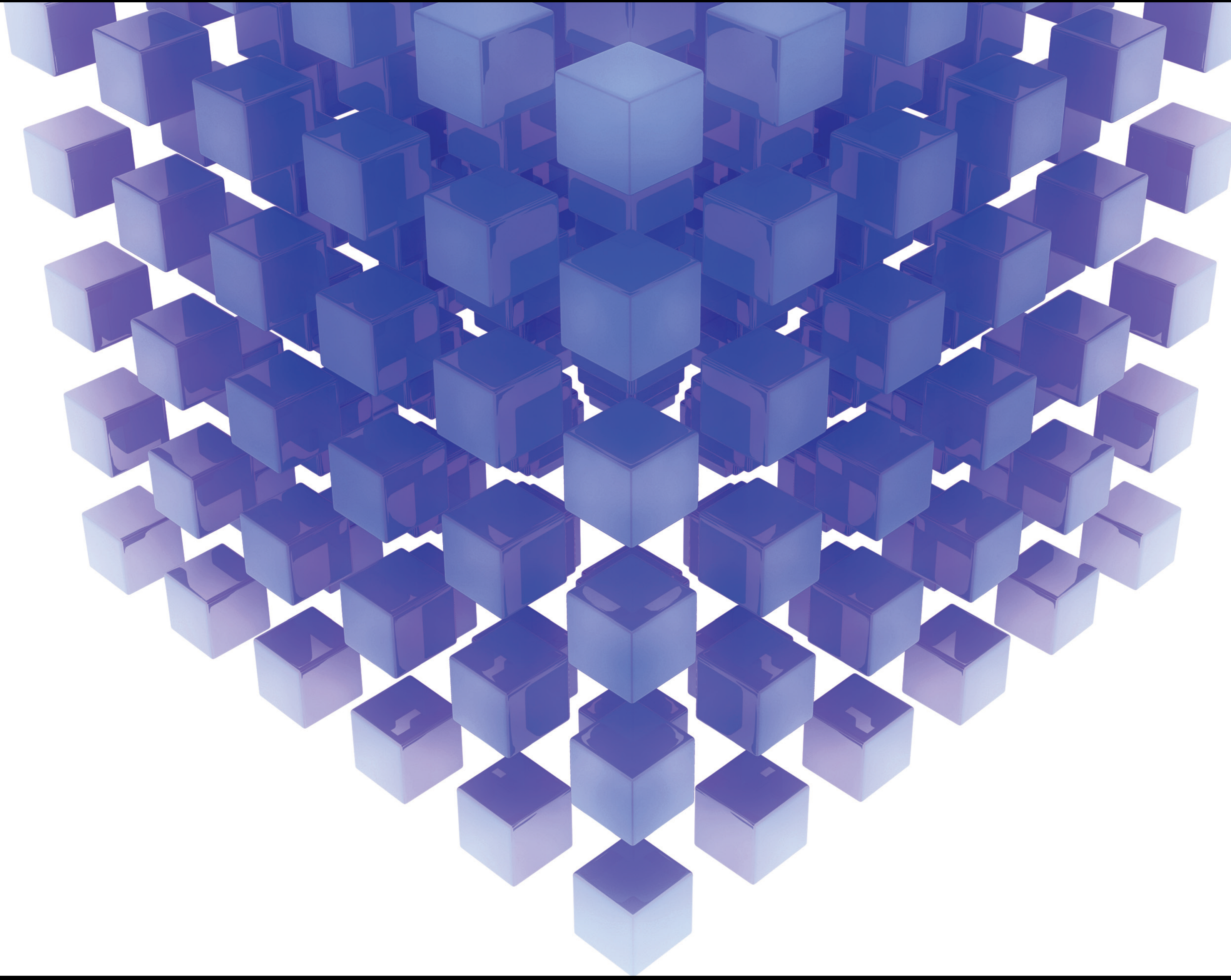
Mathematical Problems in Engineering

Applications of Optimisation Algorithms in Retailing, Logistics, and Supply Chain Management

Lead Guest Editor: Rong-Chang Chen
Guest Editors: Yan Pei and Jason C. Hung



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Research Article

Research on the Incentive Mechanism of the Pension Service Supply Chain under Asymmetric Information

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The information asymmetry between the pension service integrator and the pension service providers will affect the efficiency of the whole supply chain, and information sharing can solve this problem to a certain extent. To achieve information sharing, mutual trust is the first condition and mutual trust is also one of the important means of endogenous incentives. In this paper, the trust incentive coefficient is embedded in the principal-agent model. Considering the service capability coefficient, the communication degree coefficient, and the information sharing degree coefficient of the pension service providers, the trust incentive model of the supply chain of the pension service is constructed, the model is solved, and the conclusion is drawn. Finally, the correctness of the conclusion is verified by the numerical simulation using SAS software. The final results show that, under the condition of information asymmetry, the trust incentive coefficient of the pension service integrator to the pension service providers is positively correlated with the effort coefficient, the service capability coefficient, the communication coefficient, and the information sharing degree coefficient of the pension service providers, while it is positively correlated with the effort cost coefficient, the output sharing coefficient, and the risk aversion coefficient of the pension service providers. The variance of number and external environmental variables is negatively correlated. This research has shown that the trust is a means of incentive for pension service providers to share information. This research has a certain practical significance for improving the service efficiency of the pension services supply chain and optimizing the level of pension services.

1. Introduction

With the development of the social economy, the needs of the elderly group are becoming more and more diversified. The traditional institutional and family-style care for the aged can no longer meet the needs of the large elderly group; therefore, many industries related to the elderly service industry have been promoted, and the pension service industry has been fully activated. In recent years, the thought of service supply chain management has brought a new perspective to the management reform of the pension service industry. Different from the traditional mode, the service integrator is introduced into the service supply chain, and the service integrator outsources some service modules to some professional service providers. The structure of the pension service supply chain model includes the following: the service providers that provide the support service, the service integrator that acts as the core enterprise in the supply chain to integrate and develop the pension service resources, the customer-oriented service integrator that accepts the services provided by the service providers, and the network with other relevant support units, and the existing pension service resources into the core services, and ultimately delivered to the customers. With the help of the Internet and the big data technology, the supply chain of pension services is guided by the diversified and personalized needs of the elderly service demanders, integrating the logistics, capital flow, information flow, and service flow in the process of pension services, connecting all kinds of pension service providers, pension service integrators, and pension service demanders, so as to provide the real-time, efficient and low-cost pension services for the demanders. The supply chain of pension service is a kind of functional network chain structure. Although the pension service has developed into a relatively clear chain structure, there are still some problems to be solved in the process of providing services. In the pension service supply chain, the pension service integrator and the pension service providers constitute the principal-agent relationship. In the actual operation process, both sides make independent decisions based on their own interests, resulting in the consequences of the pension service information asymmetry, and it leads to adverse selection and some moral hazard problems and damages the overall performance of the pension service supply chain. Therefore, solving this problem can help improve the service quality and overall operation efficiency of the pension service supply chain, provide more high-quality services for the elderly, and improve their satisfaction, which is of great research value. In addition, it has been proved that the supply chain performance can be improved greatly by the supply chain coordination and the establishment of operational contract mechanism among supply chain members. Therefore, how to achieve the supply chain coordination of pension services, optimize the distribution of benefits, and provide the high-quality and efficient pension services is the focus of this paper.

2. Literature Review

2.1. Mode of the Pension Service. In recent years, most of the researches on the mode of the pension service are empirical studies. Wei and Zang used the multistage sampling method to conduct a questionnaire survey among 3260 elderly people aged 60 years or over in 44 communities in 16 subdistricts in six districts in Xiamen [1]. Alders, Peter et al. analyzed the differences in the number of people choosing institutional care between 1996–1999 and 2009–2012 to explain why the institutional care has become lower and the community care has become higher [2]. Based on the difference between urban and rural areas, Liangwen Zhang et al. used the multistage sampling method and constructed the Andersen Model to investigate 7192 elderly over 65 years old living at home and analyzed the present situation of the occupancy rate in nursing institutions and its influencing factors [3]. WenBing Mei et al. used the questionnaire survey and the fuzzy analytic hierarchy process to establish a complete evaluation system of the elderly-friendly community public environmental indicators and explore what are the important indicators of the aging-friendliness of a community public environment [4]. Fetherstonhaugh et al. investigated some home care workers in Australia from November 2018 to January 2019, using a qualitative descriptive design and the semistructured face-to-face and telephone interviews, analyzed the problems in the provision of home care to the older persons, and proposed some corrective measures [5]. Henderson et al. investigated 922 people who worked in nursing homes using both qualitative and quantitative methods to analyze the missing tasks in nursing homes and the causes [6]. Puustinen et al. collected some dates about 71 home care during the spring of 2018, analyzed these data with descriptive statistical method, analyzed the inconsistency between the client needs and the care services, and put forward some relevant solutions [7]. Schonfelder et al. conducted interviews with 16 professional caregivers to investigate how professional caregivers in home care for the elderly in Norway relate their professional tasks to the social care [8]. Suwa et al. investigated and analyzed the views of Japan, Ireland, and Finland on the participation of robots in home care for the elderly by means of questionnaires [9]. Cleland et al. conducted 41 in-depth, semistructured interviews with people over 65 years of age receiving community-based geriatric care in three Australian states to study the quality of community-based geriatric care [10].

2.2. Service Supply Chain. At present, the research on service supply chain mainly focuses on product service supply chain, logistics service supply chain, port service supply chain, medical service supply chain, and cloud service supply chain.

Choudhury et al. reviewed the research methods of service supply chain and suggested that the future research should focus on four main areas of service supply chain, namely, environmental protection measures, market relations, information technology integration, and adoption of industry-specific case studies [11]. Johnson and Mena [12] redefined the supply chain with service flow as product service supply chain, and many scholars also discussed the supply chain management in the context of service [13]. Beuren et al. argued that introducing services into supply chain networks can help many manufacturers find opportunities to change customer consumption patterns and integrated products and services to build process models for product service supply chains [14]. At the same time, a large number of scholars also study the product service supply chain, mainly concentrated in the product before and after sales [15]. Yongtao Peng constructed a product service supply chain network and studied the effects of product and service capacity constraints and product service integration rate on network equilibrium [16].

Han et al. constructed the revenue sharing model of port and shipping service supply chain based on system optimization and studied the revenue sharing decision-making problem of port and shipping service supply chain with government subsidy mechanism [17]. Liu et al. constructed a decision model of dual overconfidence behavior and studied the effects of dual overconfidence behavior and demand renewal on supply chain decision-making by using the method of empirical research [18].

Zhao used the Game Theory to study the coordination of the supply chain of geriatric medical service in a two-channel environment and analyzed the decision-making and interaction between the pension service integrator and the pension service providers in competition and cooperation [19]. De Vrie and Huijsman attempted to integrate the supply chain domain with the health services domain and defined five major research areas of supply chain management in medical institutions [20].

Lu et al. studied the collaborative supply decision problem of basic service units in cloud service supply chain [21]. Xue and Ge applied the theory of quality cost to the research of logistics service supply chain and put forward the method of constructing logistics service supply chain and cost optimization based on cloud genetic algorithm [22].

He et al. constructed a supply chain of low-carbon services, taking into account corporate social responsibility, consisting of a service providers responsible for carbon reduction and carbon services and a service integrator responsible for low-carbon advertising, and established three differential game models to explore the optimal decisions [23]. Based on the Structural Equation Model, Yingjie Ju discussed the relationship between integrated quality, value cocreation, and the elasticity of logistics service supply chain, analyzed the regulating function of digital technology, and studied the integration of supply chain from a new perspective [24]. Based on the complex network theory, Ma et al. constructed an improved structure model of logistics service supply chain, reconstructed the operation mechanism of logistics service supply chain, determined the vulnerable nodes in logistics service, and clarified the vulnerable mechanism of logistics service center [25]. Based on the structure of logistics service supply chain, Guangsheng Zhang et al. analyzed the evolution of risk and the reactions of major actors [26]. Wang et al. established a nonlinear mixed integer multiobjective optimization model for service providers selection and order assignment in mass customization logistics service mode and designed an improved genetic algorithm based on the multilayer coding technique to solve the model [27]. Li et al. constructed an evolutionary game model to explore the dynamic selection process of enterprise information synergy strategy in logistics service supply chain [28]. Liu et al. studied the impact of loss aversion preference on purchasing decision of service capacity with renewed demand in a logistics service supply chain consisting of a logistics service integrator and functional logistics service providers [29]. Ju et al. established a structural equation model and discussed the factors that affect the performance sustainability of integrators based on their opportunistic behavior [30]. Dai et al. constructed a supply chain logistics service model of blockchain and studied the application of block supply chain technology in logistics service supply chain management from three dimensions: object domain, function domain, and attribute domain [31]. Liu et al. studied the order allocation problem of a logistics service supply chain with one logistics service integrator and two competing functional logistics service providers and proposed an incentive contract [32].

2.3. Incentive Mechanism of Supply Chain. Wang et al. studied a green supply chain consisting of a risk averse downstream retailer and a risk averse upstream supplier and designed the incentive mechanism to improve the product green degree under the compensation contract of the target green degree [33]. Yu et al. proposed a supply chain agent incentive negotiation mechanism to improve the supply chain agent strategy [34]. Lin et al. studied the cooperation mechanism of the supply chain of the four-party (the third party logistics supplier, the bank, the B2B platform operator, and the small and medium-sized enterprises) [35]. Wang et al. proposed a kind of incentive method of knowledge sharing based on supervision mechanism and established the basic incentive model and optimization model of knowledge sharing in industrial building supply chain based on the principal-agent theory [36]. Based on the perspective of sustainable development of supply chain, Jeong et al. studied the effect of quantity incentive contracts on environmental performance, market performance, and profit performance of small and medium enterprises [37].

To sum up, most scholars studied the product supply chain and logistics supply chain, few scholars applied the supply chain theory to the elderly service, and the research results of information sharing incentive in the service supply chain were extremely few. In this paper, the trust degree of the service integrator to the supplier is quantitatively expressed, and the service ability, interaction degree coefficient, information sharing degree coefficient, and so on are considered, and the incentive problem of information sharing between service integrator and service providers in service supply chain is studied. Under the situation that the aging of population is becoming more and more serious, this research has certain theoretical and practical significance.

3. Problem Description and Basic Assumptions

Generally, in the pension services supply chain, the service ability and effort level of pension service providers are not easy to be observed by pension service integrator, but their service performance can be observed by the pension service integrator. Therefore, the information asymmetry often occurs in the pension service supply chain, which will bring a series of adverse selection and moral hazard problems, and the existence of these problems will affect the interests of the whole pension service supply chain. This paper attempts to use the principal-agent theory to analyze the principal-agent relationship between the pension service integrator and the providers and constructs an incentive model of information sharing based on mutual trust between them in the pension service supply chain under asymmetric information, so as to encourage the pension service providers to improve the level of pension service and efforts. At the same time, it can achieve the purpose of balancing the interests of each node enterprise and standardizing and restricting the behavior of each node enterprise. This paper makes the following assumptions for the model:

Hypothesis 1. The information about pension service between the pension service integrator and the pension service providers is not asymmetric. A trust incentive coefficient t given by the pension service integrator to the pension service providers is set $(0 \leq t \leq 1)$, and the coefficient is the trust degree of the pension service integrator to the pension service providers. The larger t is, the higher the trust degree of the pension service integrator to the pension service providers is.

Hypothesis 2. The service ability coefficient of the pension service providers is S_c (the coefficient is a parameter to measure the service ability of the pension service providers), the effort degree coefficient of the pension service providers is L_1 (the coefficient is a parameter to measure the level of effort pension service providers), and the effort cost coefficient of the pension service providers is C_1 (the coefficient is a parameter to measure the cost that the pension service providers produces in the process of providing the service), where $S_C > 0$, $L_1 \geq 1$ ($L_1 = 1$ means that the pension service providers have not made any effort), and $C_1 > 0$.

Hypothesis 3. The communication degree coefficient between the pension service providers and the pension service integrator is i (the coefficient is a parameter to measure the good communication between the providers and the integrator), the effort degree coefficient paid by the pension service providers is L_2 (the coefficient is a parameter to measure the degree of effort for the integrator in order to maintain good communication with the integrator) in order to achieve good communication, and the corresponding effort cost coefficient is C_2 (the coefficient is a parameter to measure the cost of maintaining good communication between the providers and the integrator), where $0 \leq i \leq 1$ ($i = 0$ means that there is no communication between the pension service providers and the pension service integrator at all, $i = 1$ means that the communication between the pension service providers and the pension service integrator is perfect, $L_2 \geq 1$ (1 means that the pension service providers have not made any efforts), and $C_2 > 0$.

Hypothesis 4. The information sharing degree coefficient between the pension service providers and the pension service integrator is S_d (the coefficient is a parameter to measure the degree of information sharing between the providers and the integrator), the corresponding effort degree coefficient is L_3, and the effort cost coefficient is C_3 (the coefficient is a parameter to measure the cost of information sharing between the providers and the integrator), where $0 \leq S_d \leq 1$ ($S_d = 0$ means that the pension service providers do not share any information with the pension service integrator, SD = 1 indicates that the pension service providers can directly and completely share information with the pension service integrator, $L_3 \geq 1$ ($L_3 = 1$ indicates that the pension service providers have not made any efforts in information sharing), and $C_3 > 0$.

Hypothesis 5. The external environment variable is θ, and θ obeys $N(0, \delta^2)$; θ represents the output determined by the uncertainty factors of the external environment, such as changes in market demand and changes in pension service policies.

Assumption 1. The output of pension service provider is O (this variable is a parameter to measure the benefit degree of pension service providers after their efforts), and O meets the following requirements:

$$O(L_1, L_2, L_3) = S_c L_1 + i L_2 + S_d L_3 + \theta. \tag{1}$$

Assumption 2. The fixed income of the pension service provider is m, which has nothing to do with the output; the output sharing coefficient is n (since the income of the pension service provider is partly derived from the resources of the pension service integrator, it is necessary to share part of the income with the pension service integrator), which satisfies $0 \leq n \leq 1$; the linear contract signed between the pension service integrator and the pension service provider is

$$y(O) = m + (n + t)O. \tag{2}$$

Assumption 3. The effort cost of pension service providers is C (this variable is a parameter to measure the total cost spent by pension service providers):

$$C(L_1, L_2, L_3) = \frac{C_1}{2}L_1^2 + \frac{C_2}{2}L_2^2 + \frac{C_3}{2}L_3^2. \tag{3}$$

Hypothesis 6. The actual income of the pension service provider is a, and the retained income is a_0; assuming that the risk of the pension service integrator is neutral, and the risk aversion of the pension service provider, and assuming that the risk aversion coefficient of the pension service provider is ρ, $\rho > 0$, then its utility function should be$u(a) = e^{-\rho a}$.

Assumption 4. The pension service integrator's trust in the pension service provider will also generate costs, which are recorded as $C_t(t)$. Because when the pension service integrator trusts the efforts and service level of the pension service provider too much, the efforts of the pension service integrator to the pension service provider will produce some more than rational expectations, which may increase the opportunistic behavior of the pension service provider.

$$C_t'(t) > 0\ ,\ \ C_t''(t) > 0, C_t(0) = 0. \tag{4}$$

4. Trust Incentive Model of Pension Service Supply Chain

The model of trust motivation in this paper is based on the research model of He et al. [38]. The original model is described as follows.

The expected revenue of the service integrator is as follows:

$$EU(o - r(o)) = -a + [1 - (b + g)]\left(p_c f_5 + i f_6 + s_c f_7\right). \tag{5}$$

The actual revenue of the service provider is as follows:

$$\begin{aligned} m &= r(o) - c\left(f_5, f_6, f_7\right) \\ &= a + (b + g)\left(p_c f_5 + i f_6 + s_c f_7 + \theta\right) - \frac{d_5}{2}f_5^2 - \frac{d_6}{2}f_6^2 - \frac{d_7}{2}f_7^2. \end{aligned} \tag{6}$$

Determined equivalent benefits of service providers are as follows:

$$EU(m) - \frac{1}{2}\rho(b+g)^2\delta^2 = a + (b+g)(p_c f_5 + i f_6 + s_c f_7) - \frac{d_5}{2}f_5^2 - \frac{d_6}{2}f_6^2 - \frac{d_7}{2}f_7^2 - \frac{1}{2}\rho(b+g)^2\delta^2. \tag{7}$$

This model has been used many times in supply chain construction in other fields and has achieved good results. In this paper, the model is applied to the construction of the pension service supply chain, which also has a certain theoretical and practical significance. Compared with the existing models, the innovation of this paper lies in the addition of a new variable; that is, $C_t(t)$ represents the trust cost. On the basis of the above assumptions, this paper proposes the trust incentive model of the pension service supply chain as follows:

The actual revenue of the service provider is as follows:

$$a = y(O) - C(L_1, L_2, L_3) = m + n + tS_cL_1 + iL_2 + S_dL_3 + \theta - \frac{C_1}{2}L_1^2 - \frac{C_2}{2}L_2^2 - \frac{C_3}{2}L_3^2. \tag{8}$$

Determined equivalent benefits of service providers are as follows:

$$EU(a) - \frac{1}{2}\rho n + t^2\delta^2 = m + n + tS_cL_1 + iL_2 + S_dL_3 - \frac{C_1}{2}L_1^2 - \frac{C_2}{2}L_2^2 - \frac{C_3}{2}L_3^2 - \frac{1}{2}\rho n + t^2\delta^2. \tag{9}$$

The expected revenue of the service integrator is as follows:

$$EU(O - y(O)) = -m + [1 - n + t]S_cL_1 + iL_2 + S_dL_3 - C_t(t). \tag{10}$$

Equation (9) calculates the partial derivative of L_1, L_2, and L_3 respectively, and obtains the incentive compatibility constraint (IC) of the service provider as follows:

$$L_1 = \frac{(n+t)S_c}{C_1}, \tag{11}$$

$$L_2 = \frac{(n+t)i}{C_2}, \tag{12}$$

$$L_3 = \frac{(n+t)S_d}{C_3}. \tag{13}$$

The trust incentive model of pension service integrator to the pension service providers can be expressed as follows:

$$\begin{aligned} &\max\left[-m + [1-n+t]S_cL_1 + iL_2 + S_dL_3 - C_t(t)\right] \\ &\text{s.t } m + n + tS_cL_1 + iL_2 + S_dL_3 - \frac{C_1}{2}L_1^2 - \frac{C_2}{2}L_2^2 - \frac{C_3}{2}L_3^2 - \frac{1}{2}\rho n + t^2\delta^2 \geq a_{0\ (\text{IR})} \\ &L_1 = \frac{(n+t)S_c}{C_1}, L_2 = \frac{(n+t)i}{C_2}, L_3 = \frac{(n+t)S_d}{C_3}\ (\text{IC}). \end{aligned} \tag{14}$$

In the above model, IR is the participation constraint of pension service providers, and IC is the incentive compatibility constraint of pension service providers. When the expected return of the pension service provider is less than its retained return, the game between the pension service integrator and the pension service provider will end immediately. In the optimal case, the equation of participation constraint of the pension service provider is established, from which we can get

$$m = a_0 - n + tS_cL_1 + iL_2 + S_dL_3 + \frac{C_1}{2}L_1^2 + \frac{C_2}{2}L_2^2 + \frac{C_3}{2}L_3^2 + \frac{1}{2}\rho n + t^2\delta^2. \tag{15}$$

Combining formulas (11)–(13) and (15), and making the objective function of formula (14) to calculate the partial derivative of t, the result can be obtained:

$$t = \frac{S_c^2C_2C_3 + i^2C_1C_3 + S_d^2C_1C_2}{S_c^2C_2C_3 + i^2C_1C_3 + S_d^2C_1C_2 + \rho\delta^2C_1C_2C_3} - n. \tag{16}$$

From equation (11),

$$t = \frac{C_1L_1}{S_c} - n. \tag{17}$$

From equation (12),

$$t = \frac{C_2L_2}{i} - n. \tag{18}$$

From equation (13),

$$t = \frac{C_3L_3}{S_d} - n. \tag{19}$$

Formulas (17)–(19) calculate the partial derivatives of L_1, L_2, and L_3, respectively, and obtain

$$\frac{\partial t}{\partial L_1} = \frac{C_1}{S_c} > 0, \tag{20}$$

$$\frac{\partial t}{\partial L_2} = \frac{C_2}{i} > 0, \tag{21}$$

$$\frac{\partial t}{\partial L_3} = \frac{C_3}{S_d} > 0. \tag{22}$$

Conclusion 1. According to formulas (20)–(22), the trust incentive coefficient given by the pension service integrator is positively related to the effort degree coefficient of the pension service provider. The greater the trust incentive coefficient is, the harder the pension service provider is.

Equation (16) calculates the partial derivatives of S_c, i, S_d, C_1, C_2, C_3, δ^2, n, and ρ, respectively, and obtains

$$\frac{\partial t}{\partial S_c} = \frac{2S_c\rho\delta^2 C_1 C_2^2 C_3^2}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3{}^2} > 0, \tag{23}$$

$$\frac{\partial t}{\partial i} = \frac{2i\rho\delta^2 C_1^2 C_2 C_3^2}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} \geq 0, \tag{24}$$

$$\frac{\partial t}{\partial S_d} = \frac{2S_d\rho\delta^2 C_1^2 C_2^2 C_3}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} \geq 0, \tag{25}$$

$$\frac{\partial t}{\partial C_1} = -\frac{\rho\delta^2 C_1 C_2 C_3\left(i^2 C_3 + S_d^2 C_2\right)}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} \leq 0, \tag{26}$$

$$\frac{\partial t}{\partial C_2} = -\frac{\rho\delta^2 C_1 C_2 C_3\left(S_c^2 C_3 + S_d^2 C_1\right)}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} < 0, \tag{27}$$

$$\frac{\partial t}{\partial C_3} = -\frac{\rho\delta^2 C_1 C_2 C_3\left(S_c^2 C_2 + i^2 C_1\right)}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} < 0, \tag{28}$$

$$\frac{\partial t}{\partial \delta^2} = -\frac{\rho C_1 C_2 C_3\left(S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2\right)}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} < 0, \tag{29}$$

$$\frac{\partial t}{\partial n} = -1 < 0, \tag{30}$$

$$\frac{\partial t}{\partial \rho} = -\frac{\delta^2 C_1 C_2 C_3\left(S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2\right)}{S_c^2 C_2 C_3 + i^2 C_1 C_3 + S_d^2 C_1 C_2 + \rho\delta^2 C_1 C_2 C_3^2} < 0. \tag{31}$$

Conclusion 2. It can be seen from equations (23)–(25) that the trust incentive coefficient given by the pension service integrator to the pension service provider is positively related to the service ability coefficient, communication degree coefficient, and information sharing degree coefficient of the pension service provider; that is, the more the pension service integrator trusts the pension service provider, the better the service ability of the pension service provider will be, and the pension service provider will also be more willing to actively communicate and interact with pension service integrator, and the pension service providers will be more willing to share information with the pension service integrator.

Conclusion 3. It can be seen from equations (26)–(28) that the trust incentive coefficient given by the pension service integrator to the pension service provider is negatively related to the effort cost coefficient of the pension service provider; that is, the more trust the pension service integrator gives to the pension service provider, the higher the efficiency of the work of the pension service provider is, and the lower the effort cost is. On the contrary, the less trust the pension service integrator gives to the pension service provider, the lower the work efficiency of the pension service provider is, and the greater the effort cost is.

Conclusion 4. It can be seen from equations (29)–(31) that the trust incentive coefficient given by the pension service integrator to the pension service provider is negatively related to the variance, output sharing coefficient, and risk aversion coefficient of the external environment variables of the pension service provider; that is, the more the pension service integrator trusts the pension service provider, the less the uncertainty of the external environment of the pension service provider is, and the easier it is for the pension service integrator to control the pension service provider. The more trust the pension service integrator gives to the pension service provider, the lower the risk aversion coefficient of the pension service provider is. The larger the trust incentive coefficient of pension service integrator to pension service providers, the smaller the output sharing coefficient of pension service providers.

5. Numerical Simulation of Trust Incentive in the Pension Service Supply Chain

(i) Through numerical simulation, it is verified that the effort level of pension service providers is positively related to the trust incentive coefficient of pension service providers. Assuming $C_1 = 20$, $S_c = 280$, and $n = 0.2$, substitute the values of C_1, S_c, and n into equation (17), and use SAS software to draw the graph. The result is shown in Figure 1.

(ii) It can be seen from Figure 1 that the trust incentive coefficient given by the pension service integrator to the pension service providers is positively related to the efforts of the pension service providers, which verifies the correctness of Conclusion 1. In the same way, through numerical simulation to verify that the trust incentive coefficient t is positively related to the service provider's effort L_1 and L_2, it can also verify the correctness of Conclusion 1.

(iii) Through the numerical simulation, it is verified that the service ability of the pension service providers is positively related to the trust incentive coefficient of the pension service integrator.

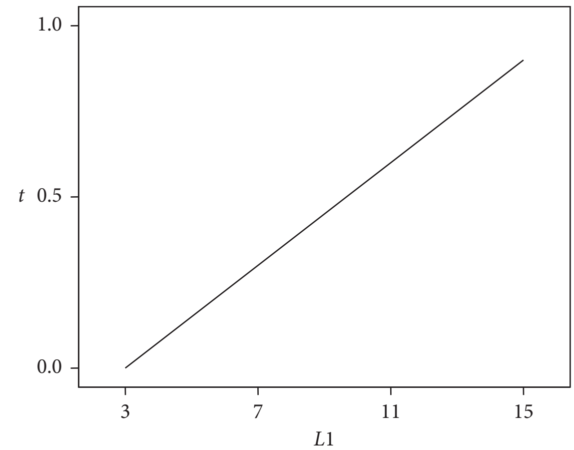

FIGURE 1: Relationship between effort L_1 and trust incentive coefficient t.

Suppose that $C_1 = 20$, $C_2 = 0.2$, $C_3 = 0.4$, $i = 0.5$, $S_d = 0.6$, $n = 0.2$, $\rho = 0.5$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 2.

(iv) It can be seen from Figure 2 that the trust incentive coefficient given by the pension service integrator to the pension service providers is positively related to the service ability coefficient of the pension service providers, which verifies the correctness of Conclusion 2.

(v) Through numerical simulation, it is verified that the communication ability of the pension service providers is positively related to the trust incentive coefficient of the pension service providers. Suppose that $C_1 = 20$, $C_2 = 0.2$, $C_3 = 0.4$, $S_c = 280$, $S_d = 0.6$, $n = 0.2$, $\rho = 0.5$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 3.

(vi) It can be seen from Figure 3 that the trust incentive coefficient given by the pension service integrator to the pension service providers is positively related to the communication degree of the pension service providers, which verifies the correctness of Conclusion 2.

(vii) Through numerical simulation, it is verified that the degree of information sharing of pension service providers is positively related to the trust incentive coefficient of pension service providers. Suppose that $C_1 = 20$, $C_2 = 0.2$, $C_3 = 0.4$, $S_c = 280$, $i = 0.5$, $n = 0.2$, $\rho = 0.5$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 4.

(viii) It can be seen from Figure 4 that the trust incentive coefficient given by the pension service integrator to the pension service providers is positively related to the information sharing degree of the pension service providers, which verifies the correctness of Conclusion 2.

(ix) Through numerical simulation to verify that the trust incentive coefficient given by the pension service integrator to the pension service providers is positively related to the effort cost coefficient of the pension service providers, suppose that $S_c = 280$, $i = 0.5$, $S_d = 0.6$, $C_2 = 0.2$, $C_3 = 0.4$, $n = 0.2$, $\rho = 0.5$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 5.

(x) It can be seen from Figure 5 that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the service effort cost coefficient of the pension service providers, which verifies the correctness of Conclusion 3. Similarly, through numerical simulation, we can verify $C_2 = 0.2$ and $C_3 = 0.4$, which is also negatively related to the trust incentive coefficient, and also can verify the correctness of Conclusion 3.

(xi) Through numerical simulation, it is verified that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the risk aversion coefficient of the pension service providers. Suppose that $S_c = 280$, $i = 0.5$, $S_d = 0.6$, $C_1 = 20$, $C_2 = 0.2$, $C_3 = 0.4$, $n = 0.2$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 6.

(xii) It can be seen from Figure 6 that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the risk aversion coefficient of the pension service providers, which verifies the correctness of Conclusion 4.

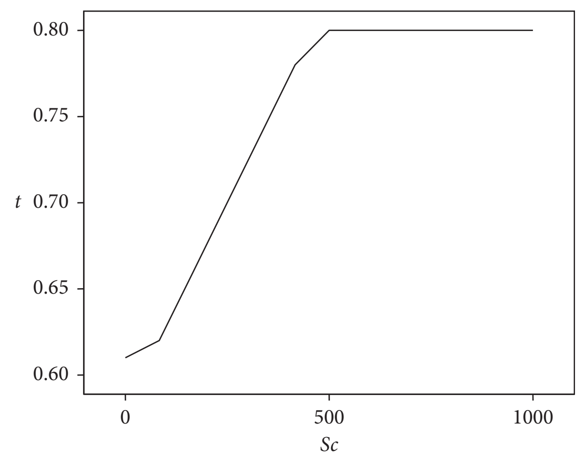

Figure 2: Relationship between service ability coefficient SC and trust incentive coefficient t of pension service providers.

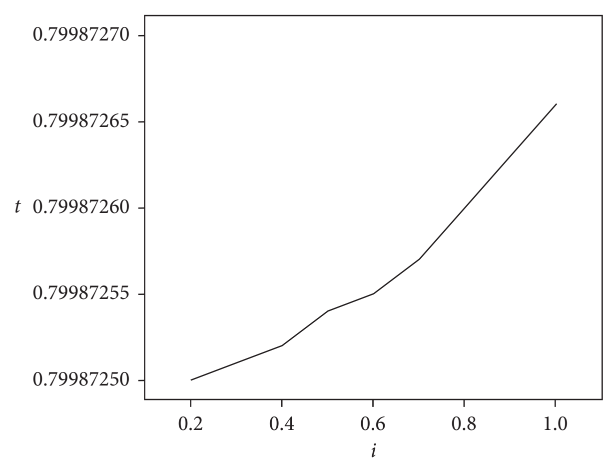

Figure 3: Relationship between communication degree coefficient i and trust incentive coefficient t of pension service providers.

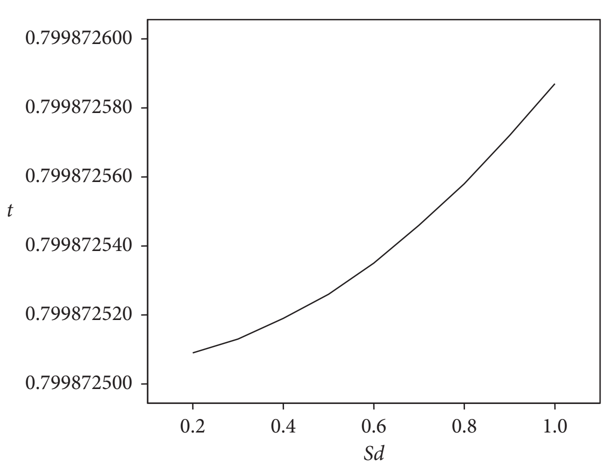

Figure 4: Relationship between information sharing degree coefficient S_d and trust incentive coefficient t of pension service providers.

