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Research Article

Equilibrium Analysis of Price Discrimination Economic Phenomenon Based on Big Data Monitoring of Netizen Sensors

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With the wide application of sensors, people's behavior in life has been transformed into data resources. The emergence of big data can more effectively deal with a large amount of information generated. Network big data is increasingly applied to the analysis of economic problems. By analyzing the common phenomenon of price discrimination in life, we can better solve the differences between buyers and sellers. Because both businesses care about the number of vested interests, it is necessary to find a way to balance the two psychologically. Sellers feel that they have made a profit, while buyers feel that they have not lost, and then they will feel that this is a fair deal. In fact, this is not absolutely fair, only their own ideas. The main purpose of this paper is to analyze the economic phenomenon of price discrimination. On this basis, this paper proposes to use the combination of big data that netizens pay attention to and network sensors to detect price changes under the background of big data. Through the analysis of the collected sample data and related economic models, the experimental data show that when $p > v$, if buyers choose to trade at this time, they will bring negative material returns to themselves. There was a significant negative correlation between second-class buyers and whether they accepted the transaction ($P < 0.01$). In the case of bringing negative material returns to themselves, vulnerable buyers are more likely to choose to refuse the transaction.

1. Introduction

Affected by the rapid development of computer technology, people have gradually entered the era of big data, and they have become more comfortable with the collection of current real-time data. Data resources have also received more and more attention from various companies, and they have become more and more closely related to people's lives. Data come from life and are also used in life. With the support of computer technology, new technologies such as big data ushered in a period of vigorous development, which also affected many industrial business models. Affected by this, the traditional industrial operation has undergone tremendous changes, and the manufacturing industry is developing in the direction of networking, digitization, and intelligence. The telecommunications, financial, and other industries are actively exploring applications such as customer segmentation, risk prevention, and control, using the accumulated rich data resources, and accelerating the pace of service optimization, business innovation, and industrial upgrading, effectively enhancing the productivity of society. Through the role of various types of sensors, every choice or behavior of people is transformed into a large number of data resources. These data resources are huge and messy. Through big data algorithms, data-to-behavior conversion can be realized. By using big data algorithms, operators can effectively and accurately predict user behaviors in order to provide customized goods and services. The value of the goods is effectively reflected, and the positioning of the value of the goods is more in line with customers' expectations. In today's era of pursuit of speed and convenience, reasonable classification and analysis of collected data samples, predictions using their relevance, and analysis of discriminatory treatment of certain commodity prices are one of the results of the use of big data algorithms.

In the past, the theory of price discrimination mainly focused on consumer surplus. It measures the extra utility that consumers get from the purchase of an item in excess of

what they pay for. With the rapid development of information technology represented by the Internet, the economic development of various countries in the world is closely related to information technology represented by computers. The analysis of the economic phenomenon of price discrimination based on computer information technology proposed in this article is helpful for sellers to better understand the various behaviors of customer groups in the face of price discrimination, when selling goods. Through the implementation of price discrimination, we explored and worked out how to make the most profitable pricing mechanism for businesses. From the perspective of producers and consumption benefits, price-discriminatory pricing has a positive impact on the social environment [1].

In today's prosperous period of computer technology, the economy is growing rapidly under the background of big data, and price discrimination is also affected by big data. In this regard, the research on price discrimination based on sensor technology has also become the focus of attention of domestic and foreign scholars. Zhu J proposed a principal component analysis method of distributed parallel design, which can build statistical modeling of large-scale processes with big data. Song L proposes a duopoly model by integrating the key features of secondary price discrimination and vertical differentiation: higher-quality companies compete with lower-quality companies, selling both basic products and additional products. The model shows that when the company differentiates vertically, add-ons play different roles. Then, it demonstrates the profit impact of the equilibrium policy by comparing the equilibrium policy with the outcome of the expansion game that allows the company to have a commitment. The results show that although the optional additional policy is unilaterally optimal, there is a dilemma, in which both companies lose their equilibrium profits [2]. Due to the importance of WSN security, researchers have developed new and effective technologies in different security schemes and protocols (such as user authentication schemes), and proposed a new wireless sensor network based on the Internet of Things for users authentication scheme. This scheme proposes a new method, and through the communication with the gateway, the Internet of things users can pass the WSN sensor node to carry on the identity verification. Bayat M proposes an enhanced scheme to eliminate the security loopholes of the scheme. This introduced provable security to their scheme and demonstrated its formal security analysis through ProVerif [3]. Chen studied the welfare impact of input price discrimination in a vertically related market, which consists of a monopoly upstream market and a duopoly downstream market. The downstream duopoly produces products with different quality at different marginal costs. Chen showed that equilibrium input prices are closely related to downstream quality gaps and cost differences. When a monopolist only charges a unit wholesale price for its input products, even if the total output remains the same, discriminatory pricing may be what society wants. Nevertheless, if two-part tariffs are feasible, then prohibiting price discrimination can increase total output and social welfare [4]. Many people believe that personalized pricing is unfair or manipulative.

Borgesius F Z analyzed how this aversion to personalized pricing is related to economic analysis and other norms or values. Next, he studied whether European data protection laws apply to personalized pricing. If personal data is processed, data protection laws apply, which is usually the case when prices are considered to be personalized. Data protection laws require companies to be transparent about the purpose of personal data processing, which means that if they personalize prices, they must notify customers [5]. The above-mentioned scholars have a certain subjective awareness of the relevant research on the phenomenon of price discrimination based on sensor big data, which cannot represent all groups, and relevant research requires a large amount of data and a large amount of calculation. Through the research method of sensor big data, there are no representative research results.

2. Sensor Big Data Monitoring System Based on Analysis of Price Discrimination Phenomenon

2.1. Sensor Network System.
Now is the information age of the new century. People are most concerned about how to obtain valuable information conveniently and quickly. Wireless sensors are based on self-organizing management of a large number of sensor nodes, which can easily collect physical information and convert it into data resources. The wireless sensor network has been widely used in various fields with its own advantages and characteristics. The main principle of its work is that the sensor nodes work through wireless communication. The sensor node has certain processing and wireless communication capabilities, and integrates a variety of sensors.

