sustainability

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A Two-Stage Sustainable Supplier Selection Model Considering Disruption Risk

Jie Lu [1], Feng Li [2,*] and Desheng Wu [3]

[1] Sino-Danish College, University of Chinese Academy of Sciences, Beijing 100190, China
[2] School of Business, Jiangnan University, Wuxi 214122, China
[3] School of Economics and Management, University of Chinese Academy of Sciences, Beijing 100049, China
* Correspondence: forestation0327@outlook.com

Abstract: The global spread of the pandemic has changed many aspects of life and placed the supply chain at risk of disruption. To solve the problem of supplier selection under the risk of supply chain disruption, in this paper, we propose a two-stage evaluation model to address the issue of supplier selection in the context where a pandemic requires a lockdown. First, we incorporate the lead time into the epidemic model that predicts the evolution of the pandemic to identify suppliers that have a high risk of disruption caused by the pandemic's evolution. Second, we propose a best–worst method combined with regret theory to rank candidate suppliers. Our model provides a dynamic link between the pandemic's evolution and supplier selection, and it allows selecting suppliers according to various criteria while avoiding supply chain disruptions due to inappropriate supplier selection. We validate the proposed model on a real case study with epidemic data from China. This paper is the first to consider the impact of lockdowns during the pandemic on supplier selection. We develop a novel MCDM model BWM-RT for supplier selection; our model can be an effective decision support approach to help decision makers better cope with the risk of supply chain disruptions.

Keywords: pandemic; supplier selection; sustainable supply chain; disruption

Citation: Lu, J.; Li, F.; Wu, D. A Two-Stage Sustainable Supplier Selection Model Considering Disruption Risk. *Sustainability* **2024**, *16*, 3821. https://doi.org/10.3390/su16093821

Academic Editor: GuoJun Ji

Received: 7 April 2024
Revised: 26 April 2024
Accepted: 29 April 2024
Published: 1 May 2024

1. Introduction

Supply chain (SC) engineering is one of the main issues in production research [1,2]. Over the recent years, SC risk management has been a growing research domain [3]. Within this research field, SC disruption risk has increasingly attracted the attention of scholars [4–7]. Earthquakes, tsunamis, strikes, epidemics, etc., may cause supply chain disruptions to varying degrees. In some cases, disruptions can be localized; in other contexts, disruptions can propagate downstream from the SC, adversely affecting network and company performance, and even causing ripple effects [8,9]. The ripple effect "refers to structural dynamics and describes a downstream propagation of the downscaling in demand fulfilment in the supply chain as a result of a severe disruption" [8]. Disruption has a serious negative impact on the supply chain and the operational performance of all members. How to avoid or mitigate the negative impact of disruption is a problem worth studying.

In the context of SC disruption, resilient supplier selection is a key strategic decision [10]. Suppliers play an important role in achieving high-quality products and customer satisfaction. To satisfy certain requirements, supplier selection aims to select the optimal supplier among the potential suppliers while considering their limitations [11]. In response to disruption risks, decision makers pay great attention to suppliers' resilience. SC disruptions may prompt some companies to re-evaluate their supply chains, to build more resilient supply chains, and to find more suppliers for the same product. Since resilient suppliers can absorb the shock of risk and recover quickly from disruptions, they reduce the negative impact of disruption on company performance. To some extent, choosing the right supplier can "avoid" the risk of a disruption. Regardless of cost and time, there are always suppliers that can meet our worldwide needs. While epidemics, earthquakes, typhoons, etc., can cause SC disruptions in some regions, such disruptions generally will not spread globally.

Supply chain disruptions may be categorized according to their frequency and performance [12]. The COVID-19 pandemic is viewed as a new type of disruption, quite unlike any seen before [9,13]. As a pandemic infectious disease, COVID-19 has brought a great challenges to global health, society, and economy [14]. According to the World Health Organization, as of 22 December 2022, a total of 650.88 million people have been infected, and 6.65 million people have died worldwide. Almost all countries in the world have been affected. After the outbreak, the production of countless goods and services around the world, from cars to smartphones, shopping to tourism, financial services to technology services, was forced to slow down or even be suspended, exposing the extreme vulnerability of global SCs, exacerbating the rise in panic, and breeding new accusations of economic globalization. Since the outbreak of the COVID-19 in December 2019, governments of various countries have adopted measures such as wearing masks and vaccinations to ensure the safety of people and strived to bring production back to its pre-epidemic level. As vaccines became widely available and the virulence of the COVID-19 strain has been greatly reduced after several rounds of mutation, more than 100 countries have completely canceled related travel restrictions or entry requirements by December 2022 [15].

Countries represented by China still implement the strict "dynamic zero-case policy" to maintain the normal functioning of society and promote economic development at the same time. This means that once an outbreak occurs in a certain area, local lockdown measures [16] are likely to be adopted to curb the spread of the epidemic as soon as possible. The policy leads to a situation where the SC is functioning normally in areas without outbreaks; however, there may be SC disruptions in blocked areas. For example, in April 2022, an outbreak in parts of the Shandong, Jiangsu, and Hebei provinces in China resulted in many governments adopting policies such as traffic control and community closure; a large number of highway junctions were closed and all businesses in the region stopped production activities. However, there were no similar policies in provinces without outbreaks.

In contrast to the low-probability and high-impact disruptions caused by earthquakes, typhoons, etc., a new context has emerged in China: the high-probability and high-impact disruptions caused by COVID-19. An important question arises in this context: how to select suppliers and arrange procurement plans under the strict "dynamic zero-case policy?" Extending to a more general context, how do we select suppliers and arrange procurement plans when the pandemic requires a lockdown? Based on this, we aim to construct a decision support methodology with the help of decision makers to avoid SC disruptions as much as possible when selecting suppliers.

To address these issues, we develop a two-stage supplier selection model. First, we use the Susceptible-Infected-Susceptible (SIS) epidemic to identify high-risk suppliers. Second, we provide a novel BWM-RT model to evaluate candidate suppliers, and we combine the results of the two rounds to obtain the optimal supplier.

As one of the multiple-criteria decision-making (MCDM) techniques, the best–worst method has attracted many scholars' attention due to its efficiency in reducing the number of pairwise comparisons and providing good performance in maintaining consistency between judgments [17–19].

At the same time, one of the most important steps in MCDM is the weighting of attributes. Most existing weighting methods are based on the judgements of experts/decision makers, and these judgements are prone to multiple cognitive biases, which BWM can effectively mitigate [20]. Also, to portray the risk preferences of decision makers, we introduce regret theory (RT) [21,22] in the decision model. Through the BWM-RT model, we can evaluate suppliers comprehensively from both objective assessment and subjective psychological aspects.

