Research Article

A Hierarchical Innovation-Related Crowdsourcing Decision in Fast Fashion Industry

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Due to scarcity of designers in fast fashion industry and proliferation of the Internet, small- and medium-sized garment makers have gradually turned to external designers to enhance their innovation efficiency via crowdsourcing initiative. However, few have investigated the issue of fast fashion customized-design matching decision in the crowdsourcing context. Different from previous works, we split crowdsourcing matching decision process into three hierarchical submodels in terms of three key factors, namely, surplus, due date, and goodwill. From a dynamic perspective, we first develop a two-sided matching model where garment makers and online designers select one another by maximizing their total surpluses with an aim to reach robust final pairs and derive the corresponding conditions under which the optimal pairs can be obtained. Then, the extensions of the matching model are conducted by incorporating the critical factors of due date and garment makers' goodwill, respectively. Followed by that, an improved Gale–Shapley algorithm is devised to solve the crowdsourcing matching problems. The results illustrate when garment makers exceed online designers in number, crowdsourcing design tasks without due-date constraint are more attractive for designers' participation than those with due-date constraint, and garment makers intend to share the incremental surpluses with designers to maximize the total surpluses. By contrast, when online designers surpass garment makers in number, designers prefer due-date design tasks to those without it. In addition, regardless of whether under the irregular or regular case, the model with goodwill concern always outperforms the two others. Moreover, celebrated garment makers are invited to post design tasks, thus enabling to entice more designers' engagement in crowdsourcing activities, which in turn facilitating to transfer myopic designers to strategic ones. Finally, sensitivity analysis further verifies the models are stable and robust.

1. Introduction

The fast fashion industry is a highly competitive business area, where new designs shift quickly and product life cycle is dramatically short as well [1]. In a fast fashion market, customers tend to purchase only what matches their anticipation and preferences; if garment makers do not offer the option of tailored design for them, which in turn makes consumers not to patronize and even give up their purchase intention accordingly [2]. It means that firms' design capabilities and innovation play a key role in a fierce market competition. Therefore, fashion designers are given a top priority in fast fashion industry.

As observed in practice, successful fast fashion firms such as H&M, Zara, Uniqlo, and among others generally possess strong innovation and design capabilities in response to market uncertainties. Conversely, the fashion firms facing woes primarily resulted from neglecting the importance of designers' roles. As a result, competitive garment makers invariably keep or recruit more apparel designers for sharpening their edges [3]. More importantly, a majority of fast fashion makers belong to small- and medium-sized enterprises (SMEs) and usually lack sufficient resources to meet customers' tailored needs, and only leveraging interfirm's professional designers may lead to the decrease in customer satisfaction. With the advent of Internet, garment makers have an access to other innovation/ design alternatives by adopting crowdsourcing paradigm, which mitigates the shortage of offline design capacities [4, 5]. With the support from crowdsourcing, SMEs could

integrate external innovations into internal ones, thus compensating for self-innovation capacity deficits and enhancing their design flexibilities as well.

Crowdsourcing is a term first coined by Howe in the *Wired Magazine* in 2006. It refers to the innovation of mass participation based on the sweep ubiquity of Internet [6], wherein a firm or an organization distributes assignments once conducted by internal staff to undefined network of people. Crowdsourcing, theoretically, can be key catalysts in attracting a group of creative and enthusiastic people capable of providing better ideas than those attained from conventional patterns [7]. Realizing its potential business values and promising prospect, either giants or startups have adopted crowdsourcing to enhance innovation and design flexibilities and competencies [8]. For example, in two Chinese popular online platforms Zhubaijie and Taobao, crowdsourcing services are offered to a plethora of garment makers and designers. For the garment makers, they post customized-design tasks on crowdsourcing platforms to solicit novel solutions from online dress designers and then chose those with superior qualities upon specific criteria, and only the winners whose solutions are selected are rewarded by garment makers. The crowdsourcing designers are heterogeneous in innovation and design style, and they usually first browse crowdsourcing websites, searching for their favorable design tasks and then submit their solutions according to garment makers' requirements such as completion duration, quality, and compensation for design tasks in a competitive format. A report from AliResearch revealed that the amounts of deals in the dress-design crowdsourcing sector reached to 7.28 million CNY in 2019, an increase of about 45% compared to the year of 2018, which obviously showing the upward trend.