2.1.1. The Network Structure of the Sensor.
Wireless sensor technology involves a wide range of knowledge points from multiple disciplines [6]. The network system structure is shown in Figure 1.

As shown in Figure 1, the sensor is equipped with a large number of processors and network nodes to process data information in multiple locations. Among them, there are mainly two types of nodes, namely Sink nodes and ordinary nodes [7]. The former can be used as a gateway to transmit collected data samples to complete the task of communicating with the outside world; internally, it can efficiently manage and maintain data [8].

2.1.2. Hardware Structure of Wireless Network Sensor.
As shown in Figure 2, the nodes in the sensor include the above three methods, that is, one of them is the sensing part responsible for data collection and conversion tasks [9]; the second is responsible for controlling the microprocessor part of all nodes and running the corresponding wireless network protocol [10]; the third is responsible for data information exchange and the communication part of communicating with other nodes [11]; that is, the node power supply does not depend on the wired power supply, which reflects its low power consumption characteristics [12].
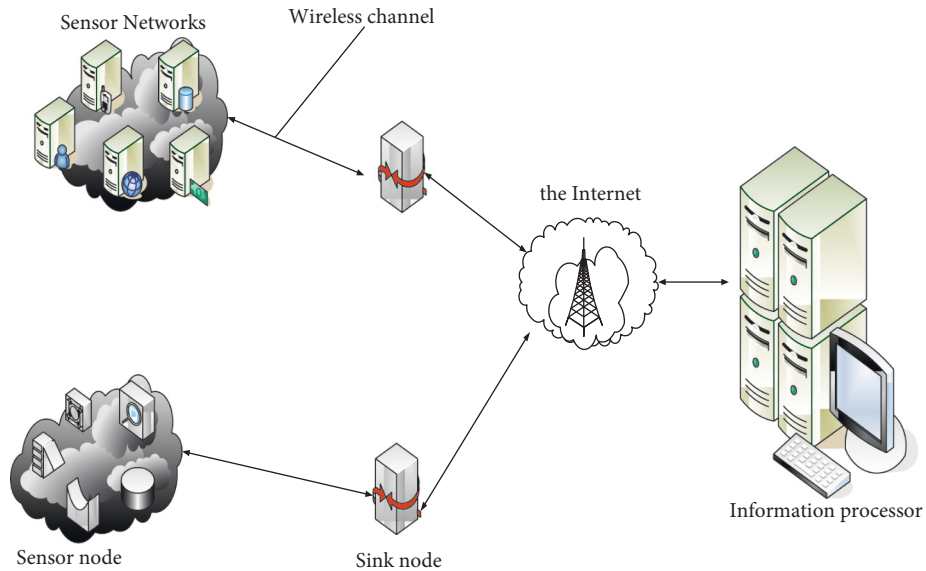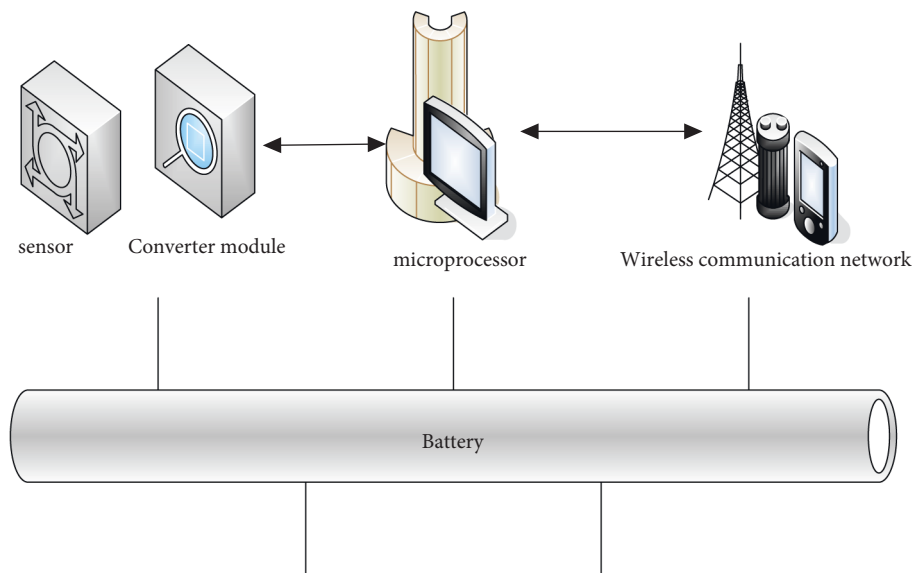
FIGURE 1: Sensor network structure.

FIGURE 2: Hardware structure of wireless sensor node.

Big data has the characteristics of "large amount," "multisource," "complex," "heterogeneous," "dynamic," and "high value but low-value density" [13]. The main purpose of the big data monitoring and analysis system is to realize the collection, storage, processing, analysis, and display of information [14]. Big data analysis mainly includes two aspects: data mining and data visualization analysis. Big data analysis technology can effectively reduce consumers' consumption of excessive time and energy due to information flooding. The manifestation of big data analysis results can assist consumers in making more scientific and effective decisions during consumption and avoid risks. The software structure is shown in Figure 3.

2.2. Sellers Based on Sensor Big Data Regard Rebates as a Monopoly Model of Conversion Costs. The consumption utility of buying products at seller 1 is expressed as $N1$, while at seller 2, the consumption utility is expressed as $N2$, assuming that price is the only factor that affects consumption, for two sellers, buyers will give priority to lower-priced products. If the buyer purchases the products of two sellers, the cost is converted into Br ($r = 1, 2$), where r represents the seller, that is, the cost of the conversion of the consumer coupon is given to the buyer in the first period. When a new buyer purchases a product, the seller will give a new rebate Vr, but to protect the situation of $Vr \le Br$, use this method to distinguish new and old customers.

