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Knowledge Sharing Strategy and Emission Reduction Benefits of Low Carbon Technology Collaborative Innovation in the Green Supply Chain

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Knowledge sharing (KS) in the green supply chain (GSC) is jointly determined by the KS efforts of suppliers and manufacturers. This study uses the differential game method to explore the dynamic strategy of KS and the benefits of emission reduction in the process of low carbon (LC) technology in the GSC. The optimal trajectory of the knowledge stock and emission reduction benefits of suppliers and manufacturers under different strategies are obtained. The validity of the model and the results are verified by numerical simulation analysis, and the sensitivity analysis of the main parameters in the case of collaborative sharing is carried out. The results show that in the case of centralized decision-making, the KS efforts of suppliers and manufacturers are the highest, and the knowledge stock and emission reduction benefits of GSC are also the best. The cost-sharing mechanism can realize the Pareto improvement of GSC's knowledge stock and emission reduction benefits, but the cost-sharing mechanism can only increase the supplier's KS effort level. In addition, this study found that the price of carbon trading and the rate of knowledge decay have a significant impact on KS. The study provides a theoretical basis for promoting KS in the GSC and LC technology innovation.

Keywords: low carbon technology, knowledge sharing, collaborative innovation, differential game, emission reduction benefits

1 INTRODUCTION

With the frequent occurrence of extreme natural disasters around the world, climate change caused by excessive CO_2 emissions has severely hindered the sustainable development of mankind and threatened ecosystems and biodiversity (Aldieri and Vinci, 2020; Hao and Li, 2020). In order to realize the sustainable development of mankind, the governments call for energy conservation and emission reduction, the implementation of carbon policies (carbon tax, carbon subsidies, carbon emission trading mechanism), and the development of a low carbon (LC) economy with practical actions (Wang et al., 2016). Some countries have set carbon peak and carbon neutral targets. The

Abbreviations: GSC, green supply chain; GSC-KS, green supply chain knowledge sharing; KS, knowledge sharing; LC, low carbon.

Chinese government firmly stated that it will reach the peak of carbon emissions by 2030 and achieve the goal of carbon neutrality by 2060. The US government has made it clear that it will achieve carbon neutrality by 2050. At present, the US federal government has not formulated a specific carbon neutral plan. However, some state governments have established relatively complete carbon emission systems and carbon market trading systems, such as the California government. But what is certain is that the US carbon neutral path mainly focuses on carbon emission reduction in energy applications, while China is more concerned about carbon emission reduction in energy supply. Regardless of the path, LC technology innovation is the fundamental driving force for achieving the goal of carbon neutrality.

The practice and exploration of LC emission reduction shows that green supply chain (GSC) and LC technology innovation are one of the important ways to develop a LC economy and reduce carbon emissions (Hoggett et al., 2014; Qu et al., 2021). Green supply chain introduces environmental protection concepts into supply chain management to improve supply chain ecology and financial performance (Khan et al., 2021c). Low-carbon technological innovations, such as Industry 4.0 and blockchain technology (Khan et al., 2021a; Khan et al., 2021d; Yu Z. et al., 2021), are essential to the sustainable development of GSC (Zhou and Ren, 2021). Knowledge is the key driving force for LC technology innovation, and acquiring knowledge can strengthen the innovation capabilities of enterprises (Rumanti et al., 2019). Collaboration refers to the process of cooperation between suppliers and manufacturers to achieve specific goals by pooling resource advantages. Collaborative innovation of LC technology is to control the carbon emissions of the GSC from an overall perspective, which can significantly reduce the carbon emissions of the GSC (Hao and Li, 2020). Under the constraints of the carbon quota system, the reduction of carbon emissions allows excess carbon allowances to be used for trading in the carbon market to obtain emissions reduction benefits. LC technology innovation relies on the sharing, capture and transformation of knowledge. Knowledge sharing (KS) is the core link of knowledge management, and it is also the key to promoting LC technology innovation (Ma et al., 2020) and improving the emission reduction benefits of the GSC. The core of knowledge management is to realize the re-creation of knowledge through the sharing, transfer, absorption, utilization and integration of knowledge between subjects, thereby completing the overall collaborative innovation process (Zhang et al., 2020). In the entire collaborative innovation process, KS is the prerequisite. This paper mainly studies the impact of KS on LC technology collaborative innovation and GSC emission reduction benefits.

Scholars have done a lot of research on LC technology innovation. Bi and Wang (2015) established an indicator system to evaluate the performance of China's manufacturing LC technology innovation. Lyu X. et al. (2020) studied the impact of the carbon emissions trading system on low-carbon technology innovation. The results show that the carbon emissions trading system can promote the increase of low-carbon technological innovation year by year, but it will inhibit the development of low-carbon technological innovation in the short term. According to research by Zhang et al. (2021), technology priority, economic scale and research and development efficiency are the main driving factors for LC technological innovation. It can be found that the promotion of LC technology innovation from the perspective of KS does not seem to have attracted much attention. Zheng (2021) used the evolutionary game method to study the KS in the LC innovation network. However, the evolutionary game cannot reflect the dynamic changes in the amount of knowledge in the game process, and it does not consider the impact of emission reduction benefits on the KS strategy of suppliers and manufacturers. A further study is needed. As time evolves, knowledge and technology are constantly updated and revised. This has a direct impact on the KS behavior of suppliers and manufacturers. In order to improve competitiveness, suppliers and manufacturers need to constantly share and acquire knowledge (Ma et al., 2020). Therefore, the KS problem in the GSC should be studied from the perspective of the dynamic evolution of the decision-making body's behavior. The differential game model is to study the conflict and cooperation of decision-making subjects in dynamic systems. More specifically, it is to study the optimal control problem of one or more state variables evolving over time according to the differential equation (Chen et al., 2012).

Therefore, from the perspective of dynamic change, a differential game model between suppliers and manufacturers is established to explore the KS strategy and emission reduction benefits in the process of LC technology collaborative innovation in the GSC. The purpose of this study is to explore the optimal degree of KS between suppliers and manufacturers under different sharing strategies and the optimal trajectory of the evolution of knowledge stock over time. In addition, this study is dedicated to exploring the law of changes in emission reduction benefits and the main factors affecting the stock of knowledge in the GSC.

The structure of the rest of this article is as follows: The **Section 2** is literature review, which reviews the relevant literature and finds out the research gaps. The **Section 3** is methodology. The KS strategy model is established, and the results of the model are compared and analyzed. The **Section 4** is numerical simulation, which analyzes the simulation results and studies the sensitivity of the main parameters. The **Section 5** is the conclusion and implication, and puts forward the future research direction.

2 LITERATURE REVIEW

2.1 Collaborative Innovation in Green Supply Chain

The green supply chain should integrate environmental factors into product design, procurement, manufacturing, sales, and distribution (Yu and Khan, 2021). Khan et al. (2021e) believed that the application of advanced technology and the establishment of contact with the external environment can break through multiple supply chain management barriers. In order to achieve more effective green innovation, companies use their social capital to generate additional competitive advantages through collaboration (Chen and Hung, 2014). Collaborative innovation provides a new direction for the development of GSCs (Zhang and He, 2018), and is an important link to gain competitive advantage and achieve sustainable development goals (Zhou et al., 2020). GSC collaborative innovation is to use the specific advantages of individual organizations to jointly solve the problem of green management through a collaborative approach (Hong et al., 2019).

Hong et al. (2019) revealed the positive impact of organization-organization collaborative innovation, organization-government collaborative innovation, and organization-institution collaborative innovation on innovation performance. Collaborative innovation partner selection is an important factor affecting the green innovation of supply chain enterprises. The technical capabilities, resource integration capabilities, and learning capabilities of partners should be focused on (Melander, 2018; Xia et al., 2020). Hao and Li (2020) explored the collaborative innovation between enterprises in a green supply chain composed of a manufacturer and a supplier. The research found that the cooperative game is the optimal scenario for collaborative innovation. In terms of the impact of consumer preferences on green innovation, He et al. (2019) found that changes in consumer preferences are a key factor in promoting green innovation by companies in the supply chain. Li Q. et al. (2020) studied the decision-making mechanism and determinants of green collaborative innovation from the perspective of transaction cost economics and social exchange theory. Yang and Lin (2020) confirmed the importance of supply chain collaboration to green innovation, and found that environmental regulations, top management commitment and social recognition are the main driving forces for the implementation of green innovation. Zhai et al. (2021) studied the positive effects of governmental incentives and punishments, the trust between enterprises on the collaborative innovation of green technology in enterprises. Song et al. (2020) analyzed the mediating role of absorptive capacity between green KS and green innovation, and suggested that companies develop their absorptive capacity to achieve green innovation.

Collaborative innovation improves the environmental performance of the GSC and is conducive to promoting the sustainable development of the GSC (Abbas and Sagsan, 2019; Shi et al., 2021). It can be found that the existing research seldom pays attention to the influence of knowledge on GSC collaborative innovation, and seldom studies the decision-making mechanism of KS behavior of suppliers and manufacturers. What is the impact mechanism between KS and LC technology innovation? It is necessary to study LC technology innovation in the green supply chain from the perspective of knowledge sharing. This is essential to improve the efficiency of LC technology innovation.

2.2 Cleaner Production

The innovation and promotion of renewable energy can curb carbon dioxide emissions, help the government develop clean industries, and achieve carbon neutrality goals (Balsalobre-Lorente et al., 2021), while having a positive impact on economic development (Khan et al., 2021b). Bekun et al. (2021) believes that sustainable economic growth can be achieved by developing clean technologies and increasing the share of renewable energy in the energy structure. Krarti and Aldubyan (2021) advocated the use of photovoltaics and wind as renewable energy technologies to achieve carbon neutrality in residential communities. Cao et al. (2021) studied the impact of cleaner production standards on the total factor productivity and resource allocation efficiency of Chinese energy companies. They found that cleaner production regulations reduce the efficiency of resource allocation in the energy industry, but increase the level of enterprise total factor productivity. Gunarathne and Sankalpani (2021) believed that clean technology should be promoted as a management technology. Gupta et al. (2021) established a framework based on the concepts of circular economy, sustainable clean production and industry 4.0 standards to evaluate the sustainable performance of manufacturing companies. Wei et al. (2022) suggested the use of photovoltaic power generation and electrolysis of hydrogen to achieve carbon emission neutrality in industrial parks, and used examples to prove that this solution would reduce emissions by 61% compared with the solution relying on the grid and natural gas. Fortes et al. (2022) analyzed the impact of climate change on the demand for renewable resources and electricity. The results showed that climate change reduces hydropower generation by 20%, which will also reduce the cost-effectiveness of solar photovoltaics.

The application and innovation of cleaner production technologies can help achieve carbon neutrality. However, it can be found that the research on knowledge management in cleaner production has not received much attention.