Although the application of crowdsourcing has numerous benefits, there still exist three problems which perplex decision-makers in practice: (i) how to appropriately and efficiently match between garment makers (crowdsourcers) and crowdsourcing designers (crowdsourcees) in process of executing crowdsourcing activities? (ii) which condition can the optimal and robust matching outcomes be obtained? (iii) for a crowdsourcing platform, what is the differences in crowdsourcing design matching in terms of three critical factors, namely, surplus, due date, and goodwill concern? As we have known, most of such matching nowadays run through a primitive individual-selection method on crowdsourcing platforms, thus leading to a lower matching rate, but solving the above problems could facilitate the shape of target and automatic matching and recommend both garment makers (crowdsourcers) and crowdsourcing designers (crowdsourcees) in an efficient way.

Motivated by such practices, this paper characterizes a two-sided matching model in a fast fashion market consisting of crowdsourcing designers and garment makers. Our work is similar to [9, 10] those addressing the matching problems; among them, Peng et al. [9] studied a vessel-cargo matching with price game mechanism and mimicked the price bid in the process of matching preferred objects. The literature [10] examines a supply-demand matching model

where three settings are taken into account including oversupply, overdemand, and supply-demand equilibrium. Unlike their work addressing one matching model statically, our model breakdowns matching decision into three hierarchical submodels in terms of three key factors and dynamically analyzes and optimizes the robust paring with respect to garment makers and designers.

Therefore, the contributions of this paper are threefold. (i) We split a designer-maker matching process into three hierarchical submodels from a dynamic perspective in the crowdsourcing context. These models capture the dynamic process of crowdsourcing decision-making, and the equilibrium state of the stable two-sided matching between designers and garment makers is analyzed. (ii) From a holistic view, we grouped crowdsourcing designers into two categories, namely, myopic and strategic ones, each of whose attributes is depicted in the proposed corresponding matching models to examine its impact on the matching outcomes. (iii) The third contribution is to integrate the practical factors of due date and garment makers' goodwill into the two-sided matching problem, which is seldom addressed in prior research.

The remainder of this paper is configured as follows. Section 2 briefly reviews the related literature. In Section 3, we present main notations used in this paper and problem description. A basic model characterizing a two-sided matching process between crowdsourcing designers and garment makers and the extensions with consideration of due date and garment makers' goodwill are proposed in Sections 4–6. The algorithm procedure is devised in Section 7. Section 8 presents computational experiments. Finally, we offer concluding remarks along with future research directions in Section 9.

2. Literature Review

The work related to the current study is primarily in the following three facets, i.e., fast fashion, crowdsourcing innovation, and matching model.

2.1. Research on Fast Fashion Industry. Fast fashion industry is characterized by seasonal demand, mass variety, short shelf life, and diverse consumer preference [2]. In such a context, fast fashion firms will encounter more market variation, hence increasing design uncertainty and volatility. Therefore, fast fashion industry has attracted much attention from scholars. Nonetheless, it is noteworthy that prior literature on this topic mainly underlines fast fashion supply chain coordination [1, 11] and pricing decision [12, 13], as well as quick response issue [14, 15]. Although how to design and evaluate new products is crucial to garment makers, there is less research related to this issue except the literature [3, 4, 16, 17].

Among them, Dou et al. [16] proposed an approach of fast fashion product collaborative customization to improve the design process, use design iteration, and configure knowledge to seek the optimal design. Hirscher et al. [17] discussed a new value creation in the fashion sector through

social manufacturing, namely, do-it-yourself, do-it-together, and participatory design strategies, and analyzed the different values in social manufacturing. We differ from their work by employing a crowdsourcing design channel to match designers and garment makers.

