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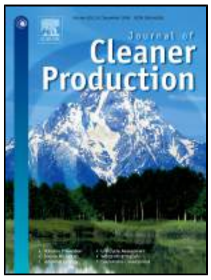

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The influence of big data system for used product management on manufacturing–remanufacturing operations

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Abstract: In these years, more and more manufacturers implement closed-loop operations and incorporate remanufacturing into its manufacturing system, which forms manufacturing-remanufacturing operations. To increase the efficiency of used product collection, many remanufacturers have established quality valuation system to acquire big data of used products. A quality-dependent acquisition process helps remanufacturers collect used products according to products' actual condition and perceived value from the perspective of consumers, but may incur extra operation cost. This study aims to explore the influence of quality valuation big data system on manufacturers' manufacturing/remanufacturing operation decisions. This paper studies a manufacturer which produces new products and remanufactures the returned products, and sells two kinds of products to the same market. We focus on quantity decisions on manufacturers' manufacturing/remanufacturing operations. Focusing on the availability of big data of used products, two optimization models, fixed collection pricing mechanism and discriminatory collection pricing mechanism, are analyzed to explore the impact of quality big data of used products on firms' manufacturing–remanufacturing operations. As the obtained conclusions, in both fixed and discriminatory collection pricing mechanisms, the manufacturer takes full/partial remanufacturing strategy under different conditions. And the manufacturer prefers different collection pricing mechanisms according to various levels of consumers' perceived value of used products and the acquisition cost of big data.
Key words: big data; used product quality; manufacturing–remanufacturing operations

1. Introduction

Given the environmental and economic benefits of recycling, remanufacturing is considered to be an imperative strategic decision for enterprises, especially manufacturers. The purpose of remanufacturing is to bring used products up to quality standards that are as rigorous as those for new products. As a similar concept, refurbished products are merely same as new products in appearance, but they are different in quality. In remanufacturing, used products are disassembled and all modules and parts are extensively inspected. Durable and valuable parts and modules are retained, and other parts and modules are replaced with new ones. Remanufacturing reduces the negative impact of waste products on the environment (Thierry, et al. 1995). In recent years, more and more manufacturers implement closed-loop operations and incorporate remanufacturing into their manufacturing system, which forms manufacturing-remanufacturing operations. Moreover, some electronic companies that produce disposable cameras, printers, ink cartridges and copiers have similar action plans. Remanufacturing has gradually become a key business aspect that electronic manufacturers should develop and promote. For example, BMW has been remanufacturing high-value components such as engines, starter motors, and alternators for a number of years. The remanufactured components are tested according to strict quality standards to become a BMW Exchange Part (Thierry, et al. 1995). Apple, Samsung and Xerox have also set up special remanufacturing sectors or subsidiaries to handle remanufacturing. These companies achieved additional operation goals in energy conservation, business development and profitability increase.

Big data, more than the typical faddish fuzz, carries with it the opportunity to change business model design and day-to-day business decision making. The applications of big data research, with growing combination of resources and tools, have had significant impact on today's businesses. To increase efficiency of collecting, many remanufacturers (manufacturers) have established quality valuation system to acquire big data of used products. In this commercial model, consumers submit their used products through collection channel of remanufacturers, the remanufacturer evaluates the quality data of used products, and a quality-based acquisition price is provided for the consumer. Based on the big data of used product quality, a quality-dependent acquisition process helps remanufacturers collect used products according to products' actual condition and perceived value from the perspective of consumers. With big data of used product quality, collectors can exclude used products with poor quality, which have no value for remanufacturing, and set collection price according to the actual quality of used products and increase the collection efficiency. When the collectors take the strategy of quality-dependent discriminatory pricing, they can set the acquisition price according to the actual quality of the certain used products and extract all the consumer surplus, and control the collection quantity and quality more accurately.

In the electronic industry, large numbers of electronic manufacturers begin to carry out recycling business in recent years, however, their business models of used product collection are quite different. Some enterprises, i.e, Samsung and Huawei, set a fixed collection price for used products and collect them without consideration of products' quality, however, some other enterprises choose to set quality-dependent collection price for used products. Quality-dependent collection pricing mechanism is applied by many Electronic devices recycling companies (Gazelle, Love2recycle.Com, uSell, eRecycling Corp, Fonebank, FLIP4NEW). The Recycling and Refurbishing Program of APPLE, in which consumers receive a gift card online or credit toward a purchase in-store if they return qualifying devices, and APPLE is responsible to either refurbish the device for resale or recycle its materials responsibly to be reused. The process of quality-dependent collection pricing mechanism is operated as follows. Firstly, the owner of a used good selects the specific model he or she holds and the specific condition of the good, and subsequently receives a provisional price offer. After accepting the offer, the good is sent by mail to the collector, the good is tested upon arrival. A standardized testing and evaluation procedure and a comprehensive assessment of the conditions of equipment are carried out, large sums of quality data of used products are obtained. The quality evaluation system of used products is based on the processing of massive data and a number of complex models. And the acquisition price is adjusted based on the standardized evaluation outcome of used product quality.

From the perspective of collectors, setting quality-dependent collection pricing mechanism based on big data system means more precise pricing and more efficient collection, but more operation cost. Therefore, is it necessary for manufacturers to set up big data system for used product management? Motivated by the above commercial practice, this study aims to explore the influence of quality valuation big data system on manufacturers' manufacturing-remanufacturing operation decisions. Our research provides a new perspective of manufacturing–remanufacturing operations, which takes used products' quality into account when setting the acquisition price. This new research perspective provides new managerial insights on role of quality big data in remanufacturing management of enterprises.

This research aims to answer the following questions.

(1) With/without big data of used product quality, how should the manufacturer control the quantity of new and remanufactured products to maximize its profit, respectively?
(2) From the perspective of manufacturers which carry out remanufacturing, is it necessary to choose quality-based pricing strategy to collect used product based on a big data system?
(3) From the perspective of the environment, is the application of big data system of used product quality beneficial to the environment?

The rest of the paper is organized as follows. Section 2 reviews the relevant literature. Section 3 provides a systematic description of big data system of used product management. In section 4, we describe the research question and introduce the relevant variables. The model is established in Section 5, and the optimal decisions and profits are derived. In Section 6, two models under different pricing mechanism are compared. Section 7 summarizes the entire article and highlights important managerial insights, and gives directions for future research.

2. Literature Review

Remanufacturing has gradually been adopted by manufacturers in various industries. On the one hand, remanufacturing reduces the negative impact of waste products on the environment, on the other hand, remanufacturing has been a new business mode of generating profits (Savaskan et al. 2004; Atasu et al. 2008; Pranab & Harry, 2010; Guide & Wassenhove 2010). Many scholars pay attention to remanufacturing or manufacturing-remanufacturing operations to explore the optimal decisions and strategies of enterprises (Toktay & Wei 2011, Arya et al. 2008, Geyer et al. 2007, Aras et al. 2006, Ferrer & Swaminathan 2006). Toktay & Wei (2011) consider a manufacturer who also undertakes remanufacturing operations and determine that a cost allocation mechanism that allocates a portion of the initial production cost to each of the two stages of the product life cycle should be used. Pranab & Harry (2010) present a two - period model of remanufacturing in the face of competition, and the original equipment manufacturer (OEM) competes with a local remanufacturer under many reverse logistics configurations for the returned items. Arya et al. (2008) consider the influences of cooperative mechanism and channel structure on the decision maker of a closed-loop supply chain. Geyer et al. (2007) build a production model that includes recycling, remanufacturing and sale while considering the life cycle of the product and component. Results show that the cost structure, recovery rate, product life cycle and service life of parts should be coordinated to minimize the cost of remanufacturing. Cost structure, recovery rate, product life cycle and service life of the parts should be coordinated. Aras et al. (2006) study a hybrid manufacturing/remanufacturing system, wherein the manufacturer buys new parts from suppliers and remanufactures waste products. The link between the manufacturer and the supplier is ignored because the manufacturer is the sole decision maker.

Based on the traditional research on the operations management of remanufacturing, some scholars explore the application of modern information technology on remanufacturing and analyze some new research questions based on the new research background. For example, Ferrer et al. (2011)

evaluate the use of radio-frequency identification (RFID) technology for improving remanufacturing efficiency, and report the results of discrete-event simulation model that analyzes how RFID creates value within the remanufacturing operation. Clottey et al. (2012) consider a manufacturer that also acts as a remanufacturer and develop a generalized forecasting approach to determine the distribution of the returns of used products. Niu & Zou (2017) investigate a remanufacturing supply chain, where demand uncertainty is significant, and the value to reduce environmental risk is large, as big data helps to obtain more accurate demand signal. Zhou & Piramuthu (2013) consider RFID tags and their applications from a remanufacturing perspective and propose a framework to assist such process based on item-level information visibility and instantaneous tracking/tracing ability enabled by RFID. The incorporation of RFID in the reverse supply chain results in cost reduction, service and production quality improvement and pollution and waste reduction. In Mashhadi & Behdad (2017), Self-Monitoring Analysis and Reporting Technology (S.M.A.R.T.) is applied to sort the used products based on both product's internal factors, such as future reusability of components, product identity data, and product health status as well as external factors such as market trends. Ketzenberg (2004) explores the value of information in remanufacturing and develops four decision-making models to evaluate the impact of yield information and supplier lead time on manufacturing costs.

