4	6 8 10				0 2 4				2 5 8			2 5 8		2 5 8	
FM3: Lack of Automation	5 7.5 10								6 8 10	6 8 10	6 8 10					2 5 8			
FM4: Inventory Overstock	5 7.5 10					6 8 10					6 8 10	6 8 10							0 2 4
FM5: Quality Issues	7.5 10 10				0 2 4		2 5 8	2 5 8	2 5 8	2 5 8				6 8 10	6 8 10	2 5 8	2 5 8	2 5 8	2 5 8
FM6: Changeover Delays	5 7.5 10			6 8 10	0 2 4						0 2 4		2 5 8					2 5 8	
FM7: Energy Inefficiency	5 7.5 10				2 5 8											6 8 10		0 2 4	
FM8: Material Waste	2.5 5 7.5									0 2 4		2 5 8			2 5 8			6 8 10	2 5 8
FM9: Long Cycle Time	2.5 5 7.5			2 5 8	2 5 8				2 5 8	2 5 8			6 8 10			0 2 4			2 5 8
FM10: High Production Cost	5 7.5 10		0 2 4			2 5 8	2 5 8	0 2 4			6 8 10				0 2 4		0 2 4		6 8 10
FM11: Inconsistent Yield	0 2.5 5						6 8 10	6 8 10	0 2 4					2 5 8	2 5 8			2 5 8	
FM12: Under-Utilized Talent	0 2.5 5																6 8 10		
FM13: Excessive Transportation	2.5 5 7.5	6 8 10	2 5 8			6 8 10						0 2 4	2 5 8				0 2 4		
RI_j		60 120 175	50 120 200	35 100 200	45 158 320	55 138 255	25 108 210	15 85 170	50 155 300	50 145 270	90 195 340	35 95 135	55 190 375	45 92.5 140	50 133 240	65 195 370	15 95 200	65 243 475	55 175 340
Crisp Value		118.75	122.5	108.75	170	146.25	112.5	88.75	165	152.5	205	90	202.5	92.5	138.75	206.25	101.25	256.25	186.25
Rank		12	11	14	6	9	13	18	7	8	3	17	4	16	10	2	15	1	5

Figure 4. Partial HOQ illustration for lean tool selection with Fuzzy QFD (Dark colored cells in the rank row indicate that associated lean tool was selected for deployment based on calculated crisp value).

The lean tool ranking derived from Fuzzy QFD revealed a complete list of lean tools with the highest potential to eliminate lean wastes within the wooden park/garden bench production process. The final set of lean tools was selected according to the threshold value specified in the methodology. The ranking of the lean tools based on the specified threshold values was as follows: Implement Kaizen and continuous improvement (LT17) with a crisp value of 256.02, upgrade machinery for energy efficiency (LT15) with a value of 206.25, Just-In-Time (JIT) (LT10) with a value of 205, optimize production processes with lean methodologies (LT12) with a value of 202.5, implement cost reduction strategies (LT18) with a value of 186.25, Total Productive Maintenance (TPM) (LT4) with a value of 170, invest in automation (LT8) with a value of 165, and Andon (LT9) with a value of 152.5.

At this stage, one should acknowledge that both deployed and not-deployed lean tools created a trade-off where direct and indirect advantages and lurking disadvantages should be accounted for. Although the Single-Minute Exchange of Dies (SMED) was identified through FMEA rankings as a potential solution for specific lean failure modes, it did not emerge in the final Fuzzy QFD results and was therefore not implemented. Nonetheless, concerns regarding its possible drawbacks—such as increased energy consumption from more frequent machine restarts—remain relevant in contexts where the SMED might eventually be adopted. This underscores the importance of evaluating lean tools' advantages and potential trade-offs, including those not ultimately selected. Maintaining a holistic view of lean interventions ensures that each initiative, whether deployed or merely considered, aligns with broader operational and sustainability objectives. This is why this study employed a two-phased selection system of lean tools for better filtered and focused economic and environmental performance improvement measures.

The lean tools determined by the Fuzzy QFD methodology were applied to the current state VSM in sequence. Initially, Kaizen activities were recommended for the Raw Material Preparation, Initial Processing, Cutting and Shaping, and Profiling and Routing operations. The Kaizen activities aimed to minimize material waste in these operations, thereby reducing costs and environmental impact. Secondly, updating machinery for energy efficiency was suggested for the Raw Material Preparation, Initial Processing, Cutting and Shaping, Profiling and Routing, and Surface Finishing operations. Although energy savings and increased energy efficiency were anticipated from the updated machinery, it was also determined that these updates would reduce high production costs, contributing to the cost reduction strategies proposed in the fifth place.

The third recommended lean tool was Just-In-Time (JIT). By applying JIT to the Raw Material Preparation operation, inventory overstock was eliminated, followed by a reduction in high production costs. Fourthly, optimizing production processes with lean methodologies was recommended for the Initial Processing, Profiling and Routing, Surface Finishing, and Assembly operations to reduce long cycle times.

Fifth, cost reduction strategies were proposed for the Initial Processing, Profiling and Routing, Assembly, and Finishing and Packaging operations. This intervention reduced high production costs, increased profitability, and ensured more efficient resource use. The sixth lean tool applied was Total Productive Maintenance (TPM). TPM was implemented in the Initial Processing, Cutting and Shaping, Profiling and Routing, Surface Finishing, and Assembly operations, establishing a maintenance plan for the machines to prevent frequent breakdowns and significantly reduce downtime. Additionally, TPM helped prevent major machine failures, avoiding substantial costs for the business.

The seventh lean tool applied was automation. All processes within the business were performed manually, resulting in slow operations and low efficiency due to the lengthy processes. Therefore, automation was introduced in the Cutting and Shaping and Profiling and Routing operations. This reduced increasing labor costs and shortened the cycle time prolonged by manual operations. The final lean tool applied was Andon. Implementing Andon in the Raw Material Preparation, Initial Processing, Cutting and Shaping, Profiling and Routing, and Surface Finishing operations helped quickly identify and prevent errors within the process. The Andon system prevented increased labor costs due to errors. The stages at which all these lean tools were integrated into the production process's current state are illustrated in the VSM shown in Figure 5.

Implementing lean projects shown in Figure 5 in the production process of wooden park/garden benches resulted in a significant reduction in total lead time, which improved by approximately 38.46%, reducing it to 352 min in the future state as presented in Table 6. The value-added time in the current state improved by approximately 22.05%, decreasing to 152 min in the future state, while the non-value-added time was reduced by 47.64%, bringing it down to 200 min. Additionally, the required number of workers in the wooden park/garden bench production decreased from 14 to 12, representing an improvement of 14.29%. Finally, the total inventory in the system was reduced from 171 to 73 units, achieving an improvement of approximately 57.31% as shown in Table 6. The future state VSM, illustrating all these improvements, is presented in Figure 6.

Table 6. Comparison of the current and future state performances.

Key Measures	Current State	Future State	Improvements (Units)	Improvements (%)
Total Lead Time (min)	572	352	220	38.46%
Total Value-Added Time (min)	195	152	43	22.05%
Total Non-Value-Added Time (min)	382	200	182	47.64%
Number of Workers Required (No's)	14	12	2	14.29%
Total Inventory	171	73	98	57.31%

As observed in Figure 6, the improvements detailed in Figure 5 have led to enhancements in the process steps. First, in the initial step of the process, Raw Material Preparation, the implementation of lean projects such as Andon, JIT, Kaizen, and machinery upgrades yielded a reduction in Cycle Time from 18 min to 14 min, achieving a 22.22% improvement. Changeover Time was reduced from 25 to 10 min, reflecting a 60% improvement. Up Time increased from 408 min to 456 min, indicating an 11.76% improvement, while Down/Idling Time decreased from 72 min to 24 min, showing a 66.67% improvement. Overall Equipment Effectiveness (OEE) improved from 85% to 95%, a gain of 11.76%, and First Pass Yield increased from 95% to 97%, an improvement of 2.11%. Production Cost Per Batch decreased from USD 250 to USD 200, marking a 20% improvement; Energy Efficiency improved from 90 kWh to 70 kWh, achieving a 22.22% improvement; and Solid Waste Amount decreased from 10 kg to 8 kg, reflecting a 20% improvement.

In the second step of the production process (Initial Processing), implementing projects such as Andon, Total Productive Maintenance (TPM), cost reduction strategies, optimized production processes, machinery upgrades, and Kaizen led to several improvements. Cycle Time was reduced from 27 min to 22 min, an 18.52% improvement, and Changeover Time was reduced from 30 min to 12 min, achieving a 60% improvement. Up Time increased from 384 min to 432 min, a 12.5% improvement, while Down/Idling Time decreased from 96 min to 48 min, showing a 50% improvement. OEE improved from 80% to 90%, a gain of 12.5%, and First Pass Yield increased from 93% to 95%, an improvement of 2.15%. Production Cost Per Batch decreased from USD 325 to USD 275, marking a 15.38% improvement; Energy Efficiency improved from 120 kWh to 90 kWh, achieving a 25% improvement; and Solid Waste Amount decreased from 15 kg to 10 kg, reflecting a 33.33% improvement.

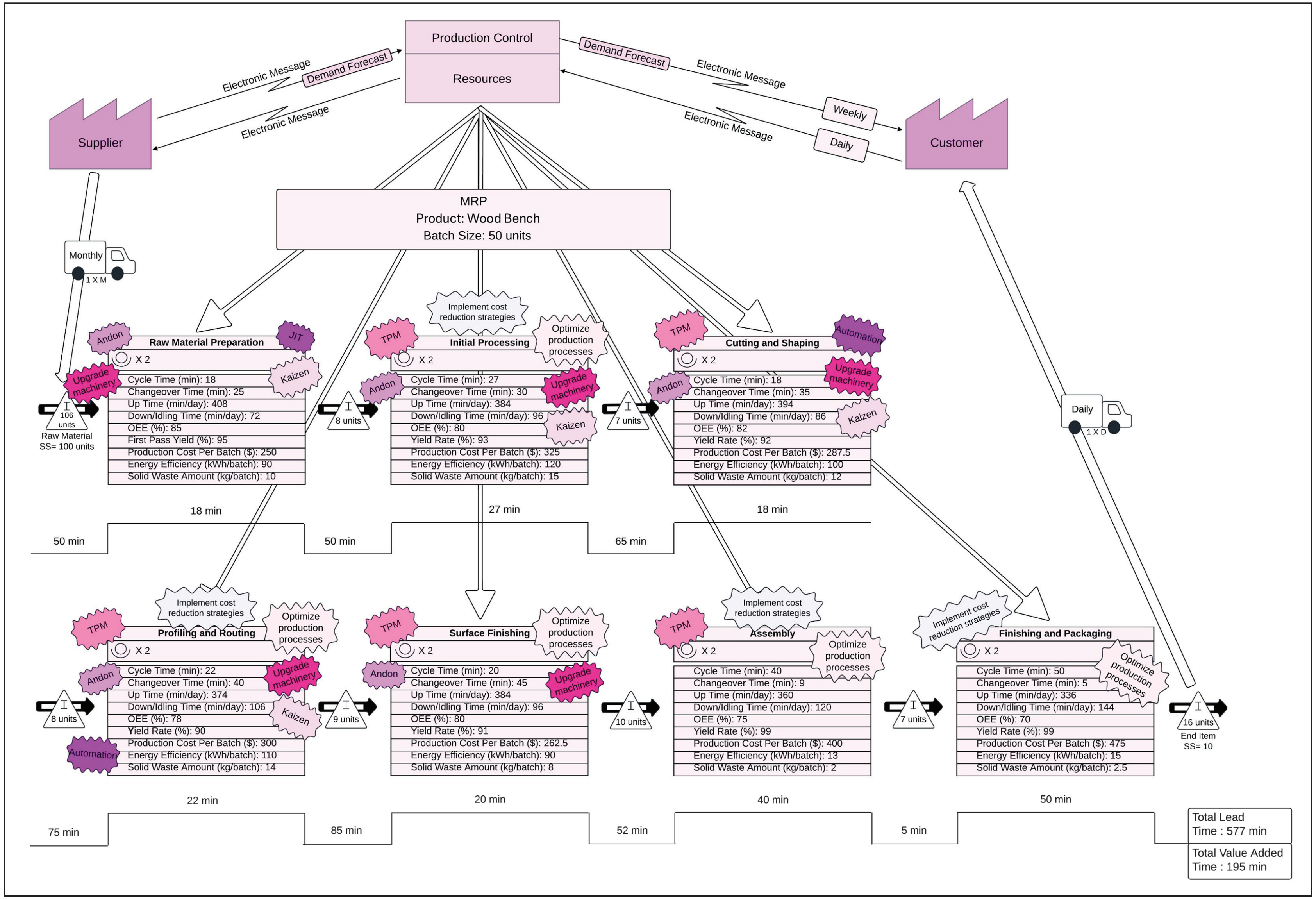


Figure 5. VSM illustrating proposed lean-based improvement projects.

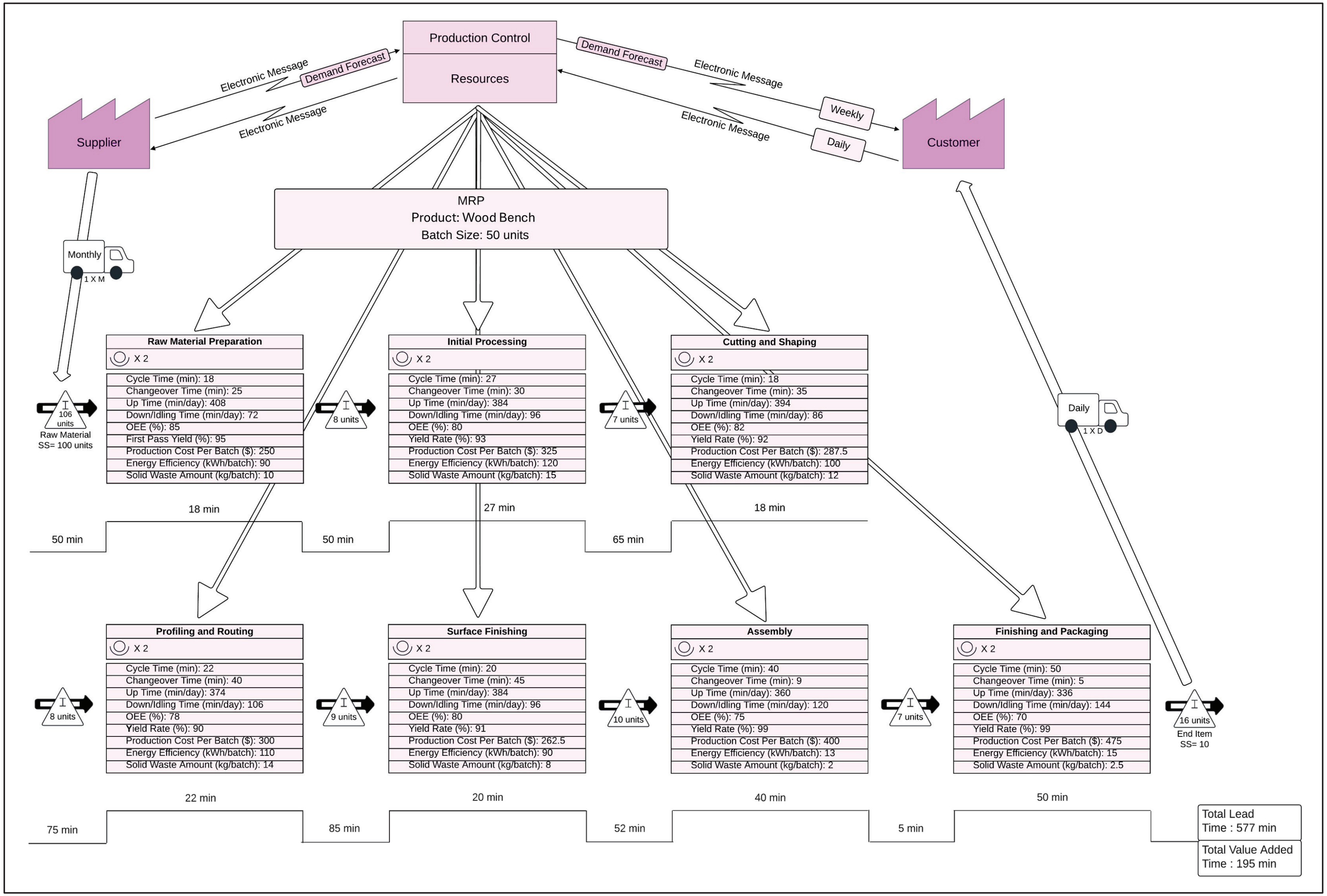


Figure 6. Future state VSM.

The third stage of the process, Cutting and Shaping, involved the elimination of identified wastes through the implementation of Andon, TPM, Automation, machinery upgrades, and Kaizen initiatives. These efforts resulted in several key improvements in the measured KPIs: Cycle Time was reduced from 18 min to 14 min, achieving a 22.22% improvement, and Changeover Time was reduced from 35 min to 15 min, reflecting a 57.14% improvement. Up Time increased from 394 min to 444 min, a 12.69% improvement, while Down/Idling Time decreased from 86 min to 36 min, showing a 58.14% improvement. OEE improved from 82% to 92%, a gain of 12.2%, and First Pass Yield increased from 92% to 94%, an improvement of 2.17%. Production Cost Per Batch decreased from USD 287.5 to USD 237.5, marking a 17.39% improvement, Energy Efficiency improved from 100 kWh to 75 kWh, achieving a 25% improvement, and Solid Waste Amount decreased from 12 kg to 8 kg, reflecting a 33.33% improvement.

In the fourth step of the process, Profiling and Routing, lean projects such as Automation, Andon, TPM, cost reduction strategies, production process optimization, machinery upgrades, and Kaizen were implemented. These implementations reduced Cycle Time from 22 min to 18 min, achieving an 18.18% improvement, and a reduction in Changeover Time from 40 min to 16 min, reflecting a 60% improvement. Up Time increased from 374 min to 420 min, indicating a 12.30% improvement, while Down/Idling Time decreased from 106 min to 60 min, showing a 43.40% improvement. Overall Equipment Effectiveness (OEE) improved from 78% to 93%, a gain of 19.23%, and First Pass Yield increased from 90% to 93%, an improvement of 3.33%. Production Cost Per Batch decreased from USD 300 to USD 250, marking a 16.67% improvement; Energy Efficiency improved from 110 kWh to 85 kWh, achieving a 22.73% improvement; and Solid Waste Amount decreased from 14 kg to 10 kg, reflecting a 28.57% improvement.

The fifth step of the process, Surface Finishing, saw the implementation of lean projects such as TPM, Andon, production process optimization, and machinery upgrades. These improvements reduced Cycle Time from 20 min to 16 min, achieving a 20% improvement, and a decrease in Changeover Time from 45 min to 18 min, reflecting a 60% improvement. Up Time increased from 384 min to 432 min, indicating a 12.5% improvement, while Down/Idling Time decreased from 96 min to 48 min, showing a 50% improvement. OEE improved from 80% to 90%, a gain of 12.5%, and First Pass Yield increased from 91% to 94%, an improvement of 3.30%. Production Cost Per Batch decreased from USD 262.5 to USD 212.5, marking a 19.05% improvement; Energy Efficiency improved from 90 kWh to 70 kWh, achieving a 22.22% improvement, and Solid Waste Amount decreased from 8 kg to 5 kg, reflecting a 37.5% improvement.

In the sixth step of the process, Assembly experts implemented lean projects such as TPM, cost reduction strategies, and production process optimization to eliminate lean wastes. These lean projects reduced Cycle Time from 40 min to 30 min, achieving a 25% improvement, and a reduction in Changeover Time from 9 min to 4 min, reflecting a 55.56% improvement. Up Time increased from 360 min to 420 min, indicating a 16.67% improvement, while Down/Idling Time decreased from 120 min to 60 min, showing a 50% improvement. OEE improved from 75% to 85%, a gain of 13.33%, and First Pass Yield increased from 99% to 100%, an improvement of 1.01%. Production Cost Per Batch decreased from USD 200 to USD 115, marking a 42.5% improvement; Energy Efficiency improved from 130 kWh to 100 kWh, achieving a 23.08% improvement; and Solid Waste Amount decreased from 2 kg to 1 kg, reflecting a 50% improvement.

Cost-reduction strategies and production-process optimization improvements were implemented in the seventh and final stage of the process. These improvements resulted in a reduction in Cycle Time from 50 min to 38 min, achieving a 24% improvement, and a decrease in Changeover Time from 5 min to 2 min, reflecting a 60% improvement. Up Time increased from 336 min to 420 min, indicating a 25% improvement, while Down/Idling Time decreased from 144 min to 60 min, showing a 58.33% improvement. OEE improved from 70% to 80%, a gain of 14.29%, and First Pass Yield increased from 99% to 100%, an improvement of 1.01%. Production Cost Per Batch decreased from USD 225 to USD 150, marking a 33.33% improvement; Energy Efficiency improved from 150 kWh to 120 kWh, achieving a 20% improvement; and Solid Waste Amount decreased from 2.5 kg to 1.5 kg, reflecting a 40% improvement.

4. Discussion

This study's results revealed findings consistent with the literature regarding the tangible gains achieved through the selected lean tools. Zahraee et al. (2021) reported a 36.36% improvement in total lead time in their study on lean waste elimination in the construction sector [37]. Similarly, this study achieved a 38.46% improvement in total lead time following the implemented improvements. Another study yielding comparable results was conducted by Sirajudeen and Krishnan (2022), which focused on identifying lean wastes in a prefabricated component manufacturing company [32]. Their study reduced lead time from 1102 min to 739 min, achieving a 32.94% improvement [32]. In their study, Bhuvanesh Kumar and Parameshwaran (2019) prioritized lean failure modes and reported a 47.3% improvement in lead time in the automotive manufacturing sector [44]. However, their study in the casting industry resulted in a markedly different outcome, with only an 11.3% improvement in lead time [44].

In contrast, Bhuvanesh Kumar and Parameshwaran's 2020 study on lean tool selection and waste elimination using MCDM methods in the manufacturing industry reported only a 5% improvement in lead time [43]. Conversely, their 2018 study achieved a significantly higher improvement rate of 64.33% in lead time [41].

Regarding value-added time, Bhuvanesh Kumar and Parameshwaran (2018) achieved a 25.93% improvement [41]. Similarly, this study observed a 22.05% improvement in value-added time. Sirajudeen and Krishnan (2022) reported a 28.21% improvement in value-added time in their research, aligning closely with the findings of this study [32]. In contrast, Mohanraj et al. (2015) reported the lowest improvement rate in the literature, with a 3.87% increase in value-added time, while Reda and Dvivedi (2022) achieved the highest improvement rate of 56.3 [40,45].

In terms of improvements in the workforce capacity, Bhuvanesh Kumar and Parameshwaran (2018) reported a 16.67% improvement, which was comparable to the 14.24% improvement observed in this study [41]. However, Reda and Dvivedi (2022) achieved a similar reduction of two workers, corresponding to an improvement rate of 0.99% [33].

However, these improvement results, while substantial, should be interpreted within the limited scope of a single product line—the wooden park/garden bench. Historically high inventory levels in this product family allowed targeted lean tools such as Just-In-Time (JIT) and Total Productive Maintenance (TPM) to be deployed with relative ease, yielding rapid gains in throughput and approximately a 60% reduction in inventory. Although initial OEE figures of 70–85% appeared robust, focused interventions revealed underutilized capacity, inadequate maintenance scheduling, and process inefficiencies that could be improved. Furthermore, the six-month timeline represents only a pilot phase; extending similar interventions to the firm's entire product portfolio would likely involve a more prolonged rollout, more complex planning, and broader training efforts. Overall, the findings of this study highlight the transformative potential of lean-based improvements for a single product while also illustrating that distinct baseline conditions and a narrower scope can facilitate sharper improvements than those expected in multi-product environments.

In a broader perspective, the findings of Abreu et al. (2017) and Bhattacharya et al. (2019) argued that companies adopting lean-green models experience significant reductions in waste and energy consumption, which has positive effects on sustainability performance and increases efficiency [26,53]. Similarly, the findings of this study have achieved results that are consistent with the extant literature by providing both a reduction in waste and significant improvements in sustainability performance in businesses implementing lean principles. Concurrent with these studies, Dieste et al. (2019) revealed that companies adopting lean production practices in the manufacturing environment also make positive improvements in sustainability performance [35]. Siegel et al. (2019) identified the most prevalent lean tools utilized by companies adopting the lean-green model, including 5S, TPM, and VSM, among others, with these tools employed at least once [21]. As supported with empirical evidences of this and past studies, the same lean tools employed to eliminate waste in this and past studies yielded similar results. Concurrently, Farias et al. (2019) developed a set of criteria to evaluate lean and green performance and found that the most common lean tools corresponding to this set of criteria were JIT/Pull and SMED, followed by Kaizen and TPM [69]. In this study, the lean tools selected to enhance lean and sustainability performance bear a strong resemblance to those identified in past studies.

Furthermore, the Waste Identification Diagram (WID) is another essential tool in waste management, providing a structured way to identify and visualize waste across various processes. The WID represents production units and their operational waste more effectively than Value Stream Mapping (VSM) [70]. Similar to VSM, by enhancing the visual representation of waste, the WID allows organizations to pinpoint the most significant waste sources and understand the complex relationships between different elements within a production environment [71]. The implementation of the WID alongside other methodologies, like Failure Mode and Effect Analysis (FMEA) and Lean principles, has proven effective in prioritizing and minimizing waste [72]. WID's efficacy is underscored by its comparative performance against VSM. Past research indicates that the WID is often more effective in identifying 'Muda' (waste) within processes, as noted by Contreras et al., who found that the WID provides more precise insights that lead to enhanced waste management strategies [71]. For instance, the incorporation of lean principles using the WID allows for a transformative approach in sectors such as healthcare and manufacturing, where waste reduction is critical to improving overall performance [73]. On the other hand, the findings of this study showed that VSM was also effective in waste identification when strengthened with proper KPIs and supported with the FMEA. Consequently, organizations embracing VSM and the WID alongside lean principles could realize significant improvements in reducing operational waste and enhancing value creation.

Overall, the results of this study could be better understood when discussed in the context of managerial, practical, and application-oriented implications. This study aimed to significantly contribute to the scientific body of knowledge by addressing the intersection of four critical research streams: sustainability, lean management, MCDM, and outdoor wood furniture manufacturing. Integrating these streams into a cohesive framework presents several scientific implications. Firstly, this study bridges the gap between sustainability, lean management, MCDM, and outdoor wood furniture manufacturing, providing a holistic framework that can be adapted to various manufacturing sectors. This integrated approach can be a foundation for future research in other industries. Secondly, this study contributes to methodological advancements in the field by applying advanced methodologies such as Value Stream Mapping, Fuzzy QFD, and Fuzzy FMEA within the context of sustainable lean manufacturing. Integrating these tools helps identify and mitigate risks, optimize production processes, and enhance decision-making capabilities. Lastly, the development and application of sustainability metrics within the lean management framework provide a new dimension to traditional lean tools, helping balance economic, environmental, and social aspects of manufacturing and contributing to the broader discourse on sustainable manufacturing practices.

The findings of this study have significant implications for managers in the outdoor wood furniture manufacturing industry. By adopting the integrated framework proposed in this study, managers can enhance decision-making capabilities by applying MCDM tools within the lean management framework, enabling more informed and balanced decisions considering all critical factors, including sustainability, cost, and efficiency. Empirical evidence showed that lean production facilitates process optimization and waste reduction, thereby enhancing operational efficiency. Research has indicated that integrating green initiatives to minimize environmental impact with efforts to reduce energy consumption or limit non-value added production can significantly improve firms' sustainability performance. This dual focus is particularly important as firms seek to meet the evolving demands of stakeholders who prioritize economic and environmental objectives [21,26,35,53,69]. Improved efficiency is another key benefit, as lean management principles integrated with sustainability practices lead to the identification and elimination of non-value-added activities, waste reduction, and optimized resource utilization, resulting in cost savings and enhanced productivity. Additionally, incorporating sustainability metrics into the production process aligns with corporate social responsibility goals, allowing managers to track and improve their environmental performance, reduce carbon footprints, and promote sustainable practices throughout the supply chain. Furthermore, using Fuzzy QFD and Fuzzy FMEA aids in identifying potential risks and prioritizing mitigation strategies, ensuring smoother operations and reducing the likelihood of disruptions.

The practical implications of this study are substantial, offering actionable insights for industry practitioners. This study provides a detailed roadmap for implementing lean tools such as VSM, 5S, and Just-In-Time in outdoor wood furniture manufacturing, enabling practitioners to streamline operations, improve workflow, and enhance overall efficiency. Practical guidelines for integrating sustainability practices into daily operations are also provided, including strategies for reducing waste, optimizing energy use, and sourcing sustainable materials, essential for achieving long-term environmental goals. Additionally, this study highlights the importance of training employees in lean and sustainable practices, and practical training programs can be developed based on this study's findings to equip employees with the necessary skills and knowledge to implement these practices effectively. Lastly, the integrated framework helps optimize the entire supply chain, from raw material procurement to end-item delivery, and practitioners can apply this study's insights to enhance collaboration with suppliers, improve inventory management, and reduce lead times.

While this study provides valuable insights and contributions to sustainability, lean management, MCDM, and outdoor wood furniture manufacturing, it has limitations. These limitations, however, open up several avenues for future research. First and foremost, this study was limited to a single product line—the wooden park/garden bench—resulting in more focused and manageable improvements that may not directly translate to the firm's entire product range, where scalability difficulties, additional complexities and extended implementation timelines could arise.

One limitation of this study is the specific focus on the outdoor wood furniture industry, which might limit the generalizability of the findings to other manufacturing sectors. Future research could explore the applicability of the integrated framework in different industries, such as automotive, electronics, or food manufacturing, to validate and refine the framework's versatility and robustness across various contexts.

Another limitation is the reliance on specific methodologies such as VSM, Fuzzy QFD, and Fuzzy FMEA. While these tools are robust and valuable, they may not capture all aspects of complex manufacturing systems, particularly those involving high variability and uncertainty. Future research could investigate integrating additional methodologies, such as digital twins or machine learning algorithms, to enhance the framework's predictive and adaptive capabilities.

This study also primarily relies on quantitative data for analysis and decision making. This approach may overlook qualitative factors such as employee satisfaction, organizational culture, and stakeholder engagement, which are crucial for successfully implementing lean and sustainable practices. Future research could incorporate qualitative methodologies, such as case studies or interviews, to gain a deeper understanding of these softer aspects and their impact on the overall effectiveness of the framework.

Moreover, this study assumes a static environment for implementing the integrated framework. Manufacturing environments are dynamic and constantly evolving due to technological advancements, market fluctuations, and regulatory changes. Future research could focus on developing adaptive frameworks that respond to these changes in real time, ensuring continuous improvement and resilience in manufacturing operations.

Another significant limitation is the potential bias introduced by the subjective judgments in the QFD and FMEA methodologies, although the introduction of the fuzzy numbers helped with alleviating this limitation. While these tools help prioritize issues and identify critical factors, the reliance on expert opinions can introduce subjectivity and bias. Future research could explore using more objective data sources and advanced analytical techniques to mitigate these biases and improve the reliability of the findings.

Finally, this study does not extensively address the economic trade-offs in implementing sustainability and lean practices. While these practices offer long-term benefits, they often require significant upfront investments. Future research could develop detailed cost–benefit analyses and financial models to help organizations understand and manage these trade-offs, ensuring that sustainable and lean practices are economically viable. Moreover, a total integration of HOQ into economic and environmental performance enhancement projects could be explored in future studies. Also, direct and indirect potential negative impacts associated with deployed improvement propositions and lean tools due to their characteristics and dynamic production process would be among intriguing future research topics. Furthermore, the WID and VSM could be comparatively studied to assess their effectiveness in waste identification and process illustration.

In conclusion, while this study significantly contributes to integrating sustainability, lean management, MCDM, and outdoor wood furniture manufacturing, several limitations provide fertile ground for future research. By addressing these limitations, future studies can enhance the integrated framework's robustness, applicability, and practical relevance, contributing to more sustainable and efficient manufacturing practices across various industries.

5. Conclusions

Market research [15–18] indicates that the global outdoor wood industry is extensive and encompasses highly complex production processes. Identifying lean wastes within these complex processes is challenging. Furthermore, selecting the appropriate lean tools to address the identified lean wastes complicates the process even further. Therefore, this study aims to identify lean wastes in the production process of wooden park/garden benches at a company manufacturing outdoor wooden furniture and to prioritize the lean tools that can be applied to these wastes.

The main findings of this study can be summarized as follows:

- The proposed systematic approach has demonstrated its merit in identifying the system's problematic components and selecting appropriate tools to tackle them.
- The resilience and effectiveness of the VSM, Fuzzy QFD, and FMEA methodologies are universal and multi-sectoral, and these tools can be co-deployed synergistically.
- The use of fuzzy sets in the decision-making process has been proven effective in eliminating uncertainty associated with economic and environmental performance.
- Within this study's scope, 13 lean failure modes (LFMs) related to fundamental wastes were identified. The identified LFMs were analyzed using the FMEA technique, and the RPN values of all failure modes were greater than 100. Consequently, lean project proposals were developed for all LFMs.
- Among the eighteen lean tools selected for use in lean projects, the following were prioritized: Implement Kaizen and continuous improvement (LT17) with a score of 256.02, upgrade machinery for energy efficiency (LT15) with a score of 206.25, Just-In-Time (JIT) (LT10) with a score of 205, optimize production processes with lean methodologies (LT12) with a score of 202.5, implement cost reduction strategies (LT18) with a score of 186.25, Total Productive Maintenance (TPM) (LT4) with a score of 170, Invest in Automation (LT8) with a score of 165, and Andon (LT9) with a score of 152.5.
- Regarding improvements in sustainability-related KPIs, economic sustainability showed the following ranges of improvement: Cycle Time improved by 0.09–25.00%, Changeover Time improved by 5.00–60.00%, Up Time improved by 11.76–25.00%, Down/Idling Time improved by 1.89–66.67%, OEE improved by 11.76–19.23%, First Pass Yield improved by 1.01–3.33%, and Production Cost Per Batch improved by 0.67–42.50%. Environmental sustainability KPIs showed improvements in Energy Efficiency by 1.82–25.00% and Solid Waste Amount by 14.29–50.00%.
- Following the application of lean tools and techniques to the production process, Total Lead Time improved by approximately 38.46%, Total Value-Added Time improved by approximately 22.05%, Total Non-Value-Added Time enhanced by 47.64%, Number of Workers Required improved by 14.29%, and Total Inventory improved by approximately 57.31%.

In conclusion, this study addresses the challenges of identifying and eliminating lean waste in manufacturing outdoor wooden furniture within the sustainability framework. The results obtained through this approach not only guide the identification and elimination of lean wastes from a sustainability perspective but also serve as a guide for decision making in fuzzy environments. This study is a valuable resource for practitioners and academics investing in lean management, sustainability, the outdoor furniture sector, and multi-criteria decision making.

Author Contributions: Conceptualization, M.N.I. and C.T.; methodology, M.N.I., E.A. and C.T.; software, M.N.I., E.A. and C.T.; validation, M.N.I., E.A., C.T. and R.G.; formal analysis, M.N.I., E.A., C.T. and R.G.; investigation, M.N.I. and C.T.; resources, M.N.I., C.T. and R.G.; data curation, M.N.I., E.A. and C.T.; writing—original draft preparation, M.N.I., E.A. and C.T.; writing—review and editing, M.N.I., C.T. and R.G.; visualization, M.N.I., E.A. and C.T.; supervision, C.T. and R.G.; project administration, C.T. and R.G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: All the data associated with this study are presented in this article.

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Towards Sustainable Supply Chains: Evaluating the Role of Supply Chain Diversification in Enhancing Corporate ESG Performance

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Abstract: Supply chain diversification (SCD) is widely acknowledged as a crucial strategy for sustainable supply chain management. However, its influence on environmental, social, and governance (ESG) performance remains unclear. This study will explore the impact of SCD on ESG performance and uncover the underlying mechanisms drawing on the structure–conduct–performance (SCP) paradigm. To achieve this, we employ a multidimensional fixed effects model for empirical analysis utilizing panel data from China's A-share listed companies from 2010 to 2023. The findings reveal that SCD enhances ESG performance. For large-scale enterprises or those engaged in highly competitive or high-pollution industries and labor-intensive or capital-intensive sectors, as well as those that are located in the eastern and central regions, the positive impact of SCD on ESG is relatively more pronounced. The mechanism analysis shows that green innovation and digital transformation act as mediators through which SCD drives ESG improvements. Furthermore, environmental uncertainty (EU) positively moderates the relationship between SCD and ESG performance. These insights provide a guiding framework, rich in theoretical depth and practical significance, for enterprises committed to developing sustainable supply chains and pursuing long-term outstanding performance within complex and dynamic market environments.

Keywords: supply chain diversification; ESG; listed company; sustainable development

1. Introduction

Given the increasingly severe global climate change and environmental issues, promoting sustainable development has become a global goal [1]. Corporate sustainability requires the coordinated development of economic, environmental, and social dimensions [2,3]. ESG (environmental, social, and governance) encompasses a company's responsibilities to improve their environmental, social, and governance performance [4]. Among these dimensions, the environmental aspect includes carbon footprint management, resource management, and climate change, among other aspects [5]. The social dimension includes employee rights, community engagement, and diversity and inclusion, among other aspects [6]. The governance dimension encompasses internal corporate governance [6], corporate behavior, and employee relations, among other aspects [7]. These dimensions have become key indicators for measuring corporate sustainability capabilities [8–10]. An increasing number of investors, consumers, and policymakers are also adopting ESG as a critical basis for assessing the long-term value of enterprises [4,11,12]. According to the Global Sustainable Investment Review 2022 report released by GSIA, the value of sustainable investment assets reached USD 30.3 trillion in 2022. Therefore, determining how to enhance corporate ESG performance has become crucial for companies to maintain competitiveness and achieve sustainable development.

However, enterprises often face internal constraints, such as limited technological and financial resources, when improving their ESG performance [4,13,14]. Simultaneously, environmental turbulence [15] also hinders the stability of resource acquisition for enterprises. The supply chain network is a critical channel for companies to access resources [16]. Supply chain diversification (SCD) emphasizes building multi-source supplier networks and diversified customer relationships, helping companies to break free from reliance on single resource pathways and enhancing the resilience and resource acquisition capabilities of supply chains [17,18]. Consequently, it may allow companies to improve their ESG performance. In practice, exemplary cases include Apple, which launched a supplier clean energy program and successfully reduced its carbon dioxide emissions by 18.5 million metric tons in 2023. IKEA, by implementing a customer diversification strategy, not only effectively met the consumption demands of different regional markets but also actively promoted the adoption of sustainable lifestyles. Therefore, exploring the driving mechanisms of ESG performance from the perspective of SCD is of significant importance. However, existing research primarily focuses on the role of internal resource allocation in improving ESG [19,20], while the potential contribution of external-level SCD to ESG performance has not been sufficiently explored.

Based on these considerations, this study addressed the following three research questions: (1) How does SCD affect ESG performance? (2) Do corporate green innovation and digital transformation serve as mediating mechanisms in the relationship between SCD and ESG performance? (3) How does environmental uncertainty influence the relationship between SCD and ESG performance? To answer these questions, we used panel data from Chinese A-share listed companies from 2010 to 2023 as our research sample. Through theoretical and empirical analyses, we aimed to reveal the impact of SCD on ESG performance and the related mechanisms.

Our study makes several contributions to the literature on supply chain management and sustainable performance. First, in response to one study [21] that considered the research on ESG in supply chain management to be insufficient, this study explores the intrinsic relationship between SCD and ESG performance from the perspective of SCD. It addresses whether and how SCD drives ESG performance, providing a new perspective and theoretical foundation for ESG research in supply chain operations management. Second, based on the SCP framework, this study reveals the critical mediating roles of green innovation and digital transformation in the relationship between SCD and ESG performance. This finding not only deepens the understanding of the mechanisms through which SCD impacts ESG performance but also offers theoretical guidance for companies on achieving sustainable development through green innovation and digital transformation in supply chain practices. Finally, this study explores the moderating role of environmental uncertainty in SCD's influence on ESG performance and further investigates the heterogeneous effects of SCD on ESG performance. This finding uncovers the boundary conditions of external environmental factors influencing the effectiveness of SCD, enriches the theoretical discussion on the relationship between environmental dynamics and ESG performance in supply chain management, and provides practical insights for companies on how to optimize supply chain strategies to achieve ESG goals under varying levels of environmental uncertainty.

The following sections are organized as follows: Section 2 is a literature review. Section 3 provides the theoretical basis and research hypotheses. Section 4 details the methodology and the data analysis. The results are presented in Section 5. Section 6 discusses the findings and their implications.

2. Literature Review

2.1. The SCP Paradigm

The SCP paradigm posits that the external structural features of an industry influence the formulation of organizational strategies, leading to rational, planned actions that motivate organizational conduct [22]. These approaches significantly impact an organization's pursuit of good performance [23–25]. The SCP framework originally stemmed from industrial organization theory and was later incorporated into research areas such as strategic management and supply chain management. For example, Ralston et al. [26] employed the SCP framework to argue that supply chain integration, as a critical structural feature, leads to quick-response strategies, thereby positively impacting firm performance. Mackelprang et al. [27] used the SCP framework to confirm that suppliers' innovation strategies enable companies to respond to industry structures, consequently affecting financial performance. Morgan et al. [28] applied the SCP framework to verify the positive influence of resource commitment and sustainable supply chain management on operational performance, while Vu and Ha [29] confirmed the relationship between diversification and corporate performance based on the SCP framework. Grover and Dresner [30], based on the SCP framework and competitive dynamics, investigated the relationships between political actions in supply network resources, supply chain strategies, and firm performance, while Hou et al. [16] employed the SCP framework to investigate the impact of green supply chain knowledge networks on ESG performance.

In this study, the SCP paradigm serves as an appropriate framework to identify the relationship between SCD and ESG. SCD involves the diversified layout of enterprises in terms of suppliers, customers, logistics channels, and other aspects [17]. This diversification may alter the position and structure of enterprises within the supply chain network [31], and it can, thus, be regarded as a form of market structure. The network structure may determine the allocation of organizational resources [22], thereby influencing the selection and direction of corporate behaviors, ultimately affecting performance [16]. Based on this logic, considering that SCD, as a market structure, may influence corporate technological transformation behaviors, and that green innovation and digital transformation are crucial technological pathways for enhancing ESG performance [6,32,33], this study employs the SCP paradigm to explain how SCD affects corporate ESG performance through both green innovation and digital transformation behaviors. Additionally, the SCP framework emphasizes that environmental conditions directly impact market structure and competition [30]. Environmental uncertainty encompasses the volatility and complexity of market demand, technological advancements, supplier relationships, and other environmental factors, which collectively determine the strategic choices and responsive behaviors of enterprises [34]. Therefore, we also incorporate environmental uncertainty into the research framework as an external shock variable to analyze the impact of the SCD structure on corporate ESG performance under conditions of market environmental uncertainty.

2.2. Influence of SCD on Enterprise Performance

SCD is a strategic structure that enables enterprises to avoid over-dependence on a small number of suppliers or customers for purchasing or sales [35,36]. As key stakeholders, suppliers and customers significantly influence corporate economic and environmental outcomes. SCD enhances corporate competitiveness, improves supply chain adaptability, boosts economic performance, and supports environmental sustainability. For instance, Lin et al. [35] demonstrated that SCD can provide firms with valuable social capital and knowledge resources, enhancing their earning capacity, while Wang et al. [17] highlighted that SCD effectively mitigates the negative impacts of supply chain disruptions on organizational performance. Similarly, Feng and Wang [36] found that SCD enhances a firm's dynamic capabilities, contributing positively to digital transformation efforts. Additionally, Sharma et al. [37] emphasized the role of stakeholder participation in sustainability practices, noting that while supplier involvement improves environmental performance, customer involvement does not significantly impact either environmental or economic outcomes, while Lin and Zhu [38] demonstrated that SCD in the renewable energy sector can enhance the total factor productivity of enterprises. However, SCD also has challenges. A more diversified supply chain can increase complexity, requiring firms to invest additional resources in management, which may negatively affect their overall performance [39].

2.3. Factors Influencing ESG Performance

The existing literature examines the factors influencing ESG from internal and external perspectives. From an internal perspective, corporate strategy plays a pivotal role in shaping ESG. For instance, Rajesh et al. [40] emphasized the importance of corporate social responsibility strategies as key indicators of ESG scores. In addition, firm characteristics are crucial determinants of ESG. These characteristics include non-financial attributes such as corporate structure [14], corporate culture [41], and human and intellectual resources [21], as well as financial attributes such as free cash flow and idle resources [8]. Finally, corporate governance is another vital aspect of ESG. Key factors identified in the literature include board diversity [42], managerial myopia [43], and executive compensation structures [44], all significantly influencing ESG.

With regard to external influencing factors, the formulation and implementation of policies and regulations play a pivotal role in shaping corporate behavior, not only through direct regulatory measures or subsidies but also by providing substantive guidance that influences ESG. Studies have shown that tax incentives [45], green financial reforms [46], and environmental tax laws [47] have positive impacts on ESG outcomes. Recent research has also highlighted the influence of public environmental awareness on ESG, with He et al. [48] demonstrating that media coverage significantly enhances corporate ESG ratings.

Moreover, given the growing body of literature on ESG research, growing scholarly attention has been paid to ESG in supply chain operations management, which is the most relevant to our study. In Table 1, we summarize the relevant literature on supply chain operations management and ESG. Past scholars have primarily focused on the impact of supply chain digitalization [13,49–51], intelligent supply chains [52], supply chain networks [53], green supply chain knowledge networks [16], and supply chain finance [54] on ESG performance.

Overall, investigating the impact of SCD on ESG is particularly urgent in current research. Firstly, the existing literature indicates that while SCD enhances corporate competitiveness and supply chain resilience, it also negatively affects management costs and complexity. This uncertainty makes the relationship between SCD and ESG worthy of in-depth exploration. Secondly, prior studies on the influencing factors of ESG have primarily focused on internal corporate characteristics and external policies and regulations. Although research on ESG in supply chain operations management has gradually gained attention, many scholars emphasize the impact of technologies (such as supply chain digitalization) on ESG. In contrast, SCD focuses on the diversity of supply chain structures and resource allocation; however, how SCD affects ESG still lacks systematic discussion.

Table 1. The literature on ESG-related antecedents in supply chain management.

Reference	Theory	Independent Variable	Key Findings
Tian et al. [13]	Stakeholder theory	Supply chain digitalization	Supply chain digitalization improves ESG by enhancing internal operational efficiency, increasing inter-firm trade credit, and strengthening external oversight
Shen et al. [50]	None	Supply chain digitalization	Supply chain digitalization can alleviate financing constraints and improve corporate governance, thereby enhancing ESG
Zhu and Zhang [51]	None	Supply chain digitalization	Supply chain digitalization can enhance ESG performance by strengthening corporate governance, improving total factor productivity, and alleviating financing constraints
Chen et al. [49]	None	Supply chain digitalization	Supply chain digitalization significantly promotes corporate ESG by reducing information asymmetry and alleviating financing constraints
Qiao et al. [52]	Resource orchestration theory	Smart supply chain	Smart supply chain practices stimulate corporate social responsibility (CSR) disclosure, thereby enhancing ESG
Yang et al. [53]	None	Supply chain network	Peer companies within the supply chain network can significantly enhance the ESG performance of the target company
Hou et al. [16]	Knowledge-based theory, social network theory, and dynamic capabilities theory, Structure–conduct–performance framework	Green supply chain knowledge network	The green supply chain knowledge network fosters corporate green technology innovation and enhances ESG performance, with knowledge integration capability exhibiting a positive moderating effect
Wang et al. [54]	None	Supply chain finance	Supply chain finance can alleviate financial constraints and strengthen oversight to enhance ESG
Our research	Structure–conduct–performance framework	Supply chain diversification	SCD can enhance green innovation and digital transformation, thereby strengthening ESG performance. Environmental uncertainty (EU) positively moderates the relationship between SCD and ESG performance

In response to the aforementioned research gaps, firstly, our study will construct a theoretical framework model based on the SCP framework to examine the impact of SCD on ESG. Secondly, we will empirically test the effect of SCD on ESG performance and further analyze the heterogeneous effects under different scenarios. Thirdly, we will explore the potential pathways through which SCD influences ESG, revealing the intrinsic mechanisms and boundary conditions related to this impact. Lastly, based on the research findings, we will provide practical guidance for enterprises on how to enhance sustainability through SCD strategies.

3. Hypothetical Development

3.1. SCD and ESG Performance

The SCP framework suggests that organizations adopt strategies in response to the market, thereby altering corporate conduct and impacting performance [22]. Diversification is crucial in enhancing an enterprise's competitive advantage [55]. SCD is regarded as a strategic structure in supply chain management [56]. This strategy drives firms to establish supply chain relationships with a larger number of suppliers and customers, which is crucial for complementary resources and capabilities, as well as effective governance within the company [57]. It facilitates corporate learning and assimilating diverse human, technological, and knowledge resources, along with sustainable development strategies from suppliers and customers [36,58,59], which are then applied to corporate ESG management practices. Moreover, ESG performance is positively correlated with the ESG performance of firms upstream and downstream of the supply chain. Outstanding ESG performance by one party may encourage partners to follow suit, thereby driving the entire supply chain toward a more sustainable direction [53]. Additionally, supplier diversification enables firms to select suppliers with superior social responsibility performance [58] that typically possess advanced environmental technologies and can provide more eco-friendly raw materials [60]. Based on this, we posit the following hypothesis:

H1: *SCD has a positive effect on ESG performance.*

3.2. The Mechanism of Green Innovation

Based on the SCP framework, we believe that SCD influences corporate green innovation, thereby promoting ESG. Specifically, the reasons are as follows: First, SCD increases opportunities for firms to acquire innovation, innovation knowledge, and talent resources [36,61]. These resources help firms to integrate and reconfigure technologies and knowledge from different fields, thereby enhancing their willingness to engage in green innovation. Second, SCD provides a foundation for external suppliers and customers to participate in product development. External resources and knowledge from the supply chain positively impact corporate green product innovation [62], and both customer and supplier involvement positively influence green product innovation [63]. This increases a firm's motivation to pursue green innovation. Finally, SCD offers firms more varied choices for suppliers and partners, forming a closer supply chain network. This network structure positively affects a firm's ability to acquire resources and enhances green innovation outcomes [64]. By utilizing green innovation, firms can reduce energy consumption and carbon emissions [65], thereby mitigating negative environmental impacts in their production processes and positively influencing their ESG [6,32]. Based on this, we propose the following hypothesis:

H2: *SCD improves ESG performance by promoting the GI.*

3.3. The Mechanism of Digital Transformation

Based on the SCP framework, the impact of SCD on corporate digital transformation is complex and multidimensional. First, SCD enables firms to obtain more digital technologies and resources from external suppliers and customers, thereby achieving optimal resource allocation and complementarity. This provides resource support for the digital transformation of corporations [36]. Second, the increased complexity of supply chain relationships due to SCD drives firms to leverage digital technology in supply chain management. The use of digital technologies helps to reduce information asymmetry and transaction costs, enhances information transparency, and improves corporate governance and social responsibility [33]. Additionally, digital technologies can enhance the visibility and traceability of the supply chain [7], enabling firms to monitor and manage carbon emissions more effectively, thereby strengthening corporate sustainability [66]. Finally, by adopting digital operations, firms can reduce information barriers [19,67], enhance operational speed and efficiency, reduce labor costs [68], and enhance customer service to improve ESG performance. Based on this, we posit the following hypothesis:

H3: *SCD enhances ESG performance by promoting DT.*

3.4. Moderating Role of Environmental Uncertainty

The SCP framework is also used to explain how the external environment is a critical factor influencing corporate strategy and performance [22,69]. A high environmental uncertainty implies frequent changes in the external environment, under which the advantages of SCD become more pronounced, as it can enhance a firm's adaptability and reduce risks [35]. Firms often prefer to acquire more social capital and knowledge through SCD in highly uncertain environments [35]. When a firm has high relational capital, its partners are more willing to engage in resource acquisition and knowledge exchange to overcome uncertainties in the external environment [70]. Similarly, Zhang et al. [71] argued that in highly uncertain environments, firms must obtain more external resources and engage more frequently in information and knowledge exchanges with partners to improve their performance. Additionally, in highly uncertain environments, suppliers' and customers' involvement in a firm's green product innovation has a positive impact [63]. Companies can enhance their social and environmental performance by strengthening cooperation with suppliers and customers and meeting market demands in more socially and environmentally friendly ways [72]. Based on this, we posit the following hypothesis:

H4: *EU positively moderates the relationship between SCD and ESG performance*.

Figure 1 presents the theoretical model of this study.

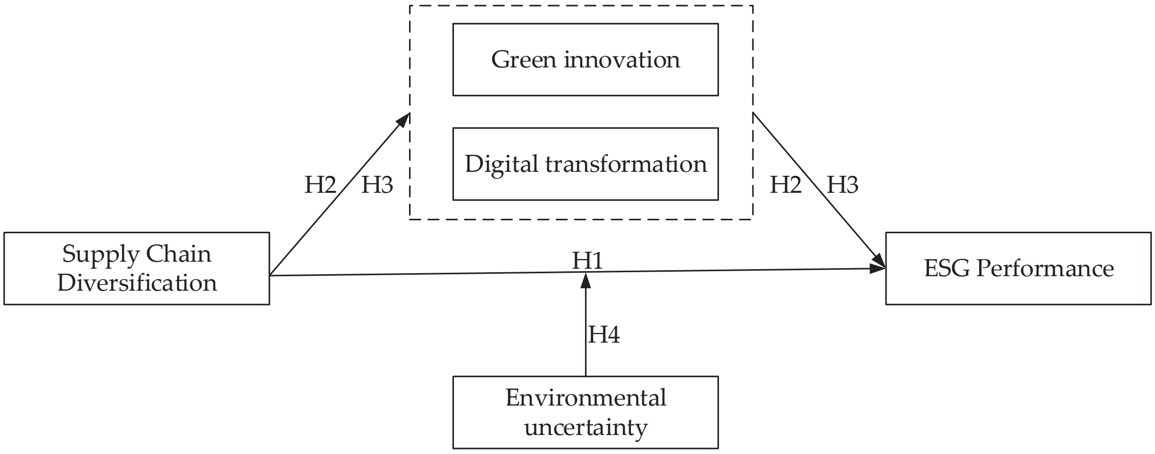

Figure 1. Conceptual framework.

4. Data and Methods

4.1. Data and Sample

China was selected as the sample for this study for the following reasons: First, as a significant participant in the global economy, the extensive and complex nature of China's supply chains provides rich data and cases spanning multiple industries, allowing us to comprehensively analyze the specific impacts of SCD strategies on the ESG of enterprises in different sectors. Second, in recent years, the Chinese government has introduced numerous policies focusing on ESG issues and promoting sustainable development, providing strong support for corporate practices. Finally, China has continuously explored diversification paths in the face of uncertainty in the global trade environment and supply chain risks. This process not only challenges traditional management models but also fosters many innovative cases with notable achievements in ESG, offering valuable lessons for global enterprises.

This study selected China's A-share listed companies data from 2010 to 2023 for the following reasons: Prior to 2010, ESG disclosure by Chinese listed companies was mainly voluntary, resulting in relatively low levels of ESG disclosure and standardization. In

2010, the Ministry of Finance of the People's Republic of China, along with four other ministries and commissions, jointly issued the "Application Guidelines for Enterprise Internal Control No. 4: Social Responsibility", which, for the first time, incorporated social responsibility covering aspects such as environmental protection and employees' rights into the enterprise internal control system. This policy shifted ESG disclosure in China from principled advocacy to operational norms. Therefore, selecting 2010 as the starting point allowed for acquiring richer and more accurate data, providing a solid foundation for the large-scale panel data analysis conducted in this study. Additionally, extending data collection to 2023 could clarify the latest developments in corporate ESG practices, thereby ensuring the timeliness and practical relevance of research results. Therefore, this study obtained SCD, ESG performance, and control variable data for China's A-share listed companies and their top five suppliers and customers from 2010 to 2023 through the CSMAR and Wind databases.

After manual collation, the companies listed in the financial sector were excluded, and samples with abnormal operations, such as ST and *ST companies, were removed. In addition, samples with missing key variables were eliminated, resulting in a final dataset of 35,316 observations from 4598 firms. In this study, all continuous variables were Winsorized at the 1% and 99% quantiles to reduce the errors caused by extreme values.

4.2. Variable Measurement

Regarding the dependent variables, this study used the Huazheng ESG rating index to measure the ESG performance of enterprises [19]. The Huazheng Index, drawing on internationally recognized methodologies and practical experience, as well as integrating China's national conditions and capital market characteristics, encompasses 16 themes with more than 40 minor indicators across the three dimensions of environmental, social, and corporate governance. It is one of the most reliable datasets currently available for assessing the ESG performance of Chinese listed companies [73]. The rating score ranges from 1 to 9, and we use the average of the four quarterly scores to measure ESG performance.

Regarding the independent variable, we used the average sum of supplier and customer diversification to measure SCD based on relevant studies [17,36]. Specifically, supplier diversification was measured via the inverse index of the purchase ratio of the top five suppliers, while customer diversification was quantified via the inverse index of the sales ratio of the top five customers. The rationale for adopting this method was that suppliers and customers are two core components of a firm's supply chain, and the average of supplier and customer diversification can more comprehensively capture the level of diversification in both upstream and downstream aspects of the supply chain [74]. The equation for calculating supplier (customer) diversification is presented in Equation (1):

$$Supplier(customer)diversification = -\sum_{j=1}^{5}\left(\frac{Procurement_{i,j,t}(Sales_{i,j,t})}{Procurement_{i,t}(Sales_{i,t})}\right) \quad (1)$$

For the mechanism variables, we adopted the natural logarithm of the total number of green patent applications plus one as a proxy variable for green innovation [75]. Patent data provided a more accurate and quantifiable measure of innovation output, and patent applications reflected the extent of a company's commitment to green innovation. Second, we used the digitization transformation word frequency from the CSMAR database to build indicators for enterprise digital transformation [75]. The word frequency in the annual report can reflect the strategic characteristics and future prospects of the enterprise and, to a large extent, the business philosophy followed by the enterprise and the development path under the guidance of this concept [33]. We added one to the counted word frequencies and then applied the natural logarithm to measure the degree of digital transformation within the enterprises.

Regarding the moderating variable, since the coefficient of variation in enterprise market sales is less susceptible to managerial manipulation, it is a more reliable and objective indicator of external environmental constraints [76]. Therefore, we adopted industry-adjusted market environmental uncertainty for assessing environmental uncertainty [34,77]. The specific calculation formula is shown in Equation (2):

$$\mathrm{EU}(\mathrm{Z_i}) = \sqrt{\sum\nolimits_{\mathrm{t}-1}^{5} \ (z_i - \bar{z})^2/5}/\bar{z} \tag{2}$$

where $\mathrm{Z_i}$ is the market environmental uncertainty for firm i in year t, while $\bar{z}$ is the five-year mean.

Regarding the control variables, based on previous studies [10,17,35,36], this study controlled for factors that may influence both the independent and dependent variables. These variables include firm-specific characteristics, corporate governance variables, etc. Additionally, we controlled for individual, year, and industry-level fixed effects in our regression models. Table 2 provides definitions and measurements of all variables.

Table 2. Variable definitions.

Type	Variable Name	Symbol	Variable Measurement
Dependent variables	ESG performance	ESG	Huazheng ESG rating index
Independent variables	Supply chain diversification	SCD	(supplier diversification + customer diversification)/2
Mechanism variable	Green innovation	GI	Ln (total number of green patent applications + 1)
	Digital transformation	DT	Ln (digital transformation word frequency + 1)
Moderating variables	Environmental uncertainty	EU	Measured by the coefficient of variation of industry-adjusted firms' sales revenue over the past 5 years.
Control variables	Company size	Size	Ln (total assets)
	Total leverage ratio	Lev	Total liabilities/Total assets
	Listing age	ListAge	Ln (2023-year of listing + 1)
	Cash holdings	Cash	(Monetary funds + trading financial assets)/ Total assets
	Number of board members	Board	Ln (number of directors)
	Proportion of independent directors	Indep	Number of independent directors/ Total number of board members
	Ownership nature	Soe	1 for state-owned holding enterprises and 0 for others
	Cash equivalents	Liqui	Short-term investments/Total assets
	Management fee ratio	Mfee	Administrative expenses/revenue
	Fixed assets ratio	Fixed	Net fixed assets/total assets

4.3. Modeling

For model selection, the Hausman tests confirmed that the fixed-effect models were appropriate for our analyses [78]. We established a linear model with high-dimensional fixed effects of individual, year, and industry to examine the impact of SCD on ESG performance. The regression model is shown in Equation (3):

$$ESG_{i,t,k} = \alpha_0 + \beta_1 SCD_{i,t,k} + \sum \beta_j X_{i,t,k} + \mu_i + \delta_t + \gamma_k + \varepsilon_{i,t,k} \tag{3}$$

In this model, $ESG_{i,t,k}$ represents ESG performance, SCD represents supply chain diversification, $X_{i,t,k}$ represents a set of control variables, i represents the individual firm, t represents time, k represents industry, α_0 represents the intercept of the model, β represents the regression coefficients of the relevant variables, and ε represents a random disturbance term. Additionally, μ_i represents individual-specific fixed effects, δ_t represents year fixed effects, and γ_k captures industry-specific fixed effects.