(xiii) Through numerical simulation, it is verified that the variance of the external environment variables of the pension service providers is negatively related to the trust incentive coefficient. Suppose that $S_c = 280$, $S_d = 0.6$, $i = 0.5$, $C_1 = 20$, $C_2 = 0.2$, $C_3 = 0.4$, $n = 0.2$, and $\rho = 0.5$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 7.

(xiv) It can be seen from Figure 7 that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the variance of the external environment variables of the pension service providers, which verifies the correctness of Conclusion 4.

(xv) Through the numerical simulation, it is verified that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the output sharing coefficient of the pension service providers. Suppose that $S_c = 280$, $S_d = 0.6$, $i = 0.5$, $\rho = 0.5$, and $\sigma^2 = 1$, the values of the above parameters are substituted into equation (16), and the SAS software is used for drawing. The results are shown in Figure 8.

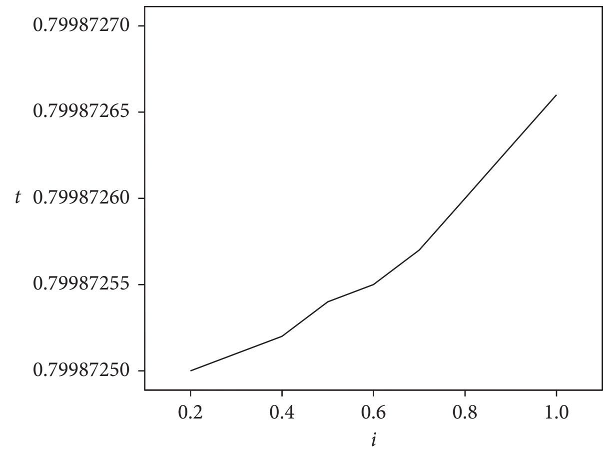

Figure 5: Relationship between effort cost coefficient C_1 and trust incentive coefficient t of pension service providers.

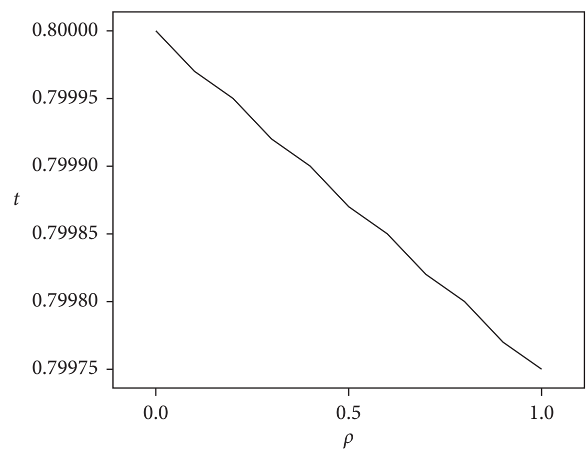

Figure 6: Relationship between risk aversion coefficient ρ and trust incentive coefficient t of pension service providers.

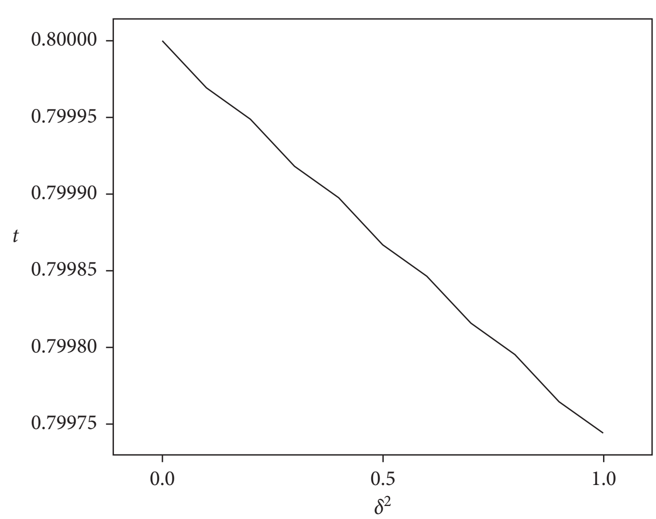

Figure 7: Relationship between variance of external environment variables δ^2 and trust incentive coefficient t.

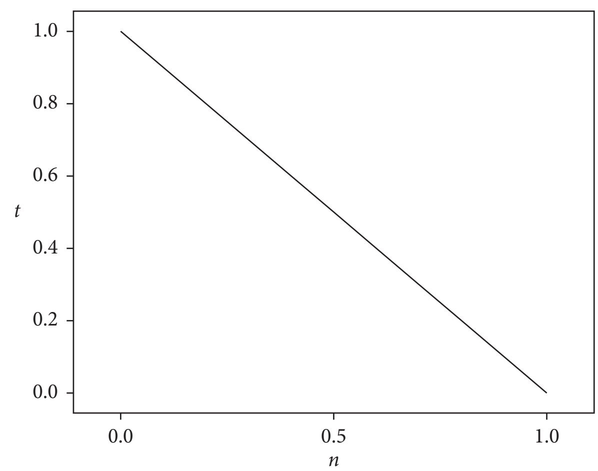

FIGURE 8: Relationship between output sharing coefficient n and trust incentive coefficient t of pension service providers.

It can be seen from Figure 8 that the trust incentive coefficient given by the pension service integrator to the pension service providers is negatively related to the output sharing coefficient of the pension service providers, which verifies the correctness of Conclusion 4.

6. Conclusion

This paper studies the incentive strategies adopted by the pension service integrator under asymmetric information to encourage the pension service providers to share the pension service information with them and strive to improve the level of pension service. In this paper, the trust coefficient is embedded in the incentive model, the trust incentive model of the pension service supply chain is constructed, and the model is calculated and solved, and the correctness of the conclusion is verified by the numerical simulation. The results show that, under the condition of asymmetric information, the degree of trust incentive given by the pension service integrator to the pension service providers is positively related to the degree of effort, service ability, communication, and information sharing of the pension service providers. The degree of trust incentive given by the pension service integrator to the pension service providers is negatively related to the effort cost, output sharing proportion, risk aversion degree, and variance of external environment variables of the pension service providers.

Based on the above conclusions, several implications are drawn as follows:

(i) The pension service integrator should choose the pension service providers with strong service ability and good communication ability to share information and, at the same time, give them enough trust, so that they can give full play to their abilities;

(ii) The pension service integrator should adopt differentiated trust incentive strategies for the pension service providers. For pension service providers willing to share information and risk, pension service, the integrator should give them full trust. For those with high risk aversion coefficient and low information sharing degree, the pension service providers give less trust;

(iii) The pension service integrator should balance the income incentive and the trust incentive, that is, balance between giving pension service providers a certain degree of trust and output sharing share, which can not only give full play to the role of trust incentive, but also effectively control the loss of opportunistic behavior caused by excessive trust;

(iv) The pension service integrator should strengthen the communication and exchange with the pension service providers, establish a smooth and perfect information sharing platform, and enhance the ability of information receiving and sending between the pension service integrator and the pension service providers.

6.1. Research Expectations. In this paper, a trust incentive model of the supply chain for the elderly service is constructed, and the practicability of the model and the correctness of the conclusion are verified by simulation. The establishment of this model is based on a series of assumptions, but the model has not been tested by empirical evidence. Therefore, the next step of this research will be to do empirical studies by collecting relevant data to verify the usefulness of the model.

Data Availability

All data and models generated or used during the study are included within the article.

Conflicts of Interest

The author declares that she has no conflicts of interest regarding the publication of this paper.

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Research Article

Research on the Scheduling of Tractors in the Major Epidemic to Ensure Spring Ploughing

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When the outbreak of COVID-19 began, people could not go out. It was not allowed to provide agricultural machinery services in different places across regions to reduce the flow and gathering of people. Improvement of utilization efficiency of agricultural machinery resources is required through scientific scheduling of agricultural machinery. With seizing the farming season and stabilizing production as the goal, this paper studied the scientific scheduling of tractors within the scope of town and established agricultural machinery operation scheduling model with the minimization of total scheduling cost as the optimization objective. Factors such as farmland area, agricultural machinery, and farmland location information and operating time window are considered in this model to improve the accuracy of the agricultural machinery operation scheduling model. The characteristics of multiple scheduling algorithms are analyzed comprehensively. The scheduling requirements of agricultural machinery operation to ensure spring ploughing are combined to design the agricultural machinery scheduling algorithm based on the SA algorithm. With Hushu Street, Jiangning District, Nanjing City, as an example, a comparative experiment is conducted on the simulated annealing algorithm (SA) designed in this paper and the empirical algorithm and genetic algorithm (GA). The results suggest that the total cost of the scheduling scheme generated by the SA algorithm is 19,042.07 yuan lower than that by the empirical scheduling algorithm and 779.19 yuan lower than that by the genetic algorithm on average. Compared with the GA algorithm, the transfer distance, waiting cost, and delay cost of the SA algorithm are reduced by 11.6%, 100%, and 98.1% on average, indicating that the transfer distance of agricultural machinery in the scheduling scheme generated by the SA algorithm is shorter, so is the waiting and delay time. Meanwhile, it can effectively obtain the near-optimal solution that meets the time window constraint, with good convergence, stability, and adaptability.

1. Introduction

China's agriculture has a small average household operation scale, high agricultural multiple cropping index, tight farming time, and other problems. The operation capacity of agricultural machinery cannot meet production needs during busy periods. The regional shortage of agricultural machinery can be solved by cross-regional operation of agricultural machinery in regular years. The cross-regional operation area of agricultural machinery for three major food crops in China reached 20,478 thousand hectares, accounting for 21% of the sown area in 2019 [1].

Due to the outbreak of COVID-19, global production and life in 2020 paused; companies suspended production and businesses shut down for a while. According to the epidemic development level, epidemic prevention measures such as shutting down countries, cities, and villages have been continuously introduced. People have to stay at home to protect themselves and avoid adding burdens to society. As a result, cross-regional operations of agricultural machinery were suspended, adding fuel to the fire of insufficient regional agricultural machinery operation. However, as the foundation of the national economy, agriculture is different from the secondary and tertiary industries. It is characterized by strong seasonality, and missing the production season will lead to huge losses. Therefore, governments of various countries have carried out massive measures to seize the farming season and stabilize production while fighting against the epidemic at the same time. Agricultural machinery management departments at all levels in China vigorously carry out agricultural machinery scheduling according to the impact of the epidemic to ensure spring ploughing.

For major catastrophic accidents, scholars have conducted extensive studies, mainly focusing on the distribution of supplies. In large-scale emergencies, the problems and challenges that arise in the management of emergency resource supply chains are significantly different from those in ordinary commercial applications [2–5]. To respond to such disasters effectively, governments and management organizations must consider multiple and unique aspects of emergency operations, such as resource scarcity and disaster uncertainty [6–8]. In addition, reducing the number of casualties and deaths in disaster-stricken areas depends, to a large extent, on the early arrival and rapid deployment of resources for emergency operations. Failure to allocate sufficient resources in time has always been the root cause of adverse effects in case of disaster [9–15].

In addition, unexpected events must be considered in emergencies because there can be multiple uncertain and unpredictable factors [16, 17]. Due to the lack of historical data and possible dissemination ways, it is difficult to set the exact parameters for this problem. The variables that must be considered to obtain a better response rate include key requirements, competition priority, time urgency, and availability of necessary resource allocation. However, potential transportation and condition restrictions have hindered the provision of emergency services [13, 18–20]. Emergency dispatch coordinators and decision-makers often make wrong decisions during natural disasters. The reason is that they rely excessively on their previous experience, are overconfident in their ability to make helpless decisions, and use simple decision heuristics [21, 22]. No relevant literature reports have been found regarding emergency scheduling in agricultural production.

Given that farmers could not organize agricultural production effectively at home in areas with COVID-19 outbreaks, an agricultural machinery operation scheduling model with the minimization of total scheduling cost as the optimization objective was established in this paper. With seizing the farming season and stabilizing production as the goal and the scheduling of tractors within the scope of town as the research object, influencing factors such as farmland area, agricultural machinery, farmland location information, and operating time window time were fully considered based on in-depth analysis of various agricultural machinery operation costs. The model solving method was designed through the improved SA algorithm. The tractor production scheme and scheduling path within the town are obtained to meet the requirements of the farmland operating time window, achieve the objective of total cost minimization, and accomplish the task of ensuring spring ploughing with high efficiency and cost-effectiveness.

2. Problem Description

In areas with the outbreak of COVID-19, it is not allowed to provide agricultural machinery services in different places across regions to reduce the flow and gathering of people. In areas with relatively less agricultural machinery, they can only try to improve the utilization efficiency of agricultural machinery resources through scientific scheduling so as not to miss any or fewer farming hours. All villages uniformly report production demand information to the town's agricultural station. The agricultural station organizes farmers who own agricultural machinery within the town to carry out production service operations. The service fee is settled by the town's agricultural station with each village in a unified manner. Agricultural machinery service households (AMSH) and farmers do not need to meet or do deals. The specific process is shown in Figure 1.

Farmers report the location, area, and operating time window of the farmland run by them to their village committee. Agricultural machinery service households report all tractor models, locations, and operating efficiency to their village committee. The village committee collects the order information based on the farmland location and time window and reports it to the town (township) agricultural station. The town's agricultural station uniformly formulates a scheduling scheme and sends it to the agricultural machinery service household. The tractors depart from their locations to the responsible areas according to the established scheme and route, providing farming services in turn.

3. Tractor Scheduling Model

The tractor scheduling issue can be expressed as follows: there are m individual entrepreneurs owning agricultural machinery. To avoid the gathering of machinery operators and farmers, the township government divides the whole township into n small operation areas according to the working needs. The farmland area of the i-th area is s_i, $i = 1, 2, \ldots, n$. The tractors should arrive within a certain time range $[\mathrm{ET}_i, \mathrm{LT}_i]$, that is, arrive no earlier than ET_i and leave no later than LT_i. When the tractor arrives earlier than ET_i, the waiting cost of agricultural machinery is caused by personnel wages and the profit loss of idle machinery. When the tractor arrives later than LT_i, it causes timely loss of crops. The route arrangement is made by solving the tractor operation with the lowest cost that meets the demand for spring ploughing within the township scope. The costs of spring ploughing operation include the cost of tillage and that of field transfer; the fixed cost of tractors is not considered yet. The specific model is as follows.

The operation area number is 1, 2, ..., N, and the parking yard number of farmers that own agricultural machinery is

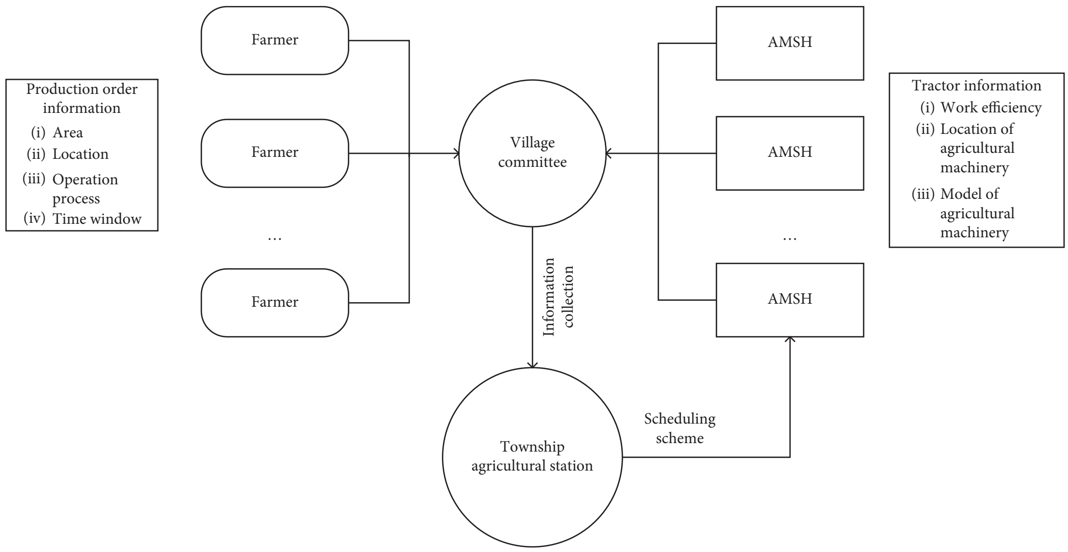

Figure 1: Flow chart of township agricultural machinery scheduling.

$N+1$, $N+2$, ..., $N+M$. The operation area and the parking yard numbers are both denoted by i and j.

i: the operation area and the parking yard numbers, $i = 1, 2, ..., \mathrm{N}, N+1, N+2, ..., N+M$

j: the operation area and the parking yard numbers, $j = 1, 2, ..., \mathrm{N}, N+1, N+2, ..., N+M$

k: tractor number, $k = 1, 2, \ldots, K$

dij: distance between points i and j

xijk: decision variable for tractor field transfer, indicating whether the k-th tractor travels from point i to point j. If so, *xijk* is 1; otherwise, its value is 0

yik: decision variable for tractor operation, indicating that if tractor k operates in operation area i, its value is 1; otherwise, its value is 0

si: area of the farmland in the i-th operation area

sik: operation area completed by tractor k in the i-th operation area

tijk: time taken by the k-th tractor to travel from point i to point j, equal to distance (*dij*) divided by speed (*vk*)

tik: time taken by tractor k to complete the tillage in the operation area i, equal to the operation area (*sik*) divided by the efficiency (*wk*)

$\check{t}_{ik}$: moment when tractor k arrives at the operation area i

$\hat{t}_{ik}$: moment when tractor k completes the task of tillage and soil preparation in the operation area i

PEk: waiting cost to be paid due to tractor k arriving earlier than ETi

PLk: penalty for timeliness loss to be paid due to tractor k completing work later than LTi

ρk: cost per kilometer traveled by tractor k for the field transfer

φk: operating cost per unit area of tractor k

3.1. Objective Function

$$\begin{aligned}\min Z = {} & \sum_{k=1}^{K}\sum_{i=1}^{N+M}\sum_{j=1}^{N+M}\rho_k x_{ijk} d_{ij} + \sum_{k=1}^{K}\sum_{i=1}^{N}\varphi_k y_{ik} s_{ik} \\ & + \sum_{k=1}^{K}\sum_{i=1}^{N} P_{Ek} y_{ik}\max\left(ET_i - \check{t}_{ik}, 0\right) \\ & + \sum_{k=1}^{K}\sum_{i=1}^{N} P_{Lk} y_{ik}\max\left(\hat{t}_{ik} - LT_i, 0\right).\end{aligned} \quad (1)$$

3.2. Constraints

$$x_{ijk}\left(\check{t}_{jk} - \check{t}_{ik}\right) \geq 0, \quad i, j = 1, 2, \ldots, N, N+1, \ldots, N+M; \quad k = 1, 2, \ldots, K, \quad (2)$$

$$\hat{t}_{ik} = \check{t}_{ik} + t_{ik}, \quad i = 1, 2, \ldots, N; \quad k = 1, 2, \ldots, K, \quad (3)$$

$$\sum_{i=N+1}^{N+M}\sum_{j=1}^{N}\sum_{k=1}^{K} x_{ijk} \leq K, \quad (4)$$

$$\sum_{k=1}^{k} y_{ik} s_{ik} = s_i, \quad i = 1, 2, \ldots, N, \quad (5)$$

$$t_{ik} = \frac{s_{ik}}{w_k}, \quad i = 1, 2, \ldots, N; \quad k = 1, 2, \ldots, K, \quad (6)$$

$$\sum_{i=1}^{N+M} x_{ijk} = y_{jk}, \quad j = 1, 2, \ldots, N; \quad k = 1, 2, \ldots, K, \quad (7)$$

$$\sum_{j=1}^{N+M} x_{ijk} = y_{ik}, \quad i = 1, 2, \ldots, N; k = 1, 2, \ldots, K. \tag{8}$$

In the model, equation (1) is the objective function, which indicates the minimal total cost required to complete all spring ploughing tasks in the township area, including field transfer costs, operating costs, and penalties for timeliness loss. Inequality (2) constrains the tractor traveling sequence; that is, when transferring from point i to point j, the time of arrival at point j must be later than that at point i. Equation (3) shows the relationship between the tractor arrival time and the operation completion time. Inequality (4) stipulates that the number of tractors dispatched from the parking yard of individual entrepreneurs owning agricultural machinery cannot exceed the total number of tractors. Equation (5) stipulates that all plots in the operation area must be tilled. Equation (6) shows the relationship between tractor operation time and efficiency. Equation (7) indicates that if tractor k works at point j, then tractor k must move from point i to point j. Equation (8) indicates that if tractor k works at point i, tractor k must move to other points j after finishing work at point i.

4. Design of Scheduling Algorithm Based on Simulated Annealing (SA)

Agricultural machinery scheduling to ensure spring ploughing during an epidemic is a typical NP-hard problem. As the operation space size ($(n-1)!$) shows a factorial increase, the exact solution cannot be obtained through the exhaustive method [23], dynamic programming [24, 25], linear programming [26], branch and bound [27, 28], and other precise algorithms for large-scale problems. With the development of computers, many intelligent optimization algorithms have emerged in the field of artificial intelligence, such as the genetic algorithm [29–31], tabu search algorithm [32], ant colony algorithm [33], particle swarm optimization algorithm [34], simulated annealing algorithm [35, 36], online-learning algorithm [37], adaptive polyploid memetic algorithm [38], many-objective evolutionary algorithm [39], and salp swarm algorithm [40]. Among them, the idea of simulated annealing algorithm (SA) is derived from simulating the cooling process of solid annealing, that is, heating the solid to a sufficiently high temperature, then allowing it to cool down slowly to balance the internal energy, avoid falling into local minimum effectively, and eventually tend to a global optimum.

4.1. Solution Coding. Based on the characteristics of the agricultural machinery job scheduling problem and related research, the solution coding can adopt a two-layer coding method, as shown in Figure 2.

The first-level code is the sorting of farmland, and the order of farmland in the entire coding is the service order of farmland orders. As shown in Figure 2, $F1$~Fn are farmland operation orders, and the operation areas are sorted according to the starting work time ET_i to study the serial and parallel issues between the operation areas. The operation is executed sequentially in the serial operation areas and in a parallel way in the parallel operation areas. The second-level code is the order of tractors in the farmland. For example, the tractor operating in the $F1$ farmland is $M11$, $M12$, and $M13$, and the tractor operations in the same farmland are in no particular order. The number of tractors required for the farmland operating site is the local code length of the farmland operating site. Assuming that F_i in the i-th area is coded, the maximum quantity of agricultural machinery required for F_i is $K_i = s_i/\min w_k (\mathrm{LT}_i - \mathrm{ET}_i)$, and M_{iKi} represents the K_i-th tractor in the i-th area. Now, partial coding is performed on F_i.

4.2. Initial Solution Settings. The initial solution is the starting point of algorithm iteration. The selection quality of the initial solution can improve the computational efficiency of the algorithm and enhance the reliability of the final solution. In this paper, the following three directions are mainly considered in setting the initial solution of the algorithm: (1) priority is given to the operation area with an early harvest time window; (2) the minimum number of tractors that can meet the production capacity requirements are arranged in each area; (3) when tractors are allocated to the operation area, idle tractors or those that can reach the target area faster are arranged first.

According to the above coding strategy, the initial solution of the SA algorithm is generated. The specific steps are as follows:

Step 1: establish the task set of the operation area and schedule the work sequence according to the direction I to build the operating agricultural machinery depot set

Step 2: determine whether the task set of the operation area is empty. If so, go to step 5; otherwise, go to step 3

Step 3: allocate tractors to area tasks according to directions II and III

Step 4: go to Step 2

Step 5: the initial scheduling scheme matching is completed

4.3. Domain Generation Rules. The neighborhood generation rule in the SA algorithm is crucial. When the initial solution is generated, what rules are used to generate a new solution is related to whether the whole algorithm can be effectively performed to achieve the goal. For this issue, it is about how to generate a new scheme based on an existing scheduling scheme for further judgment. The commonly used neighborhood generation strategy of 2-opt mapping is used in this paper to generate a new scheduling scheme. Two vertices p and q are randomly selected. Assuming $p < q$, tractor code (p, p+1,. . ., q−1, q) is reversed. The details are shown in Figure 3.

4.4. Acceptance Probability of New Solutions. Acceptance probability is the probability of accepting a new feasible solution P_{new} (another state) to replace the current feasible

<table>
<tr><td colspan="3">F_1</td><td colspan="4">F_2</td><td colspan="3">…</td><td colspan="4">…</td><td colspan="3">F_n</td></tr>
<tr><td>M_{11}</td><td>M_{12}</td><td>M_{13}</td><td>M_{21}</td><td>M_{22}</td><td>M_{23}</td><td>M_{24}</td><td>…</td><td>M_p</td><td>M_{p+1}</td><td>…</td><td>M_{q-1}</td><td>M_q</td><td>…</td><td>M_{n1}</td><td>M_{n2}</td><td>M_{n3}</td></tr>
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Figure 2: Solution coding.

<table>
<tr><td colspan="3">F_1</td><td colspan="4">F_2</td><td colspan="3">…</td><td colspan="4">…</td><td colspan="3">F_n</td></tr>
<tr><td>M_{11}</td><td>M_{12}</td><td>M_{13}</td><td>M_{21}</td><td>M_{22}</td><td>M_{23}</td><td>M_{24}</td><td>…</td><td>M_p</td><td>M_{p+1}</td><td>…</td><td>M_{q-1}</td><td>M_q</td><td>…</td><td>M_{n1}</td><td>M_{n2}</td><td>M_{n3}</td></tr>
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$\downarrow$

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<tr><td colspan="3">F_1</td><td colspan="4">F_2</td><td colspan="3">…</td><td colspan="4">…</td><td colspan="3">F_n</td></tr>
<tr><td>M_{11}</td><td>M_{12}</td><td>M_{13}</td><td>M_{21}</td><td>M_{22}</td><td>M_{23}</td><td>M_{24}</td><td>…</td><td>M_q</td><td>M_{q-1}</td><td>…</td><td>M_{p+1}</td><td>M_p</td><td>…</td><td>M_{n1}</td><td>M_{n2}</td><td>M_{n3}</td></tr>
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Figure 3: 2-opt mapping diagram.

solution P_{old} (current state). It is not fixed but decreases as the temperature parameter T drops. Metropolis criterion is generally adopted:

$$\begin{cases} 1, & Z(P_{\text{new}}) < Z(P_{\text{old}}), \\ \exp\left(-\dfrac{Z(P_{\text{new}}) - Z(P_{\text{old}})}{T}\right), & Z(P_{\text{new}}) > Z(P_{\text{old}}). \end{cases} \tag{9}$$

4.5. Temperature Attenuation Function. The temperature attenuation function is also known as the cooling strategy. The common exponential cooling strategy selected in this paper is $T_{m+1} = \alpha T_m$. In the formula, α is the temperature attenuation index, $0 > \alpha < 1$, and m is the number of temperature drops.

4.6. Stop Criterion. A reasonable stop criterion can not only ensure that the algorithm converges to an approximate solution but also make the final solution global to some extent. The SA algorithm includes inner- and outer-loop stops. In this paper, the fixed iteration step size is adopted for the inner loop, and the temperature reaching the termination threshold is adopted for the outer loop to exit the iteration.

4.7. Algorithm Flow. According to the tractor production scheduling model and solution coding, the simulated annealing algorithm process is designed as shown in Figure 4.

(1) Randomly generate an initial solution X_0, let $X_{best} = X_0$, and calculate the objective function value $Z(X_0)$; set the initial temperature $T(0) = T_0$ and the number of iterations $i = l$.

(2) Do while $T > T_{min}$.

For $i = 1$ to m (m is the number of cycles, which is related to the township scale).

For the current optimal solution P_{best} neighborhood function, generate a new solution P_{new}, calculate the new objective function value $Z(P_{new})$, and calculate the increment $\Delta Z = Z(P_{best})$- $Z(P_{new})$ of the objective function value.

If $\Delta Z < 0$, then $Z_{best} = Z_{new}$; if $\Delta Z > 0$, then $p = \exp(-\Delta Z/T)$.

If $c = \text{random } [0, 1] < p$, Pbest = Pnew; otherwise, Pbest remains unchanged.

end for.

$i = i + 1$.

End Do.

5. Example Verification

In this paper, Hushu Street, Jiangning District, Nanjing City, is taken as an example. Located at the junction of Jiangning, Jurong, and Lishui, Hushu Street is a typical suburban town, where mainly grains, vegetables, and fruits are planted, with a relatively complicated planting structure. In the season for spring ploughing before the epidemic, Hushu will attract agricultural machinery from the surrounding counties and cities to carry out operation services. However, due to the impact of the epidemic this year, agricultural machinery from other places cannot enter Hushu Street, and spring ploughing production can only be ensured through scientific scheduling of local agricultural machinery. We divided the farmland in Hushu Street into 13 operation areas on Google Earth (blue markers in Figure 5) and marked four agricultural machinery cooperatives in Hushu Street (red markers in Figure 5); distribution and area of farming sites are shown in Supplementary Table 1, distribution and machine information of agricultural machinery cooperatives is shown in Supplementary Table 2; distance matrix between

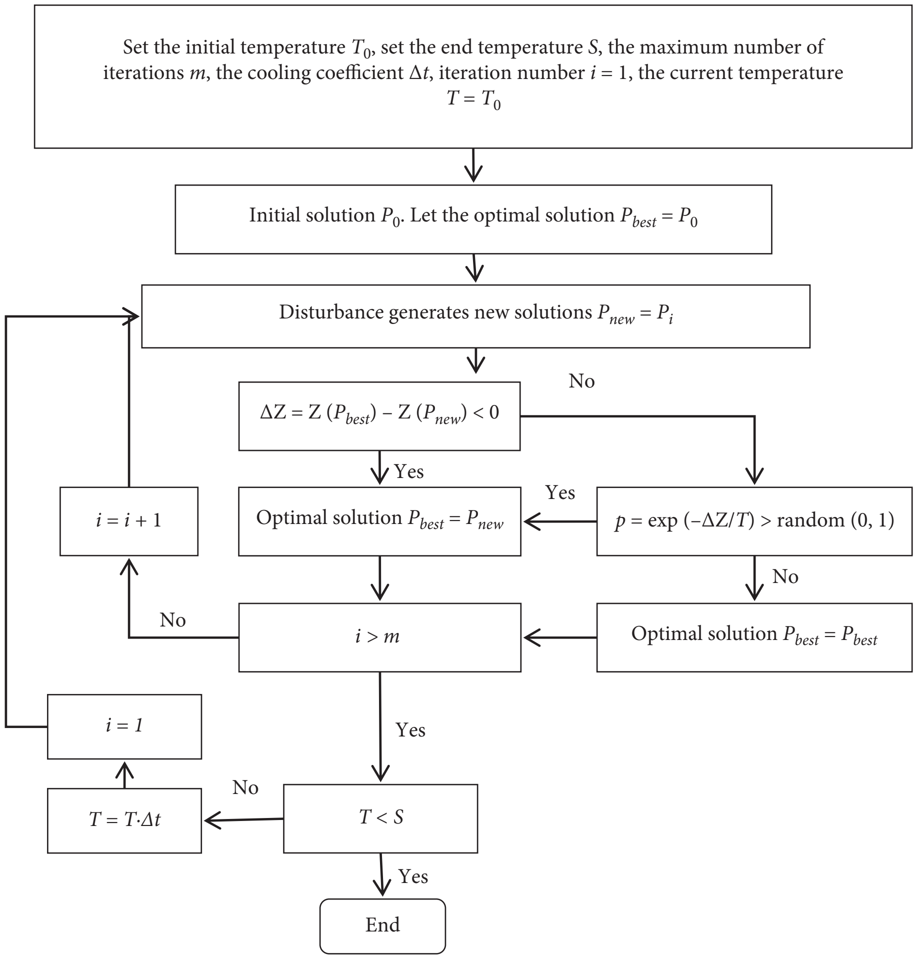

Figure 4: Algorithm flowchart.

farming sites and cooperatives is shown in Supplementary Table 3. The tractors of the cooperatives were all 80 horsepower. The average operating efficiency is $0.5\,\text{hm}^2/\text{h}$, the operating cost is 300 yuan/hm^2, the average transfer speed is 35 km/h, the transfer cost is 2 yuan/km, the waiting cost is 42 yuan/h, and the timely loss cost coefficient 5.4 yuan/h.

5.1. Example Calculation Results. In the actual production scheduling, farm management personnel usually adopt the three strategies mentioned in Section 4.2 for agricultural machinery and farmland matching and generate empirical scheduling solutions, which can be further optimized using the optimization algorithm in this paper. To further illustrate the superiority of the algorithm designed in this paper, the GA algorithm commonly used in the research of similar agricultural machinery scheduling issues is applied to comparison experiments. On a personal computer with Intel Core i5 CPU 3.0 GHz, 8.0 GB memory, and Windows 10 operating system, Matlab *R*. 2018a software programming is used to implement three algorithms to solve real cases 20 times, respectively. The calculation results are shown in Table 1.

Figure 5: Distribution map of example operation areas.

Table 1 shows that compared with the empirical scheduling algorithm, GA and SA algorithms can reduce the total cost of agricultural machinery significantly. The total cost of the scheduling scheme generated by SA designed in

Table 1: Scheduling schemes solved by 3 algorithms.

Scheduling algorithm	Total cost (yuan)	Transfer cost (yuan)	Waiting cost (yuan)	Delay cost (yuan)
Empirical scheduling algorithm	642,565.23	291.4	19,317.12	498
Scheduling algorithm based on GA	623523.16	310.54	161.45	593.17
Scheduling algorithm based on SA	622743.97	274.43	0	11.54

The solution of the scheduling algorithm based on SA and GA is the mean of 20 operations.

this paper is 19,042.07 yuan lower than that by the empirical scheduling algorithm and 779.19 yuan lower than that by GA on average. Compared with GA, the transfer distance, waiting cost, and delay cost of SA are reduced by 11.6%, 100%, and 98.1% on average, indicating that the transfer distance of agricultural machinery in the scheduling scheme generated by SA is shorter, so is the waiting and delay time.

Figure 6 shows the total cost of solving real cases 20 times by GA and SA, respectively. It can be seen that the total cost of the scheduling scheme obtained by SA is generally lower than that by GA. The standard deviation of the 20 scheduling schemes obtained by SA is 35.78, while that of various scheduling schemes obtained by GA is 1424.08, indicating that the solution obtained by SA has superior quality and higher stability. This is because SA uses the initial solution generation algorithm, with a good start for the optimization process. Moreover, based on the Metropolis criterion, the SA algorithm can avoid being trapped in local minima and implement full optimization, whereas the GA algorithm is prone to get stuck in local minima when handling such complex scheduling problems. The experimental results suggest that the agricultural machinery operation scheduling model based on the SA algorithm in this paper can satisfy the time window constraints with the lowest total cost and meet the spring ploughing scheduling demand in practice.