Another stream of papers which are relevant to our research is the quality-dependent collection. The quality is one of important characteristics of used products, and the quality-dependent pricing strategy is studied by some scholars (Guide et al. 2003; Ray et al, 2005; Bakal & Akcali, 2006; Karakayali et al, 2007; Ferguson et al, 2009; Liang et al, 2009; Galbreth and Blackburn 2010; Hahler and Fleischmann 2013; Hahler and Fleischmann 2017). Guide et al. (2003) develop a framework of the market-driven recovery system and develop an economic analysis for calculating the optimal price incentives for product returns and optima selling prices for remanufactured products. Focusing on remanufacturing operations, Ray et al (2005) study three pricing schemes: (i) uniform price for all customers, (ii) age-independent price differentiation between new and replacement customers (i.e., constant rebate for replacement customers), and (iii) age-dependent price differentiation between new and replacement customers. Karakayali et al (2007) develop models to determine the optimal acquisition price of the end-of-life products and the selling price of the remanufactured parts in centralized as well as remanufacturer- and collector-driven decentralized channels. And they find that OEM would prefer a remanufacturer- or a collector-driven channel at some certain circumstances respectively. Ferguson et al (2009) consider a tactical production-planning problem for remanufacturing when returns have different quality levels. Galbreth and Blackburn (2010) consider the acquisition and production decisions of a remanufacturer who acquires used products of variable condition and allocates remanufacturing activity to domestic and offshore facilities. The results of their research show that the remanufacturer's optimal strategy can be chosen from a finite set of simple policies in which each product is routed to a facility based on its condition. Hahler and Fleischmann (2013) propose two different approaches to grade the used products and achieve acquisition price differentiation. They compare the two strategies based on a continuous approximation model, and the analytical expressions for the optimal pricing and network density decision are obtained. Hahler and Fleischmann (2017) analyze the product assessment process of a recommerce provider in detail. They propose a sequential bargaining model with complete information which captures the individual behavior of the recommerce provider and the product holder, and determine the optimal strategies of the product holder and the recommerce provider in this game. Our research is related to the stream of quality-dependent acquisition prices for used products. However, most papers in this field explore the quality uncertainty in remanufacturing system, but don't take manufacturing into account at the same time from the perspective of manufacturers which implement closed-loop operations. The only paper, Robotis et al (2012), which studies the used product quality uncertainty in manufacturing–remanufacturing operations, doesn't consider collection pricing mechanism.

Therefore, to fill the above research gap, we study and compare two collection pricing mechanisms (Fixed collection pricing mechanism and Quality-based collection pricing mechanism), and explore the optimal manufacturing and remanufacturing decisions of the manufacturer's manufacturing–remanufacturing operations. To the best of our knowledge, there is no work which considers acquisition pricing mechanisms in manufacturers' manufacturing–remanufacturing operations and takes the quantity relationship between new and remanufactured product into account. Based on this, our research aims to provide operation guidelines on which pricing mechanism the manufacturer should chooses when it provides new and remanufactured products to the same market, and how it should set the optimal quantities in its operations.

3. Big data of used product management

From the perspective of enterprises, recycling is not easily performed because of its unpredictability, low visibility and low traceability. Moreover, returns management can be regarded as a complex system engineering, which requires intelligent selections and optimal decisions. However, many companies find that the acquisition of the data required to make accurate analyses on returns management issues is problematic. Frequently, relevant data are scattered throughout the company/consumer/product, or not available at all (Thierry, et al. 1995). As a modern management tool, big data have been gaining academic as well as practitioner attention. Building an efficient big data system for managing used products can provide the quality information of the returned devices in reverse logistics, helps to make scientific decisions, therefore raises the operating efficiency of returned devices, accelerates the process of returns, improve brand image, and promotes sustainable development of companies.

In the manufacturer's manufacturing–remanufacturing operations, large amounts of data information are produced, including product attribute information, status information, location information, geographic information, processing information, cost information, etc., and the information influence each other. Thierry, et al. (1995) summarize all the information in the returns management system into four categories:

- 1. information on the composition of products;
- 2. information on the magnitude and uncertainty of return flows;
- 3. information on markets for reprocessed products, components, and materials;
- 4. information on actual product recovery and waste management operations.

In this years, some emerging used product collection platform has been established (Aihuishou, Gazelle, Love2recycle.Com, uSell, eRecycling Corp, Fonebank, FLIP4NEW), and new information technology and data analyzation are applied in their operations. And from these emerging systems, we can find that technique Information platform based on big data technology can be used to select useful information from huge sum of data, manage, process and organize information, and provide accurate information services to support business decisions in the manufacturer's manufacturing–remanufacturing operations. By using the appropriate methods and models for statistical data analysis, mining and prediction of decision data, big data management system on the reverse logistics products connects four categories of information for the used product management system (Figure 1) and reduces the randomness and fuzziness of the reverse logistics, enhances the efficiency of the reverse logistics management, therefore improves the reverse logistics operation and service performance.

Figure 1 Input/Output data of a big data system for manufacturing–remanufacturing operations

Manufacturers recycle old devices through different collection channels, and consumers return the old ones. In this process, we can collect information such as brand, type, model, recycling location and recycling time, as the initial information of returned products. And then, the second step is evaluation on used products. The data of products' service life, usage condition, scrap reason, main problem are obtained in the step of evaluation. The big data system generates the quality data of collected products based on two aspects information: 1) life cycle data, which is owned by the manufacturer; 2) product usage condition data, which is acquired by recovery tests in products collection. Based on the initial return product quality information, manufacturers/remanufacturer determine the recycling methods (including remanufacturing, disposal, etc.). At the same time, through the big data system for enterprises, enterprises decide on the number of processing plan, remanufacturing plan, inventory strategy, the scrap processing arrangement plan and so on. On the one hand, the manufacturer provides the raw product information of the product, on the other hand, the manufacturing/remanufacturing plan can be obtained according to the data provided by the big data system for used product management. Figure 2 depicts the operation process of a big data system for a manufacturer's manufacturing–remanufacturing operations.

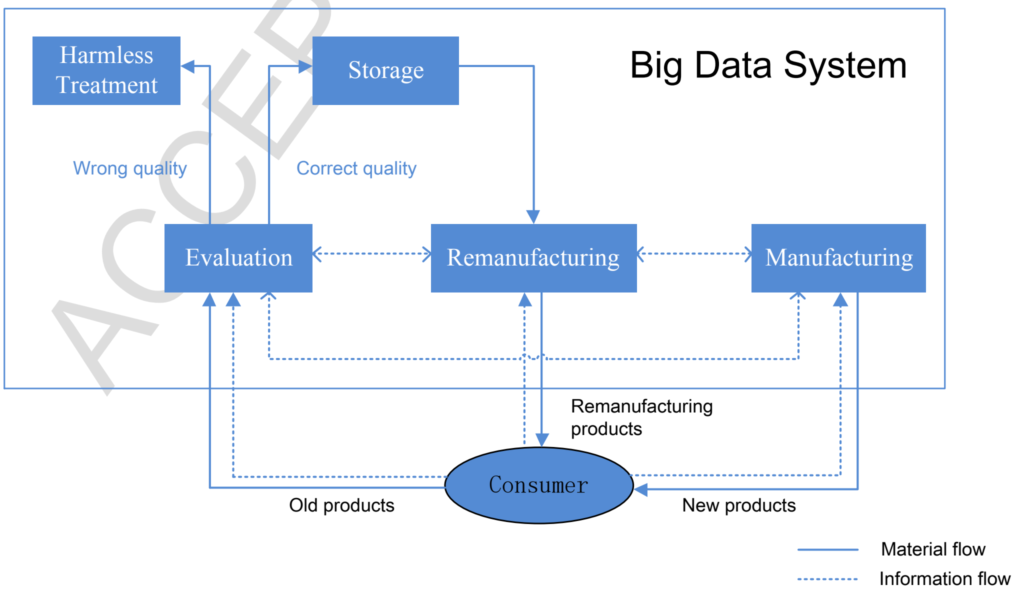

Figure 2 Operation process of a big data system for manufacturing–remanufacturing operations

The contributions of big data system for managing used products are mainly reflected in the following aspects:

(1) The collector can evaluate the actual quality of returned products more accurately, and the relevant information becomes more transparent. Because of the difference in the use condition and use time, even though the same kind of waste electronic products, the quality difference among returned devices is extremely large. In the traditional recycling mode, the actual quality information of used products is hold by consumers, and the collector can hardly realize the actual quality data, which play an important role in consumers' perceived value of used products. And when the collection price is set based on the quality of returned devices, the consumers usually choose to hide the actual quality information and the use condition of their used products. However, based on the establishment of big data system for used products, the manufacturer can evaluate the actual quality of returned products, and set the proper acquisition price.

(2) The big data system for managing used products helps to provide business support and information management to optimize reverse logistics business process of manufacturers. Based on the collection of information in reverse logistics and the data mining and analysis, the big data system for managing used products provides manufacturers with information resources, which helps to optimize business processes, reduce operating costs, and monitor the whole process.

