



Robust optimization model of anti-epidemic supply chain under technological innovation: learning from COVID-19

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Abstract

The anti-epidemic supply chain plays an important role in the prevention and control of the COVID-19 pandemic. Prior research has focused on studying the facility location, inventory management, and route optimization of the supply chain by using certain parameters and models. Nevertheless, uncertainty, as a vital influence factor, greatly affects the supply chain. As such, the uncertainty that comes with technological innovation has a heightened influence on the supply chain. Few studies have explicitly investigated the influence of technological innovation on the anti-epidemic supply chain under the COVID-19 pandemic. Hence, the current research aims to investigate the influences of the uncertainty caused by technological innovation on the supply chain from demand and supply, shortage penalty, and budget. This paper presents a three-level model of the anti-epidemic supply chain under technological innovation and employs an interval data robust optimization to tackle the uncertainties of the model. The findings are obtained as follows. Firstly, the shortage penalty will increase the costs of the objective function but effectively improve demand satisfaction. Secondly, if the shortage penalty is sufficiently large, the minimum demand satisfaction rate can ensure a fair distribution of materials among the affected areas. Thirdly, technological innovation can reduce costs. The technological innovation related to the transportation costs of the anti-epidemic

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material distribution center has a greater influence on the optimal value. Meanwhile, the technological innovation related to the transportation costs of the supplier has the least influence. Fourthly, both supply and demand uncertainty can influence costs, but demand uncertainty has a greater influence. Fifthly, the multi-scenario budgeting approach can decrease the calculation complexity. These findings provide theoretical support for anti-epidemic dispatchers to adjust the conservativeness of uncertain parameters under the influence of technological innovation.

Keywords Robust optimization model · Anti-epidemic supply chain · Technological innovation · COVID-19 pandemic

1 Introduction

The novel coronavirus pneumonia is an inflammation of the lungs caused by a novel coronavirus, called the SARS-CoV-2 virus, which is highly contagious. The first reported public health emergency for an epidemic attributed to the novel coronavirus pneumonia was in Wuhan in December 2019. Since then, the novel coronavirus pneumonia was successively detected worldwide (Chitrakar et al., 2021). The World Health Organization (WHO) announced that the infectious disease caused by the SARS-CoV-2 virus would be officially named Corona Virus Disease 2019, abbreviated as COVID-19, in February 2020 (Cucinotta et al. 2020). Then, WHO officially classified COVID-19 as a global pandemic in March 2020 (Lai et al., 2020). The ferocity, impact, spread, and duration of the COVID-19 pandemic have exceeded all expectations (Choi, 2021). The influence of the COVID-19 pandemic on the humanitarian relief chain, especially the anti-epidemic supply chain, is more severe and complex than that of previous outbreaks, such as the SARS epidemic and the H1N1 epidemic (Dubey et al., 2020a, 2020b; Guan et al., 2020). An anti-epidemic supply chain refers to the process of producing, transporting, and distributing anti-epidemic materials, such as masks, disinfectants, goggles, rubber gloves, and others, by linking suppliers, distribution centers, and demanders of anti-epidemic materials into a whole through the flow of capital, logistics, and information. The COVID-19 pandemic can be transmitted from person to person through breathing, sneezing, or coughing (Salarpour & Nagurney, 2021). Consequently, governments of various countries have increasingly taken strategies, including relying on wearing masks and spraying disinfectants, to prevent the spread of the virus (Herron et al., 2020). Under the influence of the COVID-19 pandemic, the demand for anti-epidemic materials has surged. The imbalance between the supply and demand of anti-epidemic materials, such as masks, disinfectants, goggles, gloves, and protective clothing, has become a global issue (Gereffi, 2020). The supply of anti-epidemic materials in some countries or regions is seriously inadequate. In addition, people, including doctors, nurses, and patients, do not have sufficient anti-epidemic materials, thus resulting in the shutdown of health centres (Jacobs et al., 2020). Thus, medical resources have become more scarce. As a result, addressing the shortage of anti-epidemic materials during the COVID-19 pandemic has become a hot topic of widespread concern among officials, academics, and the public. A stable and certain anti-epidemic supply chain is a prerequisite for the control of the COVID-19 pandemic and placating the worries of the public.

Research on the humanitarian supply chain has been extensively investigated in the available literature, and their themes are concentrated in three primary areas. Firstly, studies have been conducted on the facility location of the humanitarian supply chain (Mohammadi et al.,

2020), such as the positioning of the distribution center and storage warehouse (Boonmee et al., 2017; Cotes & Cantillo, 2019). Secondly, studies on the inventory management of the humanitarian supply chain have focused on the stock levels of humanitarian relief products or equipment before and after the event (Balcik et al., 2016; Kholidasari & Ophiyandri, 2018). Thirdly, studies on the route optimization of the humanitarian supply chain have involved the deployment of humanitarian relief products and personnel after a disaster (Bruni et al., 2018; Mollah et al., 2018). Nevertheless, the parameters and data associated with the models in previous literature are mostly deterministic. The COVID-19 pandemic, as a public health emergency, has many uncertainties that affect various aspects of the humanitarian supply chain, particularly the anti-epidemic supply chain. However, the issue of uncertainty in the anti-epidemic supply chain caused by the COVID-19 pandemic is scarcely discussed in previous literature. Additionally, technological innovations, such as big data technology, digital technology, and blockchain technology, present opportunities and challenges for the humanitarian supply chain. These innovations play a critical role in the resilience, sustainability, and effectiveness of the humanitarian supply chain (Akter & Wamba, 2019; Gupta et al., 2019). Conversely, they also have the potential to impede the humanitarian supply chain (Bag et al., 2020). Within the background of the COVID-19 pandemic, research on the impact of technological innovation on the anti-epidemic supply chain is imperative. Nevertheless, little investigation has been spearheaded on this issue in the available research. Technological innovation involves corporate research and development, strategic planning, and resource allocation (Yam et al., 2011). An organization can enhance its capabilities and create value by utilizing technological innovation (Wang et al., 2008). Resource-based theory suggests that organizations with sufficient technological innovation will promote inter-organizational collaboration and thus be willing to implement inter-organizational systems (Bresman, 2010). Existing research proves that such innovation has changed inter-organizational partnerships within the supply chain (Huang, 2011). Nevertheless, technological innovation may affect the ability to integrate supply chains, which may generate negative consequences for the organization. As a result, it has created more uncertainty for the anti-epidemic supply chain. According to the available literature, uncertainty in supply chains is primarily reflected in demand and supply, shortage penalty, and budget. Hence, technological innovation may affect the uncertainty of demand and supply, shortage penalty, and budget. Uncertainty in supply parameters emerges from the availability of technological innovation and the unpredictability of supplier technological innovation. Uncertainty in cost parameters is caused by the accessibility of material distribution routes under the influence of technological innovation. Meanwhile, uncertainty in demand parameters results from inaccurate estimates of technological innovation.

Some scholars have attempted to deal with uncertain parameters as their corresponding discrete probabilities through scenario stochastic programming (Elçi et al., 2018; Zahirri et al., 2017). Based on the existing literature, most humanitarian relief supply chains employ the scenario-based stochastic programming approach to address uncertainty, which has two shortcomings. Firstly, this approach requires a probability distribution for uncertain parameters. Nevertheless, insufficient historical data on the COVID-19 pandemic cannot sufficiently provide an accurate probability distribution for the uncertain parameters. Secondly, the solution depends largely on the accuracy of the defined scenario and the preferences of the decision-maker, and the final solution varies with the discrete probability of the scenario. The robust optimization approach, proposed by Bertsimas and Sim (2005), focuses on its computational intractability, strict conservatism, and impact on the complexity of the deterministic model. Every uncertain parameter in this approach is simply represented by a specific interval, and the feasibility of the solution can be guaranteed by a min–max approach. The use of less

parametric information allows the degree of conservatism of the model to be controlled. In addition, linear programming, mixed-integer linear programming, and semidefinite optimization problems retain their original structure when using the approach.

To fill these knowledge gaps, the current research focuses on the anti-epidemic supply chain and incorporates the uncertainty of demand and supply, shortage penalty, and budget caused by technological innovation into the analysis framework. On this basis, this research constructs a robust optimization model of the anti-epidemic supply chain under technological innovation and uses an interval data robust optimization to tackle the uncertainties in this model. Finally, the effectiveness of the model is verified by using Wuhan as a case study.

The contributions to this research are illustrated as follows. Firstly, this current research constructs an anti-epidemic supply chain model under technological innovation, which explores the uncertainty of technological innovation in the anti-epidemic supply chain. Secondly, this current research explores the value relationship between the degree of data volatility and the minimum demand satisfaction rate. Thirdly, this current research conducts a sensitivity analysis of the uncertainty of supply and demand under the effect of technological innovation. Moreover, it proves that demand uncertainty has a greater influence on supply chain costs, while supply uncertainty has a greater influence on the demand satisfaction rate.

The remaining part of this paper is organized as follows. Section 2 states the literature review. Then, Sect. 3 constructs an anti-epidemic supply chain model under no technological innovation. Next, Sect. 4 expands an anti-epidemic supply chain model under technological innovation, which primarily takes the uncertainty of demand and supply, shortage penalty, and budget. The robust optimization model of the anti-epidemic supply chain under technological innovation is empirically tested by using Wuhan as a case study in Sect. 5. Afterward, Sect. 6 delineates the discussion. Lastly, the final section summarizes conclusions, enumerates implications, and provides limitations and future research opportunities.