In addition, Dai et al. [3] considered a designer platform service, offering the crowdsourcing mechanism in the fashion market; the price and minimum production quantity decisions are made with consideration of the entrant designer's objective and customer demand structures. Li et al. [4] proposed multiperiod order models of crowdsourcing supply chain system, where a garment maker chooses the best one from solutions submitted by online crowdsources and utilizes wholesale price, buyback, and profit-sharing scheme to design a mixed contract with an aim to coordinate the whole supply chain. Unlike the above studies, we investigate the crowdsourcing design problem by leveraging a hierarchical matching method.

2.2. Research on Crowdsourcing Innovation.

Crowdsourcing refers to an online, distributed, problem-solving, and production model that uses the collective intelligence of networked communities for specific purposes [7]. Although several researchers question the role of crowdsourcing and highlight its negative effects, such as participants' repeatedly submitted similar solutions, sloppiness, or cheating [18], crowdsourcing is effective in enhancing design capabilities and innovative competencies for sharpening firms' competitive edges [19].

Most studies have focused on how to facilitate crowdsourcing innovation activities using empirical models from two lenses, namely, crowdsourcer (task poster) and crowdsourcee (task solver). From the crowdsourcer lens, researchers have investigated the task-specific factors regarding crowdsourcing development and found the significant impacts of task type, task specificity, monetary reward, and duration on crowdsourcing performance [8]. Specifically, task complexity has significant negative impact on the number of crowdsourcing solutions submitted, while duration for the tasks and monetary reward have significant positive effect. In addition, brand strength of the crowdsourcer also has a significant effect on number of submissions [7].

From the crowdsourcee lens, crowdsourcee individuals' extrinsic, intrinsic, and social motives are effective predictors of individuals' participation and performance in the crowdsourcing context [20]. Prior studies have also explored that competitors' experience, intrinsic motivation, and extrinsic motivation with immediate payoffs have a significant positive impact on the quantity of crowdsourcing solutions. While earning reputations, learning, improving skills, getting employed as a freelancer, and self-marketing have an effect on average quality of submissions [21]. Additionally, the significant effect of number of competitors and superstars are influencing factors on crowdsourcing performance [22].

Overall, the aforementioned papers study the influencing factors of crowdsourcing by utilizing the empirical study.

But in this paper, we use an analytical research method to examine the decision process of crowdsourcing design for matching crowdsourcers and crowdsourcees.

2.3. Research on Matching Model.

Matching models are kind of analytical tool which has been applied in many domains: hospital-resident matching [23], stable marriage problem [24], and vessel-cargo matching [9], as well as supply-demand matching problem [10, 25].

But the application of matching model in crowdsourcing design is rare, especially in the fast fashion sector. Some authors used matching models to capture two-sided matching problems in the loan market [26]. Some other authors utilized matching models to characterize supply and demand matching management. For instance, Boysen et al. [27] focused on deterministic matching problems and provided a classification scheme for the resulting optimization problems occurring in different areas of the sharing economy [27], whereas Yin and Li [28] proposed a decision-making method for matching management of supply and demand based on fuzzy sets and considered interactions among aspiration criteria, and Peng et al. [23] proposed a model of stable vessel-cargo matching with price game mechanism in the dry bulk shipping market. Similar to the latter paper, in this paper we employed the matching model to depict the dynamic hierarchy matching problem for fast fashion customized design in a crowdsourcing environment.

All in all, different from previous work addressing one matching model statically or using the empirical method to examine crowdsourcing innovation, our model splits design crowdsourcing matching decision into three hierarchical submodels in terms of three key factors and dynamically analyzed and optimized the robust paring with respect to garment makers and designers.

3. Problem Description

There is a fast fashion crowdsourcing platform community consisting of a population of garment makers and designers with different requirements and competencies, respectively. Assume that both designers and garment makers are rational, and a designer only chooses and undertakes one design task, while one task is only completed by one crowdsourcing designer. In addition, regardless of whether a submitted solution is selected or not, the solution is not allowed to be repeatedly submitted again. In this setup, garment makers distribute their crowdsourcing tasks and announce the corresponding financial rewards on the platform. However, incumbent or entrant designers choose crowdsourcing tasks based on their competencies and design styles and then submit their design proposals. To this end, the matching between garment makers and designers is proceeded.