(3) The big data system for managing used products effectively supports the integration of heterogeneous logistics data resources and promotes the data circulation and sharing between different departments of enterprises in their manufacturing–remanufacturing operations. Reverse logistics big data system of used products requires the integration of heterogeneous information resources ability from a variety of data sources, for collaborative decision-making based on the transfer of data between heterogeneous systems.

4. Problem description

This study investigates the optimal manufacturing and remanufacturing decisions of a manufacturer, which provide new and remanufactured products to the same market. Specifically, the manufacturer produces and sells new products, collects used products, remanufactures collected products and sells remanufactured products. In reverse logistics, the manufacturer collects waste products from consumers and extracts renewable components from them to produce remanufactured products for sale. Remanufacturing from the manufacturer's side decreases the quantity of new products, which leaves a cannibalism effect on new product market.

Based on the availability of big data of quality, the manufacturer may choose different collection pricing mechanisms. When the manufacturer has established a big data system for returns management, it may set the collection price according to products' quality. Otherwise, the manufacturer has to set the fixed collection price to all of the returned products. Based on the certain collection pricing mechanism, the manufacturer makes quantity decisions for the new and the remanufactured products, and the quantity of the remanufactured products is limited by the new products and determined by the collection price.

4.1 Assumptions

The assumptions in this study are presented as follows.

Assumption 1 (Quality big data): The big data system can provide information of used products' quality θ to the manufacturer.

In this research, the big data system for managing used products can provide the quality information of the returned devices in reverse logistics. Based on that, the manufacturer may choose the quality-based collection pricing mechanism and set acquisition price according to product's quality data. Otherwise, without big data system, we assume that the manufacturer has no way to master the quality information accurately, therefore it can only set the fixed acquisition price in used product collection.

Assumption 2 (The cost structure): The cost of remanufactured products is less than the cost of new products, that is, $c_r \leq c_n$.

Remanufacturing saves production cost because old components are reused instead of purchasing expensive new components. However, in the practice of remanufacturing, some used products' quality is too poor to be remanufactured, whose key components are damaged and cannot be recycled or reused. These used products have no remanufacturing value and their remanufacturing cost is approximately to the manufacturing cost c_n, and manufacturers would rather to produce a new product in this case instead of collecting them with no economic value. Therefore, given quality data, these used products should be excluded in collection to avoid extra collection cost. The minimum quality standard is denoted by $\underline{\theta}$, which requires the key components of used products are qualified for being reused. We assume that the remanufacturing cost of used products whose quality $\theta > \underline{\theta}$ is c_r, otherwise, the remanufacturing cost is c_n. The difference between c_n and c_r ($c_r \leq c_n$) shows the cost advantage of remanufacturing. The higher the advantage of remanufacturing costs, the stronger the incentive for manufacturers to collect and remanufacture waste products. We assume that $c_r = 0$ to simplify the model in this paper.

Assumption 3 (Consumer characteristics): The perceived value V for the new products of consumers is uniformly distributed in (0, 1), and the market size is normalized to 1. For the same kind of products, the consumer's perceived values of new and remanufactured products have a certain level of difference. Consumers have lower perceived value of remanufactured products. The difference is reflected by the discount coefficient δ, $\delta \in (0,1)$.

Consumers are more willing to buy new products than remanufactured ones at the same price. They believe that the quality of remanufactured products is lower than new ones. Early studies assume that consumers are willing to pay for remanufactured products and new products, but recent empirical findings show that consumers perceive the value of remanufacturing to be lower than new products. The perceived value of the new product is V, which is a random variable uniformly distributed on (0, Q). For the same kind of products, a certain difference exists between new products and remanufactured ones in the perceived value of consumers. The consumer's perceived value of remanufactured products is lower. Similar to Ondemir & Gupta(2014) and Esenduran et al. (2016), this difference is represented by discount coefficient δ, $\delta \in (0,1)$. Therefore, the consumer's perceived value for the remanufactured product is δV. The utility of consumers who buy new products is $V - p_n$. The utility of consumers who buy remanufactured products is $\delta V - p_r$.

Consumers can be divided into three categories according to consumer behavior without buying any product. The three types of consumers are uniformly distributed in (0, 1). The threshold between the first and second types of consumers is located at $(1 - q_n - q_r)$, and the threshold between the second and third types of consumers is located at $(Q - q_n)$.

For threshold consumer $V = 1 - q_n - q_r$, which is located between the first and second types, the utility of not buying any product is zero, and the utility of buying remanufactured products is $\delta(Q - q_n - q_r) - p_r$. The two utilities at the critical point are equal. Thus,

$$p_r = \delta(1 - q_n - q_r).$$

For threshold consumers ($V = Q - q_n$) located between the second and third types, the utility of buying remanufactured products is $\delta(Q - q_n) - p_r$, and the utility of buying new products is $Q - q_n - p_n$. The two utilities at the critical point are equal. Thus,

$$\delta(1 - q_n) - p_r = 1 - q_n - p_n.$$

By substituting the above p_r, the price of a new product can be expressed as $p_n = Q - q_n - \delta q_r$.

The above analysis shows that the inverse demand function of new products and remanufactured products can be expressed as

$$p_n = 1 - q_n - \delta q_r \text{ and } p_r = \delta(1 - q_n - q_r).$$

The inverse demand function shows that the retail price of new products and remanufactured products are simultaneously and negatively correlated with the sales of these two types of products.

Assumption 4 (Product life cycle): The new product can only be used for one period and be remanufactured only once.

In this research, the new product can only be used for one period. And the key component of a used product which is in good condition and without being damaged, is assumed to be qualified to be remanufacturing and remain working normally in the next life cycle as a remanufactured product. In this scenario, consumers return the used products at the end of the period, and the returned products are remanufactured by the manufacturer. The amount of used products in this stage is equal to the number of new products in the last stage. We mainly focus on the decision of decision maker at one stage by assuming $q_r \leq q_n$ to simplify the problem. Similar models are applied in many academic papers, e.g., Toktay and Wei (2011).

Assumption 5 (Decision maker characteristics): The decision makers in the model are risk neutral and they aim to maximize the revenue purely.

4.2 Variable Notations

The variables involved in this study are listed as follows.

δ	Discount coefficient of remanufactured product estimated value
ϕ	Consumers' perceived value of used products
θ	Quality of used products
$\underline{\theta}$	The minimum quality of collection for remanufacturing
T	Acquisition cost of quality data from big data system
R	Collection price of used price
c_n, c_r	Cost of producing new / remanufactured parts
p_n, p_r	Retail prices of new/remanufactured products
q_n, q_r	Output quantities of new/remanufactured products
Π_i	Profit of the decision maker i($i \in \{I, S, M\}$)

5. Model

We study a monopolist which produces new products and remanufactures the returned products within only one period. In this section, we propose the research model and the corresponding optimal decisions in manufacturing–remanufacturing operations under two different acquisition pricing mechanisms: fixed collection pricing mechanism and discriminatory collection pricing mechanism. In the fixed collection pricing mechanism, the collection price is irrelevant to the using condition and consumers' perceived value of used product. On the other hand, in the discriminatory collection pricing mechanism, the collection price is set based on the using condition of used products, and the manufacturer is able to achieve price discrimination based on the big data of used products. Subsequently, we analyze the optimal decisions in the above two pricing mechanisms, and explore the impact of key parameters in the model. In our research, we use superscripts "*f*" and "*q*" to represent fixed collection pricing mechanism and discriminatory collection pricing mechanism respectively.

5.1 Fixed collection pricing mechanism

Without big data of used product quality, the manufacturer set fixed collection price to acquire used products from consumers because the quality of used products is unknown. From the perspective of consumers, the perceived value of used products is ϕ. θ is the quality of used products, which is a random variable uniformly distributed on (0, 1). The consumer handed in the used product at a fixed price *R*, which is irrelevant to the quality of used product. The net utility that consumers obtain from submitting used products is $U = R - \theta\phi$. Consumers will choose to participate in the collection if and only if the net utility of consumers participating in the recycling is non-negative, i.e., $U = R - \theta\phi \geq 0$. Given a fixed collection price *R*, only used products with quality $\theta \in [0, \frac{R}{\phi}]$ can be collected by the manufacturer. In the practice of remanufacturing, some used products' quality is too poor to be remanufactured, and the minimum quality standard is denoted by $\underline{\theta}$. Therefore, the quantity of remanufactured products is $q_r = \frac{R}{\phi} - \underline{\theta}$.

The profit of the manufacturer consists of two parts. One part comes from the production and sales of new products and the other part comes from the production and sales of remanufactured products. Based on the above model establishment and notation hypothesis, the manufacturer profit function can be expressed as follows:

$$\pi_M(q_n, \ q_r) = \left(p_n(q_n, \ q_r) - c_n\right)q_n + \left(p_r(q_n, \ q_r) - R(q_r)\right)\left(\frac{R(q_r)}{\phi} - \underline{\theta}\right) - R(q_r)\underline{\theta}$$

$$\text{s.t. } q_r \leq q_n$$

Here, $p_n(q_n,q_r) = 1 - q_n - \delta q_r$, $p_r(q_n,q_r) = \delta\left(1 - q_n - q_r\right)$ and $R\left(q_r\right) = \phi q_r$.

To simplify the analysis process, $\underline{\theta} = 0$. And we assume that $c_n \geq \frac{1-\delta}{2}$.