Based on the above factors, buyers can be divided into three forms, namely original and based on the purchase of the original product, transferred from elsewhere, and attracted new purchasers [15], the utility functions of these three types of products selected by buyers are
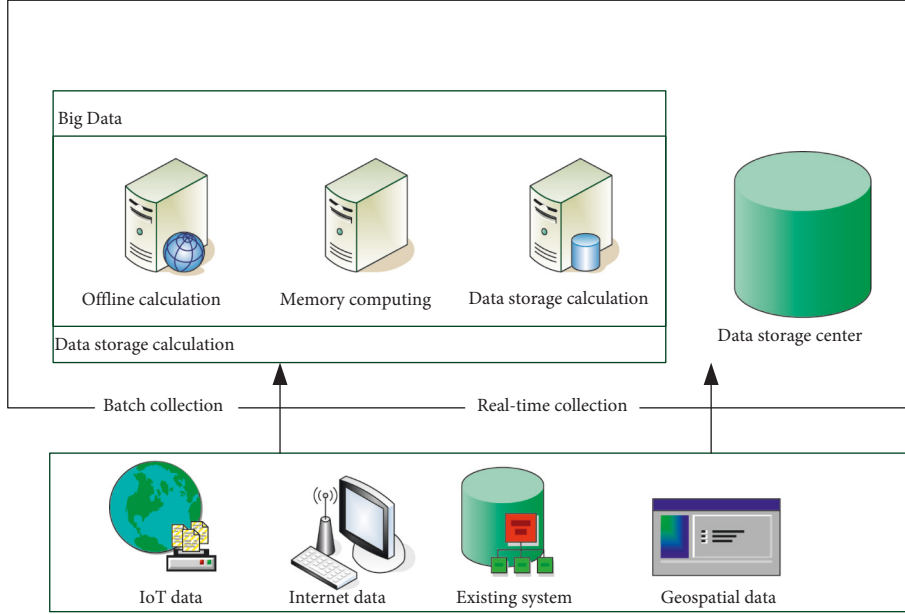
Figure 3: Architecture diagram of big data application system.

$$N_1(y) = \begin{cases} -q_1 - ty \\ -q_2 - B_1 - t(1-y) + V_2 \end{cases},$$

$$N_2(y) = \begin{cases} -q_1 - B_2 - ty + V_1 \\ -q_2 - t(1-y) \end{cases},$$

$$N_x(y) = \begin{cases} -q_1 - ty + V_1 \\ -q_2 - t(1-y) + V_2 \end{cases}. \tag{1}$$

In the above equation, qr represents the basically homogeneous commodity price, t includes the cost per unit distance, and $t > 0$, and another seller represents $t(1-y)$. Assuming that in an equilibrium state, there is no difference between the utility of a customer at position y_1 to buy goods at seller 1 and that of transferring to seller 2; then,

$$-q_1 - ty_1 = -q_2 - t(1-y) + V_2. \tag{2}$$

Then, there is

$$y_1 = \frac{1}{2} + \frac{q_1 - q_2 + B_1 - V_2}{2t}. \tag{3}$$

It is also assumed that there is no difference in utility between the products purchased by the customer at position $y2$ and the products transferred to seller 1 from seller 2 and the purchase utility of new users at the two sellers is also the same; then,

$$y_2 = \frac{1}{2} + \frac{q_2 - q_1 - B_2 - V_1}{2t}, \tag{4}$$

$$y_x = \frac{1}{2} + \frac{q_2 - q_1 + V_1 - V_2}{2t}. \tag{5}$$

Then, obtain the function Gr from the perspective of the seller r; corresponding to the three consumer groups, the demand function faced by the two sellers should be the sum of the three ways, as

$$G_1 = G\alpha_1 y_1 + G\alpha_2 y_2 + X y_x, \tag{6}$$

$$G_2 = G\alpha_1(1 - y_1) + G\alpha_2(1 - y) + X(1 - y_x). \tag{7}$$

In equations (6) and (7), α represents the share of consumers that the seller strives for, assuming there are X number of customers. Therefore, the profit of the corresponding seller is: the original consumer faces the original price qr, and the transferred from another and new consumers can get compensation, and the face price is $qr - Vr$.

$$\beta_1 = q_1 G\alpha_1 y_1 + (q_1 - V_1)(G\alpha_2 y_2 + X y_x),$$
$$\beta_2 = q_2 G\alpha_2(1 - y_2) + (q_2 - V_2)[G\alpha_1(1 - y_1) + X(1 - y_x)]. \tag{8}$$

The two sellers have been in a state of competition, approaching the market equilibrium, and eventually tend to balance. In the equilibrium state, the prices q_1' and q_2' that the two sellers can ask for maximize the profits they can ask for in the equilibrium state, namely,

$$q_1' \in \arg, \max, \beta_1(q_1, q_2^*),$$
$$q_2' \in \arg, \max, \beta_2(q_1^*, q_2). \tag{9}$$

In order to maximize the profit, it is also necessary to satisfy the first-order condition for the profit function to derive the price to be zero [16], namely, $\delta\beta r/\delta qr = 0$. The equation for substituting the profit is

$$\frac{\delta\beta_1}{\delta q_1} = G\alpha_1 y_1 + q_1 G\alpha_1 y_1 \frac{\delta y_1}{\delta q_1} + (G\alpha_2 y_2 + Xy_x) + (q_1 - V_1)\left[G\alpha_2 \frac{\delta y_2}{\delta q_1} + X\frac{\delta y_x}{\delta q_1}\right], \tag{10}$$

$$\frac{\delta\beta_2}{\delta q_2} = G\alpha_2(1-y_2) + q_2 G\alpha_2\left[1 - \frac{\delta y_2}{\delta q_2}\right] + G\alpha_1(1-y_1) + X(1-y_x) + (q_2 - V_2)\left[G\alpha_2\left(1 - \frac{\delta y_2}{\delta q_2}\right) + X\left(1 - \frac{\delta y_x}{\delta q_2}\right)\right]. \tag{11}$$

