Check for updates

Ordering Strategies That Consider Positive and Negative Incentives for Designers Under Clothing Crowdsourcing

Yipeng Li[1], Shu Zhang[1(✉)], and Kaifu Yuan[2]

[1] School of Information and Safety Engineering, Zhongnan University of Economics and Law, Wuhan 430073, People's Republic of China
zhangshufight@163.com

[2] School of Business Administration, Guizhou University of Finance and Economics, Guiyang 550025, People's Republic of China

Abstract. The combination of clothing industry and crowdsourcing supply chain (CSC) is becoming a research hotspot. For the clothing industry, "crowdsourcing" is introduced into the traditional supply chain operation. Firstly, based on the newsboy model, a basic ordering model (BM) is constructed. Then the optimal pricing and ordering decisions under decentralized decision-making and centralized decision-making are compared and analyzed. Furthermore, in order to continuously obtain high-quality creativity, considering the participation incentive of crowdsourcing designers and enterprise inventory risk avoidance, a positive and negative incentive ordering model (PNI) for designers is proposed. Through mathematical derivation and theorem proof, the optimal utility and optimal order quantity of supply chain and crowdsourcing designers are obtained. Finally, the optimal pricing order problem of the two policy models is solved through data simulation, and further sensitivity analysis of the fabric consumption rate, order quantity and other parameters are carried out. It is concluded that centralised decision-making under BM is superior to decentralised decision-making, and PNI has some practical value in improving supply chain profitability and expanding order volumes for apparel retailers.

Keywords: Clothing industry · Crowdsourcing supply chain · Ordering decision · Positive and negative incentives · Risk sharing

1 Introduction

The combination of crowdsourcing supply chain (CSC) and clothing industry is becoming a research hotspot [1]. In order to satisfy the individual needs of consumers, companies attract the community to participate in clothing design process with lower costs and reasonable incentives by the Internet platform. The earliest application of CSC in the clothing industry can be traced back to the Threadless [2], a crowdsourcing e-commerce platform which mass-produced popular designs selected by experts. In addition, ZARA's fast fashion model of "multiple styles and small batches" used the idea of "crowdsourcing" to effectively reduce inventory. H&M fast fashion products also began to build a crowdsourcing platform to try to develop private customization services.

S. H. B. D. M. Zailani et al. (Eds.): ICMSEM 2023, 259, pp. 910–924, 2024.
https://doi.org/10.2991/978-94-6463-256-9_90

Although CSC has achieved initial effects in clothing industry, it has not yet received much attention from industry practitioners and researchers. There are still two problems: 1) Unlike traditional large manufacturing enterprises (Haier, Dell, P&G, etc.), the difficulties of design and crowdsourcing remuneration in clothing industry are so lower that can not effectively incentivise designer participation.

2) To enhance supply chain profits, clothing crowdsourcing should improve incentive mechanisms and risk sharing strategies in the production decision process.

At present, research is mainly focused on crowdsourcing supply chains based on product design and incentives for contracting parties. Jizi Li et al. [3, 4] deeply coupled crowdsourcing and supply chain, and built a hybrid online and offline custom design production decision model. Chunling Liu [5] proposed the optimization of delayed production in crowdsourced supply chains based on information updates. Xiuli Meng et al. [6] constructed a crowdsourcing logistics service network model from the perspective of optimizing the quality of crowdsourcing logistics services, considering the platform penalty policy.

Bayus et al. [7] conducted experimental analysis on the transaction data of Dell's virtual crowdsourcing community, and made some strategic suggestions to maintain high-quality creative ideas. Ming [8] studied the experimental data on Kaggle, and obtained two factors that affect the participation of crowdsourcing designers: random factors and level of effort, so as to optimize the incentive mechanism of competition design. Wang [9] empirically investigated more factors affecting individual participation in crowdsourcing contests through the Kaggle platform. Tracy et al. [10] analysed Taskcn's field experiment data and proposed three comparative models: Contests, Ranked contests and All-Paying auctions to find the most appropriate mechanism, which increases the participation of the community at large. Shuchi et al. [11] proposed an optimal crowdsourcing competition theory. Chen [12] analysed the effect of competition length on crowdsourcing and added it to model building. Meng-Meng Wang [13] focused on the influence mechanism of continuous participation of answerers. Liang [14] developed a mediated mediation model to explain the interaction effect of internal and external incentives. Ayaburi et al. [15] used Expectation-Confirmation Theory (ECT) to explain the duration and performance of the competition by building a model. Patrick et al. [16] further analysed strategic decisions to improve crowdsourcing innovation performance. Philipp et al. [17] investigated the link between customer investor participation in crowdfunding and crowdsourcing related. Gerry et al. [18] focused on blockchain platforms relying on token-weighted voting to obtain user crowdsourcing information.

In short, there are few cross studies on "crowdsourcing supply chain" and "contractor incentive" in the existing literatures. Therefore, this paper firstly introduces the idea of "crowdsourcing" into the clothing design process and establishes the basic model based on actual production and operation problems of the clothing industry. Furthermore, this paper constructs a positive and negative incentive strategy for crowdsourcing designers, which encourages designer participation and constrains designer fraud at the same time, and further discusses crowdsourcing supply chain design optimization and pricing ordering decision optimization under the incentive mechanism.