Proposition 1: Under the fixed collection pricing mechanism, the manufacturer takes the strategy of full remanufacturing when consumers' perceived value of used products is relatively low, i.e., $0 < \phi \leq$

$\frac{\delta(-1+\delta+2c_n)}{1-c_n}$; the manufacturer takes the strategy of partial remanufacturing when consumers' perceived value of used products is relatively high, i.e., $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$. The optimal decisions and the optimal profits of fixed collection price model are listed in Table 1.

Table 1 Optimal decisions and optimal profits of fixed collection price model

Optimal decisions (Optimal Profit)	Full remanufacturing (FFR)	Partial remanufacturing (FPR)
	$0 < \phi \le \frac{\delta(-1+\delta+2c_n)}{1-c_n}$	$\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$
q^{f*}_n	$\frac{1+\delta-c_n}{2+6\delta+2\phi}$	$\frac{1}{2}\left(1+\frac{(\delta+\phi)c_n}{(-1+\delta)\delta-\phi}\right)$
q^{f*}_r	$\frac{1+\delta-c_n}{2+6\delta+2\phi}$	$\frac{\delta c_n}{2(\delta-\delta^2+\phi)}$
p^{f*}_n	$\frac{1+(4-\delta)\delta+2\phi+(1+\delta)c_n}{2(1+3\delta+\phi)}$	$\frac{1}{2}(1+c_n)$
p^{f*}_r	$\frac{\delta(2\delta+\phi+c_n)}{1+3\delta+\phi}$	$\frac{\delta(\delta-\delta^2+\phi+\phi c_n)}{2(\delta-\delta^2+\phi)}$
π^{f*}	$\frac{(1+\delta-c_n)^2}{4(1+3\delta+\phi)}$	$\frac{1}{4}(1+c_n(-2+\frac{(\delta+\phi)c_n}{\delta-\delta^2+\phi}))$

Proof of Proposition 1:

The Hessian of the matrix of the objective function (1) is $\begin{bmatrix} -2 & -2\delta \\ -2\delta & -2\delta-\phi \end{bmatrix}$, and the leading coefficient is negative and the determinant $4(1-\delta)\delta+2\phi$ is positive. Therefore, the Hessian matrix is negative definite and the objective function is jointly concave on $(q_n,\ q_r)$.

The optimization problem can be summarized as follows:

$$Max\,\pi_M(q_n,q_r) = \big(p_n(q_n,q_r)-c_n\big)q_n + \big(p_r(q_n,q_r)-R(q_r)\big)\frac{R(q_r)}{\phi} \tag{1}$$
$$\text{s.t. } q_r \le q_n$$

The Lagrangean function is:

$$L(q_n,q_r,u) = \big(p_n(q_n,q_r)-c_n\big)q_n + \big(p_r(q_n,q_r)-R(q_r)\big)\frac{R(q_r)}{\phi} + u(q_n-q_r)$$

The Karush–Kuhn–Tucker (*KKT*) conditions of the above constrained optimization problem can be given as follows:

$$\begin{cases} \frac{\partial L}{\partial q_n} = 1+u-c_n-2q_n-2\delta q_r \\ \frac{\partial L}{\partial q_r} =-u+\delta-2\delta q_n-2(\delta+\phi)q_r \\ u \ge 0 \end{cases} \tag{2}$$

According to different values of u, the optimization problem is solved in two cases.

Case 1 ($u = 0$):

In this case, $q_n^* > q_r^*$. By solving the two equations simultaneously, the optimal quantity decisions can be obtained: $q_n^{f*} = \frac{1}{2}\left(1 + \frac{(\delta + \phi)c_n}{(-1+\delta)\delta - \phi}\right)$,$q_r^{f*} = \frac{\delta c_n}{2(\delta - \delta^2 + \phi)}$. To ensure the condition of $q_n^{f*} > q_r^{f*}$ holds, $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$ has to be satisfied. Therefore, if $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, then $q_n^{f*} = \frac{1}{2}\left(1 + \frac{(\delta + \phi)c_n}{(-1+\delta)\delta - \phi}\right)$,$q_r^{f*} = \frac{\delta c_n}{2(\delta - \delta^2 + \phi)}$ and $u = 0$.

Case 2 ($u > 0$):

In this case, $q_n^* = q_r^*$ holds if $u > 0$. To solve q_n^* and q_r^* according to equations in (2), we obtain the optimal quantity decisions: $q_n^{f*} = q_r^{f*} = \frac{1+\delta-c_n}{2+6\delta+2\phi}$, and the Lagrange multiplier $u = \frac{(-1+\delta)\delta - \phi + (2\delta+\phi)c_n}{1+3\delta+\phi}$. We find that the condition of $u > 0$ holds if $0 < \phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$. Thus, if $0 < \phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $q_n^{f*} = q_r^{f*} = \frac{1+\delta-c_n}{2+6\delta+2\phi}$ and $u > 0$.

□

Proposition 1 indicates the following managerial insights. When the perceived value of used products of consumers is relatively low ($0 < \phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$), the manufacturer takes the full remanufacturing strategy. This is consistent with the commercial practice nowadays. In this scenario, the manufacturer can pay at a lower price to collect used products from consumers, therefore the acquisition cost of collection can be lower. In this case, the manufacturer prefers to remanufacture all available used products and sell new and remanufactured products to the same market. Otherwise, in the other scenario, when the perceived value of used products of consumers is relatively high ($\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$), the manufacturer takes the partial remanufacturing strategy. In other words, if the consumers hold the opinion that the value of used products is high, the manufactures have to collect used products at a relatively higher acquisition price. Thus, the operation cost of reverse logistics increases if the manufacturer collects too many used products, and it prefers to collect and remanufacture part of the available used products. Proposition 1 illustrates that what remanufacturing strategy the manufacturer should choose in different scenarios by considering consumer factors.

Corollary 1: In the strategy of FFR, the manufacturer remanufactures all products, and there exists $\hat{c}_{nf} = 1 - \frac{\delta(1+\delta)}{1+5\delta+2\phi}$ such that $c_n > \hat{c}_n$, then $p_n^{f*} < c_n$; when $c_n \leq \hat{c}_n$, then $p_n^{f*} \geq c_n$. In the strategy of FPR, $p_n^{f*} > c_n$.

Corollary 1 demonstrates that, when the manufacturer remanufactures all products (Strategy FFR), if the production cost of new products is too high, the manufacturer will choose to decrease the selling price below the production cost to achieve more selling quantities, and collect/remanufacture more used products. On the other hand, when the production cost of new products is relatively low, the manufacturer will set the selling price above the production cost and get profits from selling new products, because low production cost leads to stronger profitability power. When the manufacturer remanufactures part of new products (Strategy FPR), the manufacturer will never set the selling price of new products below the production cost. Therefore, the production cost plays an important role in manufacturer's pricing mechanism.

Corollary 2:

(1) In the strategy of FFR, when $c_n < \frac{2-\phi}{3}$, $\frac{\partial {q^f_n}^*}{\partial \phi} = \frac{\partial {q^f_r}^*}{\partial \phi} < 0$, $\frac{\partial {q^f_n}^*}{\partial \delta} = \frac{\partial {q^f_r}^*}{\partial \delta} < 0$, $\frac{\partial {q^f_n}^*}{\partial c_n} = \frac{\partial {q^f_r}^*}{\partial c_n} < 0$; when $c_n \geq \frac{2-\phi}{3}$, $\frac{\partial {q^f_n}^*}{\partial \phi} = \frac{\partial {q^f_r}^*}{\partial \phi} < 0$, $\frac{\partial {q^f_n}^*}{\partial \delta} = \frac{\partial {q^f_r}^*}{\partial \delta} > 0$, $\frac{\partial {q^f_n}^*}{\partial c_n} = \frac{\partial {q^f_r}^*}{\partial c_n} < 0$.

(2) In the strategy of FPR, $\frac{\partial {q^f_n}^*}{\partial \phi} > 0$, $\frac{\partial {q^f_n}^*}{\partial \delta} < 0$, $\frac{\partial {q^f_n}^*}{\partial c_n} < 0$, $\frac{\partial {q^f_r}^*}{\partial \phi} < 0$, $\frac{\partial {q^f_r}^*}{\partial \delta} > 0$, $\frac{\partial {q^f_r}^*}{\partial c_n} > 0$.

Corollary 2 indicates the impact of key parameters on the quantities of new and remanufactured products. In the strategy of FFR, when the perceived value of used products is relatively high, the manufacturer always decreases the quantities of new and remanufactured products. And a higher production cost leads to the same result. However, there exists a threshold value such that the production cost c_n is lower than that, a higher discount coefficient of remanufactured product may decrease the quantities of new and remanufactured products at the same time. On the other hand, when the production cost c_n is higher than the threshold value, the increase in discount coefficient of remanufactured product makes the quantities of products larger. In the strategy of FPR, when the perceived value of used products from the perspective of consumers is higher, the quantity of new products increases, at the same time, the quantity of remanufactured products decreases. When the discount coefficient of remanufactured product is higher, the quantity of new products decreases, but the quantity of remanufactured products increases. When the production cost of new product is higher, the quantity of new products decreases, but the quantity of remanufactured products increases.