2.3 Knowledge Sharing in Low Carbon Technology Innovation

KS and collaborative innovation are effective models for the development of LC technologies. LC technology innovation and knowledge accumulation are mutually reinforcing (Hoette et al., 2021; Vinholis et al., 2021). Technology innovation can promote knowledge accumulation (Vinholis et al., 2021), and LC technology innovation depends on knowledge accumulation (Hoette et al., 2021). KS has a significant impact on the performance of LC technology innovation (Brandao Vinholis et al., 2021; Effendi et al., 2021). Gu et al. (2021) studied the impact of global LC technology transfer on carbon emission reduction. The study found that the sharing of LC technologies has achieved a significant increase in carbon emission reduction, while the emission reduction in developing countries is mainly limited by the stock of knowledge and research and development investment. KS in the process of LC technology transfer and innovation will be affected by organizational mechanisms (Hayashi, 2018). Abbas and Sagsan (2019) studied the effect of knowledge management on the green innovation and sustainable development of enterprises. Through structural equation models, they proved that KS has a significant impact on green innovation, and green innovation can promote the sustainable development of enterprises. The willingness of enterprises to share knowledge is related to the breadth and depth of their own knowledge. Enterprises with a wide range of knowledge are more willing to share knowledge, while enterprises with deep knowledge are unwilling to share knowledge (Lyu C. et al., 2020).

From the literature review, it can be found that the current research on LC technology innovation and KS mainly focuses on the impact of KS on LC technology innovation performance, the role of KS in promoting LC technology innovation and some obstacles to the implementation of KS. However, scholars seldom pay attention to the evolution of KS strategies in LC technology innovation and the dynamic changes of knowledge stock and emission reduction benefits under different sharing strategies. As time changes, knowledge will be updated and attenuated, and the KS strategy in LC technology innovation should also be constantly changing. Therefore, from the perspective of dynamic evolution, it is necessary to study the relationship between KS and LC technology innovation and emission reduction benefits.

2.4 Differential Game

The differential game model is a combination of optimal control and game theory. It studies the problems of cooperation and conflict between game subjects in dynamic systems (Chen et al., 2012). In a continuous time frame, multiple participants play a continuous game in an effort to optimize their respective goals. Through the model solution, the strategy of the game player's evolution over time can be obtained and the Nash equilibrium can be reached. The differential game model has certain advantages for studying the optimal problem of dynamic control, and is widely used in the research of LC technology innovation and supply chain emission reduction problems. Hao and Li (2020) used the differential game model to study the collaborative innovation mechanism between enterprises in a GSC composed of a manufacturer and a supplier. Deng et al. (2021) and Wang et al. (2019b) established a differential game model from the perspective of carbon tax and studied the optimal solutions under different decision-making modes. The research results showed that carbon tax can promote LC technology innovation. Hou et al. (2020) used the differential game model to explore the dynamic emission reduction technology investment decision-making problem in the binary supply chain composed of manufacturers and retailers. Si et al. (2020) established a time-lag differential price game model, and analyzed the equilibrium strategy of price competition between technology supply and demand companies and the local asymptotic stability of the game system at the equilibrium point. Yin and Li (2018) used stochastic differential game to analyze the LC technology sharing problem in enterprise collaborative innovation. The results showed that random interference factors have the most significant impact on the level of LC technology in cooperative games. You and Zhu (2016) used the differential game model to study the LC supply chain R&D, promotion and pricing issues. Zhang et al. (2019) explored the joint dynamic green innovation policy and pricing strategy in the hybrid manufacturing and remanufacturing system. The results showed that too high or too low a carbon emission limit will reduce the manufacturer's revenue.

In addition, differential games are also used in the study of KS problems. Lin and Wang (2019) used differential game theory to establish a dynamic incentive model to study the dynamic KS of construction project teams. Zhu et al. (2017) considered random interference factors and established a stochastic differential game model to study the problem of KS in industry-university-research collaborative innovation. It can be found that few scholars use the differential game model to study the problem of KS and emission reduction benefits in the collaborative innovation of LC technologies in the GSC. In the GSC, the knowledge level of suppliers and manufacturers is constantly changing over time. Therefore, the differential game model is used to study the optimal shared effort level, emission reduction benefits and knowledge changes over time between suppliers and manufacturers in the GSC.

In summary, the following research gaps can be found through literature review: 1) there is a lack of research on KS strategies in the dynamic process of collaborative innovation between suppliers and manufacturers. 2) In LC technology innovation, the dynamic relationship between KS strategy and knowledge stock and emission reduction benefits has not received attention. Therefore, this paper establishes a differential game model from the perspective of KS to dynamically study the issue of LC technology collaborative innovation in the GSC. This research aims to explore the evolutionary laws of knowledge stock under different KS strategies, as well as the optimal degree of effort and optimal emission reduction benefits of KS between suppliers and manufacturers. This research is of great significance for promoting the KS of GSC, improving the efficiency of LC technology innovation and the ability of supply chain to reduce carbon emissions.

3 METHODOLOGY

In the collaborative innovation of the GSC, the KS behavior of suppliers and manufacturers is driven by costs and benefits (Li H. et al., 2020). This study establishes a differential game model to study the KS strategy and emission reduction benefits in the collaborative innovation of LC technologies in the GSC. As time evolves, suppliers and manufacturers continue to play games to optimize their own costs and benefits and eventually reach Nash equilibrium.

3.1 Basic Assumptions

Assumption 1. The amount of knowledge generated by the collaborative innovation of LC technologies in the GSC is determined by the KS effort of the supplier and the KS effort of the manufacturer. At the same time, knowledge is attenuated. As technology is iterated and updated, existing knowledge will be replaced by new knowledge. Therefore, the stock of knowledge is a dynamic variable that changes with time. Differential equations can be used to describe the law of the stock of knowledge with time (Plambeck, 2012; Ma et al., 2020):

$$\dot{x}(t) = \alpha E_M(t) + \beta E_S(t) - \delta x(t)$$

Among them, $x(t)$ represents the knowledge stock in the GSC at time t, and it satisfies $x(0) = x_0 > 0$ at the initial time. $E_M(t)$ and $E_S(t)$, respectively represent the KS efforts of manufacturers and suppliers at time t. α and β represent the knowledge creation level of manufacturers and suppliers, respectively, and refer to the research and development capabilities of new technologies. δ represents the natural decay rate of knowledge.

Assumption 2. When the degree of effort increases, the sharing cost also shows an increasing trend. Therefore, the shared cost C_S can be regarded as a convex function of the effort level $E_S(t)$ (Breton et al., 2005). The KS cost of suppliers at time t can be expressed as:

$$C_S(E_S(t)) = \frac{1}{2}\eta_S E_S^2(t)$$

Among them, $\eta_S > 0$ represents the cost coefficient of the supplier's KS effort. Similarly, the manufacturer's KS cost C_M can be expressed as:

$$C_M(E_M(t)) = \frac{1}{2}\eta_M E_M^2(t)$$

Among them, $\eta_M > 0$ represents the effort cost coefficient of the manufacturer's KS.

Assumption 3. In order to encourage suppliers and manufacturers to actively share knowledge and promote LC technology innovation, a government subsidy mechanism is introduced to subsidize the shared costs of suppliers and manufacturers. It is assumed that the government's subsidy coefficients of KS costs for suppliers and manufacturers at time t are $\varphi_S(t)$ and $\varphi_M(t)$, respectively.

Assumption 4. LC technology can promote carbon emission reduction and obtain certain economic benefits. The size of the benefits is related to the stock of knowledge in the GSC and the price of carbon allowances in the carbon trading market (Wang et al., 2019c). Therefore, the benefits of KS are ultimately manifested as emissions reduction benefits brought about by LC technology innovation. Let $D(x(t))$ represents the carbon emission reduction benefits created by LC technology innovation, $D(x(t)) = P[\mu + \varepsilon x(t)]$. $\mu + \varepsilon x(t)$ represents the carbon emission reduction created by LC technology innovation. P represents the price of carbon allowances in the carbon trading market. ε represents the influence coefficient of knowledge stock on carbon emission reduction. μ represents a constant. Assume that the revenue distribution ratios of suppliers and manufacturers are $\gamma (0 < \gamma \leq 1)$ and $1 - \gamma$, respectively.

Assumption 5. Suppliers and manufacturers make decisions based on complete information. And at any time t, both have the same discount rate, denoted as $\rho(\rho > 0)$ (Zhao et al., 2014). In the game process, the goal of the two is to seek the best effort coefficient and the best strategy to maximize their benefits.

When suppliers and manufacturers aim at maximizing individual benefits, this situation is a decentralized decision-making without cost sharing. This helps to study the minimum constraints for suppliers and manufacturers to participate in KS (Wang et al., 2019c). In order to promote the KS of suppliers, manufacturers introduce a cost sharing mechanism to share the cost of KS of suppliers. This situation is a decentralized decision-making of cost sharing. The collaborative sharing of suppliers and manufacturers is an ideal state of KS, and both parties aim to maximize the overall benefits of the GSC. This situation is centralized decision-making. The purpose of analyzing these three game situations is to explore the minimum constraints of KS, the optimal cost-sharing mechanism of manufacturers and the optimal KS strategy.

3.2 Decentralized Decision-Making Without Cost Sharing

In the case of decentralized decision-making without cost sharing, suppliers and manufacturers form a Nash non-cooperative game. Both parties independently share knowledge and choose their own efforts to maximize profits. At this time, the supplier's optimal profit function P_S^N and the manufacturer's optimal profit function P_M^N are as follows, respectively

$$P_S^N = max_{E_S^N} \int_0^\infty e^{-\rho t} [\gamma D(x(t)) - (1 - \varphi_S(t)) C_S(E_S(t))] dt \quad (1)$$

$$P_M^N = max_{E_M^N} \int_0^\infty e^{-\rho t} [(1 - \gamma) D(x(t)) - (1 - \varphi_M(t)) C_M(E_M(t))] dt \quad (2)$$

It can be seen from the above formula that the benefits of suppliers and manufacturers at time t are jointly determined by the benefits of carbon emission reduction, the cost of KS, and the government subsidy coefficient. In this paper, the Hamilton-Jacobi-Bellman equation (HJB equation) is used to solve the above equation to determine the equilibrium strategy of both parties. The equilibrium result is shown in Proposition 1. For the convenience of expression and writing, the time t is no longer displayed during the solution process.

Proposition 1. The equilibrium results in the case of decentralized decision-making without cost sharing are as follows:

(1) The optimal trajectory of the knowledge stock $x^{N*}(t)$ in the GSC is:

$$x^{N*}(t) = l_1 - (l_1 - x_0)e^{-\delta t}$$

where, $l_1 = \frac{\beta^2 \gamma P \varepsilon}{(1-\varphi_S)\delta(\rho+\delta)\eta_S} + \frac{\alpha^2(1-\gamma)P\varepsilon}{(1-\varphi_M)\delta(\rho+\delta)\eta_M}$.