5. Empirical Results

5.1. Summary Statistics

The descriptive statistics are presented in Table 3. The mean ESG performance score for the dependent variable was 4.155, indicating an intermediate level of ESG performance for the entire sample, with a standard deviation of 0.934, indicating a relatively large variation in ESG scores, reflecting differences in ESG practices between companies. The closer the independent variable SCD is to 0, the higher the diversification degree. The minimum value of SCD is −0.897, the maximum value is −0.033, and the average value is −0.340, indicating that the diversification degree of the supply chain is generally low. To address concerns about multicollinearity, we calculated the VIF values for all variables. The highest observed VIF value was 2.683, indicating that multicollinearity was not a significant concern.

Table 3. Descriptive statistics.

Variable	N	Mean	SD	Min	Max	VIF
ESG	35,316	4.155	0.934	1.000	6.750	-
SCD	35,316	−0.340	0.169	−0.897	−0.033	1.076
Size	35,316	22.200	1.288	18.96	26.44	1.740
Lev	35,316	0.407	0.204	0.008	0.999	2.683
ListAge	35,316	2.033	0.931	0.000	3.434	1.575
Cash	35,316	0.216	0.152	0.012	0.841	1.693
Board	35,316	2.269	0.254	1.609	2.996	1.157
Indep	35,316	0.385	0.075	0.231	0.615	1.055
Soe	35,316	0.290	0.454	0.000	1.000	1.360
Liqui	35,316	0.069	0.203	−0.602	0.613	2.343
Mfee	35,316	0.084	0.065	0.007	0.502	1.219
Fixed	35,316	0.202	0.150	0.001	0.708	1.631

Spearman's correlation tests were conducted for all variables, with the results presented in Table 4. The table reveals a positive correlation between SCD and ESG performance, suggesting that SCD has a favorable effect on ESG performance.

Table 4. Results of phase relationship analysis.

Variable	ESG	SCD	Size	Lev	ListAge	Cash	Board
ESG	1						
SCD	0.132 ***	1					
Size	0.202 ***	0.230 ***	1				
Lev	−0.124 ***	0.136 ***	0.485 ***	1			
ListAge	−0.131 ***	0.151 ***	0.451 ***	0.379 ***	1		
Cash	0.156 ***	−0.072 ***	−0.230 ***	−0.451 ***	−0.324 ***	1	
Board	−0.059 ***	0.056 ***	0.238 ***	0.174 ***	0.226 ***	−0.118 ***	1
Indep	0.078 ***	0.019 ***	−0.069 ***	−0.065 ***	−0.078 ***	0.028 ***	−0.195 ***
Soe	0.029 ***	0.040 ***	0.345 ***	0.269 ***	0.426 ***	−0.132 ***	0.279 ***
Liqui	0.147 ***	−0.091 ***	−0.356 ***	−0.619 ***	−0.349 ***	0.211 ***	−0.186 ***
Mfee	−0.142 ***	−0.031 ***	−0.347 ***	−0.233 ***	−0.053 ***	0.072 ***	−0.020 ***
Fixed	−0.081 ***	−0.053 ***	0.119 ***	0.104 ***	0.136 ***	−0.364 ***	0.117 ***
	Indep	Soe	Liqui	Mfee	Fixed		
Indep	1						
Soe	−0.163 ***	1					
Liqui	0.070 ***	−0.253 ***	1				
Mfee	0.027 ***	−0.085 ***	0.058 ***	1			
Fixed	−0.044 ***	0.166 ***	−0.400 ***	−0.082 ***	1		

Note: *** $p < 0.01$.

5.2. Baseline Regression Results

Table 5 presents the results of the main regression analysis. Column (1) contains no control variables, and column (2) lists the regression results with control variables. The results show that the regression coefficient for the relationship between SCD and ESG is 0.203 ($p < 0.01$), supporting H1. Column (3) presents the effect of customer diversification (CD) on ESG. The regression coefficient for CD is positive and significant at the 1% level, indicating a positive effect on ESG. Column (4) shows the effect of supplier diversification (SD) on ESG. The regression coefficient for SD is positive at the 10% significance level, suggesting that SD has a positive influence on ESG.

Table 5. Results of main regression.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG
SCD	0.208 ***	0.203 ***		
	(2.958)	(2.972)		
CD			0.152 ***	
			(2.824)	
SD				0.084 *
				(1.690)
Size		0.243 ***	0.245 ***	0.246 ***
		(13.574)	(13.761)	(13.827)
Lev		−0.654 ***	−0.654 ***	−0.653 ***
		(−9.026)	(−9.030)	(−8.995)
ListAge		−0.242 ***	−0.241 ***	−0.240 ***
		(−12.594)	(−12.560)	(−12.504)
Cash		0.132 **	0.131 **	0.128 **
		(2.038)	(2.020)	(1.982)
Board		−0.186 ***	−0.186 ***	−0.186 ***
		(−7.919)	(−7.900)	(−7.898)
Indep		0.382 ***	0.383 ***	0.381 ***
		(5.298)	(5.309)	(5.287)
Soe		0.057 *	0.056 *	0.056 *
		(1.851)	(1.830)	(1.828)
Liqui		0.157 ***	0.156 **	0.156 **
		(2.585)	(2.566)	(2.557)
Mfee		−1.100 ***	−1.089 ***	−1.098 ***
		(−7.762)	(−7.676)	(−7.736)
FIXED		−0.123	−0.120	−0.117
		(−1.332)	(−1.298)	(−1.260)
_cons	4.226 ***	−0.073	−0.149	−0.195
	(176.433)	(−0.181)	(−0.373)	(−0.488)
Firms/Year/Ind FE	Yes	Yes	Yes	Yes
N	35,316	35,316	35,316	35,316
R^2	0.565	0.587	0.587	0.587

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.3. The Mediation Mechanism Model

We use the three-step method to test the mediation mechanism [79] and construct the regression model as shown in Equations (4) and (5):

$$M_{i,t,k} = \alpha_0 + \beta_1 SCD_{i,t,k} + \sum \beta_j X_{i,t,k} + \mu_i + \delta_t + \gamma_k + \varepsilon_{i,t,k} \quad (4)$$

$$ESG_{i,t,k} = \alpha_0 + \beta_1 SCD_{i,t,k} + \beta_2 M_{i,t,k} + \sum \beta_j X_{i,t,k} + \mu_i + \delta_t + \gamma_k + \varepsilon_{i,t,k} \quad (5)$$

where $M_{i,t,k}$ represents green innovation and digital transformation. The other parameters are the same as those in Equation (3).

We combined Equations (3)–(5) to test the mechanisms. The regression results are presented in Table 6. Column (1) and (2) reveal that the estimated coefficient of SCD is positive and significant, indicating that SCD notably enhances ESG performance through green innovation, thereby supporting H2. Column (3) and (4) reveal that the estimated coefficient of SCD is positive and significant at the 1% level, implying that SCD significantly promotes ESG performance through digital transformation, thus supporting H3.

Table 6. Results of the mediation and moderating effects.

Variable	(1) GI	(2) ESG	(3) DT	(4) ESG	(5) ESG
SCD	0.160 **	0.196 ***	0.289 ***	0.196 ***	0.145 *
	(2.344)	(2.870)	(3.626)	(2.861)	(1.960)
GI		0.041 ***			
		(5.561)			
DT				0.025 ***	
				(3.382)	
EU					−0.048 ***
					(−7.504)
SCD×EU					0.057 *
					(1.866)
Size	0.361 ***	0.228 ***	0.210 ***	0.238 ***	0.251 ***
	(17.785)	(12.724)	(10.263)	(13.196)	(13.106)
Lev	0.007	−0.653 ***	−0.198 **	−0.649 ***	−0.576 ***
	(0.108)	(−9.032)	(−2.414)	(−8.944)	(−7.603)
ListAge	−0.061 ***	−0.240 ***	0.175 ***	−0.246 ***	−0.239 ***
	(−3.166)	(−12.503)	(7.902)	(−12.829)	(−11.210)
Cash	−0.140 **	0.138 **	−0.247 ***	0.138 **	0.132 *
	(−2.332)	(2.137)	(−3.435)	(2.136)	(1.928)
Board	0.015	−0.187 ***	0.099 ***	−0.189 ***	−0.163 ***
	(0.645)	(−7.947)	(4.283)	(−8.019)	(−6.488)
Indep	0.078	0.377 ***	−0.166 **	0.386 ***	0.330 ***
	(1.162)	(5.244)	(−2.373)	(5.354)	(4.211)
Soe	0.083 ***	0.053 *	−0.049	0.058 *	0.028
	(2.732)	(1.729)	(−1.513)	(1.894)	(0.627)
Liqui	0.054	0.156 **	−0.027	0.158 ***	0.172 ***
	(0.952)	(2.557)	(−0.411)	(2.596)	(2.642)
Mfee	0.279 **	−1.112 ***	−0.135	−1.096 ***	−1.121 ***
	(2.117)	(−7.865)	(−0.896)	(−7.738)	(−7.412)
Fixed	−0.014	−0.123	−0.544 ***	−0.110	−0.108
	(−0.154)	(−1.333)	(−5.203)	(−1.186)	(−1.107)
_cons	−6.994 ***	0.217	−3.242 ***	0.009	−0.275
	(−15.440)	(0.540)	(−7.046)	(0.023)	(−0.641)
Firms/Year/Ind FE	Yes	Yes	Yes	Yes	Yes
N	35,278	35,278	35,316	35,316	29,697
R^2	0.762	0.588	0.821	0.588	0.613

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5.4. The Moderating Mechanism Model

To investigate how EU moderates the influence of SCD on ESG performance, we formulated the regression model presented in Equation (6):

$$ESG_{i,t,k} = \alpha_0 + \beta_1 SCD_{i,t,k} + \beta_2 SCD_{i,t,k} \times EU_{i,t,k} + \beta_3 EU_{i,t,k} + \sum \beta_j X_{i,t,k} + \mu_i + \delta_t + \gamma_k + \varepsilon_{i,t,k} \quad (6)$$

Here, $EU_{i,t,k}$ represents environmental uncertainty. The meanings of the other parameters are the same as those in Model (3).

Column (5) of Table 6 presents the regression results for the moderating effect of EU. The coefficient of the interaction term was 0.057, being statistically significant at the 10% level. The moderating effect of EU is depicted in Figure 2. Calculating the slope, the results indicate that when EU is in the high-score group, the relationship between SCD and ESG is positive and significant (β = 0.212, t = 2.765, $p < 0.01$). In contrast, when EU was in the low-score group, the relationship between SCD and ESG was not statistically significant (β = 0.078, t = 0.892, $p > 0.1$). These findings support H4.

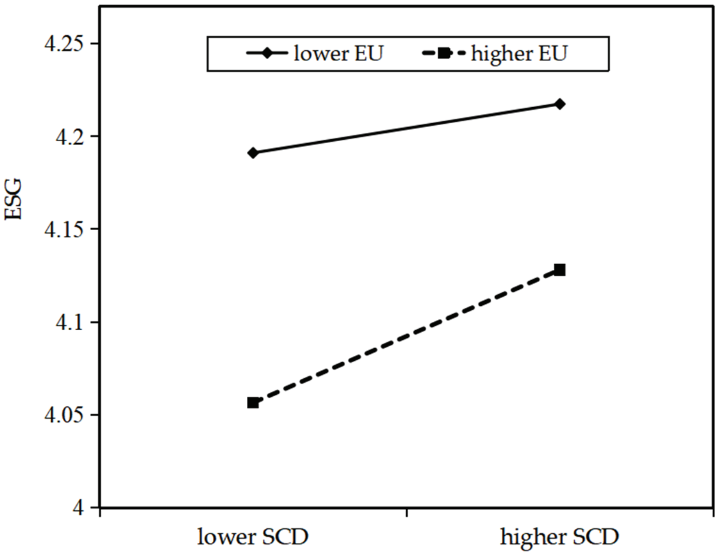

Figure 2. The moderating effect of EU.

5.5. Robustness Test

We employed several robustness-testing methods to ensure the reliability of the results. First, to eliminate the possibility of generating chance findings in this study, we changed the ESG measurement method to use the annual total score of the Huazheng ESG rating, and the results presented that the conclusion was not reliant on a single measurement methodology. The results are shown in column (1) of Table 7.

Second, we employ the inverse sum of the Herfindahl–Hirschman Index for the largest customer and supplier as an alternative SCD metric [35] to enhance robustness. The regression results are shown in column (2) of Table 7.

Third, to eliminate the potential distortion of data caused by the pandemic, the applicability of the research findings under normal economic conditions was ensured. We removed post-2020 data, restricted the sample period to 2010–2019, and then re-ran the regression analysis. The results are presented in column (3) of Table 7.

Fourth, to mitigate the impact of inter-industry variations, the analysis is concentrated on a single sector to validate the robustness of the conclusions within that specific industry. We retained only the data from the manufacturing industry and conducted the regression again; the result is shown in column (4) of Table 7.

Fifth, considering that the impact of SCD on ESG performance may exhibit a time lag, we conducted a regression analysis with SCD lagged by one period, following the method of a previous study [80]. The results presented in column (5) of Table 7 indicate that the one-period-lagged SCD has a positive effect on ESG performance at a 10% significance level, which further validates the robustness of the benchmark test.

Table 7. Robustness test.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG
SCD	0.165 **	0.205 **	0.264 ***	0.208 **	0.137 *
	(2.575)	(2.020)	(2.860)	(2.277)	(1.761)
Size	0.209 ***	0.243 ***	0.249 ***	0.252 ***	0.190 ***
	(9.964)	(11.409)	(9.336)	(10.643)	(9.296)
Lev	−0.397 ***	−0.745 ***	−0.432 ***	−0.625 ***	−0.834 ***
	(−5.557)	(−8.853)	(−4.222)	(−6.625)	(−10.064)
ListAge	−0.130 ***	−0.230 ***	−0.308 ***	−0.307 ***	−0.105 ***
	(−4.408)	(−9.735)	(−9.829)	(−12.539)	(−4.798)
Cash	−0.185 ***	0.111	0.216 **	0.112	0.239 ***
	(−3.138)	(1.460)	(2.558)	(1.419)	(3.396)
Board	−0.045 **	−0.189 ***	−0.195 ***	−0.181 ***	−0.207 ***
	(−2.142)	(−6.802)	(−5.988)	(−6.480)	(−8.147)
Indep	0.154 **	0.345 ***	0.273 ***	0.384 ***	0.524 ***
	(2.346)	(3.932)	(2.798)	(4.506)	(6.814)
Soe	−0.137 ***	0.010	0.085	0.050	0.078
	(−5.627)	(0.254)	(1.176)	(1.172)	(1.630)
Liqui	−0.016	0.144 **	0.294 ***	0.168 **	0.129 *
	(−0.280)	(2.041)	(3.372)	(2.216)	(1.904)
Mfee	−0.452 ***	−1.281 ***	−0.492 ***	−1.283 ***	−1.637 ***
	(−2.953)	(−7.851)	(−2.795)	(−6.338)	(−10.609)
Fixed	−0.064	−0.125	0.112	−0.069	−0.274 ***
	(−0.697)	(−1.153)	(0.908)	(−0.643)	(−2.761)
_cons	2.020 ***	−0.092	−0.231	−0.177	0.891 *
	(4.392)	(−0.194)	(−0.385)	(−0.335)	(1.938)
Firms/Year/ Ind FE	Yes	Yes	Yes	Yes	Yes
N	35,316	25,093	23,752	22,353	22,353
R^2	0.587	0.589	0.685	0.577	0.610

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Sixth, double machine learning was capable of more effectively addressing endogeneity issues, high-dimensional data, and complex nonlinear relationships, thereby validating the reliability and robustness of the regression analysis results. We further utilized double machine learning methods, including Random Forest, Gradient Boosting, Lasso Regression, Support Vector Machine, and Neural Networks, to estimate the impact of SCD on ESG. The results are presented in columns (1) to (6) of Table 8. The findings show that the coefficients for SCD estimated using each of these algorithms are significant at the 1% level, further confirming the robustness of our research findings.

Table 8. Double machine learning test.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
θ_0	0.248 *** (0.044)	0.361 *** (0.047)	0.392 *** (0.048)	0.579 *** (0.038)	0.198 *** (0.046)	0.462 *** (0.028)
DML model	RF	GBDT	RR	SVM	Lasso	NN
Control	Yes	Yes	Yes	Yes	Yes	Yes
Firms/Year /Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
N	35,316	35,316	35,316	35,316	35,316	35,316

Note: standard error are in parentheses; *** $p < 0.01$.

Finally, we further employed the sensitivity analysis method proposed by [81] to systematically examine the robustness of the baseline results under potential omitted variable interference. This method assumes that the omitted variable has n times the explanatory power of the comparison variable. Considering the firms' listing age had already been controlled for in the baseline model and that it was naturally correlated with potential omitted variables. Therefore, we chose listing age as the comparison variable for the sensitivity analysis. Figures 3 and 4 present the comparison results between the omitted variable and the comparison variable "ListAge". The results show that when the strength of the omitted variable is three times that of "ListAge", the regression coefficient remains positive (t-value = 1.95, $p < 0.1$). This indicates that even in the presence of omitted variables, as long as their impact on firm ESG performance does not exceed three times that of the comparison variable "ListAge", the baseline regression results will not be significantly affected. In fact, firm age is an important factor influencing firm ESG performance, and the likelihood of omitted variables having an impact strength more than three times that of firm age is low. Thus, the reliability of the baseline regression results is validated.

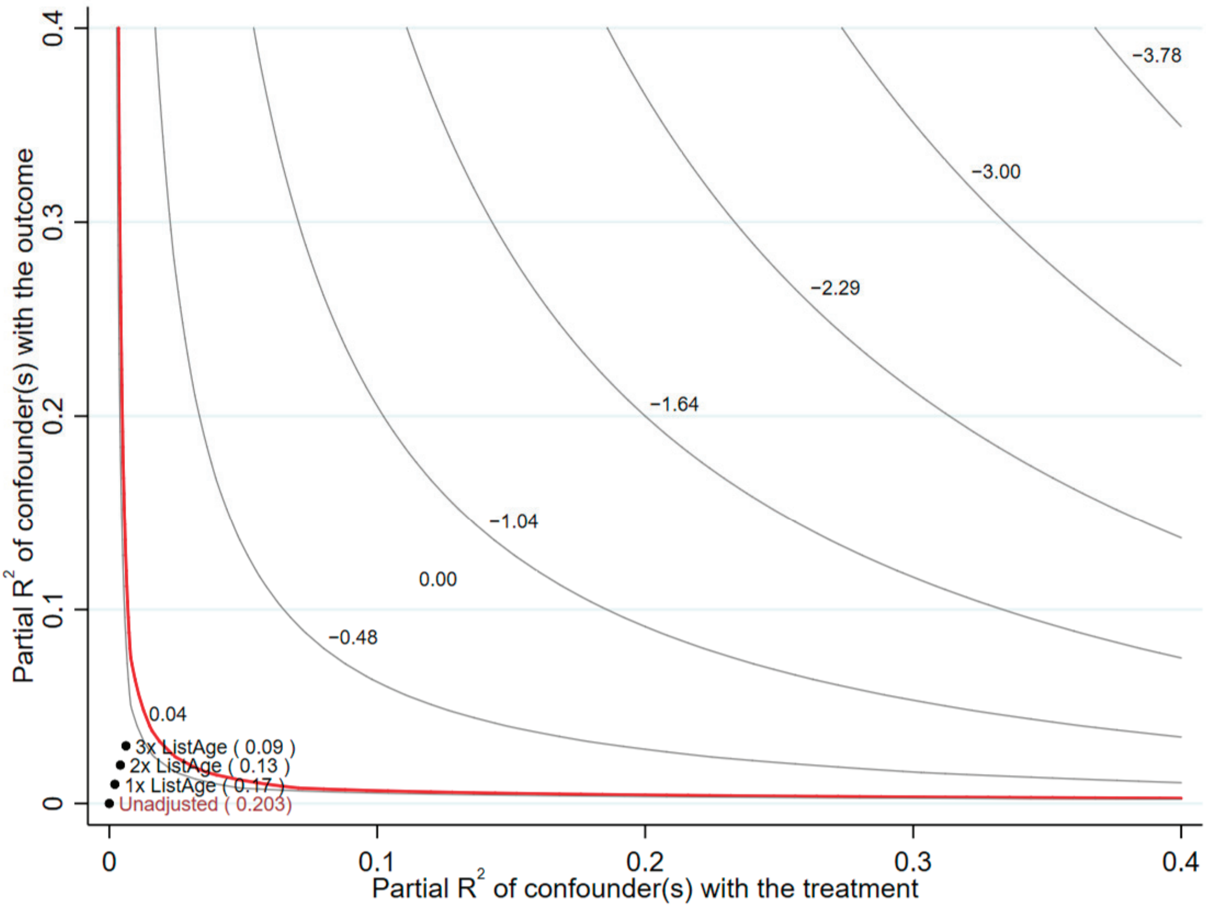

Figure 3. Sensitivity analysis coefficients.

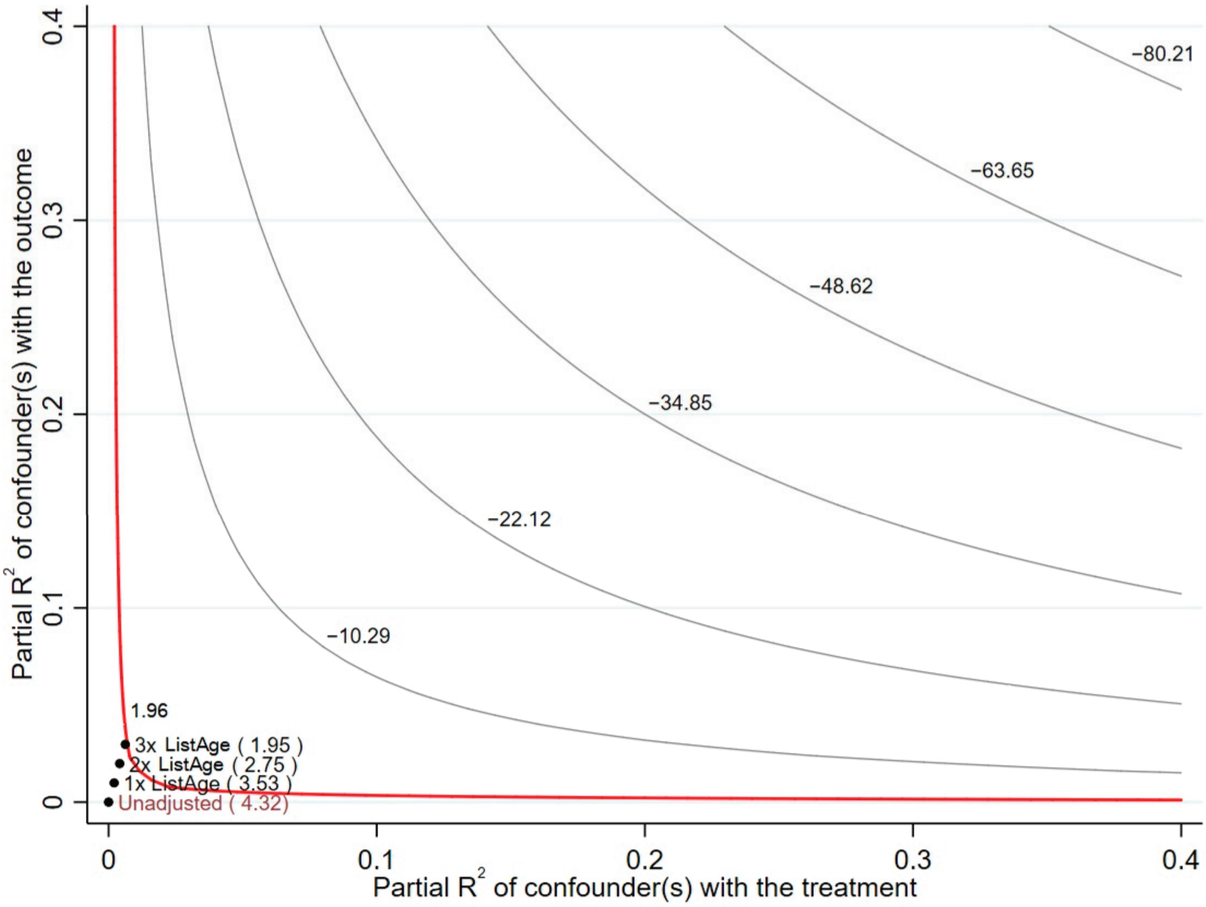

Figure 4. Sensitivity analysis t-value.

5.6. Endogeneity Test

We employed three methods for endogeneity testing. First, this study may face the issue of reverse causality, where firms with better ESG performance tend to have higher levels of SCD. To address this issue, we employed Two-Stage Least Squares (2SLS) method to mitigate potential endogeneity concerns [80]. The SCD of other firms in the same industry and year likely influences the SCD of the focal firm but does not directly affect its ESG performance, which satisfies the conditions for using an instrumental variable. Therefore, we employed the average SCD value of other firms within the same industry and year as an instrumental variable (SCD_IV1) and conducted regression. Columns (1) and (2) of Table 9 report the regression results obtained using the 2SLS method. The first-stage regression results show that the estimated coefficient of the instrumental variable is significantly positive, confirming its relevance. Additionally, the regression results passed the weak instrumental variable test and the underidentification test, indicating that the selection of the instrumental variable is reasonable. The second-stage regression results demonstrate that the coefficients of SCD, after fitting with exogenous variables, are significantly positive at the 5% levels This finding suggests that after addressing endogeneity using the instrumental variable, SCD still significantly enhances ESG performance.

Table 9. Endogeneity test.

Variable	2SLS (1) SCD	2SLS (2) ESG	Heckman Two-Step Method (3) ESG_Dum	Heckman Two-Step Method (4) ESG	PSM (5) ESG
SCD_IV1	0.896 ***				
	(28.852)				
Mandatory			0.731 ***		
			(15.548)		
IMR			−0.655 ***	−0.655 ***	
			(−8.807)	(−8.807)	
SCD		0.355 **		0.200 ***	0.203 ***
		(2.391)		(2.751)	(2.971)
Size	0.034 ***	0.278 ***	0.277 ***	0.102 ***	0.243 ***
	(16.888)	(26.269)	(17.791)	(4.122)	(13.535)
Lev	−0.001	−0.709 ***	−0.925 ***	−0.165 *	−0.651 ***
	(−0.088)	(−10.354)	(−8.652)	(−1.797)	(−8.987)
ListAge	0.011 ***	−0.210 ***	−0.233 ***	−0.168 ***	−0.241 ***
	(4.423)	(−18.579)	(−13.717)	(−7.508)	(−12.545)
Cash	−0.028 **	0.557 ***	0.531 ***	−0.075	0.133 **
	(−1.982)	(8.539)	(5.207)	(−1.028)	(2.052)
Board	0.005	−0.223 ***	−0.215 ***	−0.082 ***	−0.185 ***
	(0.790)	(−7.696)	(−4.877)	(−3.014)	(−7.877)
Indep	0.051 ***	0.885 ***	1.263 ***	−0.202 **	0.377 ***
	(2.967)	(10.478)	(9.487)	(−2.057)	(5.234)
Soe	−0.019 ***	0.185 ***	0.124 ***	−0.019	0.055 *
	(−3.923)	(7.239)	(3.404)	(−0.435)	(1.794)
Liqui	−0.022 *	0.490 ***	0.405 ***	−0.011	0.160 ***
	(−1.721)	(7.906)	(4.327)	(−0.167)	(2.620)
Mfee	0.069 **	−0.922 ***	−1.346 ***	−0.492 ***	−1.098 ***
	(2.150)	(−6.518)	(−6.257)	(−3.037)	(−7.746)
Fixed	−0.040 **	−0.082	0.356 ***	−0.259 ***	−0.123
	(−2.453)	(−1.043)	(2.912)	(−2.591)	(−1.331)
Constant	−0.830 ***	−1.124 ***	−5.808 ***	3.329 ***	−0.066
	(−18.020)	(−4.246)	(−16.506)	(5.810)	(−0.163)
Kleibergen-Paap rk LM	823.414 ***				
Cragg-Donald Wald F	6177.117 ***				
Stock-Yogo	[16.380]				
Firms/Year/Ind FE	Yes	Yes	Yes	Yes	Yes
N	35,221	35,221	31,000	30,588	35,278
R^2	0.150	0.187		0.612	0.587

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, this study employed the Heckman two-stage model for bias correction to mitigate the selection bias caused by the endogenous selection behavior of firms' SCD. In the first stage, whether a firm's ESG exceeded the annual industry average (ESG_Dum) was used as the dependent variable, and whether a firm was mandated to disclose a social responsibility report or sustainability report (Mandatory) was introduced as an exogenous explanatory variable. If a firm was required to disclose a report in a specific year, Mandatory was assigned a value of 1; otherwise, it was 0. A probit regression model was used for estimation, yielding the inverse Mills ratio (IMR) as the self-selection parameter. The IMR was then included as an additional control variable in the second-stage model for re-estimation, and the results are shown in columns (3) and (4) of Table 9. In the first stage, Mandatory is significantly positively correlated with ESG_Dum at the 1% level, indicating that firms voluntarily disclosing social responsibility reports are more likely to have higher ESG performance. The selection of the exogenous variable is reasonable and aligns with theoretical expectations. In the second stage, the coefficient of IMR is significantly negative, and the regression coefficient of SCD on ESG is 0.200 ($p < 0.01$). The results demonstrate that after controlling for sample self-selection bias, the positive impact of SCD on ESG remains.

Third, this study employed the propensity score matching (PSM) method for robustness testing to thoroughly investigate the potential impact of sample selection bias on the research conclusions. First, the sample was divided into two groups based on the annual industry average level of SCD, with samples above the average assigned to the treatment group and the rest assigned to the control group. Second, a series of matching variables were selected to filter the sample. Third, the one-to-one nearest neighbor matching was used to pair each treatment group sample with the most similar control group sample. Finally, regression analysis was conducted on the matched sample firms. Figure 5 shows the distribution differences of the matching variables before and after matching. The matching results indicate that the standardized bias of the covariates is below 5%, meaning that most control variables passed the balance test. Column (5) of Table 9 presents the regression results for the PSM subsample, with a regression coefficient of 0.203 ($p < 0.01$), demonstrating that the findings of the baseline regression are robust.

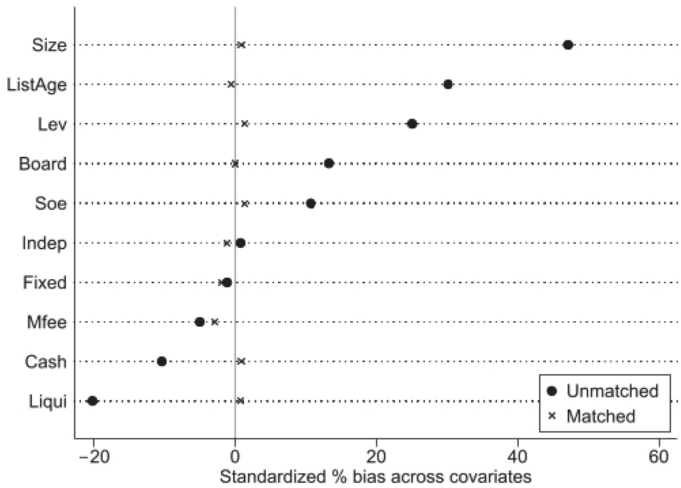

Figure 5. Distribution of standard deviation.

5.7. Heterogeneity Analysis

The empirical tests in the preceding section sufficiently demonstrated that SCD can significantly enhance ESG. However, they have not revealed whether this positive effect is heterogeneous across different types of enterprises. To gain a deeper understanding of the heterogeneous effects of SCD on ESG, we conducted analyses from the perspectives of firm characteristics, industry characteristics, and regional heterogeneity.

First, heterogeneity analysis based on firm size was performed. Large enterprises typically possess more resources, such as capital, technology, and talent, while small and medium-sized enterprises (SMEs) may have limited resources, making it challenging to effectively manage diversified supply chains and potentially increasing operational risks due to SCD. In this study, the sample was divided into large enterprises and SMEs based on the median firm size within each year and industry for group testing. The results, as shown in column (1) of Table 10, indicate that the regression coefficient of SCD on ESG for the SMEs group is 0.155 ($p < 0.1$). Column (2) of Table 10 shows that the regression coefficient of SCD on ESG for the large enterprise group is 0.214 ($p < 0.05$). These results suggest that the positive impact of SCD on ESG is more pronounced in large enterprises. A possible explanation is that large enterprises generally have stronger market influence and resources, as well as mature supply chain management systems, enabling them to optimize supply chain structures to enhance ESG performance.

Table 10. Heterogeneity analysis of firms and industries.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
SCD	0.155 *	0.214 **	0.115	0.201 **	0.176 **	0.345 **
	(1.703)	(1.969)	(1.228)	(2.069)	(2.245)	(2.497)
Size	0.209 ***	0.355 ***	0.240 ***	0.257 ***	0.260 ***	0.200 ***
	(6.029)	(11.118)	(10.023)	(10.117)	(12.314)	(5.568)
Lev	−0.649 ***	−0.727 ***	−0.676 ***	−0.657 ***	−0.668 ***	−0.605 ***
	(−6.441)	(−5.870)	(−6.782)	(−6.695)	(−7.889)	(−4.211)
ListAge	−0.349 ***	−0.087 **	−0.223 ***	−0.249 ***	−0.232 ***	−0.269 ***
	(−12.942)	(−2.325)	(−8.065)	(−9.396)	(−10.503)	(−6.467)
Cash	0.059	0.150	0.197 **	0.037	0.233 ***	−0.110
	(0.732)	(1.314)	(2.285)	(0.400)	(3.106)	(−0.851)
Board	−0.164 ***	−0.189 ***	−0.160 ***	−0.169 ***	−0.179 ***	−0.196 ***
	(−5.181)	(−5.339)	(−4.818)	(−4.829)	(−6.576)	(−4.403)
Indep	0.343 ***	0.332 ***	0.415 ***	0.344 ***	0.319 ***	0.535 ***
	(3.500)	(3.177)	(4.125)	(3.242)	(3.821)	(3.977)
Soe	0.045	0.079 **	−0.006	0.098 **	0.077 **	0.034
	(0.869)	(2.017)	(−0.135)	(2.358)	(2.210)	(0.550)
Liqui	0.104	0.158	0.209 ***	0.141	0.120 *	0.251 **
	(1.288)	(1.566)	(2.587)	(1.618)	(1.668)	(2.168)
Mfee	−1.026 ***	−0.983 ***	−1.022 ***	−0.895 ***	−1.076 ***	−1.178 ***
	(−5.935)	(−3.327)	(−5.508)	(−4.301)	(−7.074)	(−3.080)
Fixed	−0.093	−0.167	−0.258 **	−0.089	−0.186	−0.091
	(−0.769)	(−1.084)	(−2.102)	(−0.707)	(−1.623)	(−0.654)
_cons	0.776	−2.989 ***	−0.114	−0.430	−0.447	0.915
	(1.056)	(−4.068)	(−0.214)	(−0.742)	(−0.946)	(1.125)
Firms/Year/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
N	17,457	17,522	17,725	16,642	25,290	9854
R^2	0.630	0.597	0.637	0.629	0.601	0.581

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Second, we performed heterogeneity analysis of the degree of industry competition degree. Industry competition may affect companies' willingness and capability to disclose ESG information. In a fiercely competitive market, firms are more inclined to leverage external resources to address such challenges to maintain their competitiveness within the supply chain or defend against attacks from competitors. To explore how the degree of industry competition differentially impacts the effect of SCD on ESG, we used the Herfindahl Index to assess the intensity of competition in the market and divided the sample into low-competition and high-competition groups based on the annual industry median. The results show that, as presented in column (3) of Table 10 for the low-competition group, the coefficient of the impact of SCD on ESG is 0.115 ($p > 0.1$), while in column (4), for the high-competition group, this coefficient is 0.201 ($p < 0.05$). A possible reason for this is that enterprises in highly competitive industries typically face stronger market supervision and reputational risks. To maintain their competitive advantage, these enterprises may be more proactive in enhancing their ESG performance through SCD.

Third, heterogeneity analysis based on high-pollution enterprises was performed. High-pollution enterprises typically face stronger environmental pressures and regulatory requirements, making them more inclined to improve their environmental performance through SCD to comply with regulations and mitigate environmental risks. To test this effect, we categorized enterprises into high-pollution and non-high-pollution groups based on the CSMAR database. As shown in column (5) of Table 10, the regression coefficient of SCD on ESG for the non-high-pollution group is 0.176 ($p < 0.05$). Column (6) of Table 10 indicates that the regression coefficient of SCD on ESG for the high-pollution group is 0.345 ($p < 0.05$). The results suggest that the positive impact of SCD on ESG is more pronounced in high-pollution enterprises. A possible explanation is that high-pollution enterprises are typically subject to stricter environmental regulations and greater pressure to reduce emissions. They may be more inclined to replace high-pollution suppliers, introduce clean energy suppliers, or seek to collaborate with diversified suppliers, thereby reducing their environmental impact and enhancing their ESG performance.

Fourth, industry heterogeneity analysis based on production factor intensity was performed. We categorized the sample into labor-intensive, capital-intensive, and technology-intensive industries for regression analysis. As shown in column (1) of Table 11, the regression coefficient of SCD on ESG for the labor-intensive group is 0.252 ($p < 0.1$). Column (2) of Table 11 shows that the regression coefficient of SCD on ESG for the capital-intensive group is 0.267 ($p < 0.05$). Column (3) of Table 11 shows that the regression coefficient of SCD on ESG for the technology-intensive group is 0.143 ($p > 0.1$). The results suggest that the positive impact of SCD on ESG is more pronounced in labor-intensive and capital-intensive enterprises. A possible explanation is that labor-intensive enterprises often face more labor-related issues, and SCD can help these enterprises to better manage social responsibilities, for instance, by selecting compliant suppliers or promoting labor standards within the supply chain, thereby enhancing ESG performance. Capital-intensive enterprises tend to rely on substantial capital investments, typically exhibit constrained organizational agility due to the inherent rigidity of their operational and financial structures. SCD can mitigate the risk of supply chain disruptions and improve efficiency, thus boosting ESG performance. Technology-intensive enterprises depend on advanced technologies and innovation, and there is limited scope and demand for SCD, thus having an insignificantly impact on ESG performance.

Finally, based on the geographical location of enterprises, we categorized the sample into enterprises in the eastern, central, and western regions for testing. Table 11 presents the empirical results from columns (4) to (6), showing that SCD positively impacts ESG performance for enterprises in the eastern and central regions, while no significant effect is observed for enterprises in the western region. A possible explanation is that the eastern and central regions have higher levels of economic development, more advanced infrastructure [82], and greater resource allocation toward technological innovation and green development. These factors make it easier for enterprises in these regions to adopt advanced technologies and management practices when implementing SCD strategies, thereby promoting higher ESG performance.

Table 11. Analysis of industrial and regional heterogeneity.

Variable	(1) ESG	(2) ESG	(3) ESG	(4) ESG	(5) ESG	(6) ESG
SCD	0.252 *	0.267 **	0.143	0.193 **	0.560 ***	0.003
	(1.670)	(2.124)	(1.464)	(2.383)	(3.098)	(0.018)
Size	0.216 ***	0.236 ***	0.266 ***	0.236 ***	0.273 ***	0.272 ***
	(4.949)	(7.042)	(9.881)	(10.865)	(5.536)	(5.095)
Lev	−0.612 ***	−0.381 ***	−0.817 ***	−0.679 ***	−0.446 **	−0.608 ***
	(−3.855)	(−2.874)	(−7.610)	(−8.033)	(−2.132)	(−2.707)
ListAge	−0.151 ***	−0.293 ***	−0.282 ***	−0.253 ***	−0.231 ***	−0.169 ***
	(−3.139)	(−7.394)	(−10.105)	(−11.233)	(−4.141)	(−2.687)
Cash	−0.044	0.046	0.178 **	0.126 *	0.311 *	−0.173
	(−0.293)	(0.337)	(2.008)	(1.692)	(1.837)	(−0.804)
Board	−0.146 ***	−0.184 ***	−0.192 ***	−0.185 ***	−0.146 **	−0.232 ***
	(−3.166)	(−3.921)	(−5.857)	(−6.504)	(−2.365)	(−3.556)
Indep	0.331 **	0.426 ***	0.347 ***	0.465 ***	0.096	0.315
	(2.109)	(3.185)	(3.466)	(5.508)	(0.509)	(1.453)
Soe	0.030	0.075	0.037	0.063	0.074	−0.032
	(0.549)	(1.300)	(0.759)	(1.623)	(1.174)	(−0.419)
Liqui	0.054	0.350 ***	0.057	0.146 **	0.217	0.192
	(0.406)	(3.072)	(0.648)	(2.037)	(1.421)	(1.050)
Mfee	−0.568	−1.388 ***	−1.074 ***	−1.137 ***	−0.804 *	−1.252 ***
	(−1.532)	(−4.740)	(−5.587)	(−6.920)	(−1.926)	(−3.077)
Fixed	−0.396 **	0.012	−0.221	−0.148	−0.108	−0.219
	(−2.081)	(0.080)	(−1.550)	(−1.352)	(−0.438)	(−0.944)
_cons	0.255	0.072	−0.383	0.110	−0.840	−0.778
	(0.261)	(0.095)	(−0.636)	(0.225)	(−0.764)	(−0.636)
Firms/Year/Ind FE	Yes	Yes	Yes	Yes	Yes	Yes
N	7692	9496	17,293	25,554	5015	3746
R^2	0.636	0.603	0.590	0.580	0.594	0.613

Note: the t-statistics with individual cluster-robust standard errors are in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6. Discussion and Implications

6.1. Discussion

Based on the SCP framework, in this study, a model was designed to examine the impact of SCD on ESG and its potential mechanisms. Based on the empirical results, several important conclusions were drawn. First, the findings indicate a positive correlation between SCD and ESG. These results are consistent with those reported in the literature. As Zheng et al. [83] suggested, customer concentration negatively impacts ESG. Wen et al. [80] posited that customer concentration is negatively correlated with suppliers' CSR performance. Furthermore, Richard et al. [61], working from a resource-based perspective, demonstrated that supplier diversification is a valuable resource for procurement organizations to create competitive advantages. Our findings also support this view, confirming that SCD can enhance ESG.

Second, the mechanism analysis reveals that green innovation and digital transformation play significant roles in the relationship between SCD and ESG, consistent with previous research. Specifically, SCD facilitates technological exchange and cooperation among different suppliers, enhancing enterprises' ability to produce green products [63], and green innovation can significantly improve a company's ESG. Furthermore, Feng and Wang [36] argue that SCD can promote corporate digital transformation. Zhao and Cai [33] and Qi et al. [84] suggest that digital transformation has a positive effect on improving a company's ESG.

Finally, this study indicates that environmental uncertainty plays a positive moderating role between SCD and ESG. This finding aligns with prior research [85], who suggest that under higher environmental uncertainty, companies increase their corporate social responsibility practices to reduce enterprise risks. Similarly, managers may be more willing to increase ESG engagement during periods of high uncertainty, and economic policy uncertainty positively impacts ESG [12].

6.2. Theoretical Implications

This study makes several significant contributions to the theoretical research on corporate supply chain management and ESG performance. First, our research introduces the SCP framework into the study of ESG performance and expands supply chain-level factors as antecedents affecting ESG performance, providing a new perspective for enterprises to enhance their ESG performance through supply chain management. This differs from previous studies that explored various factors influencing ESG performance from the perspectives of resource-based theory [14,86], stakeholder theory [8,87], institutional theory [88], and resource dependence theory [89]. Based on the SCP framework, this study discusses how the structural characteristics and resource effects of SCD can change corporate conduct and, therefore, affect ESG performance. It also conducts comparative analyses across firm characteristics, industry characteristics, and different regions. This responds to the call for research on how sustainable supply chain management at the supply chain level can influence ESG [21]. To the best of our knowledge, this study is one of the first to explore ESG performance from the perspective of the SCP framework, expanding the theoretical horizons of ESG research.

Second, based on the SCP framework, we constructed a theoretical framework of "supply chain diversification (Structure)–green innovation and digital transformation (Conduct)–ESG Performance (Performance)". The findings not only explain how SCD affects ESG performance but also expand research on the antecedents of ESG performance. On the one hand, previous literature suggests that SCD can increase corporate access to external resources [35,36], and our study supports this view, confirming that SCD can enhance the resource effect of enterprises. On the other hand, previous studies have argued that ESG is influenced by internal strategic factors, corporate characteristics, corporate governance, board diversity [4,14,90], and external industry competition environments [91]. In contrast, we considered how SCD at the structural level affects corporate green innovation and digital transformation conduct, in turn influencing ESG. This enriched the research on the mechanism of SCD and the influencing factors of ESG, offering new perspectives on how enterprises can achieve ESG goals through managing sustainable supply chains.

Finally, we explored the boundary relationship of environmental uncertainty. The existing literature primarily considers the direct impact of environmental uncertainty on ESG [11,34]. However, there is less focus on how environmental uncertainty, as a moderating variable, influences the impact of supply chain structure on corporate non-financial performance. This study confirms that environmental uncertainty enhances the effect of SCD on ESG. This finding provides theoretical insights for formulating effective sustainable supply chain management strategies to enhance ESG in uncertain environments.

6.3. Management Implications

These findings have significant implications for guiding enterprises in formulating supply chain strategies and enhancing sustainable performance. Firstly, senior executives and operations managers should fully recognize the strategic value of SCD, reduce dependence on traditional linear supply chains, and rationally build diversified supply chain networks based on business needs and strategic objectives to gain external resources through collaborative partnerships with diverse stakeholders. Simultaneously, ESG goals should be integrated into the risk assessment and incentive mechanisms for supply chain partners, promoting sustainable procurement and collaborative innovation, enabling long-term improvements in ESG performance.

Secondly, enterprises should prioritize green innovation and digital technologies when implementing SCD strategies. On one hand, to ensure sustainable development, enterprises should actively engage suppliers and partners with green innovation advantages across various fields, establishing cross-industry green innovation collaboration networks. Through joint research and development, sharing green technology resources, and other approaches, they can jointly explore green innovation solutions for energy conservation, emissions reduction, resource recycling, etc., thereby stimulating green innovation vitality across different supply chain sectors. Simultaneously, by leveraging the abundant resources and market channels brought by SCD, enterprises can accelerate the transformation and application of green innovation achievements. On the other hand, enterprises should accelerate the deep integration of digital technologies with supply chain operations and management. By embedding technologies such as RFID, IoT, and blockchain into supply chains, they can ensure the transparency and traceability of ESG data, not only enhancing stakeholder trust but also better meeting regulatory requirements. Additionally, enterprises can further enhance the application of artificial intelligence to support demand forecasting and supplier evaluation. By integrating these digital technologies, enterprises can improve supply chain visibility and sustainability, enhance resource resource allocation efficiency, and strengthen environmental governance capabilities, thereby providing robust technological support for ESG goals.

Lastly, the implementation of SCD strategies could be adapted for different types of enterprises. From a market environment standpoint, in situations of high environmental uncertainty, enterprises can establish dynamic risk assessment mechanisms and implement SCD strategies at appropriate times to mitigate supply chain risks and effectively promote ESG practices. Regionally, enterprises located in China's eastern region can leverage their strong economic foundation and open the market environment to further enhance ESG performance by exploiting the advantages of SCD. From an industry standpoint, enterprises in highly competitive industries should utilize SCD to integrate resources from various stakeholders and strengthen collaboration with upstream and downstream partners to improve ESG performance. Enterprises in high-pollution industries should treat SCD as a critical opportunity for ESG transformation, increasing investments in clean technologies and environmental protection equipment and encouraging upstream and downstream suppliers to jointly reduce pollutant emissions, thereby achieving sustainable production. Enterprises in capital-intensive industries should focus on the in-depth integration of SCD and ESG and increase investments in technology and equipment for green supply chain construction to enhance the stability and sustainability of the supply chain. Enterprises in labor-intensive industries should diversify supply chains to strengthen cooperation with suppliers, promote social responsibility management in the supply chain and improve employee satisfaction and loyalty, laying a solid foundation for their own sustainable development. From the perspective of enterprise characteristics, large scale enterprises and those with high capital intensity should fully leverage their resource and scale advantages to guide supply chain partners in adopting ESG principles, formulate and improve industry standards, and enhance the overall sustainability of the industry.

6.4. Limitations and Future Research

This study has some limitations. First, it primarily focuses on listed companies in China's A-share market, which may limit the universality of the conclusions. Future studies could include samples from more countries or regions, which would help us to understand the relationship between SCD and ESG performance more comprehensively. Second, although this study considers green innovation and digital transformation as potential mechanisms, there may be other unidentified mediating variables. Finally, the role of environmental uncertainty as a moderating variable has only been preliminarily verified. However, future research could delve deeper into the specific impact of economic policy uncertainty on the relationship between SCD and ESG.

Author Contributions: Conceptualization, X.W., H.W. and T.W.; methodology, T.W.; software, T.W.; validation, Y.S., H.W. and T.W.; formal analysis, T.W.; investigation, X.W.; resources, X.W.; data curation, X.W.; writing—original draft preparation, X.W.; writing—review and editing, X.W.; visualization, X.W.; supervision, Y.S.; project administration, T.W.; funding acquisition, T.W. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Research and Innovation Project for Graduate Students of Northwest University (Grant No. CX2024013).

Data Availability Statement: The data used in this study are publicly available and have been correctly cited. The data sets used or analyzed in the current study are available from the corresponding authors upon reasonable request.

Conflicts of Interest: The authors declare no conflicts of interest.

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Article

Evolution Model of Emergency Material Supply Chain Stress Based on Stochastic Petri Nets—A Case Study of Emergency Medical Material Supply Chains in China

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Abstract: In this study, we conceptualize the demands imposed on emergency supply chains during extraordinary emergency events as "stress" and develop a scenario-based stress evolution (SE) analytical approach in emergency mobilization decision-making. First, we characterize emergency supply chain stress by uncertainty, abruptness, urgency, massiveness of scale, and latency. Leveraging lifecycle theory and aligning it with the event's natural lifecycle progression, we construct a dual-cycle model—the emergency event-stress dual-cycle curve model—to intuitively conceptualize the SE process. Second, taking China's emergency medical supply chain as an illustrative example, we employ set theory to achieve a structured representation of emergency supply chain stress evolution (ESCSE). Third, we propose a novel ESCSE modeling methodology based on stochastic Petri nets and establish both an ESCSE model and a corresponding isomorphic Markov chain model. To address parameter uncertainties inherent in the modeling process, the fuzzy theory is integrated for parameter optimization, enabling realistic simulation of emergency supply chain stress evolution dynamics. Finally, the SE of the ibuprofen supply chain in Beijing during the COVID-19 pandemic is presented as a case study to demonstrate the working principle of the model. The results indicate that the ESCSE model effectively simulates the SE process, identifies critical states, and triggers actions. It also reveals the evolution trends of key scenario elements, thereby assisting decision-makers in deploying more targeted mobilization strategies in dynamic and changing environments.

Keywords: emergency supply chain stress evolution (ESCSE); scenario modelling; stochastic Petri net; emergency mobilization; emergency medical supplies

1. Introduction

In recent years, many countries have faced serious challenges in emergency supply and crisis management. These challenges stem from large-scale and unconventional emergencies, including global health crises such as COVID-19 and monkeypox, as well as natural disasters like the Australian bushfires and the Türkiye–Syria earthquake. Emergency supplies serve as essential material guarantees throughout the entire emergency response process, playing a critical role in safeguarding the lives of rescue workers and the general public during such crises.

The physical reserves and production capacity reserves of emergency materials belong to stock reserves, which can only solve the resource supply problems in the early stages of extraordinary emergencies. In the event of large-scale disruptions, the demand for certain emergency materials increases in a stepwise and exponential manner [1]. The existing social stockpiles fall far short of meeting this massive demand [2], necessitating the need to ensure supply through emergency production. A review of past emergency responses consistently shows that the volume of emergency supplies produced through emergency manufacturing significantly exceeds that obtained from stockpiles. This highlights the crucial importance of emergency production as the primary source of supply during unconventional emergencies.

Under normal circumstances, enterprises adjust their production scales based on market demand and typically refrain from expanding output blindly. However, when an emergency event occurs, firms may be mobilized to revise production plans, resulting in increased output. As the foundational unit of modern production systems, the supply chain plays a critical role in enabling sustained and stable supply. Only by leveraging supply chain structures can emergency production be effectively scaled up to meet surging demand promptly.

Recent extraordinary emergencies have shown that unpredictable disruptions in emergency material supply chains can lead to severe supply–demand imbalances. These events have exposed both the vulnerability of such supply chains and the weaknesses in coordinated scheduling mechanisms. Therefore, this study takes the supply chain of emergency materials as the research object, paying particular attention to the supply and demand balance of emergency materials under extraordinary emergencies.

Current research on emergency supply chains primarily focuses on four key areas: supply chain risk management [3–5], supply chain design [6–10], supply chain optimization [11–16], and supply chain performance evaluation [17–22].

Studies on supply chain risk management center around risk identification and risk assessment. Risk identification involves detecting all potential risk points that may affect the operation of enterprises and the supply chain, including internal risks such as equipment failures and production accidents, as well as external risks like natural disasters, cyberattacks, and transportation incidents. Risk assessment typically evaluates risks based on their probability of occurrence and severity of impact, which information is used to prioritize risk management efforts. Commonly adopted methods include Bayesian analysis, bow-tie analysis, probability/severity matrices, event tree analysis (ETA), failure mode and effects analysis (FMEA), hazard and operability studies (HAZOP), and Ishikawa cause-and-effect diagrams [3]. In the domain of supply chain design, researchers construct supply chain networks using mathematical tools under constraints such as time [6,8,10], humanitarian behavior [8], cost [7,10], and disruption scenarios [9]. Research on supply chain optimization typically focuses on specific problems and defines optimization objectives to develop quantitative models. The research on supply chain design and optimization is basically interrelated. Based on the analysis of real influencing factors, the optimization objectives are centered around time [11,13], cost [12,15], reliability [14,16], path selection [13], etc., and mathematical models are designed and developed. Researchers often consider the uncertainty of parameters in the modeling process and establish robust optimization models for a solution. Research on supply chain performance evaluation mainly emphasizes the identification of influencing factors and the analysis of their effects on overall performance [17–22].

Although these research areas have become relatively mature, they all focus on specific segments or aspects of the emergency supply chain, and a holistic analysis of supply–demand imbalances across the entire lifecycle of an emergency event is lacking. Research on supply chain risk management and performance evaluation tends to emphasize the identification of risk points, the probability of disruptions, and the identification and performance of influencing factors. However, in practice, decision-makers often have limited capacity to predict low-probability but high-impact events. Regardless of the source of disruption, the critical issue lies in understanding and managing the consequences. Regardless of the cause of a disruption, its impact does not depend on the cause, and the mitigation measures adopted are typically similar across scenarios [3].

Studies on supply chain design and optimization often abstract key constraints and define optimization objectives, which provide valuable direction for improving supply chain performance. Nevertheless, due to the limitations of mathematical modeling methods, such approaches frequently rely on simplified assumptions, making it difficult to exhaust the factors that need to be considered. Consequently, these models may not adequately account for the full range of factors influencing supply chain dynamics during emergency events. Research on supply chain performance evaluation also has the same problem of not fitting the actual complex system environment of emergencies.

In the international context, the term humanitarian supply chain is often used in a manner similar to emergency supply chain [12,14], as both focus on rapid response and efficient distribution of critical materials during disruptive events to mitigate disaster impacts and ensure that basic needs are met. The methodologies applied in studying both systems are largely similar, and some studies even treat them as interchangeable. However, other research distinguishes between the two, primarily based on decision-making complexity: emergency supply chains are government-led, whereas humanitarian supply chains involve multi-stakeholder coordination among governments, businesses, and civil society organizations [23]. This study specifically addresses the supply of emergency materials during extreme and unconventional emergencies. As noted earlier, in such scenarios, emergency supplies are primarily sourced through urgent production. Therefore, the focus of this research is on emergency supply chains, in contrast to humanitarian supply chains, which often rely on broader mobilization efforts such as social donations.

Building upon the above analysis, this study conceptualizes the demand within emergency supply chains as a form of "stress". Adopting a scenario-based response framework, we examine the evolution of this stress throughout the entire lifecycle of an emergency event. This approach enables a more macro-level analysis of the emergency supply chain system. The primary objective of this research is to analyze the trend and law of the evolution of stress in emergency supply chains and to propose robust methods for accurately identifying its causes and influencing factors. We contend that this perspective is of substantial significance for enhancing emergency capacity building, strengthening mobilization capabilities, and quickly responding to the challenges brought by emergencies.

The remainder of this paper is organized as follows. Section 2 presents a comprehensive literature review. Section 3 constitutes the theoretical core of this study, where we propose a novel concept of stress in emergency supply chains, analyze its sources and characteristics, and construct an emergency event-stress dual-cycle curve model based on lifecycle theory. Section 4 introduces a method for structuring the evolution process of emergency material supply chain pressure proposed using set theory, with a detailed application and analysis based on China's emergency medical supply chain. In Section 5, we propose a new ESCSE (emergency supply chain stress evolution) modeling method· based on stochastic Petri nets. We develop both the ESCSE model and a corresponding isomorphic Markov chain model. To address inherent parameter uncertainty in the modeling process, we incorporate fuzzy theory to optimize parameters and enable realistic simulation of stress evolution dynamics. Section 6 demonstrates the application of the proposed model using the case of the ibuprofen supply chain in Beijing. Finally, Section 7 summarizes the conclusions and outlines potential directions for future research.

2. Literature Review

2.1. Research on Supply Chain Pressure

At present, there is no universally accepted definition of "supply chain stress". Existing research reveals two primary interpretations of the concept. The first interpretation draws on the psychological concept of "stress", defining supply chain stress as a form of pressure or heightened awareness induced by external environmental changes, which compels supply chain management to adapt [24–26]. The second interpretation is adapted from the idea of stress testing in the financial sector, treating supply chain stress testing as a tool for risk assessment; under this view, supply chain stress is considered a collection of factors that may lead to disruptions or disorder within the supply chain [4–10].

Studies aligned with the first interpretation are mainly related to issues of corporate competitiveness. For instance, Zhu Qinghua et al. [24] identified the key drivers of green supply chain management pressure/dynamics among Chinese manufacturing enterprises through survey analysis, offering theoretical guidance for the early-stage adoption of green supply chain practices domestically. Qu Ying et al. [25] used statistical methods to rank the influencing factors of green supply chain management, pinpointing the strengths and weaknesses in implementing green strategies within China's manufacturing sector. Similarly, Huang Wei et al. [26], based on survey data from 1268 Chinese enterprises, found that supply chain stress under globalization pressures promoted the entry of foreign enterprises into domestic supply chains, thereby enhancing corporate motivation to fulfill social responsibility.

The second interpretation draws inspiration from the idea of stress testing in the financial sector and applies it to the domain of supply chain risk management. Stress testing, originally developed as a quantitative risk assessment technique for extreme events in the financial sector, assesses the impact of macroeconomic shocks on the entire economic system by simulating extreme market scenarios and examining the robustness of key financial variables. Scholars have adapted this core idea to analyze how changes in external or internal conditions affect supply chain operations, thereby advancing the study of stress testing within supply chains.

In related theoretical studies, several scholars have explored supply chain risk management from the perspective of stress testing. Yao Weixin et al. [27] proposed a stress-testing approach for extreme supply chain risks by analyzing the unique risk transmission mechanisms within supply chains. Furthermore, Yao Weixin et al. [28] conceptualized stress testing as a proactive measure and positioned the design and construction of resilient supply chains as essential responses to extreme events. They highlighted the necessity of resilience and outlined key design principles. Specifically, they proposed core strategies for enhancing supply chain resilience, including improving responsiveness, increasing flexibility, maintaining appropriate inventory buffers, establishing a multi-layered defense structure, adopting multi-sourcing, and implementing demand postponement. Cannella et al. [29] conceptualized supply chain stress testing as the simulation of sudden and severe demand fluctuations and assessed how collaborative practices and smoothing replenishment rules could mitigate the bullwhip effect, stabilize inventories, and enhance both supply chain performance and customer service levels. Lan Luo [30,31] proposed a predictive global sensitivity analysis approach to construct a quantitative tool for supply chain stress testing. By establishing a multi-tier supply chain network linear programming model, this method simulates scenarios involving node disruptions caused by emergency events. Ivanov and Dolgui [32] advocated for the systematic review and stress testing of supply chain resilience, proposing the use of digital supply chain twins as a tool for conducting comprehensive stress tests. Building on this foundation, Ivanov [33] moved beyond the traditional focus on "recovery capability" and introduced a new framework centered on "adaptive survivability", further elaborating on the feasibility of applying digital twins for supply chain stress testing and resilience analysis.

In addition, on 18 April 2022, the SAIC Motor Corporation conducted stress testing on its vehicle, parts, and logistics enterprises, focusing on supply chain security, logistics assurance, and closed-loop production management. This initiative aimed to validate the enterprises' readiness for the resumption of operations under COVID-19 disruptions, identify strengths and weaknesses, and provide support for the gradual recovery of production capacity [34].

Among the aforementioned studies, research related to the first interpretation primarily relies on survey data and expert consultations, making the findings subject to a certain degree of subjectivity due to limitations in sample size. Research aligned with the second interpretation has effectively demonstrated, from both theoretical and practical perspectives, the applicability of stress-testing concepts within the field of supply chain risk management. However, fundamental aspects such as the basic theories of stress, its evolutionary patterns, and transmission mechanisms have yet to be systematically explored. Consequently, the theoretical foundation and implementation frameworks for supply chain stress testing still require long-term, comprehensive research.

This study focuses on the emergency supply chain under the context of extraordinary emergency events, where extreme disruptions lead to significant supply–demand imbalances. In this regard, we revisit the original meaning of "stress" as defined in the field of physics and conceptualize the demand borne by the emergency supply chain as a form of stress. A detailed discussion of this conceptualization is provided in Section 3.2.