The scheduling algorithm based on SA designed in this paper can be used to solve the agricultural machinery transfer paths of various agricultural machinery cooperatives, as shown in Figure 7. Among them, the transfer paths of some agricultural machinery in the same cooperative are overlapped, such as agricultural machinery No. 1, 2, and 3 in the cooperative N1, and agricultural machinery No. 10 and 11 in the cooperative N2. In addition, the cooperation of different cooperatives in agricultural machinery to complete orders is observed. For example, order 13 is jointly completed by agricultural machinery No. 4 and 15, which suggests that the algorithm designed in this paper can implement unified scheduling of agricultural machinery in the same cooperative and collaboration among different cooperatives to meet the needs of multimachinery coordinated scheduling of multiple cooperatives in reality. Meanwhile, it can be seen intuitively from the transfer path diagram 6 that the order tasks assigned to each agricultural machinery have spatial proximity, indicating the rationality of the experimental results.

The scheduling Gantt chart of the tractor is shown in Figure 8. The bars in the chart represent the operation scheme of each fleet, including the operation order number, operation start time, and operation ending time, which can be used for specific guidance of actual production scheduling.

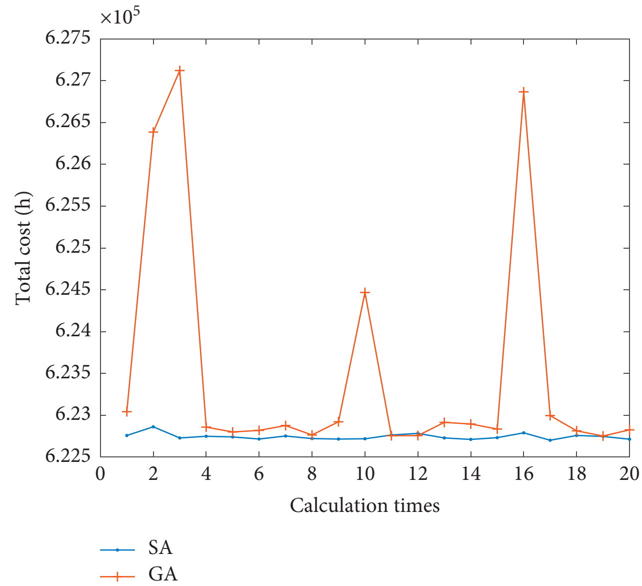

Figure 6: Total cost of solving real cases 20 times by different algorithms.

5.2. Algorithm Convergence. The change in the optimal value of each cost in the operation process is shown in Figure 9. The total cost, the total length of transfer path, waiting time, and delay time decrease as the number of iterations increases. The total cost can converge to a stable value when the number of iterations is increased to about 350; the delay and waiting time can converge to 0 within 50 iterations. The calculation results suggest that the algorithm can achieve stable convergence with relatively search performance.

5.3. Algorithm Stability and Adaptability. The stability of the algorithm is an important index for evaluating whether the scheduling algorithm can stably obtain a scheduling scheme with relatively good quality. It is usually measured by parameters such as mean, standard deviation, and coefficient of standard deviation [41]. At the same time, a case set containing 13, 26, 39, 52, and 65 orders is constructed based on the case data of Hushu Street to test the adaptability of the SA algorithm designed in this paper to the application scenarios with relatively larger order scales. The algorithm is run 10 times for each case set. Statistical comparison is performed on the mean, standard deviation, and standard deviation coefficient of the computing time and total cost of different cases to test the stability and adaptability of the algorithm. The experimental results are shown in Table 2.

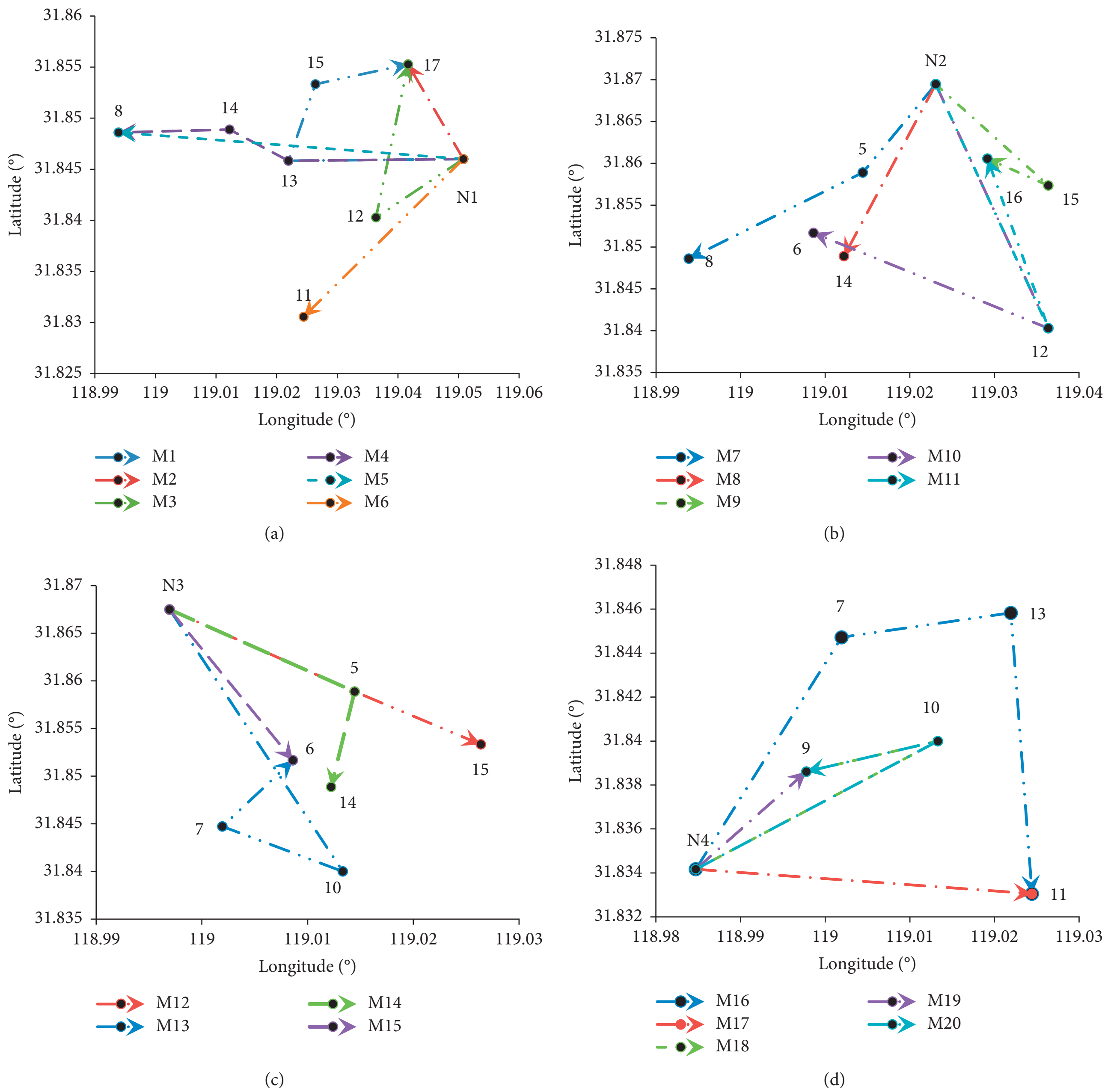

Figure 7: Transfer path diagram of agricultural machinery in each cooperative: (a) N1, (b) N2, (c) N3, and (d) N4.

Table 2 shows that when the number of orders in the case increases, the standard deviation is not multiplied, and the coefficients of standard deviation are all less than 10^{-5}. The experimental results suggest that the algorithm designed in this paper has relatively good stability. When the number of orders increases to 52, the computing time is not significantly increased but still remains within 30 seconds. The results suggest that the algorithm designed in this paper can adapt to larger-scale case operations. However, when the number of orders increases, the computing time is not significantly increased. The main reason is that when the number of orders increases, the operation area per order will decrease, and the quantity of agricultural machinery allocated to each order will decrease, which objectively reduces the complexity of the problem.

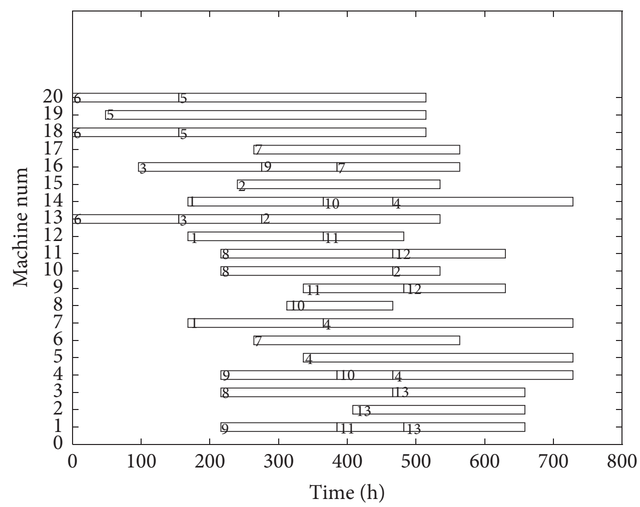

Figure 8: Gantt chart for scheduling.

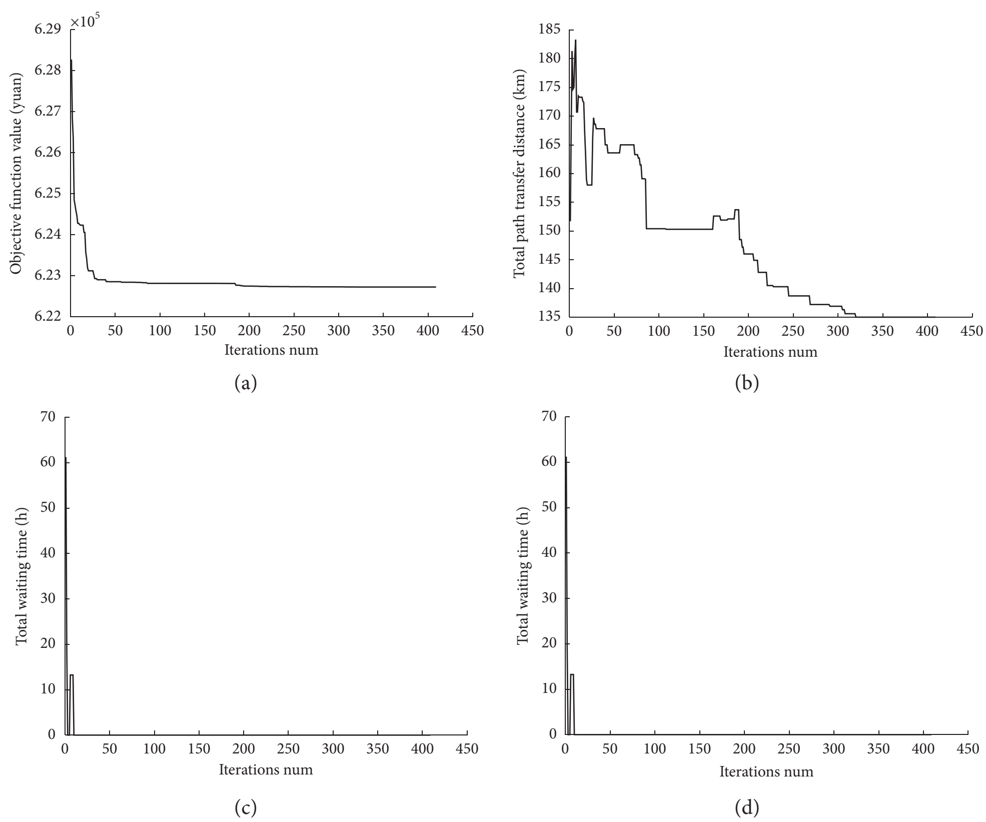

Figure 9: Iterative graph of various parameters: (a) total cost; (b) path transfer distance; (c) waiting time; (d) delay time.

Table 2: Experimental table of algorithm stability and adaptability.

Number of orders	Optimization objective function value			Computing time		
	Mean (yuan)	Standard deviation	Coefficient of standard deviation	Mean (s)	Standard deviation	Coefficient of standard deviation
13	622747.21	37.683	$6.05 * 10^{-6}$	19.1828948	5.455	0.2843
26	622754.32	51.056	$8.19 * 10^{-5}$	28.22606211	5.306	0.1879
39	622719.42	23.058	$3.70 * 10^{-5}$	23.4133504	6.220	0.2656
52	622773.65	15.248	$2.44 * 10^{-5}$	23.6478746	5.439	0.2300

6. Conclusions

(1) The agricultural machinery scheduling in the major epidemic to ensure spring ploughing is taken as the research object to analyze various costs of agricultural machinery scheduling and establish agricultural machinery operation scheduling model with the minimum total scheduling cost as the optimization objective. Factors such as farmland area, agricultural machinery, and farmland location information and operating time window are considered in this model to improve the accuracy of the agricultural machinery operation scheduling model.

(2) Agricultural machinery scheduling to ensure spring ploughing during an epidemic is a typical NP-hard problem. Through the comprehensive analysis of the characteristics of multiple scheduling algorithms, combined with the scheduling requirements of agricultural machinery operation to ensure spring ploughing, agricultural machinery scheduling algorithm based on the SA algorithm is designed. The farmland and tractor coding method is determined by two-level multilayer coding. The neighborhood generation strategy of 2-opt mapping is used to generate a new scheduling scheme, and the new solution acceptance mechanism is determined based on the Metropolis criterion. The fixed compensation is used for the inner loop of the algorithm, and the iteration ends when the threshold temperature is reached.

(3) With Hushu Street, Jiangning District, Nanjing City, as an example, a comparative experiment is conducted on the SA algorithm designed in this paper and the empirical and GA algorithms. The results suggest that the total cost of the scheduling scheme generated by the SA algorithm designed in this paper is 19,042.07 yuan lower than that by the empirical scheduling algorithm and 779.19 yuan lower than that by the genetic algorithm on average. Compared with the GA algorithm, the transfer distance, waiting cost, and delay cost of the SA algorithm are reduced by 11.6%, 100%, and 98.1% on average, indicating that the transfer distance of agricultural machinery in the scheduling scheme generated by the SA algorithm is shorter, so is the waiting and delay time. Meanwhile, it can effectively obtain the near-optimal solution that meets the time window constraint, with good convergence, stability, and adaptability.

(4) This paper does not consider unexpected situations such as infection of tractor drivers and road blockades that may occur during the epidemic. In future research, we will focus on the impact of unexpected conditions on agricultural machinery scheduling and carry out research on agricultural machinery dynamic scheduling.

Data Availability

The example data used to support the findings of this study are included within Supplementary Tables 1–3, mainly including the location of farmland in the case area, the location of cooperatives, and the parameters of agricultural machinery.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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Supplementary Materials

There are 3 tables in the supplementary materials of this paper. Supplementary Table 1: distribution and area of farming sites in Hushu Street, which mainly contains the location, area, and operation time window of farming sites. Supplementary Table 2: distribution and machine information of agricultural machinery cooperatives in Hushu Street, which mainly includes the location of the cooperatives, the number of tractors, and the main parameters of the tractors. Supplementary Table 3: distance matrix between farming sites and cooperatives in Hushu Street. (*Supplementary Materials*)

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Research Article

Optimal Strategies of Retailers Facing Potential Crisis in an Online-to-Offline Supply Chain

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We confine our interest to the O2O (online-to-offline) supply chain system consisting of an online retailer and an offline retailer. Given that the brand they sell may encounter a brand crisis that will damage the goodwill, we formulate an O2O supply chain model with the impact of random crisis to explore the countermeasures of retailers when facing a potential crisis. After analysis, we find the following: (1) The crisis happened earlier with the increase of hazard rate and retailers should lower their investment in the precrisis stage. (2) The existence of crisis divides the whole planning period into two phases and make retailers have different phase preference in different scenarios. In a word, retailers will pay more attention to the postcrisis stage with the increase of hazard rate and damage rate and therefore invest more in the postcrisis stage. (3) Crisis will decrease the investment level of retailers and therefore make the goodwill and profits lower than when there is no crisis.

1. Introduction

It is evitable for any company to encounter a brand crisis in the operation process. On the one hand, the crisis may be related to quality issues. For example, Volkswagen recalled almost four hundred thousand defective vehicles in China for its potential risk in DSG gearbox in 2013. Samsung suffered a tremendous loss in sales due to many reported explosion events of Galaxy note 7 for a fatal defect in the battery. On the other hand, the brand crisis may be triggered by illegal behavior or failing to fulfill social responsibility. See what happened to GE when their financial scandal was disclosed. Sometimes, the crisis is not due to the company's certain behavior but, for example, caused by the negative image of the endorser of the brand. This kind of event that occurs randomly and unexceptionally will inflict damage on the goodwill, sale, and profitability of the company.

Hence, farsighted companies cannot afford to ignore the likelihood and possible consequence of the crisis when making their decisions especially when the O2O pattern is gaining prevalence and the crisis may cause wider influence. O2O supply chain is a novel business pattern integrating both online and offline channels to provide consumers with a product as well as a superior shopping experience and cater for various channel preferences. Hence, in the O2O pattern, the products are sold simultaneously through online and offline channels and both channels will suffer from the crisis. In this sale system, the online retailer will popularize the products by means of advertisement on the online platform and the offline retailer will offer service to further win customers. However, the goodwill accumulated by their marketing tools may be damaged by the crisis mentioned and therefore make the investments of retailers less efficient. Hence, the retailers are forced to consider the following questions: (1) what they should do to respond to the crisis and (2) how should they adjust their investments when the hazard rate or the damage rate rises. To answer these questions, we formulate and analyze an O2O supply chain model with a random brand crisis in order to provide insights to retailers envisioning crisis.

Three streams of literature are closely related to our research: (1) study of dual-channel or O2O supply chain and showrooming; (2) study of stochastic differential game; and (3) study of brand crisis. The first related stream concerns the study of dual-channel and O2O supply chain. Dumrongsiri et al. [1] incorporate the service into the study of dual-channel supply as a marketing tool to gain the preference of customers and their analyses show that the service in the offline channel can benefit both online and offline channels. Yan and Pei [2] study the influence of offline service strategy on the decision-making of supply chain members and their results show that the elevation of offline service can help to lower wholesale price and enhance the total performance of the supply chain system. Dan et al. [3] concentrate on the service and pricing strategies of supply chain members and their results show that offline service exerts tremendous influence on pricing strategy and customers' channel loyalty also dictates. The studies mentioned above all note that offline service has a crucial role in the dual-channel supply chain but they fail to incorporate the showrooming effect into their study. He et al. [4] consider the phenomenon into their modeling of the channel demand. Showrooming, by definition, is the phenomenon that customers use the offline store to browse and experience the products but finally buy online according to [5–7]. Essentially, the existence of this effect forces the demand generated by offline service to transfer from offline channel toward the online channel. Given that this phenomenon is ubiquitous, we incorporate this effect into our model. In this paper, we assume that the online and offline channels sell homogeneous products and we mainly focus on the decision-making problem of retailers when they envision the brand crisis. The goodwill established by advertising and service will be damaged in the crisis and the dynamic of goodwill is different from that before the crisis. Hence, we introduce the stage state variable to depict pre- and postcrisis stages and use the modified Nerlove-Arrow model to describe the evolution of goodwill during the whole planning period. Based on the studies above, we formulate the basic O2O model with the showrooming effect as a foundation to further study the effect of the crisis.

In the study of the stochastic differential game, Prasad and Sethi [8] focus on the stochastic cooperative advertising strategies. Jiang et al. [9] and Fu et al. [10] tackle the pollution control problems based on the stochastic differential game. All of these researches study the uncertainty by introducing the Wiener process to explore and analyze the optimal strategies. However, the Wiener process is desirable to depict small and discrete shocks whose net impacts, on average, are zero. But the crisis occurs randomly and discontinuously and its average impact on goodwill is not zero. Hence, the Wiener process is undesirable to represent the discrete crisis event. Hence, in this paper, we use the random occurrence process to depict this kind of uncertainty caused by a rarely happening crisis. We then incorporate this process into the dynamic O2O pattern to study the optimal strategies of retailers when facing the crisis.

Another stream of literature is about the study of brand crisis. Heerde et al. [11] find that the crisis not only damages the reputation and brand equity of the company but also will attenuate the effectiveness of its marketing effort. This is because the occurrence of the crisis may let the customers feel betrayed and may have the image of customers formed before the change. Meanwhile, his opponents may take advantage of the crisis and add fuel to the fire. Similarly, MacKenzie and Lutz [12] argue that if the customers lose faith in the brand, they will also become dubious to its advertising. Ahluwalia [13] also holds that once the negative publicity of the brand is exposed to customers, they will become more resistant to the advertising trying to convince them. Furthermore, unsatisfactory customers may share their unpleasant experiences with other customers and make them less friendly to the brand according to Ouardighi et al. [14]. Zhao et al. [15] prove that the sensitivity of customers to the brand will be lowered after the crisis. In a word, the crisis will make it hard for the company to retain and win customers. Hence, we take this point into consideration when formulating the model by making the influence parameters after the crisis lower than those before the crisis.

Based on the researches mentioned above, we formulate a dynamic O2O supply chain model with a stochastic crisis to explore the decision problems of the retailers when facing a potential crisis. The rest of the paper is arranged as follows: we formulate the model and offer corresponding assumptions in Section 2; we solve and analyze the optimal strategies in Section 3; we conduct comparison analysis in Section 4; we use a numerical example to analyze and exhibit the outcomes deduced before; Section 5 concludes the whole paper.

2. Model Formulation

2.1. Channel Demand with Showrooming Effect. This paper studies an O2O supply chain system composed of an online retailer and an offline retailer. The online retailer utilizes the e-commercial platform to advertise the products through nationwide advertising, the level of which is represented by $A_E(t)$. While the offline retailer is closer to consumers and therefore will offer local service, the level of which is represented by $S_R(t)$, to further win consumers' preference. Hence, the brand goodwill is affected by both online retailer's advertising and offline retailer's service strategies and the dynamics of brand goodwill can be described as follows:

$$\begin{aligned} \dot{G}(t) &= \gamma A_E(t) + \zeta S_R(t) - \delta G(t), \\ G(0) &= G_0 > 0, \end{aligned} \tag{1}$$

where $G(t)$ represents the goodwill of the brand and $G_0 > 0$ represents the initial goodwill level. $\gamma > 0$ and $\zeta > 0$ measure the influence of advertisement and service on goodwill, respectively. $\delta > 0$ represents the decay rate of goodwill. Equation (1) depicts the dynamics of goodwill and manifests the influence of supply chain members' strategies. The reason why we use the dynamic model is that it can capture the dynamic process of recognition of customers to a certain brand. It takes time for consumers to finally accept and purchase the product, while the static model fails to depict the process. Furthermore, the other important reason for using the dynamic model is that it can also model the impact of the crisis. The goodwill may drop and evolve in a different way after the crisis.

Then, we will establish the demand for online and offline channels based on the showrooming phenomenon. According to the analysis above, the showrooming effect refers to the situation that consumers browse and experience goods in brick-and-mortar stores but buy them online afterward. Inspired by Mehra et al. [7], we divide the consumers into three groups to analyze the demand of both channels. The first group, denoted by $D_1(t)$, refers to the consumers who choose to buy products online directly. The second group denoted by $D_2(t)$ refers to the consumers who experience the products in offline stores but finally purchase them online. The third group, denoted by $D_3(t)$, refers to the consumers who choose to buy products in the offline store after experiencing the products. The significance of categorizing consumers is to reveal the essence of the showrooming effect-a critical factor affecting the division of demand between channels. The more influential the effect is, the more consumers choose to browse offline and buy online. The amount of three groups combines to determine the channel demand.

Since the first group of consumers do not visit the offline stores, the quantity of them is only related to advertising and the level of goodwill. However, since not all consumers are attracted by advertising and goodwill buys products online directly, we assumed that the first group of consumers account for α of the total numbers caused by advertising and goodwill. The other $1-\alpha$ proportion of consumers choose to experience products offline first and then make decisions. The second and third groups will first go to offline stores to experience products, so their quantities are also affected by the service efforts of offline retailers. However, the second type of consumers ultimately chooses to buy online, while the third type of consumers chooses to buy in the offline store. Assume that the proportion of the second type and the third type of consumers is π and $1-\pi$, respectively. Therefore, according to the above analysis, the number of three groups of consumers is

$$\begin{aligned} D_1(t) &= \alpha\left[\beta A_E(t) + \theta G(t)\right],\\ D_2(t) &= \pi(1-\alpha)\left[\beta A_E(t) + \theta G(t)\right] + \pi\eta S_R(t),\\ D_3(t) &= (1-\alpha)(1-\pi)\left[\beta A_E(t) + \theta G(t)\right] + (1-\pi)\eta S_R(t), \end{aligned} \tag{2}$$

where $\beta > 0$, $\eta > 0$, and $\theta > 0$ measure the efficacy of advertising, service, and goodwill on demand, respectively. α denotes the channel preference parameter and π denotes the showrooming parameter. The specific composition of channel demand is shown in the following figure.

Adding D_1 and D_2, we can get the demand of online channel D_E.

$$D_E = \left[1-(1-\alpha)(1-\pi)\right]\left[\beta A_E(t) + \theta G(t)\right] + \pi\eta S_R(t). \tag{3a}$$

Then the demand for offline retail channel D_R is

$$D_R = (1-\alpha)(1-\pi)\left[\beta A_E(t) + \theta G(t)\right] + (1-\pi)\eta S_R(t). \tag{3b}$$

We make $\mu = (1-\alpha)(1-\pi)$ in the following analysis for clarity.

In addition, by observing the expressions of $D_E(t)$ and $D_R(t)$, we can find that the total demand of the market is determined by three aspects which are goodwill, advertising, and service. We can also find that the value of online channel preference and showrooming parameters jointly determines the distribution of the total demand between online and offline channels and the change of the parameters actually reflects the transfer of demand between channels. Obviously, the demand for the online channel will increase if the two parameters increase.

2.2. Occurrence Process of Crisis. Next, we will incorporate the crisis occurrence into our study. For the sake of simplicity, we assume that the crisis just happens once at a random moment T with hazard rate χ. The occurrence process of crisis can be described by the following model:

$$\lim_{\Delta t \longrightarrow 0} \frac{P\{t \le T < t + \Delta t | T \ge t\}}{\Delta t} = \chi. \tag{4}$$

The conditional probability in equation (4) means the probability that a crisis does not occur before time t but occurs within the time interval $[t, t+\Delta t)$. Let $f(t)$ and $F(t)$ be probability density function and probability distribution function, respectively. Then the conditional probability in equation (4) can be written as

$$\begin{aligned} &\lim_{\Delta t \longrightarrow 0} \frac{P\{t \le T < t + \Delta t | T \ge t\}}{\Delta t}\\ &\quad = \lim_{\Delta t \longrightarrow 0} \frac{\left(\left(F(t+\Delta t) - F(t)\right)/\left[1-F(t)\right]\right)}{\Delta t} = \frac{\dot{F}(t)}{1-F(t)} = \chi. \end{aligned} \tag{5}$$

By solving the differential equation above, we can get $f(t) = \chi e^{-\chi t}$ and $F(t) = 1 - e^{-\chi t}$. Hence, we can find that the probability of the crisis occurring before time T turns out to be $P\{t \le T\} = 1 - e^{-\chi T}$. Apparently, the greater the hazard rate χ is, the greater the $P\{t \le T\}$ is, indicating that the crisis occurs earlier. Meanwhile, we can also find that the expected value of occurrence time is $E(t) = (1/\chi)$. In addition, we can infer from equation (4) that the probability of crisis is objective. Once certain products are launched, supply chain members cannot control their value but only have to accept them passively. This assumption is consistent with the research of Thirumalai and Sinha [16] which believes that the potential risk of serious events such as brand crisis actually existed before the product was launched. Therefore, supply chain members must estimate the possibility of crisis objectively and make the corresponding adjustment to properly respond to the potential crisis.

The existence of crisis divides the whole planning period into two phases which are precrisis and postcrisis phases. Since the crisis will damage the goodwill at the occurrence time, the goodwill will be no longer continuous during the planning period.

$$G(T^+) = (1-\phi)G(T^-), \tag{6}$$

where ϕ represents the damage rate of goodwill. $G(T^+)$ and $G(T^-)$ represent the goodwill levels just after and right before the crisis event, respectively. A higher damage rate implies more loss in goodwill accumulated before crisis. Furthermore, the occurrence of the crisis may weaken the influence of marketing activities on the goodwill and therefore make them less efficient on the establishment of the goodwill. Thus, the dynamics of goodwill evolve in different ways in precrisis and postcrisis phases which can be described as follows:

$$\begin{cases} \dot{G}_1(t) = \gamma_1 A_E(t) + \zeta_1 S_R(t) - \delta_1 G_1(t), & G_1(0) = G_0, 0 \le t < T, \\ \dot{G}_2(t) = \gamma_2 A_E(t) + \zeta_2 S_R(t) - \delta_2 G_2(t), & G_2(T^+) = (1-\phi)G_1(T^-), T \le t, \end{cases} \tag{7}$$

where $\gamma_1 \ge \gamma_2$, $\zeta_1 \ge \zeta_2$, and $\delta_1 \le \delta_2$ which indicate that, in the postcrisis phase, the influences of advertising and service on goodwill are lower than those before the crisis and the degree of consumers' forgetting is higher than that before the crisis. According to the research of [11, 17, 18] on crisis and its impact, the consumers tend to be dubious toward the brand advertising after the crisis and companies are more difficult to gain the potential buyers due to bad propaganda, indicating that the efficacy of marketing efforts will be lower after the crisis, based on which, we suppose that $\gamma_1 \ge \gamma_2$ and $\zeta_1 \ge \zeta_2$. Meanwhile, their opponents may take advantage of the crisis by negative propaganda to canvass consumers originally loyal to the business-facing crisis. Hence, the consumers may become easier to abandon the brand and we assume that $\delta_1 < \delta_2$.

Therefore, the expected profits of online retailers and offline retailers in the planning period are given by

$$J_{E,R}[A_{E1}(S_{R1}), A_{E2}(S_{R2})] = E\left[\int_0^T e^{-rt}\left(\rho_{E,R} D_{E,R} - C_{E,R}\right)dt + e^{-rT} V_{E,R2}(G)\right]. \tag{8}$$

Calculating the expectations above, we can get

$$J_{E,R}[A_{E1}(S_{R1}), A_{E2}(S_{R2}), \chi] = \int_0^\infty e^{-(r+\chi)t}\left[\left(\rho_{E,R} D_{E,R} - C_{E,R}\right) + \chi V_{E,R2}(G)\right]dt, \tag{9}$$

where $V_{E2}(G)$ and $V_{R2}(G)$ are the value functions of supply chain members in the postcrisis stage. $A_{E1}(S_{R1})$ is the advertising (service) level before the crisis and $A_{E2}(S_{R2})$ is the advertising (service) level after the crisis. $\rho_{E,R}$ and $D_{E,R}$ represent the marginal profits and channel demand of both players. We assume that the marginal profits of both members are constant for the reason that, in the perfect competitive market, the companies are only price takers instead of price settlers, making the marginal profit constant. Previous literature, such as Lu et al. [19] and Saha et al. [20], also takes this assumption. $C_{E,R}$ represent advertising and service cost and the cost are assumed to be of quadratic form which should be $(1/2)k_E A_E^2$ and $(1/2)k_R S_R^2$, where k_E and k_R are positive constant cost parameters.

According to equation (9), the expected profits of online and offline retailers are not only functions of the advertising and service strategies but also functions of the hazard rate χ. It is also worth noting that the discount rate changes from r to $r+\chi$, indicating that the retailers pay more attention to the current rather than the future profits since according to Jørgensen and Zaccour [21], the discount rate measures the time preference of players and the larger the discount rate is, the more impatient the players are. Thus, a differential game model of online and offline retailers with the brand crisis is constructed by (4)–(9).

3. Equilibrium Strategies

3.1. Equilibrium Strategies in Postcrisis Regime. According to the analysis above, the brand crisis not only damages the goodwill of the brand but also makes the efficacy of advertising and service strategies on goodwill lower than before. Therefore, the problems to be solved in precrisis and postcrisis regimes are different from the other. In order to maximize the expected profits in the whole planning period, retailers have to set the optimal strategies at every moment in the precrisis and postcrisis regimes according to Rubel et al. [22]. We use superscript IM to represent this pattern. According to the method provided in [23–27], we will first solve the optimization problem in the postcrisis stage. Let $V_E^{IM}(G)$ and $V_R^{IM}(G)$ be the value functions of both players, respectively. Hence, the optimization problem of the online retailer in the postcrisis stage is as follows:

$$\begin{aligned}
&\max_{A_{E2}^{IM}} J_{E2}^{IM} = \int_0^\infty e^{-(r+\chi)t}\left\{\rho_E\left[(1-\mu)\left(\beta A_{E2}^{IM} + \theta G\right) + \pi\eta S_{R2}^{IM}\right] - \frac{1}{2}k_E\left(A_{E2}^{IM}\right)^2\right\}\mathrm{d}t \\
&\text{s.t. } \dot{G}(t) = \gamma_2 A_{E2}(t) + \zeta_2 S_{R2}(t) - \delta_2 G(t),\ G(T^+) = (1-\phi)G(T^-).
\end{aligned} \tag{10}$$

The optimization problems of offline retailer in the postcrisis stage are as follows:

$$\begin{aligned}
&\max_{S_{R2}^{IM}} J_{R2}^{IM} = \int_0^\infty e^{-(r+\chi)t}\left\{\rho_R\left[\mu\left(\beta A_{E}^{IM} + \theta G\right) + (1-\pi)\eta S_{R1}^{IM}\right] - \frac{1}{2}k_R\left(S_{R}^{IM}\right)^2\right\}\mathrm{d}t \\
&\text{s.t. } \dot{G}(t) = \gamma_2 A_{E2}(t) + \zeta_2 S_{R2}(t) - \delta_2 G(t),\ G(T^+) = (1-\phi)G(T^-).
\end{aligned} \tag{11}$$

Proposition 1. *The optimal strategies of online and offline retailers in the postcrisis regime are*

$$\begin{aligned}
A_{E2}^{IM*} &= \frac{\rho_E\beta(1-\mu) + \gamma_2 n_1}{k_E}, \\
S_{R2}^{IM*} &= \frac{\rho_R\eta(1-\pi) + \zeta_2 m_1}{k_R}.
\end{aligned} \tag{12}$$

The optimal value functions of both players in the postcrisis regime are

$$\begin{aligned}
V_{E2}^{IM}(G) &= n_1 G + n, \\
V_{R2}^{IM}(G) &= m_1 G + m_2.
\end{aligned} \tag{13}$$

where

$$\begin{aligned}
&\begin{cases}
n_1 = \dfrac{\rho_E\theta(1-\mu)}{(r+\delta_2)}, \\
n_2 = \dfrac{(n_1\zeta_2 + \rho_E\eta\pi)S_{R2}^{IM*}}{r} + \dfrac{\left[\rho_E\beta(1-\mu) + \gamma_2 n_1\right]^2}{2rk_E},
\end{cases} \\
&\begin{cases}
m_1 = \dfrac{\rho_R\theta\mu}{(r+\delta_2)}, \\
m_2 = \dfrac{(\rho_R\beta\mu + m_1\gamma_2)A_{E2}^{IM*}}{r} + \dfrac{\left[\rho_R\eta(1-\pi) + \zeta_2 m_1\right]^2}{2rk_R}.
\end{cases}
\end{aligned} \tag{14}$$

The proof of Proposition 1 is shown in Appendix.