(2) The optimal effort level E_S^{N*} of supplier KS and the optimal effort level E_M^{N*} of manufacturer KS are respectively:

$$E_S^{N*} = \frac{\beta\gamma P\varepsilon}{(1-\varphi_S)(\rho+\delta)\eta_S},\ E_M^{N*} = \frac{\alpha(1-\gamma)P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M}$$

(3) The supplier's emission reduction revenue function $P_S^{N*}(x,t)$ and the manufacturer's emission reduction revenue function $P_M^{N*}(x,t)$ are respectively:

$$P_S^{N*}(x,t) = e^{-\rho t}\left(a_1^{N*}x + b_1^{N*}\right),\ P_M^{N*}(x,t) = e^{-\rho t}\left(a_2^{N*}x + b_2^{N*}\right)$$

where, $a_1^{N*} = \frac{\gamma P\varepsilon}{\rho+\delta}$, $b_1^{N*} = \frac{\gamma P\mu}{\rho} + \frac{\gamma(P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\frac{\alpha^2(1-\gamma)}{(1-\varphi_M)\eta_M} + \frac{\beta^2\gamma}{2(1-\varphi_S)\eta_S}\right]$, $a_2^{N*} = \frac{(1-\gamma)P\varepsilon}{\rho+\delta}$, $b_2^{N*} = \frac{(1-\gamma)P\mu}{\rho} + \frac{(1-\gamma)(P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\frac{\alpha^2(1-\gamma)}{2(1-\varphi_M)\eta_M} + \frac{\beta^2\gamma}{(1-\varphi_S)\eta_S}\right]$.

(4) The carbon emission reduction benefit function $P^{N*}(x,t)$ of the GSC is

$$P^{N*}(x,t) = P_S^{N*}(x,t) + P_M^{N*}(x,t)$$

Proof: According to the optimal control theory, from **Eq. 1**, the objective function of the supplier's optimal decision-making at time t can be obtained as

$$\begin{aligned}P_S^{N*}(x,t) &= \max_{E_S}\int_t^{\infty} e^{-\rho t}\left[\gamma D(x) - (1-\varphi_S)C_S(E_S)\right]dr\\ &= e^{-\rho t}\max_{E_S^N}\int_t^{\infty}\left[\gamma D(x) - (1-\varphi_S)C_S(E_S)\right]dr\end{aligned} \tag{3}$$

Make

$$U_S^N(x) = \max_{E_S}\int_t^{\infty} e^{-\rho(r-t)}\left[\gamma D(x) - (1-\varphi_S)C_S(E_S)\right]dr \tag{4}$$

The **Eq. 3** can be expressed as

$$P_S^{N*}(x,t) = e^{-\rho t}U_S^N(x) \tag{5}$$

At this time, the supplier's optimal decision objective function can be transformed into the following HJB equation

$$\rho U_S^N(x) = \max_{E_S}\left[\gamma D(x) - (1-\varphi_S)C_S(E_S) + U_S^{N\prime}(x)\dot{x}\right] \tag{6}$$

Expand **Eq. 6**

$$\begin{aligned}\rho U_S^N(x) = \max_{E_S}\Big[&\gamma P[\mu+\varepsilon x] - \frac{1}{2}(1-\varphi_S)\eta_S E_S^2 + U_S^{N\prime}(x)(\alpha E_M\\ &+\beta E_S - \delta x)\Big]\end{aligned} \tag{7}$$

Equation 7 is about the concave function of E_S. In order to solve E_S, this study takes the first-order partial derivative of E_S and makes it equal to zero, and the supplier's KS effort can be obtained as

$$E_S = \frac{\beta U_S^{N\prime}(x)}{(1-\varphi_S)\eta_S} \tag{8}$$

Similarly, according to the proof process of **Eqs 3–5**, the manufacturer's optimal decision objective function $P_M^{N*}(x,t)$ at time t can be obtained as

$$P_M^{N*}(x,t) = e^{-\rho t}U_M^N(x) \tag{9}$$

In **Eq. 9**, $U_M^N(x) = \max_{E_M}\int_t^{\infty} e^{-\rho(r-t)}\left[(1-\gamma)D(x) - (1-\varphi_M)C_M(E_M)\right]dr$. At this time, the manufacturer's optimal decision objective function can be transformed into the following HJB equation

$$\rho U_M^N(x) = \max_M\left[(1-\gamma)D(x) - (1-\varphi_M)C_M(E_M) + U_M^{N\prime}(x)\dot{x}\right] \tag{10}$$

Expand **Eq. 10**

$$\begin{aligned}\rho U_M^N(x) = \max_{E_S}\Big[&(1-\gamma)P(\mu+\varepsilon x) - \frac{1}{2}(1-\varphi_M)\eta_M E_M^2\\ &+ U_M^{N\prime}(x)(\alpha E_M + \beta E_S - \delta x)\Big]\end{aligned} \tag{11}$$

Equation 11 is about the concave function of E_M. Finding the first-order partial derivative of **Eq. 11** with respect to E_M and setting it equal to zero, the manufacturer's KS effort E_M can be obtained as

$$E_M = \frac{\alpha U_M^{N\prime}(x)}{(1-\varphi_M)\eta_M} \tag{12}$$

It can be seen from **Eqs 8**, **12** that the degree of KS effort is positively correlated with the government subsidy coefficient and the influence coefficient of knowledge stock, while it is negatively correlated with the effort cost coefficient of KS. Substitute **Eq. 8** into **Eqs 7**, **12** into **Eq. 11**, and get

$$\begin{aligned}\rho U_S^N(x) = \gamma P(\mu+\varepsilon x) + U_S^{N\prime}(x)\Bigg[&\frac{\alpha^2 U_M^{N\prime}(x)}{(1-\varphi_M)\eta_M} + \frac{\beta^2 U_S^{N\prime}(x)}{2(1-\varphi_S)\eta_S}\\ &- \delta x\Bigg]\end{aligned} \tag{13}$$

$$\begin{aligned}\rho U_M^N(x) = (1-\gamma)P(\mu+\varepsilon x) + U_M^{N\prime}(x)\Bigg[&\frac{\alpha^2 U_M^{N\prime}(x)}{2(1-\varphi_M)\eta_M}\\ &+ \frac{\beta^2 U_S^{N\prime}(x)}{(1-\varphi_S)\eta_S} - \delta x\Bigg]\end{aligned} \tag{14}$$

Suppose the linear expressions of $U_S^N(x)$ and $U_M^N(x)$ with respect to x are

$$U_S^N(x) = a_1^N x + b_1^N \tag{15}$$

$$U_M^N(x) = a_2^N x + b_2^N \tag{16}$$

Where, a_1^N, b_1^N, a_2^N and b_2^N are all constants. Substitute **Eqs 15**, **16** into **Eqs 13**, **14**, as shown below

$$\begin{cases}\rho a_1^N = \gamma P\varepsilon - U_S^{N\prime}(x)\delta\\ \rho a_2^N = (1-\gamma)P\varepsilon - U_M^{N\prime}(x)\delta\\ \rho b_1^N = \gamma P\mu + U_S^{N\prime}(x)\left[\frac{\alpha^2 U_M^{N\prime}(x)}{(1-\varphi_M)\eta_M} + \frac{\beta^2 U_S^{N\prime}(x)}{2(1-\varphi_S)\eta_S}\right]\\ \rho b_2^N = (1-\gamma)P\mu + U_M^{N\prime}(x)\left[\frac{\alpha^2 U_M^{N\prime}(x)}{2(1-\varphi_M)\eta_M} + \frac{\beta^2 U_S^{N\prime}(x)}{(1-\varphi_S)\eta_S}\right]\end{cases} \tag{17}$$

In this study, the undetermined coefficient method was used to solve the equation, as shown below

$$\begin{cases} a_1^{N*} = \dfrac{\gamma P\varepsilon}{\rho+\delta} \\ a_2^{N*} = \dfrac{(1-\gamma)P\varepsilon}{\rho+\delta} \\ b_1^{N*} = \dfrac{\gamma P\mu}{\rho} + \dfrac{\gamma (P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\dfrac{\alpha^2(1-\gamma)}{(1-\varphi_M)\eta_M} + \dfrac{\beta^2\gamma}{2(1-\varphi_S)\eta_S}\right] \\ b_2^{N*} = \dfrac{(1-\gamma)P\mu}{\rho} + \dfrac{(1-\gamma)(P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\dfrac{\alpha^2(1-\gamma)}{2(1-\varphi_M)\eta_M} + \dfrac{\beta^2\gamma}{(1-\varphi_S)\eta_S}\right] \end{cases}$$

a_1^{N*}, b_1^{N*}, a_2^{N*} and b_2^{N*} are substituted into **Eqs 15**, **16**. The expressions of $U_S^N(x)$ and $U_M^N(x)$ are as follows:

$$\begin{cases} U_S^N(x) = a_1^{N*}x + b_1^{N*} \\ U_M^N(x) = a_2^{N*}x + b_2^{N*} \end{cases} \tag{18}$$

Equation 18 and its first derivative $U_S^{N'}(x)$ and $U_M^{N'}(x)$ are substituted into **Eqs 8**, **12**. The equilibrium solution E_S^{N*} of the supplier's KS effort and the equilibrium solution E_M^{N*} of the manufacturer's KS effort can be obtained as

$$\begin{cases} E_S^{N*} = \dfrac{\beta\gamma P\varepsilon}{(1-\varphi_S)(\rho+\delta)\eta_S} \\ E_M^{N*} = \dfrac{\alpha(1-\gamma)P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M} \end{cases} \tag{19}$$

Equation 19 is substituted into $\dot{x}(t) = \alpha E_M(t) + \beta E_S(t) - \delta x(t)$. According to the initial condition $x(0) = x_0 > 0$, the optimal trajectory of the GSC knowledge stock can be obtained as $x^{N*}(t) = l_1 - (l_1 - x_0)e^{-\delta t}$, where, $l_1 = \frac{\beta^2\gamma P\varepsilon}{(1-\varphi_S)\delta(\rho+\delta)\eta_S} + \frac{\alpha^2(1-\gamma)P\varepsilon}{(1-\varphi_M)\delta(\rho+\delta)\eta_M}$. Substituting **Eq. 18** into **Eqs 5**, **9** can obtain the optimal function of supplier and manufacturer's income. The certificate is complete.

3.3 Decentralized Decision-Making With Cost Sharing

In order to obtain more information that is conducive to LC technology innovation, manufacturers encourage suppliers to actively share knowledge and share the cost of supplier sharing. The cost sharing ratio is $\theta(t)(0<\theta(t)<1)$. In the process of the game, a Stackellberg master-slave game with manufacturers as the leading and supplier as the subordinate is gradually formed. The manufacturer first determines its own KS effort $E_M^Y(t)$ and cost sharing ratio $\theta(t)$, and the supplier determines its own effort $E_S^Y(t)$ according to the manufacturer's cost sharing ratio $\theta(t)$. It can be determined that the supplier's revenue function P_S^Y and the manufacturer's revenue function P_M^Y is:

$$P_S^Y = \max_{E_S^Y}\int_0^\infty e^{-\rho t}\left[\gamma D(x) - (1-\varphi_S-\theta)C_S(E_S)\right]dt \tag{20}$$

$$P_M^Y = max_{E_M^Y}\int_0^\infty e^{-\rho t}\left[(1-\gamma)D(x) - (1-\varphi_M)C_M(E_M) - \theta C_S(E_S)\right]dt \tag{21}$$

In order to determine the equilibrium strategy of the supplier and the manufacturer, the HJB equation is used to solve it. The solution result is shown in Proposition 2.