2.2. Supply Chains for Emergency Medical Supplies

Research on emergency medical supply chains remains relatively limited. Existing studies can largely be categorized into two streams: (1) research focusing on the management of emergency medical supply chains and (2) decision-support studies for emergency medical supply responses from a supply chain perspective.

In the field of emergency medical supply chain management, a common methodological approach is the construction of mathematical models for problem analysis. Many researchers leverage the SEIR epidemiological model and its variants to investigate issues such as equilibrium optimization [35], resource allocation [29,36], stockpiling strategies [37], and demand forecasting [35,38]. For example, Sun et al. [35] integrated a three-tier emergency medical supply chain model with embedded resilience features and the SEIR model, developing a bi-objective mixed-integer programming model aimed at minimizing expected total supply chain costs while maximizing demand fulfillment rates. Their study explored supply chain network design that balances cost efficiency with resilience. Paul et al. [38] coupled a generalized infectious disease spread model (SEITRS) with a multi-tiered supply chain model to build an integrated system dynamics model. Using representative datasets from the 2013–2014 U.S. H1N1 influenza pandemic, they analyzed how pharmaceutical shortages impact key epidemic parameters, revealing that drug supply chains significantly affect epidemic dynamics.

Similarly, Büyüktahtakın et al. [36] embedded logistics considerations within a spatially explicit SEIR model, proposing an epidemic–logistics hybrid optimization framework that simultaneously addresses the spatial spread of infectious diseases and emergency resource allocation, thereby suggesting optimal intervention strategies. Queiroz et al. [39] systematically analyzed the impacts of epidemics on supply chains, applying optimization techniques and SEIR-based models to study both conventional resource allocation and pandemic-specific medical supply distribution, and proposed a framework for operations and supply chain management during the COVID-19 pandemic. Paul et al. [40], focusing on pharmaceutical supply chain management under conditions of deep uncertainty, found that proactive ordering and tier reduction strategies can significantly mitigate epidemic impacts, based on an extended shortage model integrated with their previous work [38]. Liu and Zhang [41] combined an SEIR-based demand prediction mechanism with a hybrid 0–1 integer programming logistics system to propose a dynamic resource allocation model, addressing transportation decisions across hospitals, distribution centers, and pharmaceutical manufacturers through the stages of forecasting, planning, execution, and adjustment. Huo et al. [37] considered both temporal and spatial dimensions in modeling demand fluctuations for masks induced by epidemic spread, proposing strategies for establishing and rotating emergency stockpiles of medical supplies.

Research specifically addressing decision support for emergency medical supply responses from a supply chain perspective is relatively sparse. The existing literature focuses on areas such as information collection during public health emergencies [42], decision-support system development [43], and supply chain decision-making under psychological biases [44]. Anparasan et al. [42] highlighted that developing countries often lack robust decision-support capabilities for infectious disease outbreaks and compiled detailed time-series datasets from the cholera outbreak following the 2010 Haiti earthquake to aid the development of descriptive and prescriptive models. Govindan et al. [43] proposed a fuzzy inference system (FIS)-based decision-support framework that uses physicians' knowledge to classify individuals by infection status, aiming to better manage medical supply chain demand and thus curb the spread of viruses. Shi et al. [44] investigated how overconfidence and other psychological biases among emergency decision-makers impact supply chain operations, offering insights into the linkage between cognitive biases and medical resource allocation strategies, thereby supporting governmental emergency response planning. Song Y. et al. [45] proposed a modeling and analysis approach for emergency scenario evolution systems based on Generalized Stochastic Petri Nets (GSPNs), aiming to enhance scenario-based response decision-making capabilities in emergency management.

Notably, most existing studies address isolated problems—such as resource allocation [29,36], stockpiling [37], and demand forecasting [35,38]—without accounting for the complex and interdependent nature of challenges that public health emergencies pose to emergency medical supply chains. Unlike natural disasters, accidents, or social security incidents, public health emergencies caused by epidemic outbreaks have distinct characteristics: unpredictable cycles and scales; compound transmission, where supply chain disruptions are entangled with virus spread through human mobility; and simultaneous breakdowns of supply, demand, and logistics infrastructures [46].

A retrospective analysis of emergency supply challenges during the COVID-19 pandemic reveals that surging demand for medical supplies quickly overwhelmed existing supply capacities. Public fear—amplified by media reports and social contagion—triggered speculative demand characterized by panic buying and hoarding. This behavior reflects a self-feedback loop in which perceived scarcity drives excessive consumer response, further exacerbating actual shortages and disrupting supply chain stability. Public fear and media influence led to panic buying and hoarding behaviors, further inflating demand. Opportunistic profiteering exacerbated resource imbalances and drove up prices, highlighting inefficiencies in resource allocation. These realities underscore the need for governments to engage in comprehensive emergency mobilization efforts encompassing potential demand assessments [47], rapid capacity expansions [48,49], efficient resource allocation [50], and media control strategies [51]. Thus, to enhance the responsiveness and resilience of emergency medical supply chains, it is critical to address overarching strategic issues through a more integrated and macro-level decision-making framework.

3. Fundamental Theories of Stress Evolution in Emergency Supply Chains

3.1. Distinction Between Traditional Commercial and Emergency Supply Chains

Traditional commercial supply chains are essentially functional network structures that deliver products to consumers—from raw material procurement to the production of intermediate and final goods—with the ultimate goal of generating profit under normal operating conditions. Emergency supply chains, in contrast, are transformed from regular supply chains and operate under crisis conditions. They are state-driven and focus on national economic infrastructure to maximize time efficiency and minimize disaster losses. These chains include government-led planning, management, and control, forming a virtual dynamic supply chain alliance. Essentially, they represent the supernormal supply of emergency materials. This results in significant differences between the two types of supply chains, which can be summarized in the following aspects.

1. Level of risk

The context of emergency supply chains is typically linked to sudden, unforeseen events. These events are characterized by randomness and high destructiveness, and when they affect any part of the supply chain, they often lead to disruptions or varying degrees of fluctuations. For example, Hurricane Katrina in 2005 severely damaged transportation infrastructure, energy facilities, and communication systems across the U.S. Gulf Coast [52]. The initial natural disaster was compounded by secondary effects—including widespread flooding, the collapse of local healthcare systems, and outbreaks of waterborne diseases—all of which significantly disrupted emergency supply chain operations. Such compound risks amplify uncertainty and response complexity in emergency supply chains. In contrast, traditional commercial supply chains typically operate under relatively stable conditions, where companies at each node forecast market demand and develop corresponding production and ordering plans.

2. Demand characteristics

Traditional commercial supply chains operate in stable environments, where demand is forecastable based on historical trends, allowing for planned production and procurement. In contrast, emergency supply chains face abrupt shifts in demand. Items that are ordinary commodities under normal conditions may become critical resources once a crisis emerges. Consequently, demand can surge unpredictably(as shown in Figure 1), accompanied by high uncertainty, urgency, and a lack of discernible patterns. These characteristics impose substantial challenges on emergency supply chains in terms of responsiveness and coordination.

3. Objectives

Traditional commercial supply chains primarily aim to maximize economic profit. In contrast, emergency supply chains focus on meeting urgent demand efficiently, reflecting weak economic orientation. Their core objective is the rapid delivery of critical supplies within limited timeframes. This is evident in several ways: First, governments regulate prices to prevent inflation during crises. Second, authorities may initiate emergency production protocols, supported by incentives such as "supply first, payment later" or post-crisis subsidies. Third, participating firms often align their actions with corporate social responsibility, adjusting production from profit-driven goals to utility maximization under emergency conditions.

Traditional commercial supply chains operate under market-driven frameworks, where firms independently make production and sales decisions, and resource allocation is guided by competition, autonomy, and pre-established agreements.

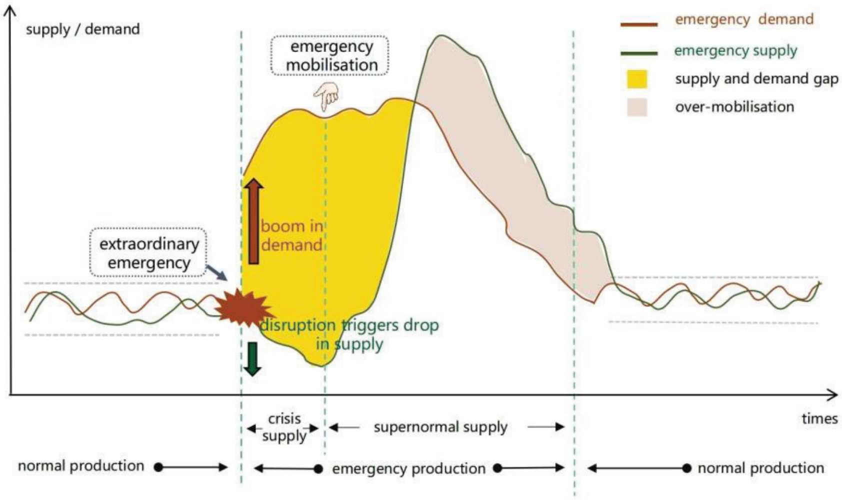

Figure 1. Supply and demand diagram for the supply chain of emergency supplies in the event of a supernormal emergency.

4. Regulatory mechanisms

In contrast, emergency supply chains are primarily directed by state authorities and function as mechanisms for resource allocation and production mobilization within a regulated economic coordination framework. In addition to commercial actors, the government plays a central role in coordinating the supply of critical goods. Depending on the nature and scale of the emergency, supply chain operations may involve joint efforts by multiple public sector agencies—including, but not limited to, emergency management departments, transportation authorities, healthcare institutions, and energy regulators. In the case of large-scale disasters, national armed forces, reserve troops, and civil defense organizations may be rapidly deployed to participate in emergency mobilization, thereby ensuring the efficient operation and responsiveness of the emergency supply chain.

5. Inventory strategies

Commercial supply chains adopt lean inventory models to reduce costs and improve efficiency. In contrast, emergency supply chains operate within a far more volatile and uncertain external environment, where internal supply network structures are highly susceptible to disruption or distortion during crisis events. As a result, material reserves emerge as a critical component and one of the primary sources for emergency supply provisioning.

Under such conditions, material reserves are not only indispensable but also sized strategically. Maintaining an appropriate level of safety stock becomes a critical buffer to absorb supply–demand shocks, mitigate lead-time uncertainties, and ensure continuity of relief operations. The scale of these reserves must be calibrated based on risk exposure, response time requirements, and supply chain criticality to balance cost and preparedness.

6. Stages

Traditional commercial supply chains are primarily driven by economic interests, with a core focus on production and sales activities. These supply chains typically operate in stable environments and do not exhibit pronounced cyclical fluctuations. In contrast, the emergency supply chain operates across distinct temporal phases that correspond to the evolution of crisis events. Specifically, the supply chain is often segmented into three phases—pre-incident, during-incident, and post-incident—based on the timing of the emergency event. This tripartite classification is consistent with widely accepted frameworks in modern emergency management and supports more effective planning and resource allocation across distinct response phases.

7. Delivery cycle

In traditional commercial supply chains, the operating environment tends to be stable, allowing for clearly defined and predictable delivery cycles. In contrast, emergency supply chains are typically activated in response to sudden-onset events and are primarily coordinated by government authorities. Within this context, supply chain actors operate under a task-oriented framework, where timeliness of emergency material delivery takes precedence over adherence to fixed delivery schedules. As a result, emergency supply chains lack standardized delivery cycles and must remain highly responsive and flexible in their operations.

3.2. The Concept of Emergency Supply Chain Stress (ESCS)

Although the explicit introduction of the concept of stress in management studies lacks a documented origin, its conceptual roots can be traced back to the late 19th century, during the latter phase of the Industrial Revolution. In Frederick Taylor's theory of scientific management, the term "stress" was not directly employed; however, the imposition of time quotas and standardized procedures effectively created a model of efficiency-driven pressure, reflecting an early form of operational stress.

In the 1930s, the Hawthorne experiments conducted by Elton Mayo and his team unveiled a nonlinear relationship between the physical work environment and psychological stress, which subsequently laid the theoretical foundation for the development of role stress models. Beginning in the mid-20th century, with the rise of organizational behavior and human resource management as distinct research domains, scholars began to explicitly examine stress within managerial frameworks. Within this context, stress has been broadly conceptualized as the physiological or psychological responses elicited by changes in workplace conditions or organizational factors. These responses may exert either beneficial or detrimental effects on employees' mental and physical health.

Contemporary research in this field predominantly focuses on three key dimensions: identifying sources of stress, defining performance-related stress thresholds, and designing effective intervention strategies. These areas form the core of stress-related inquiry in management, reflecting the interdisciplinary integration of psychological theory within organizational contexts.

While the concept of stress has been addressed within the field of management, its application has largely been confined to organizational behavior and human resource management, where it primarily draws upon theoretical and empirical developments from psychology and medicine. This study posits that the notion of "load-bearing limits" in physics offers a conceptually robust framework for analyzing emergency material supply under sudden-onset events. Fundamentally, such scenarios involve abrupt changes in external conditions—most notably, surges in emergency material demand—which exert pressure on the emergency supply chain. This type of systemic response to fluctuating demand conditions closely parallels the definition of stress in the physical sciences, where external forces induce strain on a structure or system.

Building upon the above insights, this study critically examines and integrates conceptualizations of stress across multiple disciplines and introduces the concept of stress into the context of emergency material supply chains. In this framework, emergency supply chain stress (ESCS) is defined as the level of demand exerted on the supply chain during the onset of an emergency event. Notably, this type of demand differs fundamentally from that in traditional commercial supply chains, which are typically governed by market mechanisms and driven by the goal of profit maximization. Instead, it refers specifically to demand arising under a regulated economic framework, where the timeliness of supply is the primary objective in responding to emergencies.

3.3. Sources and Characteristics of Stress in Emergency Supply Chains

3.3.1. Underlying and Direct Sources of Stress

This study posits that the fundamental source of stress within emergency supply chains lies in the urgent production demands triggered by crisis scenarios. These demands exert direct pressure on the emergency supply chain, compelling it to unlock latent capacity and convert this potential into extraordinary supply capabilities. Its direct sources can be grouped into three categories:

First, external pressure from government authorities. When unconventional emergencies occur, existing reserves and routine production capacities are often insufficient to meet the sharply increasing demand for medical and emergency supplies. In response, governments initiate emergency production, exerting pressure on the emergency supply chain through administrative mandates during crises and economic incentives or regulations in normal times. The degree of stress varies across mobilized entities, corresponding to differing intensities of government mobilization.

Second, external pressure from the general public. Social pressure on emergency supply chains is exerted via non-governmental organizations, individual citizens, and media groups. These actors disseminate information regarding supply needs and shortages, thereby intensifying public scrutiny and applying pressure on government response mechanisms, resource allocation strategies, risk communication, and the performance of enterprises in fulfilling their social responsibility during emergencies.

Third, internal pressure from enterprises responsible for emergency supply. In normal circumstances, these enterprises operate within the national economy with profit as their primary objective while also bearing social responsibilities. With the growing emphasis on corporate social responsibility (CSR), many enterprises increasingly view emergency response as part of their civic duty. When crises occur, CSR acts as an internal driver, prompting enterprises to impose pressure on themselves to mobilize resources and fulfill emergency obligations.

3.3.2. Characteristics of Stress in the Emergency Supplies Supply Chain

1. Uncertainty and suddenness

The formation and operation of emergency supply chains are fundamentally driven by internal supply–demand dynamics, wherein supply is closely guided by demand in a continuously evolving process. Stress arises from urgent, crisis-induced needs, making its emergence sudden and uncertain.

A striking example is the catastrophic flooding of the Yangtze River Basin in the summer of 1998—the most severe since 1954—which also triggered record-breaking floods in the Nenjiang and Songhua River basins. The disaster caused extensive damage to agriculture and industry across the affected regions, posing serious threats to lives and property. In response, China's National Economic Mobilization Office launched a dedicated mobilization campaign to establish field hospitals aimed at supporting epidemic prevention and medical services for flood relief forces and disaster-affected civilians. The operation unfolded in three distinct phases:

- Preparation phase (24 days): Information was gathered to assess the scope of needs, and a comprehensive mobilization plan was developed.
- Implementation phase (15 days): Establishment of an interim command structure; integration of mobilized personnel from different units into field medical support teams; deployment of transport units to deliver essential items to the front line, such as containers, field rations, medicines, and fuel.
- Recovery phase (4 days): Inventory of mobilized resources; dismantling, transport, and return of equipment; operational summary and return of personnel to their units.

The operation resulted in the establishment of fully functional field hospitals, which conducted over 10,000 on-site consultations, providing timely and efficient medical support to both frontline personnel and local residents.

2. Timeliness

In sudden disasters, time is the most critical factor. The availability of emergency supplies directly determines the effectiveness of response operations. Stress in emergency supply chains is thus highly time-sensitive. For example, the widely recognized "golden 72 h" post-disaster period is crucial for rescue. Globally, rescue efforts within this window have proven most effective. However, during the 2008 Wenchuan earthquake, China's tent stockpile was exhausted within 48 h. This sudden shortfall underscored the urgent need for emergency production to supplement depleted reserves and ensure adequate shelter provision for the disaster-stricken areas.

3. Huge volume

The operating environment of emergency supply chains is complex. When extreme shocks overlap across different scenarios, demand for certain supplies can surge dramatically, resulting in significant stress on the emergency supply chain, manifested by overwhelming volumes. For instance, in early 2020, the outbreak of COVID-19 led to an explosive demand for face masks. However, China's face masks faced severe shortages due to insufficient routine stockpiles, technological constraints, and delayed production recovery during the Spring Festival period.

4. Latency

Following the onset of an emergency event, there is often a delay in information transmission. The acquisition and dissemination of emergency supply–demand information tend to lag, and the inherent uncertainty of such events further amplifies this lag. As a result, it becomes difficult to determine real-time demand accurately, leading to a time-lagged manifestation of ESCS.

3.4. Causes and Evolutionary Mechanisms of ESCS

3.4.1. Causal Analysis of ESCS

The core driver of emergency supply chain operations is the dynamic interplay between supply and demand. Rather than operating as a static system, the emergency supply chain continuously adjusts to close supply–demand gaps, functioning as a complex and adaptive system. Specific shocks or compound disruptions can simultaneously impact both the demand and supply sides, with stress propagating along the supply chain through successive tiers as a result of imbalances in supply and demand(shown as Figure 2). Both internal and external shocks to the emergency supply chain generate new constraints for the system. For example, earthquakes may damage production facilities, disrupt transport through road destruction, and impair communication across nodes. Moreover, earthquakes may trigger secondary disasters such as landslides or mudflows, which intensify ESCS.

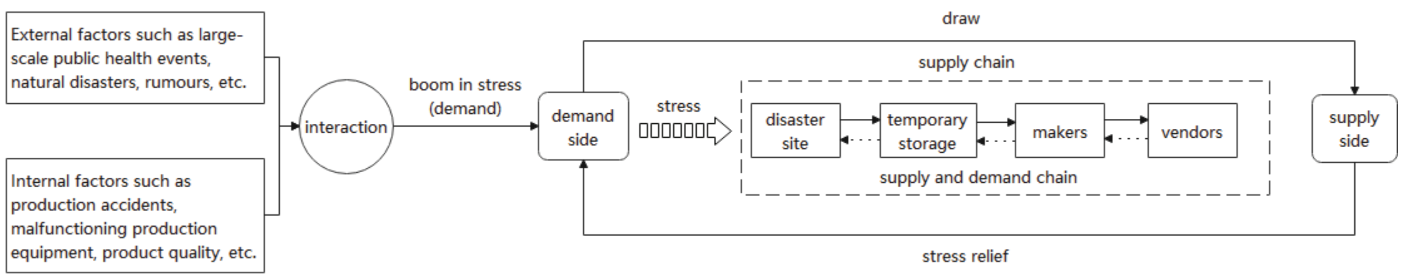

Figure 2. Schematic diagram of stress generation.

3.4.2. Mechanisms of Stress Evolution in Emergency Supply Chains

Mechanisms refer to the internal functioning of system elements and the rules governing their interactions to fulfill specific functions under certain conditions. In emergency supply chains, stress evolution reflects pressure fluctuations before and after emergency events. In current research, scholars often divide the traditional lifecycle of an emergency event into five phases: latency, indication, development, decline, and extinction [53].

This section builds upon the research on traditional event evolution mechanisms, analyzing the stress evolution mechanisms from a lifecycle perspective. Based on ESCS characteristics and the roles of emergency actors, this paper defines five phases: latency, triggering, formation, outbreak, and relief. Emergencies evolve through a multi-stage lifecycle, with each stage exhibiting distinct characteristics and varying levels of impact. The stress on emergency supply chains—from the triggering to the relief—persists throughout the entire lifecycle. Therefore, it is necessary to analyze these two aspects in conjunction, as illustrated in Figure 3.

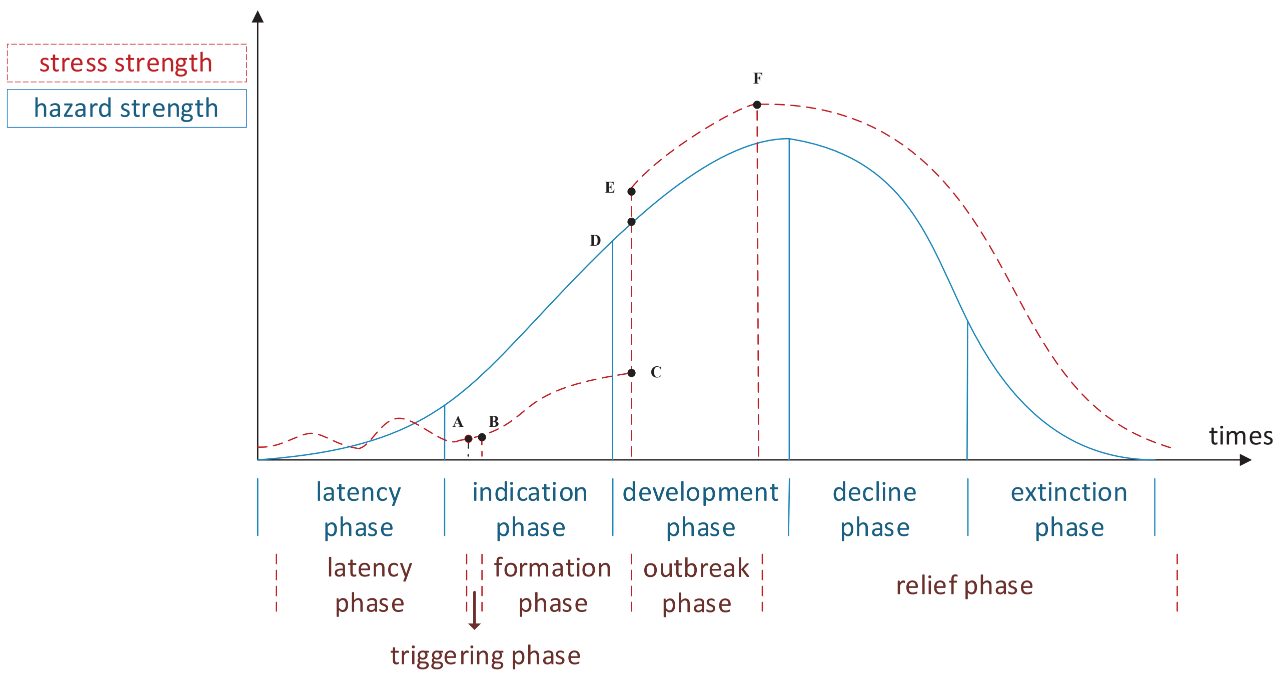

Figure 3. Emergency event-stress dual-cycle curve model.

In Figure 3, the dashed line represents the evolution cycle of ESCS, while the solid line represents the lifecycle of an emergency event. Before point A, the stress intensity is equal to the regular demand level within the supply chain and fluctuates due to market adjustments. Between points A and B, the supply chain experiences a shock, triggering the onset of stress, which gradually increases. The triggering period here is relatively short, possibly lasting several hours or days, corresponding to the warning phase of the emergency event. The further point A shifts to the right, the longer the latent period of stress, indicating more obvious signs of the event. As time progresses, the event transitions from the warning phase to the development phase. Point C represents the moment of an extreme shock, which causes a sudden surge in demand and a corresponding jump in stress intensity to point E. Point C and point E are located at the same time coordinate to emphasize the suddenness and hugeness of the shock event, e.g., an earthquake, which can cause massive damage in minutes or even seconds, resulting in an immediate and dramatic increase in supply chain stress. At this point, there is a significant supply–demand gap for emergency supplies, requiring immediate mobilization of emergency reserves and the organization of emergency production efforts. Point D marks the intersection between the intensity of the threat and the stress intensity. The stress intensity at point E exceeds that at point D due to the amplification effects of three direct sources of pressure—government agencies, the general public, and the enterprises responsible for emergency supply. These pressures may cause the stress intensity to exceed the actual demand for emergency supplies at that moment. Point F indicates that emergency mobilization efforts are beginning to work to reduce the gap between supply and demand and reduce the intensity of the pressure by providing extraordinary supply capacity. It is noteworthy that point F represents the actual peak of stress intensity. This is because stress can only be mitigated through the enhancement of supply capacity via mobilization efforts, which are inherently delayed relative to the onset of the emergency event. Consequently, even after point E—where the event occurs—the stress intensity continues to rise until the mobilization strategies begin to take effect at point F. At this point, the emergency supply chain stress transitions into the de-escalation phase. As stress is alleviated, the intensity of the event's threat gradually decreases, and the event enters the decline phase, ultimately moving toward extinction.

4. Structured Description of the Evolution of Emergency Medical Supply Chain Stress (EMSCS)

The evolution of supply chain stress constitutes a complex system characterized by a multi-attribute set structure. Given that emergency supply chain stress evolves within the highly uncertain context of extraordinary emergencies, single-indicator approaches are often insufficient for capturing its dynamics in quantitative research. To address this limitation, this study adopts a scenario–response analytical framework. Through multi-case analysis, we extract both internal and external attributes of extraordinary emergencies, integrating theoretical insights with practical relevance. Set theory is employed to enable a structured representation of the evolutionary process of emergency supply chain stress, allowing for a clearer understanding of the interrelations and mechanisms among these attributes.

Although the generalized structure of emergency supply chains may vary across different categories of materials, the methodological approach to structured description remains consistent. To demonstrate the applicability of this method, this study focuses on the case of China's emergency medical supply chain, providing a detailed methodological application and analysis.

4.1. Multiple Case Studies

To enhance the generalizability and continuity of the research findings, a multi-case study approach—one that permits cross-case comparisons—should be adopted. This methodology involves the use of multiple data collection techniques across different entities (such as individuals, groups, or organizations) to investigate a given phenomenon within its natural context [54]. Applying a multi-case study to analyze and structurally characterize the attributes of emergency events provides valuable insights into the evolutionary patterns of emergency medical supply chains. This approach contributes significantly to a deeper and more systematic understanding of how such supply chains respond and adapt under stress [55].

4.2. Case Selection

To ensure the generalizability of the conclusions, it is essential to select cases that encompass diverse types of emergency event, as well as multiple instances of the same category of extraordinary public health emergencies. This allows for both within-case analysis and cross-case comparative analysis, thereby enhancing the robustness and applicability of the research findings.

4.3. Case Analysis and Processing

The principles guiding the analysis and processing of cases are as follows:

- Information is screened and organized around the core themes of event progression, the evolution of emergency supply chain stress, and the formulation of emergency response decisions.
- Collected data are categorized and analyzed accordingly, followed by a systematic consolidation of the findings.

4.4. Case Analysis Findings

The ultimate goal of examining the evolution of stress within emergency medical supply chains is to enhance the prevention, response, and mitigation of the adverse impacts caused by unconventional public health emergencies. Through multiple case analyses, it has been identified that the evolution of such stress is influenced by a wide array of interrelated attributes and demonstrates significant extensibility across events.

The roles played by different attributes vary throughout the progression of an emergency. To better capture the structural logic underpinning this complexity, this study categorizes the identified attributes and proposes a generalized structured framework for stress evolution in emergency medical supply chains as follows:

Stress Evolution in Emergency Medical Supply Chains = {{Evolution Type (ET)}, {Key Attributes (KA)}, {Secondary Attributes (SA)}, {Environment Attributes (EA)}, {Hazard Assessment Attributes (HA)}}; it is defined as follows:

ET = gradual or radical;

KA = {KA1, KA2, KA3, ..., KAm}. The elements in the key attributes are the key factors in the evolutionary process that sway the degree of stress evolution;

SA = {SA1, SA2, SA3, ..., SAn}. Elements in the dependent attributes have an influence on the evolution of stress and the creation of hazards, assisting the key attributes in portraying the event;

EA = {EA1, EA2, EA3, ..., EAk}. Elements in environmental attributes are those that shape the development and evolution of events by influencing key and subordinate attributes;

HA = {HA1, HA2, HA3, ..., HAj}, Elements in the Hazard Assessment Attributes refer to the attributes used to estimate the hazards caused by evolution,

where m, n, k, $j \in N$.

To construct a generalized and structured representation of the stress evolution within emergency medical supply chains, this study systematically reviewed and validated key information drawn from several major public health emergencies. These include the emergencies in the supply chain for masks and thermometers during the 2003 SARS outbreak, the disinfectant supply chain during the 2009 H1N1 influenza outbreak, the mask supply chain at the onset of the COVID-19 pandemic in late 2019, and the antipyretic and analgesic drug supply chain during the normalized phase of the COVID-19 pandemic in late 2022.

This paper focuses on two representative cases to illustrate the process of event presentation, chronological analysis, and structured description of stress evolution: the mask supply chain during the initial outbreak of COVID-19 in late 2019 and the ibuprofen supply chain during the normalized response phase of the pandemic in late 2022.

1. **Stress Evolution of the Mask Supply Chain During the Initial COVID-19 Outbreak in China (Late 2019)**

Event introduction: The COVID-19 outbreak on 27 December 2019 marked the most rapidly spreading, widely affecting, and difficult-to-control public health emergency in China since the founding of the People's Republic. Given that masks serve both as personal protective equipment and as a source control measure, demand surged dramatically in a short period. The stress evolution of the mask supply chain during this period thus serves as a representative case for studying the dynamics of emergency medical supply chains under extreme conditions.

Event overview: The stress evolution of the mask supply chain in early 2020 spanned over two months and is categorized as a gradual-type emergency. The evolution was primarily driven by the outbreak of COVID-19, the skyrocketing demand for masks, government interventions, and fluctuations in supply. Key influencing factors included the rate of virus transmission, the speed of information dissemination, the volume of mask demand, the intensity of emergency mobilization, and the supply capacity. The progression of stress evolution could be gauged by indicators such as the spatial spread of the virus, the proliferation of rumors, and the implementation of emergency mobilization. Meanwhile, the supply–demand balance, price fluctuations, and public sentiment served as evaluative metrics for the impact of supply chain stress.

Structured description of events: Mask Supply Chain Stress Evolution (2020) = {{gradual}, {COVID-19 outbreak, surging mask demand (healthcare relief organizations, COVID-19 virus-infected, economically motivated stakeholders, uninfected individuals seeking protection), government intervention, mask supply}, {virus transmission rate, information dissemination speed, mask demand volume, emergency mobilization intensity, mask supply volume}, {pandemic spread, rumor proliferation, emergency mobilization practices (guiding the resumption and expansion of production, official information disclosure and expert science communication, crackdowns on counterfeit masks and price gouging), regional public mask-wearing mandates }, {supply–demand relationship, mask prices, social opinion}}.

2. **Stress Evolution of the Ibuprofen Supply Chain Following the Normalization of COVID-19 Control Measures in China (Late 2022)**

Event introduction: On 11 November 2022, China's Joint Prevention and Control Mechanism of the State Council announced 20 new measures to further optimize COVID-19 control, signaling a proactive and adaptive shift in public health policy both domestically and internationally. Subsequently, on December 7, a follow-up set of targeted adjustments, commonly referred to as the "New Ten Measures", was released to further ease restrictions [28]. These policy relaxations led to a rapid increase in population mobility. Coupled with the high transmissibility of the Omicron variant, this triggered a surge in demand for antipyretic and analgesic medications, and the ibuprofen supply chain emerged as a representative case of stress evolution in emergency medical supply systems.

Event overview: The stress evolution of the ibuprofen supply chain lasted nearly two months and is classified as a gradual-type event. Key drivers included policy changes in epidemic prevention and control, a sharp increase in ibuprofen demand, government interventions, and supply fluctuations. The pace of virus transmission, speed of information dissemination, volume of demand, mobilization efforts, and production capacity collectively influenced the dynamics of stress development. The spread of infection, dissemination of misinformation, and implementation of emergency response measures were critical indicators for tracking the evolution process. Meanwhile, supply–demand imbalances, drug price surges, and shifts in public sentiment served as key metrics for assessing the consequences of supply chain stress.

Structured description of events: Ibuprofen Supply Chain Stress Evolution (Late 2022) = {{gradual}, {epidemic control policy adjustments, surging ibuprofen demand (large enterprises and institutions, individuals infected with Omicron, economically motivated stakeholders, panic-infected), government intervention, ibuprofen supply}, {virus transmission rate, information dissemination speed, ibuprofen demand volume, emergency mobilization intensity, ibuprofen supply volume}, {infection spread, rumor proliferation, emergency response implementation (supply chain stabilization and expansion, expert-led rumor clarification and positive public guidance, crackdowns on hoarding, penalties for price gouging)}, {supply–demand dynamics, ibuprofen pricing, public sentiment}}.

A comprehensive structural framework for the stress evolution of emergency medical supply networks during major public health emergencies can be developed by analyzing exemplary cases. This framework, which is constructed as follows, encapsulates the essential elements and dynamics of such crises:

Emergency Medical Supply Chain Stress Evolution = {{gradual}, {triggering events, demand surge (bulk procurement organizations, infected individuals, profit-oriented stakeholders, panic-driven consumers), government intervention, supply}, {virus transmission speed, information dissemination rate, demand volume, emergency mobilization intensity, supply volume}, {event progression, rumor proliferation, emergency response implementation (capacity expansion, public opinion management, enforcement against illegal practices)}}, {supply–demand dynamics, pricing, public sentiment}}.

To facilitate a more comprehensive analysis of the formation, escalation, and dissipation of supply chain stress and to reveal the underlying patterns governing its evolution, this study integrates the concept of the emergency supply chain stress lifecycle. Based on this, a systematic diagram of the stress evolution process in emergency medical supply chains is developed and illustrated in Figure 4.

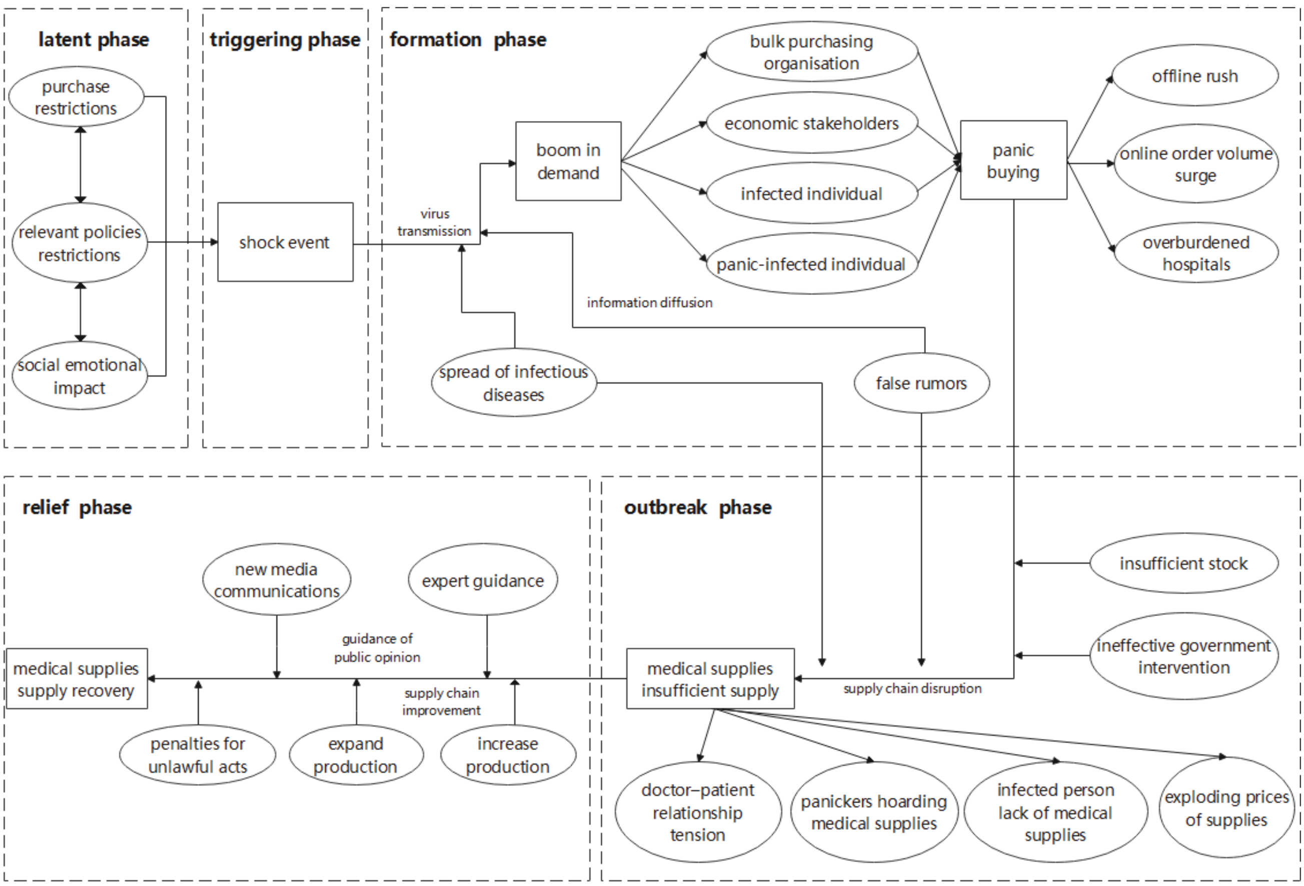

Figure 4. Systematic map of stress evolution process in the emergency medical supplies supply chain.

5. Stochastic Petri Net Model Construction for Stress Evolution of Emergency Medical Supply Chain

Through the structured analysis of stress evolution in emergency medical supply chains, this evolution can be viewed as a complex system involving numerous components characterized by stochastic behavior and dynamic interactions. Petri nets are particularly well-suited for modeling and analyzing such complex systems, as they offer a graphical framework that integrates data flow, control flow, and state transitions. In a Petri net, transitions represent the changes between different system states, while places denote these states before and after the transitions.

Therefore, this study employs the Petri net methodology proposed by Carl Adam Petri in 1962 to model the stress evolution in emergency medical supply chains. This approach enables a clear simulation of the system's dynamic processes and current state, thereby facilitating both system evaluation and the identification of improvement strategies [56].

We begin by using a stochastic Petri net to mathematically characterize the system. Building on the isomorphism between the reachability graph of the Petri net and the state space of a Markov chain, we then analyze the interrelationships among key components involved in the stress evolution process.

A stochastic Petri net is typically represented by a six-tuple, denoted as $SPN = (P,T;F,W,M,\lambda)$, where

- $P = \{P_1, P_2, \ldots P_n\} (n > 0)$ is a finite set of places;
- $T = (t_1, t_2, \ldots, t_m)$ is a finite set of transitions;
- $F \subseteq P \times T \cup T \times P$ is a set of directed arcs from places to transitions;
- $W : F \to N^+ (N^+ = \{1, 2, 3, \ldots\})$ denotes the arc weight function;
- $M : F \to \{1, 2, 3, \ldots\}$ represents the set of markings;

$\lambda = \{\lambda_1, \lambda_2, \ldots, \lambda_k\}$ is the set of average firing rates associated with the transitions. The modeling process proceeds as follows:

Step 1: SNP Modelling.

Based on the evolution process of emergency medical supply chain stress propagation illustrated in Figure 4, a corresponding stochastic Petri net (SPN) model is developed following the steps described above, as shown in Figure 5. The model in Figure 5 consists of 23 places and 15 transitions.

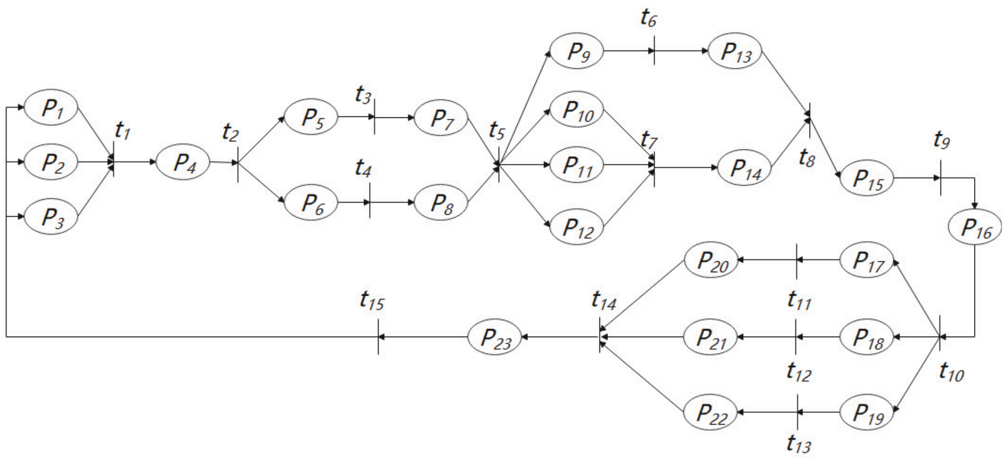

Figure 5. SPN model for stress evolution in the supply chain of emergency medical supply.

In Figure 5, the specific definitions of each place and transition within the model are detailed in Table 1.

Table 1. Definition of symbols in the SPN model of stress evolution in the supply chain of emergency medical supplies.

Place	Attribute State	Transition	Meaning of Change
P_1	Purchase restrictions	t_1	Environmental developments
P_2	Related policy restrictions	t_2	A series of chain reactions
P_3	Socio-emotional impact	t_3	Spread of viruses
P_4	Shock events	t_4	Information dissemination
P_5	Increased turnover	t_5	Demand surge
P_6	Misinformation generation	t_6	Bulk purchasing
P_7	Spread of infectious diseases	t_7	People rush to buy
P_8	Spread of rumors	t_8	Imbalance between supply and demand
P_9	Bulk purchasing organizations	t_9	Government intervention
P_{10}	Economic stakeholders	t_{10}	Emergency mobilization
P_{11}	People infected with the virus	t_{11}	Public opinion control
P_{12}	Panic infected	t_{12}	Capacity enhancement
P_{13}	Large customer order generation	t_{13}	Punishment of unruly behavior
P_{14}	Retail disorder	t_{14}	Supply and demand docking
P_{15}	Insufficient supply	t_{15}	Supply and demand balancing
P_{16}	Setting up a special team		
P_{17}	Experts to dispel rumors and provide positive guidance		
P_{18}	Replenish and fix the chain (stabilize production, reach production, change production, increase production, and expand production)		
P_{19}	Investigating and dealing with typical hoarding and sales shyness		
P_{20}	Demand for hoarding subsides		
P_{21}	Increase in supply		
P_{22}	Prices stabilize		
P_{23}	Sufficient supply		

Step 2: Generation of the Reachability Graph.

Based on the SPN model shown in Figure 5 and the transition firing rules, the initial marking of the stochastic Petri net is defined as M_1 = (1,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0), indicating that one token is initially placed in each of the places P_1, P_2, and P_3. By analyzing the enabled transitions under this marking, different subsequent markings (states) of the SPN can be derived. The full set of reachable markings, denoted as [M_0>, is listed as follows:

M_2 = (0,0,0,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0); M_3 = (0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0); M_4 = (0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0); M_5 = (0,0,0,0,1,0,0,1,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0); M_6 = (0,0,0,0,0,0,1,1,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0); M_7 = (0,0,0,0,0,0,0,0,1,1,1,0,0,0,0,0, 0,0,0,0,0,0,0); M_8 = (0,0,0,0,0,0,0,0,0,1,1,1,1,0,0,0,0,0,0,0,0,0,0); M_9 = (0,0,0,0,0,0,0,0,0,1,0,0,0,0,1,0,0, 0,0,0,0,0,0); M_{10} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,0,0,0,0); M_{11} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0, 1,0,0,0,0,0); M_{12} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,0,0,0,0,0,0,0); M_{13} = (0,0,0,0,0,0,0,0,0,0,0, 0,0,0,0,1,1,1,0,0,0,0,0); M_{14} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0,0,0); M_{15} = (0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,1,0,1,0,1,0,0); M_{16} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,0,0,0,1,0); M_{17} = (0,0,0,0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,1,1,1,0,0); M_{18} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,0,1,0,1,0); M_{19} = (0,0,0,0,0,0,0, 0,0,0,0,0,0,0,0,0,1,0,0,0,1,1,0); M_{20} = (0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1,1,1,0); M_{21} = (0,0,0,0, 0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,0,1).

In a time-continuous SNP, a random delay exists between the moment a transition becomes enabled and the moment it fires. This delay can be modeled as a continuous random variable, x, which follows an exponential distribution. The average firing rates of transitions t_1, t_2, ..., t_{15} are denoted by λ_1, λ_2, ..., λ_{15}. By representing the transitions between different markings using directed arcs, a continuous-time Markov chain (CTMC) structurally isomorphic to the SPN model can be derived, as illustrated in Figure 6.

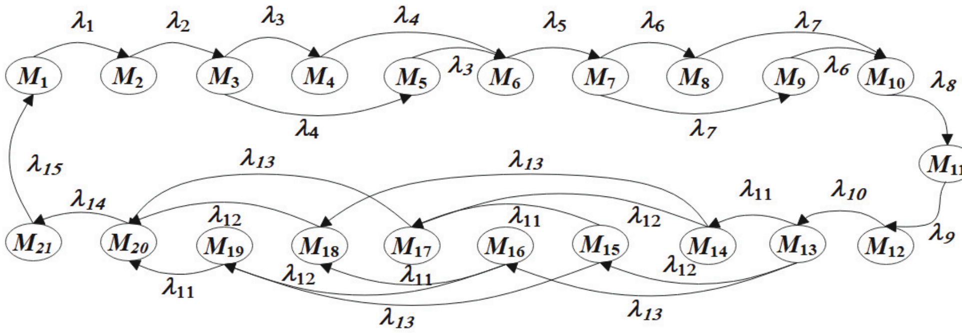

Figure 6. Markov chain isomorphic to the SNP model.

Step 3: Solve for the Probability of Stability.

Let $P(Mi)$, i ∈ {1, 2, ..., 21} denote the steady-state probability of marking Mi in the equilibrium state of the corresponding Markov chain, which also represents the probability of Mi in the steady-state of the SPN model. The following system of equations can thus be established:

$$\begin{cases} \lambda_1 P(M_1) = \lambda_{15} P(M_{21}) \\ \lambda_2 P(M_2) = \lambda_1 P(M_1) \\ \lambda_3 P(M_3) + \lambda_4 P(M_3) = \lambda_2 P(M_2) \\ \lambda_4 P(M_4) = \lambda_3 P(M_3) \\ \lambda_3 P(M_5) = \lambda_4 P(M_3) \\ \lambda_5 P(M_6) = \lambda_3 P(M_5) + \lambda_4 P(M_4) \\ \lambda_6 P(M_7) + \lambda_7 P(M_7) = \lambda_5 P(M_6) \\ \lambda_7 P(M_8) = \lambda_6 P(M_7) \\ \lambda_6 P(M_9) = \lambda_7 P(M_7) \\ \lambda_8 P(M_{10}) = \lambda_6 P(M_9) + \lambda_7 P(M_8) \\ \lambda_9 P(M_{11}) = \lambda_8 P(M_{10}) \\ \lambda_{10} P(M_{12}) = \lambda_9 P(M_{11}) \\ \lambda_{11} P(M_{13}) + \lambda_{12} P(M_{13}) + \lambda_{13} P(M_{13}) = \lambda_{10} P(M_{12}) \\ \lambda_{12} P(M_{14}) + \lambda_{13} P(M_{14}) = \lambda_{11} P(M_{13}) \\ \lambda_{11} P(M_{15}) + \lambda_{13} P(M_{15}) = \lambda_{12} P(M_{13}) \\ \lambda_{11} P(M_{16}) + \lambda_{12} P(M_{16}) = \lambda_{13} P(M_{13}) \\ \lambda_{13} P(M_{17}) = \lambda_{12} P(M_{14}) + \lambda_{11} P(M_{15}) \\ \lambda_{12} P(M_{18}) = \lambda_{13} P(M_{14}) + \lambda_{11} P(M_{16}) \\ \lambda_{11} P(M_{19}) = \lambda_{13} P(M_{15}) + \lambda_{12} P(M_{16}) \\ \lambda_{14} P(M_{20}) = \lambda_{13} P(M_{17}) + \lambda_{12} P(M_{18}) + \lambda_{11} P(M_{19}) \\ \lambda_{15} P(M_{21}) = \lambda_{14} P(M_{20}) \\ \sum\limits_{\mathrm{i}=1}^{21} P(M_{\mathrm{i}}) = 1 \end{cases} \tag{1}$$

Although the evolution of supply chain stress involves a certain degree of fuzziness and uncertainty, such uncertainties typically concentrate around a single focal point (λ_i point), rather than being distributed across multiple points simultaneously. Therefore, triangular fuzzy numbers are introduced to represent the fuzzification of the transition firing rate,λ_i. Let $\widetilde{\lambda} = \left(\widetilde{\lambda_1}, \widetilde{\lambda_2}, \ldots, \widetilde{\lambda_{15}}\right)$ denote the fuzzy set of transition firing rates, where

$\widetilde{\lambda}_i = (a_i, b_i, c_i)$ satisfies that $0 < a_i \le b_i \le c_i$ is a fuzzy number and $\mu_{\lambda i}(x) : R \to [0,1]$ is the triangular membership function of $\widetilde{\lambda}_i$, defined as follows:

$$\mu_{\lambda i}(x) = \begin{cases} \dfrac{x - a_i}{b_i - a_i}, a_i \le x \le b_i \\ \dfrac{c_i - x}{c_i - b_i}, b_i \le x \le c_i \\ 0, \text{ others} \end{cases} \tag{2}$$

The α-level cut set of $\widetilde{\lambda}_i$ is denoted as(shown as Figure 7)

$$A_{\alpha i} = [a_i + (b_i - a_i)\alpha, c_i - (c_i - b_i)\alpha] \tag{3}$$

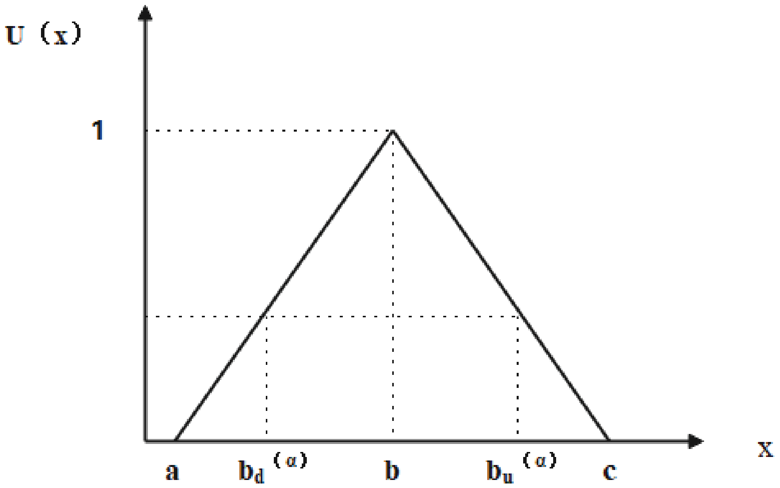

Figure 7. The α-level cut set of a fuzzy number.

The α-level cut set of the quadratic operations of fuzzy numbers X and Y can be expressed as

Set $X^{(\alpha)} = [X_d^{(\alpha)}, X_u^{(\alpha)}], Y^{(\alpha)} = [Y_d^{(\alpha)}, Y_u^{(\alpha)}], \alpha \in [0,1]$

$$\begin{aligned} &X^{(\alpha)} + Y^{(\alpha)} = [X_d^{(\alpha)} + Y_d^{(\alpha)}, X_u^{(\alpha)} + Y_u^{(\alpha)}]; \\ &X^{(\alpha)} - Y^{(\alpha)} = [X_d^{(\alpha)} - Y_u^{(\alpha)}, X_u^{(\alpha)} - Y_d^{(\alpha)}]; \\ &X^{(\alpha)} \cdot Y^{(\alpha)} = [X_d^{(\alpha)} \cdot Y_d^{(\alpha)}, X_u^{(\alpha)} \cdot Y_u^{(\alpha)}]; \\ &X^{(\alpha)} / Y^{(\alpha)} = [X_d^{(\alpha)} / Y_u^{(\alpha)}, X_u^{(\alpha)} / Y_d^{(\alpha)}] \\ &if 0 \notin [Y_d^{(\alpha)}, Y_u^{(\alpha)}] \end{aligned} \tag{4}$$

Following the algebraic operations of fuzzy numbers described above, the system of Equation (1) is solved to obtain the steady-state probability distribution. The defuzzification is then performed using the centroid method to derive the precise reliability value, representing the likelihood of the emergency medical supply chain being in each steady state during its pressure evolution. Based on this steady-state probability distribution, the decision-making processes at various stages of the pressure evolution can be optimized, thereby mitigating the adverse impacts of major public health emergencies. This analysis provides valuable theoretical guidance for improving the efficiency of emergency decision-making in such events.

6. Evolutionary Simulation Analysis of Supply Chain Stress

6.1. A Case Study of Ibuprofen in Beijing During the COVID-19 Pandemic

This study simulates the evolution of supply chain stress by using the ibuprofen supply chain in Beijing during the COVID-19 pandemic as a representative example. In the post-29 April 2020 phase, when China entered a stage of normalized epidemic prevention and control, the ibuprofen supply chain—serving as a prototypical emergency medical supply chain—underwent a nationwide wave of stress evolution at the end of 2022.

On 11 November 2022, the Standing Committee of the Political Bureau of the CPC Central Committee introduced twenty optimization measures, including the removal of the "close contact" classification, signaling a major policy shift in COVID-19 control. From 4 December 2022 to 20 January 2023, Baidu search data showed a sharp spike in interest in "ibuprofen", reflecting soaring public demand. In response, Beijing implemented ten targeted measures on 7 December to ensure access to essential medications. This led to widespread panic buying, pharmacy and online shortages, rising hospital visits, and increased drug prices. On 8 December, at the 23rd National Conference on Respiratory Diseases, Academician Zhong Nanshan called for a rational public response to the Omicron variant, emphasizing its reduced pathogenicity despite high transmissibility. Increased human mobility has led to a significant increase in the number of infections, and official published data are shown in Figures 8 and 9.

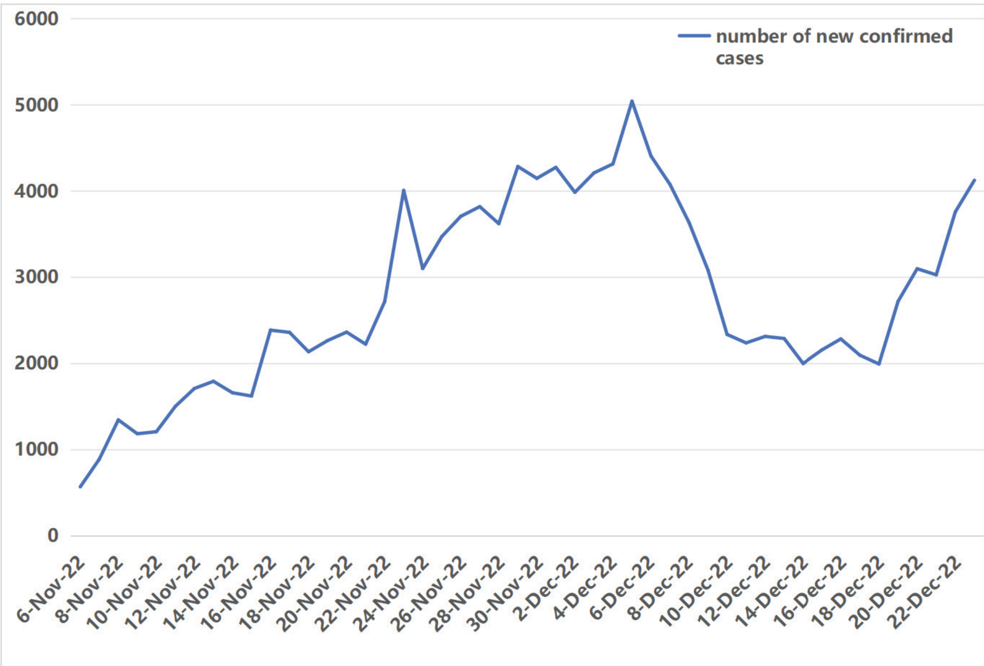

Figure 8. Number of new confirmed cases nationwide.

On 14 December, the Ministry of Industry and Information Technology (MIIT) launched an emergency initiative to ensure the production and supply of critical medical materials. A task force was established to mobilize local joint prevention and control mechanisms, accelerate pharmaceutical production, and compile a whitelist of key manufacturers. Major online pharmacies were directed to urgently develop digital platforms for medication access. On that day alone, 14 major manufacturers produced 28.25 million boxes of adult ibuprofen, while Beijing reported a cumulative allocation of 4.7 million tablets and 1.5 million bags (granules) of ibuprofen since December 11.

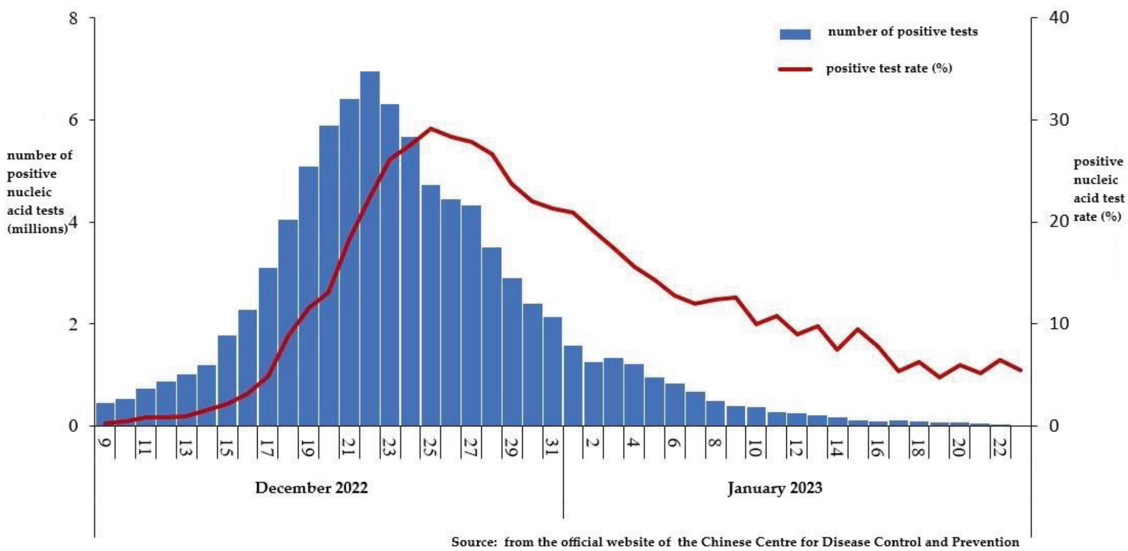

Figure 9. Trends in the number and rate of positive nucleic acid tests for novel coronaviruses in the national reporting population.

On 16 December, the MIIT expanded efforts to boost production by mobilizing pharmaceutical companies in Shanxi, Sichuan, Jiangsu, and Hubei to support Beijing's medical supply demands. In parallel, platforms such as Ali Health and JD Health were tasked with piloting targeted drug distribution systems in Shijiazhuang and Tianjin for home-based COVID-19 patients. The China National Machinery and Equipment Tendering Center was commissioned to solicit internet platforms capable of delivering urgently needed medications with precision. The Ministry of Transport urgently coordinated logistics support from China Post, SF Express, and other carriers. Regulatory authorities intensified oversight of major pharmaceutical wholesalers, cracking down on price gouging and hoarding. The National Administration of Traditional Chinese Medicine issued home-use guidelines to promote rational medication use and alleviate pressure on healthcare facilities.

On 18 December, the Joint Prevention and Control Mechanism of the State Council issued a "Daily Dispatch Plan for the Production and Supply of Medical Materials", implementing a whitelist system and designating key suppliers. Special commissioners were dispatched to ibuprofen raw-material manufacturers, covering over 80% of domestic production capacity. The Ministry of Commerce accelerated the redirection of antipyretic drug exports to the domestic market, while the MIIT facilitated the conversion of Shandong Xinhua Pharmaceutical's export production lines to domestic supply.

On 20 December, the State Administration for Market Regulation announced the second batch of typical law enforcement cases related to the pandemic, reporting 307 investigations and 92 concluded cases involving illegal pricing, with fines totaling CNY 2.581 million. The National Medical Products Administration also held a press conference to address concerns regarding ibuprofen production and registration.

By 21 December, the number of manufacturers of ibuprofen (for adult use) had increased to 64, with key enterprises reaching a daily output capacity of 81 million tablets. Between December 14 and 22, national media intensively covered the supply chain efforts, publishing over 80 original reports and more than 200,000 reposts across major websites and social media platforms.

On 29 December, the combined daily output of ibuprofen and paracetamol—two key antipyretic and analgesic drugs—reached 201 million tablets, a 4.1-fold increase compared to December 16. That evening, China Central Television (CCTV) aired a segment titled "Multi-Agency Efforts to Secure Medical Supply Chains", while the Xinhua News Agency released two in-depth reports with a combined readership exceeding one million views.

Additional coverage was released the same night by *Economic Daily*, People's Daily Online, *The Paper*, and other major outlets.

