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Dynamic game strategies of a two-stage remanufacturing closed-loop supply chain considering Big Data marketing, technological innovation and overconfidence

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ABSTRACT

In the "Internet + " era, involving third-party Internet recycling platforms (IRPs) has revolutionized the operation models of closed-loop supply chains (CLSCs) in China. This study explores the impact of technological innovation, Big Data marketing and overconfidence on supply chain member decision-making. We propose a two-stage remanufacturing CLSC dynamic model consisting of a manufacturer, an IRP, and a supplier based on differential game theory. By comparing the optimal decisions of each member in three scenarios, we find that the IRP's overconfident behavior is beneficial to both the manufacturer and the IRP but will damage the supplier's profit. Although a suitable cost-sharing ratio can enable the manufacturer and IRP to achieve a "win–win" situation, an excessive level of confidence will inhibit the incentives of the cost-sharing strategy, negatively affecting the manufacturer's interests. Interestingly, a cost-sharing contract will become inefficient under certain conditions, i.e., highly efficient level of technological innovation, highly efficient Big Data marketing, and a high level of overconfidence, negatively affecting the manufacturer's interests. Additionally, technological innovation efficiency and marketing efficiency will have different effects on the IRP's recycling price. A cost-sharing contract and the IRP's overconfidence will prompt the IRP to exert more efforts on technological innovation and Big Data marketing and to significantly reduce the manufacturing costs and recycling costs for all members. Notably, although the IRP's overconfidence and cost-sharing strategies may damage the supplier's profit, the total profit of the CLSC increases.

1. Introduction

With the deterioration of environmental resources, recycling and remanufacturing have become critical issues for enterprises and governments. In recent years, the rapid development of the Internet and e-commerce has led to the explosive growth of global data, which has also brought new opportunities and challenges to closed-loop supply chain (CLSC) management. Cloud computing technology has become a necessary means for enterprises to process large amounts of data (Liu & Yi, 2017) while also promoting innovation in traditional recycling models. Therefore, Big Data and cloud computing technology are valuable resources for all enterprises, especially in the field of supply chain management (Hazen, Skipper, Ezell, & Boone, 2016).

As an important part of CLSCs, recycling and remanufacturing are considered an indispensable strategy for many manufacturing enterprises due to the economic and environmental benefits brought by recycling activities (Heydari, Govindan, & Jafari, 2017). For example, BMW added remanufacturing to its production process many years ago and has been remanufacturing high-value components such as engines and starter motors (Xu, Li, & Feng, 2019). Moreover, BMW's remanufacturing business has driven the development of other industries, such as the testing industry. It turns out that recycling and remanufacturing can significantly improve profitability and business capabilities for manufacturing enterprises (Heydari et al., 2017).

The arrival of the Industry 4.0 era has made increasingly more companies aware of the importance of data resources (Liu & Yi, 2017). Internet platforms and data service companies have emerged to help optimize supply chain management. These Internet platforms have a large amount of user data and advanced cloud computing technology. They can accurately segment customers based on product characteristics and user behavior (Waller & Fawcett, 2013) and provide Big Data targeted advertising (BDTA) for firms or consumers (Liu & Yi, 2017).

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For example, Twitter has gained enormous benefits through its data leasing business (Naimi & Westreich, 2013). Big Data technology has also been used extensively in CLSC management. To improve recycling efficiency, many manufacturers and remanufacturers have established recycling valuation systems to obtain Big Data information on used products. In China, in addition to their own databases, manufacturers collaborate with third-party Internet recycling platforms (IRPs). Compared with manufacturers, IRPs have a variety of recycling channels and diverse data and can use various Big Data marketing strategies to achieve business goals based on different types of consumers. For instance, Apple, Huawei (a Chinese collective multinational consumer electronics company), Dell and Samsung cooperate with IRPs such as JD and Aihuishou (JD and Aihuishou are Chinese e-commerce platforms) to sell their products online/offline. IRPs can capture users' behavior trajectories from the web browsing history (e.g., information published by social networking sites, various bank card consumption records, global positioning system (GPS) location data) to analyze consumer demands. Then, IRPs develop Big Data marketing strategies to inform consumers of various recycling policies and information, to improve consumers' environmental awareness, and to encourage more people to participate in recycling activities (Xiang & Xu, 2019). Different from traditional recycling models, consumers can return used products through online recycling channels such as JD and Aihuishou (Xu, Zhang, Zhao, Cheng, & Ouyang, 2015); meanwhile, the upstream manufacturing enterprises in CLSCs can also obtain consumer information and recycled products from the IRPs and extract residual value from remanufacturing. Such practices have shown that the involvement of IRPs not only optimizes the CLSC process but also achieves a new strategy that constitutes a basis on which to compete (Hazen et al., 2016).

As recycling models become more specialized, manufacturers and IRPs must not only consider marketing strategies but also continuously optimize technologies to improve the efficiency of recycling. This article refers to such technological inputs as technological innovations (Reimann, Xiong, & Zhou, 2019). Recyclers often face risks of uncertainty regarding the quality of recycled parts. Some parts can be restored to the original quality level with minor repair, whereas some poor-quality parts require more sophisticated processing techniques to restore the original condition. Additionally, the recovery level of recycled products depends on the recycling efficiency and processing technologies of the recycler (Habibi, Battaïa, Cung, & Dolgui, 2017). For example, in China, some professional online recycling platforms, such as Aihuishou, have a complete quality valuation system and advanced processing technologies to deal with the various quality levels of used products. These innovative firms have successfully transitioned from single material recovery to value added recovery through a series of technical treatments, greatly enhancing the profitability of the recycling industry (Bhattacharya & Kaur, 2015).

Corporate leaders often make irrational decisions. For example, they may be overconfident in their investment decisions. Plous (1993) argues that "no problem in judgment and decision-making is more prevalent and potentially disastrous than overconfidence". From a traditional perspective, overconfidence is considered a disadvantage that may result in the failure of business operations, such as unbalanced stocks (Ren & Croson, 2013) and unprofitable investments (Heaton, 2002). This article further studies the traditional perspective, specifically by considering the overconfident behavior of IRPs in Big Data marketing decisions.

Although CLSC management has attracted tremendous attention, most work focuses on a CLSC system consisting of one manufacturer, one retailer or one third-party recycler, and it ignores the Big Data environment. Considering the context of the Big Data environment and the overconfident behavior of decision makers, this paper studies a CLSC system consisting of a supplier, a manufacturer and an IRP, and it analyzes the optimal decisions of supply chain members in three scenarios: pricing decisions, technological innovation investment and Big Data marketing decisions. This paper mainly explores the following issues: (1) What impact does the involvement of the IRP have on the upstream manufacturing enterprises in a CLSC? (2) How does the IRP's overconfidence affect members' decision-making? (3) Are technological innovation and Big Data marketing beneficial to all members of the supply chain in different scenarios? (4) Can the manufacturer's cost-sharing strategy increase the profitability of the CLSC?

The contributions of this paper are summarized as follows:

1) Many existing studies on CLSCs have focused on a static environment, ignoring Big Data contexts (Genc & Giovanni, 2017; Savaskan, Bhattacharya, & Van Wassenhove, 2004). Motivated by the previous literature (Giovanni, 2018; Guo, Qu, Tseng, Wu, & Wang, 2018), this article modifies a recycling function related to Big Data marketing effects and designs a differential game model of a CLSC involving an IRP to better capture realistic recycling-manufacturing processes in a dynamic environment.

2) Few studies have considered the quality levels of recycled products. In this paper, we extend a traditional static one-stage remanufacturing CLSC model to a dynamic two-stage CLSC model that involves a manufacturer, a supplier and an IRP and that considers the quality levels of recycled products. The quality characteristics of used products can be highlighted by means of classified remanufacturing. Our work supplements the studies by Giovanni (2018) and Xiang (2019) from a theoretical perspective.

3) In addition to marketing strategies, this paper considers the technological innovation investment of an IRP. Our results show that the technological innovations of an IRP can significantly reduce the production cost of the upstream enterprises in the supply chain, positively affecting the enterprise and the environment.

4) Research on overconfidence has been widely explored in field of finance and management (Sandroni & Squintani, 2013). In the supply chain, most work focuses on the impact of overconfidence on the inventory of retailers and manufacturers (Xu, Shi, Du, Govindan, & Zhang, 2018). Different from existing work, this paper explores the impact of the IRP's overconfident behavior on firms' decision-making and profit from the perspective of the IRP. The results show that under certain conditions, the IRP's overconfidence does not hurt the overall performance of the CLSC, and its effect on each member of the supply chain also varies. In addition, the IRP's overconfidence can affect the effectiveness of the manufacturer's cost-sharing strategy.

The rest of this article is organized into the following parts. Section 2 reviews the existing works relevant to our study Section 3 describes the model and theoretical assumptions in detail. Section 4 provides optimal solutions for the model in three scenarios. Section 5 discusses the comparison results of the optimal strategies of each member in three scenarios, and analyzes the sensitivity of the optimal strategies. Section 6 analyzes the profits of each member through numerical simulation. Section 7 summarizes this paper and discusses future research directions.

2. Literature review

The literature related to this paper involves four areas: CLSC decision-making issues, research on CLSC Big Data technology applications, the role of technological innovations in supply chains, and studies on overconfidence.

A CLSC consists of a forward supply chain (FSC) and a reverse supply chain (RSC) (Guide, Jayaraman, & Linton, 2003). In most studies, the CLSC consists of a manufacturer, a retailer and a third-party recycler. Comparing three recycling methods, Savaskan et al. (2004) concluded that retailer recycling is the best choice. De Giovanni and Zaccour (2014) constructed a two-period CLSC model and found that when a third-party recycler has high operational efficiency, the manufacturer licenses recycling work to the third-party recycler rather than to the retailer. Mohan, Modak, Panda, and Sankar (2018) considered the quality level of recycled products based on Savaskan's model (2004)

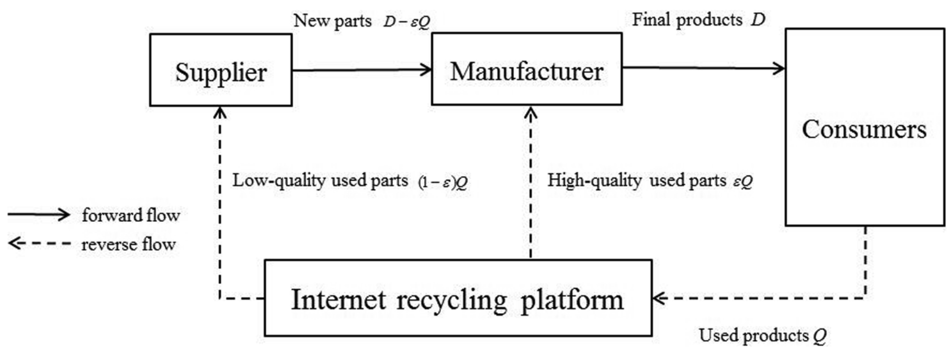

Fig. 1. Structure of the two-stage remanufacturing CLSC system.

and found that sales prices and quality levels are directly related to the amount of recycling. These studies assume that a CLSC is operating in a static environment. Guide et al. (2003) emphasized the importance of time in a CLSC because recycling-remanufacturing is a dynamic phenomenon. Huang, Nie, and Tsai (2017) used a differential game to construct a CLSC model consisting of one manufacturer and one retailer and found that the level of recycling effort increased as the recovery uncertainty increased. Taking the battery recycling industry as an example, Giovanni (2018) achieved the Pareto optimality of a dynamic CLSC by maximizing incentives in this industrial context.