According to equations (3), (4), and (5), find the expressions of $\delta y_1/\delta q_1$, $\delta y_1/\delta q_2$, $\delta y_2/\delta q_1$, $\delta y_2/\delta q_2$, $\delta y_x/\delta q_1$, and $\delta y_x/\delta q_2$, and substituting it into equations (10) and (11) to get the equilibrium price expression, that is, the reaction function of the two sellers is

$$q_1' = I_1(q_2) = \frac{1}{2}(B_1 + t + q_2 - V_2), \tag{12}$$

$$q_2' = I_1(q_1) = \frac{1}{2}(B_2 + t + q_1 - V_1). \tag{13}$$

According to equations (12) and (13), the initial equilibrium diagram is obtained, as shown in Figure 4. The solution is

$$q_1' = \frac{2}{3}B_1 + \frac{1}{3}B_2 + t - \frac{1}{3}V_1 - \frac{2}{3}V_2,$$
$$q_2' = \frac{1}{3}B_1 + \frac{2}{3}B_2 + t - \frac{2}{3}V_1 - \frac{1}{3}V_2. \tag{14}$$

The coordinates of the equilibrium point are

$$\left(\frac{2}{3}B_1 + \frac{1}{3}B_2 + t - \frac{1}{3}V_1 - \frac{2}{3}V_2, \frac{1}{3}B_1 + \frac{2}{3}B_2 + t - \frac{2}{3}V_1 - \frac{1}{3}V_2\right). \tag{15}$$

By observing the equilibrium expression, it can be found that under the conditions of market equilibrium, the coordinates of the equilibrium point indicate that if the conversion costs of two sellers and the rebates given to new customers are not equal, the equilibrium prices of the two sellers are not equal. If they are equal, the equilibrium prices of the two sellers are both $B + 1 - V$, and they are maintained at a low level.

As the information asymmetry between buyers and sellers has increased nowadays, operators can obtain most of the information of consumers, but it is difficult for consumers to know the relevant information of the operators. In this case, the economic phenomenon of price discrimination has an impact on other aspects [17].

2.2.1. Positive Impact

(1) Obtain more consumer surplus benefits for operators, and increase profits [18]; price discrimination is essentially a pricing strategy of operators. At the beginning of the designation, the strategy was to obtain more consumer surplus, in order to increase profit margins and increase revenue.

(2) Accelerating the efficiency of industry resource allocation, optimizing the industrial structure, and enhancing the overall competitiveness of the industry are conducive to enhancing the competitiveness of national operators in the international big data market competition and strengthening the overall national strength. This is essentially the inevitable result of the development of free market competition [19]; on the whole, it has promoted the improvement of the industry chain, enhanced the overall competitiveness of the industry, and is more conducive to seizing more international big data market shares in the process of economic globalization.

(3) It can increase the types of goods or services in the market to a certain extent. Price discrimination still has to be based on goods or services, and goods or services that can meet consumer demand are the prerequisite for competition [20].

2.2.2. Negative Influence

(1) Price discrimination will infringe the legitimate rights and interests of other operators [21]. Once a monopolistic operator appears in the market, it will inevitably lead to the weakening or even disappearance of market regulation on the operator, and other operators are unable to compete effectively with them, nor can they form competitive restraints. This will cause other operators to be gradually eliminated by the market or unable to compete effectively, leading to weakened market competitiveness;

(2) Price discrimination will infringe on the legitimate rights and interests of consumers and reduce the level of consumer welfare [22]. Operators' price discrimination will inevitably lead to a reduction in consumer surplus, which means that consumers pay higher prices than before, when buying goods or services of the same quality as before. For the same consideration, it can only buy goods or services of lower quality than before;

(3) Price discrimination will destroy the order of market competition [23]. Thanks to big data technical analysis, operators can obtain greater consumer surplus without improving the quality of products or services. The cost of implementing price
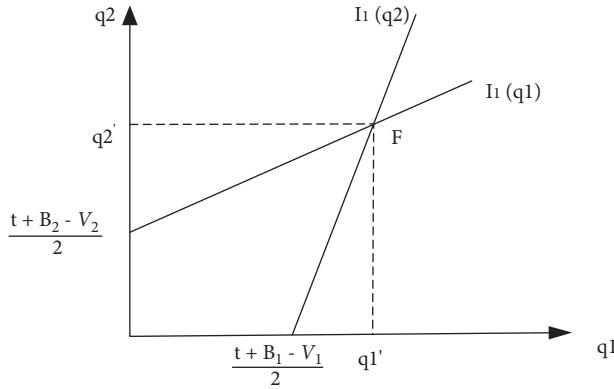
FIGURE 4: The reaction function of the equilibrium price of the prices of two sellers.

Session	Place	Number of people	Grouping
First round	On campus	54	Processing group AI
Second round	On campus	54	Treatment group BI
Third scene	On campus	54	Treatment group CI
Fourth game	On campus	54	Treatment group EI
Fifth scene	On campus	54	Treatment group FI

discrimination is far lower than the cost of developing new products and improving service quality. In the long run, operators in the market will no longer focus on improving the quality of products or services, but will turn to the exploration of consumer surplus. The laws of market competition will not be able to play a role, and the function of the price mechanism will tend to stagnate. The market competition order will no longer be able to promote social and economic development.

TABLE 2: Grouping situation table.

Serial number	The difference
Processing group AI	Belongs to the basic information processing group. The buyer knows his initial endowment, the intrinsic value of the goods, and the seller's price
Treatment group BI	The difference from AI is that the seller knows the bid price and initial endowment of the two
Treatment group CI	Unlike BI, the buyer knows the selling price of another in the same group, that is, the seller quotes both
Treatment group EI	On the basis of BI, the buyer can know the intrinsic value of the goods of another buyer in the same group
Treatment group FI	Unlike the previous group, the buyer knows the initial endowment of the other person in the same group and the seller's selling price for it. And the seller still has all the information

2.3. Price Discrimination Phenomenon Based on Sensor Big Data Network.

In this paper, students in a certain university are used as experimental samples, and 5 consecutive questionnaire survey experiments have been conducted in the university. There are 54 people in each session, and a total of 270 college students from different majors and grades were tested, including undergraduates, PhD students, and master students. The test schedule is shown in Table 1, and the 5 questionnaire tests are divided into 5 groups, as shown in Table 2.