While there has been a lot of literature published on supplier resilience, the present paper focuses on the impact of the lockdown on supplier deliveries. The lockdown is only related to the evolution of the pandemic and not on the capacity of the supplier to produce goods on time. The ability to withstand, adapt, and recover from disruptions is often referred to as resilience [23,24]. Even though supplier selection models have considerations for resilience, these models provide tools that enable us to react to pandemics. On the contrary, our article aims to provide tools for selecting s supplier before a disruption caused by a pandemic occurs. In this context, the selection of suppliers should give priority to whether there is a trend of epidemic outbreaks in the area where the supplier is located, rather than the resilience of the suppliers themselves. According to the control framework of the ripple effect [25], resilience, redundancy, robustness, and flexibility are its four main elements. The purpose of this study is to minimize the ripple effect by intervening before the risk of a disruption in the selection of suppliers occurs.

The contributions of this paper are threefold. First, to the best of our knowledge, this paper is the first to consider the impact of lockdowns during the pandemic on supplier selection. As SC planning solutions must account for uncertainty and risk [26], we combine the epidemic model with supplier selection. The model suggests a set of suppliers that prevent pandemic-induced disruptions. Second, we develop a novel MCDM model BWM-RT for supplier selection. In the decision-making process, we compare candidate suppliers, and we consider the decision-maker's subjective attitude toward risk. Such decisions not only minimize the risk but also satisfy the decision-maker's expectations to the greatest extent. Third, we evaluate the proposed model on a case study with pandemic data from China. Note that the issues studied in this article originate from the situation that occurred in China, and we extend them to a more general context. Our analysis of the case study provides guidelines to practitioners that seek to select their supplier to obtain a robust supply chain.

The rest of this article is organized as follows. Section 2 reviews and summarizes the relevant literature, and Section 3 describes the proposed methodology. Section 4 outlines the numerical results, where we provide the detailed computation steps on data from China to validate the proposed model. Section 5 analyzes and justifies the need for a two-stage supplier evaluation model. This paper ends with conclusions, where we summarize this article and discuss future research.

2. Literature Review

As companies aim to specialize and focus on their core capabilities, they tend to rely on suppliers for goods and services previously provided in-house. As a result, the supplier selection process plays an important role in procurement activities, and companies must carefully evaluate the impact of their suppliers on the overall supply chain performance [27]. For these reasons, this section reviews the literature from two aspects: SC models considering disruption and supplier selection technologies.

2.1. SC Models Considering Disruption

The studies related to SC interruption are mainly supply disruption, disruption risk, and so on [28]. Disruptions are events that occur suddenly and have a significant social, economic, and environmental impact [29]. SCs are often severely affected by natural disasters (such as earthquakes, typhoons, and floods) and by man-made events (such as strikes). Different from these events, the impact of COVID-19 on the global supply chain is wider and the damage is greater. There is a large body of work on SC disruptions. Quantitative analysis methods for SC disruption risks mainly include mathematical optimization, simulation, and control theory. These three research fields provide a wide variety of tools to control risk, respond and stabilize the execution process in case of disruptions, and recover or minimize the middle-term and long-term impact of disruptions [30,31]. Mathematical optimization includes mixed-integer linear programming, robust optimization, and stochastic optimization, and these approaches provide optimal solutions to the considered problems.

Simulations (such as agent-based simulation or discrete event simulation) evaluate "what if scenarios". Finally, the control theory is often used to analyze the dynamic performance of systems that vary with time.

Optimization models provide solutions that minimize the impact of disruptions [32]. Chen, Wang, and Zhong [33] propose a SC disruption recovery strategy. The authors propose a mixed-integer linear programming (MILP) model that balances the costs of emergency procurement on the supply side, product substitution on the manufacturing side, and backorder price compensation on the demand side. The proposed model can help manufacturers decide on the best recovery strategy in the event of a disruption. The results help manufacturers decide the best recovery strategy in the event of a disruption. Ivanov, Pavlov, Pavlov, and Sokolov [34] design a multi-objective problem with a backflow reduction function for multi-period and multi-stage SCs. The developed multi-objective-mixed linear programming system dynamics model is used to compare the effects of different recycling strategies on performance. The study found that considering a gradual recovery of capacity could minimize the backflow of upstream and downstream SC parts associated with a disruption. Based on the two-stage stochastic programming method, Vali-Siar, Roghanian, and Jabbarzadeh [35] propose a model with the goal of profit maximization, which is solved by heuristic methods and two metaheuristics, such as the improved genetic algorithm (IGA) and improved particle swarm optimization (IPSO). The study found that the use of resilience strategies can reduce risk losses and make them get ahead of competitors in terms of market share. Zhao, Ng, Tan, and Pang [36] propose a two-stage distributed robust model with adjustable uncertainty set and simplify it into a single-stage mixed-integer linear program. To account for the ambiguity of decision makers' risk preferences, an extended almost robust interruption guarantee model is proposed, which is solved using a binary search algorithm. The calculations show that the model significantly outperforms the risk-neutral model in hedging a wide range of supply distributions. A scenario-based robust bi-objective optimization model is proposed by Sun, Li, Wang, and Xue [37]. The robust method is used to express the uncertainty as interval data, and the ε constraint method is used to deal with the bi-objective model. In order to arrange the repair activities of the interrupted critical infrastructures network, Alkhaleel, Liao, and Sullivan [38] propose a two-stage risk aversion and risk neutral stochastic optimization model. This paper provides an improved fast-forward algorithm based on a wait-and-see method to reduce the number of selected scenarios. The empirical analysis shows that the use of stochastic optimization models combined with travel time related to maintenance activities has added value. In the context of stochastic availability, Fattahi and Govindan [39] develop a multi-stage stochastic program to specify optimal location, capacity, inventory, and allocation decisions. A data-driven rolling horizon method is developed to use observations of random parameters in stochastic optimization problems. Finally, the applicability of the rolling horizon procedure and the effectiveness of the risk measurement strategy are proved by numerical examples. Based on the control theory, Li, He, and Minner [40] develop a new approach to co-designing optimal supply disruption management strategies. Optimal mitigation strategies are established in a closed form by applying the Pontryagin maximum principle. They provide analytical guidance on how to dynamically adjust procurement quantities, compensation prices, etc. The quantitative analysis methods for SC disruption risk are shown in Table 1.

In general, simulation methods are more flexible than stochastic optimization models; they incorporate and deal with more complexity and even provide real-time analysis. The control theory is used to analyze the final system's dynamic performance [32]. In addition to these techniques, the graph theory (including Bayesian networks, decision trees, etc.) is also one of the tools for analyzing SC interruptions [46,49,50].

Table 1. Quantitative analysis methods for SC disruption.