2 Literature review

2.1 Influence of uncertainty environment on supply chain

The uncertainty of the supply chain is one of the important topics in the research of supply chain management, which has attracted the attention of many scholars. For instance, Chen and Xiao (2009) examined the coordination problem of a supply chain consisting of a supplier, a leading retailer, and multiple peripheral retailers when the demand has large fluctuations. In this scenario, a quantity discount contract and a wholesale price contract are used to coordinate the supply chain. Furthermore, Gurnani et al. (2010) found that the uncertainty of market demand faced by retailers will prevent their purchase quantity from reaching the optimal level. In motivating retailers, suppliers use repurchase contracts to buy back unsold products and evaluate the influence of price on demand. Merakli and Yaman (2016) set up a linear mixed-integer programming model based on the location selection of a multimodal transport hub and took the demand's polyhedral uncertainty set into account. Then, they proposed the corresponding precise solution algorithm. These studies have mainly focused on demand uncertainty. In addition to demand uncertainty, random changes in supplier supply and cost parameters are important aspects of uncertainty. Tang and Yin (2007) posited that the retailer orders seasonal products from the supplier, and the product demand is a linear function of the price. They found that the supplier's output is uncertain, but obey the discrete probability distribution. Therefore, the responsive price strategy and unresponsiveness were constructed.

Nguyen and Chen (2018) analyzed the stability of biomass supply chain feedstock supply in an uncertain environment and proposed an enhanced and regularized L-shaped decomposition algorithm to solve the model. Meanwhile, Cong et al. (2020) studied the optimal strategy of a low-carbon supply chain with capital constraints and production uncertainties that are characteristic of green finance and carbon quotas and trading plans.

2.2 Influence of COVID-19 pandemic on anti-epidemic supply chain

The COVID-19 pandemic has put unprecedented pressure on the supply chain of epidemic prevention materials. As such, academicians have paid increasing attention to the influence of the COVID-19 pandemic on the anti-epidemic supply chain (Dubey et al., 2021). Mosallanezhad et al. (2021) asserted that the COVID-19 pandemic has caused damage and uncertainty to the anti-epidemic supply chain, such as gloves, gowns, respiratory, and eye protection. Therefore, they adopted multi-objective metaheuristic algorithms to optimize the total cost and shortage of the anti-epidemic supply chain. In addition, Goodarzian et al. (2021) used a variety of algorithms, including colony optimization, fish swarm algorithm, and firefly algorithm to analyze the production, inventory and distribution of anti-epidemic drugs during the COVID-19 pandemic to evaluate superiority of their research approach. In another study, Liu et al. (2021) determined the shortest time for the supply of anti-epidemic materials during major public health emergencies. Moreover, they used a multiple dynamic programming algorithm to calculate the number of anti-epidemic materials and the order of vehicle transportation. The above literature has revealed to a certain extent that three main problems persist in the anti-epidemic supply chain under the COVID-19 pandemic. Firstly, the efficiency of raising anti-epidemic materials is low. In the early stage of the COVID-19 pandemic, the demand for anti-epidemic materials was highly concentrated, and the supply gap was large (Majumdar et al., 2020). Information on existing anti-epidemic materials supplies and capacity is vague, and some supplies do not meet the use standards. Given the asymmetry of information on the demand for anti-epidemic materials, the supply of anti-epidemic materials lacks flexibility and cannot meet the demand for anti-epidemic materials (Qin et al., 2021). This issue has led to the overproduction of personal epidemic prevention supplies by some enterprises and the insufficient supply of special medical equipment. Secondly, the dispatch of epidemic prevention materials is difficult. The COVID-19 pandemic has a long duration, a wide range of impact and a high level of harm. In the early stage of the pandemic, the overall supply of anti-epidemic resources was limited, the severity of the epidemic was different from region to region, and the intensity of material security was tilted toward the hardest-hit areas. In this context, some non-key and local disaster-stricken areas have experienced a serious shortage of anti-epidemic and medical supplies. Moreover, given the update speed of donation information and the lag in follow-up, social donations provide less assistance to these areas, and the problem of insufficient material security is prominent (Martins et al., 2017). Thirdly, the transportation capacity of epidemic prevention materials is insufficient. These problems, such as the lack of flexibility in the choice of transportation routes, the delay in tracking and monitoring the transportation status of anti-epidemic materials and the low degree of automation and intelligence in the transportation process, reduce the timeliness of the transportation of emergency supplies (Mardani et al., 2020). Thus, emergency plans are impossible to adapt flexibly. The root of the above problems is that the unpredictability of the COVID19 epidemic has exacerbated the uncertainty of the anti-epidemic supply chain.

2.3 Influence of technological innovation on supply chain

Technological innovation, which has been the common concern of scholars and entrepreneurs, is the power source of enterprise survival and development, mainly including product and process innovation (Przychodzen & Przychodzen, 2018). It emphasizes that enterprises should not only make full use of existing capabilities but also constantly explore new capabilities (Chapman & Corso, 2005). For example, logistics technology innovation is a guarantee that cannot be ignored when attempting to achieve a rapid response to the demand of the customer (Altuntaş and Aktepe, 2021). Through the use of advanced technology, such as digital information transmission, radio frequency identification, and intelligent decision-making, in the logistics link of the supply chain, products can be intelligently stored, efficiently distributed, positioned in real-time, and automatically tracked (Lee and Shen, 2020). It can realize the intelligent allocation and optimization of logistics resources, which are beneficial to improving the flexibility of the supply chain (Yang et al., 2021). Logistics technology innovation not only helps to improve the flexibility of the supply chain but also significantly enhances the timeliness and effectiveness of corporate information sharing, which is conducive to promoting supply chain collaboration. Supply chain collaboration is mainly reflected in the resource integration and related business collaboration between member companies in the supply chain (Yang & Lin, 2020). Furthermore, supply chain coordination is conducive to improving the supply chain's response speed and flexibility to the uncertainties of supply, production, logistics, sales, and other links. Thus, it is the key to achieving supply chain flexibility. However, innovation is accompanied by risks and uncertainty, and most innovative enterprises have difficulty implementing innovation, especially breakthrough innovation, due to the relative lack of resources and weak research and development strength (Chapman & Corso, 2005). With the advent of the globalization of market competition, the technological innovation environment of enterprises has changed greatly. To adapt to the diversity of market demand, the task quantity and complexity of enterprise technological innovation have increased sharply (Gershman et al., 2016). Enterprise technology innovation must be carried out by supply chain collaboration with the mode of combining between the enterprises for the complementary advantages of product innovation resources. It improves product innovation ability, shortens the development period of product innovation, and lowers the cost of new products and innovation risk.

2.4 Supply chain optimization under uncertainty environment

Four main optimization approaches are used to study supply chain optimization under uncertain environments. The first is the chance-constrained optimization approach. Chen et al. (2017) used chance-constrained optimization to solve the large-scale opportunity-constrained optimization problem of air traffic management. In a later study, Bianco et al. (2019) verified that a chance-constrained optimization approach is more efficient and easier to implement than the Project Evaluation and Review Technique and the Monte Carlo Simulation. The second is the fuzzy programming approach. Wu et al. (2018) comprehensively considered the uncertainty of customer product demand, recycled products, and facility opening costs and designed a fuzzy interactive possibilistic programming model. Meanwhile, Hocine et al. (2018) formulated a new multi-segment fuzzy goal programming model to analyze the uncertainty of the multi-standard renewable energy portfolio. The third is the stochastic programming approach. This approach uses probability distribution functions to describe the uncertainty of supply chain parameters. Aiming at the uncertain factors of supply, demand,

production, transportation, and inventory, Xu and Zhou (2009), Petridis et al. (2015), U-tapao et al. (2016), and Budiman and Rau (2019) built a multi-objective expected value model, a two-level stochastic optimization model, a probability constraint model, and a mixed integer model, respectively. These scholars also designed the Benders decomposition algorithm, sub-gradient algorithm, and LaGrange dual algorithm, respectively (Lau and Nakandala, 2012). The fourth is the robust optimization approach, which is also the most widely used research approach in supply chain research. Kim et al. (2020) used the robust optimization approach to solve the negative impact of demand uncertainty and reverse logistics on the closed-loop supply chain. Moreover, Shen et al. (2020) proposed deterministic and robust optimization approaches for energy system uncertainty. The research results found that although the energy consumption value of the robust optimization approach is higher than that of the deterministic research approach, it can adjust the optimization plan by changing the regularization parameter. Additionally, Gholizadeh and Fazlollahtabar (2020) used robust optimization approaches to model the closed-loop green supply chain network of the smelting industry. Then, they used an improved genetic algorithm to solve the problem.