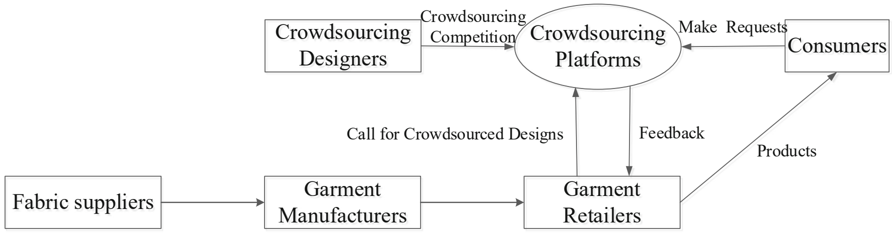

Fig. 1. CSC Structure

2 Basic Model

2.1 Problem Description and Symbolic Representation

As shown in Fig. 1, it is assumed that the supply chain consists of a fabric supplier, a garment manufacturer, a garment retailer, a crowdsourcing platform, a number of crowdsourced designers and consumers. The garment retailer is the closest supply chain member to the consumer, collecting consumer demand through the crowdsourcing platform's online community and translating it into design tasks on the platform. The designers participate in designs based on the initial demand information of the design tasks. The consumer can rate or order all the garment designs, the winning designs are selected for production by the garment manufacturer, and finally the products are delivered directly to the consumer by post.

Specific variables are defined as Table 1.

For the sake of generality, the following assumptions are made.

(1) Lead time for two-tier ordering and production time for garment manufacturers is excluded.
(2) Only one winning design is produced for each design situation.
(3) Production operations in each custom design scenario have the same cost-benefit analysis.
(4) $p_c > r > c_m > \mu > \lambda$, $c_m + c_s(p_c) < p_c$, $\Omega p_c \geq r$, There are no inventory costs.

2.2 Mathematical Models

Separate and centralised ordering decisions should be considered for garment retailers and garment manufacturers respectively.

Manufacturer Basic Model (MBM).

After receiving the winning design from the crowdsourcing platform, the garment manufacturer will order from the fabric supplier before ordering from the crowdsourcing platform, whose profit function can be expressed as (1).

$$\Pi_m = r \cdot \min(n/\theta, q_r) - p_l \cdot n - c_m \cdot n/\theta - \lambda \cdot \left[q_r - n/\theta\right]^+ \tag{1}$$

The profit of garment manufacturers is composed of four parts: the first part is total revenue, the second part is fabric ordering cost, the third part is production cost, and the fourth part is out of stock penalty cost. The decision variable is q_m.

Table 1. Description of variables

Variables	Description
k	Customised product design contexts
D_k	Consumer needs in each design context
c_m	Production costs per unit of product for garment manufacturers
r	Wholesale prices for garment manufacturers
p_c	Retail prices of garment retailers
p_l	Fabric prices
q_r	Order volumes from garment retailers to garment manufacturers
q_m	Order volumes from garment manufacturers to fabric suppliers
n	Actual number of fabrics supplied by fabric suppliers
n/q_m	Proportion of fabric supply from fabric suppliers, Exogenous random variables ν
θ	Fabric consumption rate
n/θ	Actual number of products available from fabric suppliers
μ	Unit cost of lost sales opportunities for garment retailers due to stock-outs
λ	Unit out-of-stock penalties imposed by garment retailers on garment manufacturers
Ω	Discount coefficient
S	Crowdsourcing designers
c_s	Crowdsourcing design remuneration, $c_s = f(p_c)$

Lemma 1 When the parameters satisfy certain conditions, for q_r in the design scenario k, there is an optimum q_m^* that maximises the manufacturer's profit.

Certification Supposed that the exogenous random variable ν obey the uniform distribution of U(0,1). (2) can be obtained by (1), with $n = \nu \cdot q_m$.

$$\Pi_m = r \cdot \min(\nu \cdot q_m/\theta, q_r) - p_l \cdot \nu \cdot q_m - \nu \cdot q_m \cdot c_m/\theta - \lambda\left[q_r - \nu \cdot q_m/\theta\right]^+ \quad (2)$$

As known $E(\nu) = 1/2$, $g(\nu) = 1(0 \leq \nu \leq 1)$, and $\theta \cdot q_r/q_m > 1$, and (3) could be get by expanding the expectation in integral form.

$$E(\Pi_m) = r\int_0^{\theta \cdot q_r/\mathrm{q}_m} \nu \cdot q_m/\theta d\nu - \lambda \int_0^{\theta \cdot q_r/\mathrm{q}_m} (q_r - \nu \cdot q_m/\theta)d\nu \\ - (p_l\theta + \mathrm{c}_m)/2\theta \cdot q_m \quad (3)$$

The first derivative and the second derivative of (3) can be calculated as follows.

$$\partial E(\Pi_m)/\partial q_m = 2\lambda\theta q_r^2/q_m^3 - (r+\lambda)\theta q_r^2/2q_m^2 - (p_l\theta + c_m)/2\theta \quad (4)$$

$$\partial^2 E(\Pi_m)/\partial q_m^2 = -6\lambda\theta q_r^2/q_m^4 + (r+\lambda)\theta q_r^2/q_m^3 = \theta q_r^2\left[(r+\lambda)q_m - 6\lambda\right]/q_m^4 \quad (5)$$

According to the actual situation, $\partial^2 E(\Pi_m)/\partial q_m^2 > 0$. That is, when all parameters meet the conditions $\partial E(\Pi_m)/\partial q_m = 0$, there is an optimal q_m^* maximize manufacturer's profit. Take $q_r = q_m$ into the first derivative, it can be get $\partial E(\Pi_m)/\partial q_m > 0$ and $q_m^* \geq q_r$.The certificate is completed.