In general, the designers and the garment makers select their matchers/partners considering two parts, namely, present utilities and future expected benefits. The former is the behavior of myopic designers who only concern about

present utilities, which commonly occurs under two cases, i.e., crowdsourcing without and with consideration of due-date factor. In the case of the absence of due-date factor, the designers and the garment makers merely focus on cost, reward, and design style as well and believe that the time issue is not a problem because of their confidence in being capable of on-time completion of crowdsourcing tasks. By contrast, in the presence of due-date constraint, both sides not only paid attention to the abovementioned factors, but they also took due date into account. The latter part, i.e., future expected benefits, refers to the act of strategic designers who care about next-round gains, which is strongly associated with the garment makers' current goodwill and reputation; for instance, given two different garment makers, the higher goodwill the garment maker has, the more expected benefits the designers will obtain in the next round. In this regard, we thus breakdown matching decision process into three levels, namely, basic two-sided matching without due-date constraint, two-sided matching with due-date constraint, and two-sided matching with due-date and goodwill concern. The dynamic hierarchy matching decision process is shown in Figure 1.

As shown in Figure 1, designers first filter out design tasks which they are unable to punctually complete or which are beyond their capabilities. Most importantly, pre-announced reward by garment makers is key driver for crowdsourcing designers to determine the choice of matching with crowdsourcing tasks; if online apparel designers perceive the amount of task rewards below their expectations, they tend to be likely to select other alternatives with higher monetary ones, which in turn forces garment makers to raise their subsequent rewards for attracting more and better-qualified participants. This can serve as a proxy of pricing mechanism.

Furthermore, when online designers are far-sighted for future gains, then garment maker's goodwill is taken into account by crowdsourcees, especially for strategic designers, because the garment makers' reputation and goodwill have a significant impact on the likelihood of designers' success of being selected in the future. To this end, the anticipated benefits will be transformed into designers' utilities. Since designers are inclined to choose the tasks with higher utility, each individual designer has a sequence list of preferences for design tasks.

Following the same logit as designers, garment makers also first exclude the designers whose professional capabilities cannot serve their requirements well. Generally, the garment makers' utilities are determined by the quality of designer's solution and marginal cost. Likewise, with observing prior crowdsourcing participants, garment makers will determine the current amount of crowdsourcing rewards through tradeoff between transaction cost and payoff. In other words, the simpler the tasks or the more competitive crowdsourcing is, the less the rewards are offered by garment makers. As a result, each garment maker has the sequence list of preferences with respect to designers. To this end, the designers and garment makers dynamically make decision, and the optimal match between both could be finalized until mutual gratifications are obtained.

4. Two-Sided Matching Model

In this section, we consider the case where crowdsourcing designers are myopic and only concern about present utility, rather than focus on long-term gains, i.e., myopic crowdsourcees underline the current benefits and do not care about the next-round benefits. To match both sides, the main notations used in this paper are illustrated in Table 1. The designer's and the garment maker's utilities are derived out as follows.

4.1. Designer's Utility for Ranking Garment Makers.

In the myopic designer setting, assume that each designer j, $j \in J$, (J is the set of designers or design solutions) only submits one design solution on the crowdsourcing platform and independently makes decision in choosing tasks i, $i \in I$, (I is the set of garment makers or tasks) by maximizing the utilities. Meanwhile, we deposit that the crowdsourcing platform does not charge any fees from myopic designers with an aim to encourage their participation. Considering that the designers j are short-sighted, it is reasonable if we assume each designer assesses his payoffs based on the current-round tasks i and the corresponding costs. Given a crowdsourcing task i, designer's utility is determined by the difference between payoffs $R_{ij,\text{present}}$ and incurred costs C_{ij}. Where the myopic designer j payoff $R_{ij,\text{present}}$ is the reward from the garment maker i, while the corresponding costs C_{ij} include time cost or invest cost. Thus, designer's (j) utility is expressed by

$$U_{ij}^D = R_{ij,\text{present}} - C_{ij}, \tag{1}$$

where $R_{ij,\text{present}}$ is the reward of designer j for completion of task I and C_{ij} represents the cost of completion of task i by designer j.