3 Anti-epidemic supply chain model under no technological innovation

3.1 Premise description

This current research considers a single-period three-level mathematical model of the anti-epidemic supply chain, which is composed of suppliers, anti-epidemic material distribution centers (AMDCs) and affected areas. Each level of the supply chain has multiple suppliers, anti-epidemic material distribution centers, and affected areas. A variety of anti-epidemic materials are involved in this model, and their deployment in a single-period three-level anti-epidemic supply chain is monitored. The first level is the supplier of anti-epidemic materials while the second level is the anti-epidemic material distribution center, whose role is to obtain anti-epidemic materials from suppliers and supply them to affected areas. The third level included the affected areas. The single-period three-level mathematical model has been selected to investigate the research question because the three-level mathematical model includes suppliers, anti-epidemic material distribution centers (AMDCs), and affected areas, which describe the matching relationship between supply and demand. The model is set to a single period, which is mainly an optimized calculation scheme for the initial stage of the COVID-19 outbreak. Under the repeated outbreak of COVID-19, the implementation can be superimposed on a rolling basis. In other words, this paper can use the above model as the basis to confirm the new single-cycle time window based on the time node of the new round of epidemics and re-optimize the calculation, which not only simplifies research questions but also saves research time. In addition, following Siddiqui et al. (2011) and Zokaei et al. (2016), this current research, combined with the particularity of the anti-epidemic supply chain, determines the following assumptions in the process of constructing the mathematical model of the anti-epidemic supply chain:

- (1) The supplier can provide more than one anti-epidemic material, but its supply capacity is restricted.
- (2) When affected areas experience a shortage of anti-epidemic materials, corresponding penalties will be imposed.
- (3) AMDCs have multiple alternative locations and the capacity of each AMDC is restricted.

- (4) The transportation capacity of the AMDCs is not restricted, and it can reach various affected areas using the existing transportation network.
- (5) Each supplier can provide anti-epidemic materials for multiple AMDCs.
- (6) Each AMDC can deliver anti-epidemic materials to multiple areas affected by the COVID-19 pandemic.
- (7) Anti-epidemic materials are allowed to pass through the anti-epidemic supply chain in an orderly manner, but they are not allowed to be passed between different affected areas.
- (8) Each affected area has a corresponding minimum demand satisfaction rate for each anti-epidemic material.
- (9) In the optimal solution of the model, the satisfaction rate of the affected areas should at least reach the minimum demand satisfaction rate.

3.2 Model construction

Based on the above basic assumptions, this current research constructs a single-period three-level mathematical model of the anti-epidemic supply chain. The specific formulas are expressed as follows.

$$Min F = \sum_j f_j z_j + \sum_{m,i,j} c_{ij} g_m x_{mij} + \sum_{m,j,k} c_{jk} g_m y_{mjk} + \sum_{m,k} \pi_{mk} I_{mk} \tag{1}$$

S.t. :

$$\sum_j x_{mij} \leq s_{mi} \quad \forall m, i \tag{2}$$

$$d_{mk} - \sum_j y_{mjk} \leq I_{mk} \quad \forall m, k \tag{3}$$

$$\sum_j y_{mjk} \geq \omega d_{mk} \quad \forall m, k \tag{4}$$

$$\sum_j x_{mij} = \sum_k y_{mjk} \quad \forall m, j \tag{5}$$

$$\sum_{m,i} (v_m x_{mij}) \leq V_j z_j \quad \forall j \tag{6}$$

$$x_{mij} \geq 0 \quad \forall m, i, j \tag{7}$$

$$y_{mjk} \geq 0 \quad \forall m, i, k \tag{8}$$

$$z_j \in \{0, 1\} \quad \forall j \tag{9}$$

Objective formula (1) is a minimized function, which is mainly composed of four parts, including the use cost of the AMDCs, the transportation costs from the supplier to the AMDCs, the transportation costs from the AMDCs to the affected areas, and punishment for shortages of the anti-epidemic materials in affected areas. Formula (2) is a supply constraint function, which means that the amount of each anti-epidemic material m provided by the supplier i does not exceed its supply capacity. Formula (3) is a shortage constraint function, that is, the difference between the demand and supply of anti-epidemic materials in the affected areas is the amount of the shortage. Formula (4) is the minimum satisfaction rate

Table 1 A detailed description of each symbol

Symbol	Specific Description
i	Suppliers
j	Anti-epidemic material distribution centers (AMDCs)
k	Affected areas
m	Anti-epidemic materials
f_j	Installation cost of AMDC j
c_{ij}	Transportation cost from Supply i to AMDC j
c_{jk}	Transportation cost from AMDC j to affected area k
π_{mk}	Shortage penalty of anti-epidemic material m in affected area k
v_m	Volume of anti-epidemic material m
g_m	Quality of anti-epidemic material m
V_j	Capacity of AMDC j
ω	The minimum degree of anti-epidemic material satisfaction that needs to be met
d_{mk}	Demand for anti-epidemic material m in affected area k
s_{mi}	Supply for anti-epidemic material m by supplier i
x_{mij}	Amount of anti-epidemic material m from supplier i to AMDC j
y_{mjk}	Amount of anti-epidemic material m from AMDC j to affected area k
z_j	Whether AMDC j has been constructed. It is represented by 0 and 1
I_{mk}	The affected area k lacks the number of anti-epidemic material m

constraint for anti-epidemic materials, and the number of materials supplied to the affected areas should reach the minimum demand satisfaction rate. Formula (5) demonstrates that the quantity of anti-epidemic materials transported into each AMDC is equal to the quantity of anti-epidemic materials shipped out from each AMDC. Formula (6) entails that the volume of anti-epidemic materials transported into each AMDC does not exceed its volume. Formulas (7) to (9) are the domain of decision variables.

The description of each symbol in the model is shown in Table 1.

4 Anti-epidemic supply chain model under technological innovation

Several studies have explicitly investigated whether technological innovation is beneficial to alleviating the impact of the COVID-19 pandemic on supply chains (Chowdhury et al., 2021; Gurbuz & Ozkan, 2020; Okorie et al., 2020). Therefore, this current research introduces variables $\Delta\gamma_{f_i}$, $\Delta\gamma_{c_{ij}}$ and $\Delta\gamma_{c_{jk}}$, which represent the range of change in three types of costs, including the installation costs of AMDC j , the transportation costs of anti-epidemic materials from supplier i to AMDC j and the transportation costs of anti-epidemic materials from AMDC j to affected area k . For example, \tilde{f}_j is a true value, while f_j is a theoretical value. Thus, $\Delta\gamma_{f_j}$ is expressed by formula (10).

$$\Delta\gamma_{f_j} = \frac{\tilde{f}_j - f_j}{f_j} \quad (10)$$

This current research also introduces $\Delta\gamma_{f_i}$, $\Delta\gamma_{c_{ij}}$ and $\Delta\gamma_{c_{jk}}$ into objective formula (1) to obtain objective formula (11). $\Delta\gamma_{f_i}$, $\Delta\gamma_{c_{ij}}$ and $\Delta\gamma_{c_{jk}}$ respectively affect the installation cost and different transportation costs. Moreover, the corresponding cost parameters are only reflected in the objective formula, and the constraints remain in formulas (2) to (9).

$$MinF = \sum_j (1 + \Delta\gamma_{f_i}) f_i z_j + \sum_{m,i,j} (1 + \Delta\gamma_{c_{ij}}) c_{ij} g_m x_{mij} + \sum_{m,j,k} (1 + \Delta\gamma_{c_{jk}}) c_{jk} g_m y_{mjk} + \sum_{m,k} \pi_{mk} I_{mk} \tag{11}$$

4.1 Uncertainty of demand and supply parameters under technological innovation

The robust approach, proposed by Bertsimas and Sim (2005), emphasizes the uncertainty of technical coefficients. In this approach, the conservative parameter $\bar{\Gamma}_m^k$ and $\bar{\Gamma}_m^i$ take values in the range of $[0, 1]$. Many calculations are required to determine the most suitable conservative parameters. Therefore, Bertsimas and Thiele (2006) recommended adopting a common conservative parameter to represent all conservative parameters uniformly. This paper assumes that the conservative parameters of supply and demand are Γ_m^k and Γ_m^i respectively by using this approach. Their specific forms are represented by formulas (12) and (13), respectively.

$$\Gamma_m^k = \sum_K \bar{\Gamma}_m^k \in [0, K] \tag{12}$$

$$\Gamma_m^i = \sum_I \bar{\Gamma}_m^i \in [0, I] \tag{13}$$

Given the uncertainty of supply and demand, this paper have set demand parameters (\tilde{d}_{mk}) and supply parameters (\tilde{s}_{mi}) under uncertainty, which respectively represent the true value of demand and supply under uncertain conditions. d_m and s_m are the nominal values of demand and supply, respectively. Therefore, formulas (2), (3), and (4) need to be expanded to formulas (14), (15), and (16).

$$\sum_j x_{mij} - \tilde{s}_{mi} \leq 0 \tag{14}$$

$$\tilde{d}_{mk} - \sum_j y_{mjk} \leq I_{mk} \tag{15}$$

$$\sum_j y_{mjk} - \omega \tilde{d}_{mk} \geq 0 \tag{16}$$

This paper assumes that \tilde{d}_{mk} and \tilde{s}_{mi} are all identical independent and symmetrical distributions in ranges $\tilde{d}_m \in [d_m - \hat{d}_m, d_m + \hat{d}_m]$ and $\tilde{s}_m \in [s_m - \hat{s}_m, s_m + \hat{s}_m]$. According to the expansion approach proposed by Bertsimas and Thiele (2006), conservative parameters are introduced to obtain the expressions of \tilde{d}_{mk} and \tilde{s}_{mi} .