From Lemma 1, it is clear that garment manufacturers will maximise their expected profits by appropriately scaling up orders from garment retailers.

Retailer Basic Model (RBM).

Under this supply chain structure, the profit of clothing retailer can be expressed as (6).

$$\Pi_r = p_c \min(n/\theta, D_k) + \Omega p_c[\min(n/\theta, D_k) - D_k]^+ + \lambda\left[q_r - n/\theta\right]^+ \\ - r\min(n/\theta, q_r) - \mu\left[D_k - \min(n/\theta, q_r)\right]^+ - c_s(p_c) \tag{6}$$

The profit of the clothing retailer consists of six parts: the first part is the revenue in the normal sales period, the second part is the sales revenue in the off-season clearance period, the third part is the penalty for the shortage of clothing manufacturers, the fourth part is the ordering cost, the fifth part is the shortage cost, and the sixth part is the crowdsourcing design cost.

Lemma 2 When $n/\theta = q_r = D_k$, the clothing retailer realizes the supply and demand matching and eliminates the supply uncertainty of the clothing manufacturer and the demand uncertainty of the end consumer. The maximum value of the objective function can be obtained as (7).

$$E(\Pi_r) = -a \cdot p_c^2 + (q_r - b) \cdot p_c - r \cdot q_r - c \tag{7}$$

Certification When the demand is determined, the garment retailer orders products according to the demand of the end consumer, setting $q_r = D_k$. The garment manufacturer orders products according to the order quantity of the garment retailer, setting $q_m = q_r$. When the supply is determined, the fabric supplier will supply products according to the manufacturer's order quantity, setting $n/\theta = q_m$.Substitute these equation relations into (6) to get (7). The first derivative and the second derivative of Eq. (7) could be calculated respectively as (8) and (9).

$$\partial E(\Pi_r)/\partial p_c = -2ap_c + q_r - b \tag{8}$$

$$\partial^2 E(\Pi_r)/\partial p_c^2 = -2a \tag{9}$$

When setting $a > 0$, there is an optimal $p_c^* = (q_r - b)/2a$ to maximize the profit of (7). The certificate is completed.

Lemma 3 For clothing retailers, after selecting the optimal pricing, when only eliminating consumer demand uncertainty, there is a minimum order quantity q_m for garment manufacturers to maximize the expected profits of garment retailers.

Certification When only eliminating consumer demand uncertainty, $q_r = D_k$, $\min(n/\theta, D_k, q_r) = \min(n/\theta, q_r)$. Garment retailers do not have salvage items that need to be sold at a discount, nor do they have their own out-of-stock penalties. (6) can be rewritten as (10).

$$\Pi_r = p_c \min(n/\theta, q_r) + \lambda\left[q_r - n/\theta\right]^+ - r \min(n/\theta, q_r) - c_s(p_c) \tag{10}$$

Due to the uncertainty of supply from fabric suppliers, garment manufacturers need to increase their order volumes to try to meet the orders of garment retailers. However, since consumer demand fluctuates in a stable range, even if the garment manufacturers expand their orders indefinitely, the expected profit of the garment retailers can only be maintained at a relatively stable level. The certificate is completed.

Lemma 4 For garment retailers, after selecting the optimal pricing, when only eliminating the uncertainty of actual supply of garment manufacturers, there is still an optimal retailer order quantity q_r^* to maximize their expected profits.

Certification When eliminating the uncertainty of actual supply of garment manufacturers, $\min(n/\theta, D_k, q_r) = \min(D_K, q_r)$. Garment retailers do not have out-of-stock penalties for garment manufacturers. (6) can be rewritten as (11).

$$\Pi_r = p_c \min(n/\theta, D_k) + \Omega p_c\left[q_r - D_k\right]^+ - r \cdot q_r - \mu\left[D_k - q_r\right]^+ - c_s(p_c) \tag{11}$$

The first and second order derivatives of q_r could be calculated, and it can be proved in the same way as Lemma 1. The certificate is completed.

Centralized Decision Model (CDM).

Yi-Peng Li et al. [19] argue that under decentralized decision making, due to double uncertainty, garment manufacturers will enlarge garment retailers' order quantity to maximize their own expected profit, and garment retailers will also appropriately enlarge their order quantity due to the possible lack of capacity of garment manufacturers. Therefore, the order quantity of garment manufacturers is often smaller than the order quantity of garment retailers in an attempt to increase the order quantity of garment manufacturers by initiating a centralized decision to maximize their expected profits.