Corollary 3:

(1) In the strategy of FFR, when $c_n < \frac{(1+\delta)(1-3\delta-2\phi)}{2-\phi}$, $\frac{\partial {p^f_n}^*}{\partial \phi} > 0$, $\frac{\partial {p^f_n}^*}{\partial \delta} > 0$, $\frac{\partial {p^f_n}^*}{\partial c_n} > 0$, $\frac{\partial {p^f_r}^*}{\partial \phi} > 0$, $\frac{\partial {p^f_r}^*}{\partial \delta} > 0$, $\frac{\partial {p^f_r}^*}{\partial c_n} > 0$; when $c_n \geq \frac{(1+\delta)(1-3\delta-2\phi)}{2-\phi}$, $\frac{\partial {p^f_n}^*}{\partial \phi} > 0$, $\frac{\partial {p^f_n}^*}{\partial \delta} < 0$, $\frac{\partial {p^f_n}^*}{\partial c_n} > 0$, $\frac{\partial {p^f_r}^*}{\partial \phi} > 0$, $\frac{\partial {p^f_r}^*}{\partial \delta} > 0$, $\frac{\partial {p^f_r}^*}{\partial c_n} > 0$.

(2) In the strategy of FPR, $\frac{\partial {p^f_n}^*}{\partial \phi} = 0$, $\frac{\partial {p^f_n}^*}{\partial \delta} = 0$, $\frac{\partial {p^f_n}^*}{\partial c_n} > 0$, $\frac{\partial {p^f_r}^*}{\partial \phi} > 0$, $\frac{\partial {p^f_r}^*}{\partial \delta} > 0$, $\frac{\partial {p^f_r}^*}{\partial c_n} > 0$.

Corollary 3 focuses on the impact of key parameters on the prices of new and remanufactured products. In the strategy of FFR, a higher perceived value of used products or a higher production cost of new products, leads to higher prices of both new and remanufactured products. However, the impact of the discount coefficient of remanufactured product on the prices depends on the production cost of new products. When the production cost of new products is relatively low, a higher discount coefficient of remanufactured product leads to increased price of new products. On the contrary, when the production cost of new products is relatively high, the price of new products decreases with the discount coefficient of remanufactured product. In the strategy of FPR, the price of new products is irrespective of ϕ and δ. In other words, the price of new products is not influenced by the perceived value of used products and discount coefficient of remanufactured product, but the production cost of new products. Additionally, to increase the selling price of remanufactured products, the manufacturer should increase ϕ, c_n and δ.

Corollary 4: In the strategy of FFR, (1) $\frac{\partial \pi^{f*}}{\partial \phi} < 0$; (2) when $c_n < \frac{1}{3}(1 - 3\delta - 2\phi)$, $\frac{\partial \pi^{f*}}{\partial \delta} < 0$; when $c_n > \frac{1}{3}(1 - 3\delta - 2\phi)$, $\frac{\partial \pi^{f*}}{\partial \delta} > 0$;(3) $\frac{\partial \pi^{f*}}{\partial c_n} < 0$. In the strategy of FPR, (1) $\frac{\partial \pi^{f*}}{\partial \phi} < 0$; (2) $\frac{\partial \pi^{f*}}{\partial \delta} > 0$; (3) $\frac{\partial \pi^{f*}}{\partial c_n} < 0$.

According to Corollary 4, the relationships between parameters and profits of the manufacturer are explored. Firstly, the profit of the manufacturer is decreasing in ϕ and decreasing in c_n. In other words, the higher the perceived value of used products, the lower the profit is. In the strategy of FFR, when the production cost of new products is relatively low ($c_n < \frac{1}{3}(1 - 3\delta - 2\phi)$), the manufacturer's profit is decreasing in δ; otherwise, the manufacturer's profit is increasing in δ. This means that when the increase of discount coefficient of remanufactured product helps to increase profit in a high-cost scenario. In this scenario, the manufacturer gets the most profit when consumers value the new and remanufactured products equally. Additionally, the profit is low if the production cost of new products is relatively high. In the strategy of FPR, the manufacturer's profit is increasing in δ. When the perceived difference between new and remanufactured products from the perspective of consumers is low, the manufacturer gets a higher profit. Thus, the manufacturer has an incentive to promote the quality of remanufactured products and remove misunderstanding and discrimination among consumers.

5.2 Discriminatory collection pricing mechanism

Based on the establishment of valuation system, the quality data of used products can be acquired based on the establishment of quality inspection system, which provide quality-related big data for manufacturers. Consumers submit their used products through collection channel of manufacturers, the manufacturer evaluate the quality data of used products and set the collection price according to the quality, thus a quality-based acquisition price is provided for the consumer. In the mechanism of quality-based collection price, the net utility that consumers obtain from submitting used products is $U = R(\theta) - \theta\phi$. The acquisition price R is increasing in quality θ, which means that manufacturer pays at lower price if the quality of used products is not good after quality valuation. In this research, we use a linear form to demonstrate the mechanism, i.e., $R(\theta) = S\theta$, in which S demonstrates the price coefficient of quality and S is determined by the manufacturer. Consumers will choose to participate in the collection if and only if the net utility of consumers participating in the recycling is non-negative, i.e., $U = S\theta - \theta\phi \geq 0$. Based on the establishment of quality valuation system and big data of quality, the manufacturer possesses the quality data of used products. In this scenario, the collection market is completely transparent. Given a certain quality of used products after quality valuation, the manufacturer chooses whether to collect the used product at a certain quality by setting the price coefficient S. The manufacturer will set $S = \phi$ to grasp all of the consumer surplus on product collection. For used products whose quality is below the minimum standard of remanufacturing, the manufacturer will set a lower price coefficient to avoid these low-quality products being collected. The manufacturer will collect used products whose quality $\theta \in [\underline{\theta}, \tilde{\theta}]$, and $\tilde{\theta}$ is the upper quality limit of available used products. Therefore, the remanufacturing quantity is $q_r = \tilde{\theta} - \underline{\theta}$. The acquisition cost of quality data of used products is *T.* In this research, we don't take the initial input cost into account, because It doesn't change the key conclusions of the model.

The profit function of the manufacturer is:

$$\pi_M(q_n, \ q_r) = (p_n - c_n)q_n + (p_r - \phi\frac{\tilde{\theta}(q_r) + \underline{\theta}}{2} - T)q_r \tag{3}$$
$$\text{s.t. } q_r \le q_n$$

Here, $p_n(q_n, q_r) = 1 - q_n - \delta q_r$, $p_r(q_n, q_r) = \delta(1 - q_n - q_r)$ and $\tilde{\theta}(q_r) = q_r + \underline{\theta}$.

Proposition 2: Under the quality-based collection pricing mechanism, the manufacturer takes the strategy of full remanufacturing when the acquisition cost of quality data is relatively low, i.e., $0 < T \le \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$; the manufacturer takes the strategy of partial remanufacturing when the acquisition cost of quality data is relatively high, i.e., $T > \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$. The optimal decisions and the optimal profits of fixed collection price model are listed in Table 2.

Table 2 Optimal decisions and optimal profits of discriminatory collection price model

Optimal decisions (Optimal Profit)	Full remanufacturing (QFR)	Partial remanufacturing (QPR)
	$0 < T \le \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$	$T > \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$
q_n^{q*}	$\frac{1 - T + \delta - c_n}{2 + 6\delta + \phi}$	$\frac{1}{2}(1 - c_n) + \frac{\delta(T - \delta c_n)}{-2(-1+\delta)\delta + \phi}$
q_r^{q*}	$\frac{1 - T + \delta - c_n}{2 + 6\delta + \phi}$	$\frac{\delta c_n - T}{2(1-\delta)\delta + \phi}$
p_n^{q*}	$\frac{1 + (4-\delta)\delta + T(1+\delta) + \phi + (1+\delta)c_n}{2 + 6\delta + \phi}$	$\frac{1}{2}(1 + c_n)$
p_r^{q*}	$\frac{\delta(2T + 4\delta + \phi + 2c_n)}{2 + 6\delta + \phi}$	$\frac{\delta(2(1-\delta)(T+\delta) + \phi + \phi c_n)}{4(1-\delta)\delta + 2\phi}$
π^{q*}	$\frac{(1 - T + \delta - c_n)^2}{2(2 + 6\delta + \phi)}$	$\frac{-2T^2 + 2(-1+\delta)\delta - \phi + c_n(4(1 + T - \delta)\delta + 2\phi - (2\delta + \phi)c_n)}{8(-1+\delta)\delta - 4\phi}$

Proof of Proposition 2:

The Hessian of the matrix of the objective function (1) is $\begin{bmatrix} -2 & -2\delta \\ -2\delta & -2\delta - \phi \end{bmatrix}$, and the leading coefficient is negative and the determinant $4(1-\delta)\delta + 2\phi$ is positive. Therefore, the Hessian matrix is negative definite and the objective function is jointly concave on $(q_n, \ q_r)$.