Proposition 2. The equilibrium result of decentralized decision-making under cost sharing is as follows:

(1) The optimal trajectory of the knowledge stock $x^{Y*}(t)$ in the GSC is

$$x^{Y*}(t) = l_2 - (l_2 - x_0)e^{-\delta t}$$

where, $l_2 = \frac{\beta^2 P\varepsilon(2-\gamma)}{2\delta(\rho+\delta)(1-\varphi_S)\eta_S} + \frac{\alpha^2(1-\gamma)P\varepsilon}{\delta(1-\varphi_M)(\rho+\delta)\eta_M}$.

(2) The supplier's optimal effort level E_S^{Y*} and the manufacturer's optimal effort level E_M^{Y*} are respectively

$$E_S^{Y*} = \frac{\beta P\varepsilon(2-\gamma)}{2(\rho+\delta)(1-\varphi_S)\eta_S},\ E_M^{Y*} = \frac{\alpha(1-\gamma)P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M}$$

(3) The supplier's optimal emission reduction revenue function $P_S^{Y*}(x,t)$ and the manufacturer's optimal emission reduction revenue function $P_M^{Y*}(x,t)$ are respectively

$$P_S^{Y*}(x,t) = e^{-\rho t}\left(a_1^{Y*}x + b_1^{Y*}\right),\ P_M^{Y*}(x,t) = e^{-\rho t}\left(a_2^{Y*}x + b_2^{Y*}\right)$$

where, $a_1^{Y*} = \frac{\gamma P\varepsilon}{\rho+\delta}$, $a_2^{Y*} = \frac{(1-\gamma)P\varepsilon}{\rho+\delta}$, $b_1^{Y*} = \frac{\gamma P\mu}{\rho} + \frac{\gamma(P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\frac{\alpha^2(1-\gamma)}{(1-\varphi_M)\eta_M} + \frac{\beta^2(2-\gamma)}{4(1-\varphi_S)\eta_S}\right]$, $b_2^{Y*} = \frac{(1-\gamma)P\mu}{\rho} + \frac{(P\varepsilon)^2}{2\rho(\rho+\delta)^2}\left[\frac{\alpha^2(1-\gamma)^2}{(1-\varphi_M)\eta_M} + \frac{\beta^2(2-\gamma)^2}{4(1-\varphi_S)\eta_S}\right]$.

(4) The emission reduction revenue function of the GSC $P^{Y*}(x,t)$ is

$$P^{Y*}(x,t) = P_S^{Y*}(x,t) + P_M^{Y*}(x,t)$$

(5) The manufacturer's share of the supplier's KS cost θ is

$$\theta = \frac{(1-\varphi_S)(2-3\gamma)}{(2-\gamma)}$$

Proof: Using the inverse induction method to solve, from **Eq. 20**, we can see that the supplier's optimal profit function $P_S^{Y*}(x,t)$ at time t is

$$P_S^{Y*}(x,t) = e^{-\rho t}U_S^Y(x) \tag{22}$$

where, $U_S^Y(x) = \max_{E_S}\int_t^\infty e^{-\rho(r-t)}[\gamma D(x) - (1-\varphi_S-\theta)C_S(E_S)]dr$. The supplier's optimal revenue function satisfies the following HJB equation

$$\rho U_S^Y(x) = max_{E_S}\left[\gamma P(\mu + \varepsilon x) - (1 - \varphi_S - \theta)\frac{1}{2}\eta_S E_S^2 + U_S^{Y\prime}(x)(\alpha E_M + \beta E_S - \delta x)\right] \quad (23)$$

It can be seen that **Eq. 23** is about the concave function of E_S. Find the first-order partial derivative of E_S and make it equal to zero, and the following equation is obtained

$$E_S = \frac{\beta U_S^{Y\prime}(x)}{(1 - \varphi_S - \theta)\eta_S} \quad (24)$$

In the same way, the manufacturer's optimal profit function $P_M^{Y*}(x,t)$ at time t is

$$P_M^{Y*}(x,t) = e^{-\rho t}U_M^Y(x) \quad (25)$$

where, $U_M^Y(x) = \max_{E_M}\int_t^{\infty} e^{-\rho(r-t)}[(1-\gamma)D(x) - (1-\varphi_M)C_M(E_M) - \theta C_S(E_S)]dr$. At this time, the manufacturer's optimal profit function satisfies the HJB equation, as shown below

$$\rho U_M^Y(x) = \max_{E_M,\theta}\left\{(1-\gamma)P(\mu+\varepsilon x) - \frac{1}{2}(1-\varphi_M)\eta_M E_M^2 - \frac{\theta\beta^2[U_S^{Y\prime}(x)]^2}{2(1-\varphi_S-\theta)^2\eta_S} + U_M^{Y\prime}(x)\left(\alpha E_M + \frac{\beta^2 U_S^{Y\prime}(x)}{(1-\varphi_S-\theta)\eta_S} - \delta x\right)\right\} \quad (26)$$

According to the related theory of Hessian matrix (Wang D. et al., 2019), **Eq. 26** is a concave function, and the maximum value is obtained when the partial derivative is equal to zero. In order to solve E_M and θ, let the first partial derivative of E_M and θ in **Eq. 26** be zero, the following equation can be obtained

$$E_M = \frac{\alpha U_M^{Y\prime}(x)}{(1-\varphi_M)\eta_M},\ \theta = \frac{(1-\varphi_S)(2U_M^{Y\prime}(x) - U_S^{Y\prime}(x))}{2U_M^{Y\prime}(x) + U_M^{Y\prime}(x)} \quad (27)$$

The manufacturer's share of the supplier's KS cost ratio θ is meaningful only when $U_M^{Y\prime}(x) > \frac{U_S^{Y\prime}(x)}{2}$. Otherwise, the manufacturer will not share the supplier's innovation costs.

Substituting E_S, E_M and θ in **Eqs 24**, **27** into **Eqs 23**, **26**, the following equations can be obtained

$$\rho U_S^Y(x) = \gamma P(\mu+\varepsilon x) + U_S^{Y\prime}(x)\left(\frac{\alpha^2 U_M^{Y\prime}(x)}{(1-\varphi_M)\eta_M} - \delta x\right) + \frac{\beta^2 U_S^{Y\prime}(x)[2U_M^{Y\prime}(x) + U_S^{Y\prime}(x)]}{4(1-\varphi_S)\eta_S} \quad (28)$$

$$\rho U_M^Y(x) = (1-\gamma)P(\mu+\varepsilon x) + U_M^{Y\prime}(x)\left[\frac{\alpha^2 U_M^{Y\prime}(x)}{2(1-\varphi_M)\eta_M} - \delta x\right] + \frac{\beta^2[2U_M^{Y\prime}(x) + U_S^{Y\prime}(x)]^2}{8(1-\varphi_S)\eta_S} \quad (29)$$

According to the characteristics of **Eqs 28**, **29**, it is assumed that the linear expressions of $U_S^Y(x)$ and $U_M^Y(x)$ with respect to x are

$$U_S^Y(x) = a_1^Y x + b_1^Y,\ U_M^Y(x) = a_2^Y x + b_2^Y \quad (30)$$

where, a_1^Y, b_1^Y, a_2^Y and b_2^Y are all constants. Substituting **Eq. 30** into **Eqs 28**, **29**, the equations for a_1^Y, b_1^Y, a_2^Y and b_2^Y can be obtained. Using the method of undetermined coefficients to solve the equations, the following equations can be obtained

$$\begin{cases} a_1^{Y*} = \dfrac{\gamma P\varepsilon}{\rho+\delta} \\ a_2^{Y*} = \dfrac{(1-\gamma)P\varepsilon}{\rho+\delta} \\ b_1^{Y*} = \dfrac{\gamma P\mu}{\rho} + \dfrac{\gamma(P\varepsilon)^2}{\rho(\rho+\delta)^2}\left[\dfrac{\alpha^2(1-\gamma)}{(1-\varphi_M)\eta_M} + \dfrac{\beta^2(2-\gamma)}{4(1-\varphi_S)\eta_S}\right] \\ b_2^{Y*} = \dfrac{(1-\gamma)P\mu}{\rho} + \dfrac{(P\varepsilon)^2}{2\rho(\rho+\delta)^2}\left[\dfrac{\alpha^2(1-\gamma)^2}{(1-\varphi_M)\eta_M} + \dfrac{\beta^2(2-\gamma)^2}{4(1-\varphi_S)\eta_S}\right] \end{cases}$$

Substituting a_1^{Y*}, b_1^{Y*}, a_2^{Y*} and b_2^{Y*} into **Eq. 30**, $U_S^Y(x)$ and $U_M^Y(x)$ can be determined as shown below

$$U_S^Y(x) = a_1^{Y*}x + b_1^{Y*},\ U_M^Y(x) = a_2^{Y*}x + b_2^{Y*} \quad (31)$$

Equations 31, $U_S^{Y\prime}(x)$ and $U_M^{Y\prime}(x)$ are substituted into **Eqs 24**, **27**, the supplier's KS effort E_S^{Y*} and manufacturer's KS effort E_M^{Y*} are shown as follows

$$E_S^{Y*} = \frac{\beta P\varepsilon(2-\gamma)}{2(\rho+\delta)(1-\varphi_S)\eta_S},\ E_M^{Y*} = \frac{\alpha(1-\gamma)P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M} \quad (32)$$

Equation 32 is substituted into $\dot{x}(t) = \alpha E_M(t) + \beta E_S(t) - \delta x(t)$. According to the initial condition $x(0) = x_0 > 0$, the optimal trajectory of the knowledge stock of the GSC can be obtained as $x^{Y*}(t) = l_2 - (l_2 - x_0)e^{-\delta t}$, where $l_2 = \frac{\beta^2 P\varepsilon(2-\gamma)}{2\delta(\rho+\delta)(1-\varphi_S)\eta_S} + \frac{\alpha^2(1-\gamma)P\varepsilon}{\delta(1-\varphi_M)(\rho+\delta)\eta_M}$. **Equation 32** is substituted into **Eqs 22**, **25** respectively, the optimal function of supplier and manufacturer's income can be obtained. The certificate is complete.

3.4 Centralized Decision-Making (Collaborative Sharing)

Collaborative sharing is knowledge cooperation between suppliers and manufacturers aiming at the overall technology innovation of the GSC and maximizing the benefits of emission reduction. The collaborative sharing of LC technologies between suppliers and manufacturers in the GSC can improve the level of KS, realize resource integration and complement each other's advantages. In addition, it can also reduce the information asymmetry between suppliers and manufacturers and promote LC technology innovation. In the case of collaborative sharing, it is assumed that both parties make decisions with the goal of maximizing the overall benefits of the GSC. The decision variables include the supplier's KS effort E_S and the manufacturer's KS effort E_M. It can be determined that the GSC emission reduction benefit P^C under collaborative sharing can be expressed as:

$$P^C = \max_{E_S^C, E_M^C} \int_0^{\infty} e^{-\rho t} [D(x) - (1-\varphi_S) C_S(E_S) - (1-\varphi_M) C_M(E_M)] dt$$

Using the HJB equation, the equilibrium strategy of the decision problem can be obtained, as shown in Proposition 3.