Paper	Method	Focus	Before/After Interruption
Ivanov, Pavlov, Pavlov, and Sokolov [34]; Chen, Wang, and Zhong [33]; Zhao, Ng, Tan, and Pang [36]	MILP	recovery strategy; recycling strategies; risk preferences	After interruption
Alkhaleel, Liao, and Sullivan [38]; Fattahi and Govindan [39]	stochastic optimization	optimal location, capacity, inventory, and allocation decisions	Before interruption
Wang and Chen [41]; Bertsimas and Thiele [42]	robust optimization	logistics planning; supply chain network design	Before interruption
Ivanov [43]; Lohmer, Bugert, and Lasch [44]	simulation	supply chain design performance	Before interruption
Li, He, and Minner [40]	control theory	optimal mitigation strategies	Before interruption
Hosseini and Ivanov [45]; Shi and Mena [46]	graph theory	supply chain risk, resilience, and ripple effect	Before interruption
Nagurney [47]; De Giovanni [48]	game theory	inventory decisions; distribution	Before interruption

2.2. Supplier Selection Technologies

The suppliers' section process is part of an organization's strategy, and it differs widely from one company to the next. As a result, there is no standard, and the supplier selection techniques differ in their selection processes, selection criteria, and selection methods.

Multiple-criteria decision-making technologies are often used for supplier selection, and they include Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Analytic Hierarchy Process (AHP), Analytic Network Process (ANP), Outranking method with Elimination and Choice Expressing Reality (ELECTREE), etc. These methods have yielded good results. To cope with the changes in supply and demand, Mohammed, Naghshineh, Spiegler, and Carvalho [51] developed a DEMATEL-TOPSIS method to quantify the resilience of suppliers and evaluate their performance. This approach enhances the company's ability to withstand uncertainty in demand as well as disruptions. Kaushik, Kumar, Gupta, and Dixit [52] choose seven criteria (including operational capability, product attributes, logistics, and warehousing) to evaluate suppliers. The BWM-VIKOR method is used to determine the priority of the standard and select the optimal supplier among the available ones. Wan, Liu, Du, and Du [53] propose a new model for supply chain sustainability assessment: the analytic network process (ANP) approach is used to determine the indicator weights, followed by the evidence reasoning (ER) method to process the expert evaluation information by membership function. Finally, the validity of the model is verified through a case study. Alipour, Hafezi, Rani, Hafezi, and Mardani [54] propose a comprehensive method for supplier selection: combining the entropy method and the SWARA method to calculate the criteria weight, and then using COPRAS to evaluate the ranking order of the alternatives. The research of this paper can overcome the shortcomings of objective or subjective weighting models.

Mathematical programming and cluster analysis are also two types of frequently used supplier evaluation techniques. Many scholars use the method of goal programming and linear programming to study. Considering integrated supplier selection and order allocation under disruption risk, Esmaeili-Najafabadi, Azad, and Nezhad [55] propose a mixed-integer nonlinear programming (MINLP) model. In this paper, the particle swarm optimization (PSO) algorithm is applied as a solution method and is compared with the genetic algorithm (GA) and commercial GAMS solver to verify the efficiency of the solution method. Firouzi and Jadidi [56] develop a fuzzy multi-objective model to solve the fuzzy constraints and fuzzy coefficients of the supplier selection problem. A weighting function is developed to transform the fuzzy multi-objective model into a fuzzy single-objective model, which is solved using the resolution method. Based on the problem of supplier selection and order quantity allocation in a two-stage supply chain, Ventura, Bunn, Venegas, and Duan [57] propose two mixed-integer nonlinear programming models to determine optimal supplier selection, retail price, and order quantity for each selected supplier. Liu, Hendalianpour, Fakhrabadi, and Feylizadeh [58] introduce a multi-objective linear programming model and combine the best–worst method (BWM) to rank suppliers. Fuzzy variables are used to determine the number of raw material orders that suppliers should provide, and goal programming is used to solve the required constraints. In addition, methods based on costs as well as artificial intelligence methods are also effective technologies [59–63]. The supplier selection model is shown in Table 2.

Table 2. Supplier selection techniques.

Paper	Method	Resilience	Disruption
Mohammed, Naghshineh, Spiegler, and Carvalho [51]; Liu, Hendalianpour, Fakhrabadi, and Feylizadeh [58]; Alipour, Hafezi, Rani, Hafezi, and Mardani [54]; Kaushik, Kumar, Gupta, and Dixit [52]; Wan, Liu, Du, and Du [53]	MCDM (DEMATEL/TOPSIS/BWM/VIKOR/ANP/AHP/ELECTREE)	Yes	No
Esmaeili-Najafabadi, Azad, and Nezhad [55]; Ventura, Bunn, Venegas, and Duan [57]; Tayyab and Sarkar [64]; Ho [65];	mathematical programming	Yes	No
Firouzi and Jadidi [56]; Memari, Dargi, Jokar, Ahmad, and Rahim [66]; Chen, Wang, and Tan [67]; Xu, Qin, Liu, and Martínez [68]; Mohammed, Harris, and Govindan [69]; Mondragon, Mastrocinque, Tsai, and Hogg [70]	fuzzy theory	Yes	No
Parkouhi, Ghadikolaei, and Lajimi [71]; Roy, Ali, Kabir, Enayet, Suhi, Haque, and Hasan [72]; Dobos and Vörösmarty [73]; Dutta, Jaikumar, and Arora [60]	methods based on costs	Yes	No
Dutta, Jaikumar, and Arora [60]; Gao, Ju, Gonzalez, and Zhang [74]; Chai and Ngai [75]	artificial intelligence	Yes	No

Appropriate supplier selection criteria and methods depend on the business and expectations of decision makers. Therefore, new hybrid approaches may need to be developed based on decision maker's needs and global market changes. The global spread of COVID-19 has brought changes to many aspects of our lives and additional uncertainty and disruption risk to SCs [76]. The current literature on supplier selection in relation to resilience and SC disruption is extensive, but almost all models are combined or optimized in the context of the pandemic and do not interact with the evolution of the pandemic, which in a way makes them "static" and of limited reference value.

It is notable that no models are available to help understand the quantification process of pandemic-induced disruptions or to provide a connection between the pandemic's evolution and supplier selection. Our study aims to fill this gap by modelling the dynamic link between the evolution of pandemic and supplier selection with a preventive perspective to avoid disruptions due to inappropriate supplier selection.

3. Methodology

We divide the supplier selection model into two steps. In the first step, we use the Susceptible-Infected-Susceptible (SIS) epidemic model to analyze the total population of the region, the number of infected people, the number of recovered people, etc.

The current mainstream disease models are SI, SIS, and SIR [77]. In this paper, the SIS model is chosen because during a pandemic, even if some people recover from infection, they are still potentially at risk of being re-infected. Our adoption of SIS is also consistent with other studies in the COVID-19 context [16].