The optimization problem can be summarized as follows:

$$Max\, \pi_M(q_n,q_r) = (p_n - c_n)q_n + (p_r - \frac{\phi}{2}(\tilde{\theta}(q_r) + \underline{\theta}) - T)q_r \tag{4}$$

$$\text{s.t. } q_r \le q_n$$

The Lagrangean function is:

$$L(q_n,q_r,u) = (p_n - c_n)q_n + (p_r - \frac{\phi}{2}(q_r + 2\underline{\theta}) - T)q_r + u(q_n - q_r)$$

The Karush–Kuhn–Tucker (*KKT*) conditions of the above constrained optimization problem can be given as follows:

$$\begin{cases} \frac{\partial L}{\partial q_n} = 1 + u - c_n - 2q_n - 2\delta q_r \\ \frac{\partial L}{\partial q_r} = - T - u + \delta - 2\delta q_n - (2\delta + \phi)q_r \\ u \ge 0 \end{cases} \tag{5}$$

According to different values of u, the optimization problem is solved in two cases.

Case 1 ($u = 0$):

In this case, $q_n^* > q_r^*$. By solving the two equations simultaneously, the optimal quantity decisions can be obtained: $q_n^{q*} = \frac{1}{2}(1 - c_n) + \frac{\delta(T - \delta c_n)}{-2(-1+\delta)\delta + \phi}$, $q_r^{q*} = \frac{\delta c_n - T}{2(1-\delta)\delta + \phi}$. To ensure the condition of $q_n^* > q_r^*$ holds, $T > \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$ has to be satisfied. Therefore, if $T > \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$, then $q_n^{q*} = \frac{1}{2}(1 - c_n) + \frac{\delta(T - \delta c_n)}{-2(-1+\delta)\delta + \phi}$, $q_r^{q*} = \frac{\delta c_n - T}{2(1-\delta)\delta + \phi}$ and $u = 0$.

Case 2 ($u > 0$):

In this case, $q_n^{q*} = q_r^{q*}$ holds if $u > 0$. To solve q_n^* and q_r^* according to equations in (4), we obtain the optimal quantity decisions: $q_n^{q*} = q_r^{q*} = \frac{1 - T + \delta - c_n}{2 + 6\delta + \phi}$, and the Lagrange multiplier $u = -1 + c_n - \frac{2(1+\delta)(-1 + T - \delta + c_n)}{2 + 6\delta + \phi}$. We find that the condition of $u > 0$ holds if $0 < T \le \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$. Thus, if $0 < T \le \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$, $q_n^{q*} = q_r^{q*} = \frac{1 - T + \delta - c_n}{2 + 6\delta + \phi}$ and $u > 0$.

□

When the acquisition cost of quality data is relatively low ($0 < T \le \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$), the manufacturer takes the full remanufacturing strategy. If the cost of information acquisition is low, the manufacturer can master the accurate information and set acquisition price discriminatorily based on the conditions of used products relatively easily. In this case, the full remanufacturing strategy is carried out because the manufacturer can get more profit from remanufacturing and save cost from acquisition process in the discriminatory collection pricing mechanism. In the other case, when the acquisition cost of quality data is relatively high ($T > \frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}$), the manufacturer takes the partial remanufacturing strategy. Because the acquisition cost of data based on the big data system is high, which leads to increase the collection cost of used products on the whole. The acquisition cost of data may even influence the efficiency of reverse logistics of manufacturing–remanufacturing operations, and high acquisition cost cannot counteract the saved cost of remanufacturing. Thus, collecting and remanufacturing too many used products may harm the profit of the manufacturer's profit. In this scenario, to maximize the operation profit, the manufacturer recovers some of the used products according to demand for remanufacturing. The new and remanufactured products are then sold to the same market, which means that a competition exists between new and remanufactured products.

Corollary 4: In the strategy of QFR, the manufacturer remanufactures all products, and there exists $\hat{c}_{nq} = \frac{1 + T + 4\delta + T\delta - \delta^2 + \phi}{1 + 5\delta + \phi}$ such that $c_n > \hat{c}_{nq}$, then $p^{q\,*}_n < c_n$; when $c_n \leq \hat{c}_{nq}$, then $p^{q\,*}_n \geq c_n$. And, $\hat{c}_{nq} < \hat{c}_{nf}$ if $\mathrm{T} \leq \min\{\frac{2(-1+\delta)\delta - \phi + (4\delta + \phi)c_n}{2(1+\delta)}, \frac{\delta\phi}{1 + 5\delta + 2\phi}\}$, elsewise, $\hat{c}_{nq} > \hat{c}_{nf}$. In the strategy of QPR, $p^{q\,*}_n > c_n$.

Similar to Corollary 1 in the fixed collection pricing mechanism, Corollary 4 demonstrates that when Strategy QFR is carried out by the manufacturer, in a certain circumstance ($c_n > \hat{c}_{nq}$), the manufacturer will choose to decrease the selling price below the production cost to achieve more selling quantities of both new and remanufactured products. When the production cost of new products is relatively low, the manufacturer will set the selling price above the production cost and get profits from selling new products. When Strategy QPR is carried out by the manufacturer, the selling price of new products is above the production cost. Compared to the fixed collection pricing mechanism, the relationship between threshold values of $\hat{c}_{nq}$, $\hat{c}_{nf}$ depends on the value of acquisition cost of big data, *T*. When the acquisition cost of big data is relatively low, the threshold value in the discriminatory pricing mechanism is higher than that in the fixed collection pricing mechanism. On the contrary, the threshold value in the discriminatory pricing mechanism is lower than that in the fixed collection pricing mechanism if the acquisition cost of big data is relatively high.

Corollary 5: In the strategy of QFR, $\frac{\partial q^{q\,*}_n}{\partial T} = \frac{\partial q^{q\,*}_r}{\partial T} < 0$, $\frac{\partial p^{q\,*}_n}{\partial T} > 0$, $\frac{\partial p^{q\,*}_r}{\partial T} > 0$, $\frac{\partial \pi^{q\,*}}{\partial T} < 0$; In the strategy of QPR, $\frac{\partial q^{q\,*}_n}{\partial T} > 0$, $\frac{\partial q^{q\,*}_r}{\partial T} < 0$, $\frac{\partial p^{q\,*}_n}{\partial T} = 0$, $\frac{\partial p^{q\,*}_r}{\partial T} > 0$, $\frac{\partial \pi^{q\,*}}{\partial T} < 0$.

Corollary 5 demonstrates the impact of the acquisition cost of big data on the price and quantity of new and remanufactured products in the discriminatory collection pricing mechanism. In the strategy of QFR, the prices of both new and remanufactured product are decreasing in *T*, and the quantity of both new and remanufactured product are increasing in *T*. That means, based on the establishment of big data system for used product management, a higher operation cost *T* of big data system may decrease the selling quantity of products, make the both prices higher and decrease the profit accordingly. However, in the strategy of QPR, when the operation cost *T* of big data system is high, the manufacturer always sets a larger quantity for new products, a smaller quantity and a higher price for remanufactured products. Additionally, the price of new products is irrelevant to the operation cost of big data system. On the whole, the manufacturer's profit decreases with *T*. Therefore, the manufacturer should try its best to lower the acquisition cost of data from the big data system, including optimizing the process and increasing the efficiency.

Corollary 6: In the strategy of QFR, (1) $\frac{\partial {q^q_n}^*}{\partial \phi} = \frac{\partial {q^q_r}^*}{\partial \phi} < 0$; (2) when $c_n < \frac{1}{6}(4 - \phi - 6T)$, $\frac{\partial {q^q_n}^*}{\partial \delta} = \frac{\partial {q^q_r}^*}{\partial \delta} < 0$; when $c_n > \frac{1}{6}(4 - \phi - 6T)$, $\frac{\partial {q^q_n}^*}{\partial \delta} = \frac{\partial {q^q_r}^*}{\partial \delta} > 0$; (3) $\frac{\partial {q^q_n}^*}{\partial c_n} = \frac{\partial {q^q_r}^*}{\partial c_n} < 0$. In the strategy of QPR, (1) $\frac{\partial {q^q_n}^*}{\partial \phi} > 0$, $\frac{\partial {q^q_r}^*}{\partial \phi} < 0$; (2) when $c_n < \frac{2\delta(\delta + \phi)T}{2\delta^2 + \phi}$, $\frac{\partial {q^q_n}^*}{\partial \delta} < 0$; when $c_n \geq \frac{2\delta(\delta + \phi)T}{2\delta^2 + \phi}$, $\frac{\partial {q^q_n}^*}{\partial \delta} \geq 0$; (3) $\frac{\partial {q^q_n}^*}{\partial c_n} < 0$; (4) when $\delta < \frac{1}{2}$, $\frac{\partial {q^q_r}^*}{\partial \delta} > 0$; when $\delta > \frac{1}{2}$ and $c_n < \frac{(2\delta^2 + \phi)T}{4\delta - 2}$, $\frac{\partial {q^q_r}^*}{\partial \delta} > 0$; when $\delta > \frac{1}{2}$ and $c_n > \frac{(2\delta^2 + \phi)T}{4\delta - 2}$, $\frac{\partial {q^q_r}^*}{\partial \delta} < 0$; (5) $\frac{\partial {q^q_r}^*}{\partial c_n} > 0$.