We can find from Proposition 1 that the optimal advertising strategy of online retailers consists of two parts which are $(\rho_E\beta(1-\mu)/k_E)$ and $((\gamma_2\rho_E\theta(1-\mu))/k_E(r+\delta_2))$. The first term derives from the fact that advertising strategies can directly increase the online channel demand. The second term is due to its indirect influence on demand by contributing to the goodwill. Similarly, the optimal strategy of offline retailers is also composed of two parts. By analyzing the influence of important parameters on the optimal advertising and service strategy, we can have the following results.

Corollary 1. *The impacts of key parameters on the optimal strategies can be given by*

$$\begin{aligned}
&\frac{\partial A_{E2}^{IM*}}{\partial \pi} > 0, \\
&\frac{\partial A_{E2}^{IM*}}{\partial \alpha} > 0, \\
&\frac{\partial A_{E2}^{IM*}}{\partial \rho_E} > 0, \\
&\frac{\partial A_{E2}^{IM*}}{\partial \beta} > 0, \\
&\frac{\partial A_{E2}^{IM*}}{\partial \theta} > 0, \\
&\frac{\partial S_{R2}^{IM*}}{\partial \pi} < 0, \\
&\frac{\partial S_{R2}^{IM*}}{\partial \alpha} < 0, \\
&\frac{\partial S_{R2}^{IM*}}{\partial \rho_R} > 0, \\
&\frac{\partial S_{R2}^{IM*}}{\partial \eta} > 0, \\
&\frac{\partial S_{R2}^{IM*}}{\partial \theta} > 0.
\end{aligned} \tag{15}$$

We can find the following from Corollary 1: (1) The increase of π or α indicates that some part of demand is transferred from offline channel to online channel. Hence, when π or α increases, the offline retailer should reduce the optimal service strategy while online retailers should increase the advertising strategy. Actually, the showrooming effect parameter π and online channel preference parameter α jointly determine the distribution of demand between channels and the changes of the two parameters reflect the transfer of demand between channels. This phenomenon is due to the definition of demand as illustrated in Figure 1 and consistent with intuition. (2) The marginal profit can stimulate retailers to invest more in advertising and service that contribute to improving the goodwill and demand. Therefore, the marginal profit, an indicator of profitability, is crucial in determining the optimal strategies. Both players should pay attention to the improvement of marginal profit. (3) The influence parameters of advertising and service on demand also affect the optimal strategies. The increase of influence parameters implies the increase of efficiency of advertising and service investment. Hence, when the parameters increase, both online and offline retailers should enhance their investment. (4) Since both online and offline retailers' strategies are able to boost goodwill which is directly relevant to demand, the increase of influence parameter of goodwill on demand will stimulate investment of both players. Actually, the increase of this parameter manifests the elevation of the efficacy of their efforts which underlies their motivations in augmenting investment.

3.2. Equilibrium Strategies in Precrisis Regime. When online and offline retailers decide the optimal strategy before the crisis, they should consider the situation after the crisis so as to maximize the expected profits during the whole planning period. Therefore, the optimization problem that the online retailer should solve before the crisis is as follows:

$$\begin{aligned}&\max_{A_{E1}^{IM}} J_{E1}^{IM} = \int_0^{\infty} e^{-(r+\chi)t}\left\{\rho_E\left[(1-\mu)\left(\beta A_{E1}^{IM}+\theta G\right)+\pi\eta S_{R1}^{IM}\right]-\frac{1}{2}k_E\left(A_{E1}^{IM}\right)^2+\chi V_{E2}^{IM}[(1-\phi)G]\right\}\mathrm{d}t\\&\text{s.t. } \dot{G}(t)=\gamma_1 A_{E1}(t)+\zeta_1 S_{R1}(t)-\delta_1 G(t),\ G(0)=G_0.\end{aligned}\tag{16}$$

That of offline retailers is

$$\begin{aligned}&\max_{S_{R1}^{IM}} \quad J_{R1}^{IM} = \int_0^{\infty} e^{-(r+\chi)t}\left\{\rho_R\left[\mu\left(\beta A_{E1}^{IM}+\theta G\right)+(1-\pi)\eta S_{R1}^{IM}\right]-\frac{1}{2}k_R\left(S_{R1}^{IM}\right)^2+\chi V_{R2}^{IM}[(1-\phi)G]\right\}\mathrm{d}t\\&\text{s.t.} \quad \dot{G}(t)=\gamma_1 A_{E1}(t)+\zeta_1 S_{R1}(t)-\delta_1 G(t),\ G(0)=G_0.\end{aligned}\tag{17}$$

Proposition 2. *The optimal strategies of online and offline retailers in the precrisis regime are*

$$\begin{aligned}A_{E1}^{IM*}&=\frac{\rho_E\beta(1-\mu)+\gamma_1 k_1}{k_E},\\S_{R1}^{IM*}&=\frac{\rho_R\eta(1-\pi)+\zeta_1 h_1}{k_R}.\end{aligned}\tag{18}$$

The optimal value functions of online and offline retailers in the precrisis regime are

$$\begin{aligned}V_{E1}^{IM}(G)&=k_1 G+k_2,\\V_{R1}^{IM}(G)&=h_1 G+h_2.\end{aligned}\tag{19}$$

The dynamic of goodwill during the whole planning period is

$$G^{IM}(t)=\begin{cases}\left[G_0-\dfrac{\gamma_1 A_{E1}^{IM*}+\zeta_1 S_{R1}^{IM*}}{\delta_1}\right]e^{-\delta_1 t}+\dfrac{\gamma_1 A_{E1}^{IM*}+\zeta_1 S_{R1}^{IM*}}{\delta_1}, & t\in[0,T],\\[2ex]\left[(1-\phi)G(T)-\dfrac{\gamma_2 A_{E2}^{IM*}+\zeta_2 S_{R2}^{IM*}}{\delta_2}\right]e^{-\delta_2(t-T)}+G_{\infty}^{IM}(t), & t\in(T,\infty),\end{cases}\tag{20}$$

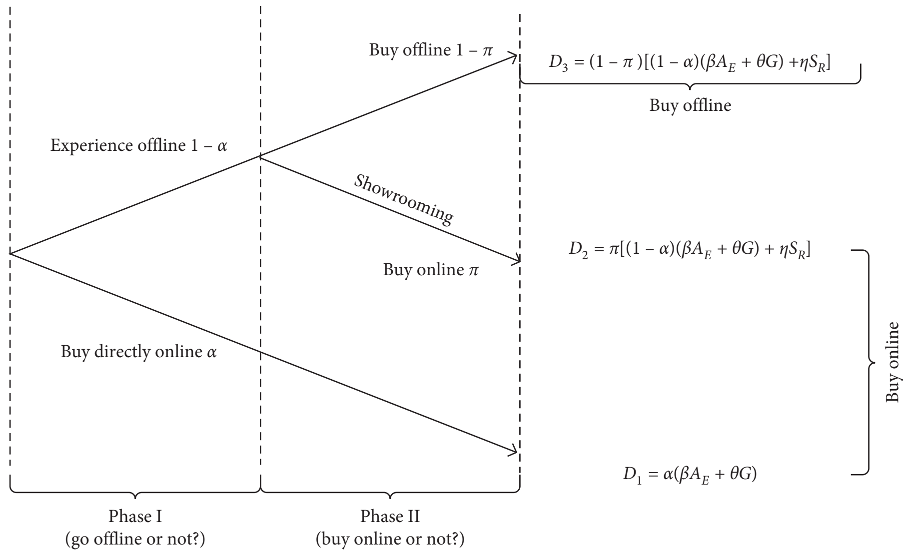


Figure 1: Demand for online and offline channels.

where

$$G_{\infty}^{IM}(t) = \frac{\gamma_2 A_{E2}^{IM*} + \zeta_2 S_{R2}^{IM*}}{\delta_2},$$

$$\begin{cases} k_1 = \dfrac{\left[\rho_E \theta (1-\mu) + \chi n_1 (1-\phi)\right]}{(r+\chi+\delta_1)}, \\ k_2 = \dfrac{\left[\rho_E (1-\mu)\beta + k_1\gamma_1\right]^2}{2k_E (r+\chi)} + \dfrac{\left[(\rho_E \eta\pi + k_1\zeta_1) S_{R1}^{IM*} + \chi n_2\right]}{(r+\chi)}, \end{cases} \tag{21}$$

$$\begin{cases} h_1 = \dfrac{\left[\rho_R \theta\mu + \chi m_1 (1-\phi)\right]}{(r+\chi+\delta_1)}, \\ h_2 = \dfrac{\left[\rho_R \eta (1-\pi) + \zeta_1 h_1\right]^2}{2k_R (r+\chi)} + \dfrac{\left[(\rho_R \beta\mu + h_1\gamma_1) A_{E1}^{IM*} + \chi m_2\right]}{(r+\chi)}. \end{cases}$$

The proof of Proposition 2 is shown in Appendix.

It can be seen from Propositions 1 and 2 that the online and offline retailers should set their optimal strategies according to the different business conditions before and after the crisis. Therefore, the optimal strategies in the precrisis for both sides are also a function of the crisis occurrence rate χ and the goodwill loss rate ϕ, showing that if online and offline retailers should evaluate the probability of crisis and its negative impact on goodwill at the beginning of making strategies to get the maximum expected profit in the whole planning period. The optimal strategies of both sides are composed of two parts, the structures and some properties of which are similar to those in postcrisis. For example, precrisis and postcrisis advertising strategies are both decreasing functions of the decay rate δ and the cost coefficient k_E but increasing functions of the influence coefficient β and θ. By analyzing the influence of parameters on the optimal strategies of online and offline retailers, we can have the following conclusion.

Corollary 2. *The impacts of key parameters on the optimal strategies can be given by*

$$\frac{\partial A_{M1}^{IM*}}{\partial \delta_1} < 0,$$

$$\frac{\partial A_{M1}^{IM*}}{\partial \delta_2} < 0,$$

$$\frac{\partial A_{M1}^{IM*}}{\partial \chi} < 0,$$

$$\begin{aligned}&\frac{\partial A_{M1}^{IM*}}{\partial\phi}<0,\\&\frac{\partial S_{R1}^{IM*}}{\partial\delta_1}<0,\\&\frac{\partial S_{R1}^{IM*}}{\partial\delta_2}<0,\\&\frac{\partial S_{R1}^{IM*}}{\partial\chi}<0,\\&\frac{\partial S_{R1}^{IM*}}{\partial\phi}<0.\end{aligned}\tag{22}$$

We can find the following from Corollary 2: (1) The precrisis strategies are not only decreasing functions of the precrisis decay rate δ_1 but also decreasing functions of the postcrisis decay δ_2, which indicates that both retailers should take into consideration the impact of the crisis on the business environment when deciding strategies at the beginning of the period. (2) The precrisis optimal advertising and service strategies are decreasing function of hazard rate χ and goodwill loss rate ϕ. Hence, retailers should adjust their decisions according to the variation of the crisis. When the hazard rate increases, retailers should reduce their investment before the crisis happens. According to the analysis in Section 2.2, the greater the hazard rate is, the greater the probability $P\{t\le T\}=1-e^{-\chi T}$ (probability of occurring before the time T) will be, which means that the crisis occurs earlier, and the accumulated goodwill will not be kept for a long time. Since the goodwill will suffer due to the crisis, part of the investment before the crisis will disappear with the loss of goodwill. Hence, if the crisis is closer or more destructive, the retailers should reduce the investment before the crisis and leave more funds for the recovery of goodwill after the crisis. In addition, although the goodwill level decreases only after the crisis, the expectation of the crisis affects the decision-making before the crisis. This is because the reverse induction principle requires both parties to anticipate the situation after the crisis and then reversely deduce the global optimal dynamic strategies. Therefore, when confronting the possible crisis, retailers should fully consider the impact of the crisis and make the corresponding actions to maximize the profit maximization based on the global consideration of both pre- and postcrisis stages.

4. Comparisons and Analyses

This section will compare and analyze the optimal strategies of members to further reveal the impact of the potential crisis on member's decisions. Firstly, comparing the strategies with no crisis with those with a potential crisis, we can have Proposition 3. And comparing the strategies of retailers before and after the crisis, we will have Proposition 4. Obviously, the situation without a crisis is the situation with a hazard rate $\chi=0$. Let $\chi=0$ in Proposition 2; we will have the optimal strategies with no crisis represented by superscript AVG.

Proposition 3. *The comparison results of the optimal strategies with or without crisis are as follows:*

$$\begin{aligned}&A_E^{AVG*}>A_{E1}^{IM*},\\&A_E^{AVG*}>A_{E2}^{IM*},\\&S_R^{AVG*}>S_{R1}^{IM*},\\&S_R^{AVG*}>S_{R2}^{IM*}.\end{aligned}\tag{23}$$

According to Proposition 3, retailers tend to lower their investment when facing a potential crisis. According to the analysis of Corollary 2, the precrisis advertising and service strategies are all the decreasing functions of hazard rate χ and when $\chi=0$; we will have $A_E^{AVG*}=A_{E1}^{IM*}$ and $S_R^{AVG*}=S_{R1}^{IM*}$. Hence, if $\chi>0$, there must be $A_E^{AVG*}>A_{E1}^{IM*}$ and $S_R^{AVG*}>S_{R1}^{IM*}$. Their envision of the crisis will reduce their precrisis advertising and service investment. Moreover, the occurrence of the crisis will also change the business environment ($\gamma_1\ge\gamma_2$, $\zeta_1\ge\zeta_2$, and $\delta_1\le\delta_2$), which will make retailers lower their investment after the crisis compared with the situation with no crisis.

Proposition 4. *The comparison results of the optimal strategies of online and offline retailers before and after the crisis are as follows:*

$$\begin{aligned}&A_{E1}^{IM*}-A_{E2}^{IM*}=\begin{cases}\ge 0, & \dfrac{\gamma_2}{\gamma_1}\le\omega,\\ <0, & \dfrac{\gamma_2}{\gamma_1}>\omega,\end{cases}\\&S_{R1}^{IM*}-S_{R2}^{IM*}=\begin{cases}\ge 0, & \dfrac{\zeta_2}{\zeta_1}\le\omega,\\ <0, & \dfrac{\zeta_2}{\zeta_1}>\omega,\end{cases}\end{aligned}\tag{24}$$

where $\omega=((r+(1-\phi)\chi+\delta_2)/(r+\chi+\delta_1))$.

From Proposition 4, we can find that retailers should consider their influence parameters of their strategies when deciding how to allocate their investment between pre- and postcrisis regimes. There is a threshold ω. If $(\gamma_2/\gamma_1)\le\omega$, online retailers should reduce their postcrisis advertising investment, while if $(\gamma_2/\gamma_1)>\omega$, online retailers should increase their postcrisis investment. The service strategy of offline retailer shares similar property.

This result reflects the regime reference in decision-making, which is essentially consistent with the conclusion of the previous analysis. According to the analysis in Section 2.2, we can find that when the hazard rate χ is small, retailers tend to pay more attention to the precrisis stage but if the crisis rate χ is large, they should put more emphasis on the postcrisis stage. Derive ω with regard to χ and we can get

$$\frac{\partial \omega}{\partial \chi} = -\frac{r + \delta_2 - (1-\phi)(r+\delta_1)}{(r+\chi+\delta_1)^2} < 0. \tag{25}$$

When the hazard rate χ decreases, the threshold ω will increase and the probability that (γ_2/γ_1) is less than ω will increase. Hence, the probability that the retailers reduce their investment after the crisis will increase and the precrisis stage is more important for retailers. Particularly, if $\chi \longrightarrow 0$, then $\omega \longrightarrow ((r+\delta_2)/(r+\delta_1)) \geq 1$ and $(\gamma_2/\gamma_1) \leq \omega$ is definite, which means that retailers do not have to consider the postcrisis stage. This because $\chi \longrightarrow 0$ means that the crisis time is infinitely pushed back and the precrisis stage duration is infinite. When the hazard rate χ increases, ω will decrease, indicating that the probability that (γ_2/γ_1) is greater than ω will increase and the retailers will be more likely to increase their investment after the crisis. Further, we can get the value range of the threshold ω.

$$1 - \phi < \omega < \frac{r+\delta_2}{r+\delta_1}. \tag{26}$$

Essentially, the stage preference of retailers is due to the different efficiency of investment in different stages. If the hazard rate χ is very large, the crisis will occur very early. Then the input of players before the crisis will be wasted soon because of the loss of goodwill. Hence, it is better to reduce the investment. However, if the crisis seriously affects the influence parameters of retailers' strategies on goodwill, then it is necessary to weigh the relationship between (γ_2/γ_1) and ω. Particularly, if $\gamma_2\,(\zeta_2) \longrightarrow 0$, indicating that the influence of member's strategies on goodwill can be ignored after the crisis, then more resources should be channeled to the precrisis regime to improve the level of goodwill even if the crisis will damage goodwill. In a word, the potential crisis will make the retailers have stage preference, and the hazard rate, goodwill loss rate, and the influence of members' strategies on goodwill determine the efficiency of investment in different regimes. The following special scenarios can be obtained by further analysis.

4.1. Scenario 1. If $\gamma_1 = \gamma_2$, $\zeta_1 = \zeta_2$, and $\delta_1 = \delta_2$, then $A_{E1}^{IM} \leq A_{E2}^{IM}$ and $S_{R1}^{IM} \leq S_{R2}^{IM}$ $\forall \chi > 0$.

In this scenario, even if the crisis will immediately damage the goodwill, it will not cause other long-term effects (such as reduce the influence parameters of strategies on the goodwill or increase consumers' forgetting effect). Hence, the goodwill has the identical evolution rules before and after the crisis. In this situation, retailers should increase their investment after the crisis so that the damaged goodwill can be recovered as soon as possible. As a consequence, retailers' investment in the second stage is higher than that in the precrisis stage regardless of the hazard rate and the degree of goodwill loss. Furthermore, the investment in the postcrisis stage is equal to that with no crisis; namely, $A_{E2}^{IM} = A_E^{AVG}$ and $S_{R2}^{IM} = S_R^{AVG}$.

4.2. Scenario 2. If $(\gamma_2/\gamma_1) \leq 1 - \phi$ and $(\zeta_2/\zeta_1) \leq 1 - \phi$, then $A_{E1}^{IM} \geq A_{E2}^{IM}$ and $S_{R1}^{IM} \geq S_{R2}^{IM}$ $\forall \chi > 0$.

Different from Scenario 1, the crisis will not only reduce the influence of advertising and service but also increase the forgetting effect consumers, and in this situation, the long-term impact of the crisis outweighs its direct impact, which makes the investment of retailers in postcrisis regime less efficient than in the precrisis regime. Hence, the retailers need to pay more attention to the precrisis stage and allocate more resources before the crisis. In addition, it is also worth noting that the impact of the reduction of the impact of advertising and services is greater than that of the increase of the forgetting effect (because in this scenario, we have $(\gamma_2/\gamma_1) \leq \omega$, but in situation 1, when $\gamma_1 = \gamma_2$ and $\delta_1 = \delta_2$, we will have $\omega < 1$).

4.3. Scenario 3. If $1 - \phi < (\gamma_2/\gamma_1) \leq ((r+\delta_2)/(r+\delta_1))$ and $1 - \phi < (\zeta_2/\zeta_1) \leq ((r+\delta_2)/(r+\delta_1))$, then $A_{E1}^{IM} \geq A_{E2}^{IM}$ for $\chi \leq \hat{\chi}$, $S_{R1}^{IM} \geq S_{R2}^{IM}$ for $\chi \leq \tilde{\chi}$, $A_{E1}^{IM} < A_{E2}^{IM}$ for $\chi > \hat{\chi}$, $S_{R1}^{IM} < S_{R2}^{IM}$ for$\chi > \tilde{\chi}$, where

$$\begin{aligned} \hat{\chi} &= \frac{\gamma_1(r+\delta_2) - \gamma_2(r+\delta_1)}{\gamma_2 - (1-\phi)\gamma_1}, \\ \tilde{\chi} &= \frac{\zeta_1(r+\delta_2) - \zeta_2(r+\delta_1)}{\zeta_2 - (1-\phi)\zeta_1}. \end{aligned} \tag{27}$$

Similar to Scenario 2, the crisis will make it more difficult for advertisement and service to attract consumers and make the goodwill decay faster detrimental to the long-term profits of retailers. But the direct impact of the crisis is greater than its long-term impact $(((\gamma_1 - \gamma_2)/\gamma_1) < \phi)$. Hence, in this scenario, the investment allocation issues depend on the value of the hazard rate. If $\chi < \hat{\chi}$, an online retailer will increase the advertising investment in the precrisis stage, and when $\chi < \tilde{\chi}$, offline retailers will increase the service investment in the precrisis stage. Since the hazard rate is relatively small, the crisis occurs later and the precrisis stage will be longer. Generally, the direct impact of the crisis will make retailers tend to invest more in the postcrisis stage and the long-term impact of the crisis will make retailers tend to invest more in the precrisis stage. Therefore, when making decisions, retailers should consider the role of their strategies in the whole planning period.

5. Numerical Analysis

In this section, we use numerical analysis to further verify and exhibit former conclusions. We analyze the impact of random crisis on optimal strategies and profits of both retailers. The basic parameters are set as follows: $G_0 = 0$; $r = 0.1$; $\gamma_1 = 1$; $\gamma_2 = 0.8$; $\zeta_1 = 0.2$; $\zeta_2 = 0.15$; $\delta_1 = 0.2$; $\delta_2 = 0.25$; $\alpha = 0.3$; $\pi = 0.4$; $k_E = 1$; $k_R = 1$; $\rho_E = 6$; $\rho_R = 6$; $\beta = 0.2$; $\theta = 0.2$; $\eta = 0.2$; $T = 5$; $\chi = 0.5$; $\phi = 0.5$.

5.1. Impact of Crisis on Retailers' Strategies. Firstly, we analyze the impact of the crisis on the strategies of both retailers at the beginning of the period. Figures 2–4 manifest the impact of hazard rate and goodwill loss rate on online retailers' advertising strategies.

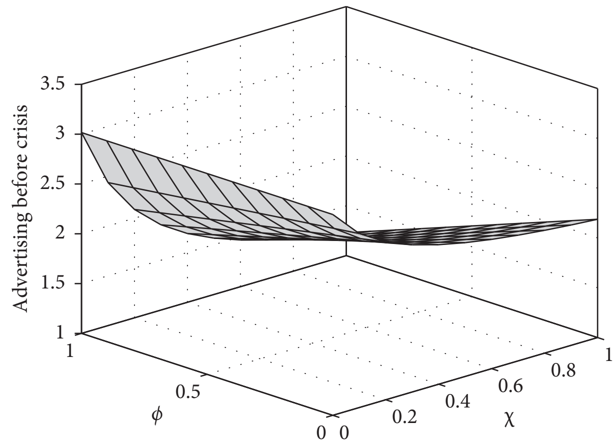
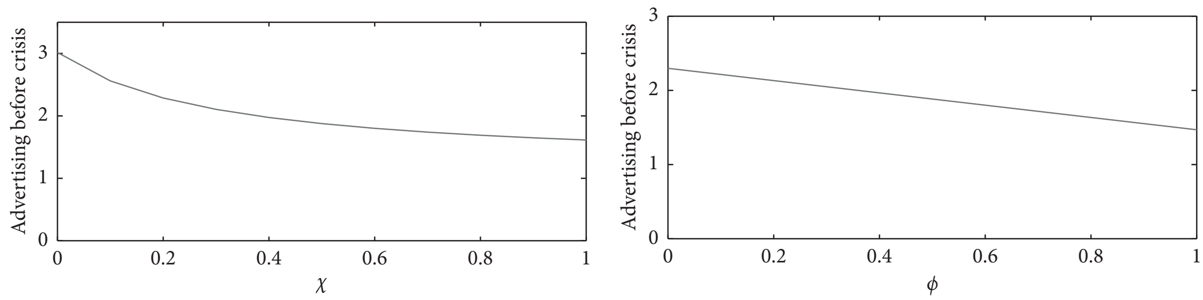


Figure 2: Advertising before crisis.



(a)

(b)

Figure 3: Changes with regard to (a)χ and (b)ϕ.

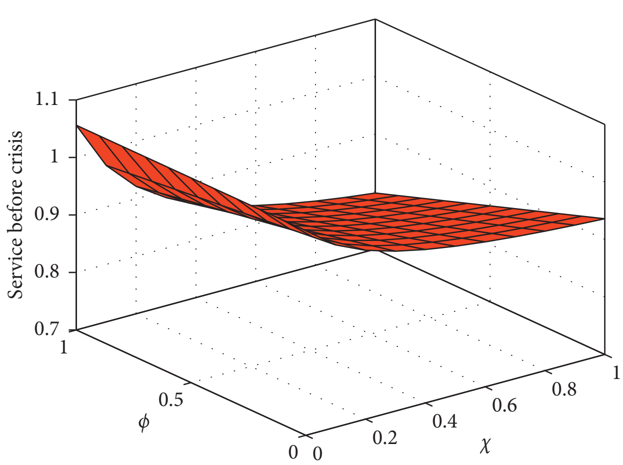


Figure 4: Service before crisis.

Figures 2 and 3 verify the conclusion of Corollary 2. When the crisis will occur, the hazard rate and the loss rate are crucial factors that should be taken into consideration when the online retailer makes the advertising strategy. And the retailer should properly respond to the changes of the parameters and make corresponding adjustments to achieve the maximum expected profit in the planning period. It can be seen from Figures 2 and 3 that when the hazard rate increases, online retailers should reduce their advertising investment, and when the loss rate of on goodwill increases, online retailers should also reduce their advertising investment. Figures 4 and 5 analyze the impact of the crisis on offline retailer's service strategy.

Similar to the online retailer's advertising strategy, the offline retailer should also reduce their service investment no matter the hazard rate or loss rate increases. Hence, when the crisis may occur, the envision of the crisis will affect the determination of the retailers' strategies. This is because the purpose of both advertising and service is to increase goodwill and expand sales, but the occurrence of the crisis will make the accumulated goodwill suffer and therefore waste the investment of retailers. This point has important management insight. In managerial practice, if the crisis will not happen, the retailers' strategies are only based on their own situation and market environment. But in actual operational activity, the brands sold by retailers have odds to confront the brand crisis and therefore have the goodwill injured. Hence, retailers should have certain knowledge of the products they sold and the manufacturers of products to analyze the probability of crisis and the impact on goodwill. For example, if the manufacturer does not do well in quality control and often receives consumer's complaints or the manufacturer has business behaviors that does not conform to business ethics, the retailers really need to know about

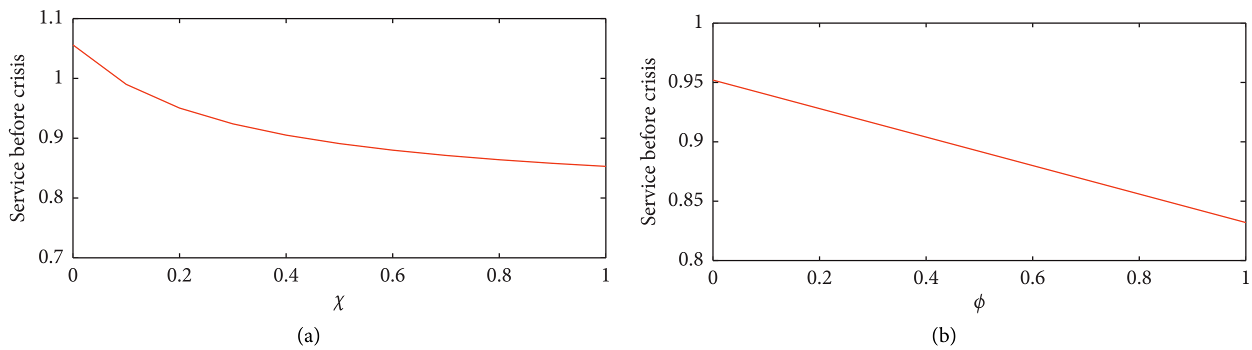


FIGURE 5: Changes with regard to (a)χ and (b)ϕ.

these situations. Because these hidden dangers may occur at any time which will lead to a crisis against the brand. The more the hidden dangers in the operation process are, the greater the probability of crisis will be. Retailers should adjust their advertising and service inputs to respond to the potential risk.

5.2. Impact of Crisis on Goodwill. The impact of the crisis on goodwill is shown in Figures 6–8. Figure 6 compares the goodwill with crisis to that without crisis. Figure 7 analyzes the impact of hazard rate on goodwill and Figure 8 analyzes the impact of loss rate.

According to the analysis of Corollary 2, when the severity of the crisis increases, both online and offline retailers should reduce their precrisis advertising and service investment. In Figure 6, even if the crisis has not yet occurred $T < 5$, the goodwill is still lower than that without the crisis. When the crisis happened $T = 5$, the goodwill suddenly loses. In addition, according to the analysis of Proposition 3, the advertising and service strategies of retailers after the crisis are also lower than those without crisis and the growth rate of goodwill in the postcrisis stage is still lower than that without crisis. Figure 7 analyzes the impact of hazard on goodwill. It can be seen that the higher the hazard rate is, the lower the level of goodwill will be. This is because the investment will decrease with the increase of hazard rate, leading to a lower level of goodwill. In addition, since the strategies of retailers after the crisis are no longer affected by the crisis but only related to the retailers themselves and the market, the strategies after the crisis are the same regardless of the situation of the crisis. Hence, in Figure 7, the goodwill in three cases converges to the same level. Figure 8 analyzes the impact of loss rate on goodwill. We can also find that the higher the loss rate is, the lower the level of goodwill will be, not only because the loss rate will reduce the investment of both sides but also because of the higher damage of the crisis.

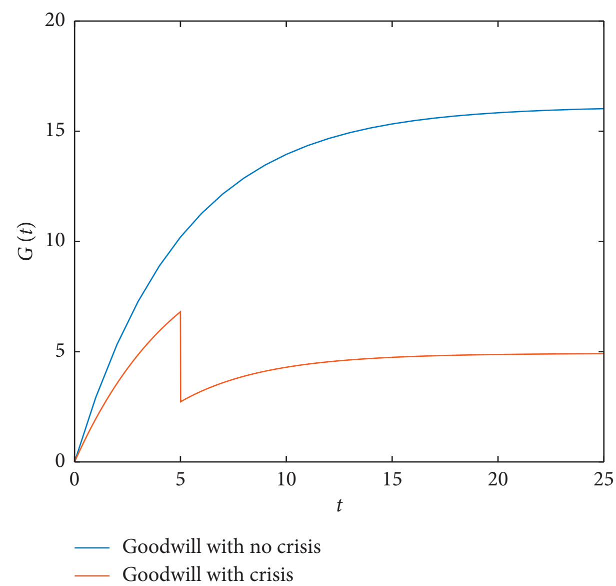


FIGURE 6: Comparison of goodwill.

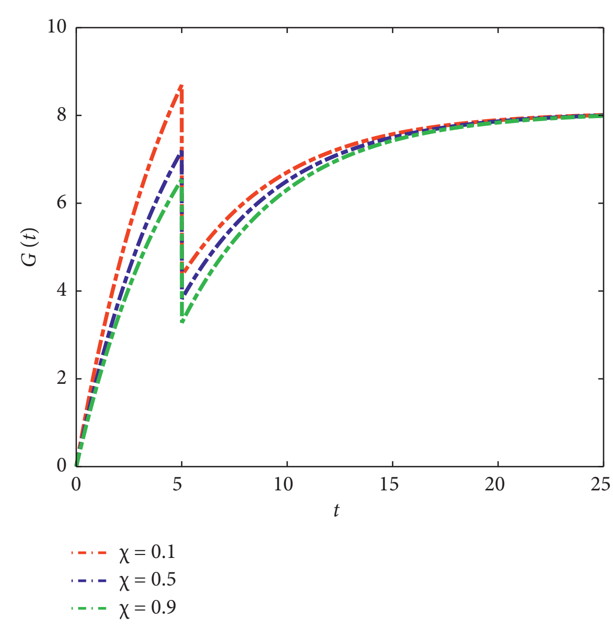


FIGURE 7: Influence of hazard rate.

5.3. Impact of Crisis on Retailers' Profits. Figures 9–11 analyze the impact of the crisis on the profits of online retailers, and Figures 12–14 analyze the impact of the crisis on the profits of offline retailers.

The impact of the crisis on profits is complex. On the one hand, according to the previous analysis, the envision of the

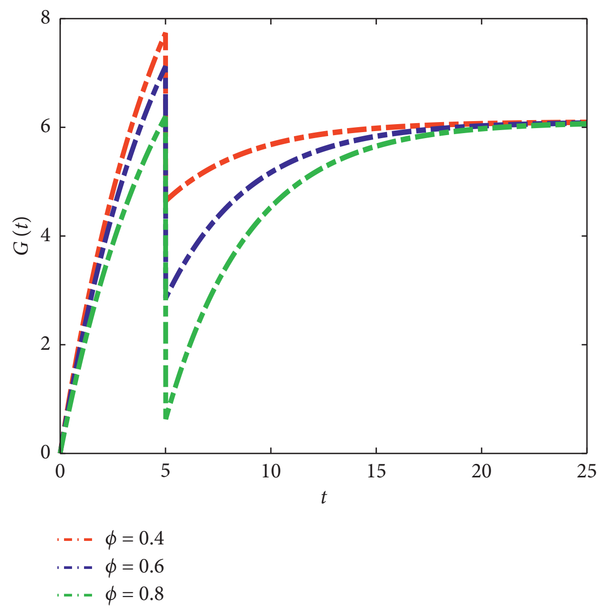


Figure 8: Influence of loss rate.