Proposition 3. The equilibrium results in centralized decision-making are as follows:

(1) The optimal trajectory of the knowledge stock $x^{C*}(t)$ in the GSC is

$$x^{C*}(t) = l_3 - (l_3 - x_0) e^{-\delta t}$$

where, $l_3 = \frac{\beta^2 P\varepsilon}{\delta(\rho+\delta)(1-\varphi_S)\eta_S} + \frac{\alpha^2 P\varepsilon}{\delta(1-\varphi_M)(\rho+\delta)\eta_M}$.

(2) The supplier's optimal effort level E_S^{C*} and the manufacturer's KS optimal effort level E_M^{C*} are respectively

$$E_S^{C*} = \frac{\beta P\varepsilon}{(1-\varphi_S)(\rho+\delta)\eta_S},\ E_M^{C*} = \frac{\alpha P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M}$$

(3) The optimal value function $P^{C*}(x,t)$ of the emission reduction benefits of the GSC is

$$P^{C*}(x,t) = e^{-\rho t}\left(a_1^{C*} x + b_1^{C*}\right)$$

where, $a_1^{C*} = \frac{P\varepsilon}{\rho+\delta}$ and $b_1^{C*} = \frac{P\mu}{\rho} + \frac{(P\varepsilon)^2}{2\rho(\rho+\delta)^2}[\frac{\beta^2}{(1-\varphi_S)\eta_S} + \frac{\alpha^2}{(1-\varphi_M)\eta_M}]$.

Proof: From **Eq. 33**, the optimal carbon emission reduction revenue function $P^{C*}(x,t)$ of the GSC at time t can be obtained as

$$P^{C*}(x,t) = \max_{E_S^C, E_M^C} \int_t^{\infty} e^{-\rho r} [D(x) - (1-\varphi_S) C_S(E_S) - (1-\varphi_M) C_M(E_M)] dr$$

Let $U^C(x) = \max_{E_S^C, E_M^C} \int_t^{\infty} e^{-\rho(r-t)} [D(x) - (1-\varphi_S) C_S(E_S) - (1-\varphi_M) C_M(E_M)] dr$, then the optimal benefit function of carbon emission reduction in the GSC at time t can be expressed as

$$P^{C*}(x,t) = e^{-\rho t} U^C(x)$$

At this time, the decision-making problem of collaborative KS satisfies the following HJB equation

$$\rho U^C(x) = \max_{E_S^C, E_M^C}\left[D(x) - (1-\varphi_S) C_S(E_S) - (1-\varphi_M) C_M(E_M) + U^{C'}(x)\dot{x}\right] \tag{33}$$

Expand the **Eq. 33** as follows

$$\rho U^C(x) = \max_{E_S^C, E_M^C}\Big[P(\mu+\varepsilon x) - (1-\varphi_S)\frac{1}{2}\eta_S E_S^2 - (1-\varphi_M)\frac{1}{2}\eta_M E_M^2 + U^{C'}(x)(\alpha E_M + \beta E_S - \delta x)\Big] \tag{34}$$

The Hessian matrix of **Eq. 34** for E_S and E_M is

$$H = \begin{bmatrix} -(1-\varphi_S)\eta_S & 0 \\ 0 & -(1-\varphi_M)\eta_M \end{bmatrix}$$

Since $det(H) = (1-\varphi_S)(1-\varphi_M)\eta_S\eta_M > 0$ and $-(1-\varphi_S)\eta_S < 0$, it can be determined that the Hessian matrix is negative definite, so **Eq. 34** is a concave function. The maximum value of E_S and E_M can be obtained, and the maximum value is obtained when the partial derivative is equal to zero. In order to find the first-order partial derivative of E_S and E_M in **Eq. 34** and set it equal to zero, the following equation can be obtained

$$E_S = \frac{\beta U^{C'}(x)}{(1-\varphi_S)\eta_S},\ E_M = \frac{\alpha U^{C'}(x)}{(1-\varphi_M)\eta_M} \tag{35}$$

Substituting **Eq. 35** into **Eq. 34** can get:

$$\rho U^C(x) = P(\mu+\varepsilon x) - \frac{\left[\beta U^{C'}(x)\right]^2}{2(1-\varphi_S)\eta_S} - \frac{\left[\alpha U^{C'}(x)\right]^2}{2(1-\varphi_M)\eta_M} + U^{C'}(x)\left(\frac{\alpha^2 U^{C'}(x)}{(1-\varphi_M)\eta_M} + \frac{\beta^2 U^{C'}(x)}{(1-\varphi_S)\eta_S} - \delta x\right) \tag{36}$$

The optimal value function of **Eq. 36** with respect to x is the solution of the HJB equation, so the linear expression of $U^C(x)$ with respect to x is

$$U^C(x) = a_1^C x + b_1^C \tag{37}$$

Equation 37 is substituted into **Eq. 36**, the constraint equations about a_1^C and b_1^C can be obtained. Use the method of undetermined coefficients to get $a_1^{C*} = \frac{P\varepsilon}{\rho+\delta}$, $b_1^{C*} = \frac{P\mu}{\rho} + \frac{(P\varepsilon)^2}{2\rho(\rho+\delta)^2}[\frac{\beta^2}{(1-\varphi_S)\eta_S} + \frac{\alpha^2}{(1-\varphi_M)\eta_M}]$.

Substituting a_1^{C*} and b_1^{C*} into **Eq. 37**, the expression of $U^C(x)$ can be determined as

$$U^C(x) = a_1^{C*} x + b_1^{C*} \tag{38}$$

Substituting the first derivative of **Eq. 38** into **Eq. 35**, the equilibrium solution E_S^{C*} of the supplier's KS effort and the equilibrium solution E_M^{C*} of the manufacturer's KS effort can be determined as

$$E_S^{C*} = \frac{\beta P\varepsilon}{(1-\varphi_S)(\rho+\delta)\eta_S},\ E_M^{C*} = \frac{\alpha P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M} \tag{39}$$

Substitute **Eq. 39** into $\dot{x}(t) = \alpha E_M(t) + \beta E_S(t) - \delta x(t)$. According to the initial condition $x(0) = x_0 > 0$, the optimal trajectory of the knowledge stock of the GSC can be obtained $x^{C*}(t) = l_3 - (l_3 - x_0)e^{-\delta t}$, where $l_3 = \frac{\beta^2 P\varepsilon}{\delta(\rho+\delta)(1-\varphi_S)\eta_S} + \frac{\alpha^2 P\varepsilon}{\delta(1-\varphi_M)(\rho+\delta)\eta_M}$. Substituting **Eq. 38** into **Eq. 36** can obtain the optimal value function $P^{C*}(x,t)$ of the carbon emission reduction benefit of the GSC. The certificate is complete.

3.5 Comparative Analysis

In the case of decentralized decision-making without cost sharing and decentralized decision-making with cost sharing, a comparative analysis of the degree of KS effort between suppliers and manufacturers can be obtained:

$$\begin{cases} E_M^{Y*} - E_M^{N*} = 0 \\ E_S^{Y*} - E_S^{N*} = \dfrac{(2-3\gamma)\beta P\varepsilon}{2(1-\varphi_S)(\rho+\delta)\eta_S} \\ \dfrac{E_S^{Y*} - E_S^{N*}}{E_N^{Y*}} = \dfrac{(2-3\gamma)}{2\gamma} > 0 \end{cases}$$

Corollary 1. When the supplier's carbon emission reduction revenue distribution ratio is $0 < \gamma < \frac{2}{3}$, $E_M^{Y*} = E_M^{N*}$, $E_S^{Y} > E_S^{N*}$. The cost-sharing mechanism does not change the degree of KS efforts of manufacturers. However, the degree of KS efforts of suppliers has increased, and the degree of improvement is related to the supplier's carbon emission reduction revenue distribution ratio γ. The introduction of a cost-sharing mechanism can increase the willingness of suppliers to share knowledge, and promote the game between the two to change from the Nash non-cooperative game to the Stackelberg master-slave game.

A comparative analysis of the degree of KS effort of suppliers and manufacturers in the three scenarios of no-cost-sharing decentralized decision-making, cost-sharing decentralized decision-making, and centralized decision-making can be obtained:

$$\begin{cases} E_S^{C*} - E_S^{Y*} = \dfrac{\beta P\varepsilon\gamma}{2(1-\varphi_S)(\rho+\delta)\eta_S} \\ E_S^{C*} - E_S^{N*} = \dfrac{\beta P\varepsilon(1-\gamma)}{(1-\varphi_S)(\rho+\delta)\eta_S} \\ E_M^{C*} - E_M^{Y*} = \dfrac{\gamma\alpha P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M} \\ E_M^{C*} - E_M^{N*} = \dfrac{\gamma\alpha P\varepsilon}{(1-\varphi_M)(\rho+\delta)\eta_M} \end{cases}$$

Corollary 2. Regardless of the supplier's carbon emission reduction revenue distribution ratio, there are $E_S^{C*} > E_S^{Y*}$, $E_S^{C*} > E_S^{N*}$, $E_M^{C*} > E_M^{Y*}$ and $E_M^{C*} > E_M^{N*}$. The KS effort of suppliers and manufacturers in the centralized decision-making situation is higher than that in the decentralized decision-making situation. The centralized decision-making situation is the most ideal state. Suppliers and manufacturers share knowledge to the greatest extent, provide information support for collaborative innovation, and strive to maximize the overall benefits of the GSC.

In the case of decentralized decision-making without cost sharing and decentralized decision-making with cost sharing, a comparative analysis of the optimal function of the carbon emission reduction benefits of suppliers and manufacturers can be obtained

$$\begin{cases} P_S^{Y*} - P_S^{N*} = \dfrac{e^{-\rho t}\gamma P\varepsilon}{\rho+\delta}\left[(x^{Y*} - x^{N*}) + \dfrac{\beta^2 P\varepsilon(2-3\gamma)}{4\rho(\rho+\delta)(1-\varphi_S)\eta_S}\right] \\ P_M^{Y*} - P_M^{N*} = \dfrac{e^{-\rho t}P\varepsilon}{\rho+\delta}\left[(1-\gamma)(x^{Y*} - x^{N*}) + \dfrac{P\varepsilon\beta^2(3\gamma-2)^2}{8\rho(\rho+\delta)(1-\varphi_S)\eta_S}\right] \end{cases}$$

Corollary 3. When the supplier's carbon emission reduction revenue is $0 < \gamma < \frac{2}{3}$, there are $x^{Y*} > x^{N*}$, $P_S^{Y*} > P_S^{N*}$, $P_M^{Y*} > P_M^{N*}$. Compared with decentralized decision-making without cost sharing, in the case of decentralized decision-making with cost sharing, the emission reduction benefits of suppliers and manufacturers have increased significantly, and the knowledge stock in the GSC has increased significantly. It shows that the cost-sharing mechanism can meet the participation constraints of supplier KS in the GSC, and promote the game between the two to change from the Nash non-cooperative game to the Stackelberg non-cooperative game. At the same time, the Pareto improvement of carbon emission reduction benefits can be realized.