$$\tilde{d}_m = d_m + \frac{\Gamma_m^k}{K} \hat{d}_m \tag{17}$$

$$\tilde{s}_m = s_m + \frac{\Gamma_m^i}{n} \hat{s}_m \tag{18}$$

The goal of robust optimization is to determine the best solution in the worst case. Hence, the worst case should be considered as much as possible. The situation is worse when demand increases or supply decreases. Therefore, only the positive deviation of demand fluctuations

and the negative deviation of supply fluctuations need to be taken into account. This paper inputs formulas (17) and (18) into formulas (14) to (16) to obtain formulas (19) to (21). Formulas (19) to (21) reflect the uncertainty of supply and demand.

$$\sum_j x_{mij} - s_m + \frac{\Gamma_m^i}{n} \hat{s}_m \leq 0 \tag{19}$$

$$\left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m \right) - \sum_j y_{mjk} \leq I_{mk} \tag{20}$$

$$\sum_j y_{mjk} - \omega \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m \right) \geq 0 \tag{21}$$

4.2 Uncertainty of the shortage penalty parameter under technological innovation

This paper has defined an auxiliary variable H_{mk} to facilitate the introduction of shortage penalty into the anti-epidemic supply chain. Given that H_{mk} is related to constraint (20), it satisfies formula (22) to add an auxiliary variable H_{mk} .

$$\tilde{\pi}_{mk} \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \leq H_{mk} \tag{22}$$

Consistent with the uncertainty of demand and supply, this paper has set the shortage penalty parameter ($\tilde{\pi}_{mk}$) under uncertainty, the nominal parameter of the shortage penalty parameter (π_{mk}), and the maximum shortage penalty ($\hat{\pi}_{mk}$). In addition, this paper defines a new variable (w_{mk}), which is in the range of $[0, 1]$. $\pi_{mk}, \tilde{\pi}_{mk}, \hat{\pi}_{mk}$, and w_{mk} satisfy formula (23).

$$\tilde{\pi}_{mk} = \pi_{mk} + \hat{\pi}_{mk} \times w_{mk} \tag{23}$$

To achieve robust optimization, the value w_{mk} should be determined to maximize the value H_{mk} . This determination can be achieved by formulas (24)-(26).

$$\max \hat{\pi}_{mk} w_{mk} d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk}^* \tag{24}$$

S.t. :

$$w_{mk} \leq \Gamma_{mk}^\pi \quad \forall k, m \tag{25}$$

$$0 \leq w_{mk} \leq 1 \quad \forall k, m \tag{26}$$

A dual transformation is performed from formulas (24) to (27), to ensure that the model is linear. λ_{mk}^π and μ_{mk}^π are dual variables and non-negative.

$$\min \lambda_{mk}^\pi \Gamma_{mk}^\pi + \mu_{mk}^\pi \quad \forall k, m \tag{27}$$

S.t. :

$$\lambda_{mk}^\pi + \mu_{mk}^\pi \geq \hat{\pi}_{mk} \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \quad \forall k, m \tag{28}$$

According to formulas (23) and (24), formula (22) can be rewritten in the following form:

$$\pi_{mk} \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) + \lambda_{mk}^\pi \Gamma_{mk}^\pi + \mu_{mk}^\pi \leq H_{mk} \quad \forall k, m \tag{29}$$

$$\lambda_{mk}^\pi + \mu_{mk}^\pi \geq \hat{\pi}_{mk} \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \quad \forall k, m \tag{30}$$

Based on the principle of robust optimization, the maximum value Γ_{mk}^π can be set to 1. Formula (29) can be combined with formula (30) into formula (31).

$$(\pi_{mk} + \hat{\pi}_{mk}) \left(d_m + \frac{\Gamma_m^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \leq H_{mk} \quad \forall k, m \tag{31}$$

4.3 Budget uncertainty in different scenarios under technological innovation

Different conservative parameters will affect the solution of the robust model. In other words, to obtain the most robust solution, an optimal combination of different conservative parameters is required. However, the calculation process will take considerable time and cannot meet the needs of the anti-epidemic supply chain. Therefore, this paper uses the approach proposed by Alem and Morabito (2012). Moreover, it introduces a set of scenarios (S), where $s \in S = \{1, \dots, S\}$. The decision-makers are assumed to be sufficiently experienced to establish the uncertainty parameters of several most likely scenarios. Each scenario has a corresponding probability of occurrence ($\sum_s p_s = 1$). At this time, the constraints change as follows:

$$\sum_j x_{mij} - s_m + \frac{\Gamma_{ms}^i}{n} \hat{s}_m \leq 0 \tag{32}$$

$$\sum_j y_{mjk} - \omega \left(d_m + \frac{\Gamma_{ms}^k}{K} \hat{d}_m \right) \geq 0 \tag{33}$$

$$(\pi_{mk} + \hat{\pi}_{mk}) \left(d_m + \frac{\Gamma_{ms}^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \leq H_{mk} \quad \forall k, m \tag{34}$$

$$\sum_s p_s H_{mks} \leq H_{mk} \tag{35}$$

Finally, a robust optimization model of the anti-epidemic supply chain under technological innovation can be written in the following form:

$$\text{Min } F = \sum_j (1 + \Delta\gamma_{f_i}) f_i z_j + \sum_{m,i,j} (1 + \Delta\gamma_{c_{ij}}) c_{ij} g_m x_{mij} + \sum_{m,j,k} (1 + \Delta\gamma_{c_{jk}}) c_{jk} g_m y_{mjk} + \sum_{m,k} H_{mk} \tag{36}$$

S.t. :

$$\sum_j x_{mij} - s_m + \frac{\Gamma_{ms}^i}{n} \hat{s}_m \leq 0 \tag{37}$$

$$\sum_j y_{mjk} - \omega \left(d_m + \frac{\Gamma_{ms}^k}{K} \hat{d}_m \right) \geq 0 \tag{38}$$

$$(\pi_{mk} + \hat{\pi}_{mk}) \left(d_m + \frac{\Gamma_{ms}^k}{K} \hat{d}_m - \sum_j y_{mjk} \right) \leq H_{mk} \quad \forall k, m \tag{39}$$

$$\sum_s p_s H_{mks} \leq H_{mk} \tag{40}$$

$$\sum_j x_{mij} = \sum_k y_{mjk} \quad \forall m, j \tag{41}$$

$$\sum_{m,i} (v_m x_{mij}) \leq V_j z_j \quad \forall j \tag{42}$$

$$x_{mij} \geq 0 \quad \forall m, i, j \tag{43}$$

$$y_{mjk} \geq 0 \quad \forall m, i, k \tag{44}$$

$$z_j \in \{0, 1\} \quad \forall j \tag{45}$$

5 Case study: Wuhan City

5.1 Case description

A case study based on approachology research was carried out in Wuhan, China. The division of administrative regions in Wuhan are Jiangnan (J-A), Jiangnan (J-H), Qiaokou (Q-K), Hanyang (H-Y), Wuchang (W-C), Qingshan (Q-S), Hongshan (H-S), Dongxihu (D-H), Hannan (H-N), Caidian (C-D), Jiangxia (J-X), Huangpi (H-P), and Xinzhou (X-Z), this paper has set 6 suppliers, 6 AMDCs, and 13 affected areas (see Fig. 1). In the actual epidemic prevention process, masks(M), disinfectants (D), and protective clothing (P) are necessary

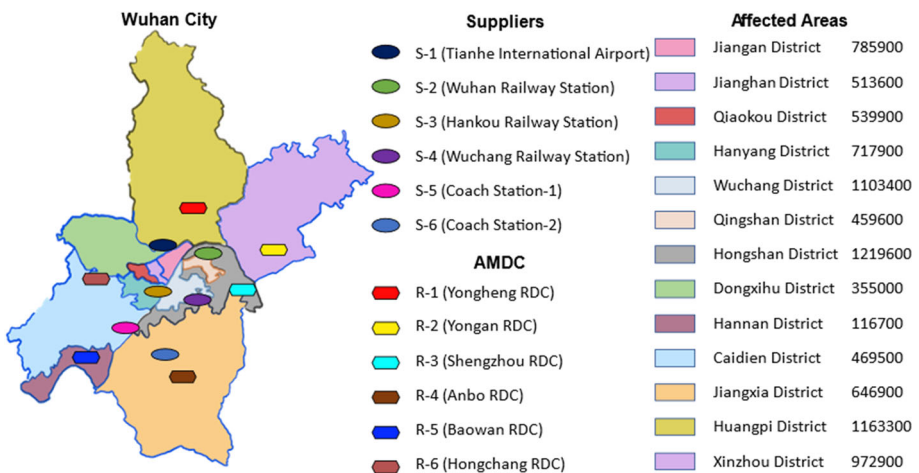


Fig. 1 The configuration diagram of the anti-epidemic supply chain in Wuhan

anti-epidemic materials (Hartanto et al. 2021; Mallakpour et al., 2021). Therefore, this paper uses masks, disinfectants, and protective clothing as typical anti-epidemic materials. Parameters are shown in Table 2.

Based on the population of each administrative area of Wuhan in 2019, this paper has set the demand data of anti-epidemic materials and the supply data of suppliers in each administrative area of Wuhan (see Table 3). Notably, the total supply of materials is assumed to be only 80% of the total demand to simulate a shortage of materials. Furthermore, the minimum satisfaction ratio of each anti-epidemic material requirement for each affected area is 0.2 ($\omega = 0.2$).