Big Data techniques have been widely used in marketing across industries. Hampton et al. (2013) found that implementing Big Data management can optimize green supply chains and the ecological environment. Hazen, Boone, Ezell, and Jones-Farmer (2014) introduced a view of data quality in supply chain management and elaborated on methods of data monitoring; additionally, they explored the impact of Big Data and predictive analytics (BDPA) on environmental and social sustainability (Hazen et al., 2016). Liu and Yi (2017) proposed pricing policies that take into account BDTA and the green degree of products in a Big Data environment. Ahearn, Armbruster, and Young (2016) argued that Big Data technology can identify potential risks in a food supply chain and help reduce management costs. Studying the recycling-remanufacturing issue, Xu et al. (2019) considered a Big Data quality valuation system and discussed the impact of the valuation system on pricing strategies. Notably, the number of studies about applications of Big Data technology in CLSCs is still limited, and most of them focus on the FSC and marketing.

Technological innovations bring new opportunities and challenges to enterprises. Wu (2012) studied the impact of the detachability of recycled products on new and remanufactured products and found that an increase in detachability has a negative impact on the sales of new products. Chavez et al. (2015) argued that technological innovation not only optimizes production but also reduces inventory waste. Rothenberg, Pil, and Maxwell (2001) discussed the application of technological innovation in green supply chains and found that technological innovation can maximize the utilization of raw materials to improve process efficiency. Genc and Giovanni (2018) pointed out that innovation-led lean programs are beneficial to manufacturers in a CLSC but have limited impact on suppliers. Most studies conclude that technological innovation can bring competitive advantages to enterprises in a fierce market competition environment (Aydin & Parker, 2018).

Enterprises often make some irrational decisions when they face the above investment decisions. Most studies agree that “overconfidence is one of the most reliable findings of decision psychology” (Grieco & Hogarth, 2009; Hilary & Menzly, 2006). In the insurance industry, Sandroni and Squintani (2013) concluded that overconfidence is a potential risk for companies and provided a contract to reduce corporate losses. Ren and Croson (2013) empirically demonstrated that overconfidence can lead to an increase in inventory and introduced a new technology that reduces the risk of increased inventory. In contrast to previous research findings, Lu et al. (2015) found that a supplier’s overconfidence does not damage supply chain performance under certain conditions. Xu et al. (2018) analyzed the impact of a retailer’s overconfidence on a duopolistic supply chain and found that a retailer with overconfidence will have a certain advantage in the market.

In summary, most of these works study the decision-making problems of members from the perspective of manufacturers or retailers in a FSC based on game theories. In comparison, this study not only considers the impact of multiple factors such as overconfidence, technological innovation, and Big Data marketing on a CLSC from the perspective of the IRP but also considers the dynamic characteristics of the CLSC.

3. Model framework

The entire CLSC system consists of an IRP (P), a manufacturer (M), and a supplier (S). All players’ decisions are aimed at maximizing their own interests. Fig. 1 depicts the decision-making process of a CLSC, and the definitions of model notation are presented in Table 1. In the entire decision-making process, the IRP is responsible for the recycling of used products through its own technical advantages and Big Data marketing. Then, the IRP filters and classifies the recycled products according to the quality level. After the recycled products are dismantled, parts of better quality can be sold to the manufacturer at a higher price f. These parts of better quality need to be restored only by performing some cosmetic changes/repairs (such as oiling/greasing, testing or repainting), which saves the manufacturer a considerable amount with regard to remanufacturing costs. Thus, the manufacturer is willing to give the IRP a higher transfer price f. The parts of lower quality cannot be remanufactured directly by the manufacturer; instead, they need to be sent to the supplier to be repaired by replacing/refurbishing some parts (Bhattacharya & Kaur, 2015). Due to the high cost of repairing parts, the transfer price g that the supplier pays to the IRP is lower than the transfer price f that the manufacturer pays to the IRP. The supplier is responsible for the production and supply of the parts required by the manufacturer. The cost of the supplier to purchase new raw materials is m, the manufacturing cost of parts is c_s, and the wholesale price of parts sold by the supplier to the manufacturer is w. There are two ways for the supplier to manufacture parts. One is to buy new raw materials for parts manufacturing; the other is to recycle used parts from the IRP for renovation or reassembly. The manufacturer is mainly responsible for producing products and selling them to consumers. Suppose that the manufacturer's production cost is c_m and that the product’s sales price is p. The manufacturer also has two ways to obtain the parts needed to make the final product: buying parts from the supplier or recycling used parts from the IRP.

Assume that the transfer prices f and g that the manufacturer and the supplier, respectively, pay to the IRP are exogenous variables. To ensure that supply chain members have sufficient recycling incentives and to ensure the sustainability of the entire CLSC system, the following economic conditions must be met: $m > g$, $w > f$, $f > 2g > p_r$, and

Table 1
Notations.

Notations	Definition	Notations	Definition
τ	The recycling quantity that the IRP attracts through Big Data marketing	p	The unit sales price for the manufacturer
A	The Big Data marketing efforts of the IRP	w	The unit wholesale price for the supplier
μ	Big Data marketing effectiveness parameter	f	The transfer price of used parts that the manufacturer pays to the IRP
k	The IRP's overconfidence level	g	The transfer price of used parts that the supplier pays to the IRP
δ	The decay rate of Big Data marketing efficiency	m	The cost of the supplier to purchase new raw materials
Q_0	The recycling quantity of used products from consumers when the unit direct recycling price equals 0	c_s	The supplier's production cost
a	The sensitivity of consumers to the unit direct recycling price	c_m	The manufacturer's production cost
b	The sensitivity of consumers to Big Data marketing	α	The market scale of products
θ	The investment cost coefficient of Big Data marketing efforts	β	The sensitivity coefficient of demand to the sales price
p_r	The unit recycling price charged by the IRP to consumers	ε	The proportion of recycled parts of good quality
Q	The total recycling quantity	φ	The technological innovation cost coefficient
D	Consumer demand	r	The discount rate
C_A	The Big Data marketing cost	C_ε	The technological innovation cost

$g > p_r$.

Unlike traditional third-party recyclers, the IRP has a large amount of user traffic and can promote recycling activities and recycling policies through online channels. To attract more consumers to participate in recycling activities, the IRP needs to invest in Big Data marketing activities, $A(t)$. Notably, Big Data marketing includes the establishment of user databases and targeted advertising services in the Big Data environment. Considering the dynamic characteristics of the Big Data marketing effect, this paper refers to the model of Nerlove and Arrow (1962) and Giovanni (2018). Suppose that the recycling quantity that the IRP attracts through Big Data marketing at time t is $\tau(t)$. The rate of change in the recycling quantity attracted by Big Data marketing is modeled as follows:

$$\frac{d\tau(t)}{dt} = \dot{\tau}(t) = \mu A(t) - \delta\tau(t),\ \tau(0) = \tau_0 \geqslant 0 \tag{1}$$

where $\dot{\tau}(t)$ is a state variable, $\mu > 0$ is the Big Data marketing effectiveness parameter. $\delta > 0$ denotes the decay coefficient and explains the natural reduction in the Big Data marketing efficiency level over time. τ_0 is the initial recycling quantity of consumers attracted by Big Data marketing.

Eq. (1) does not consider the effect of overconfidence in the dynamic recovery process; thus, Eq. (1) is a benchmark model. In fact, many studies have confirmed that leaders display overconfident behavior in decision-making (Ren & Croson, 2013) and that this behavior will have different degrees of impact on the market (L. Xu et al., 2018), such as advertising investment issues or pricing inventory issues (Ma, Li, & Bao, 2016). To further explore the impact of overconfidence on the decision-making of CLSC members, this paper refers to the model of Ma (2016) and Xu model (2018) and modifies Eq. (1) as follows:

$$\frac{d\tau(t)}{dt} = \dot{\tau}(t) = (\mu + k)A(t) - \delta\tau(t) \tag{2}$$

where $0 \leqslant k \leqslant 1$ is the IRP's overconfidence coefficient. Here, the higher the value of k, the more confident the IRP is in the effect of Big Data marketing. In particular, when $k = 0$, the IRP has no overconfidence in the effect of Big Data marketing. Additionally, as commonly seen in the marketing literature (Eyland & Zaccour, 2014; Xiang & Xu, 2019), the Big Data marketing cost function is $C_A(t) = \frac{\theta A(t)^2}{2}$, where C_A is the Big Data marketing cost and θ is the investment cost coefficient of Big Data marketing efforts ($\theta > 0$). The convex cost function shows that to obtain more recycled products, the IRP may initially invest less but must invest more efforts to further expand recycling.

Liu, Anderson, and Cruz (2012) have shown that the total recycling quantity is positively correlated with the recycling price per unit of product. Additionally, Guo et al. (2018) considered the impact of advertising on the recycling function based on the study of Liu (2012). Based on the above description, the total recycling function is expressed as follows:

$$Q(t) = Q_0 + ap_r(t) + b\tau(t) \tag{3}$$

where $Q(t)$ is the total recycling quantity at time t, Q_0 represents the recycling quantity of used products from consumers when the unit direct recycling price equals 0, $p_r(t)$ is the unit direct recycling price that the IRP pays to consumers, a is the sensitivity of consumers to the unit direct recycling price ($a > 0$), and b is the sensitivity of consumers to Big Data marketing ($b > 0$).

For the IRP, the better the quality of recycled products is, the higher the profit that the IRP can obtain. In China, many Internet recycling companies have sophisticated screening systems for recycled products. For example, JD and Aihuishou (JD and Aihuishou are Chinese e-commerce platforms) perform different technical treatments (such as refurbishment, replacement and repainting) according to the quality level of recycled products (Xiang & Xu, 2019). These companies will invest in high-tech innovations in the processing of recycled products to improve the quality of recycled products so that recycling companies can obtain higher transfer prices and higher profits (Bhattacharya & Kaur, 2015). Suppose $0 < \varepsilon < 1$ is the proportion of recycled parts of good quality (Feng, Xiao, & Chai, 2018). Based on previous assumptions, the IRP sells better-quality parts to the manufacturer; thus, the quantity of the parts obtained by the manufacturer is εQ. Conversely, the proportion of parts of lower quality is $1 - \varepsilon$; thus, the quantity of parts obtained by the supplier is $(1 - \varepsilon)Q$. Clearly, the more used parts the manufacturer obtains, the fewer used parts the supplier obtains, and vice versa. Additionally, if the IRP wants to increase the proportion of components of better quality, it must invest more in technological innovation in the process of dealing with used products. This paper assumes that the technological innovation cost of the IRP is expressed as $C_\varepsilon = \frac{\varphi\varepsilon^2}{2}$, where φ is the technological innovation cost coefficient for improving the quality level of recycled products. The higher the value of φ is, the lower the efficiency of technological innovation, and the higher the technological innovation cost required to obtain a higher proportion of high-quality parts. Clearly, the there are limits to the extent to which the IRP can improve the quality of products because technological innovation is constrained by the cost of innovation. Notably, this article assumes that the quality level and function of the products remanufactured by the supplier and the manufacturer are consistent with the new products.

In the FSC, this paper assumes that the manufacturer sells the product directly to consumers. Our model builds on the previous literature (Savaskan et al., 2004) by using the following classical linear consumer demand function:

$$D(t) = \alpha - \beta p(t) \tag{4}$$

where α is the market scale of products and $\beta > 0$ is the sensitivity of demand to the sales price.