Corollary 6 indicates the monotonicity of key parameters on the quantities of new and remanufactured products. Most of the managerial insights of Corollary 6 is similar to Corollary 2 in the fixed collection pricing mechanism. In the strategy of both QFR and QPR, the quantities of both new and remanufactured products are decreasing in ϕ. In the strategy of QFR, both the quantities of new and remanufactured products are decreasing in c_n. In the strategy of QPR, the quantity of new products is decreasing in c_n, but the quantity of remanufactured products is increasing in c_n. In the strategy of QFR, there exists a threshold value such those that when the production cost is lower than the threshold value, the quantity of both new products is decreasing in δ; when the production cost is higher than the threshold value, the quantities of both new and remanufactured products are increasing in δ. In the strategy of QPR, when both the production cost and the discount coefficient of remanufactured product are relatively high, the quantity of remanufactured products is increasing in δ.

Corollary 7:

In the strategy of QFR, (1) when $c_n < 1 + \delta - T$, $\frac{\partial {p^q_n}^*}{\partial \phi} > 0$, $\frac{\partial {p^q_r}^*}{\partial \phi} > 0$; when $c_n > 1 + \delta - T$, $\frac{\partial {p^q_n}^*}{\partial \phi} < 0$, $\frac{\partial {p^q_r}^*}{\partial \phi} < 0$; (2) when $c_n < \frac{2(1 + \delta)(-1 + 3\delta + \phi)}{-4 + \phi} - T$, $\frac{\partial {p^q_n}^*}{\partial \delta} > 0$; when $c_n > \frac{2(1 + \delta)(-1 + 3\delta + \phi)}{-4 + \phi} - T$, $\frac{\partial {p^q_n}^*}{\partial \delta} < 0$; (3) $\frac{\partial {p^q_n}^*}{\partial c_n} > 0$; (4) $\frac{\partial {p^q_r}^*}{\partial \delta} > 0$; (5) $\frac{\partial {p^q_r}^*}{\partial c_n} > 0$. In the strategy of FPR, (1) $\frac{\partial {p^q_n}^*}{\partial \phi} = 0$; (2) $\frac{\partial {p^q_n}^*}{\partial \delta} = 0$; (3) $\frac{\partial {p^q_n}^*}{\partial c_n} > 0$; (4) $\frac{\partial {p^q_r}^*}{\partial \phi} > 0$; (5) $\frac{\partial {p^q_r}^*}{\partial c_n} > 0$.

Corollary 7 shows that, in the strategy of QFR, when the production cost of new products is relatively low, the prices of new and remanufactured products are increasing in ϕ. That means, when consumers' perceived value of used products is high, the manufacturer always set high price for both new and remanufactured products. Otherwise, the prices of the above two products are decreasing in ϕ. In addition, there exists another threshold of c_n, such that when $c_n < \frac{2(1 + \delta)(-1 + 3\delta + \phi)}{-4 + \phi} - T$, with δ increasing, the price of new products is higher; when c_n is above the threshold, the price of new products is decreasing in c_n. And the monotonicity of the relevant key variables on prices in the discriminatory collection pricing mechanism is similar to that in the fixed pricing mechanism (Corollary 3). In the strategy of FPR, the price of new products is irrespective of ϕ and δ. And the selling price of new and remanufactured products are increasing in ϕ and c_n.

6. Analysis

Based on the above modeling and the corresponding optimal decisions, we compare the two acquisition pricing mechanisms in this section. Specifically, we provide the comparison of quantity and price of new and remanufactured products, profit and environment impact of the two acquisition pricing mechanisms, include fixed collection pricing mechanism and discriminatory collection pricing mechanism.

Firstly, we compare the quantity and price of new and remanufactured products between the two cases: fixed collection pricing mechanism and discriminatory collection pricing mechanism.

Proposition 3: The optimal decisions of quantities of new and remanufactured products q^{f*}_n, q^{q*}_n, q^{f*}_r, q^{q*}_r satisfy the following relationships:

(1) When $T > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, if $\phi \le \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, $q^{f*}_n > q^{q*}_n$, $q^{f*}_r > q^{q*}_r$; if $\phi > \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, $q^{f*}_n < q^{q*}_n$, $q^{f*}_r < q^{q*}_r$.

(2) When $T < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, if $\phi \le \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $q^{f*}_n < q^{q*}_n$, $q^{f*}_r < q^{q*}_r$; if $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $q^{f*}_n > q^{q*}_n$, $q^{f*}_r > q^{q*}_r$.

Proof of Proposition 3:

Firstly, we compare the two threshold values of ϕ in the two acquisition pricing mechanisms.

$$\frac{\delta(-1+\delta+2c_n)}{1-c_n} \gtrless \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$$

$$\Leftrightarrow \qquad T \lesseqgtr \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$$

Case 1: When $T > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$,

1) If $\phi \le \frac{\delta(-1+\delta+2c_n)}{1-c_n}$,

when $T < \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$, $q^{f*}_n < q^{q*}_n$; when $T > \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$, $q^{f*}_n > q^{q*}_n$. Because $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} > \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$, the only scenario in this case is $q^{f*}_n < q^{q*}_n$ if and if only $T > \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$.

2) If $\frac{\delta(-1+\delta+2c_n)}{1-c_n} < \phi \le \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$,

when $T < \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f*}_n < q^{q*}_n$; when $T > \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f*}_n > q^{q*}_n$. Because $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} > \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f*}_n > q^{q*}_n$ holds when $T >$

$\frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$.

3) If $\phi > \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$,

when $\mathrm{T} < \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$; when $\mathrm{T} > \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$. When $\mathrm{T} > \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$, as $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} > \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$.

Case 2: When $\mathrm{T} \le \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$,

1) If $\phi \le \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$,

when $\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$; when $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$. Because $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, the only scenario in this case is $q^{f\,*}_{n} > q^{q\,*}_{n}$ if and if only $\mathrm{T} \le \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$.

2) If $\frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n} < \phi \le \frac{\delta(-1+\delta+2c_n)}{1-c_n}$,

when $\mathrm{T} < \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f\,*}_{n} < q^{q\,*}_{n}$; when $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} < T < \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f\,*}_{n} < q^{q\,*}_{n}$, when $\mathrm{T} > \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f\,*}_{n} > q^{q\,*}_{n}$. Because $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} < \frac{1}{2}(-4\delta-\phi-\frac{(8\delta^2+7\delta\phi+\phi^2)c_n}{(-1+\delta)\delta-\phi})$, $q^{f\,*}_{n} < q^{q\,*}_{n}$ holds when $\mathrm{T} \le \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$.

3) If $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$,

when $\mathrm{T} < \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$; when $\mathrm{T} > \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$. When $\mathrm{T} \le \frac{\phi(1+\delta-c_n)}{2(1+3\delta+\phi)}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$, as $\frac{\delta(-1+\delta+2c_n)}{2(1+\delta)} < \frac{\delta\phi c_n}{2(\delta-\delta^2+\phi)}$.

The analysis of the quantity of remanufactured products is similar. Therefore, we can obtain the following results.

When $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$,

If $\phi \le \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$, $q^{f\,*}_{r} > q^{q\,*}_{r}$;

If $\phi > \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, when $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$, $q^{f\,*}_{r} < q^{q\,*}_{r}$.

When $\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$,

If $\phi \le \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $q^{f\,*}_{n} < q^{q\,*}_{n}$, $q^{f\,*}_{r} < q^{q\,*}_{r}$;

If $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $q^{f\,*}_{n} > q^{q\,*}_{n}$, $q^{f\,*}_{r} > q^{q\,*}_{r}$.

□

Proposition 3 indicates the quantity relationships of new and remanufactured products under two collection pricing mechanisms. When the acquisition cost of big data is relatively high ($\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$), the quantities of both new and remanufactured products in the fixed collection pricing mechanism are higher than those in the discriminatory collection pricing mechanism in the case of low-perceived-value of used products from the perspective of consumers. In this case, fixed collection pricing strategy is advantageous in selling quantities. On the other hand, high-perceived-value, the quantities of both new and remanufactured products in the fixed collection pricing mechanism are higher than those in the discriminatory collection pricing mechanism. When the acquisition cost of big data is relatively low ($\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$), in other words, it is relatively easy to get quality big of used products from big data system, lower perceived value always leads to higher quantities of products in the discriminatory collection pricing mechanism, and higher perceived value always leads to lower quantities of products in the discriminatory collection pricing mechanism.

In the following, we compare the prices of new products under two collection pricing mechanisms.

Proposition 4: When $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, ${p^f_n}^* > {p^q_n}^*$; If $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, ${p^f_n}^* = {p^q_n}^*$. When $\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}$, ${p^f_n}^* < {p^q_n}^*$; If $\phi > \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}$, ${p^f_n}^* = {p^q_n}^*$.

Focusing on the price of new products, Proposition 4 compares the price of new products under the two collection pricing mechanisms. When the operational cost of the big data system is relatively high, consumers' low perceived value of used products makes the price of new products in the fixed collection pricing mechanism higher than that in the case of discriminatory pricing. In this scenario, if the manufacturer wants to sell more new products, it should choose the fixed collection pricing mechanism and give up the establishment of big data system. However, when it costs relatively little to get quality data of used products ($\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$), the new product price in the discriminatory collection pricing mechanism is higher if consumers' perceived value of used products is low ($\phi \leq \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}$). In this scenario, if the manufacturer wants to sell more new products, it should choose the discriminatory collection pricing mechanism and give up the establishment of big data system. If the perceived value of used products is high enough, the prices of new prices are equal in the two mechanisms, in other words, it has no effect on the price of new products.