Regarding the parameters of anti-epidemic materials, this paper has established the following settings. A box of masks contains 15 masks with a volume of 0.02m^3 and a mass of 0.01 kg. A bottle of disinfectant has a specification of 150 ml, a volume of 0.2m^3 , and a

Table 2 Specific parameters of the anti-epidemic materials

	Mask	Disinfectant	Protective clothing
Unit Volume (m^3)	0.01	0.2	0.25
Unit Mass (kg)	0.01	0.2	0.1
Penalty Penalty (10^{-2}¥)	90	280	350

Table 3 Demand and supply of anti-epidemic materials

Demand	Mask	Disinfectant	Protective clothing
J-A	1,571,800	202,544	18,208
J-H	1,027,200	132,366	11,899
Q-K	1,079,800	139,144	12,508
H-Y	1,435,800	185,019	16,632
W-C	2,206,800	284,371	25,564
Q-S	919,200	118,449	10,648
H-S	2,439,200	314,319	28,256
D-H	710,000	91,492	8225
H-N	233,400	30,076	2704
C-D	939,000	121,001	10,877
J-X	1,293,800	166,721	14,987
H-P	2,326,600	299,809	26,951
X-Z	1,945,800	250,738	22,540
Supply	Mask	Disinfectant	Protective clothing
S-1	3,037,777	391,452	35,190
S-2	2,516,848	324,324	29,155
S-3	3,436,561	442,840	39,809
S-4	1,308,518	168,617	15,158
S-5	1,416,264	182,502	16,406
S-6	1,336,480	172,221	15,482

mass of 0.2 kg. The volume of protective clothing is 0.25m^3 and the mass is 0.1 kg. Shortage penalties of masks, disinfectants, and protective clothing are 0.9, 2.8, and 3.5, respectively.

Based on the spatial location and geographic distance of each administrative district in Wuhan, this paper estimates the transportation cost per unit of anti-epidemic materials from suppliers to AMDCs and the transportation cost per unit of anti-epidemic materials from AMDCs to affected areas. The specific parameters are shown in Table 4.

In addition, this paper gauges the construction costs and volume of AMDCs. The specific parameters are present in Table 5.

5.2 Data acquisition

The divided administrative regions of Wuhan and the population of each administrative region have been mainly derived from *the Wuhan Statistical Yearbook* in 2020. The specifications of anti-epidemic materials, including masks, disinfectors, and protective clothing are set by referring to their actual specifications. Furthermore, the demand and supply of anti-epidemic materials and the construction cost and volume of AMDCs are designed by referring to the research of Zokae et al. (2016). The transportation cost per unit of anti-epidemic materials has been obtained by multiplying the actual transportation distance and the cost of transporting each unit of anti-epidemic materials per kilometer. The actual transportation distance comes from *Google Earth Satellite Map*. The cost of transporting each unit of anti-epidemic materials per kilometer is obtained.

5.3 Model solution

This paper assumes that all parameters are known and certain, under the condition that no technological innovation has been made in the anti-epidemic supply chain. Therefore, it is sufficient to set the parameters of the robust optimization model, which is $\Delta\gamma_{fi} = \Delta\gamma_{cij} = \Gamma_{ms}^i = \Gamma_{ms}^k = 0, P_s = 1$, and $\omega = 0.2$. The optimal solution value of the original solution is 1.1911×10^9 , that is, the costs of the anti-epidemic supply chain are 1.1911×10^9 yuan. The values of the corresponding decision variables x_{mij} , y_{mjk} , z_j , and H_{mk} are shown in Tables 6, 7, 8 and 9. The solution of the model in this scenario is called the original solution. Furthermore, the sensitivity analysis of each parameter in the model will be conducted based on the original solution in the follow-up study.

5.4 Sensitivity analysis

5.4.1 Shortage penalty

Figure 2 presents the sensitivity analysis of the shortage penalty parameters. The greater the degree of change in the shortage penalty relative to the original shortage penalty is, the greater the change in the optimal value relative to the original solution for different anti-epidemic materials will be. The mask shortage penalty, followed by the disinfectant shortage penalty, has the greatest impact on the optimal value, whereas the shortage penalty of protective clothing has the least impact on the optimal value. When the three types of anti-epidemic material shortage penalties change simultaneously, the degree of change of the shortage penalty relative to the original shortage penalty is in the range of 0% to 7%. Moreover, the demand satisfaction rate is just the minimum demand satisfaction rate. Since then the shortage

Table 4 Transportation cost per unit of anti-epidemic materials (Unit: 10^{-2} ¥/kg)

Transportation cost per unit of anti-epidemic materials from suppliers to AMDCs						
	A-1	A-2	A-3	A-4	A-5	A-6
S-1	278	1112	1056.4	417	1251	333.6
S-2	305.8	389.2	333.6	973	1167.6	834
S-3	695	834	695	778.4	778.4	333.6
S-4	556	583.8	222.4	361.4	1056.4	1195.4
S-5	1278.8	1390	1139.8	583.8	333.6	444.8
S-6	1417.8	1529	917.4	139	444.8	639.4
Transportation cost per unit of anti-epidemic materials from AMDCs to affected areas						
	A-1	A-2	A-3	A-4	A-5	A-6
J-A	305.8	364.18	364.18	792.3	1059.18	567.12
J-H	417	505.96	391.98	669.98	978.56	517.08
Q-K	556	583.8	422.56	644.96	884.04	455.92
H-Y	639.4	611.6	394.76	533.76	697.78	422.56
W-C	556	444.8	250.2	419.78	728.36	469.82
Q-S	444.8	311.36	139	525.42	756.16	650.52
H-S	500.4	339.16	111.2	311.36	1050.84	836.78
D-H	361.4	867.36	778.4	903.5	736.7	294.68
H-N	1167.6	1195.4	1170.38	639.4	303.02	333.6
C-D	889.6	1251	892.38	669.98	425.34	250.2
J-X	1028.6	1056.4	583.8	341.94	542.1	772.84
H-P	278	366.96	861.8	973	922.96	822.88
X-Z	667.2	336.38	611.6	1167.6	1359.42	973

Table 5 The construction cost and volume of AMDCs

	Cost (10^{-2}¥)	Volume (m^3)
R-1	47,551,940	133,049.3
R-2	49,925,917	174,873.7
R-3	44,164,720	73,373.58
R-4	48,720,339	153,634
R-5	45,190,602	91,447.46
R-6	44,446,483	78,337.65

Table 6 The Value of x_{mij}

		R-1	R-2	R-3	R-4	R-5	R-6
S-1	M	3,037,800	0	0	0	0	0
	D	391,450	0	0	0	0	0
	P	33,668	0	0	1522	0	0
S-2	M	0	2,516,800	0	0	0	0
	D	0	324,320	0	0	0	0
	P	0	2.9155	0	0	0	0
S-3	M	0	1,176,800	0	0	0	2,259,700
	D	79,820	84,320	0	0	0	278,700
	P	0	39,809	0	0	0	0
S-4	M	0	0	0	1,308,500	0	0
	D	0	0	0	168,620	0	0
	P	0	15,158	0	0	0	0
S-5	M	0	0	0	1,416,300	0	0
	D	0	0	0	182,500	0	0
	P	0	0	0	16,406	0	0
S-6	M	0	0	0	1,336,500	0	0
	D	0	0	0	172,220	0	0
	P	0	0	0	15,482	0	0

penalty has increased and the demand satisfaction rate has also continued to increase. When the degree of change of the shortage penalty relative to the original shortage penalty is higher than 17%, the marginal effect of the demand satisfaction rate decreases significantly, and the demand satisfaction rate eventually reaches 72%.

5.4.2 Minimum demand rate

Shortage penalties (π) and minimum demand rates (ω) are fairly important driving factors of demand satisfaction for anti-epidemic materials in affected areas. To meet the needs of anti-epidemic materials in affected areas as much as possible, this paper has set a sufficiently

Table 7 The value of y_{mjk}

		J-A	J-H	Q-K	H-Y	W-C	Q-S	
R-1	M	557,097	154,080	0	0	0	0	
	D	151,607	19,855	0	0	0	0	
	P	0	1785	0	0	0	0	
R-2	M	828,669	0	0	0	0	919,200	
	D	39,460	0	0	0	0	118,449	
	P	18,208	0	1876	0	16,484	10,648	
R-3	M	0	0	0	0	0	0	
	D	0	0	0	0	0	0	
	P	0	0	0	0	0	0	
R-4	M	0	0	0	0	331,020	0	
	D	0	0	0	0	42,656	0	
	P	0	0	0	2495	0	0	
R-5	M	0	0	0	0	0	0	
	D	0	0	0	0	0	0	
	P	0	0	0	0	0	0	
R-6	M	0	0	161,970	215,370	0	0	
	D	0	0	20,872	27,753	0	0	
	P	0	0	0	0	0	0	
		H-S	D-H	H-N	C-D	J-X	H-P	X-Z
R-1	M	0	0	0	0	0	2,326,600	0
	D	0	0	0	0	0	299,809	0
	P	0	4933	0	0	0	26,951	0
R-2	M	0	0	0	0	0	0	1,945,800
	D	0	0	0	0	0	0	250,738
	P	14,365	0	0	0	0	0	22,540
R-3	M	0	0	0	0	0	0	0
	D	0	0	0	0	0	0	0
	P	0	0	0	0	0	0	0
R-4	M	2,439,200	0	0	0	1,291,042	0	0
	D	314,319	0	0	0	166,365	0	0
	P	13,891	0	406	1632	14,987	0	0
R-5	M	0	0	0	0	0	0	0
	D	0	0	0	0	0	0	0
	P	0	0	0	0	0	0	0
R-6	M	0	710,000	233,400	939,000	0	0	0
	D	0	91,492	17,581	121,001	0	0	0
	P	0	0	0	0	0	0	0