Under centralized decision-making, members at all levels share information and make ordering decisions with the goal of maximizing the global desired profit of the supply chain. The global profit of the supply chain can be expressed as (12).

$$\begin{aligned}\Pi_s = p_c \min(n/\theta, D_k) + \Omega p_c[\min(n/\theta, D_k) - D_k]^+ \\ - p_l n - c_m \cdot n/\theta - \mu[D_k - n/\theta]^+ - c_s(p_c)\end{aligned} \tag{12}$$

Theorem 1 The expected profit of the centralized decision is a concave function with respect to q_m, and there exists an optimal q_m^* that maximizes the profit and outperforms the decentralized decision.

Certification Expanding the expectation of (10) in integral form and calculating the first-order derivative and second-order derivative for q_m respectively, then it is proved in the same way as Lemma 1. It is verified by arithmetic analysis 4.1 that q_m^* is increased. The certificate is completed.

3 Positive and Negative Incentive Strategies for Designers (PNI)

Consider designing positive and negative incentive contracts that incentivize crowdsourced designers while optimizing the global expected profit of the supply chain. Positive incentives means increasing crowdsourcing compensation. Negative incentive that considers the crowdsourcing designer risk compensation, the winning crowdsourcing designer needs to sign a risk compensation contract with the crowdsourcing platform. Products that have not been sold out after the discount clearance need contractual compensation. The following new variables and assumptions are added as Table 2.

Assuming that M = NP ($\mu > p_c$), and crowdsourcing design remuneration is related to M and q_r, that is $c_s = \rho \cdot q_r + \beta M$. The strategy is shown in Fig. 2.

Then the profit expression of supply chain global can be rewritten as (13).

$$\begin{aligned}\Pi_s = {} & \gamma\Omega p_c[\min(n/\theta, D_k) - D_k]^+ + (1-\gamma)p_b[\min(n/\theta, D_k) - D_k]^+ \\ & + p_c \min(n/\theta, D_k) - p_l n - c_m \cdot n/\theta - \mu[D_k - n/\theta]^+ \\ & - (\rho \cdot \min(n/\theta, D_k) + \beta M) \end{aligned} \tag{13}$$

For crowdsourcing designers, their own effectiveness can be expressed as (14).

$$\mathrm{U}_s = \rho \cdot \min(n/\theta, D_k) + \beta M - (1-\gamma)p_b[\min(n/\theta, D_k) - D_k]^+ \tag{14}$$

For garment retailers, the profit function can be rewritten as (15).

$$\begin{aligned}\Pi_r = {} & p_c \min(q_r, D_k) + \gamma\Omega p_c\big[q_r - D_k\big]^+ + (1-\gamma)p_b\big[\min(q_r, D_k) - D_k\big]^+ \\ & - r \cdot q_r - \mu\big[D_k - q_r\big]^+ - (\rho \cdot \min(q_r, D_k) + \beta M) \end{aligned} \tag{15}$$

Table 2. Description of new variables

Variables	Description
p_b	Compensation price
γ	Percentage of discounted promotional products
N	Number of potential crowdsourced designers
M	Number of actual participating crowdsourced designers
μ	Crowdsourced designers' product valuation of their own design work

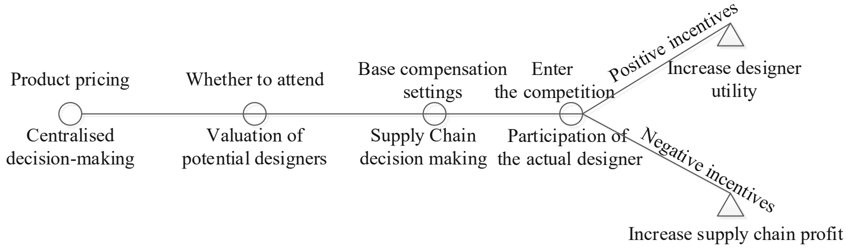

Fig. 2. Schematic Diagram of Positive and Negative Incentive Strategies

Theorem 2 Under the centralized decision, considering PNI, there exists an optimal garment retailer order quantity that maximizes the profit of the garment retailer and an optimal garment manufacturer order quantity that maximizes the global profit of the supply chain.

Certification Expanding the expectation of (13) in integral form and finding the first-order derivative and second-order derivative for q_m respectively, then it is proved in the same way as Lemma 1. When each parameter satisfies certain conditions, that is $\partial\Pi_s/\partial q_m = 0$ and $\partial^2\Pi_s/\partial q_m^2 > 0$, there exists an optimal q_m^* that maximizes Π_s. The certificate is completed.

Theorem 3 The global profit of the supply chain under the PNI is better than the BM, and the order quantity of the garment retailer increases under the same condition, while the optimal order quantity of the garment manufacturer remains unchanged.

Certification According to Theorem 2, solving the optimal garment manufacturer order quantity and substituting it into (12) and (13) respectively, this paper obtains significantly larger results under the PNI than the BM case. The details are verified in Sect. 4.1. The certificate is completed.