In general, the spread rate of an epidemic is not fixed. In the initial stage, the spread of the epidemic is slow, and it slowly decreases after reaching a peak at a certain time. When the spreading speed reaches the maximum value, the epidemic is in a state of outbreak, and the cost of taking measures at this time is much higher than before [78]. Intervention measures against the spread of the epidemic must be taken before the critical moment of the epidemic from the incubation period to the outbreak period. This is generally the time when the government adopts containment measures.

We assume the government cuts off traffic before the epidemic spreading speed reaches the maximum value. In other words, the government adopts a blockade policy, where a part of the country is locked down when the spreading speed of the epidemic reaches its peak, and we call the remaining time to reach the peak the blockade countdown (BC). These lockdown policies have a large impact on the deliveries from suppliers. There is a high risk of late deliveries if the supplier's lead time is longer than the BC. The BC in each region is different, and the delivery date of each supplier is also different. The supplier with a lead time lower than the local BC is a candidate for an evaluation in the second phase.

In the second phase, a BWM-RT multi-criteria decision-making model evaluates suppliers based on three first-level criteria: primary criteria, green criteria, and resilience criteria. Primary criteria include delivery robustness, quality of products, service, and total costs; green criteria include CO_2 emission and distance; resilience criteria include geographical segregation, surplus inventory, and backup supplier contracting.

Under the risk of disruption, resilience-related indicators should receive more attention, and different indicators should have different weights in the evaluation process. Therefore, we use the best–worst method (BWM) model to determine the weight of each indicator. At the same time, in the actual decision-making process, the decision maker will compare the selected plan with other plans. If the selected plan is better than the other plan, he will feel happy, and if the other plan is better than the selected plan, he will feel regretful [79,80]. To characterize the decision maker's attitude towards risk, we introduce the regret theory (RT) [81] into the decision-making process. The BWM-RT model we developed can objectively reflect the importance of different indicators, thereby reducing the risk of interruption, and can subjectively describe the risk aversion attitude of decision makers. The two-stage supplier evaluation framework is shown in Figure 1.

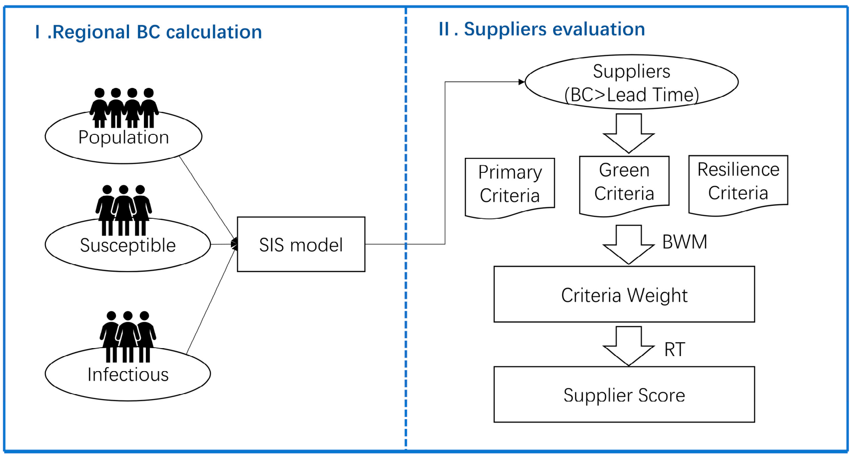

Figure 1. Two-stage supplier evaluation framework.

3.1. Regional BC Calculation

When an epidemic breaks out in a certain area, the population can be divided into three categories: Susceptible (S), Infected (I), and Recovered (R). With the development of the epidemic, people move from one state to the other in a certain proportion. More precisely, a proportion of susceptible people will become infected. After the infected people recover, they may be re-infected, or they may develop permanent resistance to the epidemic [82]. Common infectious disease models can be divided into SI, SIS, SIR, etc., according to their characteristics. Since the outbreak of COVID-19 in December 2019, a large number of people around the world has been infected. Even if vaccines have been widely used, recovered infected people still faced the possibility of being re-infected. Therefore, adopting the SIS epidemic model is a more realistic choice, and the relevant literature also supports this view [83,84].

Assume that the total number of people in the supplier's area is a constant (N) consisting of two groups: susceptible and infected. At time t, we label them as $S_{(t)}$ and $I_{(t)}$, respectively, and their proportions of the total population are $s_{(t)}$ and $i_{(t)}$, respectively. Obviously, we can obtain the following equation:

$$S_{(t)} + I_{(t)} = N \tag{1}$$

$$s_{(t)} + i_{(t)} = 1 \tag{2}$$

Assume that the infection rate and recovery rate are α and β; the evolution of the number of infected and susceptible people is described by the following differential equations [16]:

$$\frac{ds_{(t)}}{dt} = \beta i_{(t)} - \alpha i_{(t)} s_{(t)} \tag{3}$$

$$\frac{di_{(t)}}{dt} = \alpha i_{(t)} s_{(t)} - \beta i_{(t)} \tag{4}$$

Since $s_{(t)} + i_{(t)} = 1$, through the equations, the following formula can be obtained:

$$\frac{di_{(t)}}{dt} = \alpha i_{(t)} \left(1 - i_{(t)}\right) - \beta i_{(t)} \tag{5}$$

The above equation describes the evolution of disease prevalence in the population. This equation is a Bernoulli-type equation whose solution in a closed form is known and is provided by the following equation.

$$i_{(t)} = \frac{i_0(\alpha - \beta)}{((\alpha - \beta) - \alpha i_0)e^{-(\alpha-\beta)t} + \alpha i_0} \tag{6}$$

In the above equation, i_0 is the proportion of infected people in the initial stage. If λ is used to represent (α/β), it can be clearly observed that when $\alpha > \beta$ (that is, $\lambda > 1$), the $i_{(t)}$ can converge to the equilibrium:

$$i_\infty = 1 - \frac{1}{\lambda} \tag{7}$$

When $0 < \lambda \leq 1$, the infection rate is lower than the recovery rate, and the epidemic cannot spread in social groups, so $\alpha > \beta$ is the situation we need to pay attention to. The epidemic started from an initial state, and after a series of time evolution processes, it finally formed a stable proportion of infected people in the social group.