To make the results of this article more reasonable, this paper makes the following restrictive assumptions:

Assumption 1. To ensure that $0 < \varepsilon < 1$, the technological innovation cost coefficient φ and the sensitivity of consumers to the unit direct recycling price a must satisfy the following conditions: $\varphi > \frac{a\theta\delta(r+\delta)(f-g)(af+Q_0)}{2a\theta\delta(r+\delta)-b^2(\mu+k)^2}$ and $\frac{Q_0}{f-2g} < a < \frac{(\mu+k)^2(f-g)b^2+Q_0\delta\theta(r+\delta)}{(f-2g)\delta(r+\delta)\theta}$. Assumption 1 has dual purposes. First, the manufacturer cannot increase the investment in technological innovation without limit, which will cause the supplier to lose his/her enthusiasm for recycling; thus, the investment cost limit is necessary. Second, the proportion of parts of higher quality is guaranteed to be $0 < \varepsilon < 1$.

Assumption 2. When the sensitivity of consumers to Big Data marketing effort is large, the investment cost coefficient of Big Data marketing will be large; that is, $\theta > \frac{\varphi b^2(\mu+k)^2}{\delta(2\varphi-(f-g)^2a)a(r+\delta)}$. This means that when consumers in the market are sensitive to the level of Big Data marketing efforts, it is impossible for the IRP to increase the level of Big Data marketing unrestrained by cost constraints (Feng et al., 2018).

4. Model development

This section presents the differential game models developed to examine the optimal strategies in the three scenarios. Different from the previous literature, this paper considers the technical advantages and the information technology for the IRP. The decision-making order for each supply chain member is as follows: First, the IRP controls the proportion of high-quality parts ε in the recycled product, which is mainly related to the cost of technological innovation C_ε invested by the IRP. Second, the supplier determines the wholesale price w of the parts after obtaining the quality information of the recycled parts from the IRP. Third, the manufacturer determines the final sales price p of the product based on the supplier's wholesale price and the quality information of the recovered parts. Finally, the IRP determines the recycling price p_r of used products and the level of Big Data marketing investment A. Additionally, the information among the members in the entire CLSC system is completely symmetrical.

4.1. Without considering the overconfidence of the IRP (scenario N)

The **scenario N** is a benchmark model. The objective of all supply chain members is to find their own optimal strategy to maximize their profits. According to the model assumptions in Section 3, the IRP's objective functional in **scenario N** is:

$$J_P^N = \int_0^\infty e^{-rt}[f\varepsilon(t)Q^N(t) + g(1-\varepsilon(t))Q^N(t) - p_rQ^N(t) - C_A(t) - C_\varepsilon(t)]\,dt \tag{5}$$

The manufacturer's objective function in **scenario N** is as follows:

$$J_M^N = \int_0^\infty e^{-rt}[(p(t)-c_m)D(t) - w(D(t)-\varepsilon(t)Q^N(t)) - f\varepsilon(t)Q^N(t)]dt \tag{6}$$

The supplier's objective function in **scenario N** is as follows:

$$J_S^N = \int_0^\infty e^{-rt}[(w(t)-m-c_s)(D(t)-\varepsilon(t)Q^N(t)) + (m-g)(1-\varepsilon(t))\,Q^N(t)]dt \tag{7}$$

According to optimal control theory, the Hamilton functions for the IRP, manufacturer and supplier are obtained by Eqs. (8), (9) and (10), respectively. Additionally, for the convenience of writing, the time t is omitted below.

The IRP's Hamilton function is as follows:

$$H_P^N(p_r(\varepsilon), A(\varepsilon), \varepsilon, u_P^N) = f\varepsilon(Q_0 + ap_r + b\tau) + g(1-\varepsilon)(Q_0 + ap_r + b\tau) - p_r(Q_0 + ap_r + b\tau) - \frac{\theta A^2}{2} - \frac{\varphi\varepsilon^2}{2} + u_P^N(\mu A - \delta\tau) \tag{8}$$

The manufacturer's Hamilton function is as follows:

$$H_M^N(p, u_M^N) = (p - c_m - w)(\alpha - \beta p) + (w - f)\varepsilon(Q_0 + ap_r + b\tau) + u_M^N(\mu A - \delta\tau) \tag{9}$$

The supplier's Hamilton function is as follows:

$$H_S^N(w, u_S^N) = (w - m - c_s)(\alpha - \beta p - \varepsilon(Q_0 + ap_r + b\tau)) + (m-g)(1-\varepsilon)(Q_0 + ap_r + b\tau) + u_S^N(\mu A - \delta\tau) \tag{10}$$

where (u_P^N, u_M^N, u_S^N) represent the shadow price associated with the state variable $\dot{\tau}(t)$. The optimal strategies for each game player under **scenario N** are given in **Proposition 1**.

Proposition 1. *The optimal equilibrium strategies for the IRP, manufacturer and retailer under **scenario N** are given as follows:*

$$p_r^{N*}(t) = \frac{((f-g)\varepsilon^{N*}(t) + g)a - b\tau^{N*}(t) - Q_0}{2a} \tag{11}$$

$$A^{N*}(t) = \frac{u_P^{N*}(t)\mu}{\theta} \tag{12}$$

$$\varepsilon^{N*}(t) = \frac{(f-g)(ag + b\tau^{N*}(t) + Q_0)}{2\varphi - (f-g)^2a} \tag{13}$$

$$p^{N*}(t) = \frac{(w^{N*}(t) + c_m)\beta + \alpha}{2\beta} \tag{14}$$

$$w^{N*}(t) = \frac{\alpha - a(f-g)(\varepsilon^{N*}(t))^2 - (Q_0 + ag + b\tau^{N*}(t))\varepsilon^{N*}(t) + (m - c_m + c_s)\beta}{2\beta} \tag{15}$$

*Under **scenario N**, the optimal trajectory of the recycling quantity attracted by Big Data marketing is calculated as follows*:

$$\tau^N(t) = (\tau_0 - \bar{\tau}^N)e^{\chi_N t} + \bar{\tau}^N \tag{16}$$

The steady state of the system is given as follows:

$$\bar{\tau}^N = \frac{\varphi(ag + Q_0)b\mu^2}{2\delta\theta\varphi(\delta + r)a - \delta\theta(f-g)^2(\delta + r)a^2 - b^2\varphi\mu^2} \tag{17}$$

$$\bar{u}_P^N = \frac{\theta\delta\varphi(ag + Q_0)b}{2\delta\theta\varphi(\delta + r)a - \delta\theta(f-g)^2(\delta + r)a^2 - b^2\varphi\mu^2} \tag{18}$$

where $\chi_N = \frac{\Phi_N - ar\theta\varpi}{2\theta a\varpi} < 0$, $\varpi = (f-g)^2a - 2\varphi$ *and* $\Phi_N = \sqrt{\theta a(a(r + 2\delta)^2\varpi\theta + 4b^2\varphi\mu^2)\varpi}$.

For the proof, see the Appendix A.

Notably, $\bar{\tau}^N$ is the optimal recycling quantity attracted by Big Data marketing at the steady state, and $\bar{u}_P^N$ is the coordination variable at the steady state. By substituting Eqs. (17) and (18) into Eqs. (11)–(15), the optimal steady-state strategies for all members are easily obtained; that is, $(\bar{p}_r^N, \bar{A}^N, \bar{\varepsilon}^N, \bar{p}^N, \bar{w}^N)$. Additionally, by substituting $(\bar{p}_r^N, \bar{A}^N, \bar{\varepsilon}^N, \bar{p}^N, \bar{w}^N)$ into Eqs. (5)–(7) without considering time t, the optimal steady-state present values of profit for all members can be obtained as (V_P^N, V_M^N, V_S^N). Since the expression of profit is too complicated, it is omitted here.

4.2. Considering the overconfident behavior of the IRP (scenario C)

In **scenario C**, this paper considers the overconfident behavior of decision makers when the IRP determines the level of Big Data marketing investment; the expression is shown in Eq. (2). The order of the supply chain members' decisions is consistent with scenario N. The model developed in **scenario C** is expressed as follows.

The IRP's objective function in **scenario C** is as follows:

$$J_P^C = \int_0^{\infty} e^{-rt}[f\varepsilon(t)Q^C(t) + g(1-\varepsilon(t))Q^C(t) - p_r(t)Q^C(t) - C_A - C_\varepsilon]dt \tag{19}$$

The manufacturer's objective function in **scenario C** is as follows:

$$J_M^C = \int_0^{\infty} e^{-rt}[(p(t)-c_m)D(t) - w(t)(D(t)-\varepsilon(t)Q^C(t)) - f\varepsilon(t)Q^C(t)]dt \tag{20}$$

The supplier's objective function in **scenario C** is as follows:

$$J_S^C = \int_0^{\infty} e^{-rt}[(w(t)-m-c_s)(D(t)-\varepsilon(t)Q^C(t)) + (m-g)(1-\varepsilon(t))Q^C(t)]dt \tag{21}$$

Similar to **scenario N**, the Hamilton functions for the IRP, manufacturer and supplier are expressed as Eqs. (21), (22) and (23), respectively.

The IRP's Hamilton function is as follows:

$$H_P^C(p_r(\varepsilon), A(\varepsilon), \varepsilon, u_P^C) = f\varepsilon(Q_0 + ap_r + b\tau) + g(1-\varepsilon)(Q_0 + ap_r + b\tau) - p_r(Q_0 + ap_r + b\tau) - \frac{\theta A^2}{2} - \frac{\varphi\varepsilon^2}{2} + u_P^C((\mu+k)A - \delta\tau) \tag{22}$$

The manufacturer's Hamilton function is as follows:

$$H_M^C(p, u_M^C) = (p - c_m - w)(\alpha - \beta p) + (w-f)\varepsilon(Q_0 + ap_r + b\tau) + u_M^C((\mu+k)A - \delta\tau) \tag{23}$$

The supplier's Hamilton function is as follows:

$$H_S^C(w, u_S^C) = (w - m - c_s)(\alpha - \beta p - \varepsilon(Q_0 + ap_r + b\tau)) + (m-g)(1-\varepsilon)(Q_0 + ap_r + b\tau) + u_S^C((\mu+k)A - \delta\tau) \tag{24}$$

Obtaining the optimal equilibrium solutions of the Hamiltonian functions, we state **Proposition 2** as follows.

Proposition 2. *The optimal equilibrium strategies for the IRP, manufacturer and retailer under* ***scenario C*** *are given as follows:*

$$p_r^{C*}(t) = \frac{((f-g)\varepsilon^{C*}(t) + g)a - b\tau^{C*}(t) - Q_0}{2a} \tag{25}$$

$$A^{C*}(t) = \frac{(\mu+k)u_P^{C*}(t)}{\theta} \tag{26}$$

$$\varepsilon^{C*}(t) = \frac{(f-g)(ag + b\tau^{C*}(t) + Q_0)}{2\varphi - (f-g)^2 a} \tag{27}$$

$$p^{C*}(t) = \frac{(w^{C*}(t) + c_m)\beta + \alpha}{2\beta} \tag{28}$$

$$w^{C*} = \frac{\alpha - a(f-g)(\varepsilon^{C*}(t))^2 - (ag + b\tau^{C*}(t) + Q_0)\varepsilon^{C*}(t) + (m - c_m + c_s)\beta}{2\beta} \tag{29}$$

Under ***scenario C****, the optimal trajectory of the recycling quantity attracted by Big Data marketing is calculated as follows*:

$$\tau^C(t) = (\tau_0 - \bar{\tau}^C)e^{\chi_C t} + \bar{\tau}^C \tag{30}$$

The steady state of the system in ***scenario C*** *is given as follows*:

$$\bar{\tau}^C = \frac{\varphi(ag + Q_0)b(\mu+k)^2}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi(\mu+k)^2} \tag{31}$$

$$\bar{u}_P^C = \frac{\theta\delta\varphi(ag + Q_0)b}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi(\mu+k)^2} \tag{32}$$

where $\chi_C = \frac{\Phi_C - ar\theta\varpi}{2\theta a\varpi} < 0$ *and* $\Phi_C = \sqrt{\theta a(a(r+2\delta)^2\theta\varpi + 4b^2\varphi(\mu+k)^2)\varpi}$.
For the proof, see the Appendix A.