Table 8 The Value of z_j

	Value
R-1	1
R-2	1
R-3	0
R-4	1
R-5	0
R-6	1

Table 9 The Value of H_{mk}

	Mask	Disinfectant	Protective clothing
J-A	16,743,058	3,213,532	0
J-H	78,580,800	31,503,108	3,539,953
Q-K	82,604,700	33,116,272	3,721,130
H-Y	109,838,700	44,034,522	4,948,020
W-C	168,820,200	67,680,298	3,177,870
Q-S	0	0	0
H-S	0	0	0
D-H	0	0	1,152,330
H-N	0	3,498,726	804,440
C-D	0	0	3,235,908
J-X	248,222	99,582	0
H-P	0	0	0
X-Z	0	0	0

large shortage penalty. At this time, the shortage penalty only plays a role in ensuring the fair distribution of materials and avoids the demand for individual affected areas being satisfied with 0% due to high transportation costs. Figure 3 explores the impact of the minimum demand rate on the optimal solution when the shortage penalty is sufficiently large. Figure 3 shows that the optimal value is 99.73% of the original solution when the minimum demand rate is 0%. Additionally, the degree of change in the optimal value increases significantly when the minimum demand rate is higher than 67%.

5.4.3 Technical factor

This paper introduces variables $\Delta\gamma_{fi}$, $\Delta\gamma_{cij}$ and $\Delta\gamma_{cjk}$, which represent the range of change in three types of cost under the influence of technological innovation. These variables are the installation costs of AMDCs, the transportation costs of anti-epidemic materials, and the shortage penalty of anti-epidemic materials. Their values are within the range of $[-0.5, 0.5]$. Figure 4 shows the sensitivity analysis of the technical factor. As technical factors increase, the optimal solution shows an upward trend, but the degree of influence is different. When the three factors are all set to 0.5, $\Delta\gamma_{fi}$, $\Delta\gamma_{cij}$ and $\Delta\gamma_{cjk}$ respectively make the optimal solution

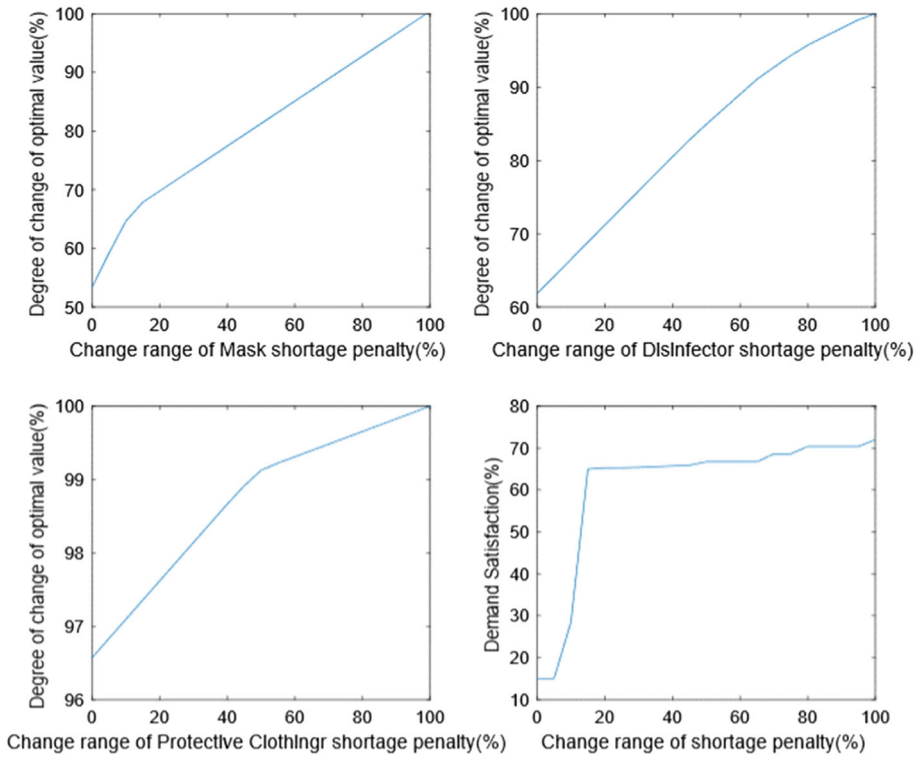


Fig. 2 Sensitivity analysis of shortage penalty

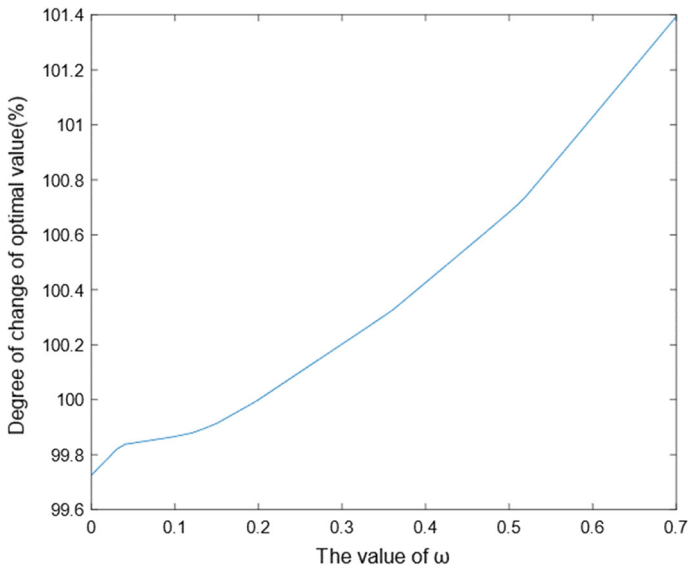


Fig. 3 Sensitivity analysis of minimum demand rate

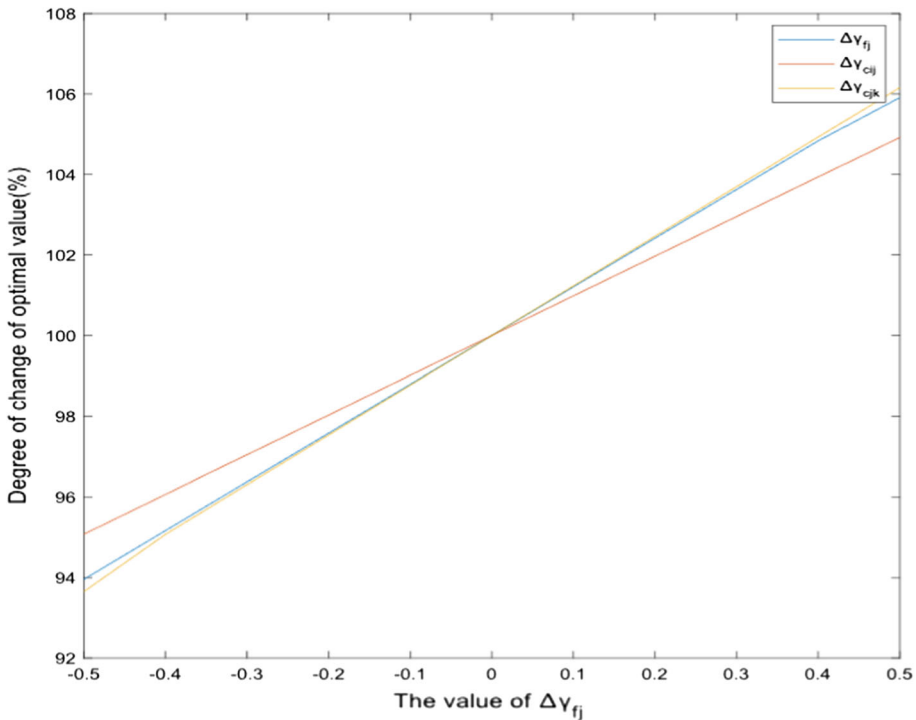


Fig. 4 Sensitivity analysis of technical factor

account for 105.9%, 104.9%, and 106.2% of the original solution. The results show that $\Delta\gamma_{cjk}$ has the greatest influence on the optimal solution. $\Delta\gamma_{cij}$ has the smallest influence.

5.4.4 Supply and demand

Supply uncertainty is determined by the data fluctuation parameter and the supply uncertainty conservative parameter. Therefore, this paper explores the change in the optimal value under the dual influence of two factors. Regarding supply, as the two factors increase, the optimal value presents a nonlinear monotonic increasing trend (see Fig. 4). When the conservative supply uncertainty parameter is 6 and the data fluctuation parameter reaches 0.5, the optimal value reaches a maximum of 150.4% of the original solution.

Consistent with supply uncertainty, the data fluctuation parameter and the demand uncertainty conservative parameter are fairly important parts of demand uncertainty. When Γ takes the maximum value of 13, and the data fluctuation parameter is 0.5, the optimal value reaches the maximum, which is 276.1% of the original solution (see Fig. 5).