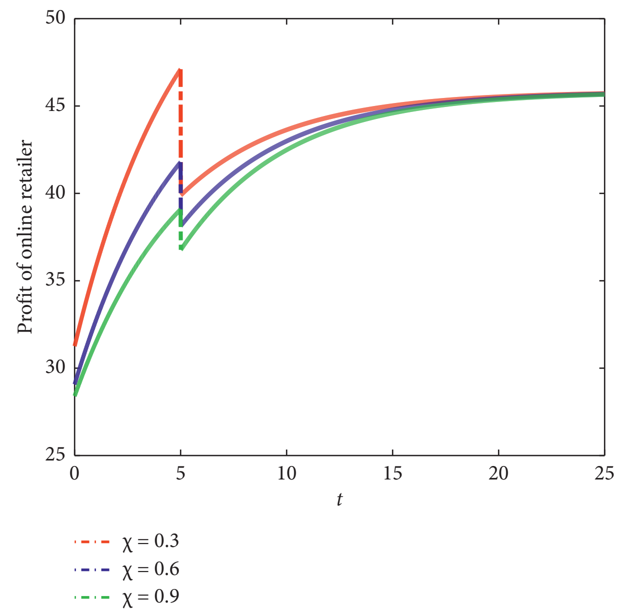


Figure 10: Influence of hazard rate.

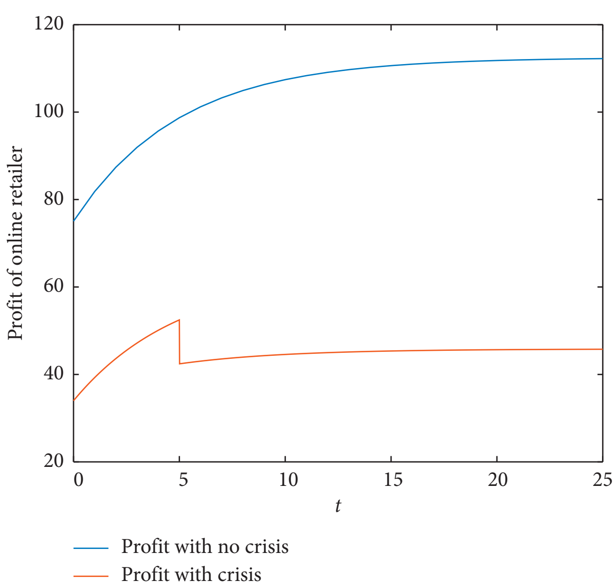


Figure 9: Comparison of online profit.

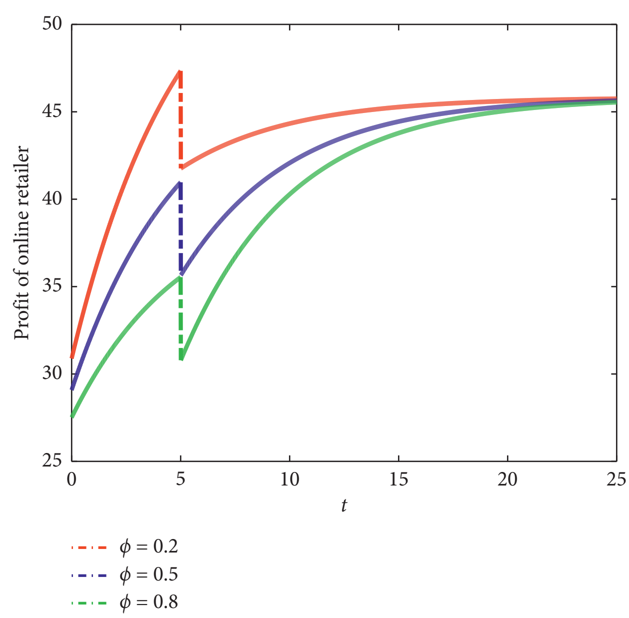


Figure 11: Influence of loss rate.

crisis will make both retailers reduce their advertising and service investment, which will not only lead to the reduction of goodwill but also directly affect demand. On the other hand, the occurrence of the crisis will lead to changes in market conditions, which will jointly lead to lower profit levels before and after the crisis than when there is no crisis. Specifically, both of the hazard rate and the loss rate will have an impact on the profits. If the loss rate is fixed and the hazard rate increases, the profits of both sides will decrease with the increase of the hazard rate. Similarly, if the hazard rate remains unchanged, the profits of both sides will decrease with the increase of the loss rate. Hence, the impact of the crisis is ultimately reflected in the impact on profits. Therefore, when the brand may encounter brand crisis, retailers should consider the overall profit before and after the crisis to maximize the expected profit.

5.4. Strategies before and after Crisis. Proposition 4 compares and analyzes the strategies of retailers before and after the crisis and considers three special situations which will be further presented and analyzed in the following figures.

Figures 15–17 show the advertising strategies before and after the crisis in three scenarios and Figures 18–20 show the service strategies before and after the crisis in three scenarios. In the first scenario, although the crisis will reduce

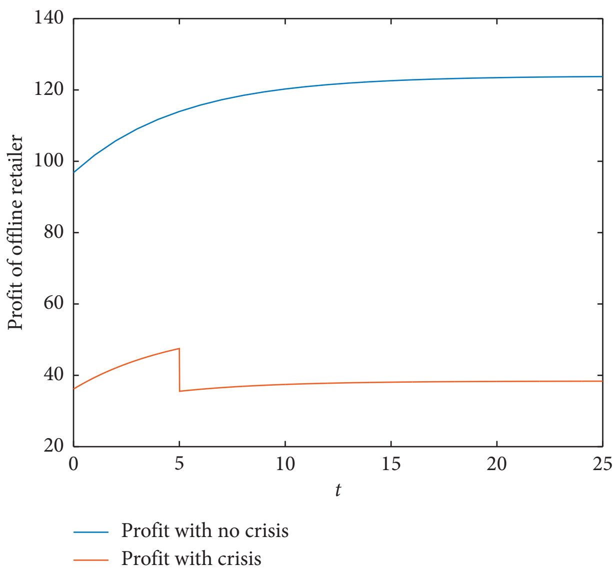


Figure 12: Comparison of offline profit.

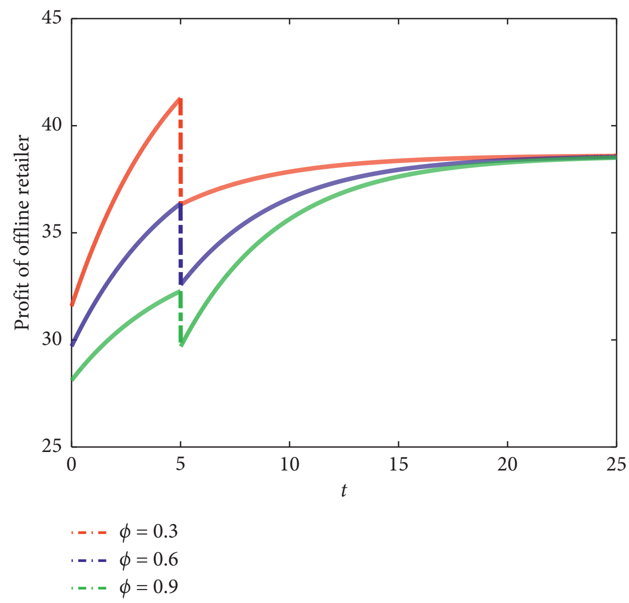


Figure 14: Influence of loss rate.

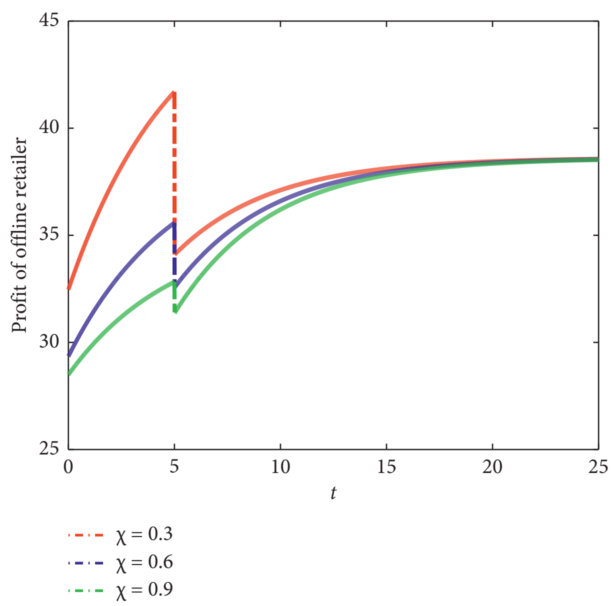


Figure 13: Influence of hazard rate.

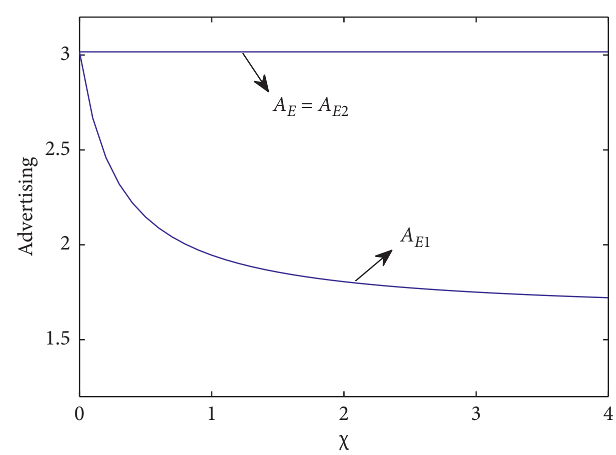


Figure 15: Comparison of advertising (Scenario 1).

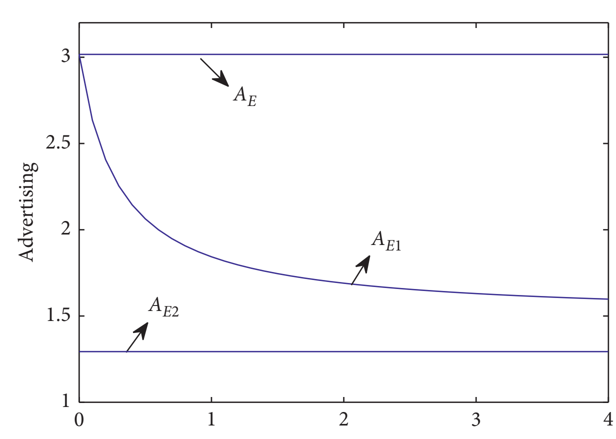


Figure 16: Comparison of advertising (Scenario 2).

the goodwill, it will not affect the long-term profitability of the retailers. For example, the occurrence of the crisis is not due to the responsibility of the brand. Hence even though the crisis will cause short-term loses, it will not affect the trust of consumers in the brand. We assume that $\gamma_1 = \gamma_2$, $\zeta_1 = \zeta_2$, and $\delta_1 = \delta_2$ in this scenario. And according to Propositions 1 and 2, the advertising strategy in the post-crisis stage is the same as that with no crisis; hence, in Figure 15, the curves of A_E and A_{E2} coincide. But the crisis will happen and will damage the goodwill, which causes the investment before the crisis to be lower than that after the crisis.

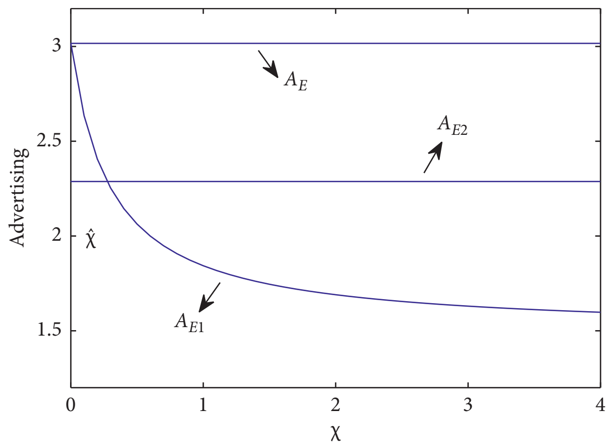


Figure 17: Comparison of advertising (Scenario 3).

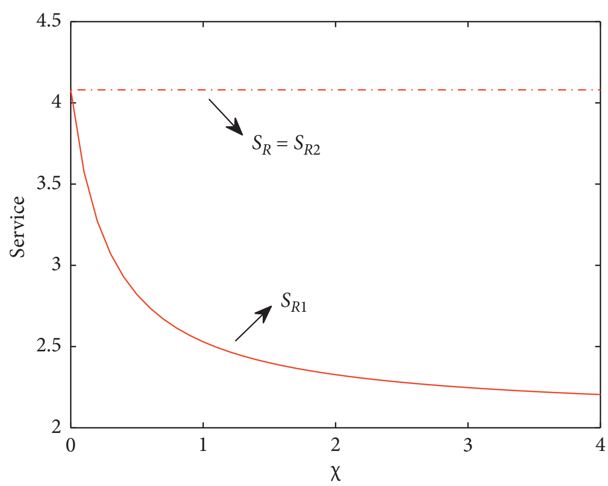


Figure 18: Comparison of service (Scenario 1).

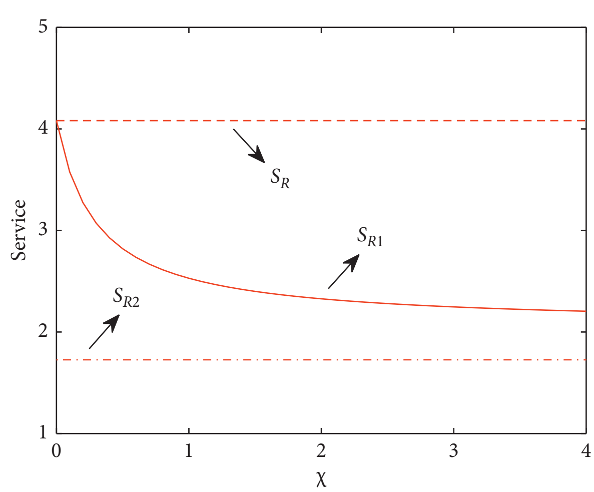


Figure 19: Comparison of service (Scenario 2).

Figure 16 depicts the scenario of $(\gamma_2/\gamma_1) \leq 1 - \phi$. At this time, even if $\chi \longrightarrow \infty$, online retailers still need to invest more before the crisis $(\partial\omega/\partial\chi) < 0$, and $\lim_{\chi \longrightarrow \infty}\omega = 1 - \phi$. $(\gamma_2/\gamma_1) \leq 1 - \phi$ shows that the crisis severely weakens the

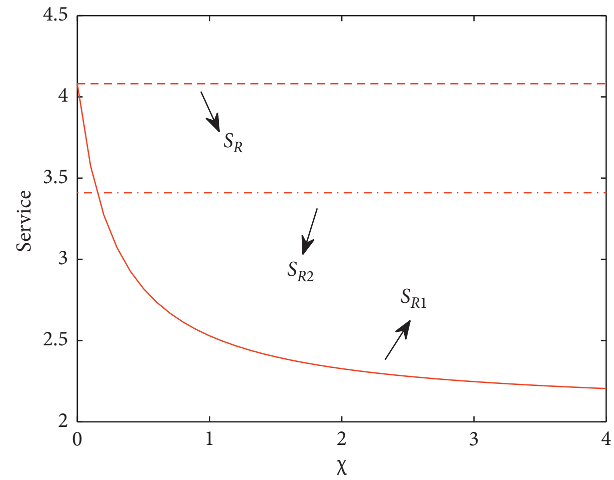


Figure 20: Comparison of service (Scenario 3).

influence of advertisement. Hence, the long-term impact of the crisis outweighs its short-term impact and the crisis will make the investment in the postcrisis stage less efficient than that in the precrisis stage. So, the retailer should increase the investment before the crisis and reduce the investment after the crisis. Figure 17 depicts the scenario of $(\gamma_2/\gamma_1) > 1 - \phi$. Compared with Scenario 2, the short-term impact of the crisis is greater than the long-term impact. Retailer should reduce the investment before the crisis unless the hazard rate is less than the threshold $\tilde{\chi}$. This indicates that although the crisis will have a greater short-term impact and waste part of the precrisis investment, the retailer should still pay more attention to the precrisis stage as long as the hazard rate is small enough and the time of the crisis is late enough. Similarly, the relationship of service strategies before and after the crisis in the three scenarios presents similar conclusions as shown in Figures 18–20. We can find from the figures above that, in any of the scenarios, the level of strategy without crisis is the highest resulting in the highest level of goodwill as illustrated in Figure 6. Moreover, when making decisions before and after the crisis, retailers should always consider which stage of investment is more effective and therefore determine the allocation strategy.

6. Conclusions

In the O2O supply chain system, products are sold simultaneously through online and offline retail channels. To improve the level of goodwill and expand the market demand, online retailers will carry out advertising activity relying on their online platforms. The offline retailer is closer to consumers and therefore offers a good service experience to win consumers. However, the brand they sold may encounter brand crisis and the occurrence of the crisis will lead to the loss of goodwill accumulated by advertising and services. Hence, the purpose of this paper is to study the strategies of both online and offline retailers when facing a potential crisis and analyze the impact of the crisis. Firstly, we describe the dynamics of goodwill under the influence of crisis by introducing stage state variables. Secondly, we construct the benchmark model of O2O supply chain with consideration of the showrooming effect. After solving and analyzing the optimal strategies and profits with and without crisis, we find the following:

(1) When facing a possible crisis, online and offline retailers should anticipate the risk in advance and take the hazard rate and the loss rate into account when deciding the advertising and service strategies. And when the hazard rate and loss rate increase, both retailers should reduce their precrisis investment. Moreover, the increase of hazard rate implies that the crisis is closer and the increase of the loss rate indicates a higher damage degree of the goodwill. Hence, if the hazard rate increases, the goodwill accumulated due to retailers' investment will be kept for a shorter time which is equivalent to wasting retailers' investment and retailers are unable to fully benefit from the goodwill. This why retailers should reduce their investment when the hazard rate increases. Similarly, when the loss rate of goodwill increases, retailers should also reduce the precrisis investment.

(2) The existence of crisis divides the planning period into two stages: precrisis stage and postcrisis stage and the efficiency of retailers' investment in different stages is different. If the efficiency of investment in the precrisis stage is high, retailers should increase the investment before the crisis and reduce the investment after the crisis otherwise. This forces retailers to decide the allocation of investment in two stages according to different situations which results in stage preference.

(3) Due to the envision of crisis, online and offline retailers should reduce their advertising and service input before the crisis, and due to changes in the market environment in the postcrisis stage, the advertising and service levels are still lower than those with no crisis. Hence, if the crisis is likely to occur, the goodwill level will be lower in the whole planning period, and so are the profits. Retailers should consider the overall profit before and after the crisis when making strategies at the beginning of the period to maximize the expected profit. Besides, when the severity of the crisis increases, they should reduce investment rather than increase investment. In a word, in managerial practice, retailers need to have a certain understanding of the products they sold and the manufacturers of the products so as to know the probability of crisis and the impact on goodwill. If there are many hidden dangers in the operation process, the probability of a crisis is large and then retailers should make corresponding countermeasures to reduce the loss when selling products.

Appendix

Proof of Propositions 1 and 2

Proof. According to the reverse induction principle, we should firstly solve the optimal strategies and profits of retailers in the postcrisis stage. Hence, the optimization problem to be solved by the online retailer after the crisis is

$$\begin{aligned}
&\max_{A_{E2}^{IM}} J_{E2}^{IM} = \int_0^\infty e^{-rt}\left\{\rho_E\left[(1-\mu)\left(\beta A_{E2}^{IM}+\theta G\right)+\pi\eta S_{R2}^{IM}\right]-\frac{1}{2}k_E\left(A_{E2}^{IM}\right)^2\right\}\mathrm{d}t\\
&\text{s.t. } \dot{G}(t)=\gamma_2 A_{E2}^{IM}(t)+\zeta_2 S_{R2}^{IM}(t)-\delta_2 G(t),\ G\left(T^+\right)\neq(1-\phi)G\left(T^-\right),
\end{aligned} \tag{A.1}$$

and the optimal problems to be solved by the offline retailer after the crisis are

$$\begin{aligned}
&\max_{S_{R2}^{IM}} J_{R2}^{IM} = \int_0^\infty e^{-rt}\left\{\rho_R\left[\mu\left(\beta A_{E2}^{IM}+\theta G\right)+(1-\pi)\eta S_{R2}^{IM}\right]-\frac{1}{2}k_R\left(S_{R2}^{IM}\right)^2\right\}\mathrm{d}t\\
&\text{s.t. } \dot{G}(t)=\gamma_2 A_{E2}^{IM}(t)+\zeta_2 S_{R2}^{IM}(t)-\delta_2 G(t),\ G\left(T^+\right)\neq(1-\phi)G\left(T^-\right).
\end{aligned} \tag{A.2}$$

Then, the HJB equations of both retailers are

$$
\begin{aligned}
rV_{E2}^{IM}(G) &= \max_{A_{E2}^{IM}}\left\{\rho_E\left[(1-\mu)\left(\beta A_{E2}^{IM}+\theta G\right)+\pi\eta S_{R2}^{IM}\right]-\frac{1}{2}k_E\left(A_{E2}^{IM}\right)^2+\frac{\partial V_{E2}^{IM}(G)}{\partial G}\left(\gamma_2 A_{E2}^{IM}+\zeta_2 S_{R2}^{IM}-\delta_2 G\right)\right\},\\
rV_{R2}^{IM}(G) &= \max_{S_{R2}^{IM}}\left\{\rho_R\left[\mu\left(\beta A_{E2}^{IM}+\theta G\right)+(1-\pi)\eta S_{R2}^{IM}\right]-\frac{1}{2}k_R\left(S_{R2}^{IM}\right)^2+\frac{\partial V_{R2}^{IM}(G)}{\partial G}\left(\gamma_2 A_{E2}^{IM}+\zeta_2 S_{R2}^{IM}-\delta_2 G\right)\right\}.
\end{aligned}
\tag{A.3}
$$

By solving the optimization problems on the right side of the HJB equation, we can have

$$
\begin{aligned}
A_{E2}^{IM} &= \frac{\rho_E(1-\mu)\beta}{k_E}+\frac{\gamma_2}{k_E}\frac{\partial V_{E2}^{IM}(G)}{\partial G},\\
S_{R2}^{IM} &= \frac{\rho_R(1-\pi)\eta}{k_R}+\frac{\zeta_2}{k_R}\frac{\partial V_{R2}^{IM}(G)}{\partial G}.
\end{aligned}
\tag{A.4}
$$

By substituting the results above into the HJB equations, we can get

$$
\begin{aligned}
rV_{E2}^{IM}(G) &= \max_{A_{E2}^{IM}}\left\{\begin{array}{c}\rho_E(1-\mu)\theta G-\delta_2\dfrac{\partial V_{E2}^{IM}(G)}{\partial G}G+\dfrac{1}{2k_E}\left[\rho_E(1-\mu)\beta+\gamma_2\dfrac{\partial V_{E2}^{IM}(G)}{\partial G}\right]^2\\ +\left[\rho_E\pi\eta+\zeta_2\dfrac{\partial V_{E2}^{IM}(G)}{\partial G}\right]\left[\dfrac{\rho_R(1-\pi)\eta}{k_R}+\dfrac{\zeta_2}{k_R}\dfrac{\partial V_{R2}^{IM}(G)}{\partial G}\right]\end{array}\right\},\\
rV_{R2}^{IM}(G) &= \max_{S_{R2}^{IM}}\left\{\begin{array}{c}\dfrac{1}{2k_R}\left[\rho_R(1-\pi)\eta+\zeta_2\dfrac{\partial V_{R2}^{IM}(G)}{\partial G}\right]^2+\rho_R\mu\theta G-\delta_2\dfrac{\partial V_{R2}^{IM}(G)}{\partial G}G\\ +\left[\rho_R\mu\beta+\gamma_2\dfrac{\partial V_{R2}^{IM}(G)}{\partial G}\right]\left[\dfrac{\rho_E(1-\mu)\beta}{k_E}+\dfrac{\gamma_2}{k_E}\dfrac{\partial V_{E2}^{IM}(G)}{\partial G}\right]\end{array}\right\}.
\end{aligned}
\tag{A.5}
$$

According to the form of the HJB equation, we assume the value functions of retailers to be

$$
\begin{aligned}
V_{E2}^{IM}(G) &= n_1 G+n_2,\\
V_{R2}^{IM}(G) &= m_1 G+m_2.
\end{aligned}
\tag{A.6}
$$

Hence, we can get the value of the coefficients of the value function

$$
\begin{aligned}
&\begin{cases} n_1 = \dfrac{\rho_E\theta(1-\mu)}{(r+\delta_2)},\\ n_2 = \dfrac{(n_1\zeta_2+\rho_E\eta\pi)S_{R2}^{IM*}}{r}+\dfrac{\left[\rho_E\beta(1-\mu)+\gamma_2 n_1\right]^2}{2rk_E},\end{cases}\\
&\begin{cases} m_1 = \dfrac{\rho_R\theta\mu}{(r+\delta_2)},\\ m_2 = \dfrac{(\rho_R\beta\mu+m_1\gamma_2)A_{E2}^{IM*}}{r}+\dfrac{\left[\rho_R\eta(1-\pi)+\zeta_2 m_1\right]^2}{2rk_R}.\end{cases}
\end{aligned}
\tag{A.7}
$$

The optimization problem of both retailers after the crisis is solved. Then, the optimization problem to be solved by the online retailer before the crisis is

$$\begin{aligned}&\max_{A_{E1}^{IM}} J_{E1}^{IM} = \int_0^\infty e^{-(r+\chi)t}\left\{\rho_E\left[(1-\mu)\left(\beta A_{E1}^{IM} + \theta G\right) + \pi\eta S_{R1}^{IM}\right] - \frac{1}{2}k_E\left(A_{E1}^{IM}\right)^2 + \chi V_{E2}^{IM}[(1-\phi)G]\right\}\mathrm{d}t\\ &\text{s.t.}\quad \dot{G}(t) = \gamma_1 A_{E1}(t) + \zeta_1 S_{R1}(t) - \delta_1 G(t),\ G\left(T^+\right) = (1-\phi)G\left(T^-\right),\end{aligned} \tag{A.8}$$

and the optimization problem to be solved by the offline retailer before the crisis is

$$\begin{aligned}&\max_{S_{R1}^{IM}} J_{R1}^{IM} = \int_0^\infty e^{-(r+\chi)t}\left\{\rho_R\left[\mu\left(\beta A_{E1}^{IM} + \theta G\right) + (1-\pi)\eta S_{R1}^{IM}\right] - \frac{1}{2}k_R\left(S_{R1}^{IM}\right)^2 + \chi V_{R2}^{IM}[(1-\phi)G]\right\}\mathrm{d}t\\ &\text{s.t.}\quad \dot{G}(t) = \gamma_1 A_{E1}(t) + \zeta_1 S_{R1}(t) - \delta_1 G(t),\ G\left(T^+\right) = (1-\phi)G\left(T^-\right).\end{aligned} \tag{A.9}$$

Through the same method, we can have

$$\begin{aligned}V_{E1}^{IM}(G) &= k_1 G + k_2,\\ V_{R1}^{IM}(G) &= h_1 G + h_2,\end{aligned} \tag{A.10}$$

where

$$\begin{cases} k_1 = \dfrac{\left[\rho_E\theta(1-\mu) + \chi n_1(1-\phi)\right]}{(r+\chi+\delta_1)},\\[2ex] k_2 = \dfrac{\left[\rho_E(1-\mu)\beta + k_1\gamma_1\right]^2}{2k_E(r+\chi)} + \dfrac{\left[(\rho_E\eta\pi + k_1\zeta_1)S_{R1}^{IM*} + \chi n_2\right]}{(r+\chi)},\end{cases}$$
$$\begin{cases} h_1 = \dfrac{\left[\rho_R\theta\mu + \chi m_1(1-\phi)\right]}{(r+\chi+\delta_1)},\\[2ex] h_2 = \dfrac{\left[\rho_R\eta(1-\pi) + \zeta_1 h_1\right]^2}{2k_R(r+\chi)} + \dfrac{\left[(\rho_R\beta\mu + h_1\gamma_1)A_{E1}^{IM*} + \chi m_2\right]}{(r+\chi)}.\end{cases} \tag{A.11}$$

Then, we will have the trajectory of goodwill during the whole planning period

$$G^{IM}(t) = \begin{cases}\left[G_0 - \dfrac{\gamma_1 A_{E1}^{IM*} + \zeta_1 S_{R1}^{IM*}}{\delta_1}\right]e^{-\delta_1 t} + \dfrac{\gamma_1 A_{E1}^{IM*} + \zeta_1 S_{R1}^{IM*}}{\delta_1}, & t \in [0, T],\\[2ex] \left[(1-\phi)G(T) - \dfrac{\gamma_2 A_{E2}^{IM*} + \zeta_2 S_{R2}^{IM*}}{\delta_2}\right]e^{-\delta_2(t-T)} + G_\infty^{IM}(t), & t \in (T, \infty).\end{cases} \tag{A.12}$$

Data Availability

All the data included in this study are available upon request by contacting the corresponding author.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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Research Article

Study on Green Supply Chain Cooperation and Carbon Tax Policy considering Consumer's Behavior

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Carbon tax policy has been shown to be an effective incentive for the reduction of carbon emissions, and it also profoundly influences supply chain cooperation. This paper explores the interaction between carbon taxes and green supply chain cooperation. Specifically, we analyze the impact of a carbon tax on green supply chain coordination and further optimize the carbon tax to achieve a win-win situation for both the supply chain and the environment. Because consumer's behavior has a significant impact on green product demand, we consider the problems above under two types of consumer's behavior characteristics: consumer's environmental awareness and consumer's reference behavior. A game-theoretic model is employed to describe a green supply chain consisting of a manufacturer and a retailer, combining important factors such as the carbon tax rate, green investment coefficient, and degree of reference effect. Then, we obtain the optimal carbon tax rate by balancing the total tax revenue and product greenness. A revenue-sharing contract is introduced to achieve green supply chain coordination, and the impact of the carbon tax on coordination is analyzed. The results show the following. (1) The carbon tax rate and the difference between the power of the manufacturer and retailer are the main factors determining green supply chain coordination. (2) Maximum greenness can be achieved when development costs are higher, while the maximum tax revenue is obtained when the development cost is lower, but with the loss of greenness. (3) If the power of the manufacturer is low, coordination can be achieved under the optimal carbon tax. If the power of the manufacturer is at a medium level, coordination can be achieved by increasing the carbon tax; as a result, increased greenness will be realized, but with the loss of tax revenue. However, when the power of the manufacturer is strong, coordination cannot be achieved. (4) Price reference behavior can promote supply chain coordination, but consumer's environmental awareness cannot.

1. Introduction

With the degradation of the environment, increasing attention has been directed toward global warming. For sustainable development, many countries have been committed to reducing carbon emissions. For example, at the 2009 United Nations Climate Conference in Copenhagen, the Chinese government declared that carbon dioxide emissions per unit of GDP would be decreased by 40%–50% in 2020 compared with the levels in 2005 [1]. Carbon dioxide is widely emitted by the transportation and manufacturing sectors [2]. Carbon tax policy has been proven to be effective for emissions reduction [3–5], but it also exerts some side effects on enterprises [6]. From the perspective of the green supply chain, carbon tax policies imposed on an enterprise could decrease the profit within the supply chain, thus affecting supply chain cooperation. However, previous research [7–9] has mostly focused on decision-making and cooperation problems within the supply chain under a given carbon tax level, rather than considering the interaction between carbon taxes and supply chain cooperation. Therefore, it is important to examine the interaction between carbon taxes and supply chain cooperation.

Currently, to meet the requirements of carbon tax regulations, a growing number of enterprises have been striving for sustainability by committing to designing, producing, and promoting green products to reduce carbon emissions [10]. In this context, green products have been regarded as one of the important factors in achieving economic growth, energy conservation, and environmental sustainability [11]. Benjaafar et al. inferred that introducing carbon emissions into a supply chain optimization models can promote emissions reduction in the supply chain [12]. Meanwhile, carbon taxes increase production costs, thus imposing burdens on enterprises. Consequently, it has been increasingly challenging for governments to enact appropriate policies to reduce carbon emissions and improve supply chain performance at the same time [13]. In addition, consumer's behavior is a crucial factor affecting product demand and sustainable decisions. In this study, we consider two types of consumer's behavior characteristics: consumer environmental awareness (CEA) and consumer's reference behavior. The former is an important factor that motivates firms to develop green products [14, 15]. The latter is a crucial factor that affects green product demand [16, 17]. In reality, many enterprises are concerned about carbon emissions, for example, HP, IBM, Ge, etc. They are not only beginning to design green products but also enhancing supply chain management and cooperation to achieve the goal of emission reduction. However, it is hard to achieve supply chain cooperation. Therefore, it is meaningful to study supply chain green decisions and cooperation considering consumer environmental awareness under a carbon tax policy. Therefore, we consider the interaction between the carbon tax rate and supply chain cooperation and optimize the tax rate in the context of CEA and consumer's reference behavior. Specifically, we aim to answer the following questions:

(i) Is carbon tax policy favorable for improving the greenness of products?

(ii) Can carbon tax policy promote supply chain coordination to incentivize supply chain members to cooperate?

(iii) Can carbon tax policy be beneficial for both product greenness and supply chain coordination simultaneously?

To investigate the above problems, a two-echelon supply chain is introduced. This is used to explore the interaction between green supply chain cooperation and carbon tax policy, where a manufacturer acts as the leader and determines the product's greenness and wholesale price, and a retailer acts as the follower and determines the retail price of green products. Moreover, traditional products without green attributes (i.e., greenness) compete with green products in the market. Through consumer utility, we obtain the demand functions for both green and traditional products. In addition, the government decides the carbon tax rate to limit carbon emissions. Unit carbon emissions are associated with the greenness of products. The higher the greenness, the higher the product R&D cost, and the lower the unit carbon emission. Finally, the impact of the carbon tax on supply chain cooperation is analyzed by introducing a revenue-sharing contract.

The results show the following. (1) When the carbon tax and development cost are at high levels, the greenness increases with the carbon tax; otherwise, the greenness decreases with increasing carbon tax. Therefore, there exists an optimal carbon tax to maximize the greenness when the development cost is high. (2) Cooperation can be promoted when the government increases the carbon tax because the retailer plays a crucial role in coordination, and the region of cooperation is expanded when the carbon tax increases. (3) When the manufacturer's power is relatively low, optimal carbon tax and supply chain cooperation can be achieved simultaneously, whereas when the manufacturer's power is relatively high, cooperation cannot be achieved. In addition, when the manufacturer's power is at a moderate level, cooperation can be achieved but with a loss of tax revenue in such a case.

The main contributions of this paper are as follows. We investigated a green supply chain cooperation problem and the interaction between carbon taxes and supply chain cooperation, taking consumer's reference behavior into consideration, which fills a research gap in supply chain cooperation. Our result provides a reference for pricing and green product design and a meaningful reference for policymakers.

The remainder of this paper is organized as follows. A literature review is presented in Section 2. Section 3 introduces the basic assumptions and notations, and the supply chain model is formulated; then, the results of the model are analyzed, and we summarize the major conclusions of the numerical analysis. Finally, Section 4 summarizes the main research content and results.

2. Literature Review

Three streams of research are closely related to our work. First, we review the research on carbon taxes in green supply chains. Second, our work is related to research on reference behaviors in operational management. Third, relevant research on supply chain coordination is reviewed. Finally, we distinguish our study from the three streams of research mentioned above.