According to the information statistics of the questionnaire in this experiment, the survey information of the experimental sample is shown in Table 3:

As shown in Table 3, the ratio of girls in the experiment is significantly greater than that of boys, girls account for about 75%, and the ratio is close to 3:1. The average age is about 20 years old, over the age of 18 to 25 years old accounted for a relatively large proportion, about 97.8%, and the students are distributed among college students, master students, and doctoral students, but the main experimental sample of this experiment is college students in a certain university. Most students' families have no siblings, accounting for nearly half, about 45.9%. The average education level of the parents of the students participating in the survey is junior high school and high school level accounting for 67.4%, with fewer students below elementary school and college accounting for 42.6%. The average monthly household income is mainly between 5000 and 10000 yuan per capita, and the monthly living expenses of students are mainly between 1000 and 2000 yuan. In this experiment, students who have

participated in the experiment before accounted for the majority, accounting for 57.1%. However, during the experiment, it was ensured that the subjects had no communication during the operation, which ensured the independence of decision-making by the subjects present.

In order to predict the forecast pricing of buyers and sellers, as well as to predict the behavior of both parties, the following economic models are used: one is the standard economic model; the other is the reference point model, the third is the inequality aversion model. Based on the above model, we predict the relevant experimental conclusions and focus on the following four issues.

(1) Investigating whether these models predict whether sellers use price discrimination strategies

(2) Using these models to predict whether the different initial endowments of the same group of buyers will affect the seller's pricing strategy

(3) Whether the seller will be overpriced, that is, the buyer's price is higher than its intrinsic value

(4) Predicting the buyer's reaction to price discrimination in different forms of circumstances

The reference point model comes from the influence of the reference point theory on behavioral decision-making.

TABLE 3: Basic sample information.

Sample characteristics		Quantity	Percentage
Gender	Male	203	75
	Female	67	25
Age	Under 20	71	26.3
	20–25	193	71.5
	26–30	4	1.5
	31–35	2	0.7
Education	Undergraduate	225	83.3
	Master, PhD graduate	45	16.7
Siblings	There is 1	126	46.7
	Two and more	20	7.4
	NO	124	45.9
Parents' education	Below junior high school	34	12.6
	Junior high school	103	38.1
	High school	79	29.3
	University and above	54	20
Household income	More than 10000	77	28.5
	5000–10000	126	46.7
	2000–5000	67	24.8
Monthly cost	Above 2000	42	15.6
	1000–2000	176	65.2
	Below 1000	52	19.3
Did you participate in other experiments?	Have	157	57.1
	No	113	41.9

TABLE 4: The difference test between the mean intrinsic value and the mean bid value.

	Endowent = 20			Endowent = 40	
	Average bidding	Intrinsic mean		Average bidding	Intrinsic mean
Average bidding	1	—	Average bidding	1	—
Intrinsic mean	−0.03	1	Intrinsic mean	0.1	1

phenomenon can be explained by the "loss aversion" theory in behavioral finance, which believes that a certain amount of loss reduces the utility of people more than the same benefit increases the utility of people. Therefore, people's balance of interests and harms in the decision-making process is unbalanced, and the consideration of "avoidance of harm" is far greater than the consideration of "advancement". Out of fear of loss, people often ask for excessive prices when selling goods.

A total of 270 student subjects participated in the experiment in this investigation. The seller's average selling price is 17 yuan, the average price of the item is 16.5 yuan, and the average intrinsic value of the item to the buyer is 19 yuan. In Experiment 1, the second sealed auction of ten items was designed so that the buyer's bid was close to the intrinsic value of the item, and the item's bid was provided as information to the seller to meet the price conditions of the seller's discrimination strategy. In the experiment, sellers participated in two different initial endowments, namely the high endowment group (endowment = 40) and the low endowment group (endowment = 20). The difference between the average value of the buyer's goods' intrinsic value and the average value of the buyer's bid price was tested, and the results showed that there was no significant difference between the two as shown in Table 4.

As shown in Table 5, for the seller, the buyer's bid in the auction link can be used as the information about the intrinsic value of the buyer's goods. In the AI group, the bid difference of buyers in the same group will affect the seller's selling price. If the bid difference increases, the seller may adopt a price discrimination strategy. When the buyer knows nothing about the price of the commodity other than his own price, the seller has every incentive to implement price discrimination. However, the seller spontaneously avoided price discrimination, because when the two parties bid unequal, he still adopts a unified pricing, which is consistent with the ethical code model.

3.1.1. Price Discriminatory Pricing. In the AI processing group, some sellers still use unified pricing without receiving any information from the buyer. This spontaneous circumvention cannot be explained by the seller's pricing strategy. Table 6 shows the probability of price discrimination for sellers with different initial endowments under different treatment groups.

It can be seen from Table 6 and Figure 5 that, overall, the AI treatment group has the highest probability of price-

In the consumer market, the price of a product is a decisive factor for its behavioral decision-making. In the consumer market, consumers will not only have a maximum willingness to pay U_i, but also set an internal reference price. This price can be a general reference price on the Internet, or an estimated price generated by consumers in a long-term buying and selling transaction, but it may also be the price p_j paid by other consumers. The establishment equation of the simple production test site model is as follows:

$$V_i(p_i, U_i, p_j) = (U_i - p_i) - \alpha_i(p_i - p_j). \quad (16)$$

Among them, α_i represents the quantified reference point intensity.

The inequality aversion model regards fairness as self-centered unfair aversion. Among them, aversion to unfairness means that people resist unfair results, that is, they are willing to give up some material rewards and pursue more fair results instead. If people do not care about inequality with others, but only care about the fairness of their material returns relative to other people's material returns, then aversion to unfairness is self-centered.

3. Price Discrimination Based on Sensor Big Data

3.1. Seller Price Discrimination. The endowment effect means that once an individual owns an item, his evaluation of the value of the item is much greater than before. This

TABLE 5: Bid price difference and price discrimination in the AI processing group.