While the final diffusion rate deserves attention to control an epidemic, in a supplier selection context, the decision maker needs to pay attention to the BC since it is highly related to the risk of an interruption. The first derivative of Equation (6) with respect to time t is

$$\frac{di_{(t)}}{dt} = \frac{i_0(\alpha - \beta - \alpha i_0)(\alpha - \beta)^2 e^{(\alpha-\beta)t}}{\left[(\alpha - \beta) - \alpha i_0 + \alpha i_0 e^{(\alpha-\beta)t}\right]^2} \tag{8}$$

As a result, the number of infected people will peak over time, i.e., $\left(di_{(t)}/dt\right)$ will reach its maximum value as t changes. The diffusion growth rate over time is shown in Figure 2:

By setting the derivative of Equation (8) equal to zero, we can obtain the time t^* of the peak.

$$\frac{d^2 i_{(t)}}{d^2 t} = \frac{(\alpha - \beta) - \alpha i_0 e^{(\alpha-\beta)t} - \alpha i_0}{\left[(\alpha - \beta) - \alpha i_0 + \alpha i_0 e^{(\alpha-\beta)t}\right]^3} \times (\alpha - \beta - \alpha i_0)(\alpha - \beta)^3 i_0 e^{(\alpha-\beta)t} = 0 \tag{9}$$

$$t^* = ln\left(\frac{\alpha - \beta - \alpha i_0}{\alpha i_0}\right)\frac{1}{\alpha - \beta} \tag{10}$$

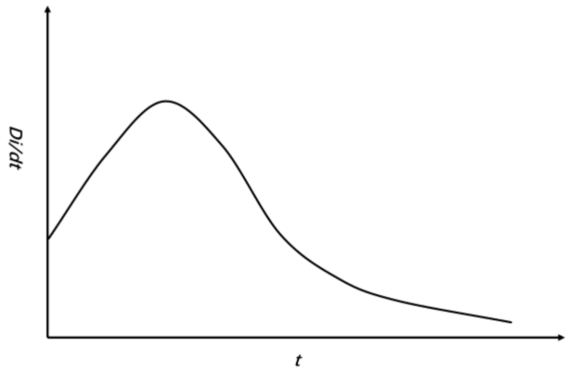

Figure 2. The diffusion growth rate over time.

The BC is equal to t^* in Equation (10). At time t, the spread speed of the epidemic in the population reaches its maximum. Obviously, the BC is related to α, β, and i_0. Since the outbreak of the epidemic, COVID-19 has continuously mutated, and the infection rate and recovery rate have changed accordingly. While these rates depend on the variant, there is, in general, a single dominant variant in each period. In the calculation process, we can regard α in different regions as the same. Due to the different number of infections in the initial stage, there will be large differences in the BC in each region.

3.2. Criteria Selection

After calculating the BC of each area, we conducted the second stage of evaluation on all suppliers whose lead time was less than the BC of the area. We divided supplier evaluation into two steps. The first step comprised the selection of evaluation criteria, and the second step consisted of the construction of an evaluation model. While there is an abundant amount of literature on supplier selection, only few works discuss evaluation criteria. With the outbreak of COVID-19 in recent years, the resilience of the supply chain has received more and more attention from researchers [85,86]. At the same time, resilience is also complementary to other criteria. For example, "gresilience" has attracted more and more attention and interest from researchers [87,88]. The combination of "green" and "resilience" can enable companies to address the pressure of "going green" in supply chains while improving their resilience to cope with unexpected supply chain disruptions [89].

We selected three indicators to evaluate the resilience criteria of suppliers: geographical segregation, surplus inventory, and backup supplier contracting. For green criteria, in addition to CO_2 emissions, we also paid attention to the distance of suppliers. This was carried out because the production process emits carbon dioxide, and the transportation process also pollutes the environment. In terms of primary criteria, indicators such as quality, service, and cost were selected. The selection criteria are shown in Table 3.

Table 3. Supplier evaluation criteria.

Criteria	Content	References
Primary	Delivery robustness	[90]
	Quality of products	[91]
	Service	[90]
	Total costs	[92]
Green	CO_2 emission	[93]
	Distance	[94]
Resilience	Geographical segregation	[11]
	Surplus inventory	[95]
	Backup supplier contracting	[11]

3.3. Evaluation Model

We developed a BWM-RT model to evaluate suppliers. The BWM model determines the weight of each criterion [96]. These weights are input to the RT, which makes the final choice of the supplier. Decision makers have different attitudes towards risks, and we introduce the RT to describe this tendency.

Assume supplier set $S = \{s_1, s_2, \cdots, s_m\}$ and criteria set $C = \{c_1, c_2, \cdots, c_n\}$. Suppose that a decision maker or expert evaluates each supplier S_i according to each criterion C_j; thus, the decision matrix is $R = (r_{ij})_{m \times n}$. The most important criterion c_B, the least important criterion c_w, and the importance of each criterion in comparison with the importance of c_B are determined by a decision maker or expert with a number between 1 and 9. Therefore, this results in

$$A_B = (a_{B1}, a_{B2}, \cdots, a_{B3})$$

where a_{B1} indicates the importance of the best criterion c_B over criterion c_j. Similarly, we can obtain the importance of all the criteria over the worst criterion using a number between 1 and 9. Therefore, this results in

$$A_W = (a_{1W}, a_{2W}, \cdots, a_{nW})$$

where a_{jW} indicates the importance of the criterion c_j over the worst criterion c_w. Clearly, $a_{BB} = 1$ and $a_{WW} = 1$. The optimal weight for the criteria is the one where, for each pair of w_B/w_j and w_j/w_W, we have $w_B/w_j = a_{Bj}$ and $w_j/w_W = a_{jW}$. To satisfy these conditions for all criteria j, we solve the following problem [96]:

$$min \max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\}$$

$$s.t. \begin{cases} \sum_j w_j = 1 \\ w_j \geq 0, j = 1, 2, \cdots, n \end{cases}$$

The above problem corresponds to the following problem:

$$min\, \xi s.t. \begin{cases} \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, j = 1, 2, \cdots, n \\ \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, j = 1, 2, \cdots, n \\ \sum_j w_j = 1 \\ w_j \geq 0, j = 1, 2, \cdots, n \end{cases}$$

Solving this problem yields the optimal weights $(w_1^*, w_2^*, \cdots, w_n^*)$ and the associated objective ξ^*. The regret theory calculates the rejoice value and regret value of each supplier and it selects the supplier that maximizes the sum of the rejoice value and the regret value.