On 6 January 2023, due to overtime production by several enterprises, the combined daily output of ibuprofen and paracetamol reached 285 million tablets, surpassing their approved capacity.

By 15 January, the MIIT confirmed that, based on a comprehensive analysis of production, supply, inventory, and demand data, the supply of these two critical medications had stabilized and was considered sufficient to meet national needs.

6.2. Scenario Analysis and Discussion

In this scenario analysis, the average transition rates (λ_1, ..., λ_{15}) were parameterized concerning the evolution of ibuprofen supply chain stress at the end of 2022, as discussed in the previous section. Since the onset of the COVID-19 pandemic in late 2019, the ibuprofen supply chain stress latency phase has been longer, largely due to lockdown measures, public fear, and purchasing restrictions. Consequently, the average implementation rate for the first transition, λ_1, was set to 100.

Based on the previous section's discussion on the implementation of China's "20 Measures" and Beijing's localized "10 Measures" for epidemic prevention and control, the surge in media coverage surrounding ibuprofen, and mobilization efforts by national government agencies to coordinate its supply, combined with fluctuations in Baidu Search Index data for the keyword "ibuprofen", the average implementation rates of transitions t_2, ..., t_{13} were assumed to be λ_2 = 0.5, λ_3 = 1, λ_4 = 1, λ_5 = 22, λ_6 = 4, λ_7 = 1, λ_8 = 3, λ_9 = 6, λ_{10} = 4, λ_{11} = 9, λ_{12} = 3, λ_{13} = 2, λ_{14} = 5, and λ_{15} = 11, respectively.

Considering the inherent uncertainties associated with the activation of transitions during the evolution of emergency medical supply chain stress—though such activations generally converge around a specific inflection point (denoted as Point λi)—a triangular fuzzy number approach was adopted. Specifically, a ±15% fuzzification was applied to parameters $\lambda_1, \ldots, \lambda_{15}$, thereby generating a fuzzy set of transition activation rates: $\widetilde{\lambda} = \left(\widetilde{\lambda_1}, \widetilde{\lambda_2}, \ldots, \widetilde{\lambda_{15}}\right)$.

According to the arithmetic rules of fuzzy numbers, variable α is defined over the interval (0, 1) with an increment of 0.1. Equation System (1) was then solved under these conditions, and the resulting computational outcomes are presented in Appendix Tables A1 and A2. Scenario analysis enables the exploration of different evolutionary states, and in this paper we carry out scenario simulation analyses by varying the average implementation rate of variations related to the chain reaction of shock events, drug procurement, and emergency mobilization.

6.2.1. Scenario 1: Variations in the Cascade of Shock Events (λ_2: Chain Reaction, λ_3: Virus Transmission, λ_4: Information Dissemination)

Assuming all other rates ($\lambda_1, \lambda_3, \lambda_4, \ldots, \lambda_{15}$) remain constant, the average transition rate λ_2 is gradually increased from 0.1 to 3. The resulting equilibrium states of the supply chain evolution are illustrated in Figure 10. Similarly, holding $\lambda_1, \lambda_2, \lambda_4, \ldots, \lambda_{15}$ constant while increasing λ_3 from 0.1 to 3 yields the results shown in Figure 11. When λ_1, λ_2, λ_3, $\lambda_5, \ldots, \lambda_{15}$ are fixed and λ_4 is varied over the same range, the corresponding evolution outcomes are presented in Figure 12.

The probability convergence trends shown in Figures 10–12 suggest that as the average transition rates λ_2, λ_3, and λ_4 increase from 0.1 to 3, the probability of a sharp rise in public demand for ibuprofen, $p(M_8)$, also increases. This pattern reflects how policy adjustments, increased population mobility, and the spread of misinformation can trigger rapid chain reactions in emergency supply chains.

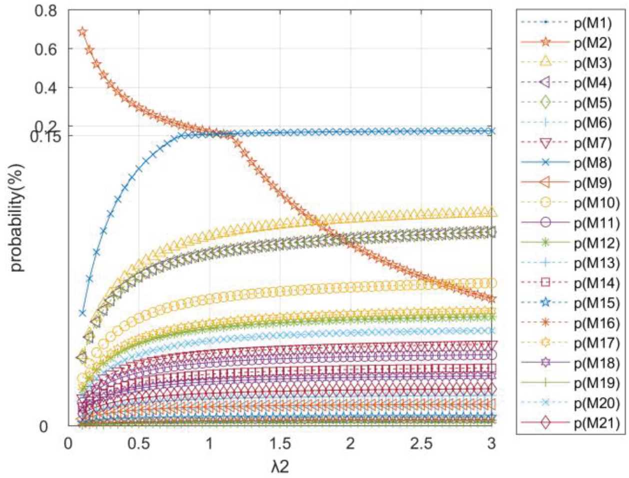

Figure 10. Equilibrium results of SCSE under λ_2 variations.

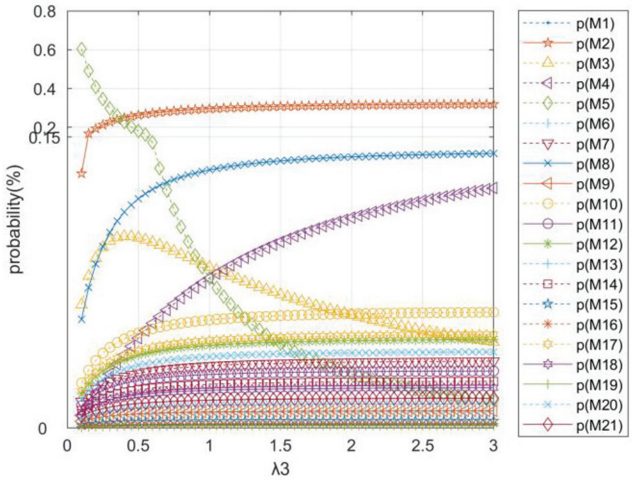

Figure 11. Equilibrium results of SCSE under λ_3 variations.

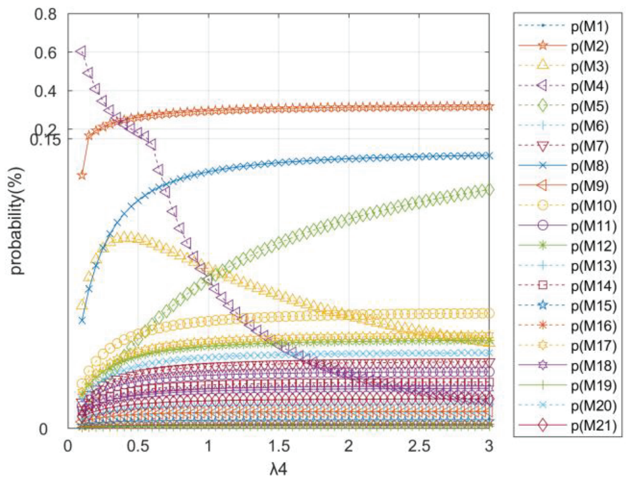

Figure 12. Equilibrium results of SCSE under λ_4 variations.

Interestingly, an inverse dynamic can be observed between the probability of virus transmission, $p(M_4)$, and rumor propagation, $p(M_5)$. In the latent phase of supply chain stress, the occurrence of a triggering shock event can rapidly activate and convert latent stress into stress, where the virus spread and public sentiment tend to influence each other in opposite directions.

To mitigate supply chain stress during major public health emergencies, it is essential for governments to strengthen emergency response mechanisms and enhance the design and implementation of contingency plans. Rapid response capabilities are critical to alleviating pressure across the supply chain. During the stress formation phase, timely and accurate dissemination of epidemic-related information—particularly in the early stages—is key. Controlling misinformation and managing public sentiment effectively can help reduce social panic and slow the development of supply chain stress.

6.2.2. Scenario 2: Variations in Pharmaceutical Procurement (λ_6: Bulk Purchasing, λ_7: Panic Buying)

Assuming that all other parameters ($\lambda_1, \ldots, \lambda_5, \lambda_7, \ldots, \lambda_{15}$) remain constant, the average transition rate λ_6 is incrementally increased from 1 to 20. The corresponding equilibrium outcomes of the system's evolution are shown in Figure 13. Similarly, holding $\lambda_1, \ldots, \lambda_6, \lambda_8, \ldots, \lambda_{15}$ constant, increasing λ_7 from 1 to 20 yields the results depicted in Figure 14.

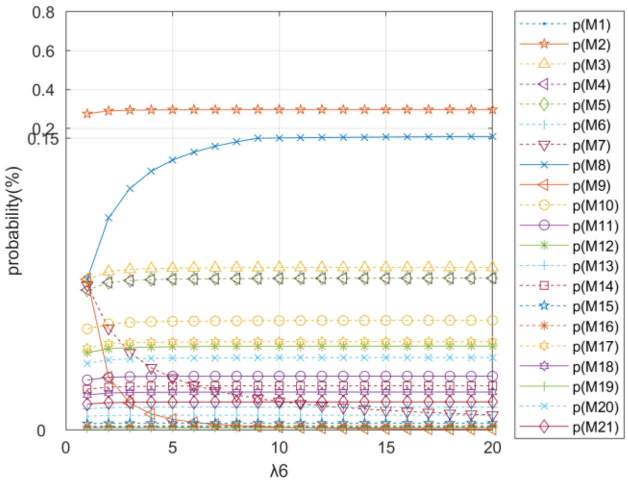

Figure 13. Equilibrium results of SCSE under λ_6 variations.

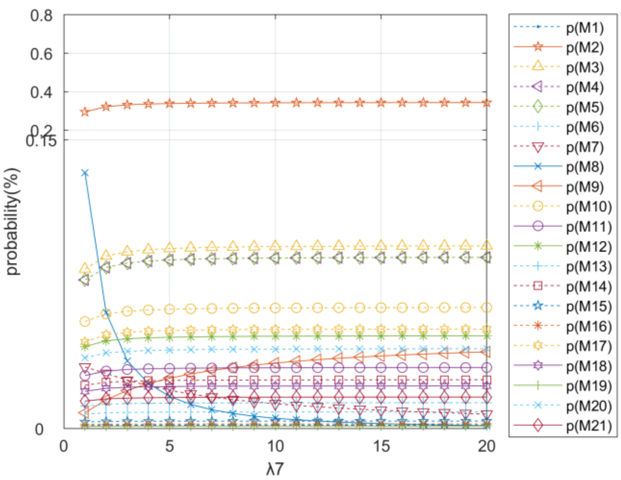

Figure 14. Equilibrium results of SCSE under λ_7 variations.

As illustrated by the convergence trends in Figures 13 and 14, when the average transition rates λ_6 and λ_7 rise from 1 to 20, the probability of a surge in ibuprofen demand across society, $p(M_8)$, increases. Concurrently, the probability of retail disorder, $p(M_9)$, decreases in the case of increased bulk purchasing but increases when panic buying intensifies. These findings indicate that during the pressure formation phase of the emergency medical supply chain, large-scale procurement by enterprises and panic buying by the public can both contribute to a supply–demand imbalance, resulting in widespread drug shortages.

Notably, once bulk procurement surpasses a critical threshold, it becomes a major source of supply chain pressure. To alleviate such pressure, government authorities should consider implementing bulk procurement control mechanisms. These measures could prioritize pharmaceutical supply to healthcare institutions while temporarily restricting non-medical entities from engaging in large-scale purchasing during periods of heightened drug scarcity. This would allow a greater proportion of the pharmaceutical supply to flow into the retail sector, ensuring that individuals with mild symptoms have timely access to medications, ultimately reducing the progression of mild cases into severe ones and helping to contain the overall spread of the epidemic.

6.2.3. Scenario 3: Variations in Emergency Mobilization Measures (λ_{11}: Public Opinion Management, λ_{12}: Capacity Expansion, λ_{13}: Enforcement Against Malpractice)

Assuming all other parameters ($\lambda_1, \ldots, \lambda_{10}, \lambda_{12}, \ldots, \lambda_{15}$) remain constant, the average transition rate λ_{11} is increased from 1 to 20. The resulting evolutionary equilibrium outcomes are shown in Figure 15. Similarly, when $\lambda_1, \ldots, \lambda_{11}, \lambda_{13}, \lambda_{14}, \lambda_{15}$ are held constant and λ_{12} is increased from 1 to 20, the corresponding results are displayed in Figure 16. Finally, increasing λ_{13} from 1 to 20 while keeping $\lambda_1, \ldots, \lambda_{12}, \lambda_{14}, \lambda_{15}$ constant yields the outcomes presented in Figure 17.

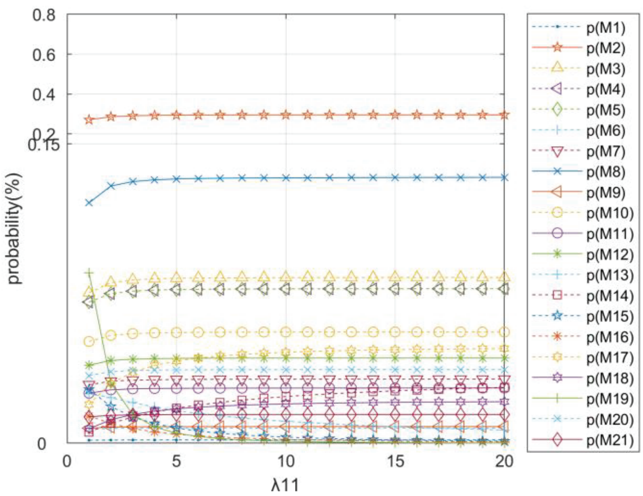

Figure 15. Equilibrium results of SCSE under λ_{11} variations.

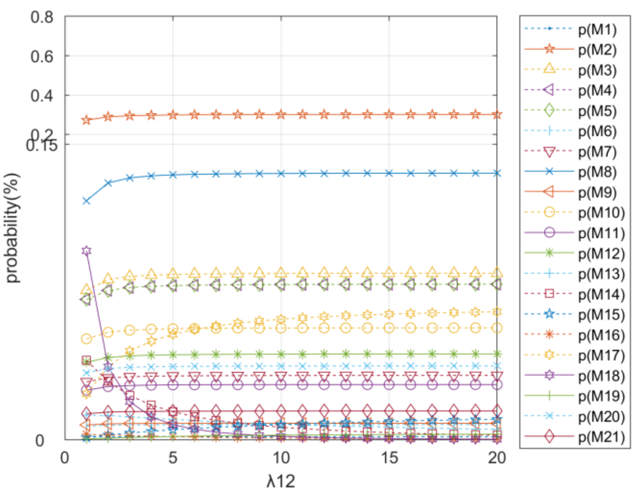

Figure 16. Equilibrium results of SCSE under λ_{12} variations.

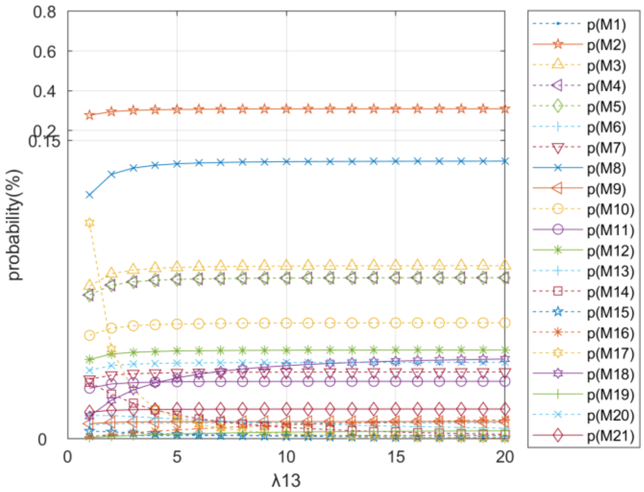

Figure 17. Equilibrium results of SCSE under λ_{13} variations.

As demonstrated by the convergence trends in Figures 15–17, increasing the implementation rates of emergency mobilization parameters—namely, public opinion guidance (λ_{11}), capacity expansion (λ_{12}), and law enforcement against hoarding and price gouging (λ_{13})—from 1 to 20 consistently enhances the probability of a stable supply–demand equilibrium, $p(M_{20})$. This suggests that these emergency response efforts—such as positive media guidance, supply chain reinforcement, and strict punishment of opportunistic behaviors—play equally critical roles in relieving pressure during the peak phases of a medical supply chain crisis.

To accelerate the mitigation of supply chain stress, it is imperative for government authorities to proactively promote expert-led dissemination of authoritative and reassuring information, organize rapid production shifts and capacity expansions across the medical supply sector, and intensify regulatory oversight of the pharmaceutical market. Through a three-pronged strategy—effective public communication, robust supply chain mobilization, and stringent legal enforcement—societies can stabilize drug prices, curb irrational demand, and facilitate a new equilibrium in the supply and demand of essential medical resources.

7. Conclusions

This study introduces a novel concept—emergency supply chain stress—and systematically explores its sources and characteristics. Anchored in lifecycle theory, the evolution of such stress is categorized into five distinct stages: the latent stage, the triggering stage, the formation stage, the outbreak stage, and the mitigation stage. Using the emergency medical supply chain as a representative case, the study provides a structured description of the stress evolution system, identifying and clarifying the interactions between internal and external factors throughout the evolutionary process.

Building on this foundation, a stochastic Petri net model is developed to mathematically capture the dynamics of emergency supply chain stress. The model integrates key contextual elements of China's infectious disease transmission patterns, emergency medical supply and demand dynamics, resource allocation decisions, and emergency mobilization mechanisms.

This research offers a new analytical lens for studying issues related to emergency supply chains and provides a foundation for further model development. With an improved understanding of stress evolution in emergency supply chains, future research can focus on developing stress-testing tools to better evaluate the performance of such systems, design mobilization strategies, and test their effectiveness. These efforts can contribute to the formulation of more robust emergency response plans and enhance preparedness for large-scale, unconventional emergencies. Further studies may also explore supply chain resilience and system security to strengthen the overall capacity of emergency supply chain systems.

Nevertheless, this study has certain limitations. As the introduction of the "stress" concept into emergency supply chains represents a novel approach, further validation using a broader range of emergency material categories is required. Additionally, emerging mobilization strategies may arise in future emergency scenarios, necessitating continuous model refinement and expansion through the application of text-driven modeling techniques.

Author Contributions: Conceptualization, Q.C. and J.Z.; Data curation, Q.C.; Formal analysis, Q.C.; Funding acquisition, J.Z.; Investigation, Q.C.; Methodology, Q.C.; Project administration, J.Z.; Resources, Q.C.; Software, Q.C.; Supervision, J.Z.; Validation, Q.C.; Visualization, Q.C.; Writing—original draft, Q.C.; Writing—review and editing, Q.C. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the Ministry of Industry and Information Technology Major Policy Research project [grant number: BIT-RDC-202327441002]; the Beijing Municipal Social Science Foundation project [grant number: 20JCC067]; and the China Academy of Engineering's Strategic Research and Advisory Project [grant number: 2022-HY-06].

Data Availability Statement: Data are contained within the article. The original contributions presented in the study are included in the article material; further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Appendix A.1

Table A1. Trust intervals for the α-intercept set (M_1–M_{11}).

α \ $\times 10^{-5}$	$P(M_1)$	$P(M_2)$	$P(M_3)$	$P(M_4)$	$P(M_5)$	$P(M_6)$	$P(M_7)$	$P(M_8)$	$P(M_9)$	$P(M_{10})$	$P(M_{11})$
0.0	(235.8584, 87.5716)	(22493.1599, 36584)	(12063.6626, 4533.0167)	(6706.4268, 8757.3139)	(6706.4268, 8757.3139)	(1026.787, 497.121)	(3227.9898, 3181.0986)	(15845.4139, 10755.0996)	(885.4026, 775.8071)	(6499.0482, 4638.6265)	(2995.095, 2527.1955)
0.1	(227.9529, 94.4511)	(23685.1996, 36264.5756)	(11611.9613, 4850.1261)	(6858.2789, 8690.2773)	(6858.2789, 8690.2773)	(991.5507, 517.16)	(3221.1286, 3178.8058)	(15460.9858, 10915.2034)	(871.6118, 775.8367)	(6349.8524, 4685.0654)	(2946.0796, 2533.2933)
0.2	(220.0964, 101.3925)	(24812.7007, 35913.5074)	(11170.4851, 5172.3337)	(7003.1877, 8620.7319)	(7003.1877, 8620.7319)	(957.5587, 537.6951)	(3214.7401, 3177.0338)	(15095.1063, 11082.3295)	(859.0667, 776.1883)	(6207.7882, 4735.5944)	(2900.8499, 2540.4848)
0.3	(212.2889, 108.3949)	(25878.3875, 35529.5474)	(10738.7064, 5499.7688)	(7141.5113, 8548.5002)	(7141.5113, 8548.5002)	(924.74, 558.7493)	(3208.8254, 3175.7726)	(14746.7092, 11256.8697)	(847.6899, 776.8984)	(6072.6156, 4790.3185)	(2859.1761, 2548.875)
0.4	(204.5304, 115.4571)	(26884.8298, 35111.4084)	(10316.141, 5832.5719)	(7273.5878, 8473.3998)	(7273.5878, 8473.3998)	(893.0287, 580.3465)	(3203.3848, 3175.0137)	(14414.8066, 11439.2299)	(837.4085, 778.0043)	(5944.104, 4849.3494)	(2820.8435, 2558.571)
0.5	(196.8212, 122.5782)	(27834.455, 34657.7594)	(9902.3438, 6170.896)	(7399.7367, 8395.2436)	(7399.7367, 8395.2436)	(862.3635, 602.5122)	(3198.4177, 3174.7494)	(14098.4819, 11629.8321)	(828.1545, 779.544)	(5822.0316, 4912.8054)	(2785.6509, 2569.6825)
0.6	(189.1618, 129.7573)	(28729.5594, 34167.2215)	(9496.9061, 6514.907)	(7520.261, 8313.8391)	(7520.261, 8313.8391)	(832.6878, 625.2735)	(3193.9235, 3174.9735)	(13796.883, 11829.1166)	(819.8634, 781.5567)	(5706.1856, 4980.8119)	(2753.4095, 2582.3224)
0.7	(181.5526, 136.9932)	(29572.318, 33638.3627)	(9099.4517, 6864.7851)	(7635.4482, 8228.9874)	(7635.4482, 8228.9874)	(803.9489, 648.6591)	(3189.9016, 3175.6808)	(13509.217, 12037.544)	(812.4749, 784.0828)	(5596.3617, 5053.5016)	(2723.942, 2596.6068)
0.8	(173.9943, 144.2852)	(30364.7942, 33069.6936)	(8709.6344, 7220.7258)	(7745.5719, 8140.4836)	(7745.5719, 8140.4836)	(776.0976, 672.6997)	(3186.3512, 3176.867)	(13234.7442, 12255.5985)	(805.9315, 787.1639)	(5492.3643, 5131.0145)	(2697.081, 2612.6561)
0.9	(166.4875, 151.6321)	(31108.9482, 32459.6614)	(8327.1354, 7582.9412)	(7850.8932, 8048.115)	(7850.8932, 8048.115)	(749.0883, 697.4278)	(3183.2722, 3178.529)	(12972.7736, 12483.7901)	(800.1791, 790.8434)	(5394.0059, 5213.498)	(2672.6682, 2630.595)
1.0	(159.0332, 159.0332)	(31806.645, 31806.645)	(7951.6612, 7951.6612)	(7951.6612, 7951.6612)	(7951.6612, 7951.6612)	(722.8783, 722.8783)	(3180.6645, 3180.6645)	(12722.658, 12722.658)	(795.1661, 795.1661)	(5301.1075, 5301.1075)	(2650.5537, 2650.5537)

Appendix A.2

Table A2. Trust intervals for the α-intercept set (M_{12}–M_{21}).

α \ $\times 10^{-5}$	$P(M_{12})$	$P(M_{13})$	$P(M_{14})$	$P(M_{15})$	$P(M_{16})$	$P(M_{17})$	$P(M_{18})$	$P(M_{19})$	$P(M_{20})$	$P(M_{21})$
0.0	(5346.0122, 3187.2822)	(1164.5871, 1185.554)	(3086.4129, 1420.8372)	(535.7226, 170.0035)	(346.6699, 91.2507)	(3367.4648, 5653.7667)	(1329.5791, 2552.9494)	(4.8279, 244.9379)	(5882.971, 1488.6412)	(835.9127, 2039.2535)
0.1	(5177.1046, 3244.7538)	(1156.3173, 1178.6735)	(2959.2829, 1467.9963)	(508.3719, 180.8783)	(327.6993, 98.9013)	(3467.2662, 5535.2927)	(1386.6374, 2492.215)	(18.1221, 234.4345)	(5557.3493, 1621.2368)	(896.258, 1982.3344)
0.2	(5015.9108, 3306.6099)	(1149.4653, 1172.0858)	(2837.7025, 1518.2564)	(482.1728, 192.3811)	(309.5066, 106.9889)	(3569.6937, 5416.1204)	(1444.5812, 2430.9125)	(31.2813, 223.7308)	(5245.0685, 1761.2364)	(956.8477, 1924.6836)
0.3	(4862.1812, 3372.9772)	(1143.9419, 1165.8401)	(2721.4946, 1571.7167)	(457.0882, 204.5339)	(292.069, 115.5285)	(3674.552, 5296.4542)	(1503.3354, 2369.1389)	(44.3094, 212.8369)	(4945.7263, 1908.9003)	(1017.6466, 1866.378)
0.4	(4715.6745, 3443.9888)	(1139.6627, 1159.9859)	(2610.488, 1628.4803)	(433.0821, 217.3594)	(275.364, 124.5358)	(3781.6517, 5176.4936)	(1562.8263, 2306.9882)	(57.2094, 201.7621)	(4658.9291, 2064.4964)	(1078.6179, 1807.4916)
0.5	(4576.1579, 3519.7837)	(1136.5486, 1154.5735)	(2504.5163, 1688.6542)	(410.1197, 230.8808)	(259.3698, 134.0266)	(3890.8082, 5056.4337)	(1622.9803, 2244.552)	(69.9831, 190.5151)	(4384.2925, 2228.3008)	(1139.7228, 1748.0956)
0.6	(4443.4066, 3600.5075)	(1134.5244, 1149.6535)	(2403.4183, 1752.3495)	(388.1668, 245.1225)	(244.0649, 144.0175)	(4001.8406, 4936.4651)	(1683.724, 2181.9191)	(82.6313, 179.104)	(4121.4406, 2400.5972)	(1200.9208, 1688.2581)
0.7	(4317.2036, 3686.312)	(1133.5188, 1145.2778)	(2307.0379, 1819.6814)	(367.1904, 260.1095)	(229.4283, 154.5252)	(4114.5709, 4816.7746)	(1744.984, 2119.1761)	(95.154, 167.5361)	(3870.0062, 2581.6776)	(1262.169, 1628.0443)
0.8	(4197.3397, 3777.3559)	(1133.4643, 1141.4992)	(2215.2238, 1890.7693)	(347.1586, 275.8676)	(215.4395, 165.5672)	(4228.8229, 4697.5456)	(1806.6863, 2056.4071)	(107.5501, 155.8179)	(3629.6307, 2771.842)	(1323.4229, 1567.5168)
0.9	(4083.6134, 3873.8046)	(1134.2958, 1138.3719)	(2127.8294, 1965.7371)	(328.0402, 292.4236)	(202.0784, 177.1611)	(4344.4214, 4578.9586)	(1868.7561, 1993.6942)	(119.8176, 143.9555)	(3399.9641, 2971.3988)	(1384.6352, 1506.7353)
1.0	(3975.8306, 3975.8306)	(1135.9516, 1135.9516)	(2044.7129, 2044.7129)	(309.805, 309.805)	(189.3253, 189.3253)	(4461.1918, 4461.1918)	(1931.1177, 1931.1177)	(131.954, 131.954)	(3180.6645, 3180.6645)	(1445.7566, 1445.7566)

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The Impact of Dual-Channel Investments and Contract Mechanisms on Telecommunications Supply Chains

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Abstract: This study examines how contract structures influence coordination and innovation incentives in dual-channel telecommunications supply chains. We consider a setting where a mobile network operator (MNO) supplies services both directly to consumers and indirectly through a mobile virtual network operator (MVNO), which competes in the retail market. Using a game-theoretic framework, we evaluate how different contracts—single wholesale pricing, revenue sharing, and quantity discounts—shape strategic decisions, particularly in the presence of investment spillovers between parties. A key coordination problem emerges from the externalized gains of innovation, where one party's investment generates value for both participants. Our results show that single wholesale and revenue sharing contracts often lead to suboptimal investment and profit outcomes. In contrast, quantity discount contracts, especially when combined with appropriate transfer payments, improve coordination and enhance the total performance of the supply chain. We also find that innovation led by the MVNO, while generally less impactful, can still yield reciprocal benefits for the MNO, reinforcing the value of cooperative arrangements. These findings emphasize the importance of contract design in managing interdependence and improving efficiency in decentralized supply chains. This study offers theoretical and practical implications for telecommunications providers and policymakers aiming to promote innovation and mutually beneficial outcomes through well-aligned contractual mechanisms.

Keywords: dual-channel supply chain; telecommunication market; supply chain coordination; technological innovation; investment spillover

1. Introduction

From a supply chain perspective, in telecommunications, the relationship between a mobile network operator (MNO) and a mobile virtual network operator (MVNO) provides a unique market structure. Unlike the traditional supply chain structure that follows a wholesale–retail–consumer sequence, the relationship between these two partners represents a cooperative dynamic where the MNO becomes a supplier to the MVNO, and the bargaining power of the supplier (MNO) is dominant. Simultaneously, it constitutes a dual-channel supply chain structure where the MNO and the MVNO compete in the retail market. Governments in many countries are encouraging MVNOs to participate in the telecommunications market to promote competition and moderate market concentration. The market share of MVNOs varies by country, ranging from 0.9% to 47.5%. Notably, Germany (47.5%), Denmark (33.5%), and Canada (28.8%) have substantial MVNO market shares. As of 2019, the average market share of MVNOs across 36 OECD countries stood at 11.7% [1]. The number of MVNOs also varies by country, with the United States having over 200, while Germany, Japan, and the United Kingdom each have around 100 MVNOs operating. These MVNOs often offer more competitive pricing to customers compared to MNOs, making them appeal to price-sensitive consumers [2].

To stimulate competition in telecommunications markets characterized by oligopolistic structures with only three to four operators per country, governments around the world have consistently pursued strategies to foster the sustained growth of MVNOs. Key elements of various policy approaches include designating MNOs as mandatory wholesale providers and compelling them by law to enter into wholesale agreements with MVNOs. In some countries, such as Austria, Japan, Spain, and South Korea, the government intervenes by setting the pricing of wholesale services between MNOs and MVNOs, rather than leaving it to voluntary negotiations between operators. This approach promotes transparency and equitable access to wholesale services, ultimately aiming to invigorate market competition.

While not widely disclosed in individual agreements, the contractual arrangements between MNOs and MVNOs can be broadly categorized into three main types, as classified by [3]. The first type is called the "Retail-Minus" contract, where the wholesale price is established by applying a fixed discount rate to the MNO's retail price, excluding avoidable costs. This approach is akin to the "single wholesale price" contract format, where the rates for voice and data services are specified and used to establish wholesale prices. The second widely employed approach is "Revenue Sharing", wherein MNOs and MVNOs divide the revenue generated by an MVNO according to a predetermined percentage. This method ensures proportional sharing of revenues between the two parties. The third approach, adopted in certain countries such as Japan, involves "Quantity Discount" contracts, where bulk discounts are negotiated between operators. This strategy often hinges on the volume of services exchanged and can lead to cost savings for MVNOs based on the quantity of services they purchase.

Another concern facing MNOs within the framework of the dual-channel supply chain is the incentive for investment when such a market structure is in place [4,5]. The market structure of MNOs and MVNOs differs from the traditional addition of a direct channel (online) to the retail channel (brick-and-mortar). Instead, the crucial difference is that it involves the emergence of another retail channel alongside the MNOs' existing direct channel. From the perspective of MNOs, investments in innovation typically aim to maximize their profits through enhancements in network quality and speed and launching next-generation communication services, such as 5G, 6G, satellite communication, and AI-based network technologies, and so on. However, in a dual-channel supply chain, the investments made by the supplier (MNO) can lead to spillover effects on the retailer's (MVNO) demand and revenue. There are arguments that this dynamic, where MVNOs also reap the rewards of investments, can lead to concerns and dampen the enthusiasm of MNOs for investment in future innovation. In innovation investment, a spillover effect refers to the impact or influence that one party's innovation efforts have on the other party within a supply chain or a collaborative setting [6,7]. It represents how an investment made by one participant affects the performance, decisions, or outcomes of the other participant in the supply chain, often in terms of increased demand, efficiency, or profitability. This effect can be either positive, where the innovation benefits both parties, or negative, where it may create challenges or conflicts. Therefore, spillover effects are crucial to understanding the coordination within supply chains involving innovation investments.

Based on the example above, this study was conducted under the premise of a formed dual-channel supply chain rather than a choice of supply chain channels. We mainly explore effective contract mechanisms among the contracting parties while considering the spillover effects of investment for innovation on supply chain coordination. First, we examine efficient wholesale contract methods that facilitate coordination between the two supply chain partners who maintain a cooperative relationship while simultaneously competing in the retail market, taking into account the characteristics of the telecommunications market. We also investigate the resulting changes in the profitability of the market participants and the supply chain. Furthermore, regarding the spillover effects of innovation, this study inherently addresses the spillover of MNO (supplier) investments given the tens of billions of dollars of substantial annual investments made by MNOs in reality. In addition, we analyze the impact on supply chain profitability when retailers engage in innovative activities such as launching new services (e.g., partnerships with Over-the-Top (OTT) providers) or investing in enhancing their own services.

Our model consists of three main aspects: First, we analyze a situation where two companies are either centralized or in a parent–subsidiary relationship, with perfect monitoring between contracting parties. This serves as the benchmark case for our analysis. Second, we incorporate three contract models commonly observed in the current market, including single wholesale price contracts, revenue sharing contracts, and quantity discount contracts, among others. By comparing these contract models with the benchmark case, we analyze the changes in the profit functions of the contracting parties, the expected profits of the entire supply chain, and overall efficiency. This allows us to examine more realistic and efficient contract mechanisms between the business partners in a dual-channel supply chain among the various contract options available. Third, we examine the spillover effect of self-initiated investments for innovation on both the MNO and the MVNO and investigate the coordination dynamics between these two partners when investment decisions are under consideration.

This study makes several contributions to the literature on dual-channel supply chain coordination in the telecommunications sector. First, it demonstrates that implementing quantity discount mechanisms alongside innovation investments can significantly enhance the overall supply chain performance. Such coordination not only improves the alignment between suppliers and retailers but also protects the supplier's returns by mitigating the negative effects of investment spillovers. In addition, we show that innovation investments by the retailer—enabled through spillovers—can positively affect the entire supply chain, providing reciprocal benefits to the supplier.

Unlike prior studies that primarily focus on single-channel coordination or channel selection with multiple retailers, our research emphasizes the contractual dynamics between the supplier (MNO) and a single retailer (MVNO), particularly in the context of innovation-driven investments such as 5G, 6G, satellite communication, and AI-based network technologies. This focus allows us to highlight the unique coordination challenges arising when the supplier bears the innovation cost. Moreover, while much of the existing literature limits itself to price and profit optimization, our work explores a broader range of contract mechanisms and considers the investment incentives of both parties. By doing so, we offer a more comprehensive view of supply chain coordination that reflects the strategic interests of telecommunications stakeholders.

The organization of this paper is as follows. Section 2 studies previous studies related to our research and emphasizes the unique aspects of this study. Section 3 describes the dual-channel supply chain contract models. In Section 4, we study the coordination within a dual-channel supply chain without investment for innovation. Section 5 explores coordination while considering the spillover effects of investment. Section 6 concludes our study with a discussion of its limitations and potential research directions.

2. The Related Literature

Earlier studies, such as the work conducted by [8], primarily focused on the contract mechanisms and coordination among supply chain partners. Subsequent research has seen active analyses of various contract types and market structures, including single-price contracts [9], flexible contracts [10], revenue sharing contracts [11], and quantity discount contracts [12]. Comprehensive reviews of this body of research can be found in references such as [13,14]. In the context of dual-channel supply chain coordination, a range of contract types has been explored to foster cooperation among suppliers and retailers in decentralized settings. For instance, ref. [15] shows the effect of the channel structure of the supply chain and channel coordination through the channel-adding Pareto zone concept. Ref. [16] examined the coordination structures within decentralized supply chains, finding that contracts involving wholesale and direct channel prices benefited retailers, but proposed complementary contracts such as two-part tariffs for mutual benefit. Ref. [17] introduced a two-way revenue sharing contract tailored to dual-channel supply chains, combining traditional revenue sharing with a reverse revenue sharing contract. Similarly, ref. [18] proposed contracts for managing manufacturer–retailer competition, investigating their impact on the pricing and recycling rates in closed-loop supply chains. They also introduced reverse revenue sharing by allowing manufacturers to share cost savings. Ref. [19] found that cost sharing contracts encouraged improvements in retailer services and discouraged price competition. Ref. [20] explored revenue and profit sharing contracts in non-cooperative and cooperative game structures, highlighting their effectiveness in different customer scenarios. For a comprehensive review of this body of research, we refer to [21].

Among various contract mechanisms, quantity discount contracts have been particularly effective in achieving supply chain coordination. Ref. [22] introduced linear quantity discount contracts designed to manage manufacturer–retailer competition. These contracts proved effective in supply chain coordination, albeit resulting in reduced retailer profits compared to those in decentralized scenarios. Ref. [23] employed hybrid mechanisms that combined quantity discounts and franchise fees to mitigate conflicts within dual-channel supply chains, yielding benefits across the entire supply chain when the expected profits aligned with those in decentralized settings. It is noteworthy that the above diverse contract types and coordination mechanisms may not entirely align with the realities of the MNO and MVNO contract relationships we examine in this study. For instance, the application of two-way revenue sharing or profit sharing concepts may not be feasible from the perspective of MNOs, which often hold negotiating leverage and significant revenue disparities. Additionally, the unique characteristics of service-based industries can make it challenging to implement concepts such as closed-loop supply chains and return policies. While the research [22] shares some similarities with our study, our research differs in that we focus on the contractual relationships between suppliers and retailers, particularly in cases involving MNO investments for innovation. Unlike scenarios involving channel selection and multiple retailers, our study considers the coordination aspects when innovation-driven investments are made by MNOs, highlighting this as a key different aspect.

Despite growing interest, the interface between investment for innovation and supply chain management remains an understudied domain. Ref. [24] investigated a scenario where a supplier invested in process innovation to improve product quality and increase consumer value. They examined three supply contracts and showed that the revenue sharing contract was capable of achieving the optimal innovation levels and channel coordination. Ref. [25] explored how cost sharing concepts within supply chains could increase innovation investments upstream. Their research demonstrated that such contracts effectively encouraged innovative investments by upstream partners. Ref. [26] examined the innovation and retail channel dynamics in a dual-channel supply chain. The findings suggested that retailer benefits could result from a supplier's entry into the retail sector, as this motivated the supplier to make cost-reducing investments. This, in turn, led to lower wholesale prices and improved the profits for both parties. Ref. [27] explored that innovators might strategically outsource to competitor CMs, aiming for market leadership in cases of technical innovations and introducing innovation uncertainties for non-technical innovations. Ref. [28] explored the collaborative innovation within supply chains, specifically focusing on products co-developed by an upstream supplier and a downstream manufacturer. Their study showed that when the manufacturer possessed sufficient resources, they were inclined to invest in new product development, whereas the supplier did not share the same inclination. This work emphasized the significance of innovation driven by manufacturers and highlighted the necessity of factoring in product the profit margins when engaging in collaborative innovation efforts. Recent studies have investigated innovation spillovers in supply chain settings from various perspectives. Ref. [29] provides empirical evidence that knowledge spillovers from customers significantly enhance supplier innovation, particularly under geographic proximity. Ref. [30] further confirms that buyer innovation positively affects supplier innovation, especially in long-term buyer–supplier relationships, though technological proximity shows limited moderating effects. While these studies deepen our understanding of the effects of spillover on innovation outcomes, our research is distinct in its focus on the coordination within a dual-channel supply chain involving innovation investments. Specifically, we investigate how contractual mechanisms can address both channel conflict and investment spillovers, facilitating strategic alignment between mobile network operators (MNOs) and mobile virtual network operators (MVNOs). While there are similarities with [24], their research primarily centered on single-channel coordination utilizing the Hoteling model, setting it apart from our study.

Research on the contract mechanisms between MNOs and MVNOs has been conducted in both economics and the telecommunications industry. Ref. [31] analyzed the legitimacy of MVNO market entry and the changes in the profits of each party when these companies compete in the telecommunications market. Ref. [32] investigated situations where facility-based vertically integrated firms compete independently with rivals on the broadband access market, studying the impact of government regulations. They argued that under regulatory conditions where the government sets wholesale prices, there is a reduction in firms' investment incentives, and competing firms providing wholesale services tend to overinvest when creating new value-added services. Similarly, ref. [33] studied how the entry of MVNOs and regulatory access policies affect MNOs' investment behavior, utilizing data from 58 MNOs across 21 OECD countries. Their findings suggested that mandated access provision is associated with a reduced intensity of MNO investments, emphasizing the importance of addressing the investment incentives when granting access to MVNOs. In addition, refs. [34,35] used non-cooperative game theory to analyze the equilibrium wholesale prices between MNOs and MVNOs, considering the market conditions. A noteworthy distinction of our research is that it extends beyond the mere computation of wholesale prices and profit functions and instead explores a range of contractual mechanisms. Furthermore, our study is conducted with a particular focus on the interests and profitability of telecommunication supply chain stakeholders, as well as the perspective of investment incentives. These factors set our research apart from the aforementioned studies.

3. The Model

We explore a dual-channel supply chain structure where a supplier (MNO) distributes products both directly to customers through their own direct channel and indirectly through an MVNO. These channels are labeled as the "direct" and "indirect" channels correspondingly. The MNO sets a wholesale price, denoted as w, for selling products to the retailer and sets the direct retail price, labeled as p_s, in the direct channel. The retailer decides on the retail price, denoted as p_r, in the indirect channel. Table 1 summarizes the notation of the variables.

Table 1. Notation for variables.

Variables	Description
w	The unit wholesale price offered by the MNO to the MVNO
p_s	The retail price of the direct channel
p_r	The retail price of the indirect channel
D_s	Demand from the direct channel
D_r	Demand for the indirect channel
a	Customer preference for the direct channel ($\frac{1}{2}$ < a < 1)
b	Cross-price elasticity $(0 < b < 1)$
c	The operating cost of the telecommunication service
x	Investment level for innovation
π_s	The supplier's (MNO's) profit
π_r	The retailer's (MVNO's) profit

We have employed prior research as the foundation for formulating the linear demand functions for both channels [36–39]. Specifically, we assume that the market demand in both the direct and indirect channels responds to price changes and is influenced by the level of investment made by the supplier. In the market composed of an MNO and an MVNO, we also assume that the products are homogeneous, but the customer demand varies in response to differences in price.

$$D_s = aA - p_s + b(p_r - p_s) + \gamma x$$
$$D_r = (1-a)A - p_r + b(p_s - p_r) + \gamma x$$

Let *Ds* represent the demand from the direct channel and *Dr* represent the demand for the indirect channel. Parameter A characterizes the baseline demand, and a (0 < a < 1) represents the level of customer preference for the MNO's direct channel. In the telecommunications market, which is typically a direct channel leading market, we assume $a > \frac{1}{2}$. Correspondingly, $1 -$ a characterizes the degree of customer preference for the indirect channel. The precise value of the initial market potential A is not a critical factor in our analytical model. The primary findings of our paper remain robust, even if the scale of the baseline demand is adjusted. Thus, for analytical tractability and without loss of generality, we standardize the value of A to one, aligning with the methodology of [36,37,40–42].

We also assume that the price elasticity coefficients for *Ds* and *Dr* are both set to one, according to [43].

The cross-price elasticity is denoted as $b(b_s = b_r = b)$, where $0 < b < 1$. A value of b = 0 would imply that the two markets operate independently, while b = 1 would indicate perfect substitutability. In the telecommunications context, services such as voice and data are similar, so we assume b is strictly between 0 and 1. Given the consumer loyalty and pricing differences between MNOs and MVNOs, it is reasonable to expect that b remains closer to 0 than to 1. Furthermore, we represent the increase in demand due to investment in technological innovation as γx [26,28,32]. While the increases in demand for the indirect and direct channels may differ, assuming the sale of products with the same attributes, we set $\gamma_s = \gamma_r$ as the initial assumption and subsequently analyze cases where these parameters differ.

The MNO incurs a quadratic network investment cost associated with investments in innovative services, such as enhancing speed, improving data quality, or adding additional features. This cost function is represented as $C(x) = k\frac{x^2}{2}$, where it satisfies the conditions $C(0) = 0$, $\frac{dC(x)}{dx} > 0$ and $\frac{dC^2(x)}{dx^2} > 0$ ([44,45]).

With the above notation, the supplier's profit is determined by

$$\pi_s = (p_s - c)D_s + (w - c)D_r - k\frac{x^2}{2} \tag{1}$$

and the profit of the retailer is determined as

$$\pi_r = (p_r - w)D_r \tag{2}$$

where w is the wholesale price charged by the MNO.

In the telecommunications market, the marginal operating cost (c) approaches zero, while the investment costs for new services and innovations can be substantially high. Therefore, we assume that the demand in the indirect channel is $(1 - a) \gg c$.

If the dual-channel supply chain undergoes vertical integration, the profit of the centralized dual-channel is given by

$$\pi_I = (p_s - c)D_s + (p_r - c)D_r - k\,\frac{x^2}{2} \tag{3}$$

Regarding investments in innovation, we assume that a significant amount of capital is invested over an extended period. Investment decisions must be made many years before final products are launched on the market. Therefore, the sequence of events in our model is as follows: First, the supplier selects the investment level x. Second, the supplier determines the retail price (p_s) of their own direct channel and the wholesale price (w). Third, the retailer, based on the wholesale price and the direct channel's retail price, determines the indirect channel's retail price (p_r). We employ a backward induction approach to obtaining equilibrium for both the supplier and the retailer. Figure 1 shows a conceptual diagram summarizing the relationships among the contract types, coordination outcomes, and investment returns.

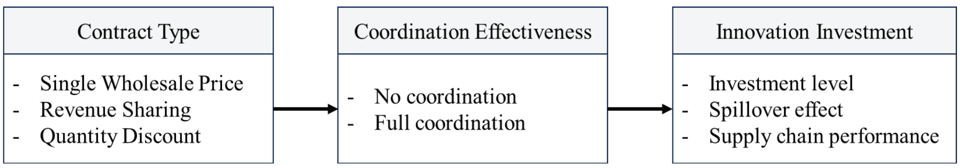

Figure 1. Conceptual diagram from contract type to coordination outcome and investment return.

4. The Equilibrium and Coordination Analysis Without Innovation Investment

Before discussing the investments made by the supplier (MNO), this section focuses on the equilibrium and coordination within the supplier-driven dual-channel supply chain. We evaluate the system-wide profit, which refers to the aggregated profit of all firms involved in the supply chain under coordinated decision-making. This concept is widely used in the literature on supply chain coordination as a normative benchmark [46,47]. First, we consider a centralized system where all decision-making is consolidated to maximize the entire channel's profit. Under this centralized system, the vertically integrated organization manages both the retail price (p_r) and the direct channel's price (p_s). Next, we explore a decentralized system within the Stackelberg game, with the supplier in a leading role. In this decentralized case, both the MNO and the MVNO make choices to maximize their expected profits.

4.1. A Centralized Dual-Channel Supply Chain

We first examine a benchmark model where both the direct channel and the indirect channel are centralized within the supply chain. The profit function (π_c) for each channel, considering the demand for both channels, is as follows:

$$\pi_c = (p_s - c)[a - p_s + b(p_r - p_s)] + (p_r - c)[1 - a - p_r + b(p_s - p_r)] \quad (4)$$

The profit-maximizing prices (p_s) and (p_r) and the expected profit (π_c) are as follows:

Proposition 1. *In a centralized dual-channel supply chain, the optimal price in each channel and maximized profit is given by*

$$p_s = \frac{a + b + (1 + 2b)c}{2(1 + 2b)}$$

$$p_r = \frac{1 - a + b + (1 + 2b)c}{2(1 + 2b)}$$

$$\pi_c = \frac{1 - 2(1 - a)a + b(1 - 2c)^2 - 2(1 - c)c}{4(1 + 2b)}.$$

From Proposition 1, we obtain the prices and profit for the benchmark case in the centralized dual-channel system. Next, we explore a decentralized system employing three different kinds of contracts. We consider a contract as coordinating the dual channel if the equilibrium outcomes of this contract are equivalent to those in the benchmark case. In addition, to ensure both channels have positive demand, we assume $a > 1 - a >> c$, as mentioned in Section 3. In the telecommunications market, significant infrastructure investments are made, while the marginal operating cost for services approaches zero.

4.2. A Decentralized Dual-Channel Supply Chain

Suppose that the MNO and the MVNO decide on a single wholesale price contract. The MNO determines the profit-maximizing wholesale price in the indirect channel and the retail price in its own direct channel; afterwards, the MVNO chooses the selling price in their indirect channel. The MNO's profit, π_s^{wp}, and the MVNO's profit, π_r^{wp}, are given as follows:

$$\pi_s^{wp} = (p_s - c)[a - p_s + b(p_r - p_s)] + (w - c)[1 - a - p_r + b(p_s - p_r)] \quad (5)$$

$$\pi_r^{wp} = (p_r - w)[1 - a - p_r + b(p_s - p_r)]. \quad (6)$$

To obtain the MNO and the MVNO's decisions in equilibrium, we solve through a backward induction approach. If the wholesale price of the MNO exceeds the MVNO's retail price, the retailer cannot make any profit and therefore ceases to participate in the retail market. This condition arises when $1 - a < c$, indicating that the demand in the direct channel approaches one, while the demand in the indirect channel nears zero. Consequently, when $1 - a > c$, a dual-channel wholesale price contract becomes feasible, and we can determine the following supply chain decisions and profits in equilibrium.

$$\pi_s^{wp} = \frac{1}{4(1 + b)}\left(\frac{(a + b - c - 2bc)^2}{1 + 2b} + \frac{(1 - a - c)^2}{2}\right)$$

$$\pi_r^{wp} = \frac{(1-a-c)^2}{16(1+b)}$$

Second, suppose that the MNO and the MVNO agree to a revenue sharing contract. We denote the initial wholesale price as w_0. In addition, let the supplier's share in a revenue sharing contract be denoted as 's' and the retailer's share be '$1-s$'. The MNO's profit, π_s^{rs}, and the MVNO's profit, π_r^{rs}, are given by

$$\pi_s^{rs} = (p_s - c)[a - p_s + b(p_r - p_s)] + (sp_r + w_0 - c)[1 - a - p_r + b(p_s - p_r)] \tag{7}$$

$$\pi_r^{rs} = [(1-s)p_r - w_0][1 - a - p_r + b(p_s - p_r)]. \tag{8}$$

Applying the same procedure, we obtain the following decisions and profits in equilibrium.

$$\pi_s^{rs} = \frac{1}{4(1+b)}\left(\frac{(a+b-c-2bc)^2}{1+2b} + \frac{(1-a-c)^2}{2-s}\right)$$

$$\pi_r^{rs} = \frac{(1-a-c)^2(1-s)}{4(1+b)(2-s)^2}$$

When the sharing ratio is $s = 0$, we observe the same results as those for the single wholesale price contract. However, when the sharing ratio is $s = 1$, the retailer's profit becomes zero, leading to non-participation in the market, which is close to the centralized dual-channel structure, as outlined in Proposition 1.

Third, suppose that the MNO and the MVNO enter into a quantity discount contract. The initial wholesale price is denoted as w_I, and it results in a discount of δ based on the quantity ordered by the MVNO. The wholesale price is $w_d = w_I - \delta D_r$, where D_r represents the MVNO's order quantity. The MNO's profits, π_s^{qd}, and the MVNO's profits, π_r^{qd}, are calculated as follows:

$$\begin{aligned}\pi_s^{qd} = (p_s - c)D_s \quad &+ (w_d - c)D_r \\ &= (p_s - c)[a - p_s + b(p_r - p_s)] \\ &+ (w_I - \delta D_r - c)[1 - a - p_r + b(p_s - p_r)]\end{aligned} \tag{9}$$

$$\pi_r^{qd} = [p_r - (w_I - \delta D_r)][1 - a - p_r + b(p_s - p_r)]. \tag{10}$$

By following the same procedure, we derive the following profits in equilibrium.

$$\pi_s^{qd} = \frac{1}{4(1+b)}\left(\frac{(a+b-c-2bc)^2}{1+2b} + \frac{(1-a-c)^2}{2-\delta-b\delta}\right)$$

$$\pi_r^{qd} = \frac{(1-a-c)^2(1-\delta-b\delta)}{4(1+b)(2-\delta-b\delta)^2}$$

When the discount parameter is $\delta = 0$, we have the same outcomes as those for the single wholesale price contract. However, when the discount parameter is $\delta \geq \frac{1}{1+b}$, the retailer cannot generate a positive profit. Therefore, we consider $\delta < \frac{1}{1+b}$ as a condition for maintaining the dual-channel structure. For instance, if the cross-price elasticity is $b = 0.7$, the maximum discount value for δ should be less than 58%.

Proposition 2. *In the dual-channel supply chain, the prices in both the direct and indirect channels, the wholesale price, and the profits in equilibrium under the single wholesale contract, the revenue sharing contract, and the quantity discount contract are presented in Table 2.*

Table 2. The equilibrium prices and profits for the decentralized supply chain based on the contract types.

	Single Wholesale Price	Revenue Sharing	Quantity Discount
w	$\frac{1-a+b+(1+2b)c}{2(1+2b)}$	$\frac{(1-s)(2(1+b)(1-a+b+c+2bc)-(2-a(2+3b)+b(4+b+c+2bc))s)}{2(1+b)(1+2b)(2-s)}$	$\frac{2a-2(1+b+c+2bc)+b(a+b)\delta+(2+b)(1+2b)c\delta}{2(1+2b)(-2+\delta+b\delta)}$
p_s	$\frac{a+b+(1+2b)c}{2(1+2b)}$	$\frac{a+b+(1+2b)c}{2(1+2b)}$	$\frac{a+b+(1+2b)c}{2(1+2b)}$
p_r	$\frac{3-a(3+4b)+c+2b(3+b+2(1+b)c)}{4(1+b)(1+2b)}$	$\frac{\frac{2+b(4+b)-a(2+3b)}{1+2b}+bc-\frac{1-a-c}{2-s}}{2(1+b)}$	$\frac{3+c+2b(3+b+2(1+b)c)-2d-b(6+c+b(5+b+3c+2bc))\delta-a(3+4b-(1+b)(2+3b)\delta)}{2(1+b)(1+2b)(2-\delta-b\delta)}$
D_s	$\frac{2a+b+ab-2c-3bc}{4(1+b)}$	$\frac{a(2+b+s)+b(1-3c-s+2cs)-c(2-s)}{2(1+b)(2-s)}$	$\frac{2a+b+ab-2c-3bc-(1+b)(a-c-b(1-2c))\delta}{2(1+b)(2-\delta-b\delta)}$
D_r	$\frac{4-6a+5b-7ab-2c-3bc}{4(1+b)}$	$\frac{2-3a+3b-4ab-c-2bc-\frac{b(1-a-c)}{2-s}}{2(1+b)}$	$\frac{2-3a+3b-4ab-c-2bc-\frac{b(1-a-c)}{2-d-b\delta}}{2(1+b)}$
π_s	$\frac{1}{4(1+b)}\left(\frac{(a+b-c-2bc)^2}{1+2b}+\frac{(1-a-c)^2}{2}\right)$	$\frac{1}{4(1+b)}\left(\frac{(a+b-c-2bc)^2}{1+2b}+\frac{(1-a-c)^2}{2-s}\right)$	$\frac{1}{4(1+b)}\left(\frac{(a+b-c-2bc)^2}{1+2b}+\frac{(1-a-c)^2}{2-\delta-b\delta}\right)$
π_r	$\frac{(1-a-c)^2}{16(1+b)}$	$\frac{(1-a-c)^2(1-s)}{4(1+b)(2-s)^2}$	$\frac{(1-a-c)^2(1-\delta-b\delta)}{4(1+b)(2-\delta-b\delta)^2}$

As illustrated in Table 2, in the supplier-led dual channel, all three contract types have the same retail price in their own direct channel. However, the wholesale price is different among the three contract types. In the single wholesale price contract, the MNO sets w to maximize the profits in both channels, and the MVNO also sets its retail price, p_r, to maximize its profits. Similar to the single channel, double marginalization also occurs in dual-channel supply chains. In the case of the revenue sharing contract, the MNO initially sets a lower w_0 (in extreme cases, $w_0 \cong c$, and with a low s, the indirect market becomes the MVNO's monopoly market) and takes a share of the revenue generated by the MVNO's sales. In the quantity discount contract, the MNO starts with a higher initial w_I (in extreme cases, $w_I \cong p_r$, making the indirect market the MNO's monopoly market) and offers linear discounts based on the MVNO's order quantity. The main difference is that revenue sharing is based on the realized profit, which allows the MVNO to set its retail price arbitrarily, while the outcome depends on the sharing ratio. In contrast, the quantity discount relies on the expected profit, as opposed to the realized profit, which results in differences. In other words, from the MNO's perspective in a single channel, a quantity discount contract represents a stable contract, while revenue sharing may yield varying realized profits depending on the uncertainties in demand.

Furthermore, dual-channel contracts exhibit distinctive characteristics compared to those of single-channel contracts. The marginal expected profit of the indirect channel in the revenue sharing contract, as the demand increases, is $\frac{\partial \pi_s}{\partial D_r} = sp_r + w_0 - c$, and it becomes a function depending on the MVNO's retail price. In contrast, for the quantity discount contract, the marginal expected profit of the indirect channel is $\frac{\partial \pi_s}{\partial D_r} = w - 2\delta D_r - c$. This equation depends on the difference between the retailer and supplier prices and the cross-price elasticity parameter, β, and is considered throughout the contract. It implies that in addition to the indirect channel retail price, the entire supply chain, including the supplier's direct channel, should be considered. In dual-channel quantity discount contracts, there is more room for coordination between the MNO and the MVNO. In markets led by the supplier, the discount parameter can be set to reduce the retailer's profit to zero in extreme cases. In single-channel contracts, both contract types depend on the retailer's price, making them equivalent in terms of their effects. In dual-channel contracts, the quantity discount contract, which affects the relationship between the direct and indirect channels, may be a more favorable environment for coordination. The majority of the literature reports that competition between the online direct channel and the conventional retail channel results in channel conflict. However, from a supply chain coordination perspective, the quantity discount contract, with its consideration of both the direct and indirect channels, offers a more favorable environment for coordination.

Moreover, for the quantity discount contract, it is possible to determine the value of δ that equals the performance in the centralized case, with the centralized dual channel ($\pi_c = \pi_s^{qd} + \pi_r^{qd}$). At the point where $\delta = \frac{1}{1+b}$, the entire supply chain profit is maximized. In contrast, for revenue sharing, only when the sharing ratio is s=1 does it align with the centralized π_c, in which case the retailer exits the market, indicating lower overall efficiency compared to that for the quantity discount contract.

Proposition 3. *When $a > \frac{1}{2}$ and $1 - a > c$, the quantity discount contract effectively coordinates the dual-channel supply chain. The contract parameters and profits are presented in Table 2. Specifically, the quantity discount contract with $\delta = \frac{1}{1+b}$ and $w = \frac{2a-2(1+b+c+2bc)+b(a+b)\delta+(2+b)(1+2b)c\delta}{2(1+2b)(-2+\delta+b\delta)}$ perfectly coordinates the dual-channel supply chain.*

When the profit of the supply chain is maximized at $\delta = \frac{1}{1+b}$, in this scenario, the MVNO's profit approaches zero, and the MNO's profit aligns with the centralized case. This indicates that the quantity discount contract has limitations for the retailer, as it brings in lower profits compared to those for a single wholesale contract. However, considering that the overall performance of the supply chain is higher than that for a simple single wholesale price contract, applying a transfer payment mechanism by the MNO can coordinate the entire supply chain. Therefore, the quantity discount contract, when combined with a proper transfer payment, can achieve perfect coordination, benefiting all firms with a Pareto improvement. In the case of revenue sharing, while it is not as straightforward as a quantity discount, by setting the sharing ratio to below 1 and implementing a transfer payment mechanism, it is possible to enhance the overall performance of the dual-channel supply chain compared to that with a single wholesale price contract.

Theorem 1. *When $a > \frac{1}{2}$ and $1 - a > c$, both a quantity discount contract with $\delta = \frac{1}{1+b} - \varepsilon$ and a revenue sharing contract with the sharing parameter s approaching 1 can effectively coordinate the dual-channel supply chain, and this creates a Pareto improvement zone. For both contract types, a transfer payment exceeding the MVNO's profit with a single wholesale price contract is required to achieve this coordination.*

4.3. A Numerical Example

For a direct channel where the demand is a = 0.7, the price elasticity is b = 0.5, and the operating cost is c = 0.1, under a single wholesale price contract, the MNO's profit is 0.1230, the MVNO's profit is 0.0035, and the total profit is 0.1265. Under a revenue sharing contract with a sharing ratio of s = 0.9, the MNO's profit is 0.1288, the MVNO's profit is 0.0011, and the total profit is 0.1299. For the quantity discount contract with a discount factor of δ = 0.625, the MNO's profit is 0.1292, the MVNO's profit is 0.0007, and the total profit is 0.1300. In both cases, the quantity discount and revenue sharing contracts outperform the single wholesale price contract in terms of their overall efficiency.

Figure 2a illustrates how the total profit of the supply chain for each contract relationship changes with increasing operating costs, while Figure 2b represents the effect of an increase in the preference of the customer for the direct channel (a) on the total supply chain profit for each contract type.