4 Example Analysis

4.1 Model Comparison Analysis

On the basis of the above analysis, this section verifies all mentioned lemmas and theorems above. Using Matlab to generate 864,000 random demand and random supply data simulating various data changes under one day per second views of the platform. Assume that D_k is correlated with the number of second views on the platform. Among them, the probability of the degree of views per second, the probability distribution of product demand, and the proportion of random supply are shown in Tables 3, 4, and 5 respectively.

Using rand function to generate 86400*3 random data with 0–1 distribution. In addition, without loss of generality, assign values to some of the parameters: $p_l = 30$, $c_m = 10$, $r = 60$, $p_c = 100$, $\lambda = 5$, $\mu = 10$, $\Omega = 0.1$, $\theta = 1.2$.

Under decentralised decision making, Fig. 3 (Simulation time is about 2604s) validates the Lemma 1 ~ 4.

For (a), under the condition $D_K = q_r$, there is an optimum $q_m^* = 96$ for the garment manufacturer to maximize its desired profit, which is 462.33. For (b), to facilitate the

Table 3. Probability of the degree of views per second

Second browsing probability	Views per second	Cumulative probability
0.2	high	0.2
0.6	secondary	0.8
0.2	low	1

Table 4. Probability distribution of product demand

Demand	High	Cumulative probability	Medium	Cumulative probability	Low	Cumulative probability
40	0.03	0.03	0.10	0.10	0.44	0.44
50	0.05	0.08	0.18	0.28	0.22	0.66
60	0.15	0.23	0.40	0.68	0.16	0.82
70	0.20	0.43	0.20	0.88	0.12	0.94
80	0.35	0.78	0.08	0.96	0.16	1
90	0.15	0.93	0.04	1	0.00	
100	0.07	1	0.00		0.00	

Table 5. Proportion of random supply

Actual supply proportion	Supply random number	Cumulative probability
0.5	0.5	0.5
0.7	0.4	0.9
0.9	0.1	1

calculation, set $c_s = 0.1p_c^2 + 5p_c + 100$. Under deterministic supply chain, $n/\theta = D_k = q_r$, as q_m rises, garment retailers' profit rises and then falls, when $p_c^* = 291$, the garment retailer maximizes its desired profit, which is 4309.9. For (c), when only eliminating consumer demand uncertainty, under optimal pricing, the expected profit of the garment retailer increases with q_m until it reaches a more stable trend. There exists a minimum $q_m = 260$, which allows the garment retailer to maximize the expected profit 4288.2. For (d), when only eliminating manufacturer's actual supply uncertainty, under optimal pricing, the expected profit of the garment retailer increases and then decreases with q_r. There exists an optimal $q_r^* = 80$, so that the garment retailer maximizes its expected profit, which is 3499.7.

Table 6 (Simulation time is about 592s) shows the impact of different retail prices p_c on decentralized decision making. As p_c increases, q_m^* stays the same and q_r^* shows a small upward trend, and is always smaller than p_c. The global expected profit rises and then falls, and the maximum profit is achieved at 4058.1 with $p_c = 260$. Due to the lack of supply from fabric suppliers and fabric wastage, garment manufacturers will scale up their orders to try to meet the orders of garment retailers.

Figure 4 (Simulation time is about 451s) validates the Theorem 1. Under the centralized decision, the global expected profit increases and then decreases with q_m. There exists an optimal $q_m^* = 166$, so that the supply chain maximizes its expected profit, which is 3602.3. It can be seen that the order volume to fabric suppliers can be increased under centralized decision making. This indicates that centralized decision making is better than decentralized decision making.

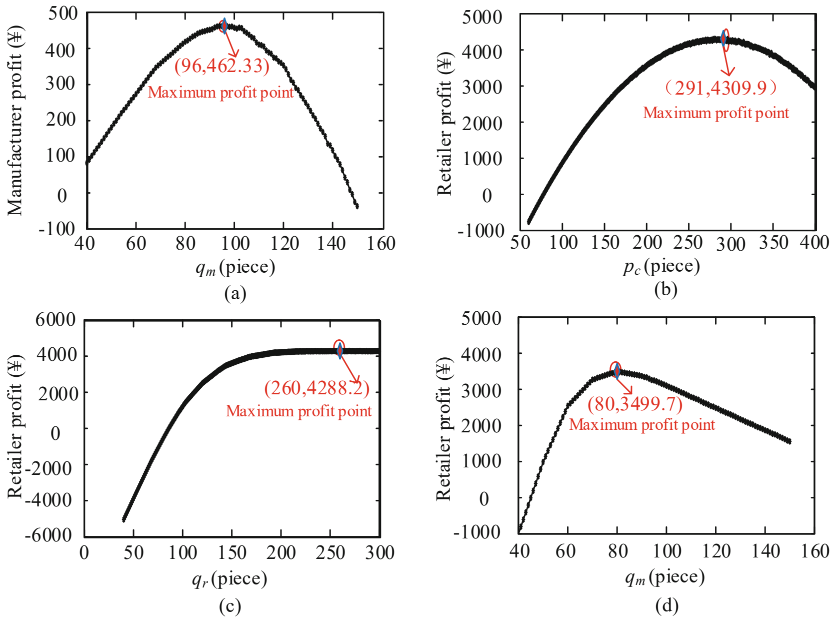

Fig. 3. Lemma 1 ~ 4verification diagram

Table 6. Impact of different retail prices on decentralized decision-making

p_c	q_r^*	q_m^*	Global profit
140	60	96	977.3
160	64	96	1552.0
180	70	96	2066.3
200	71	96	2600.2
220	75	96	3336.7
240	78	96	2651.6
260	81	96	4058.1
280	82	96	3915.8
300	79	96	3843.4

Further the new variables are assigned: $\gamma = 0.8$, N $= 500$, $\rho = 0.2$, $\beta = 0.5$, $p_b = 50$, $\mu \sim N(260, 50^2)$. Tables 7 and 8 verify Theorems 2 and 3.