Comparing demand with supply uncertainty, it is found that demand uncertainty has a great influence on the optimal value. When the conservative demand uncertain parameter takes the maximum value, the optimal value is 276.1% of the original solution. However, when the conservative supply uncertainty parameter takes the maximum value, the optimal value is only 150.7%. Supply uncertainty has a large impact on the demand satisfaction rate. When the demand is uncertain and the conservative parameter takes the maximum value, the demand satisfaction rate is 36%, which is a decrease of 36%. However, when the conservative

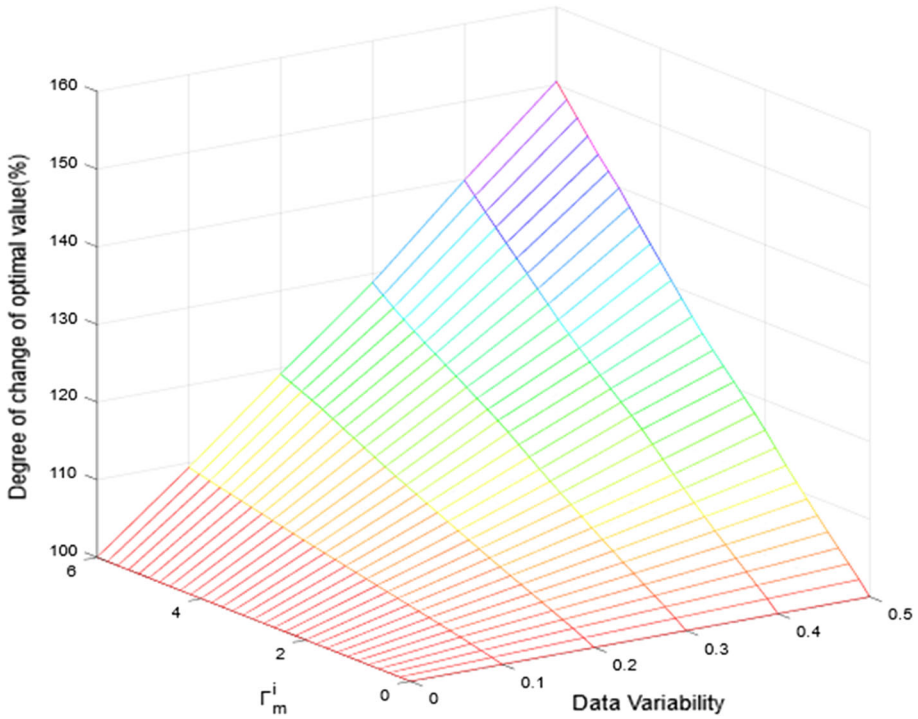


Fig. 5 Sensitivity analysis of the supply

supply uncertainty parameter takes the maximum value, the optimal value is 48%, that is, it only drops by 24%.

5.4.5 Budget scenarios

This paper has established ten scenarios and three groups of budgets based on decision makers’ judgement of the epidemic. Specific parameters are shown in Table 10. P-1 is an

Table 10 Scenarios budget parameters

	$\Delta\gamma_{f_i}$	$\Delta\gamma_{c_{ij}}$	$\Delta\gamma_{c_{jk}}$	Γ_{ms}^i	Γ_{ms}^k	P-1	P-2	P-3
Scenario-1	-0.5	-0.5	-0.5	0	0	0.20	0.05	0.05
Scenario-2	-0.4	-0.4	-0.4	1	1	0.15	0.05	0.05
Scenario-3	-0.3	-0.3	-0.3	1	3	0.15	0.10	0.05
Scenario-4	-0.2	-0.2	-0.2	2	4	0.10	0.10	0.05
Scenario-5	-0.1	-0.1	-0.1	3	6	0.10	0.20	0.10
Scenario-6	0.1	0.1	0.1	3	7	0.10	0.15	0.10
Scenario-7	0.2	0.2	0.2	4	9	0.05	0.15	0.10

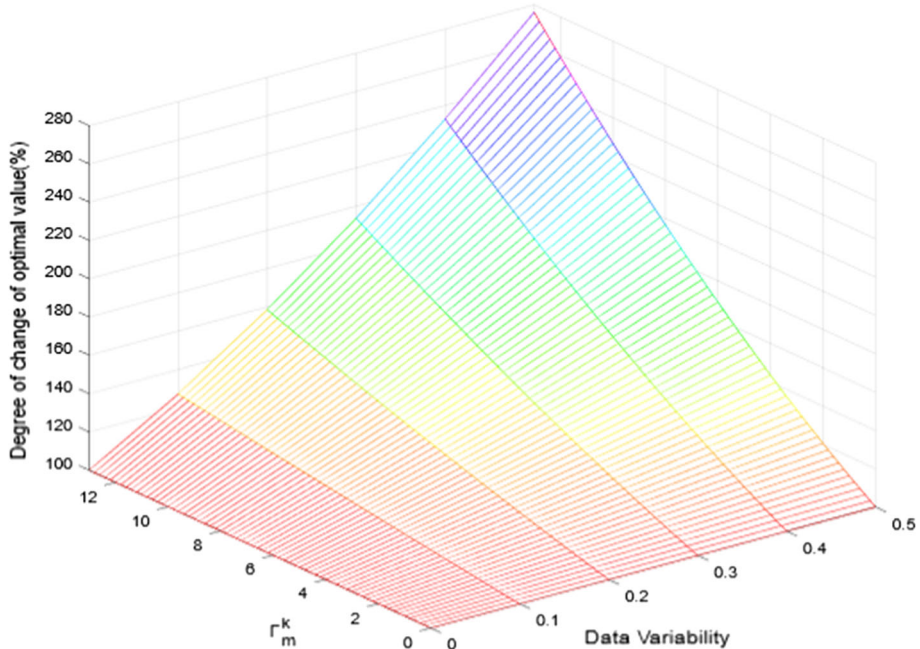


Fig. 6 Sensitivity analysis of the demand

optimistic budget. P-2 is a balanced budget. P-3 is a negative budget. On this basis, this paper explores the degree of change of the optimal value, and the results are shown in Fig. 6.

Figure 7 demonstrates that when the data fluctuation is 0.5, the optimal values of the three groups of budgets are 420%, 460.2%, and 497.5% of the original solution, respectively. The results reveal that a negative budget has the highest cost and an optimistic budget has the lowest cost.

6 Discussion

Under the influence of the COVID-19 epidemic, technological innovation has brought more uncertainty to the demand and supply, shortage penalty, and budget of the anti-epidemic supply chain (Grida et al., 2020). Nevertheless, the dynamics, high dimensionality and unpredictability of uncertain variables have long plagued the modeling and solving of such problems (Almaraj & Trafalis, 2020; Sun et al., 2020). Given that no unified standard model and algorithm have been established, the application has limitations and needs to meet a no after-effect (Gao & You, 2019; Gao et al., 2017). Although the optimization approaches, including chance-constrained optimization, fuzzy programming, and stochastic programming, are not troubled by the dimensionality of the status variables, they are prone to the challenge of dealing with comprehensive indivisible constraints (Tordecilla et al., 2021). Additionally, their role is limited to fewer optimizations. When the number of cycles increases, it will be adversely affected by the exponential expansion of the number of events

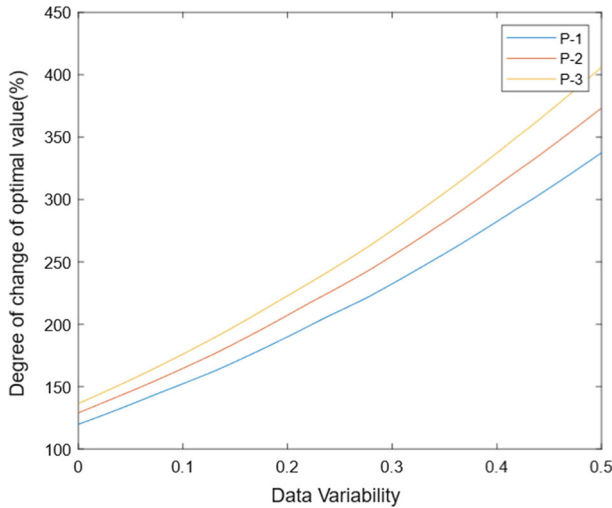


Fig. 7 Sensitivity analysis of budget scenarios

(Gholizadeh et al., 2021). In contrast to the above optimization approaches, robust optimization is more suitable for the optimization problem of the uncertain impact of technological innovation on the anti-epidemic supply chain. affected by the COVID-19 pandemic.

For the uncertain impact of technological innovation on the supply chain of anti-epidemic materials under the COVID-19 pandemic, errors are inevitable in the process of obtaining basic parameters of the supply chain. Furthermore, given the characteristics of the model, the parameter probability distribution is also unknown (Liu et al., 2019a, 2019b). The robust optimization approach is a replacement and supplement of the above research approach (Gao & Ryan, 2014; Gilani et al., 2020). This approach uses uncertain parameters to describe the uncertain impact of technological innovation in this paper on the anti-epidemic supply chain and transforms it into a corresponding model. Then, the approach uses a heuristic algorithm to solve the issue. This current research studied and constructed the anti-epidemic supply chain model under technological innovation. Furthermore, this current research used robust optimization approaches to solve the uncertainty problem so that the model has strong anti-interference performance. Analogously, this current research attempted to improve the responsiveness of the scheduling strategy for anti-epidemic materials by changing the accuracy of predicting uncertain parameters. Doing so ensures that the anti-epidemic materials are timely and play a rescue role in meeting the maximum demand.