For criteria c_j, the rejoice value and regret value of supplier s_i relative to s_k can be expressed as follows:

$$G_{ikj} = \begin{cases} 1 - exp\left(-\theta\left(\varphi(r_{ij}) - \varphi\left(r_{kj}\right)\right)\right), \varphi(r_{ij}) \geq \varphi\left(r_{kj}\right) \\ 0, \varphi(r_{ij}) < \varphi\left(r_{kj}\right) \end{cases} \tag{11}$$

$$R_{ikj} = \begin{cases} 0, \varphi(r_{ij}) \geq \varphi\left(r_{kj}\right) \\ 1 - exp\left(-\theta\left(\varphi(r_{ij}) - \varphi\left(r_{kj}\right)\right)\right), \varphi(r_{ij}) < \varphi\left(r_{kj}\right) \end{cases} \tag{12}$$

The risk aversion coefficient $\theta \geq 0$ reflects the decision maker's attitude towards risk. φ is the utility function. Generally, a power function is often used to represent the scoring utility function. In this article, we let $\varphi(r_{ij}) = (r_{ij})^{\delta}, 0 < \delta < 1$. For supplier s_i, the rejoice value and regret value obtained by the decision maker can be calculated by the following equation:

$$G(s_i) = \sum_{k=1}^{m}\sum_{j=1}^{n} w_j G_{ikj}, (i = 1, 2, \cdots, m)$$
$$R(s_i) = \sum_{k=1}^{m}\sum_{j=1}^{n} w_j R_{ikj}, (i = 1, 2, \cdots, m) \quad (13)$$

The sum of rejoice value and regret value of supplier s_i is used as the basis for a decision maker's judgment.

$$T(s_i) = G(s_i) + R(s_i) \quad (14)$$

Finally, suppliers are sorted according to the value of $T(s_i)$. The larger the value of $T(s_i)$, the better the performance of the supplier.

4. Empirical Analyses

Our model applies to any situation where a lockdown is caused by an epidemic. In this article, we choose the representative lockdown caused by COVID-19 in China as the background for our research. November 2022 is the vegetable harvest season in many provinces in China. However, a large number of vegetables are left in the field. When the supply chain is interrupted, the vegetables cannot be transferred from the farmer to the customer. Although China has always pursued strict epidemic prevention and control policies, epidemics continue to break out regionally. In response to the frequent outbreaks, the government often adopts lockdown measures until the region becomes low-risk. Under a lockdown environment, vegetable suppliers face many strict restrictions, and drivers cannot deliver products.

Assuming that a factory in the Hubei province, China, needs vegetables for processing, the vegetable suppliers in six regions bordering the Hubei province are candidates. These six regions are Henan province, Anhui province, Jiangxi province, Hunan province, Chongqing city, and Shaanxi province.

Table 4 displays the data of the National Health Commission of the People's Republic of China, as of 15 December 2022, with regard to the number of infected people, the cumulative number of infected people, the cumulative number of recovered people, and the total population in these six regions.

Table 4. Epidemic situation in six regions of China (15 December 2022).

Region	Infected	Population (Million)	Proportion	Cumulative Infection	Cumulative Recovery	Recovery Rate
Henan	2455	98.83	2.48×10^{-5}	8758	6280	0.72
Anhui	31	61.13	5.07×10^{-7}	1699	1662	0.98
Jiangxi	8	45.17	1.77×10^{-7}	1547	1538	0.99
Hunan	316	66.22	4.77×10^{-6}	2442	2122	0.87
Chongqing	1906	32.12	5.93×10^{-5}	8721	6808	0.78
Shaanxi	613	39.54	1.55×10^{-5}	5462	4846	0.89

In Table 4, we compute the proportion i_0 of infected people in the initial stage from the number of infected people and the total population, and we can obtain the recovery rate β based on the cumulative infection and recovery numbers.

Although the infection rate α is currently difficult to measure and changes over time, we can use the basic reproductive number (R_0) as an approximate substitute. R_0 is defined as the average number of secondary cases attributable to an infection by a given case after that case is introduced into a susceptible population [97]. Referring to the related research [98], we set the infection rate as 5.7, that is, $\alpha = 5.7$. Since these regions are relatively close and the type of COVID-19 is the same, we consider the infection rate of each region to be the same. On the basis of i_0, α, and β, the BC of each area can be obtained as follows:

$$BC_{Henan} = ln\left(\frac{5.7 - 0.72 - 5.7 * \left(2.48 \times 10^{-5}\right)}{5.7 * \left(2.48 \times 10^{-5}\right)}\right)\frac{1}{5.7 - 0.72} = 2.1$$

Similarly, we can obtain the BC of other regions. The BC of each region and the lead time of the suppliers are shown in Table 5. If lead time is greater than the BC, we define interrupt risk as high; if lead time is less than the BC and the difference between the two is greater than 1, we define interrupt risk as low; if lead time is less than the BC and the difference between the two is less than 1, we define interrupt risk as medium. Only suppliers with "medium" and "low" disruption risks are candidates for the second stage of evaluation. Therefore, supplier B, supplier C, and supplier D are candidates.

Table 5. Regional BC and supplier risk level.

Region	BC	Supplier	Lead Time	Disruption Risk	2^{nd} Evaluation
Henan	2.10	A	3	High	No
Anhui	3.03	B	2	Low	Yes
Jiangxi	3.26	C	3	Medium	Yes
Hunan	2.50	D	2	Medium	Yes
Chongqing	1.95	E	2	High	No
Shaanxi	2.27	F	3	High	No

In this article, the factory's production supervisor is responsible for supplier selection. Based on the production supervisor's years of experience and the advice of other experts within the factory, the most important criterion c_B, the least important criterion c_w, and the importance of each criterion in comparison with the importance of c_B are determined. For the selection of suppliers, to avoid interruption risk as much as possible, "surplus inventory" and "distance" are regarded as the best and worst criteria, respectively. The results are shown in Table 6.

Table 6. Best and worst criteria over the other criteria.

Label	1	2	3	4	5	6	7	8	9
Criteria	Delivery	Quality	Service	Costs	CO_2	Distance	Segregation	inventory	Backup
A_B	3	4	5	4	8	9	2	1	2
A_W	7	6	5	6	2	1	8	9	8

By adding A_B and A_W into linear programming, the weight of each criterion can be obtained as follows:

$$w^* = (0.11, 0.08, 0.07, 0.08, 0.04, 0.02, 0.16, 0.27, 0.16)$$

After obtaining the weight of each criterion, the next step is to calculate the rejoice value and regret value of choosing different suppliers. The factory's decision makers evaluate different suppliers based on the criteria. Scores range from 1 to 9, with higher scores indicating better performance. The score matrix of supplier B, supplier C, and supplier D is as follows:

$$\left(r_{ij}\right)_{m \times n} = \begin{bmatrix} 7 & 6 & 6 & 5 & 4 & 4 & 3 & 4 & 3 \\ 5 & 4 & 4 & 4 & 7 & 7 & 5 & 6 & 6 \\ 8 & 7 & 8 & 7 & 5 & 5 & 4 & 5 & 4 \end{bmatrix}$$

Referring to the relevant literature [99,100], $\theta = 0.5$, $\varphi(r_{ij}) = (r_{ij})^{0.9}$. The utility matrix is shown below:

$$\varphi(r_{ij}) = \begin{bmatrix} 5.76 & 5.02 & 5.02 & 4.26 & 3.48 & 3.48 & 2.69 & 3.48 & 2.69 \\ 4.26 & 3.48 & 3.48 & 3.48 & 5.76 & 5.76 & 4.26 & 5.02 & 5.02 \\ 6.50 & 5.76 & 6.50 & 5.76 & 4.26 & 4.26 & 3.48 & 4.26 & 3.48 \end{bmatrix}$$