Select the optimal pricing data in Table 8 for model comparison analysis, as shown in Fig. 5.

From a comprehensive perspective, PNI significantly increases the global expected profit of the supply chain, but reduces the crowdsourced designer utility. It is necessary to find the equilibrium price so that the CSC supply chain and the crowdsourced designer

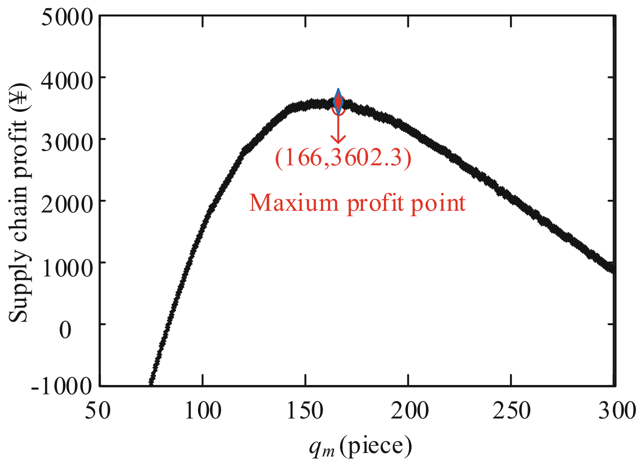

Fig. 4. Theorem 1 verification diagram

Table 7. Profit and optimal order quantity ($p_c = 100$) (Simulation time is about 1531s)

Policy model	$\Pi_r \mid q_r^*$	$\Pi_s \mid q_{ms}^*$	$U_s \mid q_{mu}^*$
BM	$308.4 \mid q_r^* = 60$	$874.2 \mid q_{ms}^* = 120$	$1600 \mid q_{mu}^* = 120$
PNI	$1640.9 \mid q_r^* = 60$	$2216.8 \mid q_{ms}^* = 120$	$262.2 \mid q_{mu}^* = 290$

Table 8. Profit and optimal order quantity ($p_c = 260$) (Simulation time is about 1532s)

Policy model	$\Pi_r \mid q_r^*$	$\Pi_s \mid q_{ms}^*$	$U_s \mid q_{mu}^*$
BM	$3421.4 \mid q_r^* = 60$	$3602.8 \mid q_{ms}^* = 152$	$8160 \mid q_{mu}^* = 152$
PNI	$11328.0 \mid q_r^* = 79$	$11621.0 \mid q_{ms}^* = 152$	$137.4 \mid q_{mu}^* = 237$

game each other to a more stable level, and the positive and negative incentives work best.

As seen in Table 9, there exists $p_r = 140$ bringing the positive and negative incentive effects to an optimal equilibrium level.

4.2 Sensitivity Analysis

To investigate the impact of relevant parameter settings on crowdsourcing supply chains and crowdsourcing designers, PNI is used as the basis, supplemented by BM for comparative analysis.

Figure 6(a)(b) shows the impact of θ on garment manufacturers and retailers. As θ increases, the optimal order quantity and the maximum profit of the garment retailer do

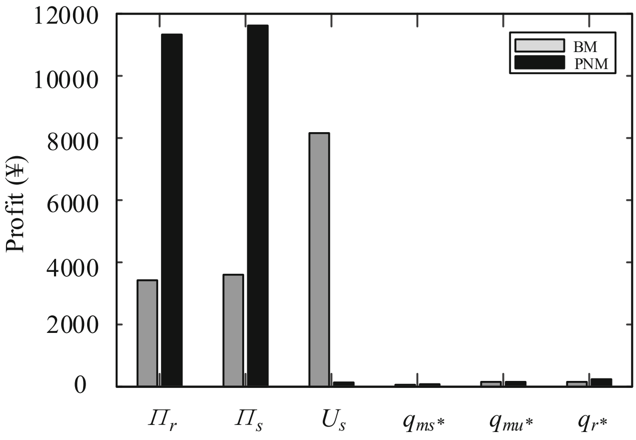

Fig. 5. PNI profit and optimal order quantity

Table 9. PNI profit and optimal order quantity (Simulation time is about 9210s)