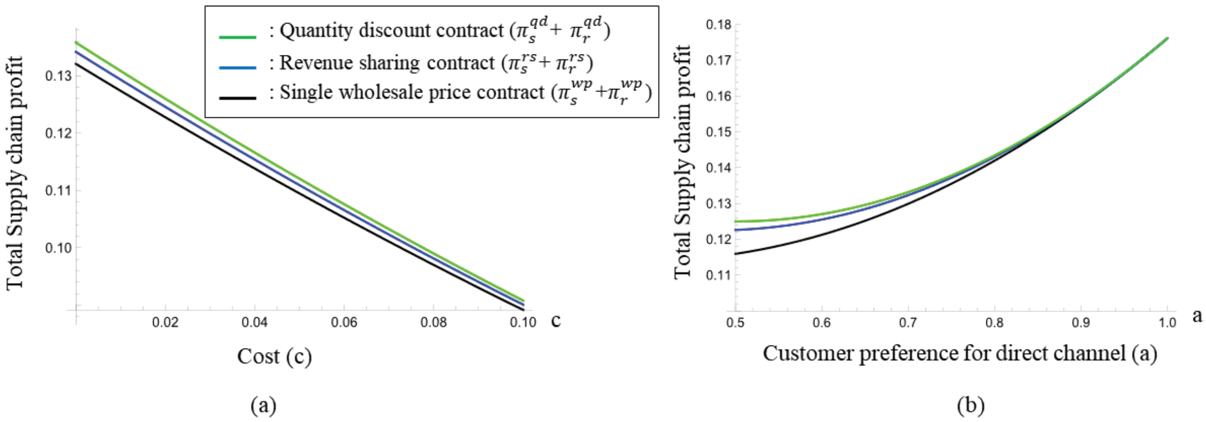

Figure 2. The performance of the decentralized dual-channel supply chain depending on the contract type with the x-axis representing cost in (**a**) and customer preference in (**b**).

The efficiency of the single wholesale price contract is the lowest (black line), followed by that of the revenue sharing contract with $s < 1$ (blue line). The quantity discount contract with $\delta = \frac{1}{1+b} - \varepsilon$ (green line) demonstrates the highest performance in terms of profit.

5. The Impact of Coordination on Investment and Spillover

In this section, we examine how investment for innovation is influenced by the coordination effect and how innovation investment affects the retailer in terms of spillover effects. As described in Section 3, the increase in demand caused by the investment is represented as γx. While the demand increases in the direct channel and the indirect channel may differ, for the sake of this analysis, we assume $\gamma_s = \gamma_r$ because both channels sell a homogeneous product of the same nature. This assumption also aids our understanding of the pure effects of the investments made by both the MNO and the MVNO on each channel.

First, the MNO determines its investment level. As in the previous section, the supplier then determines the wholesale price and the retail price of its own direct channel using the following objective function:

$$\pi_{sI} = (p_s - c)D_s + (w - c)D_r - k\frac{x^2}{2} \tag{11}$$

In this scenario, the MVNO's profit function remains unaffected. First, we analyze the centralized case as a benchmark model. Then, we proceed to analyze the coordination effect and the spillover effect when the supplier invests in innovation. In Section 5.3, we explore the case where the retailer is the innovator.

5.1. A Centralized Dual-Channel Supply Chain with Investment

First, we examine a centralized case as the benchmark model, where both channels are centralized. The profit function for each channel, considering the increase in demand resulting from investment in innovation, can be expressed as follows:

$$\pi_{cI} = (p_s - c)[a - p_s + b(p_r - p_s) + \gamma x] + (p_r - c)[1 - a - p_r + b(p_s - p_r) + \gamma x] - k\frac{x^2}{2} \tag{12}$$

The prices (p_s^* and p_r^*) and the resulting profit (π_{cI}) that maximize revenue can be determined as follows:

Proposition 4. *In a centralized case, the optimal investment level and price in each channel, in addition to the maximized profit, are*

$$x_{cI}^* = \frac{(1-2c)r}{2(k-\gamma^2)}$$

$$p_s^* = c + \frac{1}{4}\left[\frac{(1-2c)k}{k-\gamma^2} - \frac{1-2a}{1+2b}\right]$$

$$p_r^* = c + \frac{1}{4}\left[\frac{(1-2c)k}{k-\gamma^2} + \frac{1-2a}{1+2b}\right]$$

$$\pi_{cI} = \frac{1}{8}\left[\frac{(1-2a)^2}{1+2b} + \frac{(1-2c)^2 k}{k-\gamma^2}\right].$$

5.2. A Decentralized Dual-Channel Supply Chain with Supplier Investment

Based on the results from the previous section, we next evaluate the single wholesale price contract with the quantity discount contract that allows for the most effective coordination. The procedure begins with the supplier selecting the level of innovation investment, denoted as x. Afterwards, the sequence of events follows the same procedure as that outlined in the preceding section. The MNO's profit, π_{sI}^{wp}, and the MVNO's profit, π_{rI}^{wp}, in a single wholesale price contract are given by

$$\pi_{sI}^{wp} = (p_s - c)[a - p_s + b(p_r - p_s) + \gamma x] + (w-c)[1-a-p_r+b(p_s-p_r)+\gamma x] - k\frac{x^2}{2} \tag{13}$$

$$\pi_{rI}^{wp} = (p_r - w)[1-a-p_r+b(p_s-p_r)+\gamma x]. \tag{14}$$

To find the decisions of the MNO and the MVNO in equilibrium, we solve through backwards induction. Compared to the case without investment, the MNO's optimal retail and wholesale prices in the presence of investment for innovation increase by $\frac{rx}{2}$ ($p_s = \frac{a+b+c+2bc}{2(1+2b)} + \frac{\gamma x}{2}$, $w = \frac{1-a+b+(1+2b)c}{2(1+2b)} + \frac{\gamma x}{2}$). Consequently, we can obtain the profits of both the MNO and the MVNO as follows:

$$\begin{aligned}\pi_{sI}^{wp} = \frac{1}{8(1+b)(1+2b)}&[1-2a+3a^2+2b+2a^2b+2b^2-2c-2ac-8bc-4abc-8b^2c+3c^2+10bc^2 \\ &+8b^2c^2+2(1+2b)(1+a+b(2-4c)-3c)\gamma x-(1+2b)\Big(4(1+b)k+(3+4b)\gamma^2\Big)x^2]\end{aligned}$$

$$\pi_{rI}^{wp} = \frac{(1-a-c+\gamma x)^2}{16(1+b)}.$$

The MVNO benefits from the MNO's investment, and its profit increases compared to that in the scenario where no investment takes place ($\frac{(1-a-c)^2}{16(1+b)}$). For instance, if an MNO invests in a communication infrastructure with a doubled download speed, it becomes reasonable for the MNO to raise the direct channel price and generate additional profit. Meanwhile, an MVNO pays a higher wholesale price (w) but can also increase its retail price and profit because of the spillover effect. The retailer can also take an additional profit margin resulting from the supplier's investment. As illustrated in Figure 2, it is possible to determine the supplier's optimal investment level.

$$x_{sI}^{wp*} = \frac{(1+a+b(2-4c)-3c)\gamma}{4(1+b)k-(3+4b)\gamma^2}.$$

Comparing the profit-maximizing investment levels in both centralized and decentralized scenarios, as expected, the investment level is always lower for the single wholesale price contract ($x_{cI}^* > x_{sI}^*$).

Next, consider the relationship between investment for innovation and the quantity discount contract. The supplier profits, π_{sI}^{qd}, and the retailer profits, π_{rI}^{wp}, are calculated as follows:

$$\pi_{sI}^{qd} = (p_s - c)[a - p_s + b(p_r - p_s) + \gamma x] + (w_I - \delta D_r - c)[1 - a - p_r + b(p_s - p_r)] + \gamma x - k\frac{x^2}{2} \tag{15}$$

$$\pi_{rI}^{wp} = [p_r - (w_I - \delta D_r)][1 - a - p_r + b(p_s - p_r)]. \tag{16}$$

After obtaining the MNO and the MVNO's decisions in equilibrium, the profits are as follows:

$$\begin{aligned}\pi_{sI}^{qd} = {} & \frac{1}{4(1+b)(1+2b)(2-\delta-b\delta)}[1+2b+2b^2-2c-8bc-8b^2c+3c^2+10bc^2+8b^2c^2-b^2\delta-b^3\delta \\ & +2bc\delta+6b^2c\delta+4b^3c\delta-c^2\delta-5bc^2\delta-8b^2c^2\delta-4b^3c^2\delta+a^2(3+b(2-\delta)-\delta) \\ & +2(1+2b)(1+2b-3c-4bc+(1+b)(c-b(1-2c))\delta)\gamma x \\ & -(1+2b)\big(2(1+b)(2-\delta-b\delta)k+(3-\delta+b(4-3\delta-2b\delta))\gamma^2\big)x^2-2a\big(1+b\delta+b^2\delta \\ & +(1+2b)c(1-\delta-b\delta)+(1+2b)(1-\delta-b\delta)\gamma x)]\end{aligned}$$

$$\pi_{rI}^{wp} = \frac{(1-a-c+\gamma x)^2(1-\delta-b\delta)}{4(1+b)(2-\delta-b\delta)^2}.$$

As Figure 2 illustrates, the MNO's profit function is strictly concave, allowing us to determine the optimal investment level for the supplier, given by

$$x_{sI}^{qd*} = \frac{(1+a+2b-3c-4bc-(1+b)(a-c+b(1-2c))d)\gamma}{2(1+b)(2-d-bd)k-(3-d+b(4-(3+2b)d))\gamma^2}.$$

This demonstrates that the MVNO's profit increases as x increases.

Proposition 5. *The equilibrium prices in both the direct and indirect channels, the wholesale price, the investment level, and the profits in the decentralized dual-channel under single wholesale price contracts and quantity discount contracts, along with a comparison with the centralized dual-channel scenario, are presented in Table 3.* As seen in Figure 3a, when a supplier makes

an investment, the profit from a quantity discount contract (black line) is higher than that from a single wholesale price contract (blue line). The supplier's optimal investment level can also be determined, and the optimal investment level for a quantity discount contract is higher compared to that for the single wholesale price contract ($x_{sI}^{qd*} > x_{sI}^{wp*}$). Figure 3b illustrates the retailer's profit and highlights the spillover effect of innovation on the retailer. An interesting finding is that under the quantity discount contract, the spillover effect appears to be less influenced by the discount parameter δ.

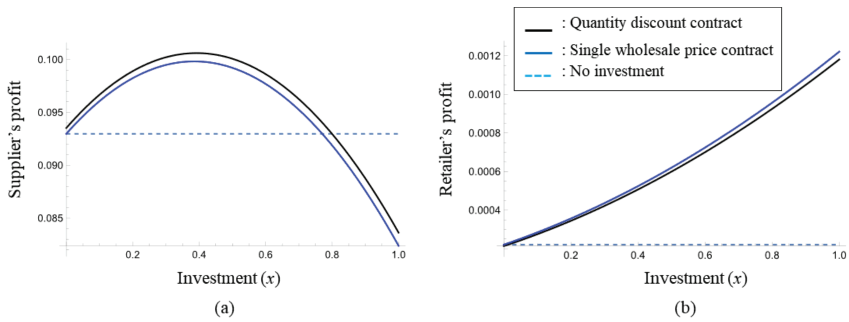

Figure 3. The profit changes with innovation investment depending on the contract type.

Table 3. The optimal investment levels, equilibrium prices, and profits depending on the contract type.

	Centralized Dual Channel	Single Wholesale Price Contract	Quantity Discount Contract
x	$\frac{(1-2c)r}{2(k-\gamma^2)}$	$\frac{(1+a+b(2-4c)-3c)\gamma}{4(1+b)k-(3+4b)\gamma^2}$	$\frac{(1+a+2b-3c-4bc-(1+b)(a-c+b(1-2c))d)\gamma}{2(1+b)(2-d-bd)k-(3-d+b(4-(3+2b)d))\gamma^2}$
w		$\frac{1-a+b+(1+2b)c}{2(1+2b)}+\frac{\gamma x}{2}$	$\frac{b(4-\delta-2b\delta)\gamma x+2(1+b+c+2bc+\gamma x)-\left(b^2+(2+b)(1+2b)c\right)\delta-a(2+b\delta)}{2(1+2b)(2-\delta-b\delta)}$
p_s	$c+\frac{1}{4}\left[\frac{(1-2c)k}{k-\gamma^2}-\frac{1-2a}{1+2b}\right]$	$\frac{a+b+c+2bc}{2(1+2b)}+\frac{\gamma x}{2}$	$\frac{a+b+c+2bc}{2(1+2b)}+\frac{\gamma x}{2}$
p_r	$c+\frac{1}{4}\left[\frac{(1-2c)k}{k-\gamma^2}-\frac{1-2a}{1+2b}\right]$	$\frac{3-a(3+4b)+c+3\gamma x+2b(3+b+2c+2bc+2(2+b)\gamma x)}{4(1+b)(1+2b)}$	$\frac{3+c+2b(3+b+2(1+b)c)-2\delta-b(6+c+b(5+b+3c+2bc))\delta-a(3+4b-(1+b)(2+3b)\delta)+3\gamma x-(2+b)(\delta-b(4-(3+2b)\delta))\gamma x}{2(1+b)(1+2b)(2-\delta-b\delta)}$
D_s	$\frac{2ak-2ck+\gamma^2-2a\gamma^2}{4(k-\gamma^2)}$	$\frac{a(2+b)+b-2c-3bc+(2+3b)\gamma x}{4(1+b)}$	$\frac{a(2+b(1-\delta)-\delta)-b(1-\delta)(1-3c+3\gamma x)-(2-\delta)(c-\gamma x)-b^2\delta(1-2c+2\gamma x)}{2(1+b)(2-\delta-b\delta)}$
D_r	$\frac{2(1-a-c)k-(1-2a)\gamma^2}{4(k-\gamma^2)}$	$\frac{1}{4}(1-a-c+\gamma x)$	$\frac{1-a-c+\gamma x}{2(2-\delta-b\delta)}$
π_s	$\frac{1}{8}\left[\frac{(1-2a)^2}{1+2b}+\frac{(1-2c)^2k}{k-\gamma^2}\right]$	$\frac{1}{8(1+b)(1+2b)}[1-2a+3a^2+2b+2a^2b+2b^2-2c-2ac-8bc-4abc-8b^2c+3c^2+10bc^2+8b^2c^2+2(1+2b)(1+a+b(2-4c)-3c)\gamma x-(1+2b)\left(4(1+b)k+(3+4b)\gamma^2\right)x^2]$	$\frac{1}{4(1+b)(1+2b)(2-\delta-b\delta)}[1+2b+2b^2-2c-8bc-8b^2c+3c^2+10bc^2+8b^2c^2-b^2\delta-b^3\delta+2bc\delta+6b^2c\delta+4b^3c\delta-c^2\delta-5bc^2\delta-8b^2c^2\delta-4b^3c^2\delta+a^2(3+b(2-\delta)-\delta)+2(1+2b)(1+2b-3c-4bc+(1+b)(c-b(1-2c))\delta)\gamma x-(1+2b)\left(2(1+b)(2-\delta-b\delta)k+(3-\delta+b(4-3\delta-2b\delta))\gamma^2\right)x^2-2a\left(1+b\delta+b^2\delta+(1+2b)c(1-\delta-b\delta)+(1+2b)(1-\delta-b\delta)\gamma x\right)]$
π_r		$\frac{(1-a-c+\gamma x)^2}{16(1+b)}$	$\frac{(1-a-c+\gamma x)^2(1-\delta-b\delta)}{4(1+b)(2-\delta-b\delta)^2}$

Let us evaluate the performance of the entire supply chain. We find that with the appropriate parameter settings for the quantity discount, as indicated in Theorem 1, we can achieve profits equivalent to those in a centralized dual channel setting. Due to tractability issues, it is challenging to express the optimal conditions analytically. However, a numerical investigation shows noteworthy insights. For instance, consider a scenario where the demand for the direct channel is $a = 0.7$, the cross-price elasticity is $b = 0.7$, the operating cost is $c = 0.1$, the innovation coefficient is $k = 0.1$, and the increase in demand due to investment is $r = 0.1$. In such a case, the total profit ties with that of the centralized dual channel, reaching 0.097 when applying the quantity discount contract with an optimal investment level of $x = 0.444$. Notably, the optimal investment level remains the same in both cases. In contrast, under the single wholesale price contract, the optimal investment level decreases to $x = 0.405$. Consequently, the profit for the entire supply chain diminishes to 0.095, indicating lower efficiency compared to that in the previous two scenarios. Figure 3 illustrates the performance of each supply chain. The appropriately coordinated quantity discount contract (blue line), with the parameters, demonstrates a performance close to that of the centralized dual channel (dashed line).

Theorem 2. *A quantity discount contract coordinates the dual channels with the supplier's investment for innovation, leading to a Pareto improvement zone. Through the quantity discount contract, the supplier achieves an equivalent investment level to that in the centralized case, effectively addressing the spillover effect of the investment.*

From the MNO's perspective as the supplier, there may be concerns about the spillover effect of investment on the MVNO. However, it is shown that the profit of the entire supply chain can be increased through an appropriate quantity discount mechanism and investment, surpassing the level achievable by a simple single wholesale price contract as shown in Figure 4. This implies that a high level of coordination can compensate for the spillover effect of innovation, and it is observed that the MNO's optimal investment level also increases.

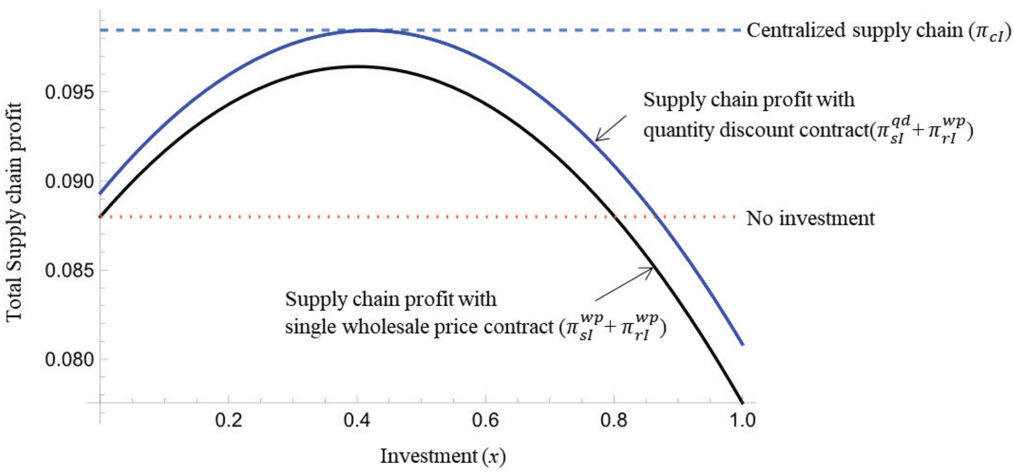

Figure 4. The supply chain performance with innovation investment depending on the contract type.

The analysis shows that coordination mechanisms—particularly quantity discount contracts—enhance the supplier's incentives to invest in innovation. In the absence of coordination, the supplier tends to underinvest due to its concerns about value appropriation by the retailer. However, coordination helps align the supplier's investment incentives with the overall efficiency of the supply chain by ensuring a more equitable distribution of the innovation gains. This results in improved profitability for both the MNO and the

MVNO, as the supplier captures a larger share of the returns while the retailer benefits from positive demand spillover.

5.3. A Decentralized Dual-Channel Supply Chain with Retailer Investment

Let us assume that the retailer makes an investment in launching new services (e.g., partnerships with OTT providers) or innovative customer services. In this case, it is supposed that this investment affects the indirect channel's demand while not impacting the direct channel. Following the same analysis as that in the previous sections, it is observed that the retailer's investment level results in lower p_s and w values compared to those for the supplier's investment. However, the retailer sets higher p_s and w values when no investment is made. An essential point to note is that when the retailer invests in its indirect channel, it seems that only the demand in the indirect channel increases. Still, since there is an upstream supplier, the MNO, even in the indirect channel, there is also a spillover effect on the supplier. Therefore, from the supplier's perspective, having an innovative retailer can provide similar benefits, leading to a desire to engage in transactions with such partners. Although the demand increase seems to be selfish, it affects the other party as well. It is also possible to determine the optimal investment level, denoted as x^*_{rI}:

$$x^*_{rI} = \frac{(1-a-c)\gamma}{8(1+b)k - \gamma^2}.$$

The value of x^*_{rI} is lower than the supplier's optimal level of investment. Nonetheless, the MNO's profit also increases with the MVNO's investment.

When the MVNO undertakes innovation, the resulting improvements in demand also extend upstream, generating positive spillover effects for the MNO. This mutual spillover dynamic highlights the potential for shared value creation within the dual-channel structure. Contractual coordination that accounts for these interdependencies can further encourage innovation efforts from both parties. Ultimately, such coordination fosters a more synergistic and strategically aligned relationship between the MNO and the MVNO.

We analyzed cases where the increase in demand for the MNO, γ_s, does not equal the increase in demand for the MNO ($\gamma_s \neq \gamma_r$). For instance, when $\gamma_s > \gamma_r$, the spillover effect on the retailer was lower than that in symmetric cases ($\gamma_s = \gamma_r$). However, this difference in the parameter values does not invalidate the implications of Proposition 5; it merely shows a minor variation. In addition, it is noteworthy that while the assumption is unrealistic, we conducted an additional analysis in a scenario where the MNO's investment had no effect on the demand in the indirect channel. In this case, the MNO's investment still leads to an increase in wholesale prices and direct channel retail prices, which, in turn, affects the retailer's indirect channel prices, causing them to rise. However, it is proven that the increase in demand in the direct channel does not have an effect on the MVNO's profit in this scenario.

6. Conclusions

This study examined how contract design and investment spillover effects jointly influence the coordination and performance in dual-channel supply chains, with a focus on the telecommunications industry. Grounded in the supplier-dominated market structure often observed in mobile network operations, the model captures the strategic interaction between a mobile network operator (MNO) and a mobile virtual network operator (MVNO). The analysis centers on how investment in innovation by one party—particularly the supplier—can generate externalities that affect the other party's performance, a phenomenon defined here as an investment spillover effect.

A key contribution of this work is the demonstration that quantity discount contracts can serve as an effective coordination mechanism in the presence of investment externalities. Compared to single wholesale price contracts, quantity discounts align the investment incentives better and enhance supplier profitability while maintaining competitive pricing on the retail market. In particular, this form of contract improves the joint profitability—interpreted as the system-level efficiency—by internalizing the externalities that arise from unilateral investment. These findings support the broader view that contractual mechanisms are not merely tools for setting prices but also function as strategic governance instruments in supply chains.

The results also reveal asymmetry in the spillover dynamics: supplier-led investments tend to generate stronger system-wide gains, while retailer-led investments yield more limited indirect benefits to the supplier. This asymmetry underscores the need for contract structures that address such imbalances, especially in sectors like telecommunications, where one party holds significant infrastructure and bargaining power.

Nevertheless, several simplifying assumptions in the model may limit the generalizability of the results. First, the assumption of product homogeneity abstracts from the practical differentiation strategies employed by MVNOs—such as customized pricing, bundling, or branding—that may influence the consumer demand across channels. Second, the model presumes symmetric and complete information between contracting parties, whereas in practice, strategic intentions and investment priorities may not be fully observable or shared. Third, the analysis is based on a bilateral MNO-MVNO relationship, while actual markets typically involve multiple players engaging in competitive and regulatory interactions. While these assumptions facilitate analytical tractability, relaxing them would allow for richer and more realistic insights. Future research could address these limitations by incorporating competitive market structures, asymmetric information, and dynamic investment behavior. In particular, analyzing the impact of regulatory interventions—such as mandated access, pricing controls, or innovation subsidies—could yield valuable implications for both policymakers and industry stakeholders. Lastly, although Theorems 1 and 2 are based on numerical observations due to analytical intractability, they are logically consistent within the model's framework and serve as theoretically grounded hypotheses that can be tested in future empirical or simulation-based studies.

These findings also carry practical implications. For policymakers, contract design may serve as an indirect yet powerful policy lever to enhance investment incentives and promote market efficiency. For firms operating in capital-intensive and innovation-driven sectors, aligning the contract terms with spillover realities is critical for achieving sustainable collaboration and mutual profitability.

Funding: This work was supported by Hankuk University of Foreign Studies Research Fund.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author(s).

Conflicts of Interest: The author declares no conflicts of interest.

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Article

Security and Resilience of a Data Space Based Manufacturing Supply Chain

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Abstract: The manufacturing supply chain has been exposed to natural disasters and geopolitical risks whose impacts, such as disruptions in the supply of materials and parts, can be devastating. In recent years, the data space has become more widely implemented, and it is expected to be used as a platform for widespread collaboration between companies. This article discusses how companies participating in the manufacturing supply chain cooperate to recover from disruption and mitigate risks using a data space platform and a flexible manufacturing system. Employing enterprise architecture modeling, we explore a comprehensive strategy for enhancing the resilience of a data space-based manufacturing supply chain. The proposed strategy adopts a comprehensive approach to addressing physical security and cybersecurity risks from a security perspective. By combining enterprise architecture modeling with the Unified Architecture Framework and conducting a scenario-based simulation, we discovered that an alternative manufacturing process with a flexible method in the data space can be a key security control measure for mitigating the risk associated with parts supply. The results of the alternative manufacturing simulation show that flexible manufacturing using BJT and MIM methods elicits better performance in terms of parts production volume and cost compared with conventional methods. The proposed method and the findings of this study contribute to consolidating a profound understanding of security and the mitigation of disruptive situations in a data space-based manufacturing supply chain.

Keywords: data space; system security engineering; alternative manufacturing; enterprise architecture modeling; manufacturing supply chain

1. Introduction

The manufacturing supply chain is becoming increasingly vulnerable to natural disasters and geopolitical risks, which can result in several challenges, including disruptions in the supply of raw materials and intermediate components [1,2]. A single company cannot adequately address such severe situations. Consequently, there is an increasing emphasis on the establishment of collaborative networks among supply chain stakeholders [3]. Such collaborative efforts are deemed crucial in the management of challenging circumstances.

The concept of smart manufacturing has been proven to enable flexible responses to changes in demand by leveraging technologies such as artificial intelligence (AI), the Internet of Things (IoT), robotics, Additive Manufacturing (AM) [4,5], and the data space as a data-sharing and collaboration platform [6]. In 2021, to maintain harmony with society, Industry 5.0 was proposed to complement *Industrie 4.0*. Industry 5.0 is an extension of *Industrie 4.0*, incorporating three visions—sustainability, resilience, and human-centric nature—as well as the use of data communication in the data space and simulations of social impact to achieve the aforementioned visions [7,8]. The challenges posed by increasingly complex social issues and the difficulty of ensuring the resilience of supply chains are examples of the opportunities that Industry 5.0 could address. The recent challenges encountered worldwide, including geopolitical conflicts and natural disasters, have caused disruptions in the parts manufacturing supply chain, raising concerns regarding the stable supply of products. In response to the increased risk of disruptions in the manufacturing supply chain, attempts have been devoted to clarifying the dynamic behavior of manufacturing supply chain systems using numerical simulation methods. Wofuru-Nyenke et al. conducted a review on this topic [9]. Özbayrak et al. defined the manufacturing supply chain system (MSCS) and demonstrated the effectiveness of information-based inventory management in response to fluctuations in demand [10].

A data-sharing and collaboration mechanism between companies has been developed to address issues that prove difficult for a single company to tackle. The International Data Space Association (IDSA) in Germany has developed technology for creating a data-sharing platform (data space) that enables the sharing and linking of mutual data to link the upstream and downstream of the supply chain and provide a connector that enables collaboration among companies [6]. The concept of data sharing in a data space necessitates a reliable mechanism, data governance, and data reliability. The Gaia-X and IDS (International Data Space) concepts of rule formation and mechanisms offer a promising approach, as they deviate from conventional centralized data control mechanisms. Although the data-sharing scope remains limited, the mechanism functions holistically [11]. As a use case for the data space, Catena-X proposes services that contribute to the visualization of CO_2 emissions throughout the automotive industry supply chain [12].

As the supply chain becomes increasingly globalized, it becomes vulnerable to disruptions. Thus, the perspective of supply chain security and resilience must be considered. The data space is a system that upholds data sovereignty, and many use cases have been developed as data-sharing and collaboration mechanisms while ensuring the safety of participants. However, when defining an architecture for deploying such a system in the manufacturing supply chain, the concerns of supply chain stakeholders need to be considered.

This study aims to elucidate the structure of collaborative manufacturing from a safety perspective to enhance resiliency. The manufacturing supply chain was explored from the perspective of security via enterprise architecture (EA) modeling. First, a strategy for enhancing security and resilience in the EA framework was explored. Second, based on the strategy, a manufacturing supply chain system that employs the data space was introduced to achieve flexible manufacturing while ensuring security and resilience for businesses engaged in the data space under conditions of unstable supply chain dynamics. To validate the effect of the concept, a comparative study of multiple manufacturing process candidates was conducted using resilience evaluation metrics. The research questions proposed in this study are as follows:

[RQ1] If partial disruption in the manufacturing supply chain occurs, what framework and capabilities are required to be able to accelerate recovery as mitigation? Refer to the results in Section 4.2.2.

[RQ2] What metrics will be used to evaluate the results of temporary risk mitigation? Refer to the results in Sections 4.3.2 and 4.3.3.

Enterprise architecture modeling encourages us to understand how enterprises work together in a data space-aided manufacturing supply chain. Enterprise architecture modeling offers us a holistic understanding of the whole supply chain structure and ways to mitigate the risks of supply chain disruption.

Based on enterprise architecture (EA) modeling and the evaluation of effectiveness measures, this study contributes to defining a plan for how products are manufactured and delivered using a data space under conditions of disruption. EA modeling explains how risks and capabilities are linked in data space-based supply chains. This knowledge proves how alternative manufacturing processes show improved performance due to collaboration in a data space. This study contributes to assisting decision-makers in providing options for understanding stability and reducing problems in manufacturing supply chains.

The rest of this paper is organized as follows. Section 2 describes the role of system security engineering in supply chain management (SCM). It presents an overview of the definition of resilience, the responsibility of systems engineering, and Gaia-X, a typical data space framework. Section 3 describes the modeling method of EA and the scenario-based evaluation model. Section 4 explains the modeling results. The diagrams are described from the viewpoints of security management concepts and resilience, and resilience metrics are defined. Section 5 discusses the results and the limitations of this study. Section 6 presents the conclusions and provides recommendations for future research.

2. Background and Literature Review

Supply chain resilience has long been a subject of research. In recent years, comprehensive system structures have begun to be revealed through systems engineering initiatives. Section 2 explains supply chain initiatives in system security engineering (SSE) and resilience engineering (RE). It also offers clear background information by explaining the recently emerging concept of a data space. Next, in Section 2.4, we will review previous studies on the progress and challenges of resilience in supply chains, thereby clarifying the focus of our research.

2.1. System Security Engineering in Supply Chain Management

System Security Engineering (SSE) is a specialized discipline that focuses on ensuring that systems can operate effectively under anomalous and disruptive conditions, including those originating in cyber-contested environments [13] (pp. 190–191). SSE applies the principles of systems engineering to evaluate security threats, address system vulnerabilities, and manage security risks across the entire system life cycle. This integrated approach blends technology, management practices, and operational guidelines to ensure that adequate protections are in place to safeguard the system and its critical assets.

The scope of SSE encompasses threats from various sources, including external factors, such as cyberattacks, theft, power interruptions, and denial-of-service attacks, as well as internal risks caused by user actions, system misuse, or malicious behavior. Such disruptions may be intentional, such as those caused by intelligent adversaries, or unintentional, resulting from errors or system failures. To mitigate such risks, SSE incorporates physical security measures, including surveillance, access control, anti-tampering technologies, and protective barriers, as well as cybersecurity principles, such as the confidentiality, integrity, and availability of information assets.

SSE practitioners require expertise in areas such as security architecture, threat assessment, vulnerability testing, and supply chain risk management. To support effective implementation, frameworks such as those outlined in the National Institute of Standards and Technology Special Publications, NIST SP 800-160 Vol. 1 [14] and Vol. 2 [15], can guide the integration of cybersecurity into systems engineering processes. These guidelines, which align with ISO/IEC/IEEE 15288 (2023) [16], highlight the inter-relationship between systems engineering and SSE, offering detailed methodologies for embedding security into technical processes. For instance, NIST SP 800-160 includes structured examples, such as the breakout of technical SSE processes that outline specific roles, activities, inputs, and outcomes to ensure the seamless integration of security measures.

In the context of supply chain security, NIST defines "supply chain" and "cybersecurity risks throughout the supply chain" as follows. The term "*supply chain*" refers to the linked set of resources and processes between and among multiple levels of an enterprise, each of which is an acquirer that begins with the sourcing of products and services and extends through the product and service life cycle. Given this definition, "*cybersecurity risks throughout the supply chain*" refers to the potential for harm or compromise that may originate from suppliers, their supply chains, their products, or their services. Cybersecurity risks throughout the supply chain are the results of threats that exploit the vulnerabilities or exposures in products and services that traverse the supply chain or threats that exploit vulnerabilities or exposures in the supply chain (NIST SP 800-161r1, [17]).

Here, the fundamental requirements for improving the resilience of supply chains as a system of systems (SoS) by maintaining supply chain security are identified. Next, we explore resilience in systems engineering.

2.2. Resilience in Systems Engineering

Resilience engineering is defined in a systems engineering handbook [13] (pp. 180–184) as "an approach that provides the required capability when facing adversity," and "resilience directs the focus of systems engineering to the ability of the system to deliver capability under adverse conditions." Additionally, the handbook suggests that the taxonomy of resilience comprises two layers. The first layer represents the *objective* category, which includes *Avoid*, *Withstand*, and *Recover* from adversities. The second layer represents the *means* category, which includes *Agility*, *Evolution*, *Graceful degradation*, *Re-architect*, *Robustness*, and *Tolerance*.

Resilience engineering focuses on ensuring that systems deliver the required capabilities under adverse conditions. Resilience emerged in systems engineering around 2006 and gained popularity by 2010; it frequently includes survivability but emphasizes functionality over maintaining structure. Traditional system design focuses on normal conditions, whereas resilience prioritizes performance under conditions of disruption.

Nemeth and Hollnagel [18] investigated the general functions of social resilience, distinguishing between the proactive and reactive aspects. They suggested that risk assessment, prediction, prevention, and mitigation measures are proactive functions, whereas impact assessment, response to and recovery from situations, and evaluation are considered reactive functions. They emphasized the importance of integrating the proactive and reactive functions to ensure a comprehensive approach to social resilience [18] (p. 7). Key aspects include the following three items: "defining essential system capabilities," "identifying adverse conditions," and "designing systems to maintain functionality." Resilience values adaptability and functionality over preserving the original architecture. It shifts the focus to ensuring a reliable performance in complex, unpredictable environments.

When a system is faced with adversity, a system transitions through various states, ranging from fully capable to minimally acceptable, with intermediate states, such as partially capable or damaged [13] (p. 181). These transitions are categorized into three types: *robustness*, where the system maintains its current capability; *tolerance*, where capability degrades to a lower level; and *recovery*, where capability improves, potentially returning to full functionality. Effective system design should incorporate principles to manage these transitions and ensure context-fit behavior. In this study, we mainly focus on a proactive approach in the case of an emergent situation of manufacturing supply chains.

2.3. Data Space

This section describes the data space being built in the European Union (EU). After *Industrie 4.0*, issues such as the pursuit of productivity, reductions in greenhouse gas emissions, and supply chain stabilization could no longer be addressed by a single company. Thus, the European Commission has turned to proposing the standardization of data that are widely shared across industries and the specific operation of a data space with high reliability and flexibility in Gaia-X [19].

The data spaces being proposed by the European Commission include industry, green deal, and mobility. In the industrial data space, data collaboration related to development and production is promoted among enterprises, focusing on the manufacturing industry, and manufacturing innovation is realized using digital technology. Herein, the background to the establishment of Gaia-X, as well as its vision and strategy, is described based on a Gaia-X white paper [19]. Gaia-X is an initiative aiming to develop an open software layer that can implement control, governance, and common policies and rules to achieve the transparency, sovereignty, and interoperability of data and services. Cloud players can use it to implement the open software layer and its associated policies and rules.

The digital economy is enabled by shared data spaces and reliable cloud-based services. A wide range of players, from innovative start-ups to established small, medium, and large enterprises, require a level playing field to benefit from the economies of scale and scope that can be achieved through regional cooperation in the EU. Thus, Gaia-X is necessary for industrial collaboration.

The architecture of the Cloud Federation is explored, including (1) developing ontologies and application programming interfaces to improve data interoperability and (2) ensuring the interconnectivity of the data space and other aspects of the Cloud Federation architecture. In addition, Gaia-X is developing over 40 use cases in areas such as manufacturing, smart housing, and mobility to build prototypes and begin operations by early 2021. In the future, as the main field in the digital dispatch race becomes the use of data at the edge created by social and industrial infrastructure, it is expected that attention to distributed data governance models, such as Gaia-X, will further increase [20–22].

Specific use cases are proposed, motivated by the need to address various opportunities and challenges, such as resource-recycling economies, supply chain stability, and smart manufacturing. A typical example is resource recycling, CO_2 emission visualization, and battery traceability of the automotive supply chain using Catena-X, where data sharing among related participating organizations is essential. End users, governments, and participating organizations exist as related stakeholders, and the framework aims to address stakeholder concerns [12,23]. When the manufacturing supply chain suffers from disruptions, which is the subject of this study, it is believed that risk can be avoided or minimized through collaboration between participating organizations in a data space.

2.4. Literature Review of Interoperable System in Supply Chain

The applications of IoT devices and mechanisms are areas of major interest to researchers in production management. Trappey et al. [24] summarized standards and patents regarding IoT devices. In addition, there are critical technologies that exist for *Industie 4.0* and Industry 5.0. Menanno et al. [25] studied how radio frequency identification (RFID) could help track food products more effectively. They showed that it could improve operations in a supply chain that is always producing the same amount of products. Pohlmeyer et al. [26] suggested a system that uses the Digital Product Passport to strictly enforce product traceability and contribute to sustainability. Mitra et al. [27] obtained quantitative data from over 500 respondents which revealed the positive impacts of various factors on IoT adoption and the transformative potential of IoT in enhancing operational efficiency. These technologies have been developed to trace products within the supply chain and share data. However, to keep the supply chain resilient, we need a way to share supply chain logistics data safely and flexibly.

Hause et al. [28] regard the supply chain as one of the most complex SoSs and attempted to construct logical architecture that responds to the concerns of stakeholders through enterprise architecture modeling of the supply chain. They adopted a security perspective for the purpose of developing a risk control plan. Although they mentioned the security risks of the supply chain, they mainly focused on the established and standard structure of the supply chain. Hosseinni et al. [29] proposed a systemic approach for supply chain resilience evaluation by using the Bayesian network. They concluded that supply chain resilience is composed of a surplus inventory, capacity flexibility, and back-up suppliers. Alexopoulos et al. [30] used a metric known as POC (Penalty of Change) to probabilistically evaluate supply chain disruptions based on an estimation model and certain scenarios. Using this model, managers can develop preliminary plans. This study adopted a predictive approach for investment. However, under the collaborative network based on the data space, a flexible supply chain with a quick decision-making process is crucial. Bakopoulos et al. [31] proposed an architecture that addresses resilience using the data space. However, the system proposal still needs to be examined in relation to system security engineering. To identify and address risks, it is necessary to analyze the entire surrounding supply chain. Table 1 lists a summary of the aforementioned studies regarding the digitally enhanced supply chain.

Table 1. Studies on supply chain resilience and digital solutions in supply chain (SC).

Author	Field and Method	Key Findings	Limitations
Menanno (2023) [25]	VCOR and PMS for RFIDs in the SC.	RFIDs in the agri-food industry are influenced by specific organizational procedures.	KPI analysis was limited to a restricted material flow. It did not include economic analysis.
Pohlmeyer (2024) [26]	A data ecosystem with a Digital Product Passport for traceability in the SC.	The findings support a sovereign data ecosystem enhancing eco-efficiency and sustainability.	It lacks real-world validation and implementation. Data sharing is hindered by confidentiality concerns and errors.
Mitra (2024) [27]	Structural Equation Mode for IoT in the SC.	Quantitative data from over 500 respondents indicate positive impacts and reveal the transformative potential of IoT in enhancing operational efficiency.	Geographical limitations affect the generalizability of the findings. Potential bias in the literature review may influence the results.
Hause (2024) [28]	Enterprise architecture modeling of the SC with UAF.	It provides strategic and operational views to define procedures and elements. Robust risk management is investigated.	The focus is on the established supply chain network. Digital technology is limited.
Hosseini (2022) [29]	Novel measurement method using Bayesian networks for the SC.	The metric can serve as a KPI for analyzing disruption impacts on the SC.	The metric is applicable only to directed graphs without cycles, limiting its broader application. The measure does not consider recovery processes, which are crucial for resident systems.

Table 1. *Cont.*

Author	Field and Method	Key Findings	Limitations
Alexopoulos (2022) [30]	Resilience qualification of the plastic parts SC by using POC (Penalty of Change).	3D printing (AM) and injection molding are compared.	The POC metrics can be used in decision-making for the initial investment.
Bakopoulos (2024) [31]	A value chain planning approach with POC metrics for a SC using the data space.	A framework for resilient manufacturing value chains is proposed, leveraging data space technology.	Decision-making is often delayed due to reliance on industrial experts. The current architecture is inflexible, hindering structured integration of planning solutions.

The motivation of this study is to provide methodologies for making comprehensive and flexible decisions under disruptive situations immediately. We aim to understand the structure of supply chains based on the data space, identify risks, and verify resilience capability under unexpected situations by utilizing data spaces from security and resilience perspectives. An enterprise architecture modeling approach allows us to capture the risks facing the manufacturing supply chain using a data space. Finally, the comparative analysis and sensitivity study enable us to select the optimal configuration, using the updated data from each candidate, which incorporates alternative manufacturing.

3. Research Methodologies

Modeling the structure of enterprises of the manufacturing supply chain as an architecture provides a comprehensive understanding of security (2.1) and resilience (2.2) issues. This paper provides strategies and practical knowledge for decision-making by comparing and evaluating the adequacy of measures to deal with supply chain disruptions using effectiveness indicators obtained through modeling.

3.1. Enterprise Architecture (EA) Modeling: Theoretical Background

The EA methodology described in the international standard ISO/IEC/IEEE 42020 (2019) [32] "software, systems, and enterprise architecture processes" is adopted in this study. This standard defines six architectural processes and their objectives. In this study, we focus on Clauses 8 and 10. We start from the architecture conceptualization process (Clause 8) which characterizes the problem space and determines suitable solutions that address stakeholder concerns, achieve architecture objectives, and meet the relevant requirements. Thereafter, we move on to Clause 10, architecture elaboration.

In the architecture elaboration process, planning EA efforts involves selecting appropriate views to ensure coherence and completeness. The planning and preparation process helps identify suitable views for various EA and non-EA efforts. An example of a non-EA effort is a solution architecture, which addresses specific real-world problems. The architecture modeling approach supports the conceptualization and evaluation of the candidate architecture. It aligns with the architecture elaboration process in ISO/IEEE/IEC 42020 (2019) [32], where models and views are developed to form the architecture description. ISO/IEEE/IEC 21839 (2019) [33] defines an SoS as "a set of systems or system elements that interact to provide a unique capability that none of the constituent systems can accomplish alone".

To maintain the original capability of the manufacturing supply chain, three phases (*robustness*, *tolerance*, and *recovery*) exist, as described in Section 2.2. It is necessary to identify and evaluate their vulnerability to external threats, and a system that improves the flexibility of supply chains and promotes reconfiguration using data spaces needs to be developed to secure the manufacturing supply chain. Concurrently, it is imperative to address the risk of cybersecurity in systems by leveraging data spaces in the *robustness* phase. In the *tolerance* to *recovery* phase, the acquisition of services to enhance resilience and augment its capacity is crucial. The efficiency of these services or recovery processes should be determined using evaluation metrics. To the best of our knowledge, no other study has applied EA modeling to examine security and resilient views of manufacturing supply chains that are firmly linked with data spaces.

The enterprise architecture (EA) process—covering analysis, design, planning, and implementation—relies on modeling to visualize systems and raise abstraction levels. This aids early-stage verification and gives designers a broad view of business and organizational aspects. EA models, kept abstract, can be adapted to various supply chain designs. System modeling also clarifies architecture, supports decision-making, and ensures traceability, helping identify the effects of changes in complex systems.

Theoretical foundations for conceptual modeling include ontological, epistemological, linguistic, and pragmatic principles [34]. A conceptual model depicted by diagrams facilitates the communication and understanding of the system models [35].

The Unified Architecture Framework (UAF; Object Management Group) can be used to model the enterprise architecture and link it to the operational performers in the enterprise [36–38]. System modeling effectively promotes decision-making by clarifying logical feasibility and trade-offs by holistically expressing a systematic architecture. As traceability is ensured, it is possible to identify the scope of the impact of partial changes to complex systems. The UAF facilitates the modeling of an SoS holistically and strategically. Its description employs the UAF modeling language (UAFML), which is based on UML 2.5.1 and System Modeling Language (SysML) [39]. UAFML expression contributes to expressing diagrams using predefined terms and maintaining the reproducibility of architectures. Furthermore, it facilitates abstract representations that can be reused for similar architectures in different domains. We used the UAF to model an SoS (System of Systems) that defines supply chain structure and behavior and elucidates its security and resilience. The architecture is expressed as a diagram from each viewpoint, and each element is kept traceable with consistency. Appendix B lists the defined words and descriptions which are defined in the UAFML and used in each diagram in this study.

3.2. Overview of Methodology

The methodology adopted for this study is described in Figure 1, and it has two steps: The first step is the execution of enterprise architecture modeling to capture a holistic structure, identify problems, and obtain strategies to ensure the resilience of a system of systems. The second step involves validation from an economic and productivity viewpoint.

3.2.1. (Step 1) Enterprise Architecture Modeling of System of Systems

System modeling effectively promotes decision-making by clarifying logical feasibility and trade-offs by holistically expressing a systematic architecture. As traceability is ensured, it is possible to identify the scope of the impact of partial changes to complex systems. The architecture is expressed as a diagram from each viewpoint, and each element is kept traceable with consistency.

The first step is composed of the following process.

(1) Capture issues and opportunities in the supply chain (Sections 4.1.1 and 4.1.2):

A Strategic Motivation (St-Mv) Diagram of the UAF [37] is utilized to define the supply chain system of systems. It is imperative to define the enterprise motivation model to enforce the supply chain from a strategic perspective.

(2) Define capabilities to develop or obtain a resilient manufacturing supply chain (Section 4.1.3):

Capabilities are linked with challenges and Opportunities.

(3) Extract risks in view of SSE and RE (Section 4.2.1):

Subsequently, as part of SSE, risks inherent in the system are identified by referencing NIST [17] and OMBOK [40].

(4) Define logical architecture of data space-based supply chain (Section 4.2.2):

These risks are mapped to the SoS being targeted in this study to gain an overview. This activity employs the resource taxonomy diagram (Rs-Tx [37]).

(5) Define MOP (Measure of Performance) and MOE (Measure of Effectiveness) (Section 4.2.3):

Based on the holistic understanding of the relationship between system elements and risks, a security taxonomy diagram (Sc-Tx) [37] is formulated to visualize the capabilities that need to be obtained for risk mitigation, as well as the risks that threaten these capabilities.

Enterprise architecture modeling activities facilitate the articulation of measures to address supply chain breakdown risks stemming from the environment surrounding the supply chain.

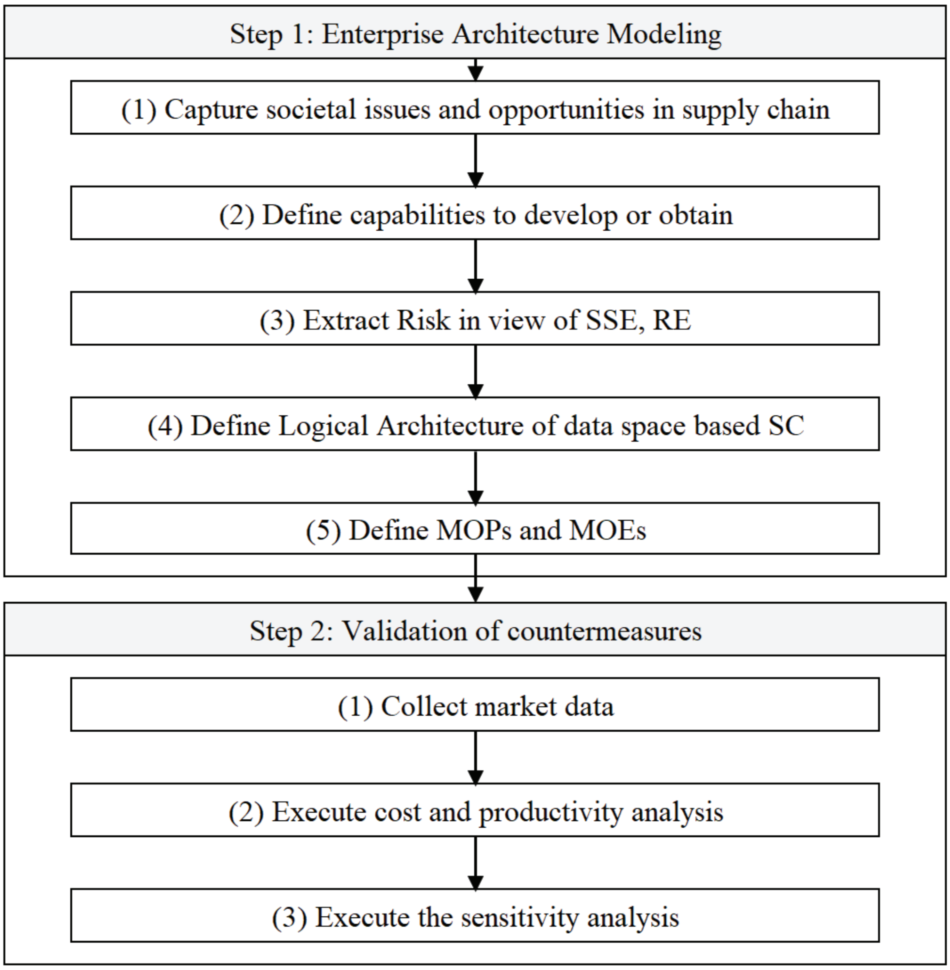

Figure 1. An overview of the flow of the methodology used in this study.

3.2.2. (Step 2) Validation: Parts Supply Disruption and Alternative Manufacturing

In the process of architecture elaboration, the quantitative approach entails the modeling and evaluation of the MOE. A methodology for assessing the effectiveness and performance of an SoS is proposed [41]. This methodology applies the UAF to calculate metrics and employs a description of the systems in the UAF. The MOE of an SoS is the metric of *Capability*. Moreover, the MOE is defined using the measure of performance (MOP) of a system in an operational process that is logically constructed. We can evaluate the resilience of manufacturing supply chains in terms of economic and effectiveness aspects by using the security taxonomy diagram of the UAF, which describes the relationship between the corresponding system, the MOP of the system, constraints, and the MOE, which functions as a metric for evaluating capability. To obtain knowledge about the risk mitigation strategy, a sensitivity analysis is conducted.

In this study, the risk mitigation scenario (Section 3.3) is based on the manufacturing supply chain using the data space and alternative manufacturing. The formulation of the MOPs and MOEs are described in Section 3.5 for the cost and performance analysis.

In this step, the scenario-based evaluation of the MOEs is examined. The viability of alternative manufacturing methods as countermeasures in a critical situation can be evaluated with MOEs regarding economical aspect and productivity.

The second step is composed of the following process.

(1) Collect data from service provider (Section 4.3.1)

In this study, we focus on the manufacturing of impellers made of stainless steel. The price of manufacturing with each method is collected from the currently available cloud-based manufacturing service data.

(2) Execute cost and productivity analysis (Section 4.3.2)

From the perspective of alternative manufacturing performance, production volume is estimated using Equation (1), and cost estimates for each method are derived from Equation (2).

(3) Execute sensitivity analysis (Section 4.3.3)

The sensitivity of MOPs (production volume and cost) to each parameter is examined based on a perturbation of one day or +10% or −1 day, especially for the recovery date t_2–t_1.

3.3. Disruption and Alternative Manufacturing Scenario

The scenario-based disruption model of a manufacturing supply chain using a data space is shown in Figure 2. Under normal operation, the parts manufacturer constantly provides parts. After a certain disruptive event (e.g., the termination of material supply due to a regional war or a large areal earthquake) at t_1, the parts supplier cannot maintain its production capability and needs time to recover. In this case, the parts supplier seeks out solutions to resume operations with minimal delay while concurrently exploring options to maintain supply chain continuity during the shutdown period. Manufacturers that offer contract manufacturing are listed in the data space, and contracts are established with them to outsource manufacturing for a specified period until recovery.

After confirming the manufacturing agreement, the contract manufacturer starts to prepare manufacturing at t_2, shown by the light-green bar in Figure 2. Then, the contract manufacturer starts alternative manufacturing at t_2 until the full recovery of the original manufacturer (t_3). During the period of alternative manufacturing by the contract manufacturer ($d_{\mathrm{al}} = t_3 - t_2$), they provide parts at the volume of T_{p} [parts/day]. The time t_1, t_2, and t_3 represent the following timings: t_1: disruption event; t_2: the start of alternative manufacturing; t_3: the end of alternative manufacturing and the recovery of the original manufacturing. d_{pr} is the duration of selection and preparation of manufacturing (from t_1 to t_2). d_{re} represents the duration of recovery (from t_1 to t_3). d_{dl} is the duration of delivery of the first lot of parts. d_{at} is the duration of alternative manufacturing.

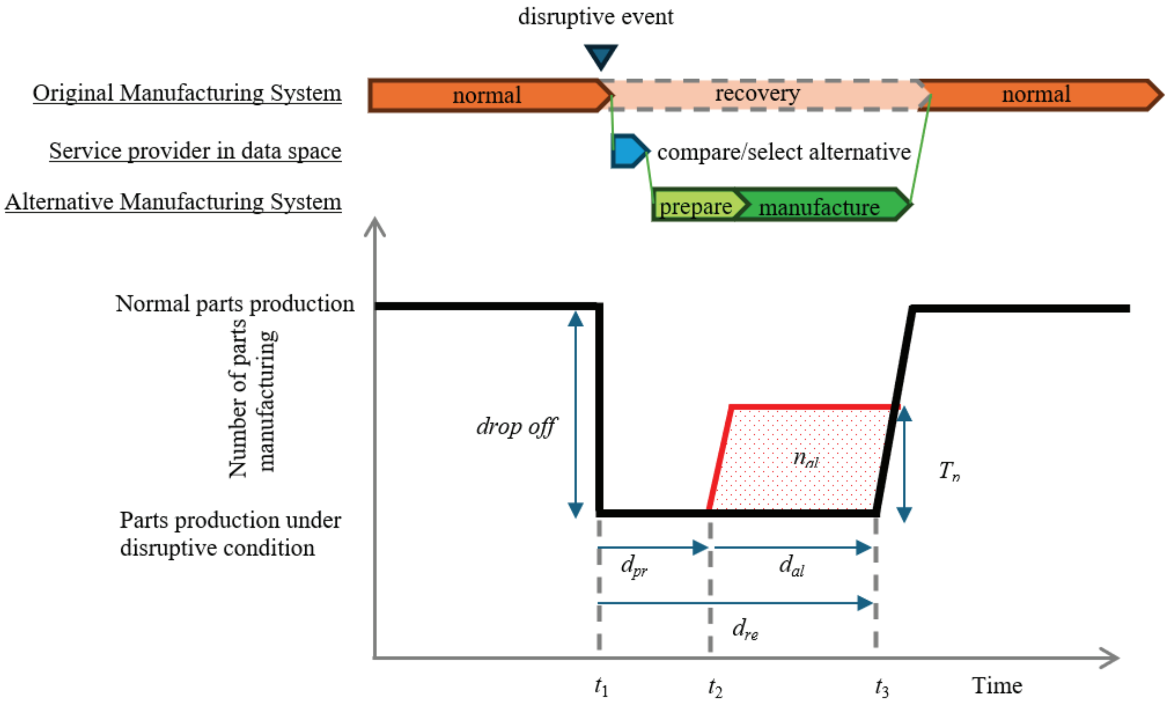

Figure 2. The scenario of alternative manufacturing and the number of manufacturing parts available with the original and alternative manufacturing systems.

3.4. Evaluation of Alternative Manufacturing Performance

T_p represents the daily production performance of alternative manufacturing during the period of alternative manufacturing (from t_2 to t_3). In this scenario, the total production volume of alternative manufacturing (n_{al}) is one MOE used to determine resilience performance and is formulated as shown in Equation (1).

$$n_{al} = \sum\nolimits_{t=t_2}^{t_3} T_p \tag{1}$$

Equation (2) represents the calculation formulation of unit cost of parts. The total cost integrates the values of the initial cost (loaded per single part), the material cost including the residuals, and the operational cost (C_{op}). The BTF (Buy-to-Fly) ratio (γ) denotes the ratio of the weight of the material obtained to the material used in the part. The BTF ratios for aircraft metal parts are referenced from Rupp et al. [42], with machining-based methods having a BTF ratio (γ) of up to 30. In contrast, AM has a lower BTF ratio due to the additive processes, with a typical BTF ratio (γ) for PBF assumed to be 1.4 in this scenario. Material cost (C_M) refers to the current market price of materials [43–45]. C_{OP} represents the operational cost, including worker wage and administrative expenses, other subsidiary materials, and electricity divided into the number of parts manufactured in a single batch process. The mold for MIM is one example of the initial additional cost (C_{in}).

$$C_U = \frac{C_{in}}{n_{al}} + \gamma C_M + C_{OP} \tag{2}$$

where

n_{al}: total manufacturing volume during alternative manufacturing [parts].
T_p: daily performance of alternative manufacturing [parts/day].
C_u: unit cost of parts during alternative manufacturing [USD/parts].
C_{in}: initial additional cost of alternative manufacturing [USD].
γ: BTF ratio, which is the ratio of total material weight and used material weight in parts [-].

C_M: cost of used material [USD/kg].
C_{op}: operational cost for single parts [USD/parts].

3.5. Sensitivity Analysis

Sensitivity analysis is a standard method used to check the uncertainty in the output of a mathematical model. In this study, a one-at-a-time (OAT) sensitivity analysis was conducted by varying each input parameter individually while keeping the others fixed. Specifically, each parameter was perturbed by +10%, or just one day short for preparation day perturbance for d_{pr}, from its nominal value, and the corresponding changes in the model output were evaluated. This approach allowed for a straightforward assessment of the relative influence of each parameter on the simulation results.

4. Results

4.1. Conceptualization of Security and Resilience Strategy

Figure 3 shows the comprehensive strategy used to ensure the security and resilience of the supply chain. This strategy was derived from the principles of *Industrie 4.0* [4] and Industry 5.0 [7,8]. The overarching vision encompasses the manufacturing supply chain's *resilience*, *sustainability*, *human-centered nature*, and efficiency, which are prerequisites for achieving security and resilience.

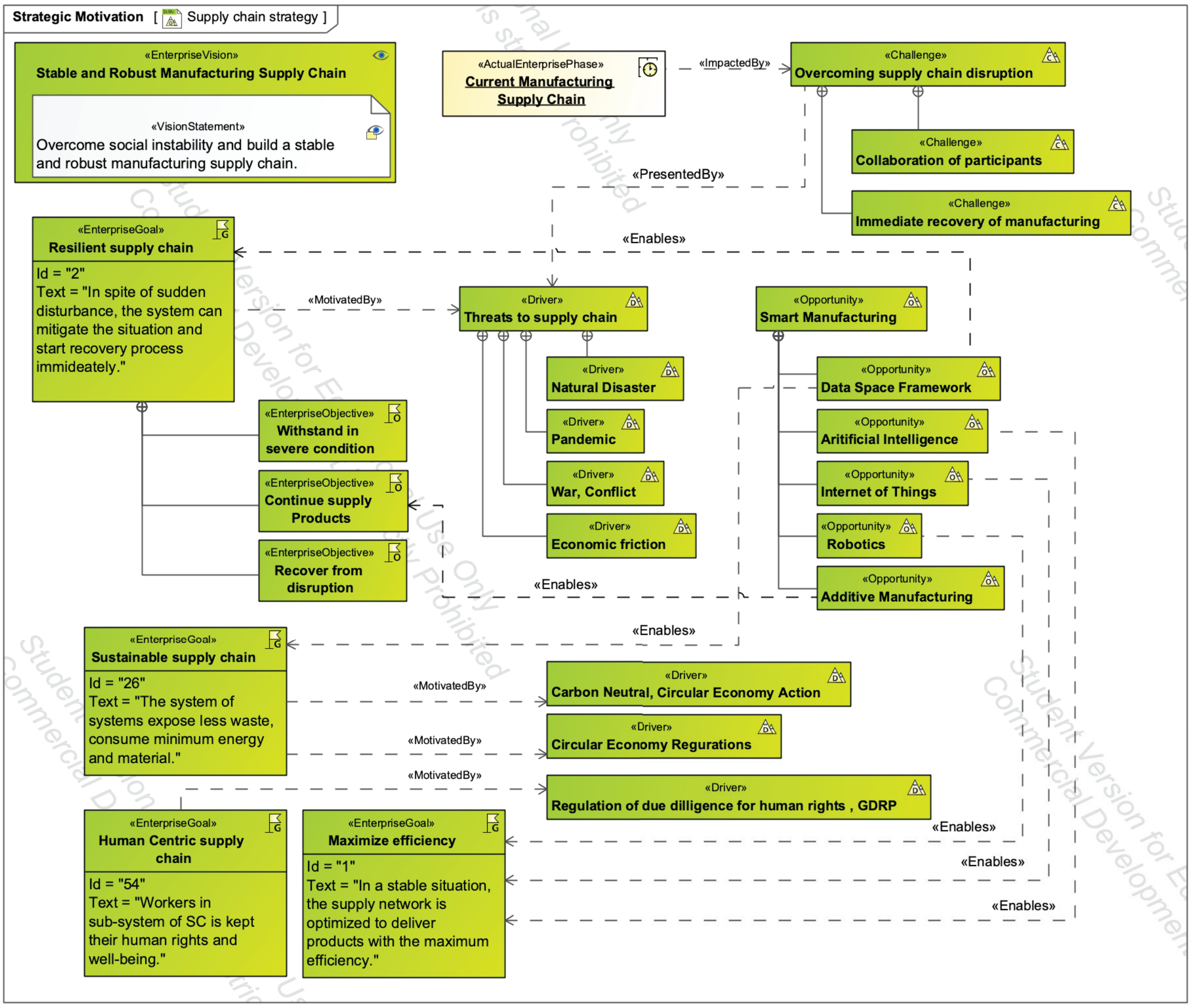

Figure 3. The strategy for pushing the supply chain toward a stable and robust manufacturing supply chain (St-Mv). The words in angle quotes are defined in [39].