Similar to **scenario N**, by substituting Eqs. (31) and (32) into Eqs. (25)–(29), the optimal steady-state strategies for all members in **scenario C** are easily obtained; that is, $(\bar{p}_r^C, \bar{A}^C, \bar{\varepsilon}^C, \bar{p}^C, \bar{w}^C)$. Additionally, by substituting $(\bar{p}_r^C, \bar{A}^C, \bar{\varepsilon}^C, \bar{p}^C, \bar{w}^C)$ into Eqs. (19)–(21) without considering time t ($t = 0$), the optimal steady-state present values of profit for all members in **scenario C** can be obtained as (V_P^C, V_M^C, V_S^C). Due to the complexity of the expression, it is omitted here.

4.3. The manufacturer shares the marketing cost of the IRP (scenario F)

In reality, the upstream enterprises in the CLSC will cooperate with the IRP to promote recycling activities to obtain more recycled products. This section considers the situation in which the manufacturer shares the marketing cost of the IRP based on **scenario C**. Assume that η is the ratio-sharing coefficient of marketing investment and represents the percentage of the Big Data marketing cost that the manufacturer shares with the IRP and that $0 \leqslant \eta \leqslant 1$. The decision order of **scenario F** is the same as that of **scenario N** and **scenario C**, and the differential game model among the three members is formulated as follows.

The IRP's objective function in **scenario F** is as follows:

$$J_P^F = \int_0^{\infty} e^{-rt}[f\varepsilon(t)Q^F(t) + g(1-\varepsilon(t))Q^F(t) - p_r(t)Q^F(t) - (1-\eta)C_e - C_\varepsilon]dt \tag{33}$$

The manufacturer's objective function in **scenario F** is as follows:

$$J_M^F = \int_0^{\infty} e^{-rt}[(p(t)-c_m)D(t) - w(t)(D(t)-\varepsilon(t)Q^F(t)) - f\varepsilon(t)Q^F(t) - \eta C_e]dt \tag{34}$$

The supplier's objective function in **scenario F** is as follows:

$$J_S^F = \int_0^{\infty} e^{-rt}[(w(t)-m-c_s)(D(t)-\varepsilon(t)Q^F(t)) + (m-g)(1-\varepsilon(t))Q^F(t)]dt \tag{35}$$

The Hamilton functions for the IRP, manufacturer and supplier are expressed as follows.

The IRP's Hamilton function is as follows:

$$H_P^F(p_r(\varepsilon), A(\varepsilon), \varepsilon, u_P^F) = f\varepsilon(Q_0 + ap_r + b\tau) + g(1-\varepsilon)(Q_0 + ap_r + b\tau) - p_r(Q_0 + ap_r + b\tau) - (1-\eta)\frac{\theta A^2}{2} - \frac{\varphi\varepsilon^2}{2} + u_P^F((\mu+k)A - \delta\tau) \tag{36}$$

The manufacturer's Hamilton function is as follows:

$$H_M^F(p,\, u_M^F) = (p - c_m - w)(\alpha - \beta p) + (w - f)\varepsilon(Q_0 + ap_r + b\tau) - \eta\frac{\theta A^2}{2} + u_M^F((\mu + k)A - \delta\tau) \tag{37}$$

The supplier's Hamilton function is as follows:

$$H_S^F(w,\, u_S^F) = (w - m - c_s)(\alpha - \beta p - \varepsilon(Q_0 + ap_r + b\tau)) + (m - g)(1 - \varepsilon)(Q_0 + ap_r + b\tau) + u_S^F((\mu + k)A - \delta\tau) \tag{38}$$

Solving the above Hamiltonian equations, we state **Proposition 2** as follows.

Proposition 3. *The optimal equilibrium strategies for the IRP, manufacturer and retailer under* ***scenario F*** *are given as follows:*

$$p_r^{F*}(t) = \frac{((f-g)\varepsilon^{F*}(t) + g)a - b\tau^{F*}(t) - Q_0}{2a} \tag{39}$$

$$A^{F*}(t) = \frac{(\mu + k)u_P^{F*}(t)}{\theta(1 - \eta)} \tag{40}$$

$$\varepsilon^{F*}(t) = \frac{(f-g)(ag + b\tau^{F*}(t) + Q_0)}{2\varphi - (f-g)^2 a} \tag{41}$$

$$p^{F*}(t) = \frac{(w^{F*} + c_m)\beta + \alpha}{2\beta} \tag{42}$$

$$w^{F*}(t) = \frac{\alpha - a(f-g)(\varepsilon^{F*}(t))^2 - (ag + b\tau^{F*} + Q_0)\varepsilon^{F*}(t) + (m - c_m + c_s)\beta}{2\beta} \tag{43}$$

Under ***scenario F****, the optimal trajectory of the recycling quantity attracted by Big Data marketing is calculated as follows*:

$$\tau^F(t) = (\tau_0 - \bar{\tau}^F)e^{\chi_F t} + \bar{\tau}^F \tag{44}$$

The steady state of the system in ***scenario F*** *is given as follows*:

$$\bar{\tau}^F = \frac{\varphi(ag + Q_0)b(\mu + k)^2}{2\delta\theta\varphi(\delta + r)a(1 - \eta) - \delta\theta(f-g)^2(\delta + r)a^2(1 - \eta) - b^2\varphi(\mu + k)^2} \tag{45}$$

$$\bar{u}_P^F = \frac{(1 - \eta)\theta\delta\varphi(ag + Q_0)b}{2\delta\theta\varphi(\delta + r)a(1 - \eta) - \delta\theta(f-g)^2(\delta + r)a^2(1 - \eta) - b^2\varphi(\mu + k)^2} \tag{46}$$

where $\chi_F = \frac{\Phi_F - (1-\eta)ar\theta\varpi}{(1-\eta)2\theta a\varpi} < 0$ *and* $\Phi_F = \sqrt{\theta(1-\eta)a(a(r + 2\delta)^2\varpi\theta(1-\eta) + 4b^2\varphi(\mu + k)^2)\varpi}$.

For the proof, see the Appendix A

By substituting Eqs. (45) and (46) into Eqs. (39)–(43), the optimal steady-state strategies for all members in **scenario F** can be obtained as $(\bar{p}_r^F, \bar{A}^F, \bar{\varepsilon}^F, \bar{p}^F, \bar{w}^F)$, Similarly, substituting $(\bar{p}_r^F, \bar{A}^F, \bar{\varepsilon}^F, \bar{p}^F, \bar{w}^F)$ into Eqs. (33)–(35) without considering time t ($t = 0$), the optimal steady-state present values of profit for all members in **scenario F** can be obtained as (V_P^F, V_M^F, V_S^F). Due to the complexity of the expression, it is omitted here.

5. Comparison and sensitivity analysis

In this section, we compare the optimal decisions of each member in the three scenarios and then compare the recycling quantity in the three scenarios. Finally, we also explore the impact of some key parameters on the optimal strategies. Due to the complexity of the profit functions, the impact of some key parameters on the profit functions cannot be ascertained analytically but will be discussed in Section 6 through numerical analysis.

5.1. Comparison of optimal strategies

The comparison results of the optimal steady-state strategies in the three scenarios are given in **Proposition 4**.

Proposition 4. *The optimal steady-state strategies under the three scenarios have the following relationships:* $\bar{p}_r^F < \bar{p}_r^C < \bar{p}_r^N$, $\bar{A}^N < \bar{A}^C < \bar{A}^F$, $\bar{\varepsilon}^N < \bar{\varepsilon}^C < \bar{\varepsilon}^F$, $\bar{p}^F < \bar{p}^C < \bar{p}^N$, *and* $\bar{w}^F < \bar{w}^C < \bar{w}^N$.

Proposition 4 shows that the level of Big Data marketing and the proportion of parts of high quality in **scenario C** are higher than those in **scenario N**. This indicates that the IRP has high expectations regarding its marketing capabilities; thus, the IRP will increase its marketing efforts and technological innovation investment. At the same time, the increase in the IRP's investment in Big Data marketing will enhance consumers' awareness of environmental protection, which can reduce the recycling price without reducing the recycling quantity to save on the unit recycling cost. Therefore, the unit recycling price in **scenario C** is lower than that in **scenario N**. Because the increase in the level of Big Data marketing will result in a greater recycling quantity, which will save more on production costs for the manufacturer and supplier, the sales price and wholesale price in **scenario C** are lower than those in **scenario N**. Additionally, the manufacturer's cost-sharing contract will further stimulate the IRP's marketing investment and technological innovation investment. Therefore, compared with the other two scenarios, in **scenario F**, the level of Big Data marketing and the proportion of parts of high quality are the highest, while the IRP's recycling price, the manufacturer's sales price and the supplier's wholesale price are the lowest. Notably, Xu et al. (2018) have proven that the retailer's overconfidence in the FSC will increase product sales. However, **Proposition 4** proves that the IRP not only has a positive impact on the FSC but also promotes the development of the RSC; this conclusion also supplements the previous literature.

Proposition 5. *The optimal steady-state recycling quantities attracted by Big Data marketing in the three scenarios are compared as follows:*

$$\bar{\tau}^N < \bar{\tau}^C < \bar{\tau}^F$$

Substituting $(\bar{p}_r^N, \bar{p}_r^C, \bar{p}_r^F)$ and $(\bar{\tau}^N, \bar{\tau}^C, \bar{\tau}^F)$ into Eq. (3), respectively, the comparison results of the optimal steady-state total recycling quantities in the three scenarios are as follows:

$$\bar{Q}^N < \bar{Q}^C < \bar{Q}^F$$

Proposition 5 illustrates that in **scenario F**, the IRP has the largest recycling quantity through Big Data marketing. The reason is that in **Proposition 4**, it is proven that due to the influence of overconfidence, the IRP will invest more resources in Big Data marketing and that the manufacturer's cost-sharing contract will further stimulate this behavior. Thus, in **scenario F**, the IRP obtains the greatest amount of recycling through Big Data marketing.

Proposition 4 and **Proposition 5** show that although overconfidence and cost sharing reduce the recycling price of the IRP, they do not reduce the total recycling quantity. This result is similar to the study by Liu and Yi (2017), who demonstrated that the Big Data environment has a positive effect on the pricing of products and the precise marketing of advertising; however, this article has been extended on the basis. **Proposition 4** and **Proposition 5** consider the impact of overconfidence on Big Data marketing decisions. The results show that Big Data marketing can not only increase the amount of recycling but also effectively reduce the unit recycling cost. Additionally, based on **scenario C**, the manufacturers' cost-sharing strategies can encourage the IRP to further increase its investment level in Big Data marketing based on **scenario C**, which can further enhance the recycling quantity and reduce the unit recycling cost.

5.2. Sensitivity analysis

Section 5.1 gives the comparison results of the optimal strategies in the three scenarios. This section conducts a sensitivity analysis to explore the impact of some key parameters on the optimal decisions of game members.