p_r	$\Pi_s \mid q^*_{ms}$	$U_s \mid q^*_{mu}$
100	$2216.8 \mid q^*_{ms} = 120$	$262.2 \mid q^*_{mu} = 290$
120	$3314.2 \mid q^*_{ms} = 135$	$461.3 \mid q^*_{mu} = 288$
140	$4464.5 \mid q^*_{ms} = 140$	$458.7 \mid q^*_{mu} = 273$
160	$5631.0 \mid q^*_{ms} = 143$	$452.2 \mid q^*_{mu} = 286$
180	$6807.5 \mid q^*_{ms} = 144$	$437.7 \mid q^*_{mu} = 277$
200	$7996.2 \mid q^*_{ms} = 144$	$410.6 \mid q^*_{mu} = 292$
220	$9197.9 \mid q^*_{ms} = 147$	$367.1 \mid q^*_{mu} = 265$
240	$10401.0 \mid q^*_{ms} = 147$	$307.3 \mid q^*_{mu} = 292$
260	$11621.0 \mid q^*_{ms} = 152$	$137.4 \mid q^*_{mu} = 237$

not change much, but the optimal order quantity of the garment manufacturer gradually increases and the maximum profit gradually decreases, which indicates the technology of garment production should be further refined to reduce the fabric consumption rate. Figure 6(c) shows the impact of q_m on CSC supply chain profit and crowdsourcing designer utility. As q_m increases, the crowdsourced designer utility remains basically the same, while the supply chain profit gradually decreases. Since the number of potential participants is larger, the crowdsourcing design payoff is more related to the number of potential participants, and the order quantity has less influence on the crowdsourcing design payoff. Therefore, it should increase the publicity of the crowdsourcing platform to explore more potential participants in order to motivate the crowdsourced designers to a greater extent. Figure 6(d) shows the impact of μ on CSC supply chain profit and crowdsourcing designer utility. In practice, designers of different ability levels value their design works differently. For some uncommon apparel such as wedding dresses

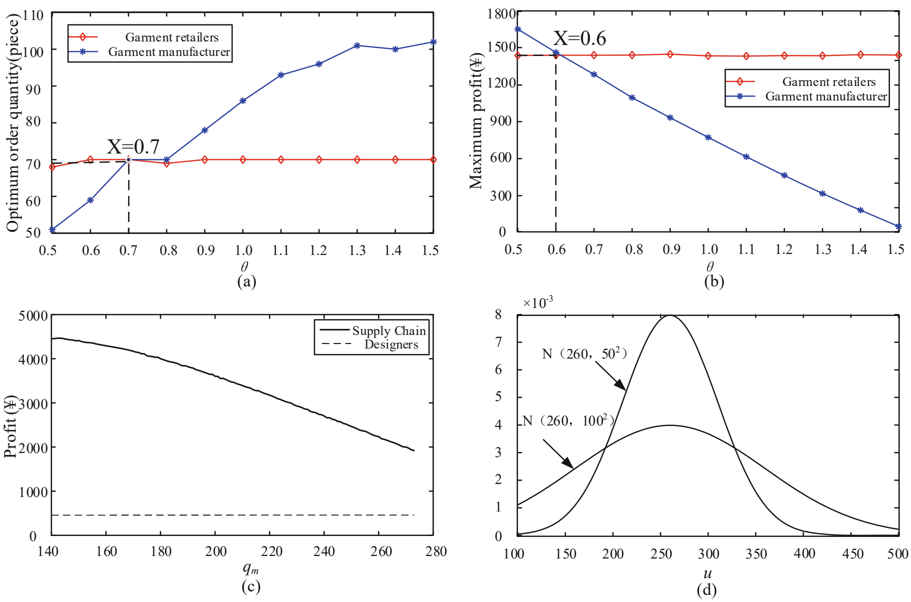

Fig. 6. Sensitivity analysis chart

Table 10. Impact of value convergence on profits

profit under PNI	$N(260, 50^2)$	$N(260, 100^2)$
Crowdsourcing Designer	458.7	410.6
Crowdsourcing supply chain	4459.8	4493.4

and evening gowns, designers have more room to create and tend to have lower value convergence.

Table 10 shows that when μ decreases, the designer utility also decreases, but the supply chain profit increases. This correlates with the intensity of the competition, the more intense the competition, the lower the probability of winning and the lower the designer's utility. However, the likelihood of obtaining high-quality creative designs increases, and so does the supply chain profit.

5 Conclusions

The clothing industry, which mainly deals with fast fashion products, has encountered bottlenecks in its development and is in need of transformation and upgrading. In view of this, this paper establishes a basic production decision model for clothing companies to reduce design cost and inventory risk. In order to obtain continuous high-quality creativity and avoid crowdsourcing fraud, a positive and negative incentive mechanism is constructed to optimize the supply chain design from the perspective of crowdsourced designers' behavior, and a risk-sharing contract is developed to maximize the expected utility of the crowdsourcing supply chain and crowdsourced designers. Finally, this paper performs example analysis and concludes that PNI is better than BM, which improves the supply chain profit and expands the order quantity of garment manufacturers.

However, this paper does not consider how to determine a series of parameter settings such as crowdsourcing designer effort and experience value, and how to further circumvent crowdsourcing fraud. It is also necessary to set up reasonable ability assessment mechanism and reputation scoring mechanism to effectively solve the above problems, and these settings will be the direction of future research.

Acknowledgements. Supported by "the Fundamental Research Funds for the Central Universities", Zhongnan University of Economics and Law.