				Endowment = 20			
Buyer bidding differences	<1	<2	<3	<4	<5	<10	ALL
Price discriminatory pricing	2.73	6.36	18.18	28.18	36.36	70	94.55
Probability	= 5	= 7	= 21	= 30	= 40	= 77	= 104
Quantity	3	7	21	30	40	77	104
Total				110			
				Endowment = 40			
Buyer bidding differences	<1	<2	<3	<4	<5	<10	ALL
Price discriminatory pricing	4.29	8.57	12.86	24.29	31.44	67.14	94.55
Probability	= 3	= 6	= 9	= 17	= 22	= 47	= 63
Quantity	3	6	9	17	22	47	63
Total				70			

discriminatory pricing strategy, followed by the BI treatment group, which is slightly lower than the AI treatment group. The overall probability of price discrimination in the FI treatment group is the lowest, and in the other treatment groups except the FI treatment group, the probability of price discrimination is significantly higher for sellers with lower endowments than for buyers with high endowments. The probability of discriminatory pricing in all treatment groups is at least more than half. Even when both buyers know the prices of both in CI and FI processing, sellers still use discriminatory pricing at a higher frequency.

3.1.2. High-Value Pricing.

The definition of high-value pricing refers to the strategy of putting new products into the market at a high price in order to obtain more profits at the beginning of the product market life cycle, recover costs as soon as possible, and then gradually reduce prices. This method takes advantage of the novelty and strangeness of early-use consumers and their insensitivity to prices and uses high prices to introduce new products into the market.

The seller's price to the buyer is based on the buyer's intrinsic value of the goods. There are three possible scenarios for the seller's pricing. (1) Equivalent pricing ($p = v$); (2) high-value pricing ($p > v$); and (3) low-value pricing ($p < v$). The reference point model can be used to explain this high-value pricing strategy.

As shown in Figure 6, the probability of using high-value pricing for low-value buyers is significantly higher than for high-value buyers. Especially in processing group *PI* and processing group *FI*, sellers rarely use this pricing strategy for high-value buyers. Overall, in the five processing groups, buyers rarely use this strategic pricing, but for low-value buyers, sellers will use this strategic pricing more.

3.2. Buyer Decision Based on Price Discrimination Phenomenon of Sensor Big Data.

As shown in Table 7, when the initial endowments of two buyers are different, the buyer who is in unfavorable price discrimination, is more likely to reject the seller's offer, especially buyers with low initial endowments, even if they can get a positive material return, they will choose to reject the seller's offer. When two buyers have the same initial endowment, the buyer with a lower endowment is more likely to reject the seller's offer than the

TABLE 6: Probability of price discrimination by sellers with different endowments.

Endowment = 20			Endowment = 40		
Treatment	X	Frequency	Treatment	X	Frequency
AI	109	100	AI	69	60
BI	59	54	BI	119	106
CI	129	105	CI	49	37
EI	109	94	EI	69	55
FI	79	58	FI	99	76

other buyer with a higher endowment. When the material return is zero, the buyer who is at a disadvantage of price discrimination is least likely to still accept the seller's offer. When the buyer receives a negative material return ($v < p$), the buyer who is in advantage price discrimination chooses to accept the seller's offer. Compared with the other two cases, the probability of accepting the price is higher. Whether it is zero material return or negative material return, buyers with lower endowments will mostly choose to reject the seller's offer, when facing unfavorable price discrimination. This is consistent with the positive material return situation. When two buyers in the same group have different initial endowments, the possibility of such rejection is particularly significant.

According to the regression results, there is a significant negative correlation between disadvantaged buyers and whether they accept the transaction ($P < 0.05$). In other words, disadvantaged buyers are more likely to choose to refuse the transaction, even if it brings positive material returns. This result is consistent with the prediction of the reference point model, that is, when a consumer is a disadvantaged buyer, due to the different selling prices of the seller and the buyer's unfair preference for refusal of the transaction, the price of another buyer in the same group will affect his decision to refuse the transaction.

Figure 7 shows the probability that the CI and FI processing group will accept the transaction when faced with the seller's pricing strategy. Among the five treatment groups in the experimental design, only the CI treatment group and the EI treatment group were informed of the sales price of the item to the same group of buyers. The subjects in the two treatment groups were first dealt with based on the difference in the material return of the transaction. It can be seen
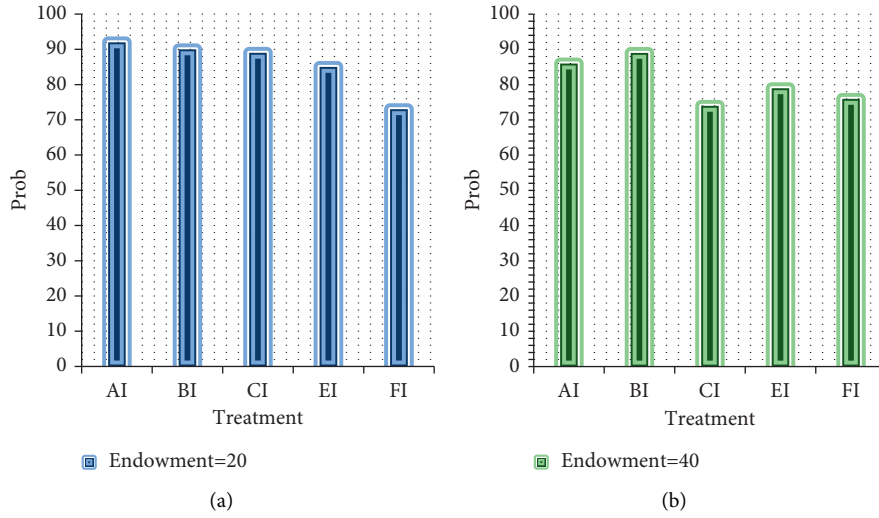
FIGURE 5: The probability of price discrimination under different seller endowments: (a) for low-endowed sellers and (b) for high-endowed sellers.
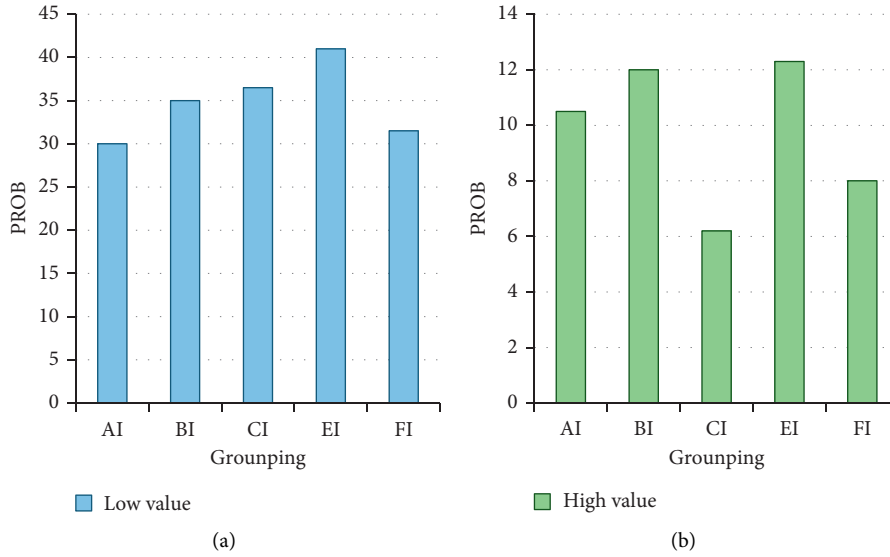