In the case of decentralized decision-making and centralized decision-making, a comparative analysis of the carbon emission reduction benefits of suppliers and manufacturers can be obtained

$$\begin{cases} P^{Y*} - P^{N*} = \dfrac{e^{-\rho t}P\varepsilon}{\rho+\delta}\left[(x^{Y*} - x^{N*}) + \dfrac{\gamma\beta^2 P\varepsilon(2-3\gamma)(2-\gamma)}{8\rho(\rho+\delta)(1-\varphi_S)\eta_S}\right] \\ P^{C*} - P^{Y*} = \dfrac{e^{-\rho t}P\varepsilon}{\rho+\delta}\left[(x^{C*} - x^{Y*}) + \dfrac{P\varepsilon}{2\rho(\rho+\delta)}\left[\dfrac{\beta^2\gamma^2}{4(1-\varphi_S)\eta_S} + \dfrac{\alpha^2\gamma^2}{(1-\varphi_M)\eta_M}\right]\right] \end{cases}$$

Corollary 4. When the supplier's carbon emission reduction revenue is $0 < \gamma < \frac{2}{3}$, there are $P^{C*} > P^{Y*}$, $x^{C*} > x^{Y*}$. When suppliers and manufacturers choose centralized decision-making, the overall benefit of the GSC is greater than the benefit of decentralized decision-making. At the same time, the stock of knowledge in the GSC has also been improved. Collaborative sharing strategies can promote KS and innovation.

4 NUMERICAL SIMULATION AND DISCUSSION

In order to further study the KS behavior and carbon emission reduction benefits of suppliers and manufacturers in the GSC. In this paper, Matlab is used to analyze three kinds of differential game situations. The parameter assignments are as follows: $\alpha = 4$, $\beta = 5$, $\delta = 0.2$, $\eta_S = 20$, $\eta_M = 15$, $\varphi_S = 0.2$, $\varphi_M = 0.15$, $\varepsilon = 6$,

$P = 30$, $x_0 = 100$, $\rho = 0.2$, $\gamma = 0.6$, $\mu = 5$. Substituting various parameters into Propositions 1–3 and Corollaries 1–4, a comparative analysis of carbon emission reduction benefits, knowledge stock and the degree of KS efforts of suppliers and manufacturers under different game situations are carried out. Finally, a sensitivity analysis of the main parameters is carried out.

4.1 Simulation Result Analysis

4.1.1 Emission Reduction Benefit Analysis

Figure 1A depicts the improvement of the cost-sharing mechanism to the carbon emission reduction benefits of suppliers and manufacturers. The abscissa represents time t, and the ordinate represents increased carbon emission reduction benefits. It can be found that the introduction of a cost-sharing mechanism can achieve Pareto improvement in the revenue of suppliers and manufacturers, and the effect of improving suppliers' emissions reduction income is better than that of manufacturers. Manufacturers share the cost of KS of suppliers, which inspires suppliers' enthusiasm for sharing. KS promotes the research and development of LC technologies, which can improve the carbon trading share of suppliers and increase emissions reduction benefits while improving environmental pollution and creating social benefits. For manufacturers, the LC knowledge provided by suppliers helps suppliers produce lower-carbon products. Consumers' LC preferences make LC products more acceptable, which increases the manufacturer's revenue. Obviously, the cost-sharing mechanism is beneficial to both parties.

Figure 1B describes the evolution of the overall carbon emission reduction benefits of the GSC over time under different sharing strategies. P^{N*} represents the carbon emission reduction benefits of the GSC under the Nash non-cooperative game. P^{Y*} represents the carbon emission reduction benefits of the GSC under the Stackelberg master-slave game. P^{C*} represents the carbon emission reduction benefits of the GSC in the context of collaborative sharing. It can be found that the overall emission reduction benefits of the GSC during the Stackelberg master-slave game and collaborative innovation are higher than those of the Nash non-cooperative game, but the degree of improvement of the emission reduction benefits by the cost-sharing mechanism is not significant when it is collaboratively shared. The cost-sharing mechanism is to redistribute the benefits of emission reduction, make up for the sharing costs of suppliers, and promote the KS behavior of suppliers. Although this situation has increased emissions reduction benefits, it still emphasizes the maximization of individual benefits. In the context of collaborative sharing, both parties concentrate resources and advantages, aiming at the overall emission reduction benefits of the GSC, emphasizing the maximization of overall benefits.

4.1.2 Comparative Analysis of Technology Stock

Figure 2 depicts the trend of the knowledge stock in the GSC over time under different sharing strategies. x^{N*} represents the knowledge stock of the GSC in the case of Nash non-cooperative game. x^{Y*} represents the knowledge stock of the GSC in the case of Stackelberg master-slave game. x^{C*} represents the knowledge stock of the GSC in the context of collaborative sharing. It can be found that at the same time, the stock of knowledge in the GSC during Stackelberg master-slave game and collaborative sharing is significantly higher than that of the Nash non-cooperative game. Moreover, the increase in knowledge stock in the context of collaborative sharing is the most significant. This shows that collaborative sharing can positively promote the KS behavior of suppliers and manufacturers. Because collaborative sharing reduces the information asymmetry between suppliers and manufacturers, it is conducive to KS and innovation efficiency. In addition, collaborative sharing avoids duplication of resources and unfair competition in the process of KS, and is conducive to the sustainable development of the GSC. Under different decision-making

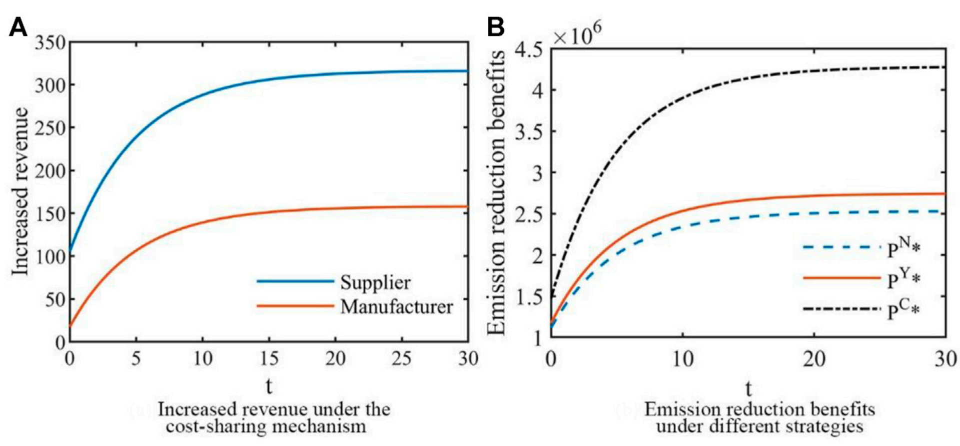

FIGURE 1 | Carbon emission reduction benefits under different KS strategies. **(A)** Increased revenue under the cost-sharing mechanism. **(B)** Emission reduction benefits under different strategies.

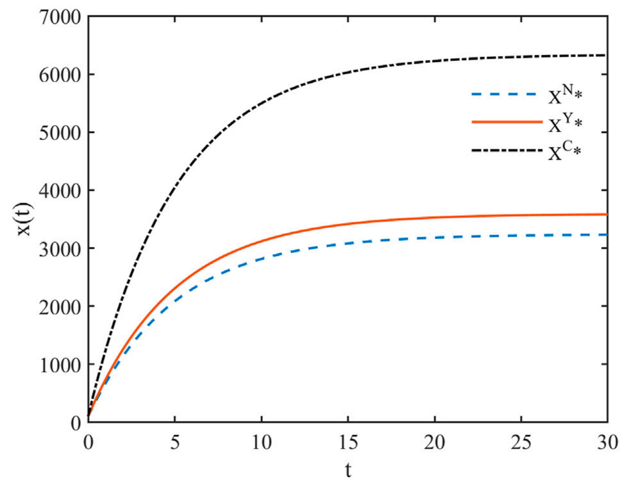

FIGURE 2 | Knowledge stock under different KS strategies.

situations, the evolution trend of knowledge stock is to increase first and then stabilize over time. This shows that the amount of knowledge in the GSC can be controlled and adjusted. For example, suppliers can increase knowledge ownership through LC technology innovation.

4.1.3 Comparative Analysis of Knowledge Sharing Effort Level

Figure 3 describes the KS effort level of suppliers and manufacturers in different decision-making situations. **Figure 3A** shows the KS effort level E_S^{N*} of the supplier and the KS effort level E_M^{N*} of the manufacturer when the cost-free decentralized decision is made. **Figure 3B** shows the supplier's KS effort E_S^{Y*} and the manufacturer's KS effort E_M^{Y*} when the cost-sharing decentralized decision is made. **Figure 3C** shows the supplier's KS effort level E_S^{C*} and the manufacturer's KS effort level E_M^{C*} during collaborative sharing. By comparing **Figures 3A,B**, it can be found that after the introduction of the cost sharing mechanism, the shared effort level of suppliers has increased significantly, and the effort level of manufacturers has not changed. This shows that the cost-sharing mechanism can reduce the cost of suppliers and significantly increase the enthusiasm of suppliers for KS. But this will not have an incentive effect on the shared behavior of manufacturers. Because the cost-sharing mechanism can reduce the sharing costs of suppliers, increase their willingness to share, and enable suppliers to actively invest in LC technology research and development, and create more green knowledge. Manufacturers can enjoy the benefits of supplier KS and LC technology innovation while maintaining their original level of effort, which reduces their willingness to share knowledge. Comparing **Figures 3B,C**, it can be found that under the collaborative sharing strategy, the KS effort of suppliers and manufacturers has been significantly improved, and the effort level is also relatively close, and collaborative sharing is effective for suppliers and manufacturers. The positive incentive effect of the quotient is better than the incentive effect under the cost-sharing mechanism.

4.2 Sensitivity Analysis

4.2.1 Sensitivity Analysis of Cost Sharing Ratio

The manufacturer's share of the supplier's KS cost is related to the supplier's carbon emission reduction income γ and the government's subsidy coefficient φ_S to the supplier. When the values of γ and φ_S change, the sensitivity analysis of θ is shown in **Figure 4**. It can be seen that as γ and φ_S increase, the value of θ gradually decreases. When the government's subsidies and the distribution ratio of the suppliers' carbon emission reduction benefits become larger, the suppliers' KS costs will decrease. At this time, the supplier is subject to the dual incentive effect of government incentives and emission reduction benefits, and the willingness to share is strong, and they will actively share knowledge. In order to reduce costs, manufacturers will gradually reduce the cost-sharing ratio to suppliers.

4.2.2 Sensitivity Analysis of Knowledge Stock

This paper analyzes the sensitivity of the main parameters of knowledge stock of GSC under centralized decision making. The sensitivity of supplier's knowledge creation level β, natural decay rate of knowledge stock δ, supplier's KS effort cost coefficient η_S, carbon quota price P, government's cost subsidy coefficient φ_S and φ_M to supplier and manufacturer are analyzed. The sensitivity analysis process for other parameters, such as manufacturer's knowledge creation level α and manufacturer's KS effort cost coefficient η_M, is similar to these analyses. **Figures 5–9** describes the change trajectory of knowledge stock under different parameters. Wherein, abscissa t represents time, and ordinate $x(t)$ represents knowledge stock in GSC.