Corollary 1. *Under the three scenarios, by taking the derivatives of the recycling price with respect to the key parameters φ and θ, the relationships are as follows:*

(1) *When* $\frac{\varphi b^2(\mu+k)^2}{\delta(2\varphi-(f-g)^2a)a(r+\delta)} < \theta < \frac{b^2\mu^2}{a\delta(r+\delta)}$, $\frac{\partial \bar{p_r}^N}{\partial \varphi} > 0$; *when* $\theta > \frac{b^2\mu^2}{a\delta(r+\delta)}$, $\frac{\partial \bar{p_r}^N}{\partial \varphi} < 0$.

(2) *When* $\frac{\varphi b^2(\mu+k)^2}{\delta(2\varphi-(f-g)^2a)a(r+\delta)} < \theta < \frac{b^2(\mu+k)^2}{a\delta(r+\delta)}$, $\frac{\partial \bar{p_r}^C}{\partial \varphi} > 0$, $\frac{\partial \bar{p_r}^F}{\partial \varphi} > 0$; *when* $\theta > \frac{b^2(\mu+k)^2}{a\delta(r+\delta)}$, $\frac{\partial \bar{p_r}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{p_r}^F}{\partial \varphi} < 0$.

(3) $\frac{\partial \bar{p_r}^N}{\partial \theta} > 0$, $\frac{\partial \bar{p_r}^C}{\partial \theta} > 0$, $\frac{\partial \bar{p_r}^F}{\partial \theta} > 0$.

Corollary 1 indicates that there exists a threshold $\bar{\theta}$ ($\bar{\theta} = \frac{b^2\mu^2}{a\delta(r+\delta)}$ or $\bar{\theta} = \frac{b^2(\mu+k)^2}{a\delta(r+\delta)}$) in the three scenarios. When $\theta < \bar{\theta}$, the IRP's recycling price increases with φ; when $\theta > \bar{\theta}$, the recycling price decreases with φ. The size of $\bar{\theta}$ is mainly determined by b, μ, a, δ and k. $\theta < \bar{\theta}$ means that the Big Data marketing efficiency is at a high level. When the efficiency of technological innovation is lower, the IRP needs to increase the recycling price to maintain a higher recycling volume, which can compensate for the loss of profit due to the quality defect of the recycled product. However, when the Big Data marketing efficiency is at a low level ($\theta > \bar{\theta}$), the IRP cannot expand its recycling volume due to excessive recycling costs, and as the efficiency of technological innovation decreases, the profit margin of recycled products decreases. Therefore, the IRP's recycling price decreases with the increase in φ. Additionally, assuming that φ is a constant, the recycling price always increases with θ. This result implies that if Big Data marketing is less efficient, then the IRP will prefer to increase the recycling quantity by enhancing the recycling price.

Corollary 2. *Under the three scenarios, for the comparative static of $\bar{A^i}$, $\bar{\varepsilon^i}$, $\bar{w^i}$ and $\bar{p^i}$ (i = N, C, F) with respect to the key parameters φ and θ, the relationships are as follows*:

(1) $\frac{\partial \bar{A}^N}{\partial \varphi} < 0$, $\frac{\partial \bar{A}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{A}^F}{\partial \varphi} < 0$, $\frac{\partial \bar{\varepsilon}^N}{\partial \varphi} < 0$, $\frac{\partial \bar{\varepsilon}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{\varepsilon}^F}{\partial \varphi} < 0$, $\frac{\partial \bar{w}^N}{\partial \varphi} > 0$, $\frac{\partial \bar{w}^C}{\partial \varphi} > 0$, $\frac{\partial \bar{w}^F}{\partial \varphi} > 0$, $\frac{\partial \bar{p}^N}{\partial \varphi} > 0$, $\frac{\partial \bar{p}^C}{\partial \varphi} > 0$, $\frac{\partial \bar{p}^F}{\partial \varphi} > 0$.

(2) $\frac{\partial \bar{A}^N}{\partial \theta} < 0$, $\frac{\partial \bar{A}^C}{\partial \theta} < 0$, $\frac{\partial \bar{A}^F}{\partial \theta} < 0$, $\frac{\partial \bar{\varepsilon}^N}{\partial \theta} < 0$, $\frac{\partial \bar{\varepsilon}^C}{\partial \theta} < 0$, $\frac{\partial \bar{\varepsilon}^F}{\partial \theta} < 0$, $\frac{\partial \bar{w}^N}{\partial \theta} > 0$, $\frac{\partial \bar{w}^C}{\partial \theta} > 0$, $\frac{\partial \bar{w}^F}{\partial \theta} > 0$, $\frac{\partial \bar{p}^N}{\partial \theta} > 0$, $\frac{\partial \bar{p}^C}{\partial \theta} > 0$, $\frac{\partial \bar{p}^F}{\partial \theta} > 0$.

Corollary 3. *Under the three scenarios, by taking the derivatives of the steady-state recycling quantity with respect to φ and θ, the relationships are as follows:*

(1) $\frac{\partial \bar{\tau}^N}{\partial \varphi} < 0$, $\frac{\partial \bar{\tau}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{\tau}^F}{\partial \varphi} < 0$, $\frac{\partial \bar{\tau}^N}{\partial \theta} < 0$, $\frac{\partial \bar{\tau}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{\tau}^F}{\partial \varphi} < 0$.

(2) $\frac{\partial \bar{Q}^N}{\partial \varphi} < 0$, $\frac{\partial \bar{Q}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{Q}^C}{\partial \varphi} < 0$, $\frac{\partial \bar{Q}^N}{\partial \theta} < 0$, $\frac{\partial \bar{Q}^C}{\partial \theta} < 0$, $\frac{\partial \bar{Q}^F}{\partial \theta} < 0$.

According to **Corollaries 2–3**, in the three scenarios, the investment level of Big Data marketing and the proportion of parts of higher quality decrease with φ and θ, while the wholesale price of parts and the sales price of products increase with φ and θ. This result indicates that due to the inefficiency of Big Data marketing and technological innovation, the IRP's recycling quantity will be insufficient; additionally, profitability of recycled products will be reduced. The supplier and the manufacturer will increase their production costs due to the lack of sufficient recycled parts; thus, they will enhance the wholesale price and sales price to maintain the profit margin of their products.

Corollary 3 shows that in the three scenarios, the recycling quantity attracted by Big Data marketing and the total recycling quantity decrease with φ and θ. However, **Corollary 1** and **Corollary 2** prove that an increase in φ and θ may lead to an increase in the recycling price, and according to Eq. (3), an increase in the recycling price will have a positive effect on the increase in the recycling quantity. This result shows that the decline rate of the recycling quantity due to the reduction of marketing efficiency is greater than the growth rate of the recycling quantity caused by the increase in the recycling price. This also implies that the IRP will prefer to attract consumers through Big Data marketing rather than through the recycling price.

Corollary 4. *Under **scenario C** and **scenario F**, the relationships of the optimal steady-state strategies with the overconfidence coefficient k are as follows:*

(1) $\frac{\partial \bar{p_r}^C}{\partial k} < 0$, $\frac{\partial \bar{A}^C}{\partial k} > 0$, $\frac{\partial \bar{\varepsilon}^C}{\partial k} > 0$, $\frac{\partial \bar{w}^C}{\partial k} < 0$, $\frac{\partial \bar{p}^C}{\partial k} < 0$.

(2) $\frac{\partial \bar{p_r}^F}{\partial k} < 0$, $\frac{\partial \bar{A}^F}{\partial k} > 0$, $\frac{\partial \bar{\varepsilon}^F}{\partial k} > 0$, $\frac{\partial \bar{w}^F}{\partial k} < 0$, $\frac{\partial \bar{p}^F}{\partial k} < 0$.

Corollary 5. *Under **scenario C** and **scenario F**, the relationships of the steady-state recycling quantity with the overconfidence coefficient k are as follows:*

$$\frac{\partial \bar{\tau}^C}{\partial k} > 0,\ \frac{\partial \bar{\tau}^F}{\partial k} > 0,\ \frac{\partial \bar{Q}^C}{\partial k} > 0,\ \frac{\partial \bar{Q}^F}{\partial k} > 0.$$

Corollary 4 and **Corollary 5** show that the investment level of Big Data marketing and the proportion of parts of higher quality increase with k, the wholesale price of parts and the sales price of products decrease with k, and the IRPs overconfident behavior also contributes to the increase in the recycling quantity. Interestingly, the result in **Corollary 4** is slightly different from the previous literature (Lu et al., 2015; Xu et al., 2018). Xu et al. (2018) find that the higher the level of overconfidence is, the higher the selling price that the overconfident retailer charges; however, overconfidence does not harm the overall performance of the supply chain. The reason for this difference is that Xu et al. (2018) mainly focus on the FSC; additionally, most of the literature ignores the impact of the recycler's overconfident behavior on the RSC and CLSC. This result is also an extension of Lu et al. (2015).

6. Numerical analysis

Due to the complexity of profit functions, the impact of some key parameters on profit cannot be directly ascertained analytically. Therefore, in this section, the impacts of various parameters on the profit of all CLSC members will be illustrated by using a numerical experimental design. This section aims to gain qualitative insights into the structures of the proposed policies and their sensitivity to key parameters.

6.1. The impact of the cost coefficient on profit

Suppose that the basic parameter values are unchanged and are those presented in Table 2. The impacts of φ and θ on the optimal steady-state present values for all supply chain members in the three scenarios are discussed in this section.

Figs. 2–4 show that the profit of the IRP and the manufacturer decreases with φ and θ, while the supplier's profit increases with φ and θ. The reason is that the reduction in technological innovation efficiency and marketing efficiency leads to a reduction in the amount of recycling

Table 2
Basic parameter values (1).

c_m	c_s	m	α	β	f	g	Q_0	a	b	r	δ	μ	k	η
1	1	2.5	20	2	4	1.5	2	2.5	0.8	0.1	0.2	0.8	0.4	0.4

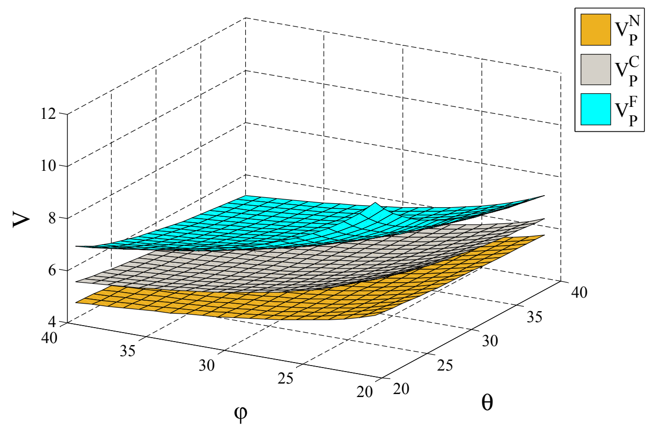

Fig. 2. The impact of φ and θ on the IRP's profit.

and a reduction in the proportion of parts of better quality, which has a negative impact on the profit of the manufacturer and the IRP. However, the manufacturer needs to buy more new components from the supplier due to the reduced recycling quantity of used components; thus, the profit of the supplier increases.