2.1. Carbon Tax. Reduction of greenhouse gas emissions is becoming a vital issue, and almost all developed and developing countries are now implementing policies for carbon emission reduction [18]. Numerous studies have focused on carbon taxes. Carbon taxes restrict the demand for fuels and thereby reduce the emissions of harmful greenhouse gases. Generally, carbon taxes are not always as high as possible. For example, a falling tax rate encourages manufacturers to produce and reduce emissions [19]. The optimization problem of carbon taxes has previously been studied [20]. Modak and Kelle integrated corporate social responsibility (CSR) investments into the supply chain strategy and operations and concluded that the optimal recycling rate and appropriate investment in recycling activities increase with an increase in the carbon tax rate [21]. There has also been other research regarding carbon taxes. For example, Ulph and Ulph analyzed the optimal time path for a carbon tax, and the numerical results suggested that a carbon tax should initially rise and then fall [22]. Kverndokk considered the optimal extraction of exhaustible resources and came to the same conclusion: the optimal carbon tax should initially rise and eventually fall [23]. Some scholars have suggested that the optimal tax should increase monotonically or follow a U-shaped pattern [24, 25]. However, the above studies did not consider the carbon tax in the context of a supply chain.

There are some research gaps in the studies on optimal carbon taxes for green supply chains. Most of the studies have focused on the decisions and cooperation problems of the supply chain under a carbon tax. Hariga et al. presented three operational models to determine the optimal lot-sizing and shipping quantities to reduce carbon emissions. In those experiments, a minor increase in operational cost with carbon tax regulation is outweighed by the cost savings resulting from carbon-related costs [26]. Turken et al. investigated the effect of environmental regulations in the form of a carbon tax on the plant capacity and location decisions of a firm. They proposed two novel policy options: (1) a per unit per mile transportation penalty and (2) a collective transportation emissions policy with a limit on total transportation emissions. Turken et al. also revealed that stricter regulations without high penalties would not ensure compliance, as the benefits from the increasing scale associated with a centralized plant frequently outweigh the regulatory penalties, and a per unit carbon tax had no effect on regional production of emissions [27]. Xu et al. investigated the joint production and pricing of a manufacturing firm with multiple products under cap-and-trade and carbon tax regulations. Their results showed that the optimal quantity of products produced under a carbon tax regulation is determined by the emissions' trading prices and the tax rate [9]. Yu and Han studied the impact of a carbon tax on carbon emissions and retail prices in a two-echelon supply chain consisting of a manufacturer and a retailer. The results indicated that with an increase in the carbon tax, both the optimal emission reduction level and the optimal retail price initially increase and then remain stable [28]. Sinha and Modak developed an economic production quantity model that elucidates a new side of CO2 emissions reduction [29]. Zhang investigated the impact of the carbon tax on enterprise operation and obtained the coopetition supply chain and carbon tax mechanism [30]. Chen et al. investigated how a carbon emissions taxation scheme can be designed to reduce carbon emissions [31].

In general, there are two streams in the previous literature: the optimization of the carbon tax and the relationship between the carbon tax and operation decisions in the supply chain. However, there exists a research gap in the existing literature: few papers focus on the relationship between the optimal carbon tax and supply chain coordination. Our results show that by adjusting the carbon tax, the government can promote the coordination of supply chains and reduce carbon emissions. The optimal carbon tax policy to promote coordination between the supplier and retailer is obtained by balancing the tax revenue and the product greenness.

2.2. Consumer's Reference Behavior. Consumers are always concerned about product value when choosing products on shelves. The final decision of consumption is a function of gains and losses with respect to a reference outcome [32]. Consumer's reference behavior plays an important role in this process of comparison, thereby influencing firms' operational decisions, such as product pricing and decisions regarding product greenness [33, 34].

Kopalle et al. studied a novel household heterogeneity translation model considering consumers' price reference behavior and developed a normative pricing policy for retailers that maximizes category profit using individual-level estimates [35]. Hsieh and Dye investigated an inventory model based on price reference effects and established an optimal dynamic pricing model to determine a pricing strategy that maximizes the discounted total profit [36]. The results suggested that the strength of the memory factor is important for a retailer to measure because a high memory factor value represents consumers with a longer memory of perceived gains or losses. The optimal discounted total profit initially increases as the memory factor increases but decreases when the memory factor is relatively high. Some dynamic price studies have also considered price reference behavior [37, 38]. In these two previous studies, the price reference effect dominated the optimal pricing and inventory policy of the firm. The expected steady-state reference price was compared to the steady-state reference price in a model with a deterministic reference price effect, and the results showed that the former was always higher. Consumer's environmental awareness is a common behavior in real life. At present, consumers are frequently concerned about environmental protection. Green preference and green product design have attracted extensive attention from scholars. Zhang et al. investigate the impacts of consumer environmental awareness and retailer's fairness concerns on environmental quality [39]. Chen studied product design and marketing decisions based on consumer preferences for environmental attributes [40]. The development of green products depends heavily on the joint efforts of both the supply chain and the government. Therefore, the government should create a regulatory environment that is benign to green product innovation. Chitra inferred that green consumers affect marketing issues, and a preference for greenness will promote the purchase of green products [41]. The higher the consumer environmental preference is, the higher the price will be that the consumer is willing to pay for low-carbon products. Consumer's green preference is in favor of supply chain performance on the environment [42]. Moreover, as competition intensifies, the profits of manufacturers with inferior eco-friendly operations will always decrease. Li et al. infer that consumers should avoid excessive pursuit of green product design; otherwise, they hurt the environment by investigating the impact of consumer preference for green product design [43].

Consumer's reference behavior plays an important role in firms' operational decisions, and consumer environmental awareness is a common behavior in real life. The literature above is about the influence of consumers' green preference on enterprises' decision-making, such as pricing and green manufacturing. There exists a gap in the existing literature, which is that the consumer's behavior has not been concerned. In our research, the green preference and price reference behavior are considered.

2.3. Cooperation. Supply chain cooperation is defined as "long-term relationships where participants generally cooperate, share information, and work together to plan and even modify their business practices to improve joint performance" [44]. In general, supply chain cooperation means achieving better performance. In the supply chain, there are many coordination strategies to choose from, such as revenue sharing, buybacks, quantity discounts, and two-part tariff contracts. Among these contracts, revenue sharing has attracted the attention of many scholars and is widely used in actual supply chains [45]. For example, Xu et al. proposed a two-way revenue sharing contract to coordinate multiple distributors in a dual-channel supply chain, and the results showed that the manufacturer could prompt the retailer to cooperate by providing this contract [46]. Shi et al. studied reverse revenue-sharing contracts in a closed-loop system and proposed a function to calculate the optimal ratio of the transfer collection price. The results also suggested that reverse revenue-sharing contracts are more attractive for manufacturers than a two-part tariff [47]. Panda et al. explored channel coordination in a socially responsible manufacturer–retailer closed-loop supply chain and found that a revenue-sharing contract resolved channel conflict [48]. Modak et al. used the subgame perfect equilibrium and alternative offer bargaining strategy to resolve channel conflict and distribute surplus profit [49]. Wang and Zhao designed a revenue-sharing contract to reduce carbon emissions, and both the supplier and the retailer achieved Pareto improvement. In addition, they developed a function to determine the revenue sharing ratio using the Rubinstein bargaining model [50]. Yu et al. considered a cooperation problem in the low-carbon supply chain and found that the environmental awareness of consumers and tax rates considerably affect the emission reduction [51]. There have also been some supply chain coordination studies conducted under carbon policies. Revenue-sharing contracts have been designed to improve the performance of supply chain members based on different carbon policies [52]. Xu et al. studied the coordination problem in a two-echelon supply chain, and the effect of government policy-making on distributing the optimal emission quota was investigated. The results showed that a reasonable revenue-sharing contract is essential to increase supply chain members' profits even under low-carbon conditions [53]. Modak et al. concluded that the optimal recycling rate increases with the CSR activity of the manufacturer, and a profit-sharing contract provides the best channel performance in a closed-loop distribution channel consisting of a socially responsible manufacturer, multiple retailers, and a third-party collector [54]. Feng infers that win-win results can be achieved by establishing profit-sharing contracts considering the preference of green consumers [55]. Previous papers often focus on two aspects, including the choice of contract and the conditions of the contract. However, the above literature still has a gap between cooperation and consumer's behavior. Therefore, we investigate the supply chain cooperation problem under the context of consumer's reference behavior and the carbon tax.

In summary, this study examines the interaction between supply chain cooperation and carbon taxes in a two-echelon supply chain considering consumer's behavior. Some important factors should be considered simultaneously to study this problem, such as the optimal carbon tax and consumer's behavior; however, previous research has only considered these factors separately. We also investigate the interaction between coordination and the carbon tax. The difference between our study and others in the literature is presented in Table 1.

3. Supply Chain Model

In this section, a two-echelon supply chain model is introduced to study green supply chain cooperation and carbon tax policy. The optimal decisions of the supply chain and the government tax are addressed. We then introduce the revenue-sharing contract used to coordinate the supply chain.

3.1. Model Assumptions. To answer the first question (is carbon tax policy favorable for improving the greenness of products?), a two-echelon supply chain model consisting of a single supplier and a single retailer without contracts is established. The manufacturer determines the product's greenness and wholesale price, and the retailer determines the retail price of the green product. The green product competes for market share with traditional products. Compared with traditional products, green products have the characteristics of low pollution and being environmentally friendly, but they may be less functional, such as electric vehicles, which has poor endurance and slow speeds. In our study, we focus on green products that are less functional than traditional products. For example, Bellos et al. noted that manufacturers offer vehicles with poor performance for customers who focus on fuel efficiency [56]. In real life, greenness reflects the environmental attributes of the product, and it is commonly used to measure how environmentally friendly a product is. In this study, we use g to denote the greenness degree of green products as a measure of their environmental attributes, which is a common practice [38, 41].

Consumers are environmentally conscious and have environmental awareness. The utility gained from environmental attributes is assumed to be kg, where k is the sensitivity of the consumer to the greenness of a green product [38]. We use V to denote the utility obtained by a consumer from a traditional product. It is commonly assumed that V is uniformly distributed on [0, 1] to simplify the problem without affecting the conclusion [57]. Then, αV is the utility from the green product, where $\alpha \in (0, 1)$ is the functional attribute coefficient of the green product that reflects its weak functional performance compared with the traditional product.

Table 1: Differences between our study and the available literature.

Literature	Decisions under the carbon tax	Optimal carbon tax	Consumer's behavior	Coordination
Yu and Han [28]	√	√		
Ulph and Ulph [22]		√		
Hsieh and Dye [34]			√	
Cao et al. [47]	√			√
Xu et al. [48]	√			√
Our paper	√	√	√	√

In real life, consumers usually compare prices between two similar products. Let β be the consumers' recognition level of the reference price [35]. Therefore, the utility of green products is obtained from four parts: a positive part from the basic utility (αV), a negative part from the price (p), a positive part from the environmental consciousness (kg), and a negative part from the price reference $(\beta(p-p_n))$. The utility to a consumer of green products and traditional products can thus be expressed as follows:

$$\begin{cases} u_n = V - p_n, \\ u_g = \alpha V - p + kg - \beta(p - p_n). \end{cases} \tag{1}$$

Table 2 summarizes the notation used in this study.

3.2. Model and Solution. Consumers choose between green and traditional products by comparing utility: when $u_g > u_n$ and $u_g > 0$, consumers will purchase the green product, whereas when $u_n > u_g$ and $u_n > 0$, consumers will purchase the traditional product. As a result, demand is obtained as shown in equation (2). The proof of the demand function is given in Appendix A.

$$\begin{cases} q = \dfrac{(\alpha+\beta)p_n - (1+\beta)p + kg}{\alpha(1-\alpha)}, \\[2ex] q_n = 1 - \dfrac{(1+\beta)(p_n - p) + kg}{1-\alpha}. \end{cases} \tag{2}$$

The manufacturer determines the wholesale price and greenness of the green product. Let γ denote the cost rate of technology development; then, the total development cost is $(1/2)\gamma g^2$, which is convexly increasing with the greenness [40]. In addition, $(e-g)$ is a linear function of the unit carbon emissions for green products [58]. Therefore, the profit function for the manufacturer is obtained from three parts: a positive part from the wholesale $((w-c)q)$, a negative part from green technology development $((\gamma g^2/2))$, and a negative part from the carbon tax $(t(e-g)q)$. The manufacturer's decision model is as follows:

$$\operatorname*{Max}_{w,g} \pi_M = (w - c - t(e-g))q - \frac{\gamma g^2}{2}. \tag{3}$$

The retailer's decision problem is then formulated as follows:

$$\operatorname*{Max}_{p} \pi_R = (p - w)q. \tag{4}$$

The optimal solutions for the retailer and manufacturer are derived as the following theorem by substituting the demand function into the equation above. The proof is presented in Appendix A.

Theorem 1. *The optimal solutions for both parties are*

$$\begin{cases} w = \dfrac{2\gamma p_n\alpha^3 + 2A_1\gamma\alpha^2 + B_1\alpha + t^2(1+\beta)(\beta p_n + ke)}{(1+\beta)\left(t^2(1+\beta) - 4\gamma\alpha(1-\alpha)\right)}, \\[3ex] g = \dfrac{((1+\beta)(te+c) - (\alpha+\beta)p_n - ke)t}{t^2(1+\beta) - 4\gamma\alpha(1-\alpha)}, \\[3ex] p = \dfrac{3\gamma p_n\alpha^3 + 2A_2\gamma\alpha^2 + B_2\alpha + t^2(1+\beta)(\beta p_n + ke)}{(1+\beta)\left(t^2(1+\beta) - 4\gamma\alpha(1-\alpha)\right)}. \end{cases} \tag{5}$$

The corresponding profits are

$$\begin{cases} \pi_m = -\dfrac{((te+c-p_n)\beta + (-k+t)e - \alpha p_n + c)^2\gamma}{2\left(t^2\beta + t^2 + 4(-1+\alpha)\gamma\alpha\right)(\beta+1)}, \\[3ex] \pi_r = -\dfrac{((te+c-p_n)\beta + (-k+t)e - \alpha p_n + c)^2(-1+\alpha)\alpha\gamma^2}{\left(4\alpha^2\gamma - 4\alpha\gamma + (\beta+1)t^2\right)^2(\beta+1)}. \end{cases} \tag{6}$$

According to this theorem, price and greenness decisions are directly affected by the carbon tax rate. Facing a higher carbon tax and development cost, the manufacturer and retailer will reduce the greenness of products and the sale price with increasing carbon tax. However, when facing a lower carbon tax, the greenness and price will increase with increasing carbon tax (the details are shown in Appendix B, equations (1) and (5)). Next, we investigate the effects of these parameters on the product greenness. The proofs are provided in Appendix B.

Proposition 1. *The effects of the carbon tax rate, price recognition level, development cost, and functional attribute coefficient on product greenness are as follows:*

(1) *There exist some thresholds, $\hat{t}_1$ and $\hat{\gamma}_1$, for which g decreases with increasing t when $\gamma > \hat{\gamma}_1$ and $t > \hat{t}_1$; else g increases with increasing t.*

Table 2: Notations.

Parameters	Definition
p, p_n	Prices of the green product and traditional product, respectively
q, q_n	Demand for the green product and traditional product, respectively
w	Wholesale price
g	Product greenness
t	Carbon tax rate
γ	Cost rate of technology development
c	Unit product cost of the green product
e	Initial unit carbon emissions
α	Functional attribute coefficient of the green product function
β	Consumers' recognition level of the reference price
k	Sensitivity of consumers to product greenness
V	Utility obtained by a consumer from the traditional product
η	Proportion of the total revenue obtained by the retailer
λ	Member strength in the supply chain

(2) *There exist some thresholds, $\widehat{t}_2$ and $\widehat{\gamma}_2$, for which g decreases with increasing β when $\gamma > \widehat{\gamma}_2$ and $t > \widehat{t}_2$; else g increases with increasing β.*

(3) *g increases with increasing k, decreases with increasing γ, and initially increases and then decreases with increasing α.*

We can conclude that the carbon tax, development cost, price recognition level, greenness sensitivity, and functional attribute coefficient all influence the greenness in Proposition 1. When the carbon tax is low, the manufacturer incurs less cost to improve the greenness of the products. As a result, the greenness increases with the carbon tax. In addition, if the carbon tax is high and the development cost is low, the greenness of the products will increase with increasing carbon tax because the tax is the crucial factor in decisions. In contrast, if the carbon tax is high and development costs are also high, the greenness of products will decrease because the manufacturer will choose to reduce development costs. Therefore, pollution will not be reduced as the carbon tax increases in some cases. Facing high development costs, the manufacturer will not improve greenness unless it is promoted by a lower carbon tax. A numerical simulation of this scenario is shown in Figure 1.

Similarly, the results show that greenness is affected by the consumers' price reference behavior. When the carbon tax is low, the negative effect of price increases when consumers have higher concerns about price. Therefore, the manufacturer will offset this negative effect by improving the greenness of products. When the carbon tax is high and the development cost is low, the greenness of products will increase under a high consumer concern about price. In contrast, if the carbon tax is high and the development cost is high, the greenness will decrease because the manufacturer will choose to reduce development costs. Numerical simulations of these scenarios are shown in Figure 2.

In addition, greenness sensitivity and the functional attribute coefficient also affect greenness. The greenness increases with increasing greenness sensitivity of consumers. High greenness sensitivity can promote more green products. This means that the government can promote green production by

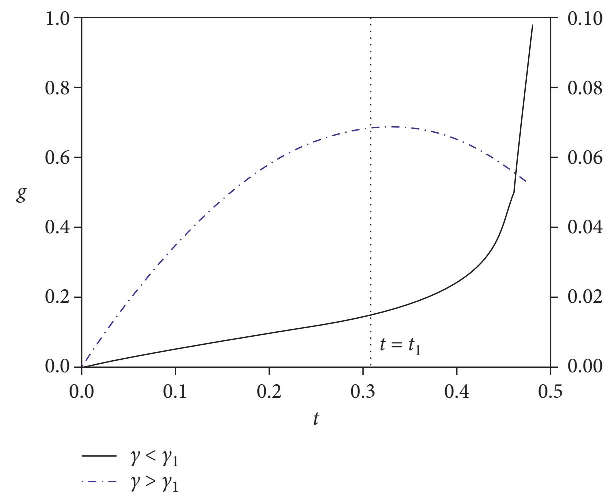
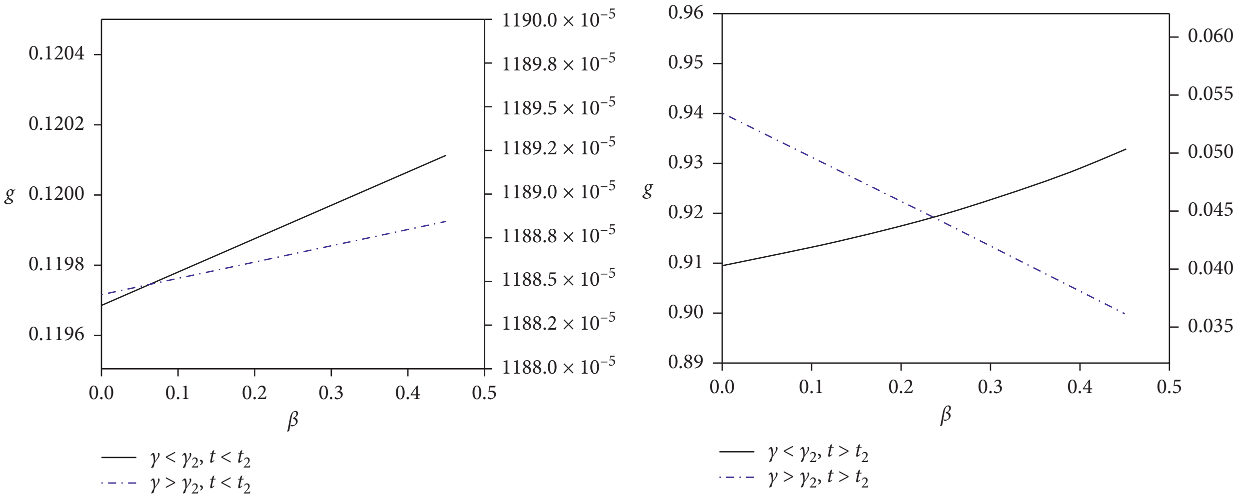


Figure 1: Effects of carbon taxes on greenness.

increasing the green consciousness of consumers. Moreover, the greenness decreases with increasing development cost. A higher degree of greenness is obtained when manufacturers face lower development costs. In addition, greenness first increases and then decreases with the increase in the functional attribute coefficient. When the functional attribute of the green product is low, the manufacturer will produce a lower greenness product with increases in the functional attribute coefficient. In contrast, the manufacturer will produce a product with higher greenness with an increase in the functional attribute after a functional threshold has been reached. Numerical simulations of these scenarios are shown in Figure 3.

Overall, consumers' reference behavior plays a positive role in promoting green production. However, the carbon tax is not effective for improving green products in some cases. For example, if the carbon tax is high and the development cost is also high, the greenness of products will decrease. Therefore, we next investigate the optimal carbon tax.

First, an optimal carbon tax is defined as that which provides the maximum greenness without losing total tax revenue. The result is provided in Proposition 2, and the proofs can be found in Appendix C.



(a) (b)

Figure 2: Effects of consumers' price reference behavior on greenness. (a) Low-carbon tax rate. (b) High carbon tax rate.

Proposition 2. *The optimal carbon tax is defined as follows:*

$$t^* = \begin{cases} \dfrac{M - \sqrt{M^2 - N}}{e(1+\beta)}, & 0 < \gamma < \hat{\gamma}_3 \\ \dfrac{P - \sqrt{P^2 - Q}}{2(1+\beta)M}, & \hat{\gamma}_3 < \gamma < \hat{\gamma}_1, \\ \hat{t}_1, & \hat{\gamma}_1 < \gamma. \end{cases} \tag{7}$$

The optimal carbon tax is obtained in Proposition 2 based on the manufacturer's development cost to maximize greenness without losing the total carbon tax revenue. We can observe that the crucial factor is the development cost. An appropriate carbon tax policy should be chosen when facing different production technologies to ensure greenness and total tax revenue. In addition, it is easily observed that the maximum greenness is obtained when the development cost is high, whereas the maximum tax is obtained when the development cost is lower, but some of the greenness is lost. A numerical simulation of this scenario is shown in Figure 4.

3.3. Supply Chain Coordination. It is also important for supply chains to establish green supply chain models by integrating internal and external resources to make decisions, which enables supply chains to achieve better performance by improving cooperation [59, 60]. However, most studies on coordination have mainly focused reducing emissions and improving profit. Few studies have investigated the relationship between carbon taxes and supply chain cooperation.

In this section, we study the impact of carbon taxes and consumer's behavior on supply chain coordination, where the manufacturer is the leader, and the retailer is the follower. A revenue-sharing contract is introduced to achieve coordination. Let η denote the proportion of total revenue obtained by the retailer; then, the manufacturer's decision model is as follows:

$$\underset{w,g}{\operatorname{Max}}\, \pi_M^C = ((1-\eta)p + w - c - t(e-g))q - \frac{\gamma g^2}{2}. \tag{8}$$

The retailer's decision problem can be described as follows:

$$\underset{p}{\operatorname{Max}}\, \pi_R^C = (\eta p - w)q. \tag{9}$$

The optimal solutions for the retailer and manufacturer are derived with the following theorem by substituting the demand function into the equation above. The proof is found in Appendix D.

Theorem 2. *The greenness is defined as follows:*

$$g = \frac{t(-\alpha p_n + et(\beta+1) + (c - p_n)\beta - ke + c)}{2\gamma(1+\eta)\alpha^2 - 2\gamma(1+\eta)\alpha + t^2(\beta+1)}. \tag{10}$$

Then, the profits of both parties are the following:

$$\begin{cases} \pi_m = -\dfrac{((te + c - p_n)\beta + (-k+t)e - \alpha p_n + c)^2\gamma}{2\left(t^2\beta + t^2 + 4(-1+\alpha)\gamma\alpha\right)(\beta+1)}, \\ \pi_r = -\dfrac{((te + c - p_n)\beta + (-k+t)e - \alpha p_n + c)^2(-1+\alpha)\alpha\gamma^2}{\left(4\alpha^2\gamma - 4\alpha\gamma + (\beta+1)t^2\right)^2(\beta+1)}. \end{cases} \tag{11}$$

We investigate the impact of the carbon tax on promoting the coordination of the supply chain by comparing the profit changes of the two partners after the introduction of the revenue-sharing contract in Proposition 3. The proofs are provided in Appendix E.

Proposition 3. *Coordination can be promoted by increasing the carbon tax.*

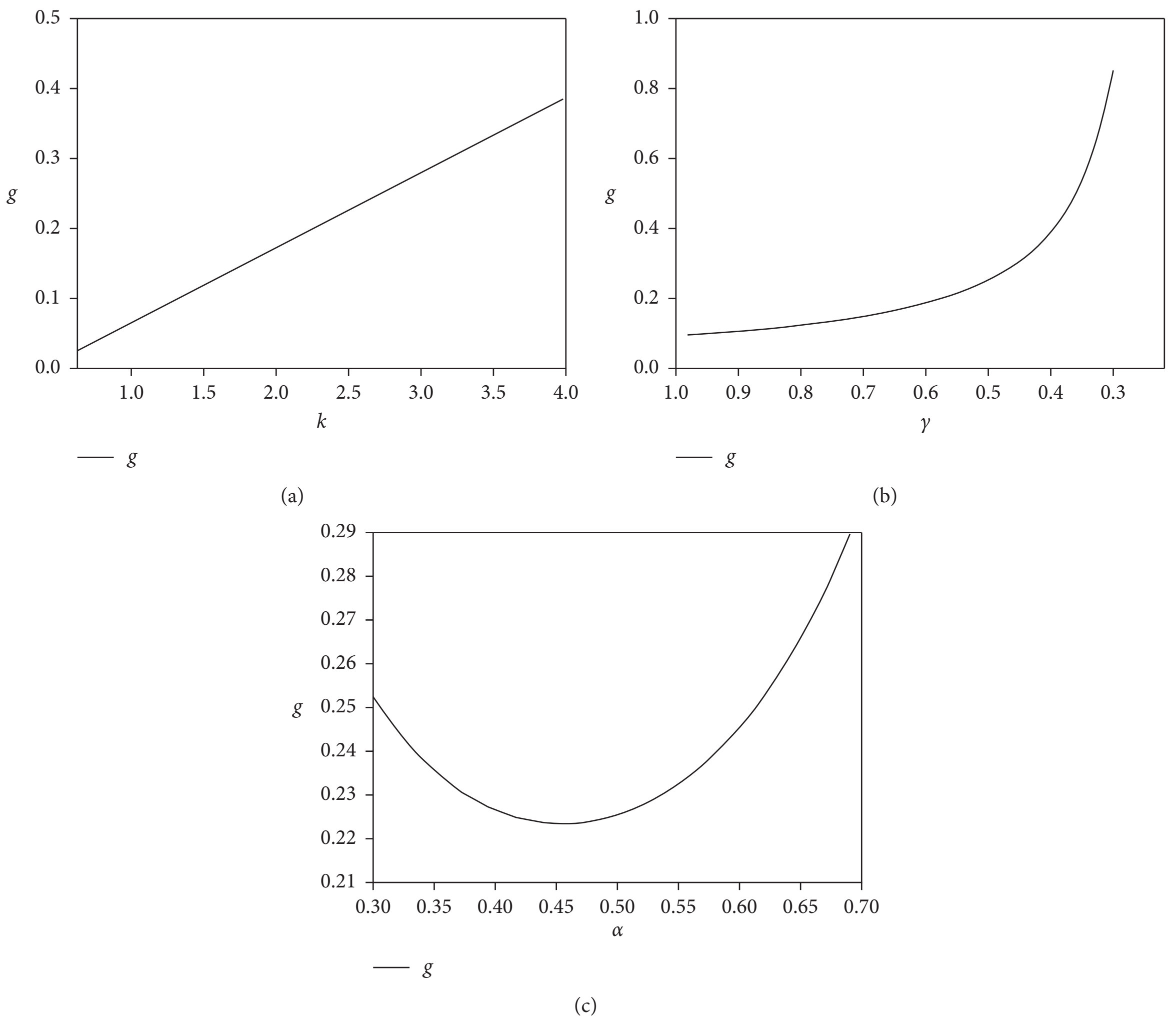


Figure 3: Effects of parameters on greenness. (a) Greenness sensitivity. (b) Development cost. (c) Functional attribute coefficient.

When the profits of both the retailer and the manufacturer improve simultaneously, coordination is achieved. By comparing equations (11) and (6), we find that the revenue-sharing contract improves the retailer's profit only when $\eta \in (\eta_1, 1)$, whereas the manufacturer always benefits from the contract. The range of η depends on the carbon tax rate. When η is in the given range, the retailer and manufacturer achieve Pareto improvement. Furthermore, the range expands as the carbon tax rate increases. Therefore, the government can promote supply chain collaboration by increasing the carbon tax. Based on the previous results for the optimal carbon tax, we next investigate how to achieve coordination when the supply chain faces the optimal carbon tax. Figure 5 shows the Pareto improvement region.

According to the assumptions described above, the manufacturer acts as the leader, and the retailer acts as a follower. It is reasonable that the proportion of profit received by the retailer is decided by the manufacturer. Therefore, it is necessary to investigate whether the proportion decided by the leader is in the region in which coordination is achieved. A parameter λ is introduced to denote the strength of a partner in the supply chain. Let $\lambda_m \in (0.5, 1)$ and $\lambda_r = 1 - \lambda_m$ represent the power of the manufacturer and the retailer, respectively. Then, we consider a simple function, (λ_r/λ_m), to determine η, which is the proportion of revenue received by the retailer. The retailer retains the maximum revenue when the power of the two parties is equal (i.e., $\lambda_m = \lambda_r = 0.5$), whereas all of the benefits go to the leader when the power of the manufacturer is overwhelming compared with that of the retailer (i.e., $\lambda_m = 1$). Similar to Proposition 2, the optimal carbon tax is obtained under the revenue-sharing contract as follows:

$$t^* = \begin{cases} \dfrac{M - \sqrt{M^2 - (1+\eta/2)N}}{e(1+\beta)}, & 0 < \gamma < \hat{\gamma}_2^C, \\[2ex] \dfrac{(1+\eta/2)P - \sqrt{(1+\eta/2)^2 P^2 - (1+\eta/2)Q}}{2(1+\beta)M}, & \hat{\gamma}_2^C < \gamma < \hat{\gamma}_1, \\[2ex] \hat{t}_1, & \hat{\gamma}_1 < \gamma. \end{cases} \quad (12)$$

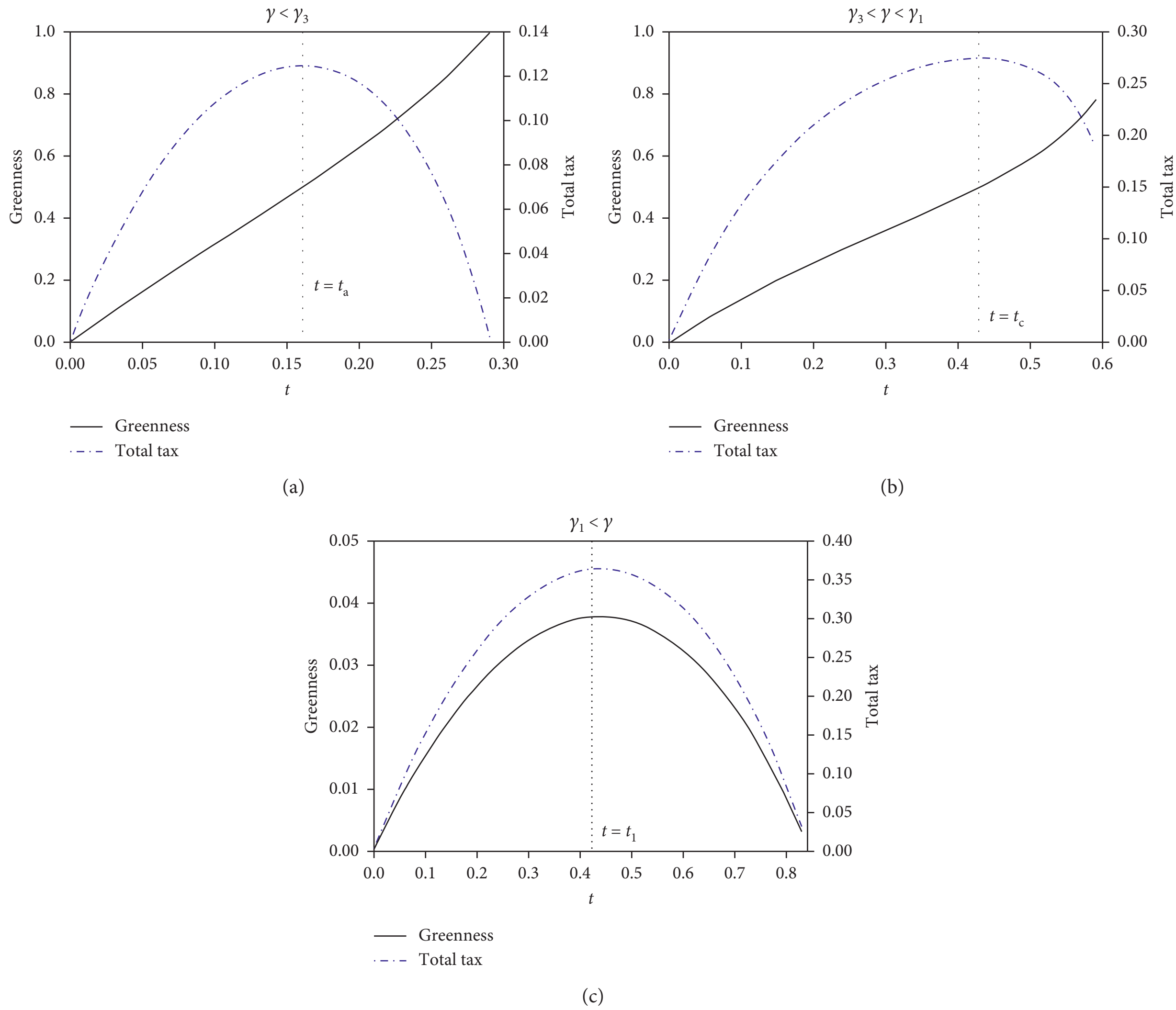


Figure 4: Determination of the optimal carbon tax. (a) $0<\gamma<\widehat{\gamma}_3$. (b) $\widehat{\gamma}_3<\gamma<\widehat{\gamma}_1$. (c) $\widehat{\gamma}_1<\gamma$.