Figures 5, **6** show that with the increase of suppliers' knowledge creation level β and carbon allowance price P, the knowledge stock in the GSC has shown an increasing trend. And the slope of the trajectory of the knowledge stock at the same time becomes larger. **Figure 5** shows that the improvement of LC technology innovation ability has a positive effect on the stock of knowledge, and the larger the parameter, the more significant the effect. The higher the level of knowledge creation, the stronger the supplier's LC technology research and development capabilities, and the amount of knowledge available for sharing will increase accordingly. Therefore, investment in LC technology research and development should be increased, new innovation models should be introduced, and the knowledge stock in the GSC should be increased. In addition, a collaborative innovation network for LC technologies in the GSC should be built to accelerate the flow of knowledge and reduce the loss of technology transfer.

In **Figure 6**, the higher the carbon allowance price, the greater the stock of knowledge in the GSC. This shows that the carbon emissions trading mechanism will have a certain impact on the behavior of decision-making entities, and this impact can be reflected through carbon prices. When the price of carbon allowances is high, decision-making entities will actively participate in LC technology research and development activities to reduce their own carbon emissions. At the same time, excess carbon allowances can be traded in the carbon market to increase their own profits. At this time, the stock of knowledge in the GSC will gradually increase. When the price of carbon allowances is low, the decision-making body will consider

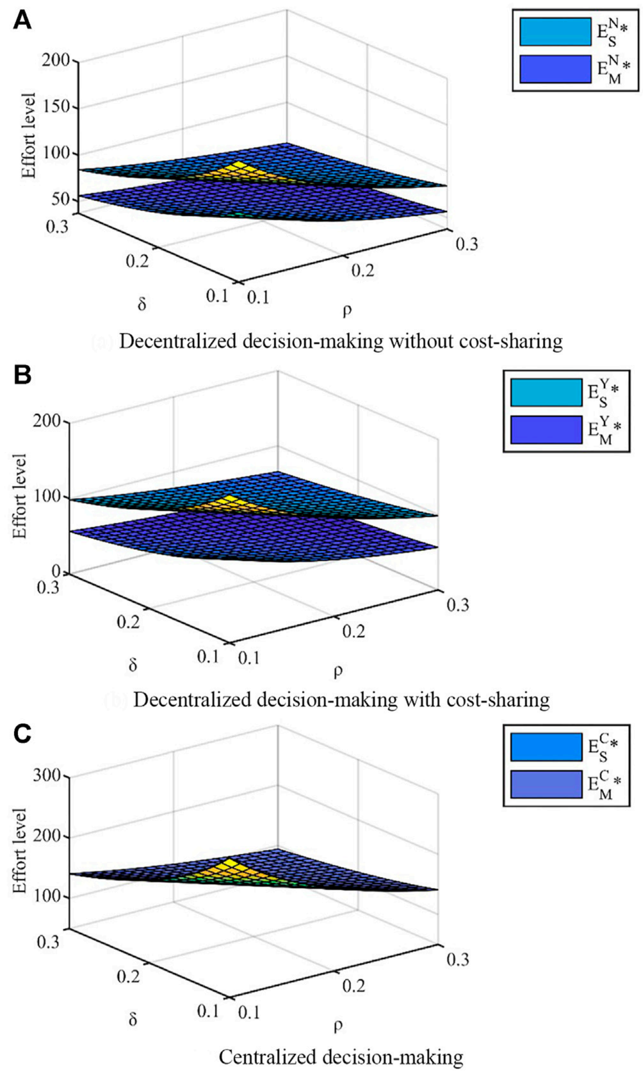

FIGURE 3 | Effort levels under different KS strategies.

whether to invest in LC technology research and development or purchase carbon allowances based on costs and benefits. At this time, the knowledge stock of the GSC is relatively small. Therefore, the price of carbon allowances plays a vital role in promoting decision-making entities to participate in LC technology research and development activities and KS. The carbon trading mechanism should be improved according to the actual situation, and the price of carbon allowances should be reasonably regulated.

Figures 7, **8** show that as the relative decay rate δ of the knowledge stock and the supplier's KS effort cost coefficient η_S increase, the knowledge stock in the GSC gradually decreases. This shows that when the cost of KS is too high, the willingness of decision-making subjects to share is weakened. When the relative decay rate δ of knowledge increases (such as technological update, technological change), the timeliness of knowledge declines rapidly with the change of time, leading to the gradual loss of original value of knowledge and the reduction of knowledge stock. At this time, suppliers need to continue to carry out LC technology innovation to maintain their advantages. When the supplier's KS cost coefficient η_S increases, the sharing cost increases, and the supplier's willingness to share weakens, and gradually tends not to share knowledge. From the comparison of **Figures 7**, **8**, it can be found that the attenuation rate of knowledge has a more significant impact on the knowledge stock of the GSC. In this case, collaborative innovation between suppliers and manufacturers becomes particularly important. Collaborative innovation can reduce the R&D cost of technology innovation and shorten the R&D cycle. This not only reduces the loss in the KS process, but

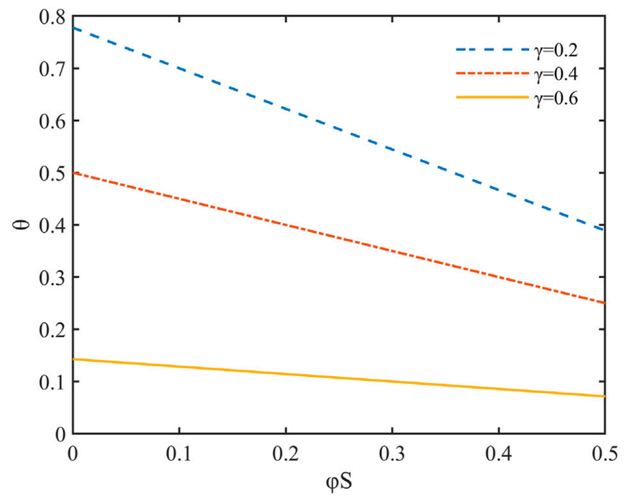

FIGURE 4 | The impact of γ and φ_S on θ.

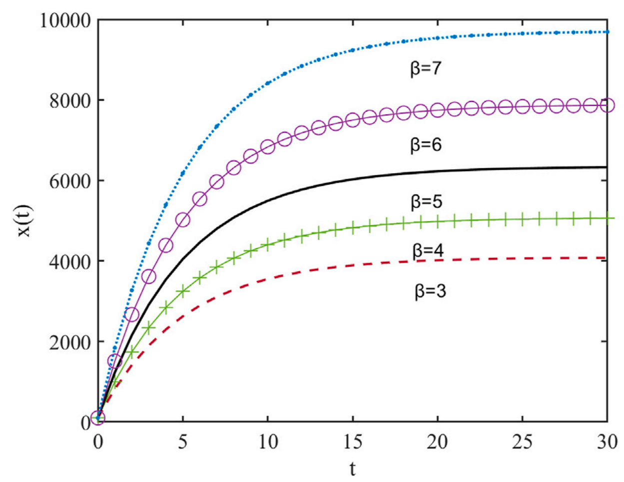

FIGURE 5 | The impact of β on $x(t)$.

also improves the efficiency of knowledge creation and increases the knowledge stock in the GSC.

Figure 9 describes the impact of the government's cost subsidy coefficient φ_S for suppliers and the manufacturer's cost subsidy coefficient φ_M on the knowledge stock. It can be seen that as the subsidy coefficient increases, the knowledge stock shows an increasing trend. The government's cost subsidy policy has reduced the sharing cost of decision-making subjects, and has produced positive incentives and guidance for KS behavior. At the same time, it can be found that compared with other parameters, as the proportion of government subsidies increases, the effect of increasing the knowledge stock is not significant, which indicates that the sensitivity of policymakers to the government subsidy coefficient is relatively low. Therefore, in the implementation process, the government should determine

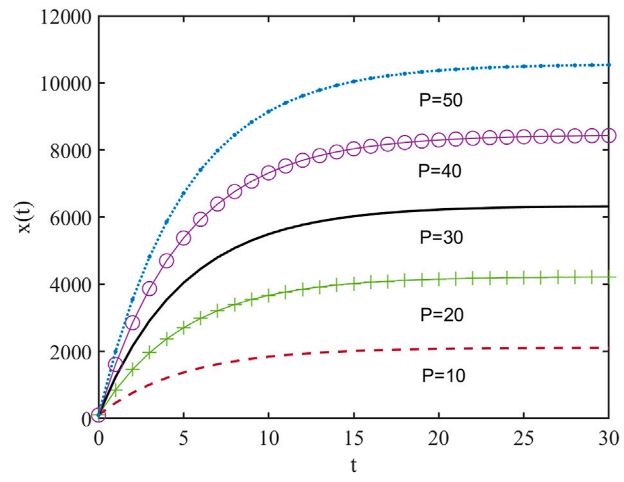

FIGURE 6 | The impact of P on $x(t)$.

a reasonable subsidy coefficient, which will not increase the government's financial burden while stimulating the enthusiasm of decision-makers for KS.

4.2.3 Sensitivity Analysis Results

From the results of the sensitivity analysis, it can be seen that the cost-sharing ratio of the manufacturer to the supplier's KS is negatively related to the supplier's carbon emission reduction benefits. At the same time, the cost-sharing ratio will be affected by the government's subsidy coefficient for supplier KS costs. The larger the government subsidy coefficient is, the lower the manufacturer's cost-sharing ratio. The knowledge stock is the most sensitive to the knowledge decay rate. When the decay rate increases, the knowledge stock decreases significantly, and it shows a decreasing trend from strong to weak. In order to cope with the phenomenon of knowledge decline caused by rapid technological development, suppliers and manufacturers should collaborate in innovation to reduce the time from R&D to commercial application of LC technologies. The stock of knowledge is positively correlated with the level of knowledge creation of the supplier. The study also found that the higher the level of knowledge creation, the stronger the supplier's ability to innovate in LC technology. Technology innovation and accumulation have increased the knowledge reserve in the GSC. The carbon price is positively correlated with the stock of knowledge. As the price of carbon increases, the stock of knowledge gradually increases. The mechanism of carbon price on knowledge stock is a feedback mechanism from emission reduction benefits to technology innovation to KS. The whole process is mainly to increase knowledge stock through LC technology innovation. The increase in carbon prices has increased suppliers' emissions reduction benefits, and LC technology innovation is the main way to increase carbon emissions reduction benefits. The government's subsidy policy has a certain incentive effect on the increase of knowledge stock, but the incentive effect is not significant, so it is necessary to determine a reasonable subsidy coefficient.

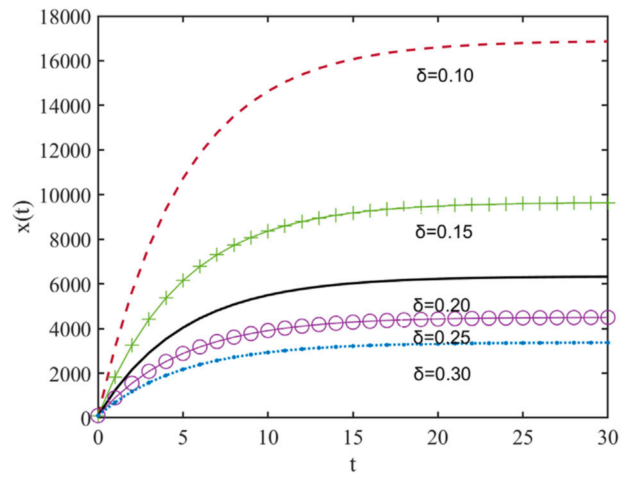

FIGURE 7 | The impact of δ on $x(t)$.