The rejoice value and regret value obtained according to different criterion can be obtained with Equations (11) and (12). Taking supplier B as an example, we show the calculation process of the rejoice value and regret value. The values of G_{1kj} and R_{1kj} for supplier B are given below.

$$G_{1kj} = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.53 & 0.54 & 0.54 & 0.32 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \end{bmatrix}$$

$$R_{1kj} = \begin{bmatrix} 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 & 0.00 \\ 0.00 & 0.00 & 0.00 & 0.00 & -2.13 & -2.13 & -1.19 & -1.15 & -2.20 \\ -0.44 & -0.45 & -1.1 & -1.12 & -0.47 & -0.47 & -0.49 & -0.47 & -0.49 \end{bmatrix}$$

The weighted sum (based on w^*), $G(s_i)$, and $R(s_i)$ of supplier B can be obtained according to Equation (13). Similarly, we can obtain the rejoice value and regret value of other suppliers, and we sum them up to obtain the final score, as shown in Table 7:

Table 7. Scores for each supplier.

Region	Supplier	Rejoice	Regret	Sum	Ranking
Anhui	B	0.16	−1.55	−1.39	3
Jiangxi	C	0.64	−1.15	−0.51	2
Hunan	D	0.59	−0.45	0.14	1

As can be seen from Table 7, supplier D is the best choice, followed by suppliers C and B. Although supplier D is not the choice with the largest rejoice value, it has the smallest regret value. The optimal supplier ranking in order from best to worst is supplier D, supplier C, and supplier B. The advantage of the proposed model is that the candidate suppliers can be selected optimally and effectively avoid disruption risks.

5. Necessity for Two-Stage Model

Since supplier A, supplier E, and supplier F were rated as high-risk when considering disruption risk, only supplier B, supplier C, and supplier D were compared in the second stage. To show the importance of the consideration of disruption risk, we consider the case where we skip the first stage of evaluation, compare the six suppliers, and score them according to the BWM-RT model. Below is the scoring matrix for the six suppliers:

$$(r_{ij})_{m\times n} = \begin{bmatrix} 7 & 6 & 6 & 5 & 4 & 4 & 3 & 4 & 3 \\ 5 & 4 & 4 & 4 & 7 & 7 & 5 & 6 & 6 \\ 8 & 7 & 8 & 7 & 5 & 5 & 4 & 5 & 4 \\ 8 & 5 & 5 & 7 & 6 & 6 & 8 & 6 & 7 \\ 6 & 8 & 6 & 7 & 7 & 8 & 7 & 8 & 6 \\ 5 & 5 & 4 & 7 & 6 & 8 & 6 & 8 & 6 \end{bmatrix}$$

Following the same steps, we can obtain the rejoice value and regret value of each supplier. By comparing the sum of the two, the optimal supplier can be obtained. Table 8 shows the results of our calculations.

Table 8. The scores for six suppliers.

Region	Supplier	Rejoice	Regret	Sum	Ranking
Anhui	B	0.37	−7.64	−7.27	6
Jiangxi	C	0.67	−3.67	−3.00	5
Hunan	D	0.94	−3.70	−2.76	4
Henan	A	1.57	−1.18	0.39	2
Chongqing	E	1.86	−0.51	1.35	1
Shaanxi	F	1.32	−1.72	−0.40	3

The following list of suppliers is listed from highest to lowest scores supplier E, supplier A, supplier F, supplier D, supplier C, and supplier B. Thus, supplier E is the best choice. However, in the two-stage evaluation model, supplier D is the optimal supplier. The optimal supplier order sequences for the two-stage and one-stage models are as follows:

$$Order^*_{2s} = (D, C, B)$$

$$Order^*_{1s} = (E, A, F, D, C, B)$$

Supplier E and supplier A have the highest scores, but they are eliminated from being the candidates at the first stage of the selection process. Without a two-stage model, decision makers may choose suppliers with high scores, a choice that faces a high risk of disruption.

We define the sum of the rejoice value and the regret value as the satisfaction value, which can be divided into three grades, comprising high, medium, and low grades, according to the value. Obviously, the category with high satisfaction includes supplier E and supplier A, the category with medium satisfaction includes supplier F and supplier D, and the category with low satisfaction includes supplier C and supplier B. Taking the disruption risk as the horizontal axis and the satisfaction value as the vertical axis, we can obtain Figure 3, as shown below:

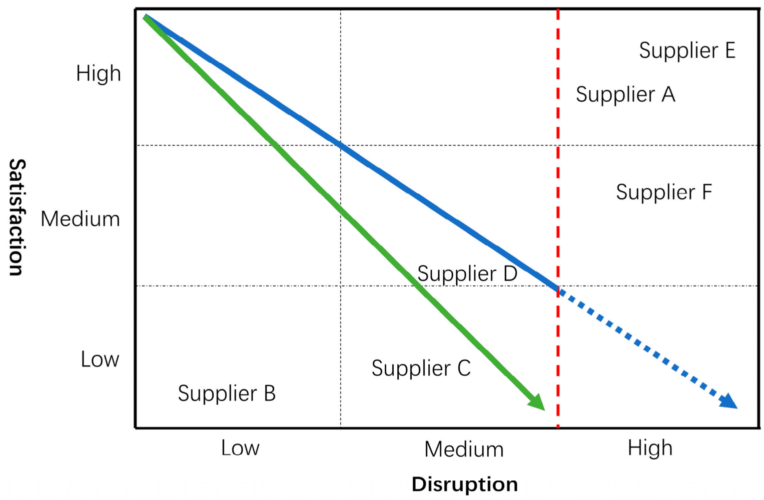

Figure 3. Supplier evaluation based on two-stage model.

If only satisfaction is considered, it can be clearly seen that supplier E scored the highest. In Figure 3, suppliers located to the right of the red line face a high risk of supply chain disruption. Although supplier E, supplier A, and supplier F can all provide high satisfaction, in order to avoid the risk of disruption, the alternative suppliers can only be in the left area of the red line.

Considering the disruption risk and satisfaction at the same time, we can draw a blue trend line, as shown in the Figure 3. Moreover, the direction of the arrow shows the trend of the supplier selection from good to bad. In this paper, we divide the risk of disruption into three levels: high, medium, and low. Suppliers in regions with a high level of disruption risk will not be evaluated in the second stage. In fact, it is entirely possible to divide the disruption risk in more detail according to the needs, that is, the intersection of the blue line and the red line must not be fixed, and will have to be moved left or right according to the risk preference of the decision maker.