4.1.1. Enterprise Goals

A. Resilience

In the EA process, the first step in setting goals is to clarify the relationship between the <<Challenge>> that impacts the current supply chain, the <<Driver>> that motivates the enterprise, and the <<Opportunity>> that enables the <<EnterpriseGoal>>. *Resilient Supply Chain*, as an enterprise goal, is described in the top and middle rows of Figure 3. The manufacturing supply chain circumstances have been identified as <<Driver>> elements of *Natural Disaster*, *Pandemic*, *War*, *Conflict*, and *Economic Friction*. The supply chain faces the <<Challenge>> of *Overcoming supply chain disruption*. This <<Challenge>> comprises two elements: *collaboration of participants* in the manufacturing supply chain and *immediate recovery of manufacturing* (top right in Figure 3). Considering the above situation, we set the resilient supply chain as the first enterprise goal. As explained in Section 2.2, Resilience Engineering, the three elements of withstand, continue, and recover are defined as <<EnterpriseObjective>>.

B. Sustainability

The second goal is to establish a *sustainable supply chain* (middle left in Figure 3). The supply chain shall produce less waste and consume minimal energy and materials. Sustainability, along with resilience, is an important pillar of Industry 5.0. The <<Driver>> elements are *Carbon Neutral*, *Circular Economy Action*, and *Circular Economy Regulations*.

C. Human-Centric Nature

The third goal is the *human-centric supply chain* (bottom left, Figure 3). This is the third vision of Industry 5.0. Workers in the subsystem of the supply chain maintain their human rights and well-being. This is the <<Driver>> of the *Regulations of the due diligence for human rights* and the General Data Protection Regulation (*GDPR*) [46].

D. Maximize Efficiency

The fourth goal is to *maximize efficiency* (bottom center, Figure 3). In a stable situation, the supply network is optimized to deliver products with maximum efficiency. This is the goal of *Industrie 4.0*, and it employs approaches to automate and improve supply chain efficiency.

4.1.2. Opportunities

The <<Opportunity>> that achieves the four goals is located in the middle right part of Figure 3. As enabling technologies for *Industrie 4.0* and Industry 5.0, smart manufacturing technologies, and specifically the technologies described in Figure 3, are included. The data space framework is explained in Section 2.3. As mentioned above, Gaia-X has been launched and is being vigorously promoted, particularly in Europe, and there is room for utilizing smart manufacturing technologies, such as *AI*, the *IoT*, *Robotics*, and *AM*.

4.1.3. Capability Identification of a Secure and Robust Manufacturing Supply Chain

To realize a stable and robust supply chain, it is necessary to clarify the capabilities required to execute the enterprise strategy. The first step is to identify the current supply chain capabilities and determine the required capabilities. A traditional manufacturing supply chain aims to deliver products on time, in an effective manner, and maintain the quality of the products. It has the <<Capability>> elements of effective product supply, such as *Supplier Assurance*, *Parts Assurance*, *Product Transportation*, *Product Manufacturing*, *Parts Inventory*, *Parts Supply*, and *Resource Procurement*. In the *Data space-based manufacturing supply chain*, additional capabilities are required to enhance its recovery capabilities and ensure the continued supply of goods, such as *Data Trust*, *Transportation Recovery*, *Manufacturing Recovery*, *Flexible Manufacturing*, and *Continuity of Business* (<<Capability>> elements).

Data Trust and *Flexible Manufacturing* were introduced as <<Capability>> elements, and their derivation is explained in Figure 4. *Collaboration of participants* and *Immediate manufacturing recovery* are defined as <<Challenges>> to overcome. It is possible to address these elements using the *Data space framework* and *Additive Manufacturing* (AM), respectively, compared to other candidate technologies, aiding the recent *Industrie 4.0* and Industry 5.0. As described in Section 2.3, the data space framework is a mechanism that ensures secure data exchange between participating companies in the data space, and it is a basis for collaborative activities. Thus, *Data Trust* is one of the crucial capabilities of the data space. In addition, as pointed out by Eyers et al. [47] and Jimo et al. [48], AM can be employed for flexible production by providing data to three-dimensional printers as an AM system located on site. Thus, it can impact *Flexible Manufacturing*.

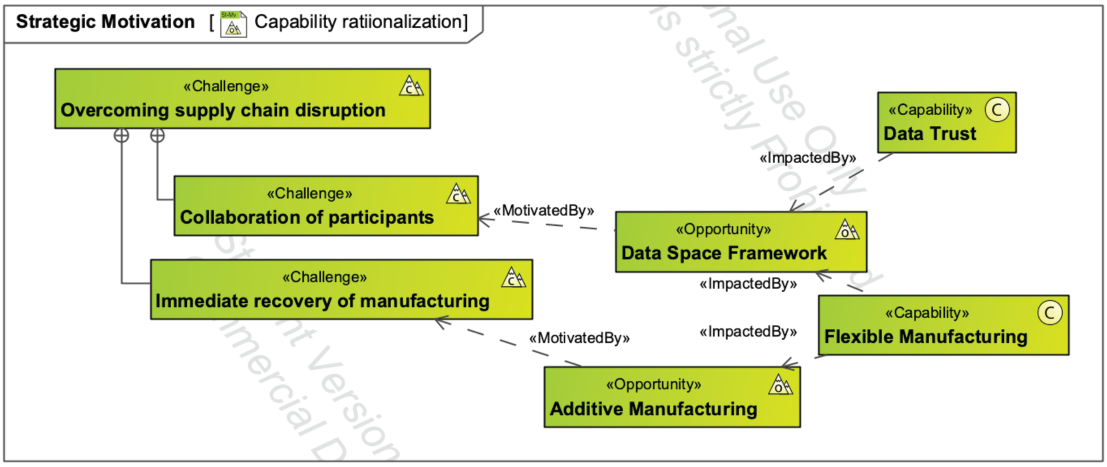

Figure 4. Gaining capabilities to overcome supply chain disruption.

4.2. Structural Overview of Supply Chain with Data Space

4.2.1. Investigation of Security in Manufacturing Supply Chain

The security perspectives of a manufacturing supply chain incorporated with the data space are investigated. This step includes identifying risks, affected assets, and security controls. Based on the *NIST SP 800-161r1* [17] and *Operations Management Body of Knowledge* (*OMBOK*) [40], the potential harm of cybersecurity risks throughout the supply chain is extracted (Figure 5). This taxonomy is at a conceptual level, and more specific events should be described as subordinate concepts in each case. We extracted and described the risks that have been made concrete in light of the subject of this study. From the *NIST SP 800-161r1* [17], *Resource Depletion*, *Supplier Failure*, *Lack of Cooperation*, and *Data Leak* are identified for consideration in this study. From *OMBOK* [40], the <<Risk>> of *Loss of Business Opportunity* is identified, as shown in the bottom row in Figure 5.

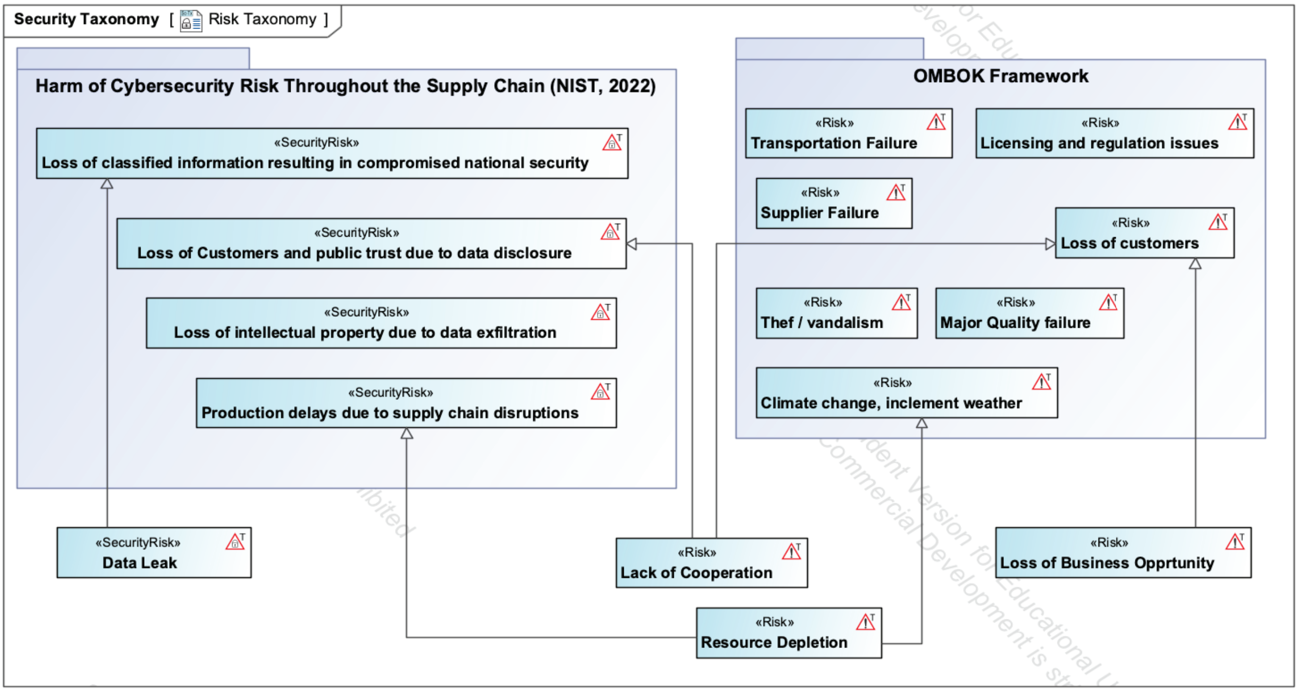

Figure 5. Risk taxonomy referred to from NIST [17] and OMBOK [39].

4.2.2. System of Systems of Supply Chain with Data Space and Risk Mapping

The <<Risk>> elements identified in Figure 5 affect the <<System>> elements that comprise the SoS of the manufacturing supply chain and its <<Capability>> elements. Figure 6 shows a resource taxonomy diagram that describes the relationship among the <<System>>, <<Capability>>, and <<Risk>> elements. A conventional *Manufacturing* supply chain System of Systems (upper center in Figure 6) is composed of the *Material Production System*, *Inventory*, *Transportation System*, *Parts Manufacturing System*, and *Product Manufacturing System*, as well as external environments, such as the *Societal Environment* and *Natural Environment*. Hause et al. described the traditional supply chain with the UAF diagram [28]. They addressed the security aspect in a traditional supply chain explored by using the UAF.

We introduce the *Data Space* into the SoS (top right in Figure 6). As a subsystem of the *Data Space*, the *SCM Service Provider* coordinates supply chain production to exhibit the <<Capability>> of *Flexible Manufacturing*. Another role of the *Data Space* is to address the <<SecurityRisk>> of a *Data Leak*, which will become the trigger of another <<Risk>> of the *Lack of Corporation* (expressed in the middle right in Figure 6). The *Lack of Corporation* affects the <<Capability>> of Continuity of Business (expressed in the top right in Figure 6). One of the <<Risk>> elements, *Lack of Cooperation*, affects the *Parts Manufacturing System* and impairs *Manufacturing Recovery*. Thus, it is necessary to mitigate the risk and utilize a secure communication mechanism in the data space that guarantees data sovereignty and security and does not interfere with each business. Using the data space allows for responses to cybersecurity concerns and the facilitation of rapid data sharing between companies in a secure environment through the IDS (International Data Space) safe data communication mechanism [6]. The implementation of *Connector* technology facilitates the secure exchange of information among companies operating within the data space. The procedures and technologies for this information exchange are described in Bakopoulos et al. [31] and the Gaia-X Architecture documents [11]. The next step of this study is to elucidate the correlation between risks and capabilities, as illustrated in Figure 4. This will be followed by deriving metrics to address the identified risks and acquiring means to verify the efficacy of these metrics.

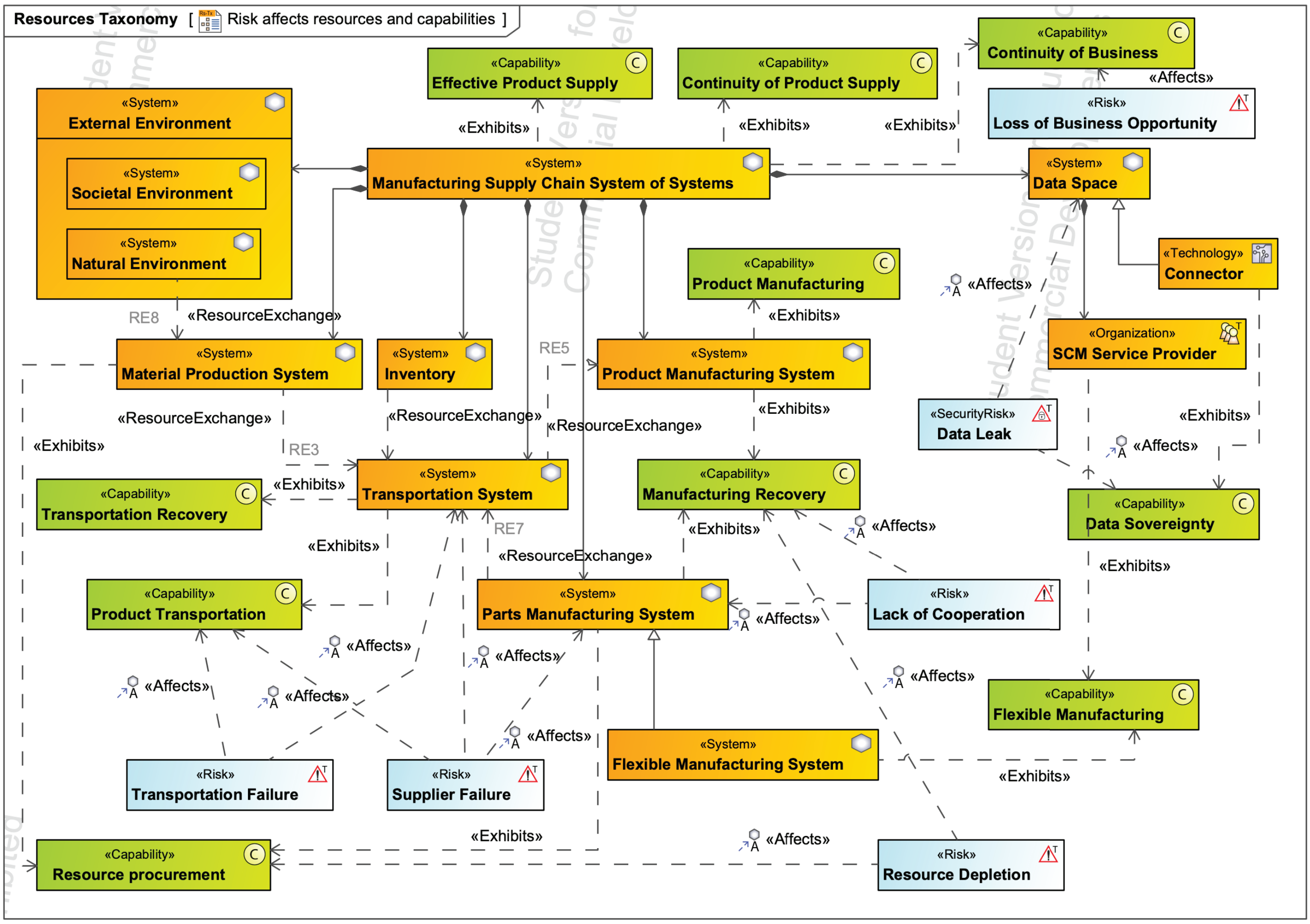

Figure 6. Overall view of SoS and risk relations in resource taxonomy.

4.2.3. Measure of Effectiveness and Performance of Risk Mitigation

Figure 7 shows the traceability of the types of elements, <<Risk>>, <<Security Control>>, <<OperationalPerformer>>, and <<Capability>>, affected by supply chain disruption. Noteworthily, cybersecurity risks and information leaks may appear in an emergent manner, thereby diminishing the propensity of participating companies to engage with the data space. The role of ensuring data security in the data space, such as protecting from a data leak, can be applied as a risk control measure.

<<SecurityControl>> alternative manufacturing is a method used for reducing the number of nodes in the supply chain via local manufacturing and consuming materials and parts during manufacturing; the application of AM has the potential to become an effective option in that sense [48]. Participating in the data space and data-sharing mechanism is essential for the temporal adoption of such alternative methods.

To evaluate the effectiveness of the SoS, the MOPs of the flexible manufacturing system are linked rationally to the respective MOEs of Continuity of Business (i.e., Total Cost) and Continuity of Product Supply (i.e., Duration of Alternative Manufacturing and Number of Parts) by the behavior of <<Security Control>>, as shown in the top left side of Figure 7. The MOPs of the flexible manufacturing system exhibit a relationship with the MOEs of <<Capability>>, namely Continuity of Business and Continuity of Product Supply (top left of Figure 6). The equations are investigated in the specific use case in Section 4.3.

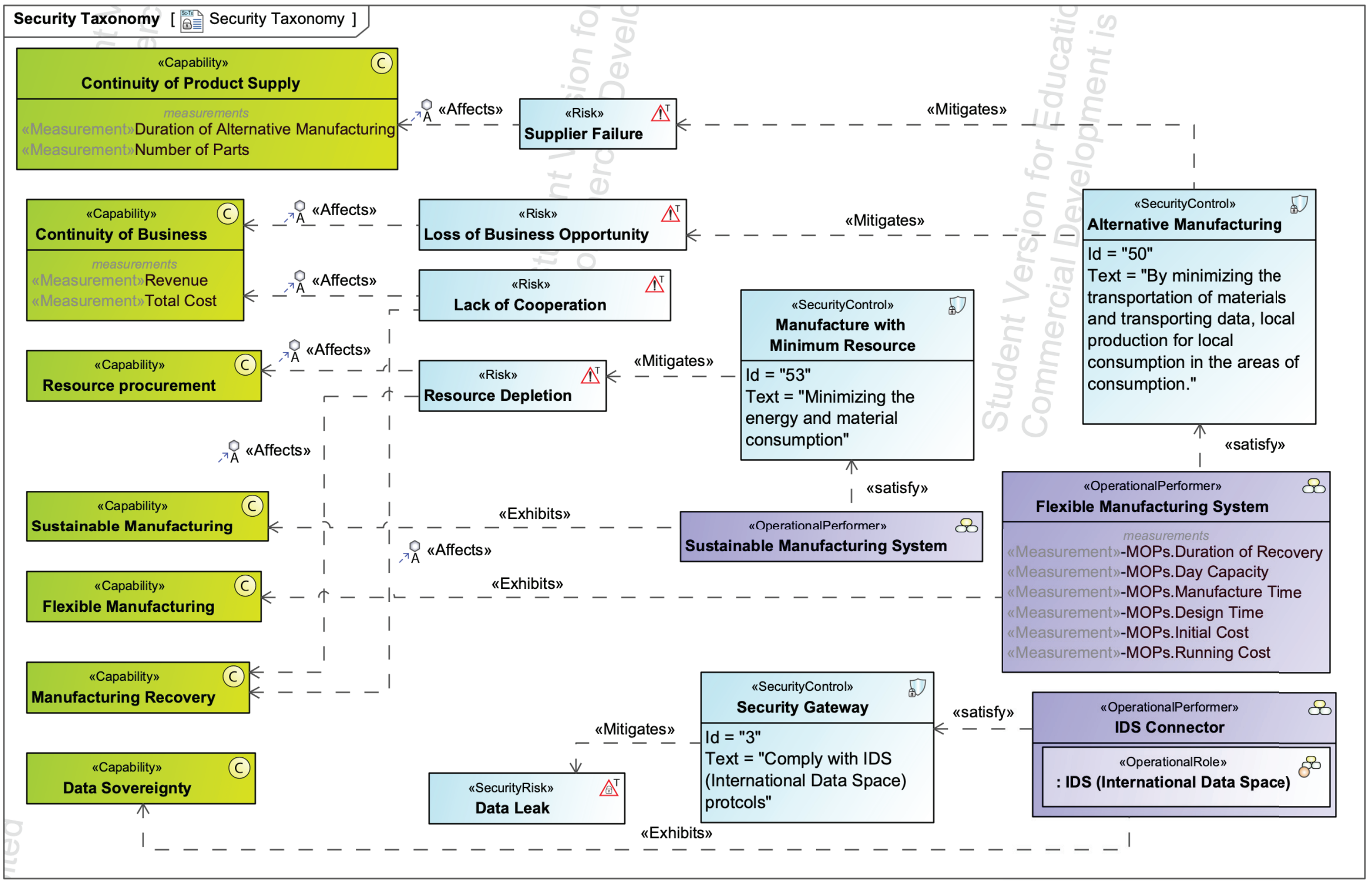

Figure 7. Relationship among supply chain risks, security controls, and affected capabilities.

4.3. Parts Supply Disruption and Alternative Manufacturing

4.3.1. Evaluation Result of Alternative Manufacturing Performance

Number of Parts during alternative manufacturing is an appropriate MOE of *Continuity of Product Supply* in view of the security of the supply chain's capability and resilience. As an MOE of *Continuity of Business*, *Parts Cost* is appropriate as well. By simulating the two MOEs, we are able to evaluate the effect of alternative manufacturing to make better decisions.

Table 2 shows candidates for relatively small parts that would allow for a short-term setup process for manufacturing. In the event of a supply chain disruption, it is assumed that possible manufacturing alternatives will be identified through data space service providers in a secure way. The data space offers a contract service for participants [11], and the service enables the smooth start of business between participants. After the contract, parts data and manufacturing information can be safely exchanged in the data space.

After selecting an alternative manufacturer, it is necessary to prepare for manufacturing. The preparation procedures for each manufacturing method and the operational process refer to the literature [46,49]. Regarding the manufacturing preparation period, adopting the jig preparation layout and CAD/CAM design period, we have assumed that a minimum of two days is required, with one day secured for equipment layout, enabling startup three days later. For BJT, we have assumed that a trial run will be conducted before molding, debinding, and sintering, and the associated costs have been included in the initial costs.

Table 2. Candidate methods of alternative manufacturing.

Manufacturing Method	Description
MIM	Metal Injection Molding (MIM) is a manufacturing process that combines the design flexibility of injection molding with the strength and integrity of metal. It is ideal for producing small, complex, high-volume metal parts with tight tolerances. Feedstock made by mixing metal powder with binder is injected into a mold to produce a molded body (green body). The green body undergoes a debinding and sintering process to become a metal part. It is necessary to prepare the mold.
CNC	Computational Numerical Control Machining is a manufacturing process in which pre-programmed computer software controls the movement of tools and machinery. It is widely used to produce precise and complex parts from various materials such as metals, plastics, and composites. CNC can be utilized for both prototyping and mass production.
PBF-LB	Laser Beam Powder Bed Fusion is an Additive Manufacturing process used to produce metal parts directly from a digital model. PBF-LB is ideal for complex, low-volume parts and rapid prototyping, especially when traditional tooling is impractical.
BJT	Binder Jetting Technology (BJT) is an Additive Manufacturing process in which a liquid binding agent is selectively deposited onto a bed of metal powder to form parts layer by layer. After curing, the green body undergoes a debinding and sintering process similar to MIM.

Regarding manufacturing capacity, sintering is a batch process, and the daily production capacity is limited by the number of parts that can be loaded into the sintering furnace, which is the bottleneck in both MIM and BJT. In MIM, the cycle time for one shot required for molding is typically 60–90 s. Assuming two parts are molded per shot and 480 shots per day, 960 molded parts can be produced. Subsequent processes include degreasing and sintering. Assuming a sintering capacity of 100 parts per batch per furnace, this is based on the Nabertherm VHT 80/15 MIM furnace (two batches per day) [50] with a 60% loading rate. Assuming a degreasing cycle of 8 h, a sintering cycle of 12 h, and a manufacturer with two furnaces, continuous operation of two batches per day results in a throughput of 600 degreased parts and 400 sintered parts per day. The maximum daily production capacity of the process is 400 parts. This is the same for BJT, with the sintering process being the bottleneck process.

Additionally, the time taken for CNC processing is the bottleneck factor. For PBF-LB, the number of parts that can be produced is determined by the number of parts that can be placed within the build area. Parts are fixed to the build plate (bottom surface) and can only be arranged in a single layer, so the number of parts per batch directly corresponds to the production capacity.

Regarding additional costs for this specific parts manufacturing process, in the MIM case, initial investment is required for mold design and manufacturing. Mold costs and preparation time depend on the complexity of the shape, but we have adopted the estimated values from Asami et al. [51]. In the CNC case, since it can accommodate flexible manufacturing, large initial investments such as molds are not required. However, in some cases, special small-scale additional investments may be necessary for fixed jigs; we have assumed that dedicated jigs would be prepared and included them in the additional cost. For PBF-LB and BJT, we have added costs for minor jigs, but these have little impact on the final price. These costs are allocated equally to the parts produced during the alternative manufacturing period (d_{al}).

A case study is currently underway to verify the manufacturing process of an impeller [52], a part used in industrial pumps that is composed of stainless steel and evaluated in a previous study [42]. This assertion is founded upon existing manufacturing information, and the temporal requirements for manufacturing preparation are presumed to fall within the prevailing range. Although the impeller is utilized as a model example, the daily production volume may fluctuate depending on factors such as the dimensions of the component. Subsequently, a sensitivity analysis will be conducted to ascertain how alterations in these parameters influence the MOE. The results of this analysis will identify the factors that are sensitive to changes.

In this study, we focus on the manufacturing of impellers of stainless steel (Figure 8). The price of manufacturing with each method was obtained from currently available cloud-based manufacturing services [53] to represent the actual manufacturing service, along with specific examples calculated from the literature and online services (Appendix B).

The higher the BTF ratio, the more excess material is generated and discarded during processing. MIM and BJT use little material, so the amount of material input matches the amount used in the parts, resulting in $\gamma = 1$. In the case of CNC, complex shapes like the impeller in this case generate a lot of material that needs to be removed and discarded. In this calculation, the amount of material input is ten times the number of parts produced, resulting in $\gamma = 4.47$ [42]. In the case of PBF-LB, $\gamma = 1.41$ [42], and operational costs include labor costs. These vary significantly depending on the country and service provider.

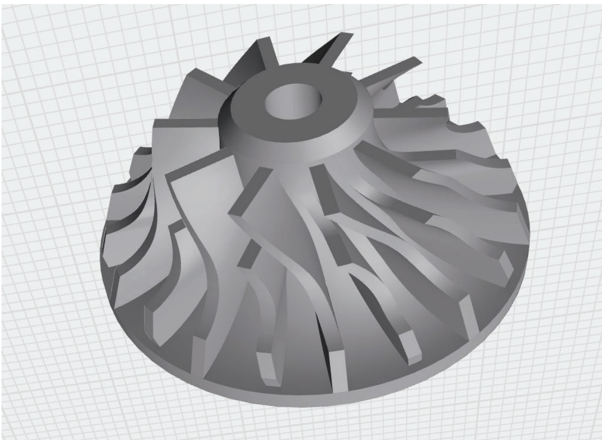

Figure 8. The design of impeller parts for this study [52], with a volume of 31.0 [cm^3] (scale = 1.0).

Cost information was collected from publicly available online platforms operated by contract manufacturers [53] that offer cloud-based production services and cost estimation tools. This selection was made to reflect realistic and practical solutions in the context of cloud manufacturing. It is acknowledged that manufacturing costs can vary significantly depending on region, company, and market conditions. Therefore, while the data provide valuable insights into current practices, they are not intended to represent universally applicable or reproducible benchmarks. Instead, they serve as demonstrative examples to support the feasibility and relevance of the proposed approach. Cost estimation comes from the calculated by estimation tool [53]. The calculation results are presented in Appendix B. Table 3 shows the parameters for estimating the productivity and cost for each manufacturing method.

Table 3. Parameters of each manufacturing method for estimation of alternative manufacturing.

	MIM	CNC	PBF-LB	BJT
Additional Cost [USD]	50,000 [1]	100	100	100
Operational Cost [USD]	1.3	16	140	18
Material Cost [USD/kg] [3]	49.5 [4]	22	106	62
BTF ratio (γ)	1.0	4.47 [2]	1.41 [2]	1.0
Preparation [day]	45 [1]	2	3	7
Capacity [parts/day]	400	50	30	400

[1]. Mold cost [51]; [2]. BTF ratio [42]; [3]. Appendix B; [4]. MIM material cost [43], CNC [44], and PBF-LB [45].

4.3.2. Cost and Productivity Analysis

From the perspective of alternative manufacturing performance, production volume is estimated using Equation (1), and cost estimates for each method are derived from Equation (2). Based on the calculation formula described in Section 3.5, we estimated the production volume and unit cost under the specified conditions. Figure 9 illustrates the number of parts that can be manufactured within the alternative manufacturing period for each method. The duration until recovery from disruption (d_{re}) is shown on the horizontal axis. During the initial termination period, the daily production volume is zero due to manufacturing preparation; however, manufacturing begins after the preparation period for each method.

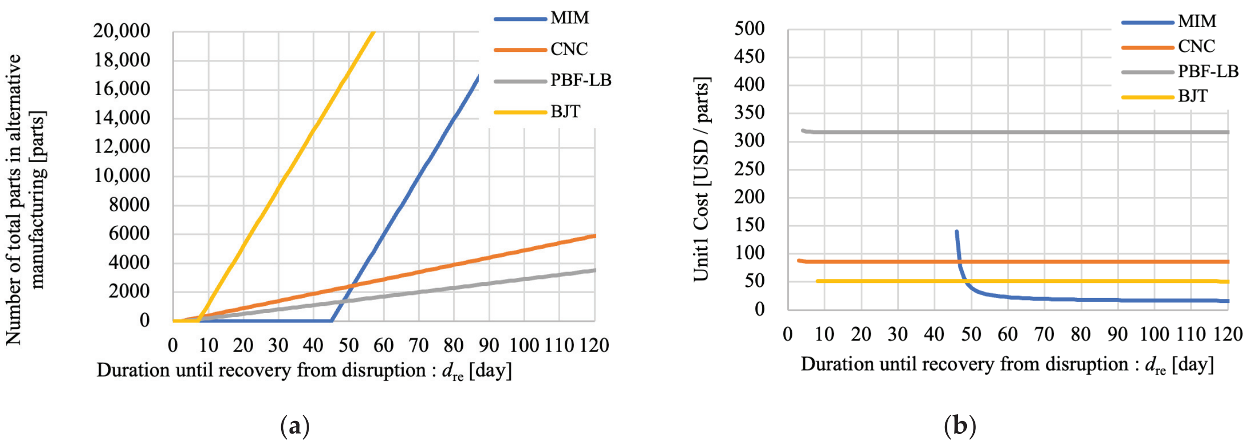

Figure 9. Relationship between duration until recovery (d_{re}) and MOEs. (**a**) Number of total parts in alternative manufacturing. (**b**) Unit cost of parts.

The results shown in Figure 9a,b reveal that MIM requires a long preparation period, resulting in a slow launch of manufacturing. However, the high productivity of MIM results in a lower unit cost of parts in the end. Table 4 shows the number of parts and the unit price of the parts manufactured using alternative manufacturing methods when the recovery date of the original manufacturing method is set to $t_3 = 60$. During the relevant period, BJT has the highest number of manufactured parts, followed by MIM, CNC, and PBF-LB. On the other hand, MIM has the lowest cost, followed by BJT, CNC, and PBF-LB. In addition to the stainless steel impeller, aluminum parts that were investigated in a previous comparative study of PBF-LB and CNC [54] are analyzed under the assumption that all parts can be manufactured using each alternative manufacturing method. The weight and BTF ratio of CNC are varied. As a result, there is no significant change in the overall trend of parts costs. Furthermore, assuming that differences in parts do not affect the number of days required for each process, the total production volume remains constant.

Table 4. Total production volume and unit cost of 60 days of alternative manufacturing for each manufacturing method.

Parts Property			BTF (γ)				Unit Cost [USD/parts] [1]			
Type	**Material**	**Weight [kg]**	**MIM**	**CNC**	**PBF-LB**	**BJT**	**MIM**	**CNC**	**PBF-LB**	**BJT**
Impeller	SUS316L	0.25	1	4.47	1.41	1	23.1	56.1	316.7	51.2
Holder	A7075-T6	0.63	1	5.9	1.41	1	13.4	55.6	285.0	38.0
Clamp	A7075-T6	0.022	1	8.6	1.41	1	11.8	66.4	281.7	36.7
Guard	A7075-T6	0.0025	1	7.9	1.41	1	11.0	63.6	280.3	36.1
Housing	A7075-T6	0.063	1	11.7	1.41	1	13.4	78.8	285.0	38.1
							Total Number of Parts [parts]			
							6000	2900	1710	21,200

[1]. Material cost of aluminum for CNC rod [55] and powder [56].

4.3.3. Sensitivity Analysis Results

The sensitivity of MOEs (production volume and cost) to each parameter is examined for the impeller parts under conditions of change of 10% at d_{re} = 60 (after 60 days, the original manufacturing has recovered). The manufacturing preparation period is varied with single day. This reveals the sensitivity of the total production volume of parts to the duration of preparation and the production capacity. Moreover, it demonstrates the sensitivity of the unit cost of parts.

The increase in the manufacturing preparation time or the decrease in the production capacity (orange bar) contributes to the increase in the total parts volume in Figure 10. MIM shows high sensitivity to the manufacturing preparation time because of its high production capacity and slow start of manufacturing.

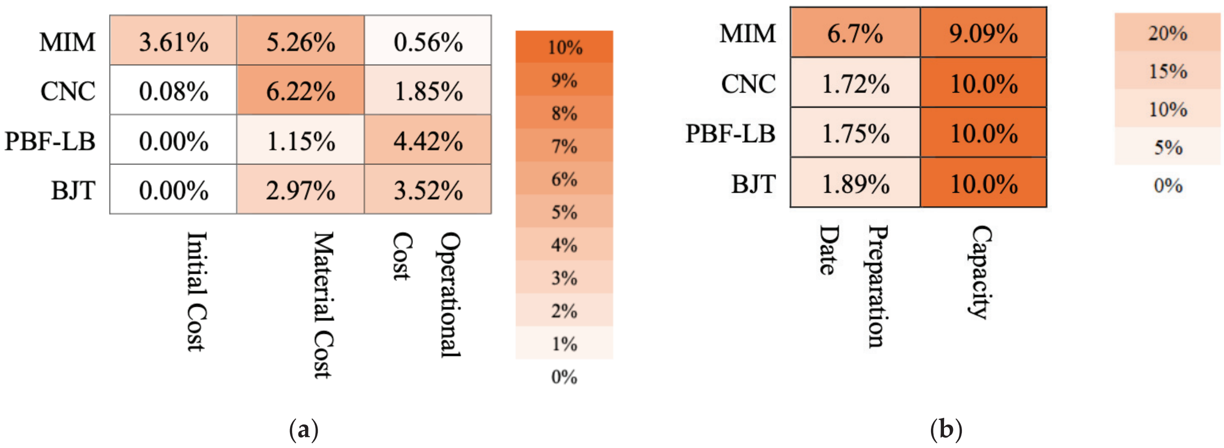

Figure 10. The results of the sensitivity analysis. (**a**) The production volume of parts; (**b**) the unit cost of parts.

Regarding the cost sensitivity in Figure 10, the sensitivity of each method differs in terms of the factor with the largest impact. For MIM, initial and material costs are sensitive. For CNC, material costs have a significant impact, while operating costs are sensitive for PBF-LB. In the case of BJT, material and operating costs have the same level of influence.

5. Discussion

5.1. Architecture Definition and Elaboration

Bakopoulos et al. [31] proposed the use of Gaia-X as a digital-twin value chain. They used PoC (Penalty of Charge) metrics to predict the resiliency of the potential supply chain structure. They state that companies can access Resilience Assessment Services and

Reconfiguration Services by connecting to Gaia-X. However, they do not address the risks associated with collaboration between a large number of companies or the operation of collaborative manufacturing. This study employed the UAF diagram (Figure 6) to map risks across the entire supply chain, identify relationships between risks and elements, and propose alternative manufacturing mechanisms as risk mitigation measures. Although this approach is expected to mitigate risks through collaboration, enhancing cybersecurity capabilities is also crucial. The emergence of the data space, as represented by Gaia-X, provides a framework of security and leads to the acquisition of more participants. With more participants, the coordination of manufacturing becomes more flexible, and a virtuous cycle begins to turn. In general, the SoS is classified into four types according to the attributes of their governance: directed, acknowledged, collaborative, and virtual [57]. In this sense, the data space-based manufacturing supply chain can behave as a collaborative SoS. There has been no quantitative evaluation of the benefits of participating in a data space, and we believe that the proposed architecture can be utilized as a useful reference of the collaborative supply chain. This will promote rapid decision-making in situations that require resilience under a collaborative SoS.

By utilizing the data space, it is possible to quickly identify suppliers with the appropriate facilities and capabilities in a short period of time, enabling continuous manufacturing using alternative methods with minimal additional investment and lead time. Once the existing supply chain is restored, it will be possible to end this temporary situation and return to the original production system. This kind of temporal solution is viable for short-term contract manufacturing based on the data space.

Gaia-X is a mechanism that enables small and medium-sized enterprises (SMEs) in Europe to enter the market as service providers by establishing the necessary environment. This allows them to enter the market with relatively low barriers to entry, eliminating the need for large-scale infrastructure investments. However, it will be difficult for Gaia-X to be recognized as a business opportunity unless large enterprises adopt it. Therefore, widespread adoption and participation from the entire industry are key. SMEs operating as manufacturing service providers face the challenge of demonstrating competitive advantages, such as cost efficiency and rapid deployment, in the data space.

This real-time decision support system enables flexible manufacturing adjustments at a low cost by providing options other than experience-based decisions. However, it is considered necessary to ensure appropriate operation and training, as there is a possibility that decisions may be made that result in high costs if the recovery period is misjudged.

5.2. Evaluation of Alternative Manufacturing

For the evaluation of MOE, Equation (2) assumes the case of alternative manufacturing. The initial investment is not included as capital investment. Only auxiliary materials and jigs that must be prepared individually are required. This makes it possible to minimize the cost of mitigation to resilience. By using the proposed set of flow and equations, it becomes possible to appropriately evaluate the costs of flexibly manufacturing AM and other technologies to effectively enhance resilience.

MIM and CNC are conventional and highly mature in parts manufacturing. When adopting MIM, a new mold should be prepared for the alternative manufacturing term. The residual duration of alternative manufacturing is short. The time it takes to fabricate a new mold needs to be taken into account when employing MIM as an alternative manufacturing method. The mold preparation period generally lasts a long time, contingent upon the specific geometry and dimensions. Consequently, the duration of the production volume recovery phase in an alternative manufacturing system prior to the restoration of the original manufacturing system is short, and it is not considered viable. Additionally, the fabrication of new molds for such temporal manufacturing should be avoided, as this would necessitate the storage of molds and thus excess investment. However, if a sufficient period of alternative manufacturing can be obtained, profitability will be enhanced. Similar to other AM methods, PBF requires a short design time and a similar production time. Because it can only build a small number of parts per time, it is not extremely profitable [58]. Note that BJT has a lower technical readiness level than PBF [59]; therefore, the time required for parts manufacturing design is longer than that of PBF, and the duration of production is slightly shorter. However, because it can produce numerous parts at a time, it is highly profitable.

The findings of this study indicate that in collaborative manufacturing with the data space, AM technologies such as BJT and flexible manufacturing methods such as CNC are useful options in cases where immediate recovery for continuity of manufacturing is a main concern. Even in relatively short-term manufacturing periods of several months, MIM offers significant cost advantages. This is because MIM allows for the transfer of mold amortization costs to parts, enabling the production of large quantities of parts even in short periods. However, mold preparation takes one to two months, and in this study, it was set at 45 days. This preparation period cannot be replaced by alternative manufacturing methods, so it is important to note that MIM is not a viable option if the goal is to minimize production downtime.

The sensitivity analysis results indicate that production volume is highly sensitive to the manufacturing preparation period, with shorter lead times enabling higher total production volumes. Parts costs vary depending on the manufacturing method, although both parts costs and operational costs have significant influences. The sintering process is a bottleneck for MIM and BJT productivity. Developing a temperature profile that allows for shorter sintering times and increases the number of parts that can be input per batch or the number of furnaces can improve performance. The insights gained from this study contribute to the flexible selection of alternative manufacturing methods by leveraging the data space. Alternative manufacturing methods offer significant advantages, such as the ability to flexibly respond to design changes and shape modifications, for example, by utilizing AM. Although AM is generally considered expensive, it offers flexibility for temporary manufacturing.

From a practical standpoint, manufacturing enterprises should proactively engage in data space-based collaboration platforms to prepare for potential supply chain disruptions. Specifically, SCM service providers can implement real-time simulation tools, as proposed in this study, to evaluate alternative manufacturing agents based on updated data such as material costs, labor availability, and preparation time. For example, in the event of a sudden disruption event induced by regional war, the system enables rapid selection and activation of Additive Manufacturing methods like PBF or conventional CNC depending on cost and time constraints. This approach allows companies to maintain operational continuity and minimize financial losses.

The reliability and integrity of the data space must be guaranteed by the data space mechanism to achieve the engagement of enterprises. The information required is the MOPs presented in this study, with particular emphasis on the critical information of the preparation period for manufacturing launch, material costs, and labor costs. MIM and BJT have high sensitivity to the preparation period, while CNC is more practical for reducing material costs. Additionally, PBF could be an effective option by reducing operational costs.

The proposed architecture, while demonstrated in the context of manufacturing supply chains, is inherently modular and scalable. Its credibility with data space mechanisms and service-oriented architecture allows for adaptation to more complex supply chains involving multiple tiers, multifunctional corporations, and cross-border operations. For instance, in sectors such as aerospace or pharmaceuticals, where traceability, compliance, and rapid reconfiguration are critical, the architecture can be extended by incorporating domain-specific data protocols and governance models. Moreover, the collaborative SoS framework supports integration across heterogeneous systems, making it suitable for diverse industrial ecosystems.

5.3. Limitations

This study has some limitations. AM technologies (PBF-LB and BJT) are still under development, so the performance properties or costs may be changed. The main reasons for this are that AM technology is flexible in terms of free-form shapes and adjustable in terms of production volume but has limitations in terms of applicable materials and sizes.

The proposed architecture is versatile and offers a high level of deliverability. The subsequent systems engineering phase, i.e., the design definition process, should be undertaken when contemplating specific implementation. However, this study does not address this aspect.

Simulation results are dependent on the underlying conditions. We covered general conditions with the currently available information. However, the key to increasing the resilience of the manufacturing supply chain to disruptions is to rapidly share and respond to ever-changing conditions, such as regional differences, distance effects, and manufacturing capacity, at any given time. Active data exchange is necessary among participating companies in the data space. This article does not provide measures to encourage companies to share their data. Further refining of the architecture model is necessary to increase motivation.

5.4. Next Steps and Recommendations

In terms of further research to improve supply chain security and resilience, the following actions are recommended for future works. (1) Defining a detailed system architecture as a model-based systems engineering architecture by utilizing SysML is a useful way to implement the system of systems. In particular, EA modeling and real-world data-sharing processes should be the main focus. (2) Investigating the mechanisms in the data space based on this architecture and defining the data to be provided and the protocols should be carried out. Furthermore, evaluating the impact of product shortage and localized supply chain disruptions is also crucial. The flexible manufacturing system and the sustainable manufacturing system have been introduced as measures to mitigate risk, and there is a possibility that they will correlate and exhibit emergent behavior.

6. Conclusions

A previous study by Hause et al. [28] analyzed the security of a typical manufacturing supply chain and examined how to address risk using an enterprise architecture modeling approach. In contrast, this study examines a manufacturing supply chain that can be flexibly recombined based on the data space. This approach increases supply chain security, ensures data security, enables quick decision-making in disruptive situations, and facilitates the development of appropriate strategies. While Alexopoulos et al. [30] proposed a probabilistic measure for initial investment decisions, this study introduces a decision-making instrument for the immediate and timely reconfiguration of the supply chain.

This study examines a data space-based manufacturing supply chain from the perspectives of security and resilience. The risk of a data leak triggers the loss of collaboration without the data transaction secured by the connector technology. However, by adopting the data space for the manufacturing supply chain, the participants are able to collaborate in a secure environment. Utilization of the evaluation method proposed in this study facilitates the assessment of the effectiveness of alternative manufacturing methods and the selection of candidate manufacturing methods under the appropriate SoS. Cooperation between companies participating in the manufacturing supply chain can improve profits in situations where the supply chain is partially disrupted.

The adoption of the UAF facilitates a comprehensive understanding of the relationship between the risks and capabilities of the constituent elements of the manufacturing supply chain system. We found that the lack of cooperation among the accompanied companies in the SoS induces a risk of a loss of business opportunity, affects the parts manufacturing systems, and impairs the manufacturing system's recovery. Thus, it is necessary to mitigate the risk and utilize a secure communication mechanism in the data space to guarantee data sovereignty and security and prevent interference with each business.

In the case where the manufacturing capacity during normal operation is reduced due to a disruptive event, we proposed a system in which the SCM service provider evaluates and selects alternative manufacturing candidates and decides on an alternative agent based on the simulation with updated information in the data space. In addition, it is necessary to achieve the start of manufacturing using alternative manufacturing agents in a short period until the original manufacturing system recovers and fills in the partial gaps. The ability to quickly alternate chain coordination by utilizing updated manufacturing data and to start manufacturing in a short preparation period is an important capability.

This article makes two contributions to the existing literature. First, it defines the architecture of a manufacturing supply chain that incorporates the data space as an SoS and comprehensively elucidates the relationship between the risks and capabilities of its elements. Second, it extracts the risks of the supply chain and indicates that utilizing SCM service providers in the data space and flexible manufacturing methods like Additive Manufacturing as mitigation methods can address such risks from the perspectives of security and resilience. As we look to the future, we will be implementing the logical architecture into a system through the pursuit of practical system architecture implementations and specific forms of services that promote inter-company communication. At the same time, we will focus on integrating architectures that balance sustainability and resilience.

Author Contributions: Conceptualization, Y.N. and H.N.; methodology, Y.N.; validation, Y.N. and H.N.; writing—original draft preparation, Y.N.; writing—review and editing, H.N.; supervision, H.N.; project administration, Y.N. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The original contributions presented in this study are included in the article; further inquiries can be directed to the corresponding author.

DURC Statement: As an ethical responsibility, the authors strictly adhere to the relevant national and international laws regarding DURC. The authors advocate responsible deployment, ethical considerations, regulatory compliance, and transparent reporting to mitigate misuse risks and foster beneficial outcomes.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A. Predefined Words in UAF Models

In this study, UAF diagrams are based on the UAFML rule. Table A1 describes the diagrams, and Table A2 details the terminations.

Table A1. Types of diagrams in UAF [37].

Diagram	Figure	Description
Strategic Motivation Diagram (St-Mv)	Figures 3 and 4	Assemble Strategic Drivers—for enterprise transformation that deal with national, department, community, joint, coalition, business, technology, or other kinds of considerations [37] (p. 24). Capture Enterprise Challenges and Opportunities—Identify challenges, opportunities, and concerns that pertain to enterprise transformation efforts. [37] (p. 24).
Security Taxonomy Diagram (Sc-Tx)	Figures 5 and 7	Establish security taxonomy to define the hierarchy of kinds of security and protection assets and asset owners that mitigate threats. [37] (p. 90).
Resource Taxonomy Diagram (Rs-Tx)	Figure 6	A set of resource performers are described, including any that have been preliminarily identified. [37] (p. 65).

Table A2. Predefined terminology in UAFML [39,60].

Terminology	Extension	Figure	Description
ActualEnterprisePhase	Instance specification	Figure 3	An individual that describes the phase of an actual enterprise endeavor. [39] (p. 50).
EnterpriseVision	Class	Figure 3	Describes the future state of the enterprise without regard to how it is to be achieved. [39] (p. 42).
EnterpriseGoal	Class	Figure 3	A statement about a state or condition of the enterprise to be brought about or sustained through appropriate means. An Enterprise Goal amplifies an Enterprise Vision, i.e., it indicates what must be satisfied on a continuing basis to effectively attain the Enterprise Vision. [39] (p. 41).
EnterpriseObjective	Class	Figure 3	A statement of an attainable, time-targeted, and measurable target that the enterprise seeks to meet in order to achieve its goals. [39] (pp. 41–42).
MotivatedBy	Dependency	Figures 3 and 4	A tuple denoting the reason or reasons one has for acting or behaving in a particular way. [39] (pp. 36–37).
ImpactedBy	Abstraction	Figure 4	A dependency relationship denoting that a Capability is affected by an Opportunity. [39] (p. 35).
Enables	Dependency	Figure 3	A dependency relationship denoting that an Opportunity provides the means for achieving an Enterprise Goal or objective. [39] (p. 35).
Challenge	Class	Figures 3 and 4	An existing or potential difficulty, circumstance, or obstacle that will require effort and determination from an enterprise to be overcome so they can achieving their goals. [39] (p. 33).

Table A2. *Cont.*

Terminology	Extension	Figure	Description
Opportunity	Class	Figures 3 and 4	An existing or potential favorable circumstance or combination of circumstances which can be advantageous for addressing enterprise Challenges. [39] (p. 38).
Driver	Class	Figure 3	A factor which will have a significant impact on the activities and goals of an enterprise. [39] (p. 34).
Risk	Class	Figures 5 and 6	A type that represents a situation involving exposure to the danger of Affectable Elements (e.g., Assets, Processes, Capabilities, Opportunities, or Enterprise Goals) where the effects of such exposure can be characterized in terms of the likelihood of occurrence of a given threat and the potential adverse consequences of that threat's occurrence. [39] (p. 186).
SecurityRisk	Class	Figures 5 and 6	The level of impact on enterprise operations, assets, or individuals resulting from the operation of an information system given the potential impact of a threat and the likelihood of that threat occurring. [NIST SP 800-65]. [39] (p. 141).
System	Class	Figure 6	An integrated set of elements, subsystems, or assemblies that accomplish a defined objective. These elements include products (hardware, software, firmware), processes, people, information, techniques, facilities, services, and other support elements (INCOSE SE Handbook V4, 2015). [39] (p. 110).
Technology	Class	Figure 6	A subtype of ResourceArtifact that indicates a technology domain, i.e., nuclear, mechanical, electronic, mobile telephony, etc. [39] (p. 127).
Capability	Class	Figures 4, 6 and 7	An enterprise's ability to achieve a desired effect realized through a combination of ways and means (e.g., Capability Configurations) along with specified measures. [39] (p. 40).
OperationalPerformer	Class	Figure 7	A logical entity that is capable of performing operational activities which produce, consume, and process resources. [39] (p. 68).
SecurityControl	Class	Figure 7	The management, operations, and technical control (i.e., safeguard or countermeasure) required to protect the confidentiality, integrity, and availability of the system and its information [NIST SP 800-53]. [39] (p. 133).
OperationalRole	Property	Figure 7	The usage of an Operational Performer or Operational Architecture in the context of another Operational Performer or Operational Architecture. Creates a whole-part relationship. [39] (p. 69).

Table A2. *Cont.*

Terminology	Extension	Figure	Description
Affects	Dependency	Figure 7	A dependency that asserts that a risk is applicable to an asset. [39] (p. 173).
Mitigates	Dependency	Figure 7	A tuple relating security control to a risk. Mitigation is established to manage the risk and could be represented as an overall strategy or through techniques (mitigation configurations) and procedures (security processes). [39] (p. 183).
Exhibits	Abstraction	Figure 7	A tuple that exists between a Capable Element and a Capability that it meets under specific environmental conditions. [39] (p. 61).
Satisfy	-	Figure 7	A stereotype of the SysML relationship in the requirement diagram [60].

Appendix B. Estimation Result of Online Parts Manufacturing

To confirm the online manufacturing service price, the impeller model (SUS316L) is examined in the CraftCloud [53], providing the unit cost for each number of orders. Figure A1 shows the result of prices for CNC, PBF-LB, and BJT.

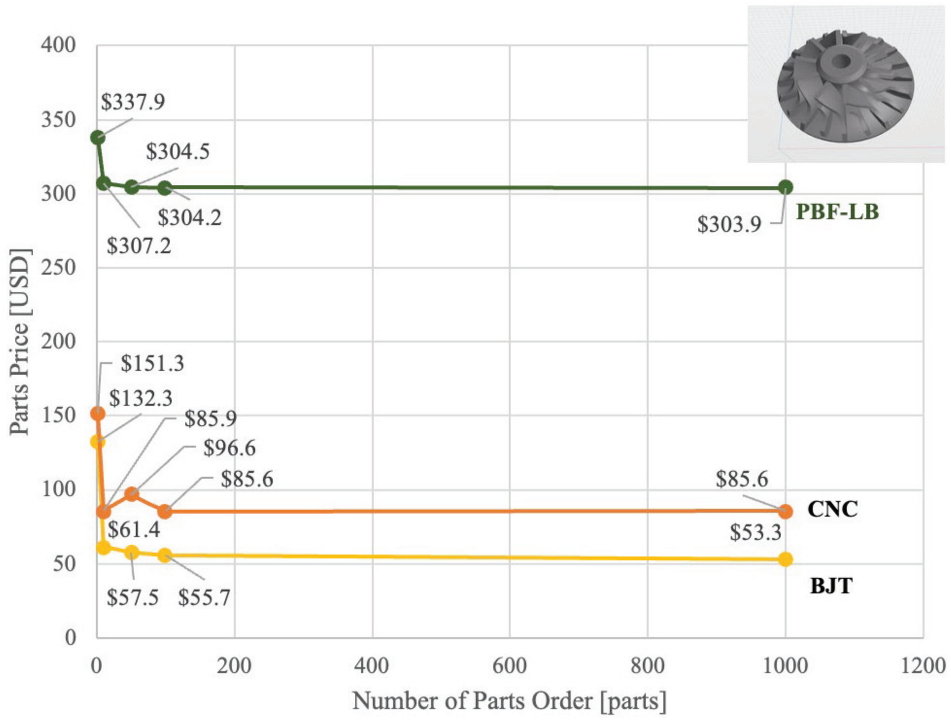

Figure A1. Impeller manufacturing price based on cloud service with the number of parts–orders [53].

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Article

AI-Powered Insights: How Digital Supply Networks and Public–Private Alliances Shape Socio-Economic Paths to Sustainability

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Abstract: By weaving together cutting-edge AI robotics, resilient global supply chains, universal school enrollment, and dynamic public–private energy investments, this study unveils a powerful, integrated blueprint for driving environmental sustainability in the 21st century. In doing so, the study employed advanced machine-learning techniques—specifically, it introduced an ANN-enhanced wavelet quantile regression framework to uncover the multiscale determinants of China's ecological footprint. Leveraging quarterly data from 2011/Q1 through 2024/Q4, it reveals dynamic, quantile-specific relationships that conventional approaches often miss. The result from the study demonstrates that robotics, supply-chain integration, public–private energy investments, gender-parity enrolment, and economic growth each exert a positive—and often escalating—upward pressure on the nation's ecological footprint over short, medium, and long horizons, with the strongest effects in high ecological footprint contexts. The study proposes a significant, tailor-made policy based on these findings.

Keywords: AI robotics; global supply chains; socio-economic factors; public–private energy investments; environmental sustainability

1. Introduction

China's ecological situation presents a complex interplay between rapid economic growth and environmental challenges. Over the past decades, China's pro-growth agenda has propelled it to become the world's second-largest economy, accompanied by significant reductions in poverty and advancements in industrialization and urbanization [1]. However, this rapid development has also led to substantial ecological degradation, including air and water pollution, habitat loss, and greenhouse gas emissions. According to reports, China's economic growth has been coupled with environmental concerns, where the pace of economic expansion has sometimes outpaced environmental protection measures [2,3]. In response to these challenges, China has implemented rigorous measures aimed at curbing environmental degradation and promoting sustainable development. These include stringent environmental regulations, investment in renewable energy sources such as solar and wind power, and initiatives to enhance energy efficiency across industries. Despite these efforts, China faces significant hurdles in achieving carbon neutrality by 2060, as outlined in its climate goals. Challenges include balancing economic growth with environmental protection, addressing regional disparities in environmental standards, and transitioning away from coal dependency, which remains a cornerstone of its energy landscape [4,5]. These complexities underscore the need for sustained policy innovation and international cooperation to navigate the path towards environmental sustainability and carbon neutrality.

Global supply chain management (GSCM) refers to the interconnected network of suppliers, manufacturers, distributors, and retailers across international borders. It plays a crucial role in modern economies by enabling the efficient production and distribution of goods worldwide. However, the expansion of global supply chains has significant environmental implications. The integration of complex logistical operations often leads to increased transportation activities, which contribute to carbon emissions and air pollution. According to [6], GSCM activities have been associated with rising carbon dioxide emissions due to increased freight transport and energy consumption in logistics operations. This underscores the environmental challenges posed by globalized trade and supply chain dynamics [7]. Moreover, the environmental impact of GSCM extends beyond greenhouse gas emissions. Ref. [8] notes that global supply chains contribute to biodiversity loss and habitat destruction through land use changes associated with industrial agriculture and deforestation for raw material extraction. These activities not only degrade natural ecosystems but also threaten biodiversity and ecosystem services essential for global ecological balance. The complex interplay between economic imperatives and environmental consequences highlights the urgent need for sustainable supply chain practices.

The measurement of artificial intelligence (AI) by the number of robots installed reflects a growing trend in industrial automation aimed at enhancing productivity and operational efficiency. As AI-driven robots become increasingly integrated into manufacturing, logistics, and service sectors, their environmental impact comes under scrutiny [9]. The deployment of robots often leads to increased energy consumption, primarily from electricity, which can contribute to carbon emissions and environmental degradation. This phenomenon is exacerbated in regions where electricity generation relies heavily on fossil fuels. Studies suggest that the lifecycle of AI robots, from production to disposal, poses significant challenges in managing electronic waste (e-waste) and minimizing ecological footprints [10]. Efforts to mitigate the environmental impact of AI robots include advancements in energy-efficient technologies, the adoption of renewable energy sources, and improvements in waste management practices. Initiatives such as recycling programs for electronic components and regulatory measures promoting sustainable manufacturing play crucial roles in addressing these challenges [11]. By integrating sustainable practices into the design, operation, and disposal of AI robots, industries can mitigate their environmental footprint while harnessing the benefits of technological innovation for economic growth and competitiveness [12].

Public–private investments in energy represent collaborative efforts between governmental bodies and private enterprises to fund and develop energy infrastructure projects. While these investments aim to enhance energy security, expand access to clean energy, and stimulate economic growth, they also exert significant environmental impacts [13]. The construction and operation of energy facilities funded through these initiatives often involve land use changes, resource extraction, and energy-intensive processes that contribute to environmental degradation. Studies underscore the dual challenge of meeting energy demand while mitigating ecological impacts, emphasizing the importance of integrating sustainable practices into energy development strategies [14,15]. The environmental implications of public–private investments in energy vary by project and location. For instance, large-scale renewable energy projects, such as solar and wind farms, can reduce reliance on fossil fuels and lower greenhouse gas emissions. However, these initiatives may also disrupt ecosystems, affect biodiversity, and require extensive land use, particularly in sensitive habitats [16]. Balancing energy development with environmental conservation requires careful planning, environmental impact assessments, and regulatory frameworks to ensure sustainable outcomes. By prioritizing renewable energy sources, promoting energy efficiency measures, and fostering stakeholder engagement, public–private partnerships can contribute to both energy security and environmental sustainability [17].

Based on the comprehensive analysis presented, this study aims to address critical research inquiries pertinent to China, probing into the following key questions:

1. What is the effect of school enrollment on the ecological footprint?
2. What is the effect of AI robots on the ecological footprint?
3. What is the effect of global supply chain management on the ecological footprint?
4. What is the effect of public–private partnership investment in energy on the ecological footprint?
5. What is the effect of economic growth on the ecological footprint?

These questions frame the investigation into the intricate relationships between technological advancements, economic strategies, and social dynamics, aiming to elucidate their combined influence on environmental sustainability in the Chinese context.

1.1. Contribution of the Study

1.1.1. Contribution 1 (Linked to RQ3)

Despite a growing body of research identifying socioeconomic, institutional, and technological drivers of the ecological footprint, no study has investigated how global supply chain management—encompassing procurement policies, logistics optimization, and supplier engagement—shapes environmental outcomes. As the world's second-largest economy and leading manufacturing hub, China's supply chain strategies critically influence its energy demand profile and decarbonization trajectory. By empirically linking supply chain governance mechanisms with ecological footprint indicators, this study fills a pivotal gap in the literature and equips policymakers with actionable guidance on embedding sustainable trade and logistics practices within national energy and climate frameworks.