4.2. Garment Maker's Utility for Ranking Designers.

As the same logical way as myopic designers, garment makers, $i \in I$, (I is the set of garment makers or tasks) are rational and individually determine their crowdsourcing tasks being assigned to the desirable designer j, $j \in J$, (J is the set of designers or design solutions) by using a utility-maximization method. Also, assume that each task only matches one solution. Given a crowdsourcing solution j, garment maker's utility is evaluated with the gap between the benefit B_{ij} from crowdsourcing solution j and the compensation-for-designer cost $R_{ij,\text{present}}$.

Additionally, consider that the crowdsourcing platform serves as an interface between online designers and garment makers, such that the garment makers are charged at a platform service fee S_{ij}, thus implying the garment maker's (i) cost includes two parts $R_{ij,\text{present}}$ and S_{ij}. Therefore, the garment maker's utility is defined as follows:

$$U_{ij}^M = B_{ij} - R_{ij,\text{present}} - S_{ij}. \tag{2}$$

The first term of the right side of equation (2) B_{ij} indicates the benefit of the garment maker i from design
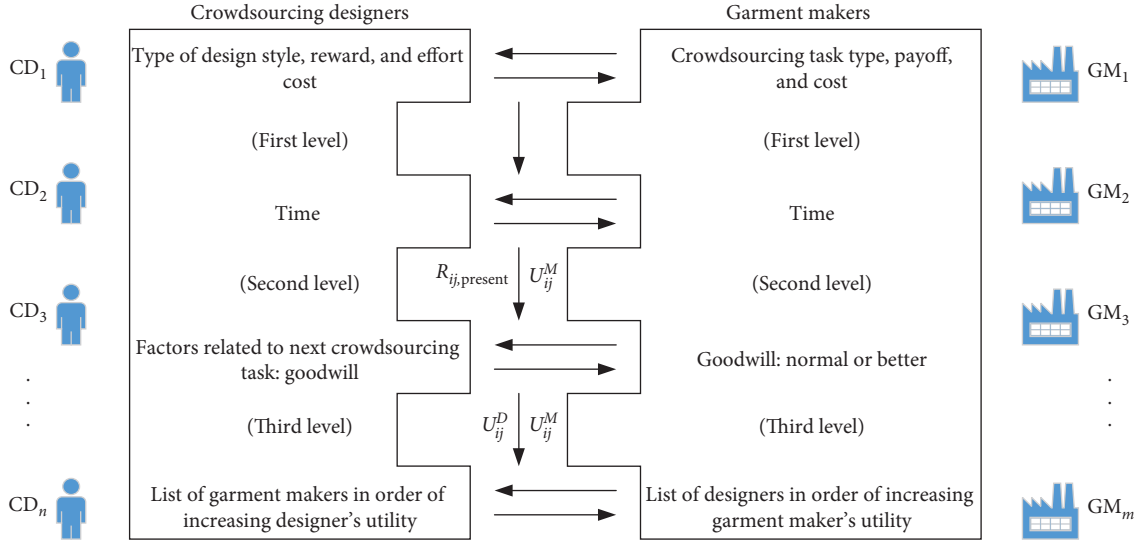
FIGURE 1: Criteria of hierarchical matching between garment makers and designers.

TABLE 1: Main notations used in this paper.