The green line is the trend line of the optimal choice in the feasible region. Similar to the blue trend line, the arrow direction indicates that the quality of supplier selection gradually decreases. Supplier D can be seen closest to the upper left of the feasible region, which defines this supplier as the optimal choice.

In summary, the significance of the two-stage model is that it can help us define the boundaries of the feasible region according to our risk preference. We can choose the most satisfactory solution on the premise of avoiding a supply chain disruption.

6. Conclusions

The low-probability and high-impact disruptions of material flows in global supply chains and the resulting losses may threaten company performance [101]. For example, SC disruptions in some areas can be caused by earthquakes, floods, etc. Unlike these events, COVID-19 has had an unprecedented impact on supply chains around the world, and few countries have been spared. In this context, supply chain resilience and ripple effects have gained significant attention. Risks, resilience, and the ripple effect are expected to become major determinants in the "new normal" world shaped by uncertainty [30].

Based on the real case that took place in China, where the pandemic required a lockdown, we studied the problem of supplier selection and proposed a solution. We designed a two-stage model to evaluate suppliers. First, the SIS model was used to measure the regional BC, and a comparison with the lead time of the supplier was carried out to identify the disruption risks caused by lockdown control. Then, we evaluated the candidate suppliers according to different criteria with the proposed BWM-RT model. Finally, the evaluation results of the two rounds were combined to obtain the best supplier. Unlike the previous literature on supplier selection, we focused on how to avoid pandemic-induced disruptions at the supplier selection stage, rather than choosing the most resilient supplier to withstand the shock of the disruption or recover from it as quickly as possible. Our designed solutions offer a more forward-looking perspective.

We validated our model using data from China. Using the SIS model and the epidemic data of Henan province, Anhui province, etc., we calculated the BCs of these regions, compared them with the lead time of the suppliers in their regions, respectively, and identified three candidate suppliers. Combining the results of the two rounds of evaluation, we concluded that supplier D is the most appropriate choice. We also discussed the need for a two-stage evaluation model. Assuming that we rely solely on the one-stage model to evaluate suppliers, we find that while the supplier ranking does not change, the top-ranked choices are highly likely to be at risk of disruption. SC disruptions can severely impact company performance, and the two-stage model is a solution that combines efficiency and security.

We constructed a decision support methodology with the help of decision makers to determine which of them can avoid SC disruptions to the greatest extent when selecting suppliers. Our study not only enriches the research on supplier evaluation, but, more importantly, our model can be a powerful tool for experts/decision makers to deal with the risks of supply chain disruptions.

Although countries with a strict "dynamic zero-case policy" are adjusting their restrictive policies, it does not mean that our two-stage evaluation models and solutions have lost their application value. COVID-19 has mutated into many different variants and it is difficult to predict the harmfulness of the next variant, which means that lockdown policies may be re-adopted in different countries. At the same time, the proposed model is applicable in any pandemic context where a lockdown is required and is not specific to

COVID-19. The model presented in this article presents a new preventive perspective to avoid SC disruptions caused by pandemics.

In this paper, the effectiveness of our two-stage model in dealing with SC disruptions due to the pandemic is verified. In the first stage, we mainly selected real infectious disease data, such as the number of people in different regions and the number of infected people; in the second stage, we mainly selected data on suppliers' greenness and resilience. Our research conclusions have general guiding significance and are of greatest significance to manufacturing enterprises with widely distributed suppliers, large purchase volumes, and low purchase frequencies. This is because SC disruptions may be categorized according to their frequency and performance, wherein the frequency of the pandemic is low, but the devastation is immense.

The conclusions of our study are consistent with previous studies but also have differences. The consistency is that we also paid a lot of attention to the disruption risk during our model's construction process and designed a model to enhance supply chain resilience. The difference is that most previous studies focused on the impact of the pandemic on production and that most models were static models [16]. No models are available to help understand the quantification process of pandemic-induced disruptions or to provide a connection between pandemic evolution and supplier selection. The findings of our study could well bridge this gap.

Our method can be easily applied in production practice. In production, since suppliers and evaluation criteria do not change frequently, the optimal solution can be obtained by entering some simple data. At the same time, our model is very suitable for being made into an application installed on a computer or mobile phone for daily use.

In practice, the SIS model can also be applied to simulate the spread of public opinions [102]. If data on the media communication and public relations ability of the selected suppliers are used in the second stage, our model can also be used to assess the ability of different suppliers to maintain their goodwill and thus avoid being negatively influenced by a supplier with a poor reputation. This has important implications in practice as consumer demands can also be influenced by a company's goodwill. There are many similar topics that are worth investigating.

We have evaluated suppliers in terms of both satisfaction and risk of disruption, which can lead to a comprehensive optimal solution. Our model is a flexible and scalable model, and the evaluation indicators can be adjusted according to the needs of decision makers. For example, if decision makers prefer suppliers with excellent performance in sustainability, greenness, etc., the model can be easily altered to fit reality.

In this article, we focused mainly on supplier selection. However, in this context, more aspects of procurement planning need to be studied in more depth. For example, in the face of a high-probability and high-impact epidemic, we should study how stock preparation and warehousing should be adjusted with regard to the development of an epidemic. At the same time, we present a model on the premise that there is no interaction in each region; however, in reality, there is an exchange of people and materials in each region at every moment, which can have an impact on the BC of each region. Moreover, the effects of the infection rate and recovery rate and how they affect the model were not further discussed; these are all directions that can be further studied.

Theoretically, resilience increases with the selected characteristics of the supplier. If we select more criteria regarding supplier resilience, the optimal solution is the one that performs best in terms of resilience. It can be inferred that this impact has a marginal effect. However, further research should be conducted in subsequent studies.

As discussed in the literature review, there are no models available to help understand the quantification process of pandemic-induced disruptions or to provide a connection between a pandemic's evolution and supplier selection. Our study aimed to fill this gap by modelling the dynamic link between the evolution of a pandemic and supplier selection. There is already a lot of literature focusing on supplier evaluation, but there is still relatively little literature portraying the dynamic link between supplier selection and disruptions caused by emergencies, such as pandemics, tsunamis, etc. Modeling these links and proposing solutions is a worthwhile direction for moving forward.

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

Funding: This work was supported in part by the Ministry of Science and Technology of China under Grant 2020AAA0108400 and Grant 2020AAA0108402; in part by the National Natural Science Foundation of China under Grant 71825007; in part by the Chinese Academy of Sciences (CAS) Frontier Scientific Research Key Project under Grant QYZDB-SSW-SYS021; in part by the International Partnership Program of CAS under Grant 211211KYSB20180042; and in part by the Strategic Priority Research Program of CAS under Grant XDA23020203.

Data Availability Statement: The data used to support the findings of this study are included within this article.

Conflicts of Interest: The authors declare no conflicts of interest regarding the publication of this paper.

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