1.1.2. Contribution 2 (Jointly Linked to RQ2 and RQ4)

Second, by combining the study of advanced AI-driven robotics with the analysis of public–private investment in energy infrastructure, this research breaks new ground: no prior work has jointly assessed how these technological and financial mechanisms interact to shape the ecological footprint. In isolating this intersection, we address a significant blind spot in the environmental economics literature, where automation and collaborative energy financing have typically been examined in isolation. By integrating these dimensions, we inaugurate a fresh discourse on the synergies and trade-offs between cutting-edge technology adoption and innovative funding models for clean energy, thereby equipping scholars and policymakers with a novel framework to guide both empirical inquiry and strategic decision-making.

1.1.3. Contribution 3 (Method; Supports All RQs, Especially Policy Targeting)

Third, methodologically, this study advances the field by integrating artificial neural networks with wavelet-based quantile regression to form an ANN–WQR framework. Unlike traditional regression techniques, this approach nonlinearly maps complex relationships while decomposing the time series into distinct frequency bands and quantile levels, thereby uncovering how drivers influence the ecological footprint across short-, medium-, and long-run horizons as well as at low, median, and high impact quantiles [18,19]. By delivering scale and distribution-specific insights, the ANN–WQR method empowers policymakers to design targeted decarbonization measures and allocate resources more effectively, pinpointing the periods and risk segments where interventions will yield the greatest environmental gains.

The subsequent sections are organized as follows: Section 2 presents the theoretical framework and literature review; Section 3 describes the data and methodology; Section 4 discusses the findings; and Section 5 concludes the study.

2. Theoretical Framework and Synopsis of Studies

2.1. Theoretical Framework

Ecological footprint analysis posits that the adoption of AI robots in production processes can enhance resource efficiency—optimizing energy use, reducing material waste, and streamlining logistics—thereby exerting a mitigating effect on environmental pressure [10,20]. Similarly, sustainable global supply chain management—characterized by lean transportation, circular procurement, and collaborative planning—attenuates ecological impacts through lower emissions, reduced handling losses, and improved material recycling [8,21]. In parallel, expanding school enrollment fosters human capital development and environmental literacy; evidence suggests that higher enrollment rates correlate with greater adoption of sustainable consumption patterns and more effective community engagement in conservation initiatives, thus lowering per-capita ecological footprints [22,23]. Moreover, public–private partnerships in the energy sector mobilize private capital and expertise to deploy renewable infrastructure—such as solar parks and wind farms—driving down carbon intensity and curtailing ecological footprints more rapidly than reliance on public financing alone [13,14].

Economic growth, meanwhile, operates as a dual force: it can scale up resource use and enlarge ecological footprints, yet it also creates the fiscal and technological capacity for cleaner production and structural transformation toward less resource-intensive industries [24–26]. Through a composition effect, growth fueled by AI-driven productivity gains and a better-educated workforce can shift the economic mix toward high-value, low-impact services and digital industries, thereby dampening environmental pressures. Concurrently, technique improvements—catalyzed by innovations financed via public–private partnerships—enhance energy efficiency and resource productivity, offering pathways to decouple GDP expansion from ecological degradation. This framework thus hypothesizes both direct effects of AI robots, supply chain management, education, and energy investment on the ecological footprint, and indirect, growth-mediated channels that amplify or attenuate these relationships.

2.2. Synopsis of Studies

The literature on drivers of the ecological footprint (EF) reveals a nuanced interplay between technological innovation, investment flows, supply-chain practices, and economic expansion. First, studies on robotics (ROBOT) consistently show that automation can mitigate environmental pressures, though with important caveats. Ref. [10] employ both the entropy method on global data (2010–2019) and SYS-GMM across 67 countries (1993–2019) to demonstrate that greater robotic adoption is associated with a statistically significant reduction in EF [1]. Similarly, Rasheed et al. (2024) use NARDL techniques for seven Asian developing economies (1990–2020) and corroborate that robotics dampens ecological impact [20]. However, as shown in [12], panel estimators in over 128 countries suggest no clear directional effect, highlighting that context and model specification matter. In China, Ref. [9] find a threshold relationship—robotics reduces EF up to a point, beyond which gains plateau or reverse, while [27] apply neural network models to G20 data (1999–2018) and detect no robust net effect. Collectively, these findings argue that robotics' environmental benefits hinge on the intensity of deployment, energy mix, and complementary policies that guide green automation [20].

Public–private investment in energy (PPE) exhibits similarly mixed outcomes. ARDL analyses in Pakistan [28] and South Asia–Pacific [15] report that higher PPE inflows drive up EF, suggesting that capital injections without stringent environmental safeguards may lock in fossil-based infrastructure. By contrast, Ref. [14] use FMOLS for Pakistan (1980–2019) and find that PPE actually decreases EF, implying that targeted investments in renewables can deliver environmental dividends. Ref. [16] further illustrates this debate by showing that in Bangladesh (1997–2019), PPE raises CO_2 emissions—a proxy for EF—when directed toward conventional power. Ref. [29] confirm in South Africa (1960–2020) that, absent regulatory oversight, PPE tends to exacerbate ecological pressures. Together, these studies underline that the sign of PPE's effect on the environment depends critically on sectoral allocation, financing terms, and the regulatory framework governing investment quality.

Global supply-chain management (GSCM) research paints a more consistently cautionary tale regarding environmental impact. In emerging economies (1997–2020), QARDL models by [6] reveal that intensified supply-chain activities amplify CO_2 emissions—a core component of EF—due to increased production and logistics emissions. Refs. [7,8] confirm this pattern in global and Japanese contexts, respectively, albeit using different methods and panel estimators. Recent WQQR analysis for the United States (2000 Q1–2022 Q4) by [21] also documents a robust positive relationship between GSCM and CO_2 output. These convergent findings highlight that, without green logistics, carbon pricing, and optimized inventory practices, the integration of global value chains can substantially heighten ecological burdens.

Finally, economic growth (EG) remains a powerful driver of EF across varied contexts. Panel quantile regressions by [30] for OECD countries (2001–2020) show that growth uniformly elevates EF across the distribution, though the effect size intensifies at higher quantiles. ARDL estimations in China (1990–2019) by [31] and panel regressions covering 160 developing nations [32] both confirm that output expansion translates into greater ecological impact. DOLS analysis for the G20 (Naseem et al., 2024) and the novel D2C algorithm in Russia [26] similarly document a positive and significant EG–EF nexus. These consistent results imply that, absent structural shifts toward low-carbon technologies and efficiency gains, aggregate growth pressures will continue to push ecological footprints upward. Table 1 presents a summary of the findings.

2.3. Gap in the Literature

While this literature is extensive, several limitations constrain inference and motivate our study. Findings are highly model-dependent—ranging from SYS-GMM and FMOLS to NARDL and panel estimators—yielding sign reversals for robotics (ROBOT) and public–private energy investment (PPE) that reflect differences in identification, control sets, and functional form (e.g., neglected nonlinearity and thresholds). Measurement choices also blur comparability: many papers proxy ecological footprint (EF) with CO_2 emissions, overlooking land use, materials, and biodiversity components; GSCM is often captured by coarse trade or logistics aggregates that omit procurement policies, supplier engagement, inventory practices, and carbon pricing exposure; PPE metrics rarely disaggregate by technology (renewables vs. conventional), financing terms, or regulatory quality, making the environmental content of capital flows opaque. Cross-country panels mask contextual heterogeneity in energy mixes, industrial composition, and policy regimes, while China-focused evidence on supply-chain governance remains sparse. Dynamic features are underexplored: most studies do not distinguish short-, medium-, and long-run responses or distributional (quantile) heterogeneity, despite evidence of thresholds and plateau effects for automation. Endogeneity—via reverse causality (e.g., EF shaping investment/technology), omitted variables (energy prices, standards), and weak instruments—further limits causal claims. Finally, the literature seldom jointly models interactions among ROBOT, PPE, and GSCM, precluding a coherent view of synergies and trade-offs. These gaps justify an approach that (i) measures GSCM as governance and operational practices, (ii) separates PPE by energy type and institutional quality, and (iii) traces scale- and quantile-specific EF effects while explicitly testing technology–finance–supply-chain interactions.

Table 1. Summary of past studies.

Author(s)	Nations	Timeframe	Method(s)	Findings
AI Robot (ROBOT) and Ecological Footprint (EF)				
[10]	Global Economy	2010–2019	Entropy method	ROBOT ↓ EF
[10]	67 countries	1993–2019	SYS-GMM	ROBOT ↓ EF
[20]	seven Asian developing countries	1990–2020	NARDL	ROBOT ↓ EF
[12]	128 countries	Undefined	Panel Estimator	ROBOT → EF
[9]	China	2018–2022	Panel threshold	ROBOT ↑↓ EF
[27]	G20 countries	1999–2018	Artificial neural network	ROBOT → EF
Public Private Investment in Energy (PPE) and Ecological Footprint (EF)				
[28]	Pakistan	1992–2018	ARDL	PPE ↑ EF
[14]	Pakistan	1980–2019	FMOLS	PPE ↓ EF
[16]	Bangladesh	1997–2019	FMOLS	PPE ↑ CO_2
[15]	South Asia and the Pacific region	1990–2017	ARDL	PPE ↑ EF
[29]	South Africa	1960–2020	ARDL	PPE ↑ EF
Global Supply Chain Management (GSCM) and Ecological Footprint (EF)				
[6]	1997–2020	emerging economies	QARDL	GSC ↑ CO_2
[8]	Undefined	Global	Undefined	GSC ↑ CO_2
[7]	Undefined	Japan	SEM	GSC ↑ CO_2
[21]	2000Q1–2022Q4	United States	WQQR	GSC ↑ CO_2
Economic Growth (EG) and Ecological Footprint (EF)				
[30]	OECD countries	2001–2020	Panel quantile regression	EG ↑ EF
[31]	China	1990–2019	ARDL	EG ↑ EF
[32]	160 developing countries	2001–2022	Panel Regression	EG ↑ EF
[33]	G20 countries	1990–2020	DOLS	EG ↑ EF
[26]	Russia	1970–2017	New D2C algorithm	EG ↑ EF

Note: ↓ decrease, ↑ increase, → direct relationship.

3. Data and Methods

3.1. Data

This study examines the drivers of the ecological footprint in China. Table 2 provides an overview of the key variables used in our empirical analysis, detailing how each is measured, its abbreviation, and its primary data source. The adoption of industrial automation is captured by the annual number of industrial robots installed (ROBOT), drawn from [34]. Global supply chain management (GSCM) is represented by a composite index designed to reflect firms' ability to coordinate logistics and procurement activities across borders. Human capital is proxied by tertiary school enrollment expressed as a gender parity index (SE), and investment in energy infrastructure is measured by the monetary value of public–private partnership projects in energy (PPE), both sourced from [35]. Environmental pressure is quantified via the ecological footprint in global hectares per capita (EF), as reported by [36]. Finally, economic performance is captured by real GDP per capita (EG), measured in constant 2015 U.S. dollars, also from [35]. The study data span from 2011Q1 to 2024Q1. All variables, except GSCM, have been logarithmically transformed. Figure 1 presents the trend of the variables.

Table 2. Data source and measurement.

Variables	Measurement	Abbreviation	Sources
AI Robot **	Annual industrial robots installed	ROBOT	[34]
Global supply chain management **	Index	GSCM	[37]
School enrollment **	School enrollment, tertiary (gross), gender parity index (GPI)	SE	[35]
Public–private partnerships investment in energy **	Current USD ($)	PPE	[35]
Ecological Footprint *	Gha Per Capita	EF	[36]
Economic Growth **	GDP Per Capita Constant USD ($) 2015	EG	[35]

Note: * denotes dependent variable, $ denotes United States dollar (USD), and ** denotes independent variables.

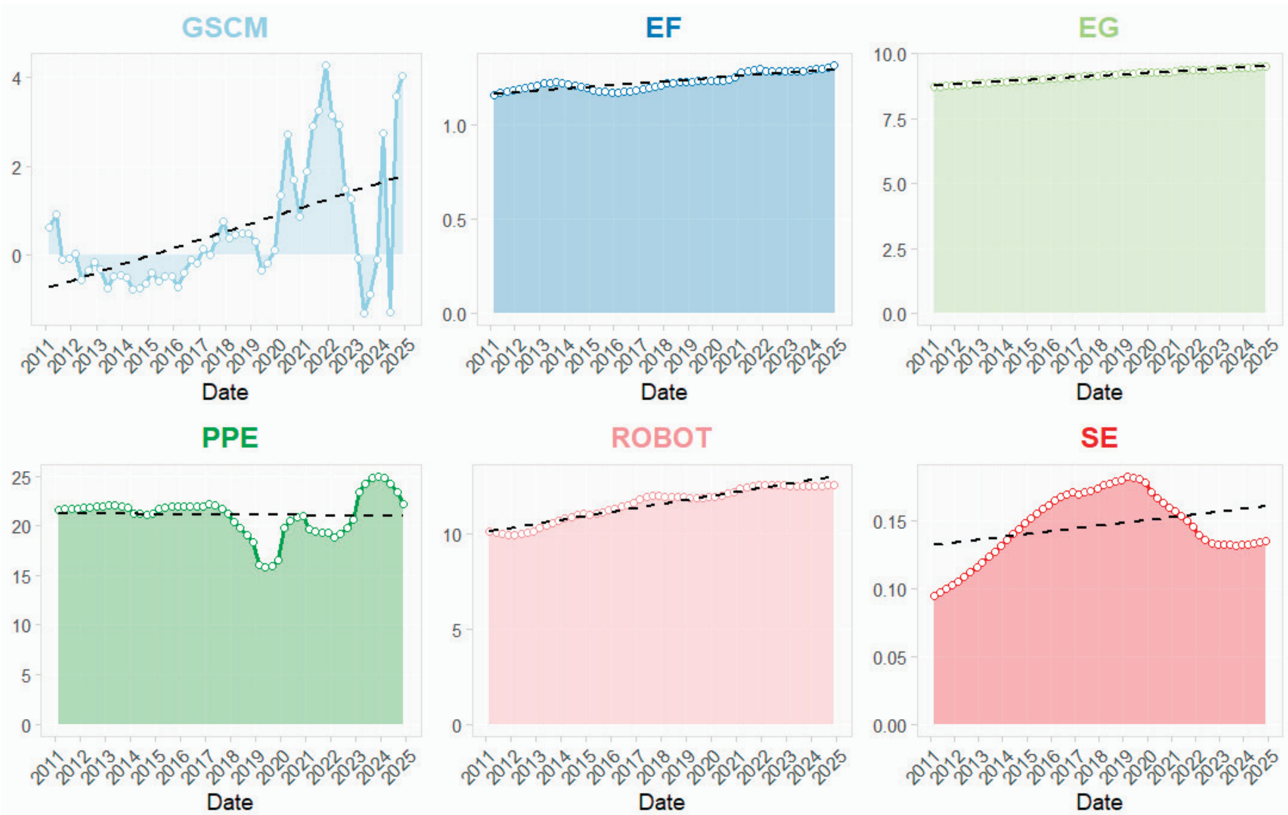


Figure 1. Trend of the variables.

Determinants of EF are theoretically and policy-relevant because they span the principal channels through which economies transform resource use and emissions across scale, composition, and technique effects. AI-driven robotics can lower EF by raising process and energy efficiency, improving defect rates, and enabling predictive maintenance, yet may also induce rebound effects (higher output/throughput, energy-intensive data centers) and shift footprints upstream via equipment manufacture—making its net impact contingent on the energy mix, deployment intensity, and complementary environmental standards. GSCM governs Scope-3 pressures—procurement policies, logistics optimization, inventory practices, and supplier engagement—thereby mediating embodied carbon, material throughput, and transport emissions along global value chains; without green logistics and carbon-aware sourcing, trade integration can magnify EF even when on-site efficiency improves. School enrollment (human capital) influences EF through preferences and productivity: higher education can foster environmental literacy, compliance, and innovation that reduce EF, but also raises lifetime income and consumption aspirations that may expand material and energy demand, implying heterogeneous effects across the income/consumption distribution. PPP-E shapes EF via the composition of energy infrastructure and governance of capital: partnerships targeted to renewables, grids, and storage can decouple growth from footprints, whereas PPPs that lock in fossil-based assets increase EF; contract design, risk allocation, and regulatory quality determine which path dominates. Finally, EG is the baseline macro driver of EF through scale effects, with potential mitigation via composition (structural change toward services/cleaning industry) and technique (clean technologies, efficiency)—so its sign and magnitude depend on the speed of decarbonization relative to output expansion.

3.2. Methods

The study fused the artificial neural network with the wavelet quantile regressions (WQR) suggested by [38]. Let $\{Y_t\}$ and $\{X_t\}$ be the original series. A three-level Maximal Overlap Discrete Wavelet Transform (MODWT) suggested by [19] yields detailed coefficients

$$w_{Y,j,t}, w_{X,j,t} = \text{MODWT}(Y_t; J=3), \text{MODWT}(X_t; J=3) \tag{1}$$

Aggregate into three bands $h \in \{\text{ Short, Medium, long }\}$:

$$Y_t^{(h)} = \sum_{j \in L_h} w_{Y,j,t}, \tag{2}$$

$$X_t^{(h)} = \sum_{j \in L_h} w_{X,j,t}, \tag{3}$$

where $L_{\text{Short}} = \{1\},\ L_{\text{Medium}} = \{2\},\ L_{\text{Long}} = \{3\}$.

For each h and quantile τ, estimate

$$Q_{Y_t^{(h)}|X_t^{(h)}}(\tau) = \alpha_h(\tau) + \beta_h(\tau) X_t^{(h)} \tag{4}$$

by solving

$$\left(\hat{\alpha}_h(\tau), \hat{\beta}_h(\tau)\right) = \arg\min_{a,b} \sum_t \rho_\tau \left(Y_t^{(h)} - \left(a + bX_t^{(h)}\right)\right) \tag{5}$$

This yields $\hat{\beta}_h(\tau)$, its bootstrap SE, and p-value.

Normalize each band:

$$\tilde{Y}_t^{(h)} = \frac{Y_t^{(h)} - min\left(Y^{(h)}\right)}{max\left(Y^{(h)}\right) - min\left(Y^{(h)}\right)}, \tag{6}$$

$$\tilde{X}_t^{(h)} = \frac{X_t^{(h)} - min\left(X^{(h)}\right)}{max\left(X^{(h)}\right) - min\left(X^{(h)}\right)} \tag{7}$$

Fit a single–hidden-layer net with five neurons:

$$\hat{\tilde{Y}}_t^{(h)} = \sum_{k=1}^{5} v_{h,k} \sigma\left(u_{h,k} \tilde{X}_t^{(h)} + b_{h,k}^{(1)}\right) + b_h^{(2)}. \tag{8}$$

Rescale back:

$$\hat{Y}_t^{(h)} = \hat{\tilde{Y}}_t^{(h)} \left[max\left(Y^{(h)}\right) - min\left(Y^{(h)}\right)\right] + min\left(Y^{(h)}\right), \tag{9}$$

and compute

$$\mathrm{MSE}_h = \frac{1}{N_{\text{test}}} \sum_t \left(\tilde{Y}_t^{(h)} - Y_t^{(h)} \right)^2. \tag{10}$$

4. Findings and Discussion

4.1. Descriptive Statistics

Figure 2 summarizes eight key univariate statistics for each of the six series—EF, EG, GSCM, PPE, ROBT, and SE—using a common color scale (yellow = low values, purple = high). Starting with location, EF and EG both sit at very low magnitudes (means of 1.23 and 9.14, medians 1.22 and 9.16), whereas PPE is by far the largest series (mean $\approx$ 21.11, median 21.72) and SE the smallest (mean = median = 0.15). Dispersion follows suit: standard deviations run from only 0.02 in SE and 0.04 in EF, to 2.04 in PPE and 1.41 in GSCM. Skewness reveals that GSCM is positively skewed (1.16), indicating occasional large spikes, while PPE (-0.71), ROBT (-0.56), and SE (-0.33) exhibit moderate left-tail weight. Kurtosis values above 3 for GSCM (3.32) and PPE (3.84) signal heavier tails than Gaussian, whereas EG (1.85) and EF (1.82) are platykurtic. Finally, the Jarque–Bera statistics show that GSCM ($\approx$12.87) and PPE ($\approx$6.36) most strongly reject normality at conventional levels (JB > 5.99 at 5%), with ROBT (5.36) borderline, while the other series remain closer to Gaussian behavior. Overall, PPE dominates in scale and tail-risk, GSCM is the most skewed and heavy-tailed, and EF, EG, and SE are comparatively well behaved.

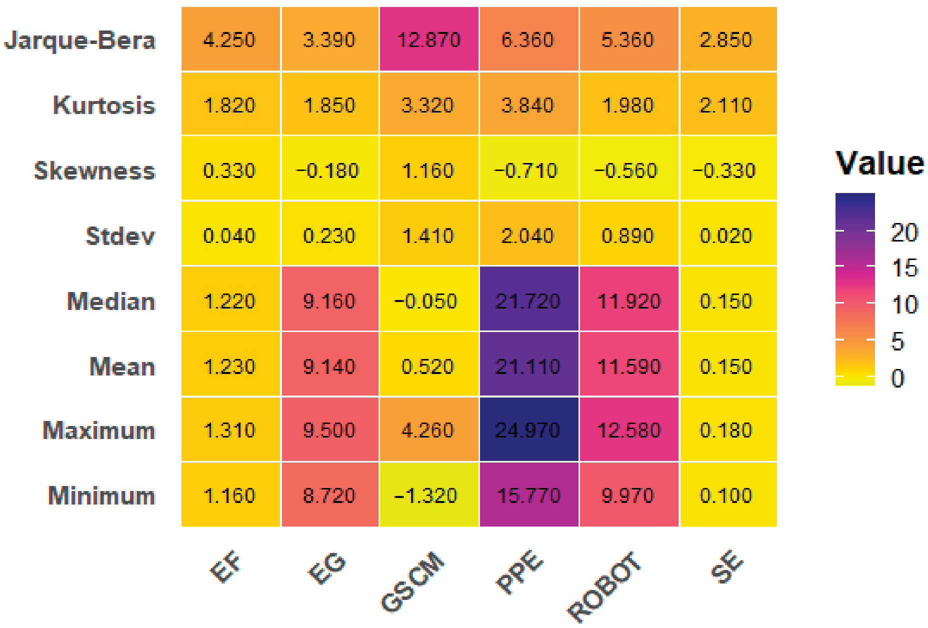


Figure 2. Descriptive statistics.

4.2. Nonlinearity and Normality Test Results

Table 3 brings together a battery of univariate diagnostic checks on each of our six series to assess (Panel A) departures from Gaussianity and (Panel B) evidence of nonlinearity. In Panel A, the robust Jarque–Bera and Bootstrap symmetry tests flag highly significant departures from normality for GSCM, PPE and ROBOT, while EF and EG show weaker evidence of skewness/kurtosis non-Gaussianity (their Jarque–Bera statistics fall below conventional cut-offs, but their difference-sign and Mann–Kendall tests remain strongly significant, indicating asymmetric distributional features and trends). Across all variables, the Runs and Bartels tests are overwhelmingly significant, confirming serial dependence and further refuting the iid–Gaussian assumption. Moving to Panel B, the Tsay and Keenan tests—both tailored to detect specific forms of threshold-type nonlinearity—only register significance for ROBOT, suggesting that simpler nonlinear structures may be present there. By contrast, the White neural network and Teraesvirta NN tests, which are more general tests for neglected nonlinear dynamics, reject linearity at the 1 percent level for every series. Taken together, these diagnostics tell us that none of our six drivers conforms to the twin benchmarks of normal, linear behavior; instead, each exhibits at least some combination of heavy tails, asymmetry, serial dependence, or richer nonlinear dependence that justifies our use of wavelet-quantile and ANN methods.

Table 3. Diagnostic test results.

Panel A. Normality test results							
	Bartels test	Robust Jarque–Bera test	Test of normality SJ test	Bootstrap symmetry test	Difference sign test	Mann–Kendall rank test	Runs test
GSCM	−5.126 ***	25.642 ***	3.131 **	4.473 ***	2.523 **	3.908 ***	−4.855 ***
EF	−7.364 ***	2.6422	−0.881	1.1971	5.735 ***	7.767 ***	−6.743 ***
EG	−7.462 ***	2.5611	−1.877	−0.879	11.700 ***	10.820 ***	−7.282 ***
PPE	−6.880 ***	20.471 ***	4.150 ***	−3.400 ***	0.229	−0.657	−6.203 ***
ROBOT	−7.386 ***	3.7984	−0.53336	−3.649 ***	6.017 ***	9.252 ***	−6.743 ***
SE	−7.380 ***	2.4399	−1.7813	−0.214	4.358 ***	2.509 **	−7.012 ***
Panel B. Nonlinearity test results							
	Tsay Test	White NN test	Keenan test	Teraesvirta NN test			
GSCM	2.004	9.941 ****	1.978	5.213 *			
EF	0.060	29.08 ***	0.042	22.455 ***			
EG	0.016	96.59 ***	0.001	92.151 ***			
PPE	0.696	155.49 ***	0.607	144.21 ***			
ROBOT	7.771 ***	62.027 ***	4.614 ***	62.315 ***			
SE	0.413	159.97 ***	0.384	129.28 ***			

Note: ***, ** and * denotes 0.01, 0.05 and 0.10 significance level, respectively.

4.3. Kernel Plot Results

Figure 3 presents the kernel plot of the studied variables. Panels (a) through (f) each overlay the kernel-density estimates for the training sample (bottom ridge) and the held-out testing sample (top ridge) of six variables—GSCM, ROBOT, EG, PPE, EF, and SE—using a continuous hue scale to map density height to the variable's value. Grey ticks along each axis mark the individual observations, and faint vertical grid lines denote key quantiles. In panel (a), GSCM exhibits a clear bimodal shape in both splits, with a dominant mode just above zero and a secondary hump near +3, suggesting two distinct regimes in supply-chain digitalization; the testing distribution closely mirrors the training but with slightly less mass in the upper mode. ROBOT in panel (b) is largely unimodal and roughly symmetric around 12–12.5 in both samples, indicating consistent robotics penetration, though test-set values are marginally more concentrated. Panel (c) shows EG to be mildly right-skewed, peaking near 9.2%, with both ridges almost superimposed—evidence of stable growth dynamics across training and testing. PPE (panel d) stands out with a pronounced right tail and peak around 21–22, reflecting occasional surges in public–private environmental expenditure; the test ridge is slightly taller on the right, hinting at a few higher-expenditure observations. EF (panel e) is centered near 1.25, with a slight left skew and broad shoulders, indicating occasional dips in ecological footprint; again, the training set has somewhat fatter tails than the test set. Finally, SE (panel f) is the narrowest of all, concentrated around 0.14–0.16, showing very little dispersion between the two samples and underscoring the relative stability of social equity measures across periods. Overall, these kernel-density plots reveal that—while most distributions remain remarkably similar between training and test—the tail behavior and modality can differ subtly, an important consideration when fitting models to each variable.

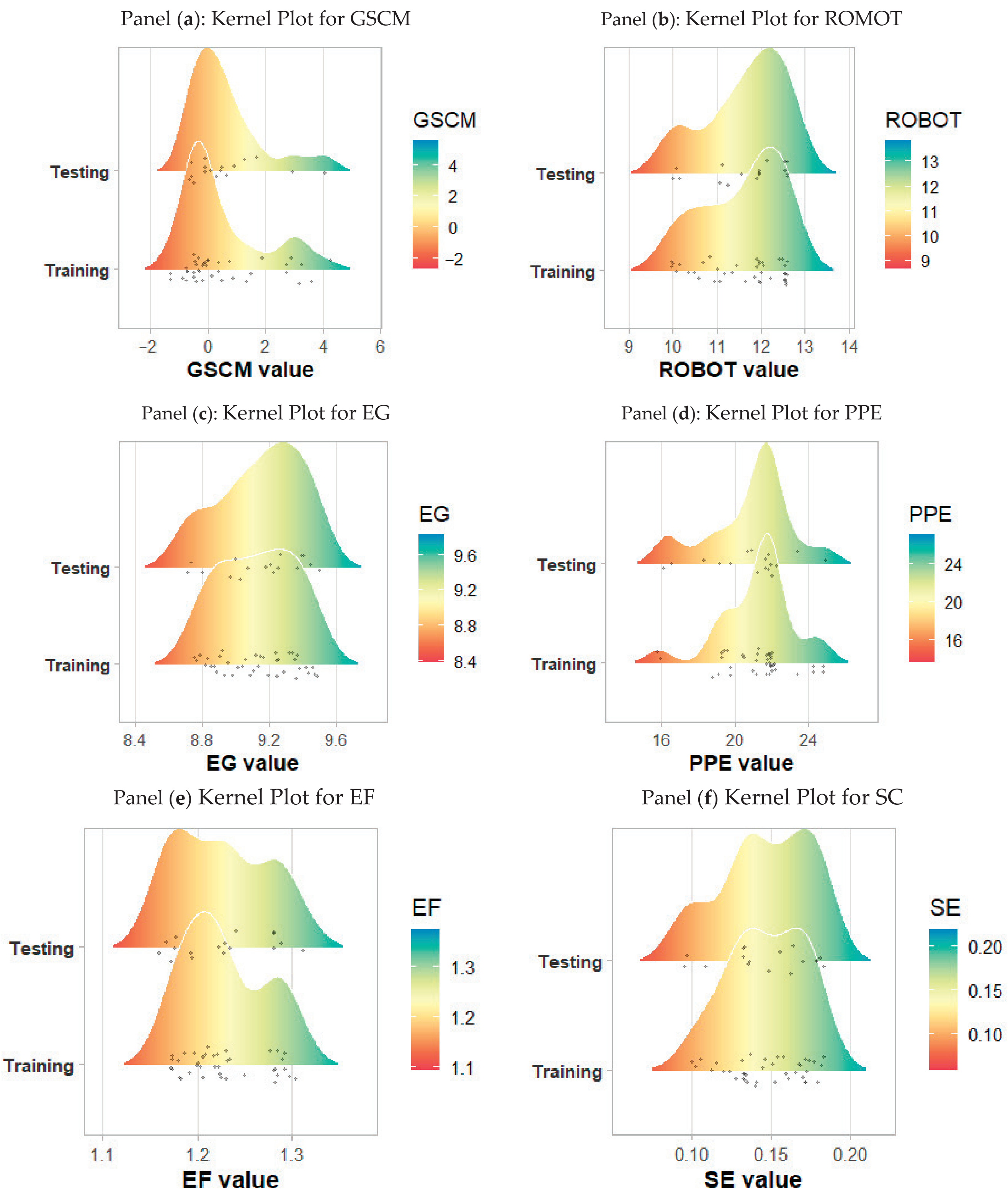


Figure 3. Kernel density plot of EF, PPE, EG, SE, ROBOT, and GSCM.

4.4. ANN Models Results

Figure 4 presents the ANN's hold-out predictions of ecological footprint (EF) by the independent variables. Each panel plots the ANN's hold-out predictions of EF against the actual EF values. The 45° dashed line denotes perfect prediction. In the GSCM panel, the red points scatter widely around the line, yielding an RMSE of 0.0418 and an R^2 of only 0.2496—indicating that supply-chain digitalization alone explains about 25% of the variation in EF. By contrast, SE achieves moderate accuracy (blue, RMSE = 0.0311, R^2 = 0.5978), suggesting a stronger but still incomplete linkage. EG (economic growth) produces the tightest clustering along the 45° line (green), with the lowest RMSE (0.0172) and highest R^2 (0.9235), which implies that growth dynamics are the dominant predictor of EF in this sample. PPE (public–private environmental expenditure) falls in between (purple; RMSE = 0.0386, R^2 = 0.3595), and ROBOT (robotics penetration) also performs very well (orange; RMSE = 0.0180, R^2 = 0.8764). Overall, EG and ROBOT each account for over 87% of EF's out-of-sample variance, SE about 60%, PPE roughly 36%, and GSCM only about 25%, highlighting the relative predictive power of these drivers under the ANN framework.

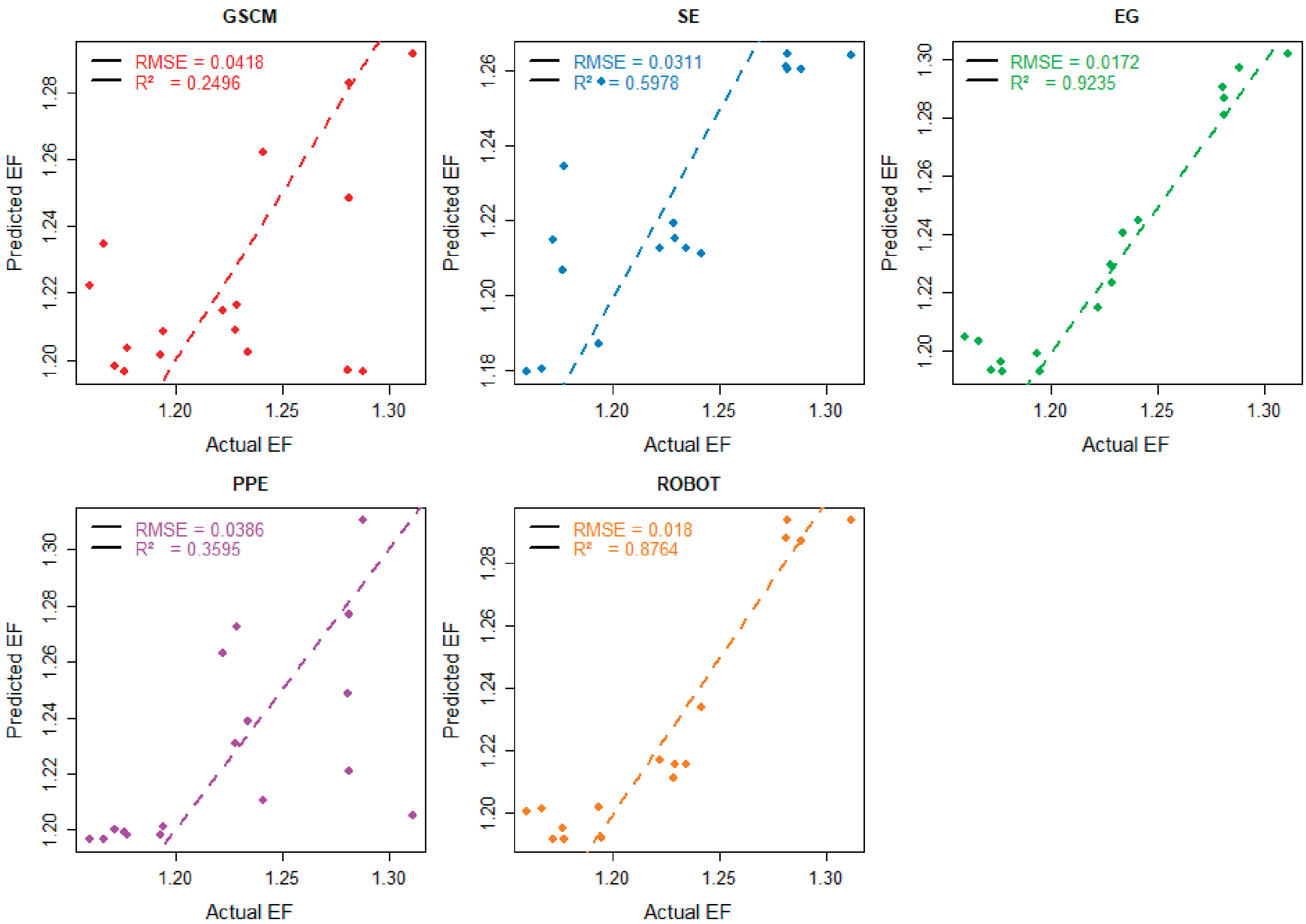
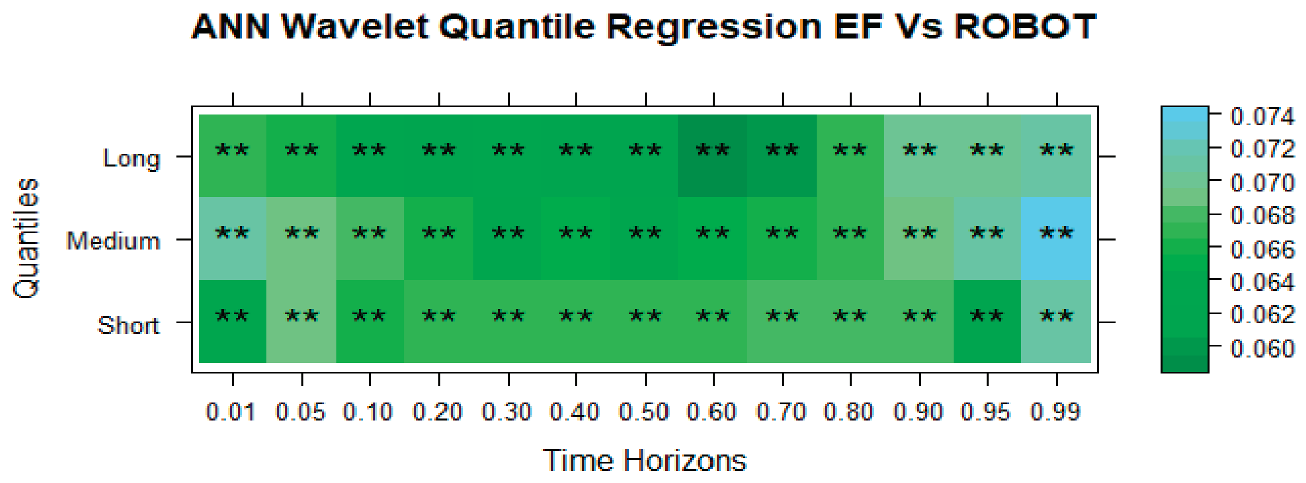


Figure 4. ANN models: each predictor → EF.

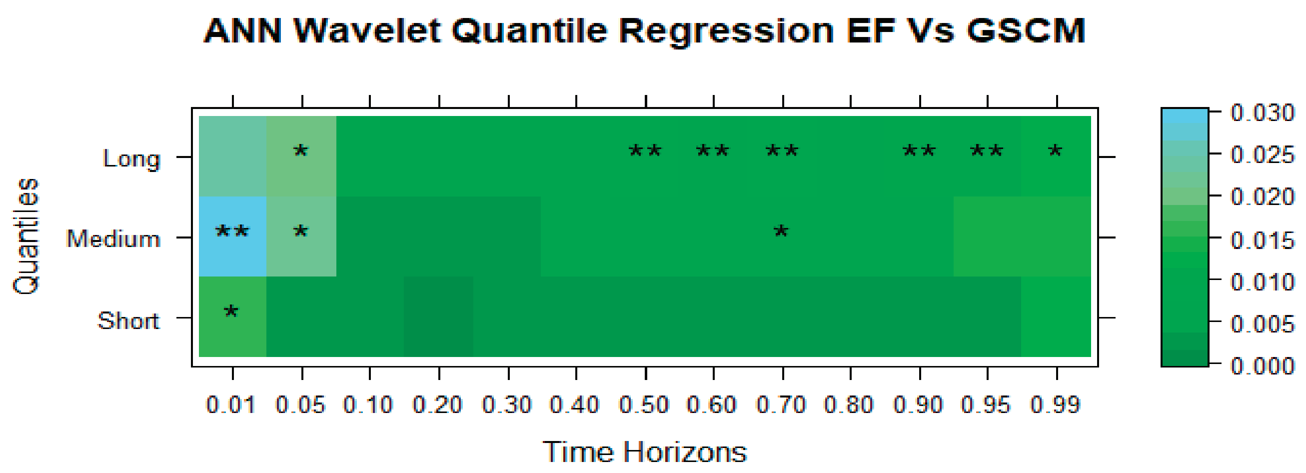
4.5. ANN Wavelet Quantile Regression Results

Next, we used the ANN wavelet quantile regression (see Figure 5) to examine the association. This approach helps in identifying the association between the variables with a focus on various periods and quantiles.

(**a**) EF vs. ROBOT



(**b**) EF vs. GSCM



(**c**) EF vs. PPE

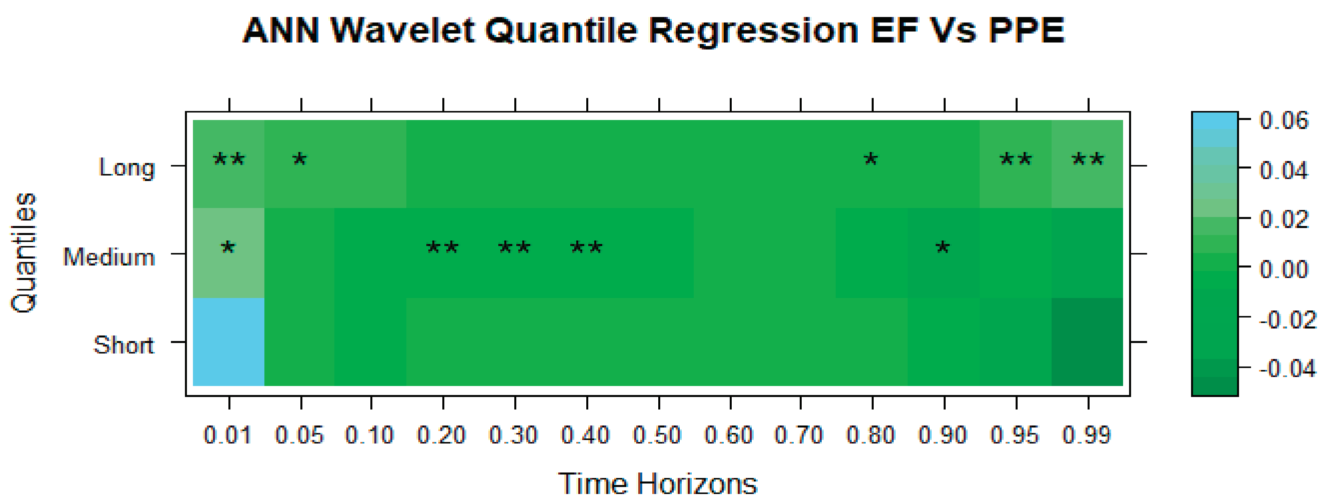
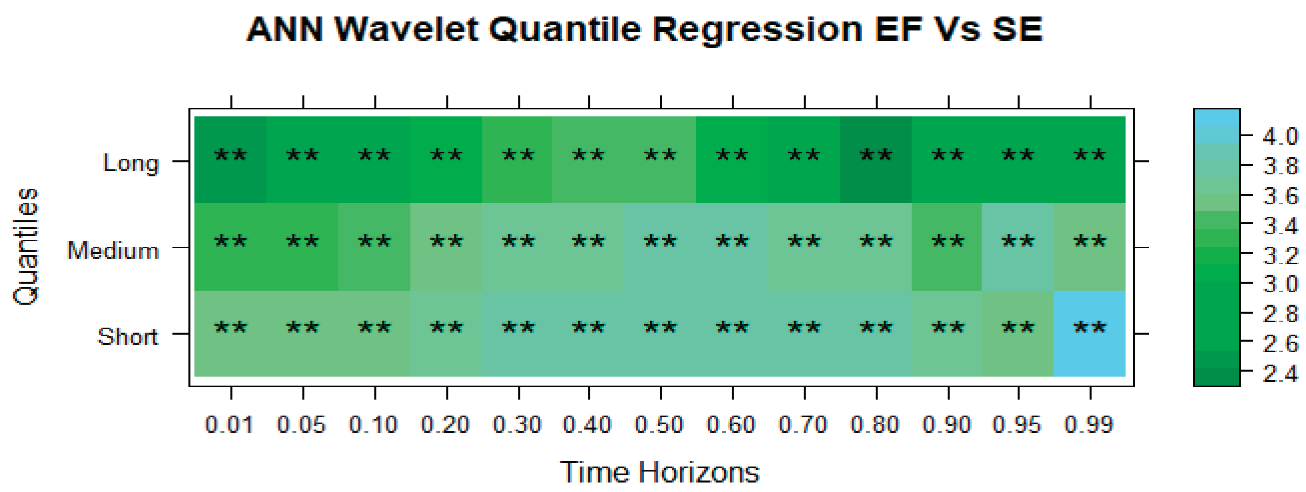


Figure 5. *Cont.*

(**d**) EF vs. SE



(**e**) EF vs. EG

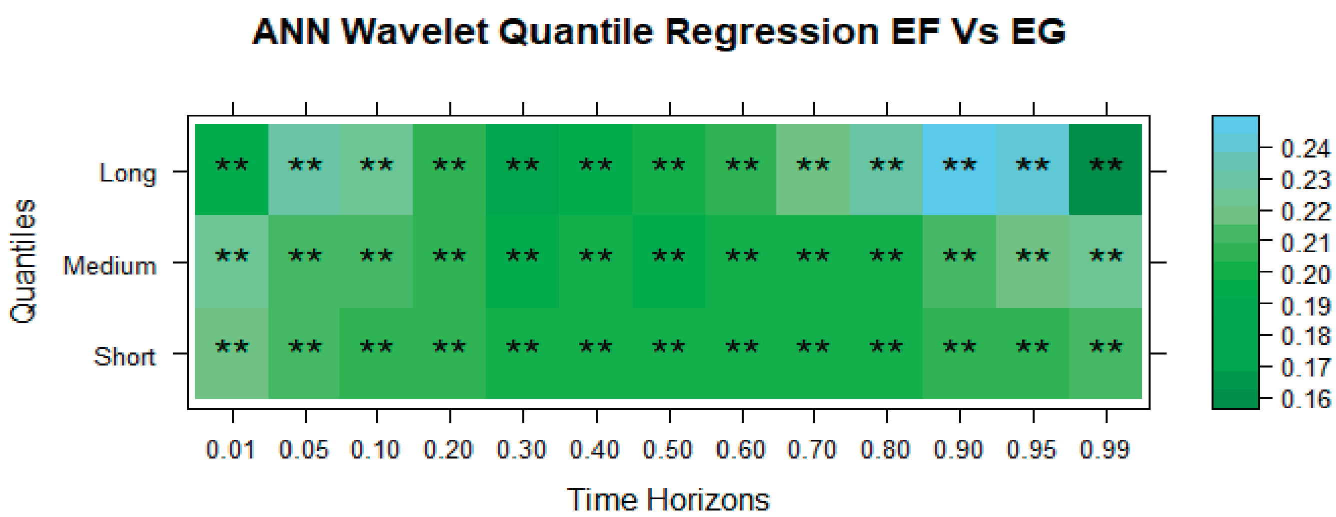


Figure 5. ANN wavelet quantile regression estimates. Note: ** and * denotes 0.05 and 0.10 significance level, respectively.

Figure 5a presents the effect of ROBOT on ecological footprint (EF). In the short run, robotics is positively associated with China's ecological footprint: the wavelet–quantile coefficients rise from +0.060 at the 10th percentile ($\tau = 0.10$), to +0.064 at the median ($\tau = 0.50$), and to +0.070 at the 99th percentile. At low EF quantiles ($\tau \leq 0.20$), the modest positive coefficient (~+0.060) reflects that when baseline energy use is low, early automation primarily substitutes labor without expanding output, so the net energy increase remains limited [20]. Around the median, the positive effect grows as mid-level producers leverage robots to ramp up throughput, drawing additional power for both machinery operation and auxiliary services. At the upper tail ($\tau \geq 0.90$), the largest short run coefficient (≈+0.070) occurs because high footprint firms already operate near capacity, and any added automation demands disproportionately more cooling, maintenance energy, and peak load electricity, thus amplifying their footprint [11]. Over the medium horizon, robotics continues to have a positive effect on EF, with coefficients rising to approximately +0.063 at low quantiles, +0.066 at the median, and +0.071 at the top quantiles. Here, low EF units gradually expand production lines around new robots—so even small initial deployments yield sustained positive energy draws. Median producers reinvest early efficiency gains into complementary processes (e.g., real-time analytics), further increasing electricity demand. Meanwhile, high EF firms use medium term automation rollouts to scale up entire facilities, lock in higher energy intensity capital stocks, and trigger larger supply chain emissions, driving the continued upward shift in β (τ) with τ [39]. In the long run, the positive relationship between robotics and EF persists: coefficients reach about +0.065 at low quantiles, +0.068 at the median, and peak at +0.074 for the highest quantiles. At lower EF states, long-term diffusion of robotics spurs new plant constructions and grid upgrades, so even once modest adopters remain on a permanently higher energy trajectory. Median tier firms, after several investment cycles, adopt complementary technologies (e.g., AI driven HVAC control) that cumulatively raise both direct and embodied energy use. Additionally, at the upper tail, decades-long integration of robotics into every production stage—from raw material handling through finished goods packaging—locks in very high energy intensities.

Figure 5b presents the effect of global supply chain management (GSCM) on ecological footprint (EF). In the short run (level 1 band), GSCM is positively associated with China's ecological footprint only at the very lowest quantile. At $\tau = 0.01$, the coefficient is $\beta \approx +0.008$ *, indicating that when EF is minimal, even early-stage improvements in logistics coordination and supplier integration can temporarily boost energy and material throughput (e.g., new shipment routes or ramped-up inventories) [7]. At $\tau = 0.05$, all three horizons show positive coefficients that now reach statistical significance: short-run $\beta \approx +0.010$ *; medium-run $\beta \approx +0.012$ **; and long-run $\beta \approx +0.009$ *. Beyond the bottom 10 percent ($\tau \geq 0.10$), the short-run effect remains small and insignificant ($\beta \approx 0$), suggesting that once basic supply-chain systems are in place, marginal GSCM upgrades do not immediately alter ecological loads [40]. Over the medium and long horizons, the positive GSCM–EF relationship resurfaces at higher quantiles. In the medium term, significant returns around $\tau = 0.70$ with $\beta \approx +0.015$ *—reflecting how deeper supplier integration and more frequent cross-border shipments lock in additional energy use for warehousing and transport. In the long run, positive coefficients are significant from $\tau = 0.60$ through $\tau = 0.99$, rising from $\approx$+0.013 * at the lower bound to $\approx$+0.028 ** at the upper tail. This pattern indicates that in provinces where EF is already high, sophisticated just-in-time logistics, automated sorting centers, and expanded port infrastructures cumulatively increase energy-intensive operations, magnifying environmental impacts over time [7].

Figure 5c presents the effect of public–private investment in energy (PPE) on ecological footprint (EF). In the short run, PPP-backed energy investments in China are positively related to the national ecological footprint, but the effect is generally insignificant at the extreme low end ($\tau = 0.01$, $\beta \approx +0.06$, no star) and negligible ($\beta \approx$ +0.00–+0.01) across τ = 0.05–0.80. Only at the very upper tail—when EF is already high—does PPE register a modest but positive and significant effect (τ = 0.95–0.99, $\beta \approx$ +0.015–+0.020, * or **), reflecting the one-off commissioning and start-up phase energy costs of new renewable plants and grid upgrades in provinces with heavy baseline footprints [14]. Moving into the medium term, the positive footprint increasing effect of PPE becomes statistically significant across a broad swath of quantiles. From the lower middle quantiles (τ = 0.10–0.50, $\beta \approx$ +0.010–+0.020, **), PPP projects transition from pilot to commercial operation, deploying commercial-scale turbines, transmission lines, and substations that draw both embodied and operational energy. Moreover, at $\tau = 0.90$ ($\beta \approx +0.018$, *), high footprint provinces—where large-scale PPP wind and solar farms dominate—experience notable spikes in electricity consumption for maintenance and ancillary services, cementing a positive medium run impact on EF [15]. By the long horizon, PPE's influence on China's ecological footprint remains positive and significant at the extremes of the distribution, both lowest ($\tau = 0.01$, $\beta \approx +0.015$, **) and highest quantiles (τ = 0.95–0.99, $\beta \approx$ +0.022–+0.025, **). In low footprint settings, long-term PPP rollouts lock in new grid infrastructure and permanent plant operations, sustainably raising baseline energy use. At the upper tail, decades long maturation of PPP pipelines—from mega solar parks in Xinjiang to strategic interprovincial transmission corridors—ensures that renewable projects and their support networks yield the largest positive cumulative EF increases where pressures were already greatest [13].

Figure 5d presents the effect of school enrollment gender parity (SE) on ecological footprint (EF). In the short run, increases in China's tertiary school enrollment gender parity index (SE GPI) are positively linked to the national ecological footprint across all quantiles, with coefficients climbing from about +2.8 at the 1st percentile (when overall EF is lowest) to +4.0 at the 99th percentile (when EF is highest) (all **). At low-footprint conditions ($\tau \leq 0.10$), marginal gains in gender parity trigger modest expansions—such as additional dormitory wings or improved sanitation blocks on university campuses—so the immediate footprint rise is smaller ($\beta \approx +2.8$), reflecting the relatively limited scale of tertiary infrastructure at the outset [23]. By the median quantile ($\tau = 0.50$), as parity approaches balance nationwide, universities collectively upgrade energy-intensive facilities—modern laboratories, high-capacity data centers for e learning, and enhanced campus lighting—producing a larger positive effect ($\beta \approx +3.2$). At the upper tail ($\tau \geq 0.90$), where China's overall EF is at its peak, further parity-driven infrastructure deployment—such as 24-h computing facilities and expanded research complexes—yields the strongest short-run footprint increase ($\beta \approx +4.0$). Over the medium horizon, the positive SE GPI–EF relationship persists across every quantile (**, $\tau = 0.01$–0.99) but the coefficient gradient moderates: $\beta \approx +2.9$ at the lowest EF quantile, $\beta \approx +3.1$–3.3 around the median, and $\beta \approx +3.8$ at the top quantile. As parity gains consolidate nationally over one to three years, the initial burst of campus construction transitions into sustained operational energy demands—ongoing maintenance of gender inclusive facilities, continuous server loads for blended learning platforms, and expanded university transportation networks—so each incremental rise in SE GPI translates into a uniformly positive yet quantile-sensitive uplift in EF [41,42]. In the long run, the positive effect of SE GPI on China's ecological footprint stabilizes at $\beta \approx +2.6$ for the lowest quantile, $\beta \approx +3.0$ at the median, and $\beta \approx +3.7$ at $\tau = 0.99$ (all **). At low-EF states of national development—reflecting earlier phases of tertiary expansion—the energy impact per parity improvement diminishes as campus capacity reaches saturation.

Figure 5e presents the effect of economic growth (EG) on ecological footprint (EF). In all three horizons, economic growth (EG) exerts a positive and highly significant (**) effect on China's ecological footprint across every quantile ($\tau = 0.01$–0.99). In the short run, the estimated coefficients start at roughly 0.17 at the 1st percentile and rise modestly to about 0.18 at the 99th percentile, indicating that even an incremental uptick in provincial GDP yields an immediate increase in resource use and emissions [25]. At low footprint states ($\tau \leq 0.10$), this reflects firms tapping existing energy-intensive production without major new investment, while at the upper tail ($\tau \geq 0.90$), heavy industry clusters amplify that effect through intensified operation of coal-fired plants and high-energy machinery [26]. Over the medium horizon, coefficients uniformly increase to approximately 0.18–0.21 across quantiles, with the median effect around 0.19. This stronger linkage emerges because sustained growth in China typically translates into fresh capital expenditures on manufacturing lines, transport infrastructure, and urban construction—all of which lock in elevated energy and material throughput for several years [43]. Lower quantile regions slowly build out this infrastructure, mid-level provinces expand manufacturing capacities, and high quantile areas see the largest rebound effect as robust demand spurs continual capacity utilization. In the long run, EG's footprint multiplier peaks—rising from about 0.20 at $\tau = 0.01$ to nearly 0.24 at $\tau = 0.99$—underscoring how decades-long growth trajectories embed high carbon capital stocks, urbanization patterns, and consumption habits. The Summary of ANN–WQR heatmaps is showed in the Table 4.

Table 4. Summary of ANN–WQR heatmaps.

Driver	Direction	Short-Run	Medium-Run	Long-Run	Distributional Emphasis (Quantiles)
ROBOT	Positive	Positive	Positive	Positive	Broadly across τ; pockets of stronger effects at mid–high τ in long horizon
GSCM	Positive	Weak/near zero	Positive (selective)	Positive (clearer, especially mid–high τ)	Signals at low τ ≈ 0.01–0.05 and mid–high τ ≈ 0.50–0.95 depending on horizon
PPE	Mixed (context-dependent)	Weak/negative at very low τ (≈0.01), otherwise small	Positive at mid τ (≈0.20–0.50)	Positive at high τ (≈0.90–0.99)	Tail emphasis: very low and very high τ show clearer signals
SE	Positive	Positive	Positive	Positive	Significant across almost all τ; strong cells at upper τ (e.g., τ ≈ 0.99)
EG	Positive	Positive	Positive	Positive (strengthens at upper τ)	Broad distribution; strengthening at τ ≈ 0.90–0.95 in long horizon

5. Conclusions and Policy Initiatives

5.1. Conclusions

Harnessing the power of AI, China's digital supply networks and public–private partnerships are rewriting the rulebook on sustainable growth—turning data-driven efficiency gains into real-world carbon reductions. By strategically aligning cutting-edge automation with collaborative investment models, these innovations open a new path toward a greener, more resilient socio-economic future. This study applies an ANN-enhanced wavelet quantile regression framework to uncover the multiscale determinants of China's ecological footprint. Leveraging quarterly data from 2011 Q1 through 2024 Q4, it reveals dynamic, quantile-specific relationships that conventional approaches often miss. The result from the study demonstrates that robotics, supply-chain integration, PPP energy investments, gender-parity enrolment, and economic growth each exert a positive—and often escalating—upward pressure on the nation's ecological footprint over short, medium, and long horizons, with the strongest effects in high-EF contexts.

5.2. Policy Recommendations

In provinces where ecological footprint levels are relatively low, China should expand its existing Energy Conservation Law by mandating rapid energy-efficiency audits for new robotic installations and renewable-project start-ups. Provincial regulators can require that any automation or PPP-financed plant demonstrate real-time monitoring of peak electricity draws and participate in demand-response programs operated by grid companies. In high-footprint hubs such as Shanghai or Guangdong, authorities should enforce stricter energy performance standards on new robotics deployments and campus expansions, tying construction permits to guaranteed reductions in per-unit energy use during the commissioning phase.

Over the next three years, aligned with China's 14th Five-Year Plan goals for carbon intensity reduction, central and local governments should condition subsidies for automation and PPP renewables on verified carbon-savings benchmarks. Firms that integrate advanced logistics solutions must adopt the national Green Freight Demonstration Program standards—using low-emission vehicles and optimized routing—to blunt any unintended footprint increases. Universities expanding gender-balanced enrolment can tap dedicated funds from the Higher Education Green Development Initiative to co-finance on-campus micro-grids and smart-meter installations, ensuring that higher enrolment does not translate into proportionally higher energy consumption.

Looking further ahead, China should update its Renewable Energy Law and Industrial Green Development Plan to include carbon intensity benchmarks for all new manufacturing zones and energy projects. Regions rolling out full-scale robotics should be required to demonstrate declining CO_2 per unit of industrial output over a 5-year cycle. The national rollout of the Emissions Trading Scheme can be refined to allocate allowances based on these benchmarks, incentivizing grid upgrades, large-scale energy-storage deployments, and low-carbon campus design (net-zero buildings and district energy systems).

5.3. Managerial Implications

For operations, supply-chain, and campus managers in China, the results translate into a concrete playbook: before commissioning any new robotic line or PPP-financed energy asset, run fast-track energy-efficiency audits, install granular sub-metering and energy-management systems, and enroll facilities in demand-response with the local grid to cap peak loads; in high-footprint hubs (e.g., Shanghai, Guangdong), make construction and expansion permits contingent on verified reductions in energy intensity during ramp-up. Over the next three years, design automation and renewables projects so that subsidy eligibility is tied to third-party–verified carbon-savings benchmarks (robust M&V plans, baseline setting, periodic re-certification). In logistics, adopt Green Freight standards—low-emission fleets, route optimization, and load consolidation—to ensure GSCM upgrades do not raise the footprint. Universities expanding enrollment should pair growth with microgrids, smart meters, and real-time analytics to keep energy per student falling. For the five-year horizon, set plant- and supplier-level carbon-intensity targets aligned with forthcoming benchmarks, build allowance strategies for the national ETS, and prioritize grid-interactive equipment, storage, and high-performance building design. Embed these requirements in supplier contracts and PPP agreements, and create a sustainability PMO to track multiscale KPIs (robotics, logistics, PPP capex, education infrastructure) and adjust budgets/internal carbon prices as incentives evolve—protecting margins while meeting the 2060 carbon-neutrality path.

5.4. Limitations and Future Suggestions

Despite the rich multiscale insights afforded by the wavelet–quantile ANN framework, this study has several limitations that point to avenues for future work. First, by focusing on quarterly, country-level data, we obscure important provincial and sectoral heterogeneity; future research should leverage disaggregated panel data to tailor policies to regional dynamics. Second, potential endogeneity between ecological footprint and key drivers—such as economic growth or robotics adoption—is not fully addressed; applying instrumental variables or local-projection quantile methods would help establish causal links. Third, while ANNs enhance predictive accuracy, they reduce model interpretability; integrating explainable AI techniques or simpler structure-learning algorithms could clarify the mechanisms at play. Fourth, our driver set omits variables like energy prices, technological spillovers, and behavioral interventions; expanding the covariate space and allowing for interactive and nonlinear effects would yield a more holistic picture. Finally, the choice of a single wavelet filter and fixed decomposition levels may influence results; future studies might experiment with alternative filters, adaptive multiresolution schemes, and higher-frequency data to better capture transient shocks. Addressing these gaps will deepen our understanding of China's eco-economic dynamics and support more finely tuned policy designs on the path to carbon neutrality.