The comparison of the three scenarios shows that the profit of the IRP in **scenario F** is higher than that in the other two scenarios. This result shows that overconfidence and the manufacturer's cost-sharing strategies are beneficial to the operation of the IRP. For the manufacturer, there are two thresholds for $\hat{\varphi}$ and $\hat{\theta}$. When $\varphi < \hat{\varphi}$ or $\theta < \hat{\theta}$, the profit of the manufacturer in **scenario C** is higher than that in **scenario F** and **scenario N**; when $\varphi > \hat{\varphi}$ or $\theta > \hat{\theta}$, the profit of the manufacturer in **scenario F** is higher than that in **scenario C** and **scenario N**. This finding shows that when the operation efficiency and technological innovation efficiency of the IRP are at a low level, the cost-sharing strategy can make the IRP and the manufacturer achieve a "win–win" situation. However, when marketing efficiency and technological innovation efficiency are at a high level, the cost-sharing strategy make the marginal profit of the manufacturer less than the marginal cost, which leads to a decrease in the profit of the manufacturer. Additionally, according to the above corollaries, the increase in overconfidence and cost sharing will reduce the sales of new parts for the supplier; thus, the profit of the supplier is the highest in **scenario N,**

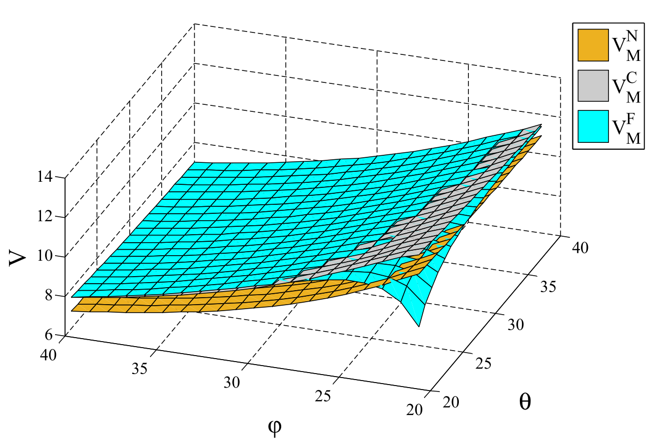

Fig. 3. The impact of φ and θ on the manufacturer's profit.

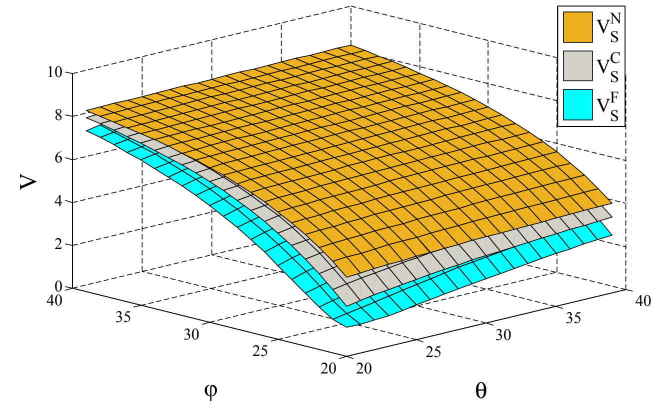

Fig. 4. The impact of φ and θ on the supplier's profit.

and the profit in **scenario C** is higher than that in **scenario F**.

6.2. The impact of the cost-sharing rate on profit

To examine the impact of the cost-sharing rate η on profit under different scenarios, this section assumes that the values of the parameters are those in presented in Table 3. Additionally, V_T^N is the total optimal present value under **scenario N**, V_T^C is the total optimal present value under **scenario C**, and V_T^F is the total optimal present value under **scenario F**, where $V_T^N = V_P^N + V_M^N + V_S^N$, $V_T^C = V_P^C + V_M^C + V_S^C$ and $V_T^F = V_P^F + V_M^F + V_S^F$. First, this section gives the trajectory of the total profit of the CLSC with η in the three scenarios, as shown in Fig. 5. Then, this section discusses the impact of η on the profit of each member.

Fig. 5 shows that in **scenario F**, there exists a threshold $\hat{\eta}$. When $\eta < \hat{\eta}$, the total profit of the CLSC increases with η; when $\eta > \hat{\eta}$, the total profit of the CLSC decreases with η. The comparison result of Fig. 5 shows that the total profit of the CLSC in **scenario C** is always higher than that in **scenario N**. Additionally, only when the manufacturer's cost-sharing ratio is in a suitable range will the total profit in **scenario F** be higher than that in **scenario C**; otherwise, the excessive cost-sharing ratio will damage the total profit of the CLSC.

As indicated by Figs. 2–5, the profit of the IRP and the manufacturer in **scenario C** is always higher than that in **scenario N**, and the supplier's profit in **scenario C** is always lower than that in **scenario N**. Additionally, referring to the results of **Corollaries 1–5**, in both **scenario N** and **scenario C**, each parameter has a consistent influence on the profit of each member in the two scenarios. Therefore, to ensure the simplicity of the figures, the effects of some parameters on the profit of each member in **scenario N** will not be discussed in subsequent sections.

As shown in Fig. 6, the profit of the IRP always increases with η, and the supplier's profit always decreases with η. For the manufacturer, when $\eta < \hat{\eta}$, the profit increases with η; when $\eta > \hat{\eta}$, the profit decreases with η. This result implies that the cost-sharing strategy is always beneficial to the IRP but damages the supplier's profit. The manufacturer needs to determine a suitable cost-sharing ratio to extract more profit; otherwise, an excessive cost-sharing ratio will lead to increased operating costs and lower profits. The size of the cost-sharing ratio depends on the negotiation capabilities of the manufacturer and the IRP.

Table 3
Basic parameter values (2).

c_m	c_s	m	α	β	f	g	Q_0	a	b	r	δ	μ	k	φ	θ
1	1	2.5	20	2	4	1.5	2	2.5	0.8	0.1	0.2	0.8	0.4	30	30

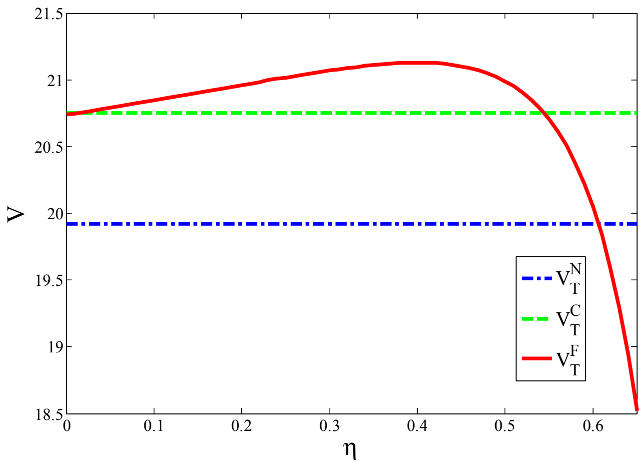

Fig. 5. The impact of η on the total profits of all CLSC members.

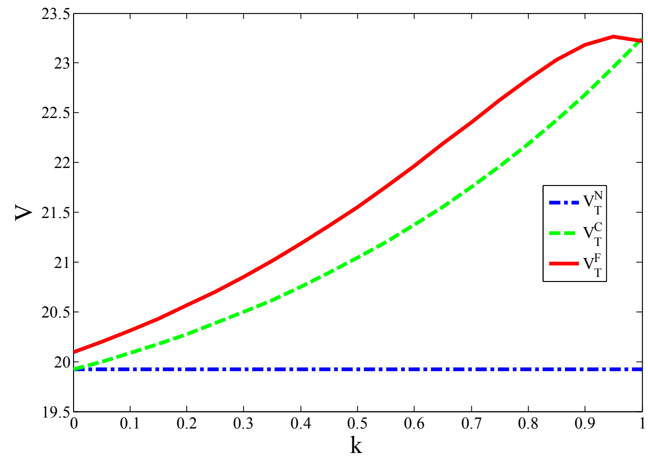

Fig. 7. The impact of k on the total profits of all CLSC.

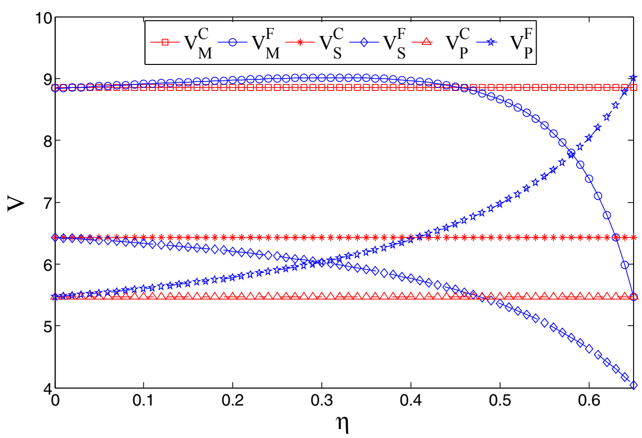

Fig. 6. The impact of η on the profits of all members.

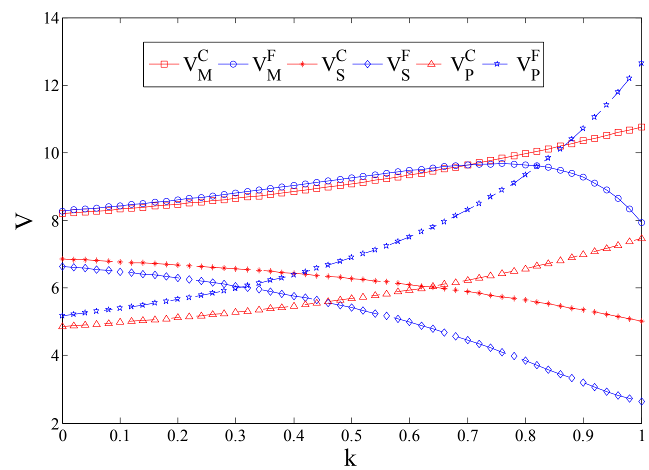

Fig. 8. The impact of k on the profits of all members.

6.3. The impact of overconfidence on profit

This section focuses on the impact of overconfidence on profit, and the values of some key parameters are assumed, as shown in Table 4.

Fig. 7 shows the relationship between the level of overconfidence and the total profit of the CLSC. Since **scenario N** does not consider the overconfidence factor, the total profit remains unchanged with the increase in overconfidence k. In **scenario C**, the total profit of the CLSC always increases with k. In **scenario F**, there is a threshold $\hat{k}$; when $k < \hat{k}$, the total profit of the CLSC increases with k; however, when $k > \hat{k}$, the total profit of the CLSC decreases with k. Next, this article will illustrate the impact of overconfidence on the profit of each member in **scenario C** and **scenario F**, as shown in Fig. 8.

Fig. 8 shows that for both **scenario C** and **scenario F**, the profit of the IRP always increases with k and the profit of the supplier always decreases with k. In **scenario C**, the manufacturer's profit increases with k. However, combined with the results of Figs. 7 and 8, the size of threshold $\hat{k}$ has different effects on the profit of the manufacturer in **scenario F**. In **scenario F**, when $k < \hat{k}$, the manufacturer's profit increases with k; however, when $k > \hat{k}$, the manufacturer's profit decreases with k.

Table 4
Basic parameter values (3).

c_m	c_s	m	α	β	f	g	Q_0	a	b	r	δ	μ	η	φ	θ
1	1	2.5	20	2	4	1.5	2	2.5	0.8	0.1	0.2	0.8	0.4	30	30

The results of Figs. 7 and 8 and **Corollaries 1–5** show that the IRP's overconfidence prompts the IRP to exert more efforts on technological innovation and Big Data marketing and enhances the profit of the IRP. The increase in the recycling quantity and the increase in the proportion of high-quality parts are also helpful in improving the profit of the manufacturer. However, for the supplier, although the total recycling quantity has increased due to the increase in overconfidence of the IRP, this increase has also led to a decrease in the number of new parts purchased by the manufacturer from the supplier, harming the interests of the supplier. Notably, the degree of overconfidence of the IRP has a different impact on the cost-sharing ratio and the profit of the manufacturer. Although the manufacturer's cost-sharing strategy will further encourage the IRP to invest more in technological innovation and Big Data marketing, as the IRP's overconfidence increases, the incentive role of the cost-sharing strategy will be weakened, negatively affecting the manufacturer's interests.