Based on the uncertainty influences caused by technological innovation for supply chains in demand and supply, shortage penalty, and budget, this current research introduces relevant variables to construct an anti-epidemic supply chain model under technological innovation. By combining a variety of possible scenarios, a scenario budget solving approach is proposed, and the effectiveness of the approach is verified in the example experiment, which enriches the theoretical research in the anti-epidemic supply chain model under technological innovation.

This current research also presents a robust optimization model of the anti-epidemic supply chain under technological innovation, which can provide decision-making reference for the distribution plan of anti-epidemic materials, and prompt relevant decision-makers to make optimal decisions quickly. Transporting anti-epidemic materials to the infected areas during

the golden period will help minimize casualties and the loss of economic property in the infected areas.

7 Conclusions and implications

7.1 Conclusions

Based on a single-period three-level mathematical model of the anti-epidemic supply chain, which is composed of suppliers, anti-epidemic material distribution centers, and affected areas, this paper presents a robust optimization model of the anti-epidemic supply chain under technological innovation and uses *MATLAB* to solve the solution. The study has shown that although the shortage penalty in the objective function increases the costs, it can also effectively increase the demand satisfaction rate. When the shortage penalty is sufficiently large, the supply will be sent to the affected areas to meet demand as much as possible. At this time, the minimum demand satisfaction rate can ensure the fair distribution of materials among affected areas, so that the demand satisfaction rate can reach the minimum requirement. However, the increase in the minimum demand satisfaction will also increase the costs slightly in this case. Another conclusion is that technological innovation can reduce expenses. The technical parameters related to the transportation costs of AMDCs have the greatest impact on the optimal value. The technical parameters related to suppliers' transportation costs have the least impact on the optimal value. Furthermore, both supply uncertainty and demand uncertainty will have a greater impact on spending. In contrast, demand uncertainty has a greater impact on costs and a smaller impact on demand satisfaction rates. In addition, the multi-scenario budget solution approach can effectively reduce the computational complexity and obtain a reasonable feasible solution in a limited time. However, the budget setting has a certain impact on the cost. Consequently, exploring ways to set a reasonable budget for different scenarios is crucial.

7.2 Theoretical implications

A steady supply of anti-epidemic materials is a necessary material condition to control the spread of the COVID-19 pandemic and eliminate social panic. This current research differs from previous research and contributes to the existing literature on responsible innovation in three dimensions.

The first dimension is a multi-perspective exploration of the uncertain impact of technological innovation on the anti-epidemic supply chain in the context of the COVID-19 pandemic. The available literature on the mechanisms of the COVID-19 pandemic transmission, prevention and control approaches, and material deployment provides a solid research basis for this paper. In contrast, the research perspective in this current research focuses on the uncertain influence of technological innovation on the anti-epidemic supply chain in the context of the COVID-19 pandemic, which is a research perspective that has been neglected by available research.

The second dimension is the construction of an uncertainty model of technological innovation affecting the anti-epidemic supply chain in the context of the COVID-19 pandemic. Some decision models in existing research have considered the characteristics of infectious diseases and predicted the demand for emergency supplies by utilizing infectious disease

dynamics models, such as the model of susceptible-exposed-infected-recovered. Nevertheless, most research has not given adequate attention to the uncertainty model related to the anti-epidemic supply chain in the evolutionary context of the COVID-19 pandemic. Hence, this current research constructed an uncertainty model of technological innovation affecting the supply chain of anti-epidemic materials under the COVID-19 pandemic, which provides a new mathematical model for the research of uncertainty in the anti-epidemic supply chain.

The third dimension is the proposal of a scenario budget-solving approach and its validity is proven by example experiments. Conventional solution approaches require first setting a number of conservative degree parameters to obtain the most robust solution at that conservative degree. Nevertheless, decision-makers have difficulty giving a set of parameters of reasonable conservatism in the usual decision-making scenarios. Accordingly, this current research proposes a scenario budget-solving approach, in which a set of conservative parameters is called a scenario. Its probability of occurrence is called a budget, while multiple scenarios are introduced into the model to obtain a reasonable solution, thus avoiding the disadvantage of excessive conservatism in the optimal solution. Where partial information is known to the decision-maker, this approach can incorporate known information into the model, thereby effectively reducing uncertainty and improving the quality of the decision. Additionally, as the approach avoids the estimation of uncertain parameters, it can produce a reasonable feasible solution in a limited time.

7.3 Practical implications

Research on the uncertain impact of technological innovation on the anti-epidemic supply chain under the COVID-19 pandemic has great practical significance.

Firstly, technological innovation is a crucial part of anti-epidemic supply chain management that cannot be ignored. Moreover, it plays an active role in the cost-efficient operation the supply chain of anti-epidemic materials. Faced with the complex and changing environment of the COVID-19 pandemic, technological innovation should receive adequate attention and corresponding measures should be taken to promote it. This current research verifies that technological innovation has a greater impact on the transportation costs of the anti-epidemic distribution centers than that of the anti-epidemic suppliers. Consequently, enterprises related to the distribution center of anti-epidemic materials should strengthen the introduction, digestion, absorption, and self-development of technological innovation, and drive the synergy and linkage of various parties in the anti-epidemic supply chain through technological innovation to reduce the costs of the anti-epidemic supply chain. As the leader and coordinator of epidemic prevention and control, the government should adopt the strategy of focusing on epidemic prevention and distribution centers, supplemented by epidemic prevention and supply suppliers. Moreover, it should provide appropriate financial subsidies for the technological innovation of all parties in epidemic prevention and supply chain. These studies can stimulate the technological innovation of all parties in the epidemic prevention and supply chain and ensure that their technological innovation is adequately funded.

Secondly, reducing uncertainty in supply and demand plays a key role in reducing supply chain costs for the anti-epidemic supply chain. This current research finds that both supply uncertainty and demand uncertainty have a greater negative influence on costs, with the former having a significantly lower negative impact than the latter. As a result, technological innovation in the anti-epidemic supply chain should be demand-driven. Additionally, it should focus on information sharing and collaboration between suppliers of anti-epidemic materials, distribution centers, and affected areas. By sharing and collaborating information

across the anti-epidemic supply chain, costs and operational processes can be greatly optimized. While technological innovation creates challenges for supply and demand uncertainty in the anti-epidemic supply chain, it also provides the potential for information sharing and collaboration across the anti-epidemic supply chain. Technological innovation, especially digital technology innovation, can enhance the information processing capability of the supply chain of materials for epidemic prevention, and provide timely monitoring and feedback on various aspects of this supply chain. Moreover, Technological innovation can improve dynamic risk response capability and help the epidemic-prevention supply chain to respond quickly in the face of the COVID-19 pandemic.

Thirdly, in the context of the COVID-19 pandemic, technological innovation has brought about uncertainty in the anti-epidemic supply chain in various ways. Hence, the elemental support system of the anti-epidemic supply chain must be strengthened. From the policy perspective, risk and crisis management methods and management mechanisms for the anti-epidemic supply chain must be developed. From the system perspective, the division of labor among departments based on the anti-epidemic supply chain should be clarified, key nodes should be grasped, and the supply chain system should be emphasized, to achieve a coordinated and smooth transition of the anti-epidemic supply chain from peacetime-crisis-wartime-peacetime. From the financial perspective, the financial guarantee mechanism should be improved for the networked and systematic construction of supply chain emergency reserves and emergency facilities. Doing so can ensure the regular maintenance, intelligence, and modern development of facilities and equipment, as well as the rotation of emergency agricultural reserves. From the talent perspective, a team of emergency personnel must be established. This team can rely closely on the industrial system and industry-specific technologies to give full play to the role of a think tank for risk prevention in the anti-epidemic supply chain. **7. 4 Limitations and future research opportunities.**

This research has several limitations that must be addressed in future research. Firstly, this paper focuses on a single-period three-level anti-epidemic supply chain. Thus, it is only suitable for anti-epidemic material dispatching for the first time after the COVID-19 pandemic. Follow-up research may look into multiperiod supply chain scheduling, which can address the problem regarding the continuous supply of materials. In a practical decision situation, uncertainty in demand and supply decreases as the number of deployments increases. Hence, a dynamic robust optimization model can be used to estimate the uncertainty parameters and optimize the deployment decision in multiple cycles simultaneously, with the uncertainty decreasing and the conservatism of the optimal solution decreasing as the number of deployments increases. Secondly, this paper did not take vehicle routing and scheduling optimization into account. Hence, the issue of vehicle path and scheduling optimization can be considered in further research. Moreover, path planning, location-allocation, and decision-making in transportation selection can be integrated to make the anti-epidemic supply chain more realistic. Thirdly, the premise of the multi-scenario budget solution approach in this current research is that the decision-maker is sufficiently experienced to give limited sets of uncertain parameters. If no such assumption exists, heuristic algorithms can be used to optimize the uncertainty parameters to find a better combination of uncertainty parameters in a limited time. Fourthly, the trade-off between cost and demand fulfillment is primarily assessed in this research. However, in practice, the speed of response is also a factor to take into account. In humanitarian supply chains, the speed of response is critical, and a faster response means more lives saved. Therefore, in future research, the trade-off between cost, demand fulfillment, and response speed can be simultaneously examined through a multi-objective optimization approach.

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