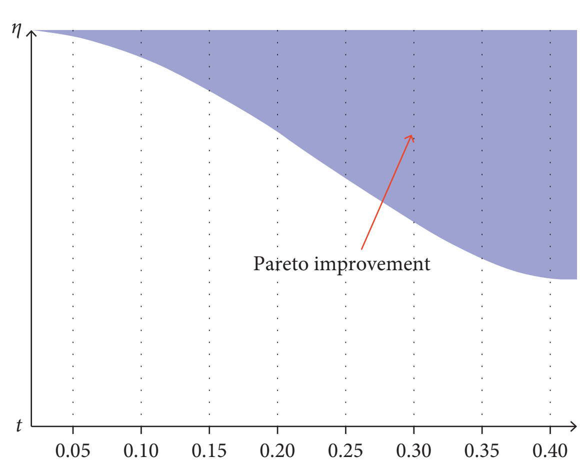


Figure 5: Pareto improvement region with increasing carbon tax.

Proposition 4 is designed to answer the question of whether cooperation will be achieved; the proofs are found in Appendix F.

Proposition 4. *Coordination will be achieved if the power of the manufacturer is low (i.e., $0.5<\lambda_m<\widehat{\lambda}_1$). Moreover, when the power of the manufacturer is at a medium level (i.e., $\widehat{\lambda}_1<\lambda_m<\widehat{\lambda}_2$), coordination can be achieved, but part of the total tax revenue will be lost, if the development cost is low (i.e., $\gamma<\widehat{\gamma}_1$). In other cases (i.e., $\gamma>\widehat{\gamma}_1$ or $\widehat{\lambda}<\lambda_m$), coordination cannot be achieved because the power of the manufacturer is overwhelming.*

Coordination situations for different manufacturer power levels are present in Table 3. The achievement of coordination is decided by the power of the manufacturer and the optimal carbon tax faced by the supply chain. Based on Proposition 3, coordination can be promoted if the government adjusts the carbon tax. On the other hand, coordination can easily be achieved under the optimal carbon tax if the power of the manufacturer is low. In addition, there are two possibilities when the power of the manufacturer is at a medium level. If the development cost is too high, adjusting the tax will lead to an unknown result: the greenness and total tax revenue may both decline at the same

Table 3: Coordination situations for different manufacturer power levels.

Power of the manufacturer	Coordination	Greenness	Total carbon tax revenue
$0.5 < \lambda_m < \widehat{\lambda}_1$	Achieve	Improve	Improve
$\widehat{\lambda}_1 < \lambda_m < \widehat{\lambda}_2, \gamma < \widehat{\gamma}_1$	Achieve	Improve	Decline
$\widehat{\lambda}_1 < \lambda_m < \widehat{\lambda}_2, \gamma < \widehat{\gamma}_1$	Cannot achieve		
$\gamma > \widehat{\gamma}_1$	Cannot achieve		

time. If the development cost is lower, the greenness may be improved with a loss of revenue by increasing the carbon tax. However, when the power of the manufacturer is strong, the region $\delta = (\eta_1, 1)$ cannot be achieved.

According to our theory, the government can promote the coordination between the manufacturer and the retailer by adjusting the carbon tax. When the power of the manufacturer increases, the government still achieves coordination by raising the carbon tax. In general, cooperation is achieved, and the government plays a key role in promoting cooperation.

The effects of consumers' behavior on supply chain coordination are also investigated in the next proposition. The proofs are provided in Appendix G.

Proposition 5. *Price reference behavior can promote supply chain coordination, but green preference cannot.*

From the previous results, price reference has a complex impact on the supply chain. First, the increasing sensitivity of customers to price will promote supply chain coordination because this negative impact can be mitigated by cooperation. In addition, price reference behavior also affects the green decisions of the supply chain in a complex manner. In contrast, the mechanism by which consumer' green preferences influence the supply chain is relatively simple. Greenness increases with increasing greenness preference, and green preference has no effect on the coordination of the supply chain.

4. Conclusion

This study examines the interaction between supply chain cooperation and the carbon tax problem in a two-echelon supply chain under consumer's reference behavior. The optimal carbon tax policy is obtained based on analysis of the carbon tax, green investment coefficient, and degree of consumer's price reference. The optimal carbon tax is defined as the simultaneous optimization of total tax revenue and product greenness. In addition, coordination is achieved by introducing revenue-sharing contracts. The impact of consumers' reference behavior and the carbon tax on supply chain coordination is also investigated. The results are as follows:

(1) The greenness increases with increasing carbon tax when the carbon tax is low. In addition, if the carbon tax is higher and the development cost is low, the greenness of products will increase with increasing carbon tax. Conversely, if the carbon tax is higher and the development cost is also high, the greenness of products will decrease.

(2) When the carbon tax is low, the negative effect of price increases as consumer concerns about price increase. Therefore, the manufacturer offsets the negative effect by improving the greenness. When the carbon tax is higher and development cost is low, the greenness of products will increase with high consumer's concern about price. In contrast, if the carbon tax is higher and the development cost is high, the greenness will decrease.

(3) The greenness increases with an increasing greenness preference of consumers. Their preference behavior can promote more green products. This means that the government can promote green production by promoting the green consciousness of consumers. Moreover, the greenness decreases with increasing development cost. A higher greenness is obtained when manufacturers face lower development costs. In addition, greenness first increases and then decreases with increases in the functional attribute coefficient. When the functional attribute of the green product is low, the manufacturer will produce a lower greenness product with an increase in the functional attribute. In contrast, the manufacturer will produce a higher greenness product with an increase in the functional attribute after a functionality threshold.

(4) We investigated the impact of the carbon tax on promoting the coordination of the supply chain by comparing the profit changes of two partners after the introduction of a revenue-sharing contract in Proposition 3. We found that coordination could be promoted by increasing the carbon tax.

(5) The achievement of coordination depends on the type of manufacturer. If the power of the manufacturer is low, coordination can be achieved under the optimal carbon tax. If the power of the manufacturer is at a medium level, coordination can be achieved by increasing the carbon tax, and improved greenness will be realized with a loss of revenue. However, when the power of the manufacturer is strong, coordination cannot be achieved.

In this study, we focused on the interaction between a carbon tax and supply chain cooperation. However, other carbon policies (e.g., a cap-and-trade policy) and supply chain structures are worth exploring. For example, it would be interesting to investigate the effects on a supply chain structure consisting of the retailer as the leader under a complex carbon policy.

Appendix

A. Proof of Theorem 1

The demand function can be written as

$$\begin{cases} q = P\{u_g \geq u_n, u_g \geq 0\}, \\ q_n = P\{u_n > u_g, u_n \geq 0\}. \end{cases} \tag{A.1}$$

After replacing u_n and u_g, we have

$$\begin{cases} q = P\{\alpha v - p + kg - \beta(p - p_n) - (v - p_n) \geq 0, \alpha v - p + kg - \beta(p - p_n) \geq 0\}, \\ q_n = P\{v - p_n - (\alpha v - p + kg - \beta(p - p_n)) > 0, v - p_n \geq 0\}. \end{cases} \tag{A.2}$$

Given that V is uniformly distributed on [0, 1], the demand function is

$$\begin{cases} q = \dfrac{(\alpha + \beta)p_n - (1 + \beta)p + kg}{\alpha(1 - \alpha)}, \\ q_n = 1 - \dfrac{(1 + \beta)(p_n - p) + kg}{1 - \alpha}. \end{cases} \tag{A.3}$$

The condition $k > ((1 + \beta)p - (\alpha + \beta)p_n/g)$ is necessary to ensure nonnegativity. The retailer problem is addressed first, and we have

$$p = \frac{(\alpha + \beta)p_n + (1 + \beta)w + kg}{2(1 + \beta)}. \tag{A.4}$$

Then, substitute p into the manufacturer's profit function. Solving the optimal w and g simultaneously yields

$$\begin{aligned} w &= \frac{(\alpha + \beta)p_n + (1 + \beta)(c + t(e - g)) + kg}{2(1 + \beta)}, \\ g &= \frac{t((\alpha + \beta)p_n - (1 + \beta)w + ke)}{2\gamma\alpha(1 - \alpha)}. \end{aligned} \tag{A.5}$$

Then we have

$$\begin{cases} w = \dfrac{2\gamma p_n \alpha^3 + 2A_1\gamma\alpha^2 + B_1\alpha + t^2(1 + \beta)(\beta p_n + ke)}{(1 + \beta)\left(t^2(1 + \beta) - 4\gamma\alpha(1 - \alpha)\right)}, \\ g = \dfrac{((1 + \beta)(te + c) - (\alpha + \beta)p_n - ke)t}{t^2(1 + \beta) - 4\gamma\alpha(1 - \alpha)}, \\ p = \dfrac{3\gamma p_n \alpha^3 + 2A_2\gamma\alpha^2 + B_2\alpha + t^2(1 + \beta)(\beta p_n + ke)}{(1 + \beta)\left(t^2(1 + \beta) - 4\gamma\alpha(1 - \alpha)\right)}, \end{cases}$$

$$\begin{cases} A_1 = (1 + \beta)(c + te) + ke - (1 - \beta)p_n, \\ A_2 = (1 + \beta)(c + te) + 3ke - (3 - \beta)p_n, \end{cases}$$

$$\begin{cases} B_1 = -2\gamma((1 + \beta)(c + te) + ke + \beta p_n) + t^2(1 + \beta)p_n, \\ B_2 = -\gamma((1 + \beta)(c + te) + 3ke + 3\beta p_n) + t^2(1 + \beta)p_n. \end{cases} \tag{A.6}$$

Notes that we have $(\alpha + \beta)p_n + ke - (1 + \beta)(te + c) > 0$. The concavity condition is $4\alpha\gamma(1 - \alpha) - (1 + \beta)t^2 > 0$.

B. Proof of Proposition 1

(1) The first derivative of g in t is

$$\frac{\partial g}{\partial t} = \frac{-4\gamma\alpha^3 p_n + 4\gamma A_3\alpha^2 + B_3\alpha - t^2(1 + \beta)((1 + \beta)c - ke - \beta p_n)}{\left(t^2(1 - \beta) - 4\gamma\alpha(1 - \alpha)\right)^2},$$

$$\begin{cases} A_3 = (1 + \beta)(c + 2te) - ke + (1 - \beta)p_n, \\ B_3 = -4\gamma((1 + \beta)(c + 2te) - ke - \beta p_n) + t^2(1 + \beta)p_n. \end{cases} \tag{B.1}$$

We have a threshold

$$\begin{aligned} \widehat{\gamma}_1 &= -\frac{t^2(1 + \beta)((\alpha + \beta)p_n + ke - (1 + \beta)c)}{4\alpha(1 - \alpha)((\alpha + \beta)p_n + ke - (1 + \beta)(c + 2te))}, \\ \widehat{t}_1 &= \frac{(\alpha + \beta)p_n + ke - (1 + \beta)c}{2(1 + \beta)e}. \end{aligned} \tag{B.2}$$

When $\gamma > \widehat{\gamma}_1$ and $t > \widehat{t}_1$, g is decreasing in t. By contrast, g is increasing in t in other cases.

(2) The first derivative of g in β is

$$\frac{\partial g}{\partial \beta} = \frac{-4\alpha(1 - \alpha)(te + c - p_n)\gamma + t^2(ke + \alpha p_n - p_n)}{\left(t^2(1 + \beta) - 4\alpha(1 - \alpha)\gamma\right)^2}. \tag{B.3}$$

We have a threshold

$$\begin{aligned} \widehat{\gamma}_2 &= -\frac{t^2(ke - (1 - \alpha)p_n)}{4\alpha(1 - \alpha)(te + c - p_n)}, \\ \widehat{t}_2 &= \frac{p_n - c}{e}. \end{aligned} \tag{B.4}$$

Review we have $(\alpha + \beta)p_n + ke - (1 + \beta)(te + c) > 0$; therefore we can find that

$$t < \frac{p_n - c}{e} + \frac{ke - (1 - \alpha)p_n}{(1 + \beta)e}. \tag{B.5}$$

(i) When $ke - (1 - \alpha)p_n < 0$, then $t < \widehat{t}_2$ is inevitable. Therefore $(\partial g/\partial \beta) > 0$ is correct.

(ii) When $ke - (1 - \alpha)p_n > 0$, we can find that $(\partial g/\partial \beta) < 0$ if $\gamma > \widehat{\gamma}_2$ and $t > \widehat{t}_2$; $(\partial g/\partial \beta) < 0$ in other cases.

(3) The first derivative of g in k and γ is

$$\begin{cases} \dfrac{\partial g}{\partial \gamma} = -\dfrac{4\alpha(1-\alpha)((\alpha+\beta)p_n + ke - (1+\beta)(te+c))}{\left(4\gamma\alpha(1-\alpha) - t^2(1+\beta)\right)^2} < 0, \\ \dfrac{\partial g}{\partial k} = \dfrac{te}{4\gamma\alpha(1-\alpha) - t^2(1+\beta)} > 0. \end{cases} \tag{B.6}$$

(4) The first derivative of g in α is

$$\frac{\partial g}{\partial \alpha} = \frac{-Xt}{\left(4\alpha(1-\alpha)\gamma - t^2(1+\beta)\right)^2}. \tag{B.7}$$

And $X = -4\alpha^2\gamma p_n + (4(1+\beta)(te+c) - 4ke - 4p_n)(2\alpha+1)\gamma + p_n t^2(1+\beta)$ is a quadratic function. The range of α in $4\alpha\gamma(1-\alpha) - (1+\beta)t^2 > 0$ is

$$\begin{cases} \alpha_1 = \dfrac{\gamma + \sqrt{\gamma^2 - \gamma t^2(1+\beta)}}{2\gamma}, \\ \alpha_2 = \dfrac{\gamma - \sqrt{\gamma^2 - \gamma t^2(1+\beta)}}{2\gamma}. \end{cases} \tag{B.8}$$

By substituting those into X, we have

$$\begin{cases} X|_{\alpha=\alpha_1} = 4\sqrt{\gamma^2 - \gamma t^2(1+\beta)}\,T - 2\left(\gamma - t^2(1+\beta)\right)p_n, \\ X|_{\alpha=\alpha_2} = -4\sqrt{\gamma^2 - \gamma t^2(1+\beta)}\,T - 2\left(\gamma - t^2(1+\beta)\right)p_n < 0. \end{cases} \tag{B.9}$$

And $T = (1+\beta)(te+c) - ke - ((1/2)+\beta)p_n < 0$. We can find

$$\begin{aligned} X|_{\alpha=\alpha_1} \times X|_{\alpha=\alpha_2} = {} & -4\left(\gamma - t^2(1+\beta)\right) \\ & \cdot \left(4(\beta p_n + ke - (1+\beta)(te+c))^2 \right. \\ & \left. + p_n^2 t^2(1+\beta)\right) < 0. \end{aligned} \tag{B.10}$$

Therefore, $X|_{\alpha=\alpha_1} > 0$. There only exist a $\widehat{\alpha} \in (\alpha_2, \alpha_1)$ that makes $(\partial g/\partial\alpha) = 0$. And $(\partial g/\partial\alpha) > 0$ if $\alpha \in (\alpha_2, \widehat{\alpha})$; $(\partial g/\partial\alpha) < 0$ if $\alpha \in (\widehat{\alpha}, \alpha_1)$.

(5) The first derivative of p in t is

$$\begin{gathered} \frac{\partial p}{\partial t} = -\frac{2\alpha(\alpha-1)\left(\left(e(1+\beta)t^2/2\right) + \left(-p_n\alpha - ke + (c-p_n)\beta + c\right)t - 2e\alpha\gamma(\alpha-1)\right)\gamma}{\left((1+\beta)t^2 + 4\alpha\gamma(\alpha-1)\right)^2}, \\ \begin{cases} A_3 = (1+\beta)(c+2te) - ke + (1-\beta)p_n, \\ B_3 = -4\gamma((1+\beta)(c+2te) - ke - \beta p_n) + t^2(1+\beta)p_n. \end{cases} \end{gathered} \tag{B.11}$$

The discriminant of quadratic function

$$\frac{e(1+\beta)t^2}{2} + \left(-p_n\alpha - ke + (c-p_n)\beta + c\right)t - 2e\alpha\gamma(\alpha-1), \tag{B.12}$$

is

$$\Delta = \left((-\beta-1)c + ke + \beta p_n + p_n\alpha\right)^2 + 4e^2(1+\beta)t^2\alpha\gamma(\alpha-1). \tag{B.13}$$

We have a threshold

$$\frac{2\sqrt{\gamma}\left(-p_n\alpha - ke + (c-p_n)\beta + c\right)\sqrt{-(1+\beta)\alpha(\alpha-1)} - 4e\alpha\gamma(\alpha-1)(1+\beta)}{1+\beta}. \tag{B.16}$$

$$\widehat{\gamma} = -\frac{\left((-\beta-1)c + ke + \beta p_n + p_n\alpha\right)^2}{4e^2(1+\beta)t^2\alpha(\alpha-1)}. \tag{B.14}$$

Review we have $(\alpha+\beta)p_n + ke - (1+\beta)(te+c) > 0$; therefore we can find that

$$t_m = \frac{2\sqrt{-(1+\beta)\alpha\gamma(\alpha-1)}}{1+\beta}. \tag{B.15}$$

Substituting it into above quadratic function:

And we have a same threshold:

$$\widehat{\gamma} = -\frac{\left((-\beta-1)c + ke + \beta p_n + p_n\alpha\right)^2}{4e^2(1+\beta)t^2\alpha(\alpha-1)}. \tag{B.17}$$

It could be found that $(\partial p/\partial t) > 0$ because $\Delta < 0$ when $\gamma < \widehat{\gamma}$. And when $\gamma > \widehat{\gamma}$, we have another threshold $\widehat{t}$ and $\partial p/\partial t|_{t=\widehat{t}} = 0$ because $\Delta > 0$ and $\partial p/\partial t|_{t_m} < 0$. Therefore, when $\gamma > \widehat{\gamma}$ and $t > \widehat{t}$, p is decreasing in t. And when $\gamma > \widehat{\gamma}$ and $t < \widehat{t}$, p is increasing in t.

C. Proof of Proposition 2

(1) Let $R = t(e-g)q$ denote total carbon tax, and the first derivative of R in t is

$$\frac{\partial R}{\partial t} = \frac{2\gamma\left(A_2t^2 + B_2t + c\right)\left(A_3t^2 + B_3t + c\right)}{\left(4\gamma\alpha(1-\alpha) - t^2(1+\beta)\right)^3}. \tag{C.1}$$

Among them

$$\begin{cases} A_2 = \dfrac{(1+\beta)e}{2} > 0, \\ B_2 = -((\alpha+\beta)p_n + ke - (1+\beta)c) < 0, \\ C_2 = 2\gamma e\alpha(1-\alpha) > 0, \end{cases}$$

$$\begin{cases} A_3 = ((\alpha+\beta)p_n + ke - (1+\beta)c)(1+\beta) > 0, \\ B_3 = -8\gamma e\alpha(1-\alpha)(1+\beta) < 0, \\ C_3 = 4\gamma\alpha(1-\alpha)((\alpha+\beta)p_n + ke - (1+\beta)c) > 0. \end{cases} \tag{C.2}$$

Let $\Phi = A_2t^2 + B_2t + C_2$ and $\Psi = A_3t^2 + B_3t + C_3$, and we can find that $\partial R/\partial t$ and $\Phi \times \Psi$ have a same sign. By solving Δ_1 and Δ_2, a threshold is

$$\widehat{\gamma}_3 = \frac{\left((\alpha+\beta)p_n + ke - (1+\beta)c\right)^2}{4e^2\alpha(1-\alpha)(1+\beta)}. \tag{C.3}$$

There are two positive real numbers of solutions for Φ if $\gamma < \widehat{\gamma}_3$, and let $0 < t_a < t_b$ denote it. Similarly, let $0 < t_c < t_d$ denote the solutions for Ψ if $\gamma > \widehat{\gamma}_3$. Review we have $4\alpha\gamma(1-\alpha) - (1+\beta)t^2 > 0$, therefore let $t_m = \sqrt{4\gamma\alpha(1-a)/1+\beta}$. Substituting t_m into Φ and Ψ:

$$\begin{cases} \Phi|_{t_m} = -2\sqrt{\dfrac{\gamma\alpha(1-\alpha)}{1+\beta}}((\alpha+\beta)p_n + ke - (1+\beta)c) + 4e\gamma\alpha(1-\alpha), \\ \Psi|_{t_m} = -8\gamma\alpha(1-\alpha)\left(2(1+\beta)e\sqrt{\dfrac{\alpha(1-\alpha)}{1+\beta}}\gamma - ((\alpha+\beta)p_n + ke - (1+\beta)c)\right). \end{cases} \tag{C.4}$$

If $\gamma < \widehat{\gamma}_3$, $\Phi|_{t_m} < 0$, and $\Psi|_{t_m} > 0$, then $\partial R/\partial t|_{t_m} < 0$; If $\gamma > \widehat{\gamma}_3$, $\Phi|_{t_m} > 0$, and $\Psi|_{t_m} < 0$, then $\partial R/\partial t|_{t_m} < 0$. Therefore, we have $t_m \in (t_a, t_b)$ or $t_m \in (t_c, t_d)$. Furthermore, $R = t(e-g)q$ is maximized when $t = t_a$ if $\gamma < \widehat{\gamma}_3$; $R = t(e-g)q$ is maximized when $t = t_c$ if $\gamma > \widehat{\gamma}_3$. Totally, we have

$$t^* = \begin{cases} t_a, \gamma < \widehat{\gamma}_3, \\ t_c, \gamma > \widehat{\gamma}_3. \end{cases} \tag{C.5}$$

(2) Review Proposition 1. If $\gamma > \widehat{\gamma}_1$, g is maximized when $t^* = \widehat{t}_1$. If $\gamma < \widehat{\gamma}_1$, g is maximized when $t^* = t_m$.
When $t > \widehat{t}_1$, $\widehat{\gamma}_1 > \widehat{\gamma}_5$. And $\widehat{\gamma}_1 < 0 < \widehat{\gamma}_5$ if $t < \widehat{t}_1$. Substituting $\widehat{t}_1$ into Φ:

$$\Phi|_{\widehat{t}_1} = -\frac{3\left((\alpha+\beta)p_n + ke - (1+\beta)c\right)^2}{8e(1+\beta)} + 2e\gamma\alpha(1-\alpha). \tag{C.6}$$

A threshold is $\widehat{\gamma}_4 = (3/4)\widehat{\gamma}_3$. Therefore, we have (i) when $0 < \gamma < \widehat{\gamma}_4$, $t^* = t_a$ because of $\Phi|_{\widehat{t}_1} < 0$ and $\widehat{t}_1 > t_a$; (ii) when $\widehat{\gamma}_4 < \gamma < \widehat{\gamma}_3$, $t^* = t_a$ because of $\widehat{t}_1 < t_a$; (iii) $t^* = t_c$ when $\widehat{\gamma}_3 < \gamma < \widehat{\gamma}_1$; and (iv) $t^* = t_c$ when $\widehat{\gamma}_1 < \gamma$. The result is obtained by solving Φ and Ψ.

D. Proof of Theorem 2

Similar to Appendix A. The retailer problem is addressed first, and we have

$$p = \frac{\alpha\eta p_n + \beta\eta p_n + \eta kg + \beta w + w}{2\eta(\beta+1)}. \tag{D.1}$$

Then, substituting p into the manufacturer's profit function. Solving the optimal w and g simultaneously yields

$$\begin{cases} w = \dfrac{(\alpha\eta p_n + \beta et + \beta\eta p_n - \beta gt + e\eta k + c\beta + et - gt + c)\eta}{(1+\eta)(\beta+1)}, \\ g = -\dfrac{(\alpha\eta p_n + \beta\eta p_n + e\eta k - \beta w - w)t}{2(\alpha-1)\gamma\alpha\eta}. \end{cases} \tag{D.2}$$

By solving the equation above, we have

$$\begin{cases} w = \dfrac{2\gamma p_n\alpha^3 + 2A_1\gamma\alpha^2 + B_1\alpha + t^2(1+\beta)(\beta p_n + ke)}{(1+\beta)\left(t^2(1+\beta) - (1+\eta)\gamma\alpha(1-\alpha)\right)}, \\ g = \dfrac{t(-\alpha p_n + et(\beta+1) + (c-p_n)\beta - ke + c)}{t^2(1+\beta) - (1+\eta)\gamma\alpha(1-\alpha)}, \\ p = \dfrac{(2\eta+1)\gamma p_n\alpha^3 + A_2\gamma\alpha^2 + B_2\alpha + t^2(1+\beta)(\beta p_n + ke)}{(1+\beta)\left(t^2(1+\beta) - (1+\eta)\gamma\alpha(1-\alpha)\right)}, \end{cases} \tag{D.3}$$

$$\begin{cases} A_1 = (et + \eta p_n + c)\beta + et + (ke - p_n)\eta + c, \\ A_2 = ((2\eta+1)p_n + et + c)\beta + (-2\eta - 1)p_n + et + (2\eta k + k)e + c, \end{cases}$$

$$\begin{cases} B_1 = ((-2et - 2\eta p_n - 2c)\beta - 2e\eta k - 2et - 2c)\gamma + t^2 p_n(\beta+1), \\ B_2 = (((-2\eta - 1)p_n - et - c)\beta - et + (-2\eta k - k)e - c)\gamma + t^2 p_n(\beta+1). \end{cases}$$

Note that we have $-\alpha p_n + et(\beta+1) + (c-p_n)\beta - ke + c < 0$. The concavity condition is $(1+\beta)(t^2(1+\beta) - (1+\eta)\gamma\alpha(1-\alpha)) < 0$.

Substituting solutions into the profit function, we have

$$\begin{cases} \pi_m = -\dfrac{((te + c - p_n)\beta + (-k+t)e - \alpha p_n + c)^2\gamma}{2\left(t^2\beta + t^2 + 4(-1+\alpha)\gamma\alpha\right)(\beta+1)}, \\ \pi_r = -\dfrac{((te + c - p_n)\beta + (-k+t)e - \alpha p_n + c)^2(-1+\alpha)\alpha\gamma^2}{\left(4\alpha^2\gamma - 4\alpha\gamma + (\beta+1)t^2\right)^2(\beta+1)}. \end{cases} \tag{D.4}$$

E. Proof of Proposition 3

$$\begin{cases} \pi_M = \dfrac{((\alpha+\beta)p_n + ke - (1+\beta)c)^2\gamma}{2(1+\beta)\left(4\gamma\alpha(1-\alpha) - (1+\beta)t^2\right)^2}, \\ \pi_M^C = \dfrac{((\alpha+\beta)p_n + ke - (1+\beta)c)^2\gamma}{2(1+\beta)\left(2(1+\eta)\gamma\alpha(1-\alpha) - (1+\beta)t^2\right)^2}. \end{cases} \tag{E.1}$$

By comparing the profits of two partners change after the revenue-sharing contract introduced, we found that the manufacturer always benefits from cooperation:

$$\begin{cases} \pi_R = \dfrac{\gamma^2\alpha(1-\alpha)((\alpha+\beta)p_n + ke - (1+\beta)(te+c))^2}{(1+\beta)\left(4\gamma\alpha(1-\alpha) - (1+\beta)t^2\right)^2}, \\ \pi_R^C = \dfrac{\eta\gamma^2\alpha(1-\alpha)((\alpha+\beta)p_n + ke - (1+\beta)(te+c))^2}{(1+\beta)\left(2(1+\eta)\gamma\alpha(1-\alpha) - (1+\beta)t^2\right)^2}. \end{cases} \tag{E.2}$$

A threshold is

$$\eta_1 = \left(\frac{2\gamma\alpha(1-\alpha) - (1+\beta)t^2}{2\gamma\alpha(1-\alpha)}\right)^2. \tag{E.3}$$

When η is in the region $\delta = (\eta_1, 1)$, the retailer will accept cooperation. And the first derivative of η_1 in t is

$$\frac{\partial\eta_1}{\partial t} = \frac{\left(2\alpha^2\gamma - 2\alpha\gamma + t^2(\beta+1)\right)t(\beta+1)}{\alpha^2\gamma^2(-1+\alpha)^2} < 0. \tag{E.4}$$

Therefore, η_1 is decreasing in t. That means the region $\delta = (\eta_1, 1)$ is expanding when tax rises. And the revenue-sharing contract is accepted easily than before.

F. Proof of Proposition 4

We consider a simple function (λ_r/λ_m) to decide the practical η, where $\lambda_m \in (0.5, 1)$ and $\lambda_r = 1 - \lambda_m$. Given the carbon tax t^*, we have a region $\delta = (\eta(t^*), 1)$ of cooperation. It is clear that the gap of strength between two partitions in the supply chain is a crucial factor in cooperation. By comparing practice η, decided by strength, and $\eta(t^*)$, decided by the carbon tax, we have

$$\frac{1}{\lambda_m} - 1 = \frac{\left(2\alpha^2\gamma - 2\alpha\gamma + t^2(\beta+1)\right)^2}{4\alpha^2\gamma^2(-1+\alpha)^2}. \tag{F.1}$$

A threshold is

$$\hat{\lambda}_1 = \frac{4\alpha^2\gamma^2(-1+\alpha)^2}{8\alpha^4\gamma^2 - 16\alpha^3\gamma^2 + 4\left(2\gamma + t^2(\beta+1)\right)\gamma\alpha^2 - 4t^2\gamma(\beta+1)\alpha + t^4(\beta+1)^2}. \tag{F.2}$$

When $0.5 < \lambda_m < \hat{\lambda}_1$, the practical η is in the region $\delta = (\eta(t^*), 1)$; therefore, the cooperation is achieved facing the optimal carbon tax.

However, the practical η is out of the range $\delta = (\eta(t^*), 1)$ when $\hat{\lambda}_1 < \lambda_m$. Review previous result, the region $\delta = (\eta_1, 1)$ is expanding when tax rises. Therefore, there exists a possibility that the government increasing carbon tax to coordinate the supply chain. We assume a realistic thing: the government is willing to boost the greenness of the product even reducing part of the revenue from the carbon tax.

Based on it, the carbon up to $\hat{t}_1$ which means the greenness is maximized. Therefore, The cooperation is achieved when $\gamma < \hat{\gamma}_1$ because the greenness is decreasing in the carbon tax when $\hat{\gamma}_1 < \gamma$. Then we have the second threshold:

$$\hat{\lambda}_2 = \frac{1}{\eta_1(\hat{t}_1) + 1}. \tag{F.3}$$

The cooperation could not be achieved when $\lambda_m > \hat{\lambda}_2$.

The conclusion is as follows: (1) Coordination would be achieved when the manufacturer is democratic (i.e., $0.5 < \lambda_m < \hat{\lambda}_1$). (2) Coordination could be achieved but part of the total tax will lose if development cost is lower when the manufacturer is moderate (i.e., $\hat{\lambda}_1 < \lambda_m < \hat{\lambda}_2$). (3) The cooperation could not be achieved if the manufacturer is a dictator (i.e., $\lambda_m > \hat{\lambda}_2$).

G. Proof of Proposition 5

The first derivative of η_1 in β is

$$\frac{\partial \eta_1}{\partial t} = \frac{\left(2\alpha^2\gamma - 2\alpha\gamma + t^2(\beta+1)\right)t^2}{2\alpha^2\gamma^2(-1+\alpha)^2} < 0. \tag{G.1}$$

Similarly, η_1 is decreasing in β. That means the region $\delta = (\eta_1, 1)$ is expanding when β rises.

And it is apparent that $\eta_1 = (2\gamma\alpha(1-\alpha) - (1+\beta)t^2/2\gamma\alpha(1-\alpha))^2$ is independent with k.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Research Article

The Recommending Agricultural Product Sales Promotion Mode in E-Commerce Using Reinforcement Learning with Contextual Multiarmed Bandit Algorithms

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In recent years, sales of agricultural products in Taiwan have been transformed into electronic marketing, and agricultural products with better consumer orientation have been recommended, and farmers' income has been improved through sales websites. In the past, *A*/*B* testing was used to determine the degree of preference for website solutions, which required a large number of tests for evaluation, and could not respond to environmental variables that made it difficult to predict the actual recommendation in advance. Therefore, in this study, the reinforcement learning model combined with different contextual Multiarmed Bandit algorithms can be tested in data sets of different complexity, which can actually perform well in changing products. It is helpful to predict the preferences of the promotion model.

1. Introduction

In recent years, governments of various countries have spared no effort to promote electronic sales of agricultural products. They have not only cooperated with private businesses to set up websites for selling agricultural products [1] but also guided local farmers' associations to establish online shopping malls [2]. This shows that it is important for the electronic sales of agricultural products. The same agricultural products sales websites are also facing the problem of how to market and promote agricultural products websites.

Therefore, in e-commerce websites [3], to increase sales has always been an important issue for website operation. In the field of e-commerce, understanding consumer characteristics and behaviors and to sell recommending products is one of the important goals in e-commerce websites.

In order to predict the will of the consumer, we must rely on the model and find the relevance from different features, such as age, gender, and region. However, because of the user characteristics, we cannot see the correlation with consumer promotion preferences manually, so we must rely on models to find the correlation from the features. In order to improve the traditional solution selection problem, more and more websites use predictive models to solve traditional selection problems. Generally speaking, predictive models are usually implemented using machine learning methods, and there is supervised learning in machine learning, unsupervised learning, semisupervised learning, and reinforcement learning. Among them, reinforcement learning is the situational dobby algorithm that will be used in this article. Reasons for choosing reinforcement learning in this article are as follows:

(1) The e-commerce website will not obtain any data that can train the model before consumers actually come to browse and consume, so it cannot directly use supervised learning
(2) The consumer trend environment of e-commerce websites is constantly changing, and a known data set cannot be used for training and prediction

The situational Multiarmed Bandit algorithm is one of the most commonly used algorithms in reinforcement learning [4]. The contextual Multiarmed Bandit algorithm mainly uses feature vectors to perform calculations. Therefore, when the e-commerce website obtains consumer characteristics, the model can immediately use the contextual Multiarmed Bandit algorithm to obtain the best sales strategy to recommend products and then meet consumers' behavior to enhance purchase intention. The most famous one is the LinUCB algorithm because the LinUCB algorithm is widely known because it has obtained good results in the research using the data set of the Yahoo homepage recommended news in the United States [5]. With the development of the LinUCB algorithm, a variety of situational Multiarmed Bandit algorithms are proposed, each with different operating characteristics.

The goal of this research is to use the contextual Multiarmed Bandit algorithm to perform operations with contextual features, and the context is the environmental feature. The environmental characteristics refer to the characteristics carried by the user and the characteristics of the lever itself, such as the user's gender, age, the product characteristics of the lever itself, the type of product, and the brand. Therefore, the situational Multiarmed Bandit algorithm uses environmental characteristics to do calculations.

In the experimental results, we simulated an agricultural shopping website for an e-commerce website, using instant consumer feedback data to study the recommendation effect of the situational Multiarmed Bandit algorithm on the e-commerce website. We use LinUCB, Hybrid-LinUCB, CoLin, and hLinUCB, and they are the effect of the four situational Multiarmed Bandit algorithms, and then, analyzing and testing the situational Multiarmed Bandit algorithm in the three discount modules of buy one get one free, 10% off, and free shipping. In the simulation, users like to recommend the situation, and the advantages of the UCB algorithm selection method compared with the traditional *A/B* testing scheme, and the noncontextual Multiarmed Bandit algorithm are proved by experiments.