FIGURE 6: Strategic high-value pricing: (a) low value and (b) high value.

TABLE 7: Probability of buyer accepting transaction.

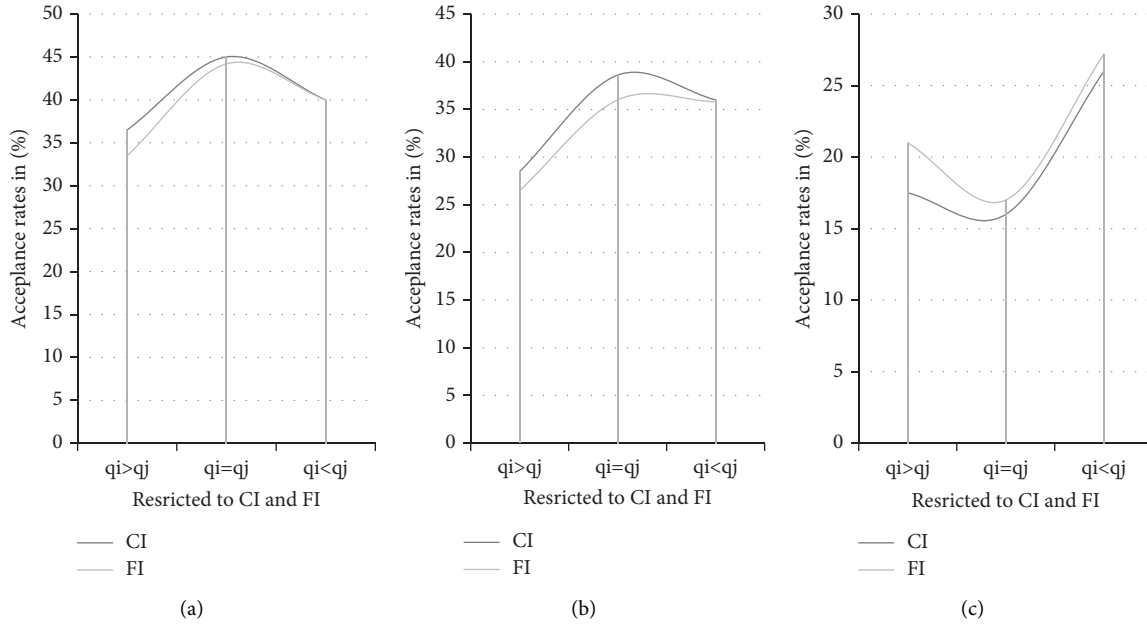| Model	1	2	3	4	5
Does the buyer know the selling price of another buyer	Yes	No	Yes	Yes	Yes
The relationship between selling price and intrinsic value	All categories	All categories	$P > V$	$P = V$	$P < V$
Myprice	−0.02	−0.04	−0.01	−0.05	−0.002
	0.003	0.003	0.005	0.014	0.006
Value	0.02	0.03	0.021	0.04	0.01
	0.004	0.003	0.006	0.014	0.007
Disadvantage	−0.2	−0.3	0.28	−0.1	−0.13
	0.04	0.03	0.06	0.014	0.01
Cons	0.74	0.71	0.54	0.87	1.15
	0.06	0.05	0.1	0.13	0.1
R2	0.09	0.11	0.1	0.1	0.06
N	721	540	300	137	258

Figure 7: Probability of buyer accepting transaction: (a) $P < V$, (b) $P = V$, and (c) $P > V$.

from the figure that when the transaction brings negative material returns, the overall probability of choosing to accept the transaction is the lowest, but when $p_i < p_j$, the number of buyers who choose to accept transactions increases significantly in both the PI treatment group and the FI treatment group. Similarly, it can be seen that when the transaction can bring positive material returns to the buyer, the overall probability of accepting the transaction is the highest. When $p_i > p_j$, the probability of accepting the transaction is slightly lower than other cases. Moreover, regardless of the material return, the probability of accepting the transaction for a buyer in a superior position ($p_i < p_j$) is always greater than that of a buyer in a disadvantaged position ($p_i > p_j$).

3.3. Seller Pricing Strategy and Revenue.

3.3. Seller Pricing Strategy and Revenue. Whether it is a price-discriminatory pricing strategy or a unified pricing strategy, sellers are all in order to obtain more consumer surplus to maximize their own profits. Sellers have price-discriminatory pricing strategies in different processing groups, but price-discriminatory pricing strategies have varying degrees of impact on sellers' revenue under different information conditions.