References

1. He, MT. (2016) Research on apparel supply chain design models based on crowdsourcing conditions. Modern Commerce and Trade Industry, Commun., 37: 10–11. https://doi.org/10.19311/j.cnki.1672-3198.2016.01.006.
2. Xu, Y., Sun, Y., Cruz, Ignacio., Fulk, J. (2021) Creating the path to success: The impact of crowdsourced exploratory and exploitative activities of expert graphic designers on creativity performance. Telematics and Informatics, Commun., 58. https://doi.org/10.1016/j.tele.2020.101520.
3. Li, JZ., Zhang, N., Liu, CL. (2018) Analysis of On/OffLine hybrid custom design production decision models for crowdsourced supply chains. Chinese Management Science, Commun., 26: 132–144. https://doi.org/10.16381/j.cnki.issn1003-207x.2018.11.014.
4. Li, JZ., Zhang, N., Liu, CL. (2019) Crowdsourcing supply chain order production decision optimisation based on omni-channel design. Computer Integrated Manufacturing System, Commun., 25: 1248–1258. https://doi.org/10.13196/j.cims.2019.05.021.
5. Liu, CL., Zhang, N., Li, JZ., Zhou, YP. (2019) Supply chain delayed production optimisation based on information updates under online crowdsourcing design. Computer Integrated Manufacturing System, Commun., 25: 2963–2972. https://doi.org/10.13196/j.cims.2019.11.025.
6. Meng, XL., Yang, J., Wu, YF. (2022) Optimal quality control of crowdsourced logistics services considering reward and penalty mechanisms and cost sharing. Chinese Management Science, Commun., 30: 182–195. https://doi.org/10.16381/j.cnki.issn1003-207x.2020.0746.
7. Bayus, BL. (2013) Crowdsourcing New Product Ideas over Time: An Analysis of the Dell IdeaStorm Community . Management Science, Commun., 59: 226–244. https://doi.org/10.1287/mnsc.1120.1599.
8. Hu, M., Wang, L. (2021) Joint vs. Separate Crowdsourcing Contests. Management Science, Commun., 67: 2711–2728. https://doi.org/10.1287/mnsc.2020.3683.
9. Wang, X., Khasraghi, HJ., Schneider, H. (2020) Towards an Understanding of Participants' Sustained Participation in Crowdsourcing Contest. Information Systems Management, Commun., 37: 213–226. https://doi.org/10.1080/10580530.2020.1696586.
10. Liu, TX., Yang, J., Adamic, LA., Chen, LA. (2012) Crowdsourcing with all-pay auctions: A field experiment on Taskcn. Journal of the American Society for Information Science, Commun., 60: 2020–2037. https://doi.org/10.1287/mnsc.2013.1845.

11. Chawla, S., Hartline, JD., Sivan, B. (2019) Optimal crowdsourcing contest. Games and Economic Behavior, Commun., 113: 80–96. https://doi.org/10.1016/j.geb.2015.09.001.
12. Chen, PY., Pavlou, P., Wu, SY., Yang, Y. (2021) Attracting High-Quality Contestants to Contest in the Context of Crowdsourcing Contest Platform. Production and Operations Management, Commun., 30: 1751–1771. https://doi.org/10.1111/poms.13340.
13. Wang, MM., Wang, GG., Zhang, WN. (2019) How to enhance solvers' continuance intention in crowdsourcing contest The role of interactivity and fairness perception. Online Information Review, Commun., 44: 238–257. https://doi.org/10.1108/OIR-11-2017-0324.
14. Liang, HG., Wang, MM., Wang, JJ., Xue, YJ. (2018) How intrinsic motivation and extrinsic incentives affect task effort in crowdsourcing contests: A mediated moderation model. Computers in Human Behavior, Commun., 81: 168–176. https://doi.org/10.1016/j.chb.2017.11.040.
15. Ayaburi, EW., Lee, J., Maasberg, M. (2022) Understanding Crowdsourcing Contest Fitness Strategic Decision Factors and Performance: An Expectation-Confirmation Theory Perspective, Commun., 22: 1227–1240. https://doi.org/10.1007/s10796-019-09926-w.
16. Pollok, P., Luttgens, D., Piller, FT. (2019) Attracting solutions in crowdsourcing contests: The role of knowledge distance, identity disclosure, and seeker status. Research Policy, Commun., 48: 98–114. https://doi.org/10.1016/j.respol.2018.07.022.
17. Cornelius, PB., Gokpinar, B. (2020) The Role of Customer Investor Involvement in Crowdfunding Success. Management Science, Commun., 66: 452–472. https://doi.org/10.1287/mnsc.2018.3211.
18. Tsoukalas, G., Falk, BH. (2020) Token-Weighted Crowdsourcing. Management Science, Commun., 66: 3843–3859. https://doi.org/10.1287/mnsc.2019.3515.
19. Li, YP., Ma, SH., Yuan, KF. (2018) Manufacturer pre-sale strategy for ATO supply chain under multiple uncertainties. Computer Integrated Manufacturing System, Commun., 24: 186–194. https://doi.org/10.13196/j.cims.2018.01.019.