Proposition 5: When $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}$, ${p^f_r}^* < {p^q_r}^*$; If $\phi > \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}$, ${p^f_r}^* > {p^q_r}^*$. When $\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, ${p^f_r}^* > {p^q_r}^*$; If $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, ${p^f_r}^* < {p^q_r}^*$.

Proposition 5 indicates the relationships between different remanufactured products prices under two collection pricing mechanisms. Specifically, the price relationships are dependent on the acquisition cost of big data T and the consumers' perceived value of used products ϕ. When both the acquisition cost of big data T and the consumers' perceived value of used products ϕ are relatively high or extremely low, the price of remanufactured products in the fixed collection pricing mechanism is higher than that in the discriminatory collection pricing mechanism. However, if the acquisition cost of big data is relatively high but consumers' perceived value of used products is low, or the acquisition cost of big data is relatively low but consumers' perceived value of used products is high, the price of remanufactured products in the fixed collection pricing mechanism is lower than that in the discriminatory collection pricing mechanism.

Proposition 6:

When $\phi \le \min\{\frac{\delta(-1+\delta+2c_n)}{1-c_n}, \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}\}$, the manufacturer should choose the strategy of discriminatory collection price if $c_n < 1+\delta-T\sqrt{\frac{2+6\delta+2\phi}{\phi}}$; and it should choose the strategy of fixed collection pricing if $c_n \ge 1+\delta-T\sqrt{\frac{2+6\delta+2\phi}{\phi}}$. When $\phi > \max\{\frac{\delta(-1+\delta+2c_n)}{1-c_n}, \frac{2(\delta^2+2\delta c_n-T-\delta-T\delta)}{1-c_n}\}$, the manufacturer should choose the strategy of fixed collection pricing if $c_n < \frac{2T(\delta-\delta^2+\phi)+T\sqrt{2(2(1-\delta)^2\delta^2+3(1-\delta)\delta\phi+\phi^2)}}{\delta\phi}$, and it should choose the strategy of discriminatory collection price if $c_n > \frac{2T(\delta-\delta^2+\phi)+T\sqrt{2(2(1-\delta)^2\delta^2+3(1-\delta)\delta\phi+\phi^2)}}{\delta\phi}$.

To maximize the profit, the manufacturer will choose the strategy which can get more profit when making the collection pricing mechanism decisions. According to Proposition 6, the pricing mechanism preferences of the manufacturer depends on both the value of the production cost of new products and consumers' perceived value of used products. When the perceived value ϕ is relatively high, if the production cost of new products is relatively low, in other words, the production cost difference between new and remanufactured products is unconspicuous, the discriminatory collection pricing mechanism is more profitable from the perspective of the manufacturer. On the other hand, when the production cost of new products is relatively high, the manufacturer will prefer to choose fixed pricing mechanism because it aims to get more profit from the remanufacturing. On the other hand, the managerial insight in the high-perceived-value case is opposite. Therefore, from the perspective of the manufacturer, when the product cost of new products is relatively, the collection pricing mechanism choice depends on the characteristics of consumers. When the perceived value of consumers in some certain area is high, the manufacturer should choose fixed collection pricing mechanism; when the perceive value is low, the discriminatory collection pricing mechanism is a better strategy. That is an important conclusion for manufacturers to choose the collect pricing strategy. Two kinds of products are appropriate to set collection price based on quality: high-cost and high-evaluation, low-cost and low-evaluation,

And then, besides the economic benefit, we will analyze the influence of big data system on the environment. From the perspective of the environment, the environment negative impacts of new and remanufactured products are different, and new products' environment impact is higher. Because producing new products costs more materials and release more hazardous substances to the environment, remanufactured products are much more environment-friendly compared to new products. To measure the environmental performance of producing and using products, the environmental impact of new products is expressed as $E_n = mq_n$, and the environmental impact of new products is negligible. To simplify the analysis, we assume that $m = 1$. Proposition 7 can be obtained as follows.

Proposition 7:

When $\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, the environment impact $E^f > E^q$; If $\phi > \frac{2(T+\delta+T\delta-\delta^2-2\delta c_n)}{-1+c_n}$, $E^f < E^q$. When $\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$, If $\phi \leq \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $E^f < E^q$; If $\phi > \frac{\delta(-1+\delta+2c_n)}{1-c_n}$, $E^f > E^q$.

Based on Proposition 7, we can obtain the following managerial insights. When the acquisition cost of big data is relatively high ($\mathrm{T} > \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$), the environmental impact of the fixed collection pricing mechanism is higher than the discriminatory collection pricing mechanism in the case of low-perceived-value of used products from the perspective of consumers. On the other hand, high-perceived-value, the environmental impact of the fixed collection pricing mechanism are higher than that in the discriminatory collection pricing mechanism. When the acquisition cost of big data is relatively low ($\mathrm{T} < \frac{\delta(-1+\delta+2c_n)}{2(1+\delta)}$), lower perceived value always leads to larger environmental impact in the discriminatory collection pricing mechanism, and higher perceived value always leads to lower environmental impact in the discriminatory collection pricing mechanism. From the above results, the fixed collection pricing mechanism is more environment-friendly when both T and ϕ are high or low. In these scenarios, the manufacturer may choose the fixed collection pricing mechanism to maximize the environment performance to improve the brand image. Otherwise, in other scenarios, the discriminatory collection pricing mechanism is a more environment-friendly strategy. This is a counter-intuitive conclusion that quality-based pricing within big data system is not always good for the environment.

7. Conclusions

Our research investigates the optimal manufacturing and remanufacturing decisions of a manufacturer, which provide new and remanufactured products to the same market. This paper studies a firm which produces new products and remanufactures the returned products, and sells two kinds of products to the same market. We focus on quantity decisions on manufacturers' manufacturing/remanufacturing operations. Focusing on the availability of big data of used products, two optimization models, fixed collection pricing mechanism and discriminatory collection pricing mechanism, are analyzed to explore the impact of quality big data of used products on firms' manufacturing–remanufacturing operations. Our theoretical research provides some managerial insights on three questions about manufacturers' manufacturing/remanufacturing operations as follows.

1) *With/without big data of used product quality, how should the manufacturer control the quantity*

of new and remanufactured products to maximize its profit respectively? In both fixed and discriminatory collection pricing mechanisms, the manufacturer takes full/partial remanufacturing strategy under different conditions. Without big data of used product quality, i.e., in the fixed collection pricing mechanism, when the perceived value of used products of consumers is relatively low, the manufacturer takes the full remanufacturing strategy. When the perceived value of used products of consumers is relatively high, the manufacturer takes the partial remanufacturing strategy. With big data of used product quality, i.e., in the discriminatory collection pricing mechanism, when the acquisition cost of quality data is relatively low, the manufacturer takes the full remanufacturing strategy. On the other hand, when the acquisition cost of quality data is relatively high, the manufacturer takes the partial remanufacturing strategy.

2) *From the perspective of manufacturers which carry out remanufacturing, is it necessary to choose quality-based pricing strategy to collect used product based on a big data system?* And the manufacturer prefers different strategies on big data system according to various level of consumers' perceived value of used products and the acquisition cost of big data. If the production cost of new products is relatively low, the fixed collection pricing mechanism is more profitable from the perspective of the manufacturer. On the other hand, when the production cost of new products is relatively high, the manufacturer will prefer to establish a big data system to choose discriminatory pricing mechanism because it aims to get more profit from the remanufacturing.
3) *From the perspective of the environment, is the application of big data system of used product quality beneficial to the environment?* Besides the economic performance of the pricing mechanisms, this paper explores the environmental impact of them, too. Specifically, the relative superiority of environmental impact of two collection pricing mechanisms depends on different consumers' perceived value of used products and the acquisition cost of big data. When the acquisition cost of big data is relatively high, the environmental impact of the fixed collection pricing mechanism is higher than the discriminatory collection pricing mechanism in the case of low-perceived-value of used products from the perspective of consumers. On the other hand, high-perceived-value, the environmental impact of the fixed collection pricing mechanism is higher than that in the discriminatory collection pricing mechanism. When the acquisition cost of big data is relatively low, lower perceived value always leads to larger environmental impact in the discriminatory collection pricing mechanism, and higher perceived value always leads to lower environmental impact in the discriminatory collection pricing mechanism.

This study can be extended in the following aspects in the future research. Firstly, in this research, we assume that the remanufacturing cost of used products whose quality is above a certain standard is the same. In the future study, we can consider the different remanufacturing cost among used products in various quality. Secondly, we assume that consumers in the market are homogeneous in their perceived value difference between new and remanufactured products. However, in today's market, consumers usually have different awareness, acceptance and willingness levels towards remanufactured products. In the future study, the perceived value difference of consumers can be considered to make the research model more realistic. Thirdly, we can expand this research problem into multi-period model and explore the decisions in different phases of production and remanufacturing. Fourthly, we can study the case in which the manufacturer collects not only its own products, but also products in other brands for remanufacturing. Last but not least, the research model can be studied in the context of supply chain. The manufacturer can sell the new and remanufactured products through a supply chain, or even dual-channel supply chain. The research problem can be analysed in a more comprehensive way. Additionally, some more characteristics of consumers can be further considered based on our model. This research problem will then be more consistent with reality.

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