As shown in Table 8, the experimental data shows that sellers are more cautious in implementing price discrimination in the CI and FI treatment groups. Only when the difference between the bidding bids of the two buyers reaches a large level, will there be more discrimination pricing behavior. This phenomenon can also be found in the NI processing team. When the bidding differences between two buyers are not large, there are fewer price discrimination behaviors. Only when the difference is at least greater than 5, will about half of the sellers choose a price-discriminatory pricing strategy. Second, the experiment found that when

Table 8: Price discrimination and seller benefits.

	AI	BI	CI	EI	FI
Profit	0.51	0.454	−0.02	−0.011	−0.82
	0.001	0.77	0.79	0.81	0.12
Constant	1.069	0.891	0.72	0.851	0.981
	0	0	0	0	0
R^2	0.056	0.001	0.034	0.034	0.034
N	180	180	180	180	180

the seller faces two buyers of different values, they will choose the buyer with a lower value as the unified pricing standard. However, when the value difference between the two gradually increases, the buyer with a higher value will be selected as the standard for unified pricing. At this time, the selling price of the product is already higher than the intrinsic value of the buyer with a lower value.

After completing the main part of the experiment, the experimental subjects will be measured for unfair aversion, and the model will predict their unequal aversion preferences based on the decision-making behavior of the experimental samples. When a seller implements a price-discriminatory pricing strategy, if his selling price is lower than that of buyers in the same group, then the buyer is at an unequal advantage. In the same way, if one's own price is higher than that of buyers in the same group, the seller will deal with unequal disadvantages at this time.

As shown in Figure 8, there are three different regression testing methods. The dependent variable is whether the buyer rejects or accepts the transaction. The results of the regression test show that when buyers are in a situation of unequal disadvantages, buyers have a lower tolerance for unfairness, and most of them will choose to reject the seller's offer. The experimental results are consistent with the measurement results of the inequality aversion table, but the
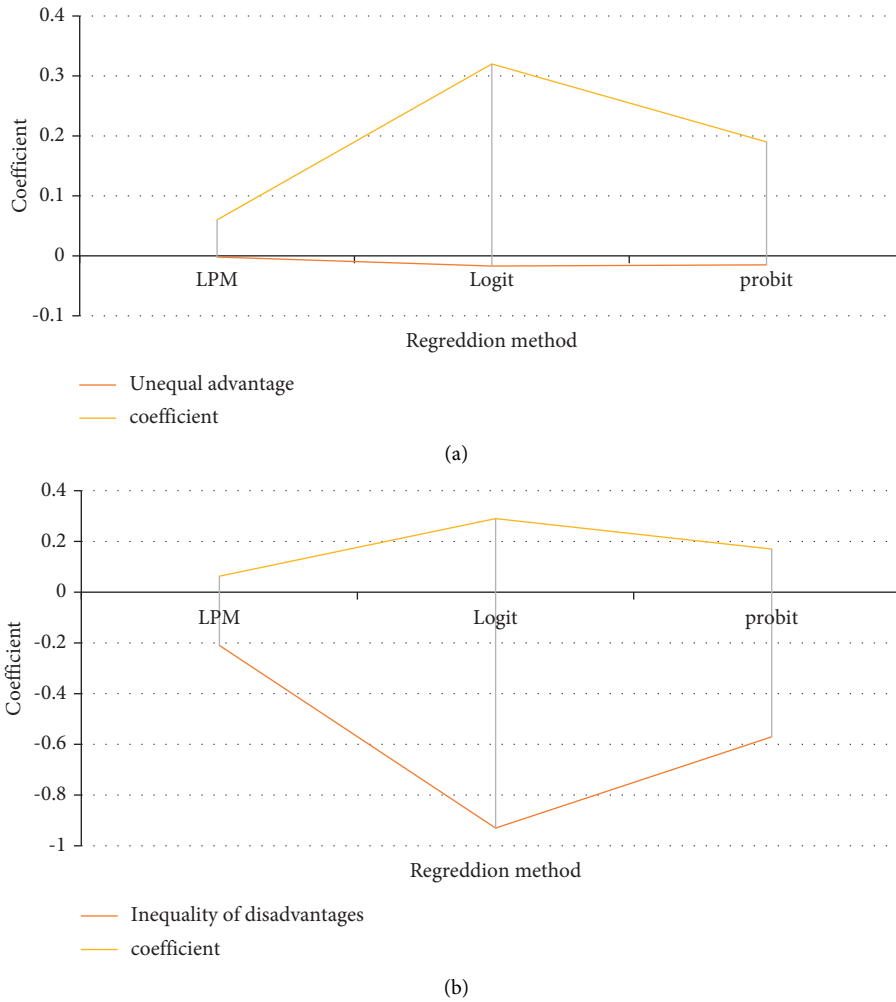
(a)

(b)

FIGURE 8: Actual regression test of inequality aversion: (a) inequality of advantages; (b) inequality of disadvantages.

experimental results are not significant when the buyer is in unequal dominance.

4. Conclusions

The research results of this article show that after predicting the behavior of price discrimination between buyers and sellers under certain circumstances, it is found that, first of all, not all entrepreneurs who sell goods use price discrimination to set price, sellers have a certain degree of spontaneity to avoid price discrimination. There is also the phenomenon of strategic avoidance in order to obtain better profits, which shows that the merchants have taken into account personal rights and interests, when setting prices. Secondly, commodity pricing is not the only key factor that affects consumption. Other merchants who play the same role in commodity pricing will also affect customers' purchasing decisions to a certain extent. If the customer encounters unfavorable price discrimination, he will choose to abandon the transaction. Third, in addition to the AI and BI processing groups, price-discriminatory pricing strategies can have a positive impact on the seller's income. None of the other three information processing groups can prove

that the seller's price-discriminatory pricing strategy can have a positive or negative impact on his own income. This means that sellers cannot significantly increase revenue through discriminatory pricing behavior. The regression results show that buyers who have a low tolerance for unfairness are more likely to reject sellers' offers when they are in a disadvantageous situation. The experimental results are consistent with the measurement results of the Unfair Disgust Scale, but the experimental results are not significant when the buyer is in a favorable situation.

Data Availability

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

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

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