Type	Notation	Definition
Sets	I	Set of garment makers or tasks, $i \in I$
	J	Set of designers or design solutions, $j \in J$
	Θ_j	Set of designer's (j) completion tasks
	μ	Set of stable parings, $\mu = \left\{ (i, j) \mid Z_{ij} = 1, \forall i \in I, \forall j \in J \right\}$
	C_{ij}	Cost of completion of task i by designer j
	$P_{ij, \text{next}}$	Expected payoff for the next task if designer j completes the present design task i
	T_{ij}	Duration of task i completed by designer j
	c_{ij}	Unit time cost of task i completed by designer j
	$C(T_{ij})$	Cost of completion of task I within the time limits by designer j
Parameters	P_{N-L}	Anticipated payoff for the case in which a normal-goodwill garment maker will offer a low reward in the near future
	P_{N-H}	Anticipated payoff for the case in which a normal-goodwill garment maker will offer a high reward in the near future
	P_{B-L}	Anticipated payoff for the case in which a better-goodwill garment maker will offer a low reward in the near future
	P_{B-H}	Anticipated payoff for the case in which a better-goodwill garment maker will offer a high reward in the near future
	B_{ij}	Benefit of garment maker i from designer's (j) solution
	S_{ij}	Payment to the crowdsourcing platform by garment maker i
	α, β	Estimated parameters
	t_j^E	Earliest start time of designer j
	t_i^L	Latest submission time required by garment maker i
	$\underline{U}_{ij}^M$	Minimum utility obtained when garment maker i chooses designer j
	$\underline{U}_{ij}^D$	Minimum utility obtained when designer j accomplishes task i
Decision variables	Z_{ij}	$Z_{ij} = 1$ if garment maker i and designer j match as a pairing, $Z_{ij} = 0$, otherwise
	$R_{ij,\text{present}}$	Reward for design solution i is selected by garment maker j
Auxiliary variables	U_{ij}^D	Total utility of designer j taking on task i
	U_{ij}^M	Total utility of garment maker i selecting the designer's (j) solution
	$V_{CD}(i, j)$	Total surpluses of designer j if he matches with garment maker i
	$V_{GM}(i, j)$	Total surpluses of garment maker i if he matches with designer j

solution j, the second term demonstrates the garment maker's (i) payment (or reward) to designer j, and the third term S_{ij} denotes the service fee charged by the crowdsourcing platform only if the garment maker i and designer j match successfully.

4.3. Matching Model. To obtain a robust garment maker-designer matching equilibrium, we consider a decision problem in which the garment makers and the designers act as a single entity to make decision with a goal of the overall surplus maximization. Conversely, if designers and garment

makers separately make decision on their own interests rather than jointly as a whole. As a sequence, crowdsourcing design cannot be sustainable and even end up with platform's operational inefficiency or disclosure. Parallelly, from the crowdsourcing platform perspective, the optimal match both sides from the whole systematic way is aligned with platform's purpose. Hence, we formulate the model by maximizing the surplus of both garment makers and designers as follows:

$$\max \sum_i \sum_j \left[V_{CD}(i, j) + V_{GM}(i, j) \right] \times Z_{ij}, \tag{3}$$
$$\text{pair}(i, j),$$

which is subject to

$$V_{GM}(i, j) = U_{ij}^M - \underline{U}_{ij}^M \geq 0, \quad \forall i \in I, \forall j \in J, \tag{4}$$

$$V_{CD}(i, j) = U_{ij}^D - \underline{U}_{ij}^D \geq 0, \quad \forall i \in I, \forall j \in J, \tag{5}$$

Equation (3) aims to maximize the total surpluses of garment makers i and designers j. Equations (4) and (5) represent the surplus of garment makers i and designers j, respectively, and guarantee that the surpluses of both sides are nonnegative.

$$\sum_{i \in \{j\} \cup I} Z_{ij} = 1, \quad \forall j \in J, \tag{6}$$

$$\sum_{j \in \{i\} \cup J} Z_{ij} = 1, \quad \forall i \in I, \tag{7}$$

$$Z_{ij} \in \{0, 1\}, \quad \forall i \in I, \forall j \in J. \tag{8}$$

Equation (6) guarantees that one designer j undertakes no more than one task. Equation (7) guarantees that one task is completed by only one designer j. Equation (8) denotes that Z_{ij} is a 0-1 variable, and if garment maker i and designer j successfully match as a pair, $Z_{ij} = 1$; otherwise, $Z_{ij} = 0$.