6.4. The change in profit over time

To highlight the dynamic characteristics of the CLSC, the trajectory of the profit of all members over time will be explored in this section. The values of the parameters are assumed to be those presented in Table 5. Notably, since the change trend of profit in **scenario N** is consistent with that in **scenario C**, to make the figure more concise, this section omits the change trajectory of profit in **scenario N**. When t ranges from 0 to 40, the numerical result is that outlined in Fig. 9.

Fig. 9 shows that the profits of the IRP and the manufacturer

Table 5
Basic parameter values (4).

c_m	c_s	m	α	β	f	g	Q_0	a	b	r	δ	μ	k	φ	θ	τ_0	η
1	1	2.5	20	2	4	1.5	2	2.5	0.8	0.1	0.2	0.8	0.4	30	30	0	0.4

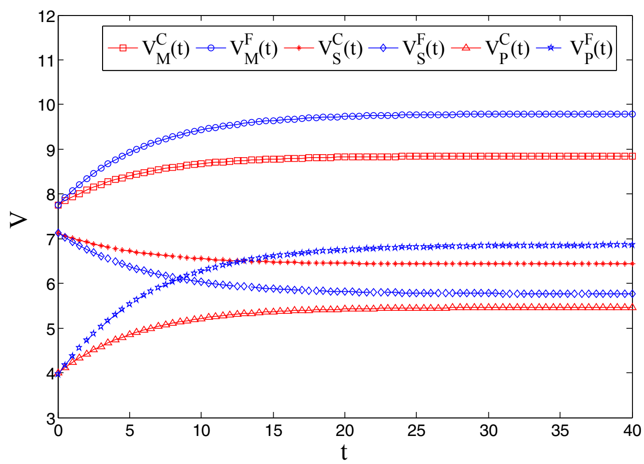

Fig. 9. The impact of t on the profits of all members.

increase with time and then show a stable trend in **scenario C** and **scenario F**, while the profit of the supplier decreases over time and then shows a stable trend.

Based on Figs. 2–9 and the results of **Corollaries 1–5**, the IRP's overconfidence prompts the IRP to exert more efforts on technological innovation and Big Data marketing, which is beneficial to the IRP and the manufacturer. This result is consistent with the study of Lu et al. (2015). Differently, however, the supplier will lose part of his/her profits due to the reduction in components purchased by the manufacturer from the supplier. Additionally, the high degree of overconfidence of the IRP will inhibit the incentive of the cost-sharing contract and increase the operating costs of the manufacturer; thus, only by finding a suitable cost-sharing range can a "win–win" situation be achieved for the manufacturer and the supplier. Although overconfident behavior and the cost-sharing contract may cause the supplier to lose some profits, they will increase the overall value of the CLSC system.

7. Conclusions and limitations

In this paper, we study decision-making problems for members of a CLSC system in the "Internet + " era. The research content and future research directions of this paper are summarized and discussed below.

7.1. Significances

Managing CLSCs with Big Data technologies in an "Internet + " environment is a research topic that has attracted growing interest because Big Data technologies can improve the efficiency of the circular economy. The objective of this paper is to explore the decision-making problems of CLSC members, including pricing and irrational investment, in the Big Data environment.

This research makes the following contributions. Our work extends traditional static one-stage remanufacturing CLSC models (Ramani & De Giovanni, 2017; Reimann et al., 2019) to a dynamic two-stage remanufacturing CLSC model consisting of one manufacturer, one supplier and one IRP. Considering the dynamic nature of the recycling model in a Big Data environment, we revised the recycling function introduced by Guo et al. (2018) to highlight the dynamic characteristics of the recycling process. In the model, we also consider several influencing factors, such as the quality levels of recycled products, Big Data marketing and technological innovations of the IRP. Big Data marketing and technological innovation can serve two purposes: highlighting the dissemination nature of the Internet environment and improving recycling efficiency. Additionally, this paper compares the equilibrium solutions in three scenarios when IRPs show overconfident behaviors, and it explores the impact of key parameters on the equilibrium solutions. Our research confirms that the participation of the IRP and the supplier makes decision problems more complicated.

We also provide numerical examples to demonstrate the effectiveness of our model. Our meaningful results offer a decision basis and theoretical guidance to help CLSC members implement cooperation strategies and pricing policies in different game scenarios in practice.

7.2. Conclusions

The results of this research can be summarized as follows:

1. The IRP's overconfidence prompts it to exert more efforts on technological innovations and Big Data marketing and enhances the profit of the IRP. Increased investment in technological innovation and Big Data marketing brings two benefits to CLSC members: an improved recycling quantity and profit margin for the IRP and reduced production costs and recycling costs for the supplier, the manufacturer and the IRP. Additionally, the wholesale price and sales price will be reduced accordingly due to the reduction in production costs.
2. In this paper, the sensitivity analysis obtains some interesting results. Since the overconfidence of the IRP indirectly affects the production costs of the supplier and the manufacturer, the wholesale price and the sales price decrease as the level of overconfidence increases. This result is slightly different from the findings of Lu et al. (2015) and Xu et al. (2018), who did not consider the impact of the recycling platform on the RSC. Additionally, the IRP's recycling price increases with the technological innovation cost coefficient when the Big Data marketing cost coefficient is lower than a threshold but declines with the technological innovation cost coefficient when the Big Data marketing cost coefficient is high. The size of the threshold of the Big Data marketing cost coefficient depends on the system parameters.
3. Due to the IRP's overconfident behavior, the quantity and quality of recycled products improve. Hence, such overconfidence is beneficial for the IRP and the manufacturer. However, the improved quality and quantity of recycled products have a negative impact on the sales of the supplier and then have a detrimental effect on the supplier.
4. A suitable cost-sharing ratio can further stimulate the IRP to exert more efforts on technological innovations and Big Data marketing and achieve a "win–win" situation for the manufacturers and the IRP. Notably, however, an excessive level of confidence will inhibit the incentives of the cost-sharing strategy, reducing the profit of the manufacturer. Interestingly, when marketing efficiency and technical efficiency are at a high level, the cost-sharing strategy will also have a negative impact on the profit of the manufacturer. The reason is that when marketing efficiency and technological innovations are at a higher level, the IRP can easily achieve its business goals; additionally, in this case, the cost-sharing strategy will have a limited incentive effect, which will cause the marginal cost of

the manufacturer to be greater than the marginal benefit. Additionally, although the platform's overconfidence and cost-sharing strategies may damage the supplier's profit, the total profit of the CLSC increases (compared to the benchmark model).

7.3. Limitations and future research

Importantly, this research has a few limitations. First, this paper ignores the complexity of a CLSC system by considering only a single channel. However, the single-channel CLSC model can be extended to a dual-recycling channel model or a multiple-recycling channel model in future research. Second, for simplicity, this paper assumes a linear demand function; in realis, however, demand follows a variety of distributions. More complex demand functions will be considered in our future work to make the model more consistent with reality. Third, we consider only a single contract in the model. In fact, in a complex CLSC, how the supply chain leader designs incentives to motivate all members and achieve the Pareto optimality of the supply chain is also an interesting research topic that warrants exploration.

Acknowledgments

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Appendix A

Proof of Proposition 1. According to the optimal control theory, the Hamilton functions for the IRP, manufacturer and supplier are obtained as Eqs. (8), (9) and (10), respectively. Additionally, for the convenience of writing, the time t is omitted below.

The IRP's Hamilton function is:

$$H_P^N(p_r(\varepsilon), A(\varepsilon), \varepsilon, u_P^N) = f\varepsilon(Q_0 + ap_r + b\tau) + g(1-\varepsilon)(Q_0 + ap_r + b\tau) - p_r(Q_0 + ap_r + b\tau) - \frac{\theta A^2}{2} - \frac{\varphi\varepsilon^2}{2} + u_P^N(\mu A - \delta\tau) \tag{A.1}$$

The manufacturer's Hamilton function is:

$$H_M^N(p, u_M^N) = (p - c_m - w)(\alpha - \beta p) + (w - f)\varepsilon(Q_0 + ap_r + b\tau) + u_M^N(\mu A - \delta\tau) \tag{A.2}$$

The supplier's Hamilton function is:

$$H_S^N(w, u_S^N) = (w - m - c_s)(\alpha - \beta p - \varepsilon(Q_0 + ap_r + b\tau)) + (m - g)(1-\varepsilon)(Q_0 + ap_r + b\tau) + u_S^N(\mu A - \delta\tau) \tag{A.3}$$

The equilibrium conditions of Eq. (A.1) are:

$$\frac{\partial H_P^N}{\partial p_r} = a\varepsilon f + g(1-\varepsilon)a - Q_0 - 2ap_r - b\tau = 0 \tag{A.4}$$

$$\frac{\partial H_P^N}{\partial A} = u_P^N\mu - A\theta = 0 \tag{A.5}$$

$$\frac{\partial H_P^N}{\partial u_P^N} = A\mu - \delta\tau = \tau' \tag{A.6}$$

$$u_P^{N'} = ru_P^N - \frac{\partial H_P^N}{\partial\tau} = (\delta + r)u_P^N - ((f-g)\varepsilon + g - p_r)b \tag{A.7}$$

By substituting Eqs. (A.4)–(A.7) into Eq. (A.2), the following is easily obtained:

$$p^{N*} = \frac{(w^{N*} + c_m)\beta + \alpha}{2\beta} \tag{A.8}$$

Similarly, by substituting Eqs. (A.4)–(A.8) into Eq. (A.3), we obtain the following:

$$w^{N*} = \frac{\alpha - a(f-g)(\varepsilon^{N*})^2 - (Q_0 + ag + b\tau^{N*}(t))\varepsilon^{N*} + (m - c_m + c_s)\beta}{2\beta} \tag{A.9}$$

By substituting Eqs. (A.4)–(A.8) into Eq. (A.1) and taking the derivative of Eq. (A.1) with respect to ε, we obtain the following:

$$\varepsilon^{N*} = \frac{(f-g)(ag + b\tau^{N*} + Q_0)}{2\varphi - (f-g)^2 a} \tag{A.10}$$

Substituting Eq. (A10) into Eqs. (A.4) and (A.5), we obtain:

$$p_r{}^{N*} = \frac{((f-g)\varepsilon^{N*} + g)a - b\tau^{N*} - Q_0}{2a} \tag{A.11}$$

$$A^{N*} = \frac{u_P^N\mu}{\theta} \tag{A.12}$$

Eq. (A.13) can be obtained by inserting Eq. (A.12) into Eq. (A.6):

$$\frac{\partial H_P^N}{\partial u_P^N} = \frac{u_P^N\mu^2}{\theta} - \delta\tau = \tau' \tag{A.13}$$

Taking the derivatives of both sides of Eq. (A.13) with respect to t, we obtain:

$$\tau'' = \frac{u_P^{N'}\mu^2}{\theta} - \delta\tau' \tag{A.14}$$

Substituting Eq. (A.7) into Eq. (A.14) and then combining Eqs. (A.8)–(A.12), we obtain the following:

$$\frac{\partial^2\tau}{\partial t^2} - r\frac{\partial\tau}{\partial t} - \frac{(\theta\delta(f-g)^2(r+\delta)a^2 - 2\theta\varphi\delta(r+\delta)a + \varphi b^2\mu^2)\tau}{((f-g)^2a - 2\varphi)\theta a} = \frac{\varphi b\mu^2(ag+Q_0)}{((f-g)^2a-2\varphi)\theta a} \tag{A.15}$$

By solving the eigenvalue of Eq. (15), the expression of $\tau(t)$ can be obtained. Moreover, based on the previous assumption $\tau(0) = \tau_0 \geqslant 0$ and $\lim_{t\to\infty} = \bar{\tau}$, we obtain the following:

$$\tau^N(t) = (\tau_0 - \bar{\tau}^N)e^{\chi_N t} + \bar{\tau}^N \tag{A.16}$$

where $\chi_N = \frac{\Phi_N - ar\theta\varpi}{2\theta a\varpi} < 0$, $\varpi = (f-g)^2a - 2\varphi$, $\Phi_N = \sqrt{\theta a(a(r+2\delta)^2\varpi\theta + 4b^2\varphi\mu^2)\varpi}$, and $\bar{\tau}^N = \frac{\varphi(ag+Q_0)b\mu^2}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi\mu^2}$.