Author Contributions: K.A. contributed to the original draft preparation and led the manuscript writing. K.I. was responsible for supervising the research and designing the methodological framework. A.A. provided critical review of the manuscript and oversaw project administration. H.Y.A. contributed to the review process and offered expert consultation throughout the study. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data will be made available on request by the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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systems

MDPI

Article

Digital Transformation Through Virtual Value Chains: An Exploratory Study of Grocery MSEs in Mexico

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Abstract: This study explores the readiness of Micro and Small Enterprises (MSEs) in Mexico, specifically grocery stores, to implement the Virtual Value Chain (VVC) through Information and Communication Technologies for Development (ICT4D). A mixed-methods approach was used, combining diagnostic tools, structured surveys, and interviews. Quantitative data were analyzed using descriptive statistics, correlation analysis, and machine learning to identify digital adoption patterns. The results indicate that limited technology adoption remains the main obstacle to VVC integration. Significant associations were found between digital engagement and the age and educational level of store managers. Key digital gaps persist in inventory control, supplier coordination, and demand forecasting. Although machine learning models did not significantly outperform baseline predictions on willingness to adopt technology, the findings emphasize the potential of targeted training and accessible mobile solutions. The study proposes a new diagnostic and predictive framework to assess VVC readiness in low-resource contexts. It shows that ICT, when strategically aligned with business operations and paired with adequate training, can enhance sustainability and livelihoods. Although the study is limited to one geographic area and one business sector, it offers a foundation for scaling similar initiatives. The findings support context-sensitive strategies and capacity-building efforts tailored to the realities of MSEs in emerging economies.

Keywords: micro and small enterprises (MSEs); virtual value chains (VVC); grocery retail; ICT for development; machine learning

1. Introduction

Micro and Small Enterprises (MSEs), especially family-owned ones, rely heavily on the entrepreneurial and managerial skills of their owners [1]. In Mexico, enterprises are classified by employee count and annual sales: micro-enterprises have 1–10 employees, while small enterprises have 11–30 in commerce or services and 11–50 in manufacturing, with annual sales limits of 4 million MXN for micro-enterprises and 4–100 million MXN for small enterprises [2]. MSEs face challenges such as limited education, access to technology, capital, and expertise, often needing external support [1,3,4]. Given their prevalence, the study of MSEs is crucial to understanding economic development in emerging economies.

Approximately 90% of companies in Latin America are classified as micro firms, mainly in the wholesale and retail sectors [5]. In 2020, Mexico had around 4.7 million micro businesses. These firms contribute significantly to employment in commerce and services, while large companies dominate manufacturing. However, despite their quantitative importance, research on MSEs, particularly in commerce, remains limited, restricting our understanding of their strategies compared to larger firms.

Following COVID-19, over 50% of Mexican SMEs still relied on traditional sales methods or short-term online strategies. For non-online SMEs, 35% emphasized digital communication (social networks, search engines, ads), and 16% aimed to digitize customer services [6]. Also, more than 60% of businesses in Mexico close within their first three years, largely due to cash flow difficulties, according to the National Institute of Statistics and Geography (INEGI). This evidence highlights persistent barriers to digital adoption, which have become a critical factor in resilience and competitiveness in the post-pandemic context [7].

Despite the growing body of research on Information and Communication Technologies (ICTs) and their role in development, few studies explore how MSEs adopt and benefit from ICTs in their value chains. Existing ICT4D literature often focuses on larger firms, overlooking MSEs, which face unique constraints in technology adoption. Moreover, the Virtual Value Chain (VVC) remains underexplored in MSE contexts, particularly in Latin America. This represents a clear research gap.

This study addresses the gap by asking: How does the adoption of the Virtual Value Chain (VVC) influence the operational practices and digital development of Micro and Small Enterprises (MSEs) in Mexico? By focusing on underrepresented grocery microenterprises, we contribute to ongoing ICT4D debates on digital inclusion, technological capability building, and grassroots innovation.

This research develops and applies a methodology to diagnose the level of VVC integration in MSEs. The methodology assesses essential factors to support these businesses in improving operations and ensuring survival through digital development, focusing on grocery stores in Pachuca, Hidalgo. Although the VVC concept is beneficial for enhancing SME operations, it is underexplored in MSE contexts.

It is important to note that this study is limited in scope to grocery SMEs in Mexico. These businesses primarily operate within downstream segments of the supply chain. The analysis does not extend to the entire value chain, which remains beyond the focus of this research.

This paper offers three main contributions to the ITD literature:

1. To the best of the author's knowledge, this is the first known empirical study on VVC adoption among MSEs.
2. It introduces an original instrument for assessing VVC stages in low-tech businesses.
3. It presents quantitative findings based on field data, analyzed through statistical and machine learning methods.

Finally, the paper is organized as follows: Section 2 presents the literature review, which covers the theoretical framework, including ICT for Development (ICT4D) and the Virtual Value Chain, as well as an overview of MSEs worldwide, their challenges, opportunities, and models. It also includes research on MSEs in Mexico and concludes with field studies on Virtual Value Chains (VVC). Section 3 outlines the methodology, explaining the context, instrument design, data collection, and analysis. Section 4 presents the results and discussion, and Section 5 provides the conclusions.

2. Literature Review

In recent decades, research in Information and Communication Technologies for Development (ICT4D) has explored how digital technologies can foster economic growth, enhance social inclusion, and support human development in low-resource settings. ICT has enabled small and medium enterprises (SMEs) to become more integrated and operate more efficiently; however, developing economies rarely have access to these resources [8–10].

According to Heeks [11], the developmental impact of ICT depends not only on access and infrastructure, but also on the relevance of these technologies to local needs and the capacity of organizations to absorb and integrate them. It also depends on social responsibility rather than the type of technology used. This perspective is particularly important in the context of Micro and Small Enterprises (MSEs), which often operate under significant constraints in capital, knowledge, and digital skills.

ICT4D studies show that technology only makes a real difference when it matches local needs and operates within existing social and institutional structures [12,13]. While early ICT4D literature focused on large-scale infrastructure and e-government programs, more recent studies have shifted attention to bottom-up, grassroots innovation, especially among small firms and informal actors [14,15]. However, little research has addressed issues related to small enterprises adopting ICT [16]. In these contexts, digital technologies can enable new forms of value creation, participation, and resilience.

In the context of ICT4D, the VVC model offers a promising framework for examining how MSEs in emerging economies can leverage ICTs to expand market access, optimize operations, and strengthen customer relationships. The VVC, developed by Weiber and Kollmann [17], provides a conceptual lens to understand how digital information can be used not just to support traditional value chains, but also to transform and virtualize business processes. Unlike the physical value chain, the VVC captures the generation, processing, and distribution of digital content as a source of economic value. This includes activities such as data collection, online interaction with customers and suppliers, and digital service delivery. However, as noted by Thapa and Sæbø [18], empirical studies of ICT use in underprivileged communities and among disadvantaged stakeholder groups remain scarce.

This study positions itself at the intersection of ICT4D theory and VVC research, aiming to investigate whether and how MSEs in Mexico, particularly grocery stores, are adopting elements of the VVC in their daily operations. In doing so, it contributes to ongoing scholarly debates on the developmental role of ICTs and addresses a critical empirical gap in the literature.

As this study focuses on exploring the potential of MSEs in Mexico, the literature review is divided into three sections: (1) MSEs worldwide, (2) MSEs in Mexico, and (3) studies on the Virtual Value Chain. It is important to note that the academic literature specifically addressing MSEs is limited. Therefore, selected studies on SMEs are included when relevant, ensuring that their inclusion does not compromise the generalizability or relevance of this research.

2.1. MSEs Worldwide

MSEs face challenges in adopting technologies. Bag and Pretorius [19] identified technology as a critical barrier, while Culot [20] emphasized data management and production technologies. In Ethiopia, Abagissa [21] highlighted the need for education, credit, and incentives. Funding constraints impact small service businesses [22]. Digitalization holds transformative potential for regional development [23], and technologies like big data, IoT, blockchain, and AI can enable supply chain digitalization in India [24].

In Latin America, Velázquez-Martínez and Tayaksi [8] linked supply chain management to MSE productivity. Chatterjee [25] suggested blockchain and AI for post-COVID-19 performance in India, and Trinugroho [26] found that digital adoption improved business in Indonesia. Mikhaylova et al. [27] examined digital strategies and Fintech, García-Salirrosas [28] presented the PERVAINCONSA Scale for online retail metrics in developing countries, and Garay-Rondero [29] proposed a digital supply chain model for mass customization.

The growing attention to the digital transformation of small businesses in emerging economies aligns with current ICT4D discussions, particularly regarding how technological capabilities contribute to inclusive economic growth [11,12]. A key question in this debate is whether ICTs directly drive development or whether they serve as enablers for operational improvements that create competitive advantages, such as through the implementation of VVC [11]. If ICTs are considered development drivers in themselves, then disparities in access often reflect structural inequalities based on location, age, gender, and other socio-economic factors. Nevertheless, most of these studies focus on SMEs or larger firms, leaving a significant gap in our understanding of how microenterprises engage with and benefit from ICT-based value creation.

2.2. MSEs in Mexico

In Mexico, most research on Small and Medium Enterprises (SMEs) has focused on identifying challenges and success factors, while studies specifically addressing Micro and Small Enterprises (MSEs) remain scarce and lack formal models. Tanoira and Valencia [30] emphasize the importance of knowledge transfer in Yucatan's support programs, noting finance and sales as key weaknesses [31]. Aguilar [31] also cites customer acquisition, staffing, and financial constraints as major issues. Hernández-Gracia and Duana-Avila [32] call for stronger entrepreneurial orientation and financing access. Success factors include economic knowledge and dynamism [33,34].

Digitalization strategies have been documented mainly for medium-sized enterprises, while MSEs remain underrepresented in both academic studies and national innovation policies. Mexican MSEs face ongoing challenges in innovation, operations, management, marketing, and technology, with no comprehensive studies on their supply chain or technological needs.

2.3. Virtual Value Chain

Technology-based companies are well-positioned for growth in competitive markets. Autio [35] suggests that small tech firms that leverage technology can be seen as smaller versions of large companies. The Virtual Value Chain (VVC), introduced by Weiber and Kollmann [17], allows companies to enhance their traditional market presence through effective digital activities. The VVC involves similar activities to the traditional value chain but uses digital information to unlock new market opportunities [17], as can be observed in Figure 1. Global market access enables small companies to compete with large firms by sharing information across suppliers, distributors, manufacturers, and retailers [36,37]. The Internet supports this information exchange, bolstering B2B and B2C relationships [38].

The Virtual Value Chain (VVC) offers advantages such as increased efficiency, ease in offering products and services, and better insights into customer needs [36,37]. It also helps businesses predict trends [37]. However, challenges include the need for creativity, flexible payment options, customer integration, and internet access [38]. Other issues involve knowledge management [39], security and privacy concerns, cultural factors, and complex software applications. Various case studies on VVC, as shown in Table 1, examine methodologies across micro, small, and medium enterprises.

Table 1 shows that the studies primarily focus on SMEs, with sample sizes ranging from 1 to 429 companies. Some studies aim to understand the client's perspective, while others explore factors influencing the Virtual Value Chain (VVC). Berrone [54] focuses on MSEs, examining whether human capital, innovation, and the use of own capital affect company performance. However, this study does not specifically address these factors in the context of the VVC.

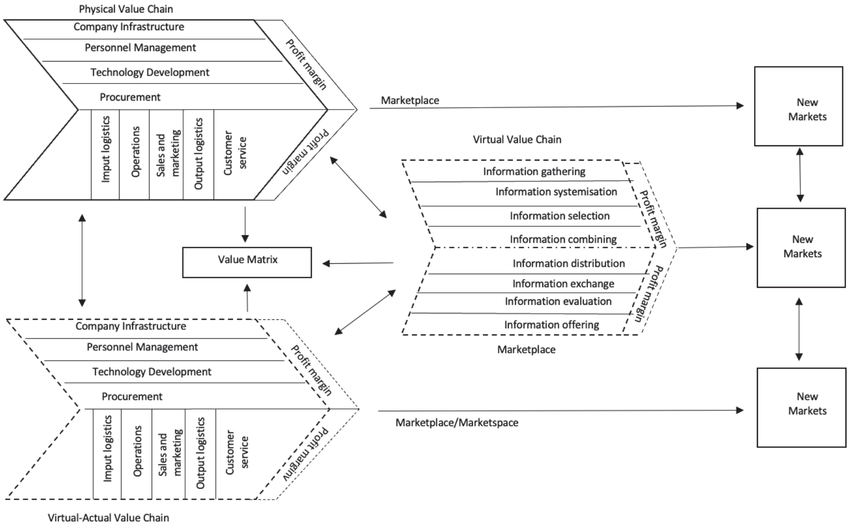

Figure 1. Virtual Value Chain. Source: Weiber and Kollmann [17].

Table 1. Field studies in VVC.

Author	Location	Methodology	Case Study	Purpose
Hongmei and Jincheng [40]	Thailand	Survey and analytic hierarchy process	Travel agencies (SMEs)	Build a VVC for travel agencies
Ramantoko et al. [41]	Indonesia	340 questionnaires with 9 dimensions	SMEs in three different regions in Indonesia.	Build a digital capability model, using the value chain analysis framework.
Corso et al. [39]	Piedmont and Lombardy	Questionnaire and cluster analysis	127 Italian SMEs	Contribute to sustainable organizations in terms of technology
Piscitello and Sgobbi [42]	Prato Italy	Empirical analysis and interviewing	Textile industry (12 SMEs)	Examining whether the industries are taking advantage of the e-business opportunities.
Arrifin et al. [43]	Malaysia	Focus Group Approach	Cattle beef and halal production (SMEs)	The effectiveness of VVC in cattle beef production
Fromhold-Eisebith et al. [44]	Germany	Workshop with 40 textile industries	Textile industries	Enablers' identification of Industry 4.0 in the German textile industry
Gyenge et al. [45]	Hungary	Surveys, clusters, and discriminant analysis	SMEs	Generate directions for SMEs to benefit from communications changes
Hermawan et al. [46]	Indonesia	Multivariate statistical study	168 consumers of online SMEs	To build an e-mail design concept that elaborates the physical and virtual value chain.
Hu et al. [47]	United States of America	Text mining data approach	0.72 million online customer reviews	To understand the Virtual Queue
Taherinia et al. [48]	Iran	Factor analysis and structural equation modeling	50 experts in marketing, management, e-commerce, human resources, and managers in Iran	Evaluate factors that influence the evolution of VC.
Zumstein et al. [49]	Switzerland	Surveys and descriptive statistics	365 online retailers	Compare practice before and after the COVID-19 station.
Liu et al. [50]	China	Collection, processing, transmission, storage, and feedback	1 company	Understand the path in the Virtual Chain considering digital technology.

Table 1. *Cont.*

Author	Location	Methodology	Case Study	Purpose
Eng et al. [51]	America, Europe, Africa, and Asia	Surveys, interviews, and hypothesis tests	500 companies of different sizes that use logistic apparel retailers' supply chains.	Understand ambidexterity and wireless information technology (IT) for enhancing innovative capacity.
García-Salirrosas et al. [28]	Perú, México and Colombia	KMO and Barlett test	238 questionnaires from users of online clothing stores	Validate an instrument design to measure Variable Value perception, purchase intention, trust, and satisfaction.
Omoruyi and Makaleng [52]	South Africa	Quantitative study and SMART PLS 3.0	439 SMEs	To determine if the supply chain has a disruption after COVID-19.
Sharma et al. [53]	India	30 experts from the electronic manufacturing of SMEs	Identify barriers for SMEs in adapting to the technologies of Industry 4.0	Fuzzy analytic hierarchy and PROMETHEE.

2.4. Research Gaps and Objectives

All previous studies have focused on the Virtual Value Chain (VVC) in SMEs, with limited attention to MSEs or Mexico's retail sector. García-Salirrosas [28] included Mexico in their research alongside Peru and Colombia, concentrating on online clothing stores. Gupta and Ramachandran [55] studied retailers in emerging economies, suggesting that differences between traditional and tech-focused retailers require further investigation. Others, such as Hwang and Kim [56] and Roth and Rosenzweig [57], highlighted a gap in quantitative and empirical studies on the topic. Moreover, Sharma and Dutta [58] found that the COVID-19 pandemic shifted retail strategies toward omnichannel models, requiring technological convergence, customer focus, and internal reorganization. Compared to previous studies, this study investigates the digital transformation and processes within the VVC, particularly for MSEs in the retail sector.

Although digitalization has been highlighted as a key element of the ITC4D [11], most frameworks focus on national or large-firm adoption, not the micro-level experiences of small grocery businesses. The studies that examined grocery retailing within the Virtual Value Chain (VVC) framework are scarce. This is particularly relevant given that digital transformation has been shown to positively influence business models [59], and digitalization further enhances that flexibility, enabling the company to better adapt to a changing or uncertain environment [60]. Weyer [61] observed that, due to the broad spectrum of available technological innovations and the limited resources characteristic of small businesses, it remains unclear which technologies should be prioritized or at which stages of the VVC they should be implemented. Similarly, Bierganz [62], in his doctoral dissertation, analyzed the challenges associated with leveraging the VVC in the UK grocery retail sector.

These gaps underscore the need to better understand how ICTs can promote development at the microenterprise level. This research aims to diagnose MSEs, with a particular focus on grocery stores in Mexico, to assess whether they are currently integrating technology into their business operations and whether they possess the necessary resources to implement the VVC. Our review of the existing literature revealed a lack of studies addressing the application of the VVC in the context of MSEs in Mexico, with emphasis on the retail grocery sector. As our main contribution, we have developed diagnostic tools and a survey instrument specifically designed to fill this gap. These tools not only support the evaluation of technological adoption among Mexican MSEs but are also adaptable for use in similar MSE contexts internationally.

Based on the identified research gaps, the objectives of this study are captured in the following research questions:

RQ1: Do grocery stores in Mexico possess sufficient technological advancements to implement VVC with their suppliers and customers?
RQ2: Is the ability to generate VVC positively correlated with the cultural and behavioral issues of grocery store managers in Mexico?
RQ3: Given specific characteristics of grocery store managers, can we predict their willingness to adopt technological changes?

3. Methodology

The scope of this research is restricted to grocery MSEs in Pachuca, Hidalgo, Mexico. These enterprises represent downstream actors in the supply chain, and the study does not attempt to cover the entire value chain.

In this study, the methodology developed by Sampieri [63] was adapted to answer the research objectives, as detailed in Figure 2. Summarizing the methodology, from the fundamental redefinitions of the final version, it begins with (1) designing the instrument, followed by (2) data collection, and concludes with (3) data analysis and machine learning predictions. Detailed measurements, estimation methods, and results are provided in the subsequent subsections.

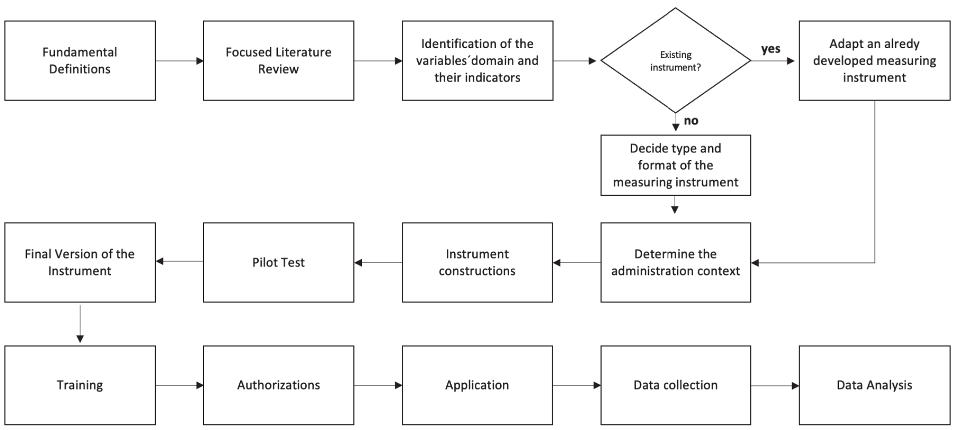

Figure 2. Methodology for study. Source: Adapted from Sampieri [63].

3.1. Design of the Instrument

This design was carried out in two phases. The first phase involved a qualitative analysis, where the study context was reviewed, and 10 MSEs in the retail sector were interviewed to understand their needs. The second phase consisted of a literature review to identify the areas to be included in the survey.

3.1.1. Context of the Study

Pachuca de Soto, the capital of Hidalgo, Mexico, covers 20,813 km^2 in the center-east of the country. In 2022, Hidalgo's economically active population was 1.46 million, with retail trade accounting for 45.6% of economic units, 71.8% of which are in informal employment. According to INEGI [64], there are 14,753 grocery stores in Hidalgo, with 1842 in Pachuca, highlighting their economic significance.

Before the research, 10 businesses were visited for interviews and process observations. Most were newly opened and financially unstable, facing challenges like low shelf fill levels and disorganization. To remain competitive, they sourced products from wholesalers or directly from large companies. Shelf organization was based on expiry dates but adjusted for supplier requests. While some stores used computer systems and barcode readers, inventory tracking was often inaccurate. The customer base primarily consisted of local residents, emphasizing the role of personal relationships in sales and payment methods.

Additionally, inconsistent order quantities made it difficult to predict supplier orders. Most orders were placed in-store or via phone and WhatsApp, with store owners or 1–2 employees managing all operations. Due to a lack of financial support, they aimed to minimize costs, sometimes renting taxis and vehicles to avoid stockouts. Suppliers often faced difficulties finding parking for their vehicles. Figure 3 illustrates the supply chain, while Table 2 summarizes grocery store operations.

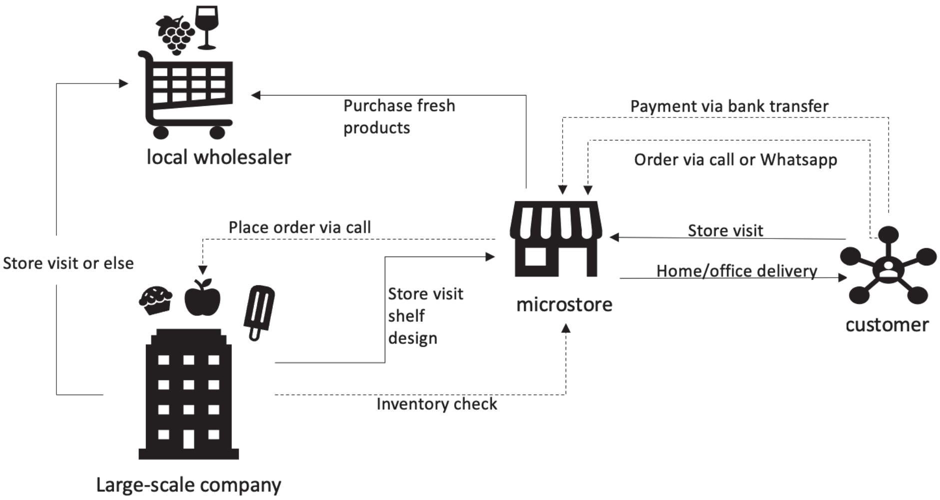

Figure 3. Supply chain network diagram of a micro store. Source: Own elaboration.

Table 2. Details of company infrastructure, personnel management, technology development, and procurement processes.

Dimension	Area	Description
Company infrastructure	Space	4×5 m^2 or less, no additional space
	Equipment	refrigerators and shelves
	Parking	no parking area
Personnel management	Management	the owner themselves or family members
	Employment	1–2 external employees
	Operations	assistance from suppliers (e.g., to accommodate shelves, etc.)
Technology (ICT4D)	Inventory tracking	computers (<10% of stores), barcode readers, mobile phones for calls and SMS to suppliers
	Payment	electronic payment with credit card, bank transfer
	CRM	mobile phones with Internet connection
Procurement	Sales tracking	notebook for tracking sales (<15% of stores)
	Purchase tracking	no record of available stock quantity
	Payment terms	mostly defined by large-scale supplier companies
	Products	preferably more economical and fresh products
	Supplier selection	preferably wholesalers (e.g., Walmart, Sam's, City Club, Central, etc.) or large-scale enterprises (e.g., Bimbo, Coca-Cola, etc.)
	Delivery terms	owned vehicles (e.g., automobiles or pick-up trucks), rented vehicles (e.g., taxi) or suppliers' choice (e.g., truck, van, etc.)

3.1.2. Measuring Instrument

To design the survey, a literature review was conducted, particularly focusing on VVC, identifying common areas across various studies. The survey was designed to evaluate eight areas; the questions are presented in Appendix A:

Profile: According to Piscitello and Sgobbi [42] and Gurdur [65], key variables include name, number of employees, working hours, and turnover.

Managerial characteristics: Gurdur [65], Peutz and Post [66], and Bierganz [62] identified name, gender, age, education level, and adaptability to change as important variables.

Personal management: Hongmei and Jincheng [40] and Zumstein et al. [49] highlighted teamwork, adaptability to change, learning, and organizational culture as relevant factors.

Company infrastructure: Merchán [67] emphasized the importance of shelf space, inventory, and transportation (e.g., van, car, motorcycle, bicycle) for SMEs.

Procurement: Gurdur [65], Zumstein et al. [49], and Hongmei and Jincheng [40] stressed the importance of information on top-selling products, inventory, daily sales, demand planning, and access to supplier data.

Technology: Corso et al. [39], Piscitello and Sgobbi [42], Elkhouly et al. [68], and Naimi-Sadigh et al. [69] identified key indicators such as internet access, Wi-Fi, sales and inventory systems, and devices like computers and mobile phones [12].

E-commerce: Zumstein et al. [49], Gyenge [45], Elkhouly et al. [68], and Bierganz [62] emphasized the significance of e-payment methods, websites, social media platforms, telephone sales, and digital marketplaces.

Challenges to introduce technology: Winkler [70], Peutz and Post [66], and Wasan et al. [71] identified challenges in technology adoption, including external support, government assistance, training, and issues related to payments and taxes. Additionally, Heeks [11] emphasized that ICT4D outcomes are influenced by contextual factors such as location, age, gender, and education level.

A self-administered questionnaire was chosen, and a pilot test was conducted with 30 randomly selected grocery stores. The survey achieved a Cronbach's alpha value of 0.8638, validating its reliability. The final version of the instrument is available in a repository [72] under surveyfinalingles.docx.

3.1.3. Sample Size

To ensure a representative sample, the formula described by Devore [73] was used. Inclusion criteria required grocery stores to be located in Pachuca, with respondents being company owners and of legal age. The formula is presented in Equation (1).

$$n = \frac{z^2 N\sigma^2}{(N-1)e^2 + z^2\sigma^2} \tag{1}$$

The sample size n was determined using the formula described by Devore [73], where N is the population size (1842 grocery stores in Pachuca, according to INEGI [64], σ is the standard deviation (typically assumed as 0.5 if unknown), z is the confidence level (1.96 for 95% confidence), and e is the acceptable error limit (5% for this study). Using (1), a sample size of 233 enterprises was obtained.

The sampling procedure was conducted with the support of undergraduate students, each of whom was assigned to distribute approximately 5 surveys. Students were instructed to approach grocery microenterprises located near their place of residence and to select stores in a non-systematic manner, avoiding repeated chains or pre-selected businesses. This procedure introduced a convenience component but also incorporated a random-like element at the local level, since students did not target specific stores a priori. In total, 233 surveys were distributed, of which 187 valid responses were obtained, corresponding to a non-response rate of approximately 19.7%

3.2. Data Analysis

Data analysis will be conducted in four steps: (1) data visualization using bar and pie charts, (2) descriptive statistics for proportion inferences, (3) inferential statistics with confidence intervals to estimate population fluctuations, and (4) relationship analysis between variables using Pearson correlation, chi-square test of independence, and ANOVA.

3.2.1. Data Visualization

To better understand the collected data, visualizations were created using matplotlib in Python 3.10. An example, shown in Figure 4, corresponds to question 32 in the survey. The complete set of visualizations is available in the repository under surveyresults.docx [72].

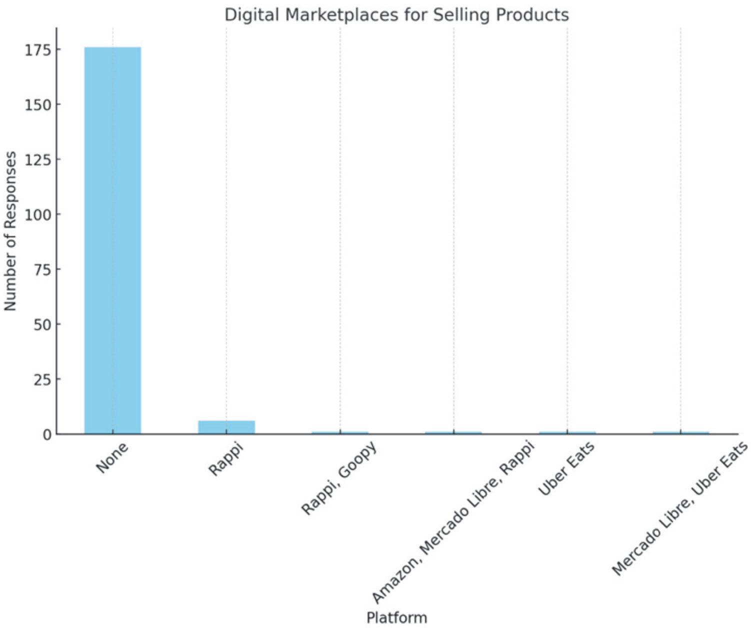

Figure 4. Data visualization. Source: Own elaboration.

3.2.2. Descriptive and Inferential Statistics

The descriptive statistics using Minitab 19.0, for the 187 respondents, reveal the following:

Profile: 60.96% of businesses have been operating for over 5 years (95% CI: 53.97, 67.95). 52.41% operate 8-12 h daily (95% CI: 45.25, 59.56).

Managerial characteristics: 33.16% of managers are aged 30-40 years (95% CI: 26.40, 39.91). 44.39% of managers have a high school education (95% CI: 37.26, 51.50). 47.06% of respondents are men (95% CI: 39.90, 54.21), and 52.94% are women (95% CI: 45.78, 60.09). 62.57% are willing to implement changes (95% CI: 55.63, 69.50). 53.4% expect to make changes within 6 months (95% CI: 46.32, 60.62).

Personnel management: 61% of businesses have staff (95% CI: 53.97, 67.95), with 60.42% having 2-5 employees (95% CI: 53.42, 67.44). 57.75% of employees collaborate (95% CI: 50.67, 64.83), and 57.21% can adapt to changes in under 3 months (95% CI: 50.13, 64.31). 52.94% offer training (95% CI: 45.79, 60.10).

Company infrastructure: 33.16% organize shelves by product type (95% CI: 26.41, 39.90). 57.22% receive merchandise directly (95% CI: 50.12, 64.31), and 29.41% use their own vehicles for transportation (95% CI: 22.88, 35.94). 77.01% have a car or small truck (95% CI: 70.97, 83.04). 68.98% lack a loading area (95% CI: 62.35, 75.61).

Inventory: 47.06% lack additional storage space, and 68.98% do not forecast sales (95% CI: 62.35, 75.61). 42.16% buy 10–30% of items from wholesalers. 55.1% do not track inventory (95% CI: 48.49, 62.73).

Technology: 60.43% have a cell phone (95% CI: 53.42, 67.44), and 36.90% have a computer (95% CI: 29.98, 43.81). 67.91% have internet access (95% CI: 61.22, 74.61). 44.92% lack a system for sales/inventory (95% CI: 37.79, 52.04), and 60.87% record sales manually (95% CI: 53.42, 67.44).

E-commerce: 58.82% accept electronic payments (95% CI: 51.77, 65.87), 66.2% have card terminals (95% CI: 59.53, 73.08), and 31.2% accept bank transfers (95% CI: 24.89, 38.21). 95.18% lack a website (95% CI: 92.11, 98.25), and 93.58% have never sold on platforms like Rappi or Uber Eats (95% CI: 90.07, 97.09). 71.66% have never sold via WhatsApp, phone, or Facebook (95% CI: 65.20, 78.12).

Challenges to introduce technology: 88.2% have never received government support (95% CI: 83.62, 92.85). 51.33% do not need help digitizing (95% CI: 44.17, 58.50), while 48.66% do (95% CI: 41.50, 55.82). The most needed assistance is training (48.96%) and infrastructure (47.92%).

3.2.3. Relationship Between Variables

The correlation matrix in Figure 5 highlights key relationships between demographic factors and business attributes. Significant associations (p-value < 0.05) include a strong link between Electronic Payment Methods and Educational Level, as well as between a Computerized Inventory System and Educational Level. Although no high correlations are found, ANOVA is used to explore the impact of the manager's profile on these variables. Additionally, one of the strongest correlations is observed between Sales on digital media and Sales on social media.

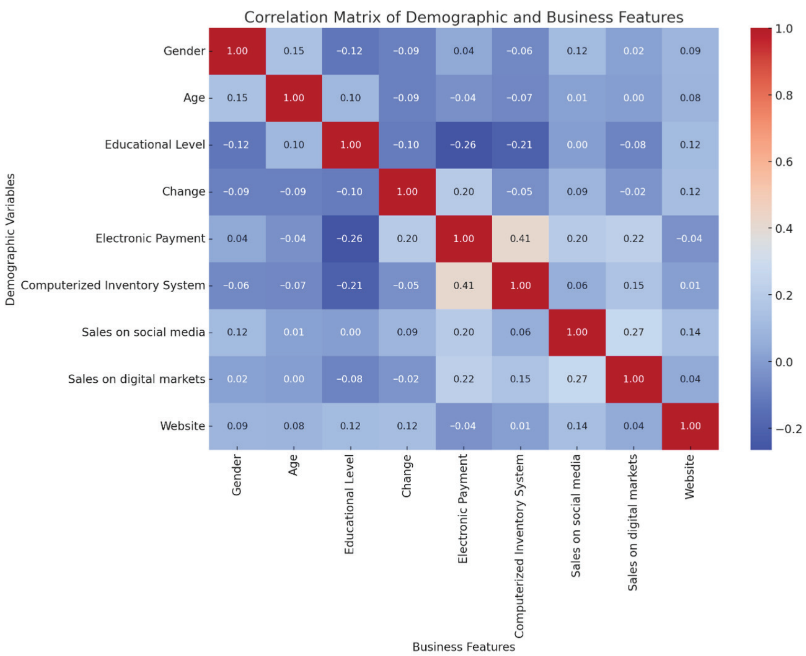

Figure 5. Matrix correlation. Source: Own elaboration.

To address RQ2 (Is the ability to generate VVC positively correlated with the cultural and behavioral issues of the MSE's managers in Mexico?), a variance analysis (ANOVA) was conducted, and the following relationships were tested:

Change vs. gender change and education level: ANOVA was applied to questions 5 (Gender, age, and educational level of the manager) and 6 from the database using Minitab 19). The results can be seen in Table 3. For the ANOVA, we tested the homogeneity of variances assumption using Levene's test (p = 0.997), which indicated that the groups did not differ significantly in variance. This confirmed that the assumption of homogeneity was met, supporting the validity of the ANOVA results.

Table 3. Analysis of variance change vs. gender, age, and education level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	3.5645	0.4456	1.97	0.052
Gender	1	0.5833	0.5833	2.58	0.110
Age	4	2.0771	0.5193	2.30	0.061
Educational Level	3	1.2315	0.4105	1.82	0.146
Error	178	40.2323	0.2260		
Lack-of-Fit	22	2.8146	0.1279	0.53	0.957
Pure Error	156	37.4177	0.2399		
Total	186	43.7968			

In addition to the parametric ANOVA, we performed a robustness check using a rank-based factorial ANOVA (Conover–Iman approach). The response variable was transformed into mid-ranks and analyzed with a three-factor General Linear Model in Minitab 19. The results were consistent with the parametric ANOVA, showing no significant changes in the interpretation of factor effects (Gender: $p = 0.110$; Age: $p = 0.061$; Educational Level: $p = 0.146$). This analysis supports the robustness of our conclusions against violations of normality assumptions. It is important to mention that this analysis was made in every ANOVA.

The analysis indicates no statistically significant association between Educational Level and the willingness to implement Change, with a *p*-value of 0.324, above the 0.05 alpha level. Similarly, Change is not related to Gender, Age, or Educational Level at the 0.05 alpha level. However, the *p*-value for Age suggests a potential trend that might become significant with a larger sample size or different age group classification.

For electronic payments, ANOVA results show that only the manager's educational level affects the outcome, with a *p*-value of 0.00, as is observed in Table 4. Neither gender nor age has an impact. The mean effects plot in Figure 6 reveals that managers with a bachelor's or graduate degree are more willing to adopt electronic payments

Table 4. Analysis of variance, electronic payment vs. gender, age, and educational level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	6.0673	0.75842	3.44	0.001
Gender	1	0.0049	0.00493	0.02	0.881
Age	4	1.3911	0.34778	1.58	0.182
Educational Level	3	4.7396	1.57986	7.17	0
Error	178	39.2268	0.22038		
Lack-of-Fit	22	4.3914	0.19961	0.89	0.603
Pure Error	156	34.8354	0.2233		
Total	186	45.2941			

The analysis in Table 5 shows that both age and educational level significantly impact the likelihood of having a computerized inventory system (Questions 5 and 26 are utilized for this analysis), with *p*-values of 0.009 and 0.011, respectively. The main effects plot in Figure 7 reveals that younger individuals are more likely to use technology frequently for managing a computerized inventory.

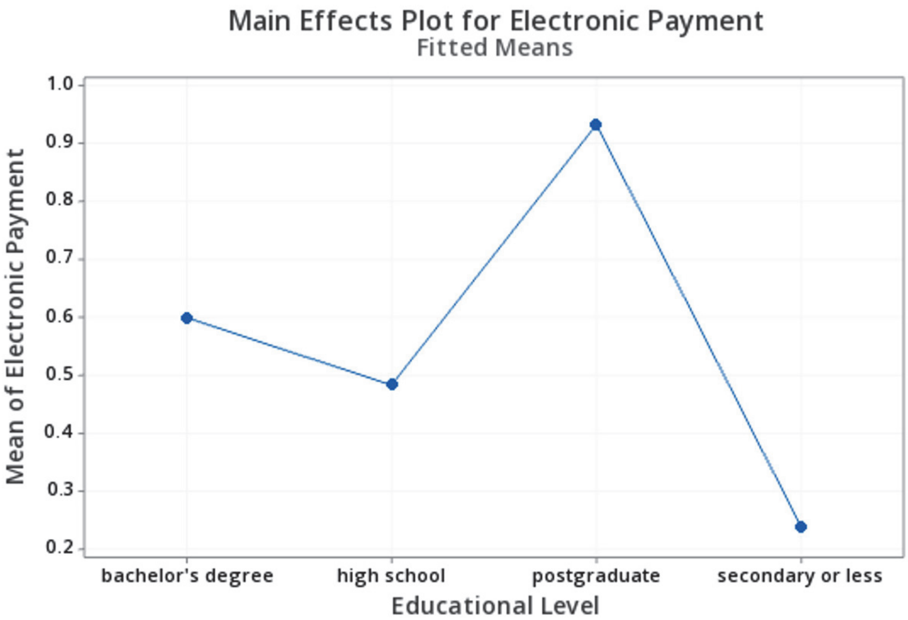

Figure 6. Main effect plot: electronic payment vs. educational level.

Table 5. Analysis of variance, computerized inventory vs. gender, age, and educational level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	5.8838	0.7355	3.79	0
Gender	1	0.1924	0.1924	0.99	0.32
Age	4	2.7114	0.6779	3.5	0.009
Educational Level	3	2.2185	0.7395	3.82	0.011
Error	178	34.5012	0.1938		
Lack-of-Fit	22	6.2854	0.2857	1.58	0.057
Pure Error	156	28.2158	0.1809		
Total	186	40.385			

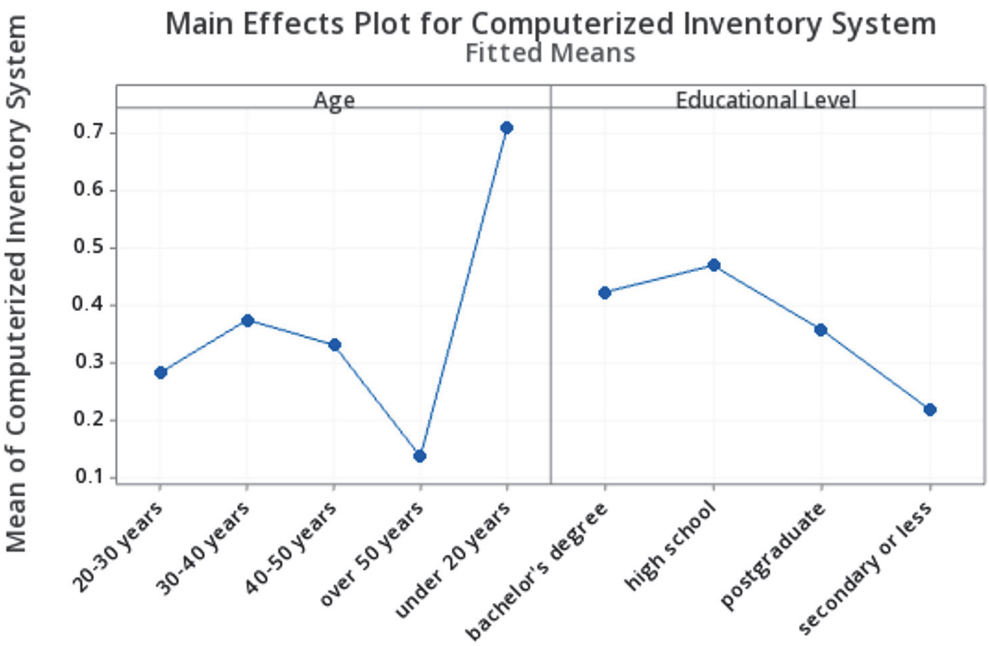

Figure 7. Main effect plot: computerized inventory vs. age and educational level.

For sales on social media regarding payment vs. gender, age, and educational level, Table 6 shows that none of the profile variables affect sales on social media platforms like Facebook and WhatsApp. Questions 5 and 31 were used for analysis.

Table 6. Analysis of variance, sales on social media: payment vs. gender, age, and educational level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	0.6252	0.07815	0.37	0.934
Gender	1	0.4952	0.495226	2.36	0.126
Age	4	0.0227	0.005664	0.03	0.999
Educational Level	3	0.0568	0.018926	0.09	0.965
Error	178	37.3534	0.209851		
Lack-of-Fit	22	5.9594	0.270882	1.35	0.15
Pure Error	156	31.394	0.201244		
Total	186	37.9786			

For sales on digital markets vs. gender, age, and educational level, in this case, questions 5 and 32 were used. Again, the level of education is the only variable that affects the outcome variable, as is observed in Table 7. Figure 8 shows that administrators with postgraduate degrees are the most determined to make sales on platforms like Rappi, Uber, etc.

Table 7. Analysis of variance, sales on digital markets vs. gender, age, and educational level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	0.7281	0.09102	1.54	0.145
Gender	1	0.0127	0.01268	0.21	0.643
Age	4	0.0912	0.02281	0.39	0.818
Educational Level	3	0.6514	0.21714	3.68	0.013
Error	178	10.5018	0.059		
Lack-of-Fit	22	1.7416	0.07917	1.41	0.117
Pure Error	156	8.7602	0.05615		
Total	186	11.2299			

The analysis of the website variable, using questions 5 and 30, shows that both age and educational level significantly affect the likelihood of having a website, with *p*-values of 0.000 and 0.099, respectively, as is observed in Table 8. The main effects plot in Figure 9 reveals that managers with postgraduate degrees are most likely to have a website. A chi-square test indicates that age is related to both the computerized inventory system and sales on websites, while educational level is associated with the computerized inventory system and sales on digital markets. Gender does not show a significant relation to any variable.

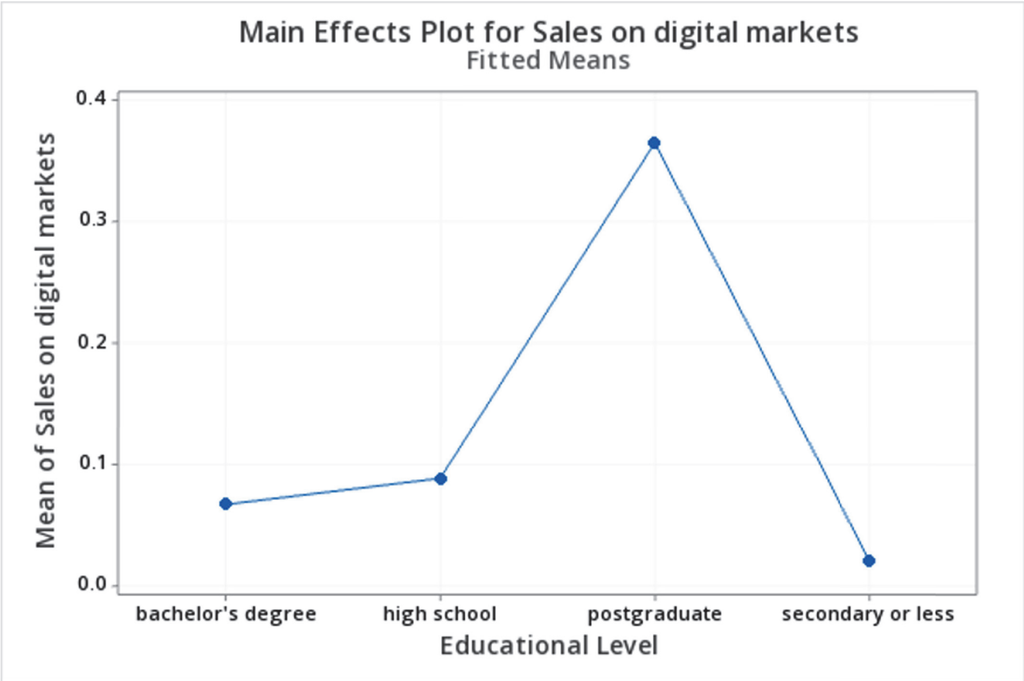

Figure 8. Main effect plot: sales on digital markets vs. educational level.

Table 8. Analysis of variance, website vs. gender, age, and educational level.

Source	DF	Adj SS	Adj MS	F-Value	*p*-Value
Regression	8	1.17406	0.14676	3.53	0.001
Gender	1	0.07372	0.07372	1.78	0.184
Age	4	0.88907	0.22227	5.35	0
Educational Level	3	0.26492	0.08831	2.13	0.099
Error	178	7.39278	0.04153		
Lack-of-Fit	22	2.33564	0.10617	3.27	0
Pure Error	156	5.05714	0.03242		
Total	186	8.56684			

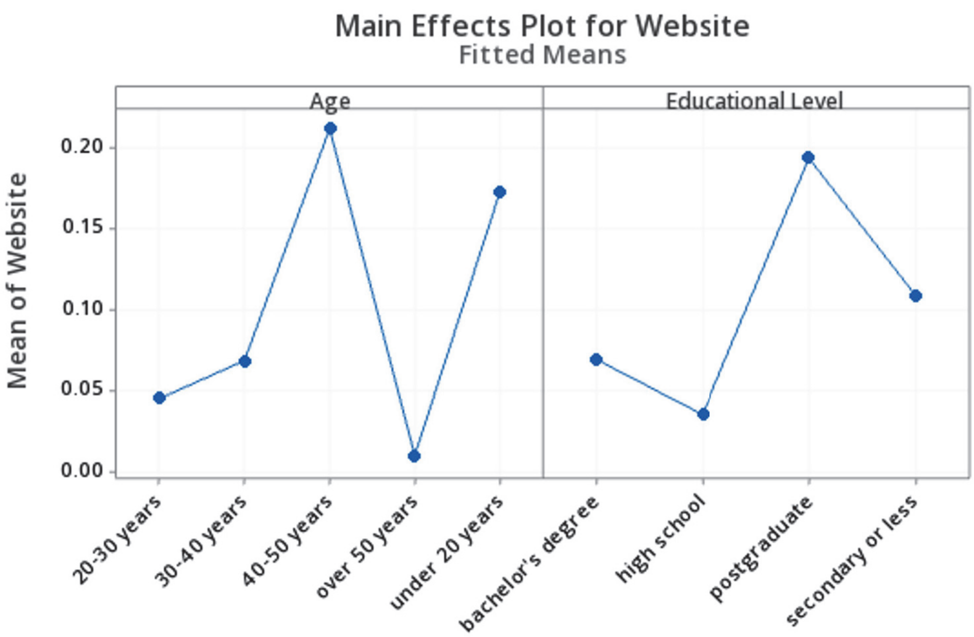

Figure 9. Main effect plot: website vs. age and educational level.

3.2.4. Prediction of VVC Adoption by MSEs

To provide greater methodological clarity, a brief overview of the machine learning techniques employed is included here. Logistic Regression is a linear model commonly used for binary classification tasks. K-Nearest Neighbors (KNN) classifies new observations based on their similarity to nearby cases in the dataset. Support Vector Machines (SVMs) aim to find the optimal boundary that separates classes. Random Forest and Gradient Boosting are ensemble methods that combine multiple decision trees to improve prediction accuracy and reduce overfitting. Finally, neural networks are flexible models capable of capturing non-linear relationships in the data. These techniques were selected because they represent a balance of interpretability, robustness, and predictive power in classification problems.

In this section, we detail the implementation of machine learning techniques to evaluate whether it is possible to predict, based on certain managerial features, their willingness to adopt a VVC. To address this, we first analyze the dataset obtained from the survey using visualizations, descriptive statistics, and a correlation matrix. It is important to note that the dataset is unbalanced, and since this is a binary classification problem, the F1 score is the most suitable metric for evaluating the performance of the tested models.

A pipeline was used using scikit-learn [74], in order to evaluate if the use of machine learning has value to predict if a manager adopts a VVC, and a set of baseline models was used. Scikit-learn uses a dummy classifier with some easy strategies to generate predictions. The most frequent strategy always predicts the most frequent class from the training set. The stratified strategy generates predictions while respecting the class distribution of the training set. The uniform strategy makes random predictions for each class with a uniform distribution. Finally, the constant strategy always predicts a specific class, which must be defined beforehand, in our case, the constant value of 1 in change label prediction.

The machine learning (ML) models used included Logistic Regression, K-Nearest Neighbors, Support Vector Machine, Random Forest, Gradient Boosting, and a neural network. Stratified random sampling was applied due to the unbalanced dataset, with an 80% training and 20% validation split. Cross-validation was performed using five folds. Finally, hyperparameter optimization was conducted using Optuna [75].

The results shown in Figure 10 show the F1 Score values for both the training and validation sets across different models, including the Dummy classifiers and ML algorithms. In general, the baseline models exhibit consistently high performance in both the training and validation sets, with an F1 Score close to 0.77 and a low standard error. This suggests that these models are consistent, as they rely on trivial predictions. However, more sophisticated models, such as Logistic Regression, K-Nearest Neighbors, Random Forest, and neural networks, achieve similar or slightly better validation results. Notably, Random Forest stands out with a validation F1 Score of 0.79, indicating superior generalization performance compared to other algorithms. In summary, perhaps Random Forest appears to be the most robust option, offering a good balance between a strong validation F1 Score and a moderate standard error; some dummy models maintain good F1 Scores, and it is thus concluded that, at least for this dataset generated, the use of ML models does not notably increase the performance metric (F1 Score).

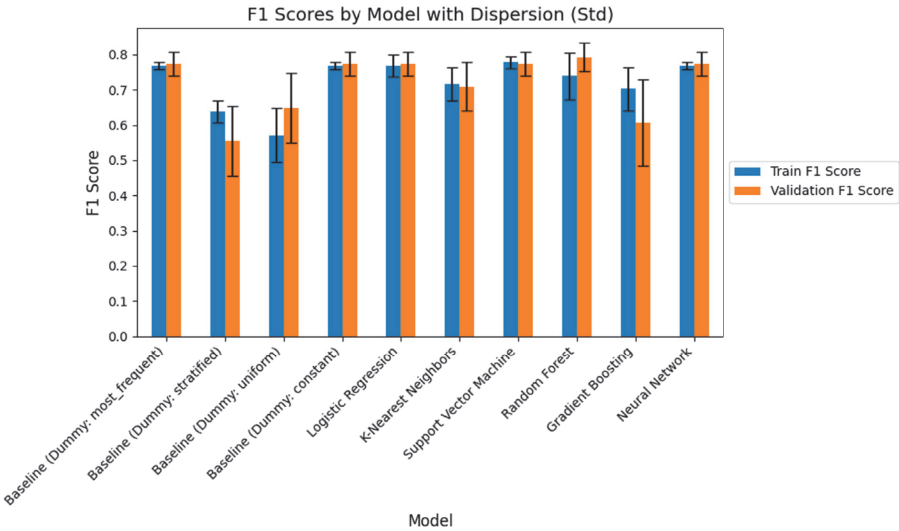

Figure 10. Results of the ML models and the baselines.

4. Results and Discussion

Regarding the first research question (RQ1), which explores whether grocery stores in Mexico possess the technological capabilities necessary to implement Virtual Value Chains (VVCs) with suppliers and customers, the analysis of the collected data indicates that they do not. Between 60.43% and 67.44% of stores only have access to a mobile phone, and between 53.42% and 67.4% still record sales manually in notebooks, lacking clear insight into their inventory levels. Only 18.43% to 30.77% of stores use an inventory system, which makes it currently unfeasible to implement a demand forecasting system that would enable timely orders from suppliers.

Between 50.12% and 64.31% receive products directly from suppliers; however, these deliveries mostly consist of beverages and soft drinks, which account for only 17.39% of their top-selling items. In contrast, their best-selling products, perishables (32.3%), are typically self-procured and transported in store-owned vehicles. Additionally, while 54.03% to 73.03% of stores have card payment terminals, only 31.2% accept electronic transfers.

The analysis revealed that most grocery stores lack the technological infrastructure needed to implement a Virtual Value Chain. A majority of businesses rely on mobile phones and manual sales recording, with only a small portion using inventory systems or accepting digital payments beyond card terminals. This limited technological maturity constrains both data generation (input) and information dissemination (output), two critical stages in the VVC model.

The findings align with global challenges in digitalizing small retailers, particularly in logistics and infrastructure [76]. However, the widespread access to mobile phones presents a viable entry point for digital integration. Designing a user-friendly mobile app, complemented by digital skills training (between 83.92% and 92.85% of managers have never received any), could enable store managers to initiate VVC processes incrementally, starting with inventory tracking and supplier communication. As Heeks [11] points out, MSEs only require access to a mobile device to benefit effectively from ICT4D initiatives.

Despite these technological gaps, most micro-stores have been operating for more than five years (60.96%), indicating strong market resilience. While large grocery chains dominate urban areas, small stores remain competitive due to their flexibility: they sell individual items, offer fresh and less-processed goods, remain open late, and are located in convenient neighborhoods, factors that continue to attract customers. Future analyses will examine the drivers that lead customers to prefer small stores over larger chains.

Regarding the second research question (RQ2), the results suggest that the age and education of store managers are significant determinants of digital tool adoption. Younger and more educated managers are more likely to use digital platforms and engage with external systems (e.g., delivery apps, websites), thus enabling data flow across the value chain. In contrast, resistance among older managers, often due to a lack of training or fear of technology, creates informational bottlenecks.

These behavioral barriers inhibit the input–mediation–output cycle of the VVC. Without reliable digital data (input), insight generation (mediation) and online customer/supplier interaction (output) are severely limited. These insights reinforce existing ICT4D literature that highlights the critical role of local agency, digital literacy, and managerial mindset [11,13].

These findings are consistent with Weyer [61], who argues that beyond resource scarcity, managerial mindset plays a critical role in determining which technologies are adopted and how effectively they are integrated into the value chain. In the context of Mexican MSEs, a limited technological mindset hinders the transformation of traditional supply chain operations into digital flows of information and value, the essence of the VVC concept.

Finally, regarding the third research question (RQ3), machine learning models applied to predict a manager's likelihood of adopting digital tools yielded inconclusive results. The lack of predictive power suggests that additional variables, such as managerial attitudes, trust in digital systems, or prior exposure, may be necessary for accurate modeling. This reinforces the complexity of behavioral dynamics in ICT adoption and indicates the need for more qualitative or mixed-methods approaches in future studies, exploring dimensionality reduction techniques or feature-label discrimination using covariance analysis to enhance data quality and model performance.

5. Conclusions

This research demonstrates that while grocery MSEs in Mexico exhibit operational resilience and social embeddedness, their potential for digital development through the VVC remains largely untapped. Despite some progress in payment technologies, there is a substantial gap in digitalizing supply chain operations, particularly in the areas of inventory management, supplier coordination, and data-driven decision-making like demand forecasting.

Our findings suggest that education and training are pivotal for enabling the VVC in microenterprise contexts. A mobile-based application, combined with capacity-building programs (over 80% of store managers have never received any form of technology training), could empower MSEs to engage more actively in digital value networks. Additionally, community-based logistics models, such as shared delivery services or app-enabled cooperatives, may offer scalable solutions in low-resource environments [77,78]. These alternatives align with the four key characteristics of ICT4D proposed by Heeks [11]: readiness, availability, sustainability (uptake), and impact.

This study contributes to ICT4D discourse by illustrating how VVC theory can be operationalized in the context of urban retail microenterprises in Mexico. It highlights the dual importance of technological enablers and behavioral readiness, bridging the gap between macro-level ICT policy and micro-level business practice.

Limitations of the Study and Future Research

The study is limited in geographic scope and does not incorporate consumer perspectives directly. Future work should explore how consumer trust, digital behavior, and generational preferences shape the success of digitalization strategies. Factors such as personalized service, proximity, and product flexibility appear to contribute to their sustained relevance [79].

Additionally, the sampling relied on surveys distributed by undergraduate students to nearby grocery stores, which introduces a convenience component. Out of 233 surveys distributed, 187 valid responses were obtained (a non-response rate of 19.7%). While this dataset provides valuable insights, the findings should be interpreted with caution and cannot be generalized to the more than 1,000,000 grocery stores that exist nationwide. Future studies should aim to apply stricter random sampling methods across a wider geographical scope.

Another limitation of this study is that the survey instrument did not incorporate items related to policy and regulatory changes, which can play a significant role in shaping MSEs' supply chains. While the present research prioritized operational and technological readiness, future work should integrate institutional and regulatory dimensions to provide a more comprehensive understanding of the factors influencing VVC adoption.

Although this study employed machine learning techniques to explore managers' willingness to adopt digital tools, the predictive power of the models was limited and yielded inconclusive results. This indicates that additional variables, such as managerial attitudes, trust in digital systems, or prior exposure to technology, may be required to improve accuracy. Furthermore, while Artificial Intelligence (AI) was not fully implemented in this study, we recognize its potential as a smart tool for future research. AI techniques could support dimensionality reduction, feature-label discrimination, and advanced behavioral modeling to enhance the analysis of Virtual Value Chain adoption. Future studies should explore these avenues to complement mixed methods approaches and strengthen predictive insights.

While technology and digital services play a crucial role in shaping consumer experiences and offer retailers the potential to enrich in-store engagement [80], a deeper understanding of consumer preferences remains essential. In some cases, habitual shopping practices and age-related factors prevent customers from feeling comfortable with alternatives to face-to-face purchasing [81].

Ultimately, this research reinforces the idea that development through ICT is not solely a matter of infrastructure, but of human capability, strategic design, and context-aware innovation. In the case of grocery MSEs, ICT does not inherently lead to development; however, when it is used to strengthen operations through the VVC, it can effectively support their growth. Importantly, complex technologies are not always required; access to a mobile phone, combined with proper training, can be sufficient to initiate meaningful digital engagement.

Author Contributions: Conceptualization, E.S.H.-G. and S.D.; methodology, A.I.R.M., J.E.G.-R. and E.S.H.-G.; software, A.I.R.M., J.E.G.-R. and E.S.H.-G.; validation, A.I.R.M.; formal analysis, E.S.H.-G.; investigation, E.S.H.-G.; data curation, E.S.H.-G., J.E.G.-R. and S.D.; writing—original draft preparation, E.S.H.-G. and J.E.G.-R. writing—review and editing methodology, A.I.R.M. and E.S.H.-G.; visualization, E.S.H.-G.; supervision, E.S.H.-G. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The data are available at the repository https://doi.org/10.6084/m9.figshare.25977001.v1 [65] and can be requested from the corresponding author when necessary.

Acknowledgments: We would like to thank Andrés Tellez for his valuable comments.

Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

Table A1. Questions included in the survey.

Area	Question
Profile	What is the name of your business? How many personnel have you employed? Please provide your working hours per day. How much can your business earn monthly?
Managerial characteristics	Please provide your full name. Please select your gender, age, and highest level of education. Are you interested in making some changes in your business? If so, how long does it take for you to get familiar with these changes
Personnel management	Do your personnel collaborate with each other during work? How long does it take for your personnel to adapt to a new condition or a new decision in your business? How long does it take for your personnel to learn and apply new ways of doing operations? Are your personnel act as a part of your business with others?
Company infrastructure	How do you manage space in your shelves? Do you have a specific place for loading/unloading? Which types of vehicles do you prefer when transporting your products?
Procurement	Which products are sold more than others? How much space do your stocks occupy in your store? Do you know the average sales number for the next periods? Do you inform your suppliers about your orders? /If so, in which way?
ICT4D	Do you have a convenient internet connection in your store? Do you have an IT/paper-based system to monitor your sales and inventory? Which devices do you use to track your orders?
E-commerce	Do you receive electronic payments from customers? Do you have a website to introduce your business or to sell your products online? Do you sell your products via Facebook, WA, or other social media channels? Do you receive orders via phone calls? Do you sell your products via digital marketplaces (e.g., Mercado Libre, Amazon, etc.)?
Challenges to introducing technology	Do you receive any financial/technical/educational support from the government? Do you need external support to engage with digitalization and political changes? Do you distribute products provided by NGOs?

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ISBN 978-3-7258-6315-0