In summary, there are three main contributions of this work as follows:

(1) In the absence of a known data set for model training and prediction, we propose a reinforcement learning method to train the model based on the consumer trend environment.

(2) The situational Multiarmed Bandit is applied to the e-commerce website. The pull bar and user characteristics are used as feature input, and the model is adjusted with real-time feedback data to enhance consumers' purchase intention.

(3) Four algorithms are applied to e-commerce problems, and then, it is analyzed that the situational Multiarmed Bandit has better performance than traditional *A/B* testing.

(4) We design multiple sets of different experimental environments to evaluate the effects of different algorithms under different mechanisms. LinUCB has a high degree of recognition of user characteristics and product characteristics, and Hybrid-LinUCB has better results under consideration of effective changes.

The remainder of this paper is organized as follows: Section 2 discusses the related work of this research. Section 3 will describe our proposed method. Section 4 shows the effectiveness of the method and compares it with other methods. Finally, we will make a conclusion of this research in Section 5.

2. Related Work

2.1. Traditional Sampling Method A/B Testing. *A/B* testing is mainly based on a random nature of testing user preferences. First, the two schemes with only one variable difference between them are randomly recommended to users, and the same number of test results must be obtained. It is also necessary to ensure that the user combination characteristics between the schemes are similar to ensure fairness and then determine which scheme is compared to receive user preferences. In the study [6], *A/B* testing was used to evaluate the block format of the homepage of the website which scheme can achieve a better conversion rate.

2.2. Multiarmed Bandit Algorithm. The Multiarmed Bandit algorithms are mainly to study how to obtain the best total return in the least number of attempts. The core concept that mainly affects the algorithm of the Multiarmed Bandit is how to balance exploration and exploitation. Exploration refers to obtaining feedback results through trial methods, and development refers to the prediction of the algorithm through the feedback results of previous exploration and the number of explorations. That will be the highest return method and uses this method to get the expected better return.

Multiarmed Bandit algorithm is divided into two types. One is the Context-free Multiarmed Bandit algorithm, and the other is the contextual Multiarmed Bandit [6].

2.3. Noncontextual Multiarmed Bandit Algorithm. The epsilon-greedy algorithm was the first proposed by Chirs Watkins et al. [6], which mainly uses the e parameter to affect the probability of exploration and utilization. In each round of selection of the tie bandit, there is a probability of e to randomly select a tie bandit to explore. This strategy is used to avoid the initial selection error of the chance that the best tie bandit cannot be found. As for the exploit lever, in formula (1), the probability of $1 - \varepsilon$ is used to select the lever with the largest average reward $\widetilde{p}$, and the average reward $\widetilde{p}$ is the sum of each reward_i divided by the lever, the number of times k is used.

$$\widetilde{p} = \frac{\sum \text{reward}_i}{k}. \quad (1)$$

The core algorithm of the Thompson sampling method is to use the beta distribution to take into account the concept of exploration and utilization [7]. In formula (2), when the lever is selected ($X\_t = k$), if feedback is obtained, the number of positive feedback α_k is added. If no positive feedback is obtained, then the number of negative feedback β_k will be increased by 1.

$$(\alpha_k, \beta_k) \leftarrow \begin{cases} (\alpha_k, \beta_k), & \text{if } x_t \neq k, \\ (\alpha_k, \beta_k) + (r_t, 1 - r_t), & \text{if } x_t = k. \end{cases} \tag{2}$$

Because the probability density function beta distribution is calculated using (α, β) parameters, the following characteristics are produced:

When α is higher and β is lower, there is a higher probability of achieving higher expectations (α, β). The higher the sum of the two parameters, the more concentrated the probability range of obtaining the expected value.

In order to improve the situation that the greedy algorithm may abandon the potential best pull bar and the inaccuracy of the Thompson sampling method beta distribution, Auer [8] proposed the UCB algorithm. In formula (3), the UCB uses times $T_{j,t}$. The total number of times the tie bandit used is t, and the average reward of the tie bandit j and $\overline{x_j}$ is used to calculate the expected value as show in the following formula:

$$\overline{x}_j(t) + \sqrt{\frac{2\ln t}{T_{j,t}}}. \tag{3}$$

From the formula (3), it can be known that, in the initial trial stage, the natural logarithm on the right has a considerable initial impact, so every tie bandit will be tried, but when the number of tie bandits $T_{j,t}$ is greater, at that time, the probability of choosing to use the lever will be higher and higher to achieve the goal of increasing the total income.

2.4. Situational Multiarmed Bandit Algorithm. Because the noncontextual Multiarmed Bandit algorithm does not add features to the calculation, it only calculates the profit and the number of attempts. Under such conditions, it is difficult to meet the current complex forecasting needs. Therefore, in 2010, Lihong Li et al. proposed the LinUCB algorithm, which is a situational Multiarmed Bandit algorithm [5].

The LinUCB algorithm here sets the expected return characteristic of each tie bandit a as $x_{t,\alpha}$ and then sets an unknown coefficient θ_a^* for the tie bandit, so the combination is $x_{t,a}^{\top}\theta_a^*$. The expected payoff of the drawbar (expected payoff) $r_{t,a}$ is the feedback of the current drawbar and feature combination, as in the following formula:

$$\mathbf{E}\left[r_{t,a} | x_{t,a}\right] = x_{t,a}^T \theta_a^*. \tag{4}$$

Hybrid-LinUCB was also proposed by Lihong Li and others who proposed LinUCB. The main difference from LinUCB is that Hybrid-LinUCB has an additional array of $z_{t,\alpha}$, A_0, and b_0 as a whole array of environmental parameters. The expected value formula (5) is as follows: $z_{t,\alpha}$ refers to the feature dimension array of all users and levers, β is the expected value coefficient of $z_{t,\alpha}$, $x_{t,a}$ is the input feature, and θ_a is the expected value coefficient of the tie bandit.

$$\mathbf{E}\left[r_{t,a} | x_{t,a}\right] = z_{t,a}^T \beta^* + x_{t,a}^T \theta_a^*. \tag{5}$$

In [9], the author believes that the traditional situational dobby algorithm ignores the interaction between users, so the relationship array W is added to the algorithm for the feature influence between products. The intention of the algorithm is that if user A likes product C, user B, who has highly similar characteristics, will also like product C. In the CoLin algorithm formula (6), C_t is used to calculate the influence of the relational array, W is the relation matrix of the tie rods, and I is the unit matrix of the number of tie rods multiplied by the number of tie rods. It is used to calculate the characteristics of the tie rods and the user. The specific gravity of the C_t array is affected by the value of α, so the value of α here does not simply represent a parameter for exploration and utilization.

$$C_{t+1} \leftarrow \left(W^T \otimes I\right) A_{t+1}^{-1} (W \otimes I). \tag{6}$$

hLinUCB was also proposed by Qingyun Wu et al. [10]. In the hLinUCB algorithm, it is assumed that the hidden characteristics of consumers affect the value of θ. In the research of Koren et al. [11], it was confirmed that, it can be achieved through matrix factorization. Obtain the hidden interaction parameters between features. In the actual situation, in a large part of the situation, it is impossible to obtain all the characteristic data, so the author believes that the influence of hidden characteristics can be obtained by ridge regression. The author adds v_{a_t} and θ_u^v to formula (7) to calculate hidden features; v_{a_t} represents the hidden feature, θ_u^v represents the θ value of the hidden feature, $r_{a_t,u}$ is the feedback value, and η_t is the environmental noise.

$$r_{a_t,u} = \left(x_{a_t}, v_{a_t}\right)^T (\theta_u^x, \theta_u^v) + \eta_t. \tag{7}$$

In addition, another feature of hLinUCB is that the algorithm adds a new random initial array to predict the θ parameters of hidden features can get a fast convergence effect.

2.5. Research on User Preferences of E-Commerce. In the past, many researchers used various methods to predict user preferences on promotion models. Wan et al. proposed a matrix decomposition framework with nested features to model preferences and price sensitivity simultaneously, which can be used to obtain economic insights into consumer behavior and provide personalized promotions [12]. Ling et al. proposed a combined deep learning method FC-LSTM, aiming at multiple online promotion channels, using the characteristics of interactive communication between customers and promotion channels to estimate users' purchase intentions. The result proves that the deep learning method proposed in the paper does improve the accuracy and $f1$ score [13]. Vanderveld et al. use the customer relationship management system for analyzing every aspect of the relationship between each customer and our platform based on the life cycle value. It can quickly iterate new products and find the current buyer frequency in the best inventory [14]. Cai et al. coded each state to establish a Markov model as a decision, using deep deterministic policy gradient, gated recurrent unit model, greedy myopic, and linear UCB methods, through ϵ-Greedy, ϵ-First strategy, UCB1 strategy, and Exp3 strategy, to compare the reward of each time step to show different performance and integration guarantees [15]. Broden et al. proposed the Thompson Sampling Bandit Policy, using Multiarm Bandit within bandit ensemble for e-commerce recommendations, which can coordinate the collection of basic recommendation algorithms for e-commerce and various behavior-based and attribute-based predictions. The problem was found that the context turns into a Multiarmed Bandit, using precision, recall, and normalized discounted cumulative gain as an evaluation indicator [16].

3. Materials and Methods

3.1. Planning Stage. When performing a Multiarmed Bandit algorithm, the most necessary thing is to first define the data features we will need to use and then obtain the data. We simulate different numbers of users and user characteristics according to the determined data features and randomly define the user's preference sales plan, agricultural product preference, and user characteristics. These preference sales plan preference features include time characteristics in order to satisfy the characteristics of e-commerce websites with great changes.

In the Multiarmed Bandit algorithm, we must first define the roles of the user and the lever. In LinUCB, for example, the lever maintains its own feature pattern for recording feedback or other parameters, such as A and B arrays in LinUCB. Therefore, it should be noted here that although in the Multiarmed Bandit algorithm, the lever can be added and changed; the increase of the lever will increase the calculation time and memory consumption. Hence, the role defined as a tie rod should be a fixed and identifiable role, such as a product in an e-commerce website or the subject matter itself in financial investment, rather than selecting items that will continue to increase as a tie rod, such as consumers or users.

In the literature [5], the article was used as a lever, but in the literature [9], the user was used as a lever. The difference between the two articles is that the former article is due to many users but the number of articles is fixed. And in the latter case, due to the experimental environment, there are few users but a considerable number of articles [9]. So, in the Multiarmed Bandit algorithm, the definition of the lever role must also be considered in accordance with the environment.

The following lists the features of the lever role in the Multiarmed Bandit algorithm:

(1) Noninfinitely new data, for example, products will not be added infinitely to the website

(2) Recognizable data, for example, can correspond to a certain drawbar and maintain the drawbar array continuously

Then, the three-stage experimental process is shown in the Figure 1. In the first stage, we use the data set that simulates the browsing of users of agricultural shopping websites to evaluate the Multiarmed Bandit algorithm. These simulated levers are defined as products and then use the data set to apply to the Multiarmed Bandit algorithm to obtain the best choice of product solution and further obtain the reward value to compare the performance of the Multiarmed Bandit algorithm. Therefore, because we use a data set that simulates the user's browsing, we emphasize the sensitivity of the algorithm in using the data set features.

The second stage will use the optimal setting parameters obtained in the first stage to apply to each algorithm. Using simulated agricultural products shopping websites to browse the web and purchase action programs will generate different feedback scores due to different actions. In addition, it is possible to modify the product promotion strategy by simulating the promotion strategy suggested using the Multiarmed Bandit algorithm under the limited commodities by the merchants of the agricultural shopping website and even compare the total and average revenue.

The third stage uses the better-performing algorithm obtained in the second stage to test the preferences of simulated consumers. The predicted benefits of the three discount modules are buy one get one free, 10% off, and free shipping. By analyzing the recommended discount module of the algorithm and simulating the change of user preferences, it can prove the advantages of the situational Multiarmed Bandit algorithm compared with the traditional A/B testing method.

3.2. Simulation Data. The generation of simulation data must produce the characteristics of multiple users and multiple products, which are used to compare the performance of the multiarmed bandit algorithms between the number of users and the number of different products.

Feature standardization is mainly used to avoid the uneven impact of feature parameters on the array [17]. For example, assuming that the user's feature browsing time is morning, afternoon, evening, and early morning, we can divide it into 0.01, 0.33, 0.66, and 0.99. The following parameters are between 0 and 1.

The feature parameters used in this article are common consumer feature data. From the literature, we can see that some operators use the number of consumer web views, stay time, clicks, page scrolling, and mouse movement trajectory data as a consumer's group characteristics. And then use algorithms to push discount modules to consumers according to the feature data to improve performance. In our experiment, we selected the following user characteristics data and the current environment state, and we organized the following characteristics as shown in Table 1.

The user features are the data filled in by the user, and the time feature represents the user's shopping habits, such as buying in the morning or afternoon, buying things on Mondays, and the month representing the festive period that affects shopping.

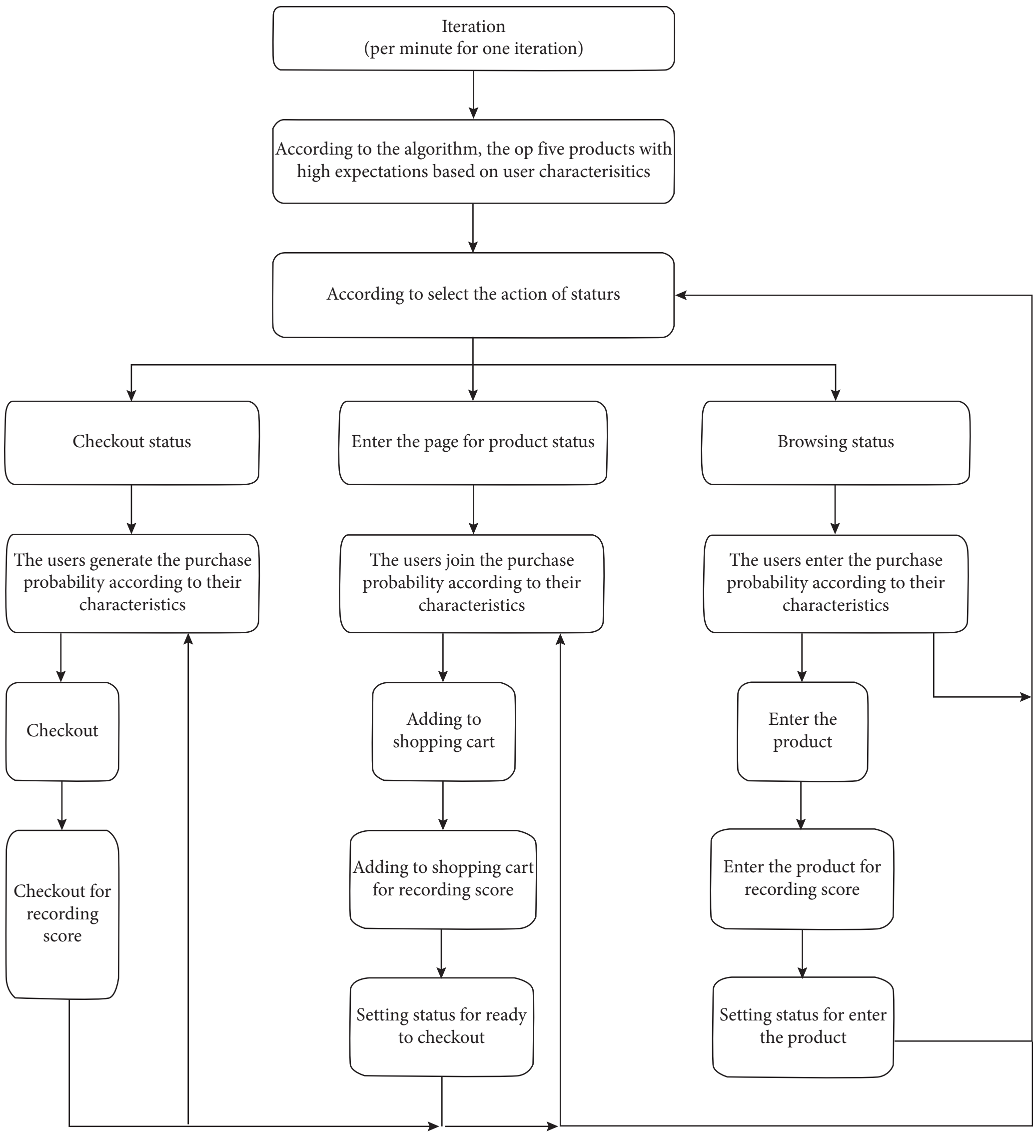

Figure 1: Planning the experiment process.

Table 1: Features collected by users.

Parameter type	Feature	Description of data
User feature	Sex	Male or female or unfilled
User feature	Year of birth (age)	\A.D.
User feature	Occupation	Occupation type, ex: agriculture, animal husbandry, technology, military, and public education.
User feature	Income	Using level distance, ex: less than 30,000 yuan, 30,000 to 60,000
User feature	Marriage	Ex: married and unmarried
User feature	Education level	Ex: elementary school, middle school, and university
Time variable	Current time	Ex: Morning, afternoon, evening, and early morning
Time variable	Month of date	Ex: January and February
Time variable	Day of the week	Ex: Monday and Tuesday

The lever selected in the situational Multiarmed Bandit algorithm defined in this paper is a promotion scheme for agricultural products. In the Multiarmed Bandit algorithm, not only the characteristic of the user is included in the calculation but also the characteristics of the product itself.

On the agricultural product sales website that we used to test our simulation in this article, we will provide merchants with instructions for filling in the characteristics of agricultural products. Some important characteristics are shown in Table 2.

Table 2: Characteristics of agricultural products on agricultural product sales websites.

Parameter type	Feature	Description of data
Product	Types of agricultural products	Ex: Chinese cabbage, cabbage, and green.
Product	Counties and cities of agricultural products	Ex: Taichung, Taipei, and Kaohsiung.
Product	Special attributes of agricultural products	Ex: organic label, production and sales resume, safe fruits and vegetables, and label of Jiyuan Garden.
Promotion mode	Main promotion mode	Ex: immediate product discount, free shipping, and full discount.

After we define the user features and the agricultural features, then formalize the user features, and use the user's features to calculate the degree of preference for the product, calculate the probability of purchasing the product, and finally record.

The data set is divided into three data sets, with 800 people to 5 products on 30 days, 800 people on 30 days to 10 products, and 30 days 800 people to 20 products. The number of people fixed at 800 is the daily number of visitors to the simulated site, and the change in the number of products is the complexity of the simulation environment selection. The reason why the products are divided into 5, 10, and 20 is also due to the increase in the calculation and quantity of products between the two algorithms, Hybrid-LinUCB and CoLin. Therefore, it must be limited to 20 products in order to complete the experiment. The main reason for dividing 30 days is that date features are also included in user parameters, so the performance sections of the algorithm are listed daily for comparison.

3.3. Stage 1: Algorithm Parameters and Efficiency. In this paper, the first phase of the experiment will compare the different performance between the different situational multiarm machine calculations. The simulated agro-shopping site user browsing data set is used to test the algorithm's learning ability for the dataset and the reward is recorded, and the effect between the number of different products and the different algorithm parameters on different multiarmed bandit algorithms is tested.

In the collection of experimental results, at least 30 repeated experiments will be taken in each experimental stage to make an average value, because we have added the concept of sampling to the use of simulated agricultural shopping website user browsing data sets. Therefore, in each update of the contextual Multiarmed Bandit algorithm, different feedbacks will be generated due to different sample records, which have a chance of affecting factors. So, an average value must be obtained to review the performance to obtain an objective argument.

3.4. Stage 2: Simulation of Browsing Experiments on Agricultural Product Sales. In terms of the previous theory, we use a simulated agricultural shopping website user browsing data set to test the efficiency of the algorithm to select the best lever, but this is far from the actual user browsing consumption. Because the feedback of the real-life algorithm will directly affect the user's next consumption, and we also need to verify the effectiveness of the algorithm for maximizing the promotion plan and website revenue; we will use the simulated agricultural shopping website environment to achieve this research aims.

Simulated products will randomly produce 5, 10, and 20 different agricultural products with different prices and product characteristics. In this product, the promotion plan aims to provide the simulated agricultural shopping site users with the opportunity to purchase and update the product promotion plan every day. Simulated users purchase products at certain time intervals to perform operations, click products or add shopping carts, and check out, and there is a purchase limit, a total of 24 hours a day, simulated agricultural shopping site 30 days of data, and calculate the total daily income. And total feedback score changes to compare the efficiency of the algorithm.

In addition, this side not only simulates the consumer action of the agricultural shopping website but also adds the decision-making simulation of the agricultural business. There will have some feature argricultural products in a year, such as strawberries in spring, watermelons in summer, and pears in autumn. Therefore, in this simulation experiment, we will trigger the update of the promotion strategy event at a fixed time every day to simulate the characteristics of seasonal replacement of agricultural products.

The algorithm will be based on the user features of the previous day to determine the promotion strategy to be used in the day's products, and the promotion strategy has a corresponding degree of preferential, the higher the degree of preferential, the lower the business score, the lower the level of concessions, the higher the business, but the relative consumer purchase rate will also decline. This side simulates the complex action of consumers and merchants of agricultural shopping website, mainly to be closer to the reality of agricultural product selling sites will encounter seasonal replacement of products, so as to compare the different situational Multiarmed Bandit algorithms, the more details for each action type, score, and description are shown in Table 3.

3.5. Stage 3: Comparison of Discount Recommendation Methods. In the second stage, we can obtain a better algorithm in the simulation of agricultural shopping sites, and then, we apply the algorithm into the discount module, in which we will have three simulation experiments. First of all, we define buy one-to-one, 10% discount, and free shipping as three preferential modules.

Table 3: Simulated user website action score.

Action type	Score	Description
Click on the product	1	Write a score when you click to enter the product page
Adding to shopping cart	Product price multiplied by coefficient	When adding a product into the shopping cart, write a score
Shopping cart checkout	Commodity price multiplied by coefficient	Write the product price into a score when the shopping cart is checked out

In the third phase of experiment one, we assume that consumers have a higher willingness to buy goods with a lower average unit price after total shopping cart plus freight and that consumers have the highest return on buying one-to-one preferential module merchandise, but pay more at a time. Then, there is the 10% discount group merchandise merchants slightly less for free shipping, the highest merchant income, but to bear the cost of freight. This experiment compares the situational Multiarmed algorithm in three preferential modes with the average unit price orientation of users recommended to reflect the situation.

In the third phase of experiment II, we will simulate consumers plus their own preferences and assume the correlation between user characteristics and preferences, to determine whether the algorithm can correctly identify the relationship between features and preferences, and compared with the traditional A/B testing method and the UCB algorithm of the Non-multiarmed bandit algorithm, whether it can save the number of times and achieve the advantages of learning with the user's preferences.

4. Results and Discussion

4.1. Arrangement of Parameters. After our experiments, we can know that the α constant in LinUCB, Hybrid-LinUCB, CoLin, and hLinUCB is related to the characteristics of the data set. The constant α does not only have to be larger or smaller but does also have setting which was based on the current environment. Therefore, it must be noted that, in each performance of the algorithm, the current sample will determine the difference in user characteristics, and there will be a certain degree of uncertainty in the simulation test.

Finally, based on the above test, we can sort out the α constants that perform better in the browsing data set of 800 people and 20 product simulated users among LinUCB, Hybrid-LinUCB, CoLin, and hLinUCB, as follows in Table 4.

We will use the above parameters in the second stage of the simulation experiment to obtain the performance of the algorithm in the experiment that simulates user browsing.

4.2. Simulate In-Service User Browserling. As for the calculation of the feedback score, here we add a feedback parameter to write the feedback score. For example, when a user enters the product's inner page, the feedback parameter is updated to the situational Multiarmed Bandit algorithm. Furthermore, for the score feedback added to the shopping cart and shopping cart checkout, we formulate a formula equation (8) for the score feedback based on the principle of "the higher the profit, the higher the score".

Table 4: Sorting out the α constants that the algorithm performs better in the 20 product simulated user browsing data sets.

Algorithm	A
LinUCB	0.05
Hybrid-LinUCB	0.8
CoLin	0.4
hLinUCB	0.2

$$\text{reward} = \left(C' - C\right) \cdot q \cdot \beta. \tag{8}$$

C' is the sales amount, C is the cost of sales, q is the number of products, and β is a constant to affect the size, and because the initial array of the situational Multiarmed Bandit algorithm is 0 to 1.

In this experiment, we added a mechanism that simulates the daily update of agricultural products shopping website merchants. Generally speaking, the total product categories on the sales website have small changes, so the products recommended by the contextual Multiarmed Bandit algorithm are recommended for the products; for example, there are a total of A to Z products; we follow the user's characteristics and product characteristics entering into the algorithm, and we can obtain the products with the highest expected value and recommend them to consumers. If the consumer clicks to enter the product or it adds to the shopping cart, the algorithm will be updated.

Therefore, our method of updating the discount module is to first list the combination of the product and the discount module as a product and then only take "the same product, different discount modules" as the discount that will be used for the product that day module. Then, the sum of the expected value of each consumer feature and each discount module of each product browsed on the previous day is obtained, and then, the discount module with the highest expected value of each product is taken as the discount module combination of the product of the day.

$$p_{t,s} = \sum_{i=0}^{u} \alpha_{t,s}. \tag{9}$$

4.3. The Influence of Random Users and Products. In order to accurately test the performance, we first do 30 experiments from 5 products and go to the extreme value to get the average value to see the experimental results. Here, we use the converged value to compare the performance. Converged means that the average daily income does not increase due to the increase in the number of days, so we take the last 7 days of the 30-day experimental data as the converged performance as shown in Figures 2-3 and Table 5.

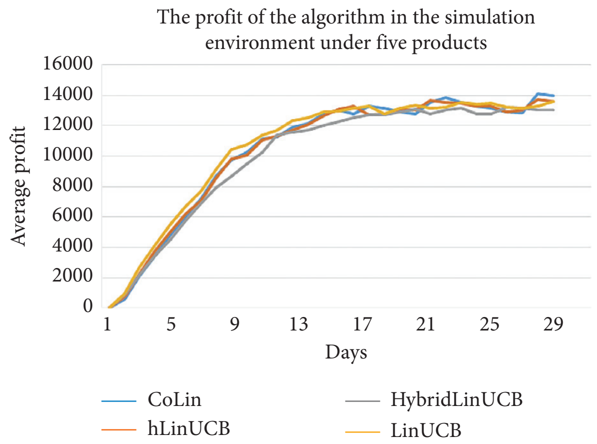

Figure 2: Algorithmic revenue performance under 5 products.

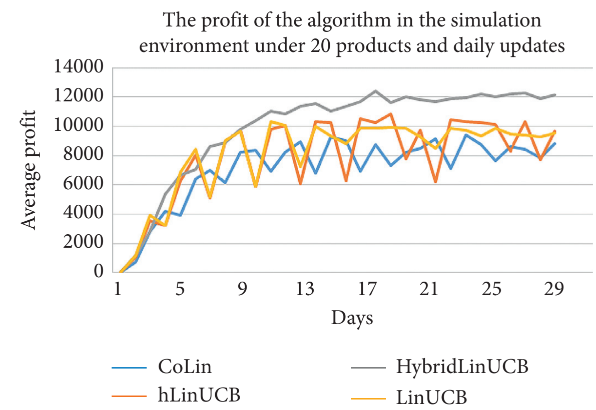

Figure 4: The performance of algorithm revenue updated daily under 20 products.

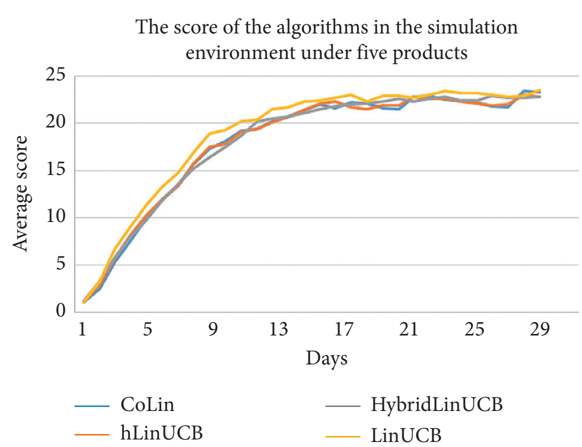

Figure 3: Algorithm score performance under 5 products.

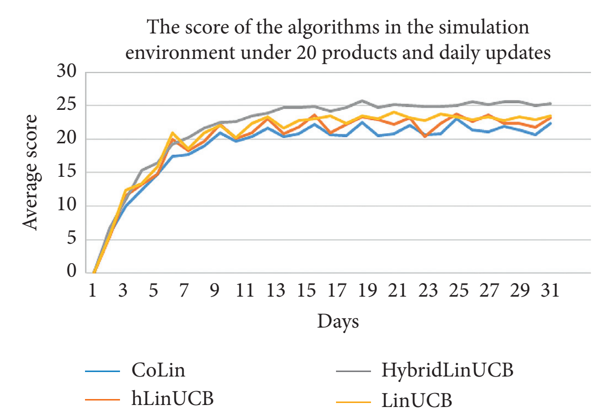

Figure 5: The performance of the algorithm scores updated daily under 20 products.

Table 5: The average performance of the algorithm revenue and scores in the last 7 days under 5 products.

Algorithm	Income	Score
LinUCB	13384.55	**23.133**
Hybrid-LinUCB	13036.29	22.6591
hLinUCB	13326.1	22.3913
CoLin	**13417.69**	22.481

Table 6: The average performance of the last 7 days of the algorithm updated daily under 20 products.

Algorithm	Income	Score
LinUCB	9509.5	23.1692
Hybrid-LinUCB	**12104.6**	**25.3376**
hLinUCB	9515.7	22.7945
CoLin	8502.6	21.6711

4.4. Comparison of Promotion Plan. In general consumer websites, promotion schemes are an important part of selling products. Because each consumer has a different degree of adaptation to promotion schemes, how to choose products and promotion schemes is also a key issue. So here we follow the daily update mechanism mentioned earlier to simulate the impact of the daily update of the promotion plan on the benefits of each algorithm as shown in Figures 4-5 and Table 6.

4.5. Comparative Advantages of Preferential Recommendation. In this phase of the experiment, we assume that male users have a higher choice of 80% for buy one get one free, 50% for other schemes, simulate male users' reaction actions when browsing schemes, and are in line with traditional A/B Testing methods. Comparing the UCB algorithm of the noncontextual Multiarmed Bandit algorithm, the following results can be obtained as shown in Figure 6.

From the above experimental data, it can be proved that using the situational Multiarmed Bandit algorithm can save the number of experiments and can automatically select the best plan. Then we continue to assume the following conditions as shown in Table 7.

Such a setting environment is mainly to test the reaction ability of the situational Multiarmed Bandit algorithm when the user's preference orientation changes. Then, the results are obtained as shown in Figure 7.

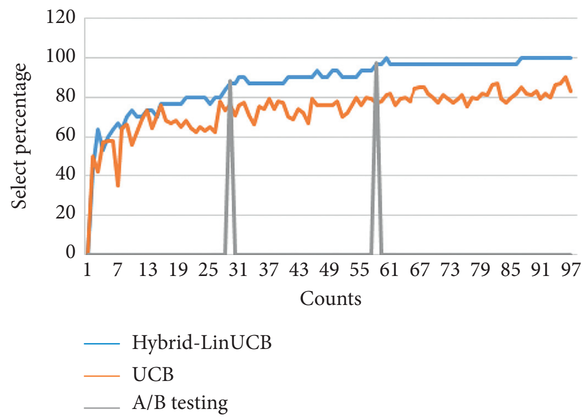

Figure 6: Hybrid-LinUCB, UCB, and A/B testing have 80% selection probability, number of attempts, and recommendation probability.

Table 7: User preferences and frequency change settings.

	Testing for 100 times ago (%)	After 100 testing (%)
Probability of buy one and get one free	80	50
Probability of free shipping	50	80

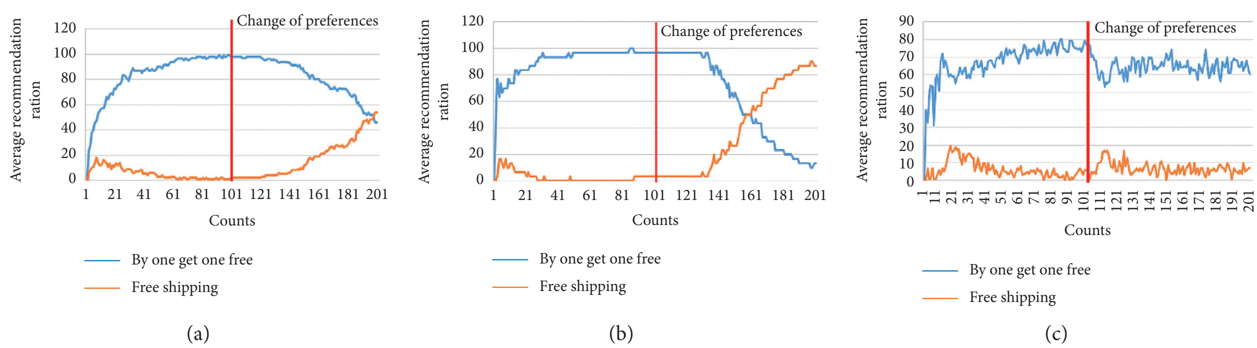

Figure 7: (a) Probability of recommendation of A/B testing changes in user preferences. (b) Recommendation probability of Hybrid-LinUCB algorithm in user preferences. (c) Probability of recommendation of UCB algorithm in changing user preferences.

5. Conclusions

In this research, we can know that the LinUCB algorithm is highly recognizable for the linear relationship between user characteristics and product characteristics and can be used in most cases. The Hybrid-LinUCB algorithm has common environmental characteristics, and it has better results for changing products and can avoid the problem of cold start of expected value. If it is for agricultural sales websites that often change products now, the Hybrid-LinUCB algorithm is the best choice. Moreover, from the experiment on contextual Multiarmed Bandit algorithm for recommending preferential modes, it shows that when users have their own preferential modules, the algorithm can predict the user's preferential module preferences through user characteristic data and compared with traditional A/B testing and non-contextual Multiarmed Bandit algorithm; it has the advantages of faster and automatic acquisition of prediction results and changes with the environment.

In terms of research limitations, it is difficult to simulate the complex factors of agricultural shopping websites with different complexity every time from different algorithms, which can effectively have significant parameters.

In future works, it is possible for establishing questionnaires from the website, collecting relevant characteristics from customer data, using exploratory factor analysis, or confirmatory factor analysis to obtain significant characteristics. Then, integrating several types of LinUCB algorithms with agricultural sales websites and browsed and consumed by real consumers can be compared in practice for improving product sales performance.

Data Availability

The raw research data are are provided in Supplementary Materials.

Conflicts of Interest

The authors declare that they have no conflicts of interest regarding the publication of this paper.

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Supplementary Materials

The supplementary data file includes the raw research data. (*Supplementary Materials*)

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