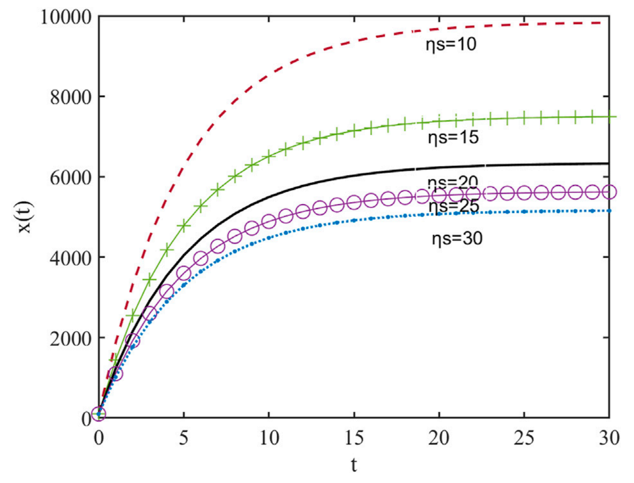

FIGURE 8 | The impact of η_S on $x(t)$.

5 DISCUSSION

KS is the key to achieving green innovation (Zhou et al., 2020). The absorption and utilization of knowledge in the supply chain can achieve outstanding green innovation (Song et al., 2020). Existing studies have pointed out that the sharing strategy affects the level of KS between suppliers and manufacturers (Ma et al., 2020; Zheng, 2021). When choosing different sharing strategies, the level of KS has a certain improvement, which is related to the benefits, costs and the degree of communication between the knowledge receiver and the sharer (Li H. et al., 2020). However, this study found that the effect of different strategies on the improvement of knowledge stock is not continuously increasing. Under different strategies, the evolution trend of the knowledge stock in the GSC is that it first increases and then stabilizes over time, which indicates that the knowledge amount in the GSC can be controlled and adjusted.

This research further analyzes the change trajectory of knowledge stock and the change law of emission reduction benefits under different strategies. The study found that collaborative sharing significantly increased the supply chain's knowledge stock and emission reduction benefits. The collaborative sharing strategy can improve the KS level of suppliers and manufacturers, and can promote LC technology innovation. This is because low-carbon supply chains can only be coordinated through revenue sharing-cost sharing (Jiang and Chen, 2016). Collaborative innovation can promote green technology research and development (Chen et al., 2017; Ardito et al., 2019; Yu X. et al., 2021). The research results of this article can explain this conclusion from another angle. Sensitivity analysis results show that the stock of knowledge has the strongest sensitivity to knowledge decay rate. However, as the decay rate increases, the timeliness of knowledge decreases rapidly over time, knowledge gradually loses its original value, and knowledge stock decreases. Collaborative innovation can reduce the research and development costs of technology innovation and shorten the research and development cycle, which can reduce the loss in the KS process and improve the efficiency of knowledge creation and green technology research and development. Cost sharing contracts can induce manufacturers to increase investment in clean technology (Shen et al., 2017), and the same cost sharing mechanism can promote the level of knowledge sharing between manufacturers and suppliers.

The carbon emission trading mechanism leads to higher operating costs for companies (Hu and Ding, 2020), because companies invest more in LC technology research and development. With the increase in carbon prices, the stock of knowledge in the GSC has increased significantly. The mechanism of carbon price on knowledge stock is a feedback mechanism from emission reduction benefits to technology innovation to KS. The whole process is mainly to realize the increase of knowledge stock through LC technology innovation. The research of Cong et al. (2020) shows that low-carbon subsidies have a positive effect on reducing emissions in the GSC. However, the research results of this article find that the knowledge sharing subsidy policy cannot significantly promote the participation of suppliers and manufacturers in the GSC in KS, and the government should reasonably set the subsidy ratio.

6 CONCLUSION AND IMPLICATION

This paper uses a differential game model to study the KS and emission reduction benefits of suppliers and manufacturers in the process of collaborative innovation of LC technologies in the GSC. Three game models are established: decentralized decision-making without cost sharing, decentralized decision-making with cost sharing, and centralized decision-making. This study analyzes the changes in GSC's knowledge stock and emission reduction benefits under three scenarios, as well as the optimal effort level of KS between suppliers and

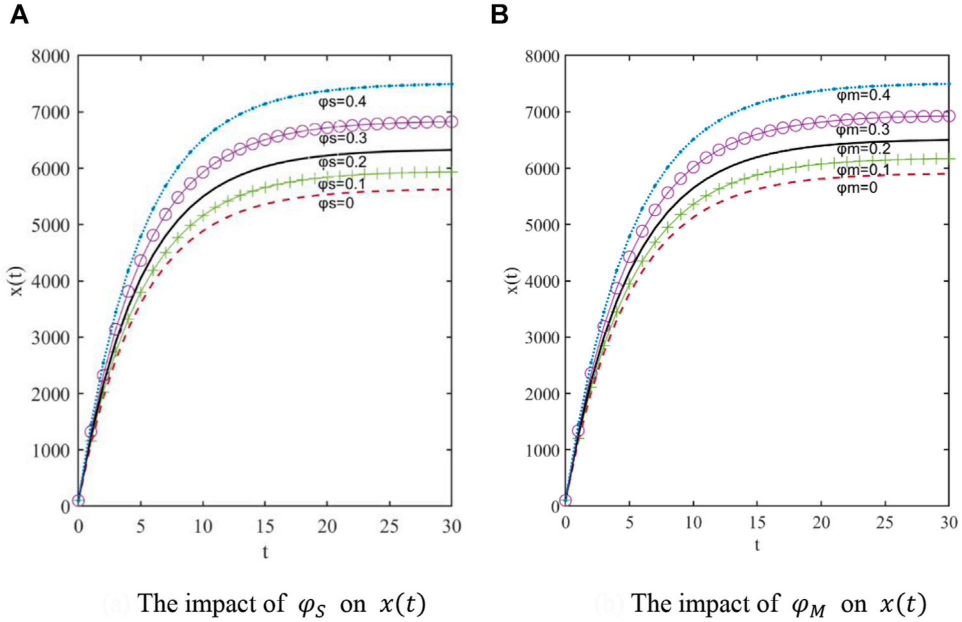

FIGURE 9 | The impact of government subsidies on $x(t)$. **(A)** The impact of φ_S on $x(t)$. **(B)** The impact of φ_M on $x(t)$.

manufacturers. A comparative analysis of the results in various situations is carried out, and a sensitivity analysis of the main parameters is also done. The conclusions of this paper are as follows: 1) the cost-sharing mechanism can only increase the supplier's KS efforts, and the degree of improvement is related to the supplier's carbon emission reduction income distribution ratio. 2) In the case of the Stackelberg master-slave game, the emission reduction benefits of suppliers and manufacturers and the stock of knowledge in the GSC have increased significantly. It shows that the cost-sharing mechanism can promote the shift of the game between suppliers and manufacturers from Nash non-cooperative game to Stackelberg master-slave game, and realize the Pareto improvement of carbon emission reduction benefits. This indicates that the cost-sharing mechanism is to promote the sharing of LC technology knowledge and is an effective measure to increase GSC's emission reduction benefits. 3) In the centralized decision-making situation, the overall benefits of the GSC and the KS efforts of suppliers and manufacturers are greater than in the decentralized decision-making situation. At the same time, the stock of knowledge in the GSC has also been improved. Explain that the collaborative sharing strategy can promote KS, acquisition and LC technology innovation. 4) The price of carbon trading and the rate of knowledge decay have a significant impact on KS in the GSC, while the impact of government subsidy policies is not significant. Therefore, the government should promote the establishment of a carbon market trading system and industry alliances to promote the sharing of GSC-LC technical knowledge, and at the same time formulate a reasonable subsidy coefficient.

This research has three contributions to GSC's KS research. 1) This study uses the differential game method to study the KS and emission reduction benefits of suppliers and manufacturers in the process of GSC's collaborative innovation of LC technology from the perspective of dynamic changes. This makes up for the ignorance of the game problem in continuous time in previous studies. This research is of great significance for promoting KS in GSC and LC emission reduction. 2) In terms of GSC knowledge management, this research gives the optimal choice of KS strategy for suppliers and manufacturers. The cost-sharing mechanism can significantly promote the KS of suppliers, and the collaborative sharing strategy is the most ideal choice for suppliers and manufacturers. This provides guidance for KS between suppliers and manufacturers. 3) This study reveals the internal influence mechanism of main factors on the GSC knowledge stock and the KS behavior of suppliers and manufacturers. Carbon trading price and knowledge decay rate are the main driving factors of KS in GSC. The government subsidy policy cannot significantly promote the sharing of knowledge between suppliers and manufacturers and retrograde. The research results are of great significance to promote the innovation of LC technology and improve the efficiency of KS in GSC.

In order to increase the level of KS between suppliers and manufacturers and the benefits of emission reduction, and to promote LC technology innovation, this article proposes the following suggestions:

(1) The government should encourage the establishment of LC technology innovation alliances. Innovation alliances can reduce the information asymmetry between suppliers and manufacturers, and can reduce the barriers to knowledge sharing between the two. This is helpful to promote the innovation of LC technology. The government also needs to provide some tax subsidies to alliance members to improve the KS cost and risk tolerance of suppliers and manufacturers.

(2) The GSC-KS incentive mechanism needs to be reformulated or improved. First of all, the amount of government subsidies for LC technology innovations of suppliers and manufacturers should be moderate. This study shows that an excessively high subsidy ratio will not significantly promote GSC's KS, but will increase the government's burden. Second, suppliers and manufacturers need to establish a cost-sharing mechanism for LC technology innovation. Suppliers and manufacturers must determine the cost-sharing ratio based on emission reduction benefits and government subsidies. This is an effective means to improve suppliers' KS levels and GSC emission reduction benefits.
(3) The government needs to promote the establishment of a unified regional carbon emissions trading mechanism and reasonably regulate carbon trading prices. The carbon quota system needs to be established and implemented quickly. The government must strictly implement the allocation, management and assessment mechanism of carbon allowances. The price of carbon has a significant impact on the stock of GSC knowledge. Through reasonable adjustments to the carbon market allowance transaction price, the LC technology innovation and KS willingness of suppliers and manufacturers will be improved.

In the research process of this paper, only the KS between a single supplier and a single manufacturer is considered, and the retailer is not taken into consideration. At the same time, the problem of KS between multiple suppliers and multiple manufacturers is not considered. In the future, we can further study the KS of multi-agent and multi-channel GSC networks. In addition, it is important to study the influence mechanism of consumers' green product preference on the KS behavior of suppliers and manufacturers in the GSC.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

FW and HL contributed to conception and design of the study. YR organized the database. CZ performed the statistical analysis. FW wrote the first draft of the manuscript. YC and HL wrote sections of the manuscript. All authors contributed to manuscript revision, read, and approved the submitted version.

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