It is worthy to note that the abovementioned analytical model could derive out the total surplus, yet the corresponding pairing is probably not stable due to that there exists double marginalization effect in some pairs (i, j). In such a context, we give the following equilibrium conditions under which garment makers and designers can match with stable final pairing:

$$V_{CD}(i^*, j^*) \geq V_{CD}(i, j^*) + \left[V_{GM}(i, j^*) - V_{GM}(i, j) \right], \tag{9}$$

$$V_{CD}(i, j) \geq V_{CD}(i^*, j) + \left[V_{GM}(i^*, j) - V_{GM}(i^*, j^*) \right], \quad \forall (i, j), (i^*, j^*) \in \mu, \mu = \left\{ (i, j) \mid Z_{ij} = 1, \forall i \in I, \forall j \in J \right\}. \tag{10}$$

Equations (9) and (10) ensure that the final pairings are stable. In detail, when garment i matches with designer j^*, garment i can obtain the surplus of $V_{GM}(i, j^*) - V_{GM}(i, j)$, more than current matching with designer j. Assuming garment maker i wants to change the current matching, garment maker i is willing to at most transfer $V_{GM}(i, j^*) - V_{GM}(i, j)$ to crowdsourcing designer j^* to change his rank. But right now, designer j^* is assigned to garment maker i^*, and $V_{CD}(i^*, j^*) \geq V_{CD}(i, j^*) + \left[V_{GM}(i, j^*) - V_{GM}(i, j) \right]$ implies that there is no incentives for the designer j^* to change the current matching. Following the same logic, garment maker i^* has no motivation to change the present pairing.

5. Extended Model with Due-Date Constraint

As we know that fashion products such as dresses, bags, footwears, and among others belong to the fast consumption industry, in which product design renews swiftly. For instance, both H&M and Zara, two famous multinational fashion companies, require that its each chain store launches new product styles twice a week and that all items on sales must be off shelf and totally replaced by new ones a month later.

Therefore, in the crowdsourcing context, crowdsourcing tasks usually have deadline request or due-date constraint for solution submission; herein the due date is denoted by T_{ij}, thus warranting garment makers in a quick response to consumers' diverse needs. In addition, myopic designer's cost is directly associated with the length of time they expend such that we assume that designer's cost is measured or quantified by task's due date T_{ij} and unit time cost c_{ij}. Hence, the utility of myopic designer with due-date constraint is represented as

$$U_{ij}^{D-II} = R_{ij,\text{present}} - C(T_{ij}), \tag{11}$$
$$C(T_{ij}) = c_{ij} \times T_{ij},$$

whereas the utility for garment makers is the same as before.

With the aforementioned analysis, we incorporate the factor of due-date constraint into the abovementioned matching model and obtain the extended one as follows:

$$\max \sum_i \sum_j \left[V_{CD}^{II}(i, j) + V_{GM}^{II}(i, j) \right] \times Z_{ij}, \tag{12}$$
$$\text{pair}(i, j),$$

which is subject to (6)–(10), and

$$V_{GM}^{\text{II}}(i,\,j) = U_{ij}^{M-\text{II}}\underline{U}_{ij}^{M} \geq 0, \quad \forall i \in I, \forall j \in J, \tag{13}$$

$$V_{CD}^{\text{II}}(i,\,j) = U_{ij}^{D-\text{II}} - \underline{U}_{ij}^{D} \geq 0, \quad \forall i \in I, \forall j \in J, \tag{14}$$

$$C\left(T_{ij}\right) = c_{ij} \times T_{ij} \geq 0, \quad T_{ij} \geq 0, \tag{15}$$

$$\left(t_{j}^{E} + T_{ij}\right) \times Z_{ij} \leq t_{i}^{L}, \quad \forall i \in I, \forall j \in J, \tag{16}$$

$$V_{CD}^{\text{II}}(i^{*},\,j^{*}) \geq V_{CD}^{\text{II}}(i,\,j^{*}) + \left[V_{GM}^{\text{II}}(i,\,j^{*}) - V_{GM}^{\text{II}}(i,\,j)\right], \tag{17}$$

$$V_{CD}^{\text{II}}(i,\,j) \geq V_{CD}^{\text{II}}(i^{*},\,j) + \left[V_{GM}^{\text{II}}(i^{*},\,j) - V_{GM}^{\text{II}}(i^{*},\,j^{*})\right], \quad \forall(i,j),\,(i^{*},\,j^{*}) \in \mu\,,\ \mu = \left\{(i,j) \mid Z_{ij} = 1, \forall i \in I, \forall j \in J\right\}. \tag{18}$$