Substituting Eqs. (A.12) and (A.16) into Eq. (A.6), the expression of $u_P(t)$ is calculated as follows:

$$u_P^N(t) = \frac{\theta(\tau_0 - \bar{\tau}^N)(\delta - \chi_N)e^{\chi_N t}}{\mu^2} + \bar{u}_P^N \tag{A.17}$$

where $\bar{u}_P^N = \frac{\theta\delta\varphi(ag+Q_0)b}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi\mu^2}$. When $t\to\infty$, the steady state of the system is $(\bar{\tau}^N, \bar{u}_P^N)$. Substituting $(\bar{\tau}^N, \bar{u}_P^N)$ into Eqs. (A.8)–(A.12), the optimal steady-state strategies for all members are given as follows:

$$\bar{p}_r^N = \frac{((f-g)\bar{\varepsilon}^N + g)a - b\bar{\tau}^N) - Q_0}{2a} \tag{A.18}$$

$$\bar{A}^N = \frac{\bar{u}_P^N\mu}{\theta} \tag{A.19}$$

$$\bar{\varepsilon}^N = \frac{(f-g)(ag + b\bar{\tau}^N + Q_0)}{2\varphi - (f-g)^2a} \tag{A.20}$$

$$\bar{p}^N = \frac{(\bar{w}^N + c_m)\beta + \alpha}{2\beta} \tag{A.21}$$

$$\bar{w}^N = \frac{\alpha - a(f-g)(\bar{\varepsilon}^N)^2 - (Q_0 + ag + b\bar{\tau}^N)\bar{\varepsilon}^N + (m - c_m + c_s)\beta}{2\beta} \tag{A.22}$$

The optimal steady-state present values of profit for all members without considering time are as follows.

The optimal steady-state present values of profit for the IRP in **scenario N** are as follows:

$$V_P^N = f\bar{\varepsilon}^N(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N) + g(1-\bar{\varepsilon}^N)(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N) - \bar{p}_r^N(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N) - \frac{\theta(\bar{A}^N)^2}{2} - \frac{\varphi(\bar{\varepsilon}^N)^2}{2} \tag{A.23}$$

The optimal steady-state present values of profit for the manufacturer in **scenario N** are as follows:

$$V_M^N = (\bar{p}^N - c_m - \bar{w}^N)(\alpha - \beta\bar{p}^N) + (\bar{w}^N - f)\bar{\varepsilon}^N(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N) \tag{A.24}$$

The optimal steady-state present values of profit for the supplier in **scenario N** are as follows:

$$V_S^N = (\bar{w}^N - m - c_s)(\alpha - \beta\bar{p}^N - \bar{\varepsilon}^N(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N)) + (m-g)(1-\bar{\varepsilon}^N)(Q_0 + a\bar{p}_r^N + b\bar{\tau}^N) \tag{A.25}$$

Thus, **Proposition 1** is proven.

Appendix B

The proofs of **Proposition 2** and **Proposition 2** are similar to that of **Proposition 1**; thus, the proof process is omitted. In **scenario C**, the expressions of $\tau^C(t)$ and $u_P^C(t)$ are as follows:

$$\tau^C(t) = (\tau_0 - \bar{\tau}^C)e^{\chi_C t} + \bar{\tau}^C \tag{B.1}$$

$$u_P^C(t) = \frac{\theta(\tau_0 - \bar{\tau}^C)(\delta - \chi_C)e^{\chi_C t}}{(\mu+k)^2} + \bar{u}_P^C \tag{B.2}$$

where $\chi_C = \frac{\Phi_C - ar\theta\varpi}{2\theta a\varpi} < 0$, and $\Phi_C = \sqrt{\theta a(a(r+2\delta)^2\theta\varpi + 4b^2\varphi(\mu+k)^2)\varpi}$.

The steady state of system $(\bar{\tau}^C, \bar{u}_P^C)$ is given by:

$$\bar{\tau}^C = \frac{\varphi(ag+Q_0)b(\mu+k)^2}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi(\mu+k)^2} \tag{B.3}$$

$$\bar{u}_P^C = \frac{\theta\delta\varphi(ag+Q_0)b}{2\delta\theta\varphi(\delta+r)a - \delta\theta(f-g)^2(\delta+r)a^2 - b^2\varphi(\mu+k)^2} \tag{B.4}$$

Substituting $(\bar{\tau}^C, \bar{u}_P^C)$ into Eqs. (25)–(29), the optimal steady-state strategies for all members in **scenario C** are given by:

$$\bar{p}_r^C = \frac{((f-g)\bar{\varepsilon}^C + g)a - b\bar{\tau}^C - Q_0}{2a} \tag{B.5}$$

$$\bar{A}^C = \frac{(\mu+k)\bar{u}_P^C}{\theta} \tag{B.6}$$

$$\bar{\varepsilon}^C = \frac{(f-g)(ag + b\bar{\tau}^C + Q_0)}{2\varphi - (f-g)^2 a} \tag{B.7}$$

$$\bar{p}^C = \frac{(\bar{w}^C + c_m)\beta + \alpha}{2\beta} \tag{B.8}$$

$$\bar{w}^C = \frac{\alpha - a(f-g)(\bar{\varepsilon}^C)^2 - (ag + b\bar{\tau}^C + Q_0)\bar{\varepsilon}^C + (m - c_m + c_s)\beta}{2\beta} \tag{B.9}$$

The optimal steady-state present values of profit for all members without considering time in **scenario C** are as follows.
The optimal steady-state present values of profit for the IRP in **scenario C** are as follows:

$$V_P^C = f\bar{\varepsilon}^C(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C) + g(1-\bar{\varepsilon}^C)(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C) - \bar{p}_r^C(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C) - \frac{\theta(\bar{A}^C)^2}{2} - \frac{\varphi(\bar{\varepsilon}^C)^2}{2} \tag{B.10}$$

The optimal steady-state present values of profit for the manufacturer in **scenario C** are as follows:

$$V_M^C = (\bar{p}^C - c_m - \bar{w}^C)(\alpha - \beta\bar{p}^C) + (\bar{w}^C - f)\bar{\varepsilon}^C(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C) \tag{B.11}$$

The optimal steady-state present values of profit for the supplier in **scenario C** are as follows:

$$V_S^C = (\bar{w}^C - m - c_s)(\alpha - \beta\bar{p}^C - \bar{\varepsilon}^C(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C)) + (m-g)(1-\bar{\varepsilon}^C)(Q_0 + a\bar{p}_r^C + b\bar{\tau}^C) \tag{B.12}$$

In **scenario F**, the expressions of $\tau^F(t)$ and $u_P^F(t)$ are as follows:

$$\tau^F(t) = (\tau_0 - \bar{\tau}^F)e^{\chi_F t} + \bar{\tau}^F \tag{B.13}$$

$$u_P^F(t) = \frac{(1-\eta)\theta(\tau_0 - \bar{\tau}^F)(\delta - \chi_F)e^{\chi_F t}}{(\mu+k)^2} + \bar{u}_P^F \tag{B.14}$$

where $\chi_F = \frac{\Phi_F - (1-\eta)ar\theta\varpi}{(1-\eta)2\theta a\varpi} < 0$ and $\Phi_F = \sqrt{\theta(1-\eta)a(a(r+2\delta)^2\varpi\theta(1-\eta) + 4b^2\varphi(\mu+k)^2)\varpi}$.
The steady state of system $(\bar{\tau}^F, \bar{u}_P^F)$ in **scenario F** is given as follows:

$$\bar{\tau}^F = \frac{\varphi(ag + Q_0)b(\mu+k)^2}{2\delta\theta\varphi(\delta+r)a(1-\eta) - \delta\theta(f-g)^2(\delta+r)a^2(1-\eta) - b^2\varphi(\mu+k)^2} \tag{B.15}$$

$$\bar{u}_P^F = \frac{(1-\eta)\theta\delta\varphi(ag + Q_0)b}{2\delta\theta\varphi(\delta+r)a(1-\eta) - \delta\theta(f-g)^2(\delta+r)a^2(1-\eta) - b^2\varphi(\mu+k)^2} \tag{B.16}$$

Substituting $(\bar{\tau}^F, \bar{u}_P^F)$ into Eqs. (39)–(43), the optimal steady-state strategies for all members in **scenario F** are given as follows:

$$\bar{p}_r^F = \frac{((f-g)\bar{\varepsilon}^F + g)a - b\bar{\tau}^F - Q_0}{2a} \tag{B.17}$$

$$\bar{A}^F = \frac{(\mu+k)\bar{u}_P^F}{(1-\eta)\theta} \tag{B.18}$$

$$\bar{\varepsilon}^F = \frac{(f-g)(ag + b\bar{\tau}^F + Q_0)}{2\varphi - (f-g)^2 a} \tag{B.19}$$

$$\bar{p}^F = \frac{(\bar{w}^F + c_m)\beta + \alpha}{2\beta} \tag{B.20}$$

$$\bar{w}^F = \frac{\alpha - a(f-g)(\bar{\varepsilon}^F)^2 - (ag + b\bar{\tau}^F + Q_0)\bar{\varepsilon}^F + (m - c_m + c_s)\beta}{2\beta} \tag{B.21}$$

The optimal steady-state present values of profit for all members without considering time in **scenario F** are as follows.
The optimal steady-state present values of profit for the IRP in **scenario F** are as follows:

$$V_P^F = f\bar{\varepsilon}^F(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F) + g(1-\bar{\varepsilon}^F)(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F) - \bar{p}_r^C(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F) \\ -(1-\eta)\frac{\theta(\bar{A}^F)^2}{2} - \frac{\varphi(\bar{\varepsilon}^F)^2}{2} \tag{B.22}$$

The optimal steady-state present values of profit for the IRP in **scenario F** are as follows:

$$V_M^F = (\bar{p}^F - c_m - \bar{w}^F)(\alpha - \beta\bar{p}^F) + (\bar{w}^F - f)\bar{\varepsilon}^F(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F) - \eta\frac{\theta(\bar{A}^F)^2}{2} \tag{B.23}$$

The optimal steady-state present values of profit for the supplier in **scenario F** are as follows:

$$V_S^F = (\bar{w}^F - m - c_s)(\alpha - \beta \bar{p}^F - \bar{\varepsilon}^F(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F)) + (m - g)(1 - \bar{\varepsilon}^F)(Q_0 + a\bar{p}_r^F + b\bar{\tau}^F) \tag{B.24}$$

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