Equation (12) aims to maximize the total surpluses of the whole matching system between garment makers and myopic designers under due-date constrain. Equations (13) and (14) represent the surplus of garment makers and designers, respectively. Equation (15) characterizes designer's expenditure cost. Equation (16) guarantees that designers punctually submit their design solution. Equations (17) and (18) are the conditions under which the robust and stable final parings can be obtained.

6. Extended Model with Goodwill Concern

Different from the two aforementioned matching models where designers are near-sighted. In this section, we assume that designers are strategic rather than myopic ones, it means that strategic designers underline both the current utilities and the next-round expected utilities as well.

Considering that the market fluctuates with the changes in time and demand, garment makers anticipate the better-qualified designers to participate; the practical way of assessing qualified designers is to observe which company designers worked before. To this end, the designers who employed by sound goodwill firms are apt to be regarded as more capable candidates, which elicits designers not only to focus on the present utilities but also care about present selected garment makers' goodwill, thus in turn help the designers to probably win next-round tasks, since goodwill refers to an intangible asset taken into account in reflecting its commercial reputation, customer connections, etc. Therefore, strategic designers prefer the tasks from makers with a higher goodwill.

Based on the model with due-date constraint and goodwill concerns, the strategic designer's utility is the sum of current task utility $(R_{ij,\text{present}} - C)$ and expected task utility $P_{ij,\text{next}}$, which is illustrated as

$$U_{ij}^{D-\text{III}} = R_{ij,\text{present}} - C\left(T_{ij}\right) + P_{ij,\text{next}}. \tag{19}$$

For the expected task utility $P_{ij,\text{next}}$, assume that the incumbent garment makers' goodwill can be grouped into two parts, namely, normal and better ones, and suppose that the strategic designer facing next-round tasks exist in two available utilities: low or high. In such a setup, low utility with normal or better goodwill is denoted by P_{N-L} and P_{B-L}, while high utility with normal or better goodwill is set by P_{N-H} and P_{B-H}. In addition, the parameters α and β indicate the probabilities of strategic designers' taking on tasks with a normal and better goodwill, respectively. Thereby, the strategic designer's expected task utility $P_{ij,\text{next}}$ can be demonstrated as $\alpha P_{N-H} + (1-\alpha)P_{N-L} + \beta P_{B-H} + (1-\beta)P_{B-L}$.

For the garment makers' utility, it remains the same as before.

In the context of goodwill concern, the extended model is formulated as follows:

$$\max \sum_{i}\sum_{j} \left[V_{CD}^{\text{III}}(i,\,j) + V_{GM}^{\text{III}}(i,\,j)\right] \times Z_{ij}, \quad \text{pair}\,(i,\,j), \tag{20}$$

which is subject to (6)–(8), (15), and (16),

$$V_{GM}^{\text{III}}(i,\,j) = U_{ij}^{M-\text{III}} - \underline{U}_{ij}^{M} \geq 0, \quad \forall i \in I, \forall j \in J, \tag{21}$$

$$V_{CD}^{\text{III}}(i,\,j) = U_{ij}^{D-\text{III}} - \underline{U}_{ij}^{D} \geq 0, \quad \forall i \in I, \forall j \in J, \tag{22}$$

$$P_{ij,\text{next}} = \alpha P_{N-H} + (1-\alpha)P_{N-L} + \beta P_{B-H} + (1-\beta)P_{B-L}, \tag{23}$$

$$V_{CD}^{\mathrm{III}}(i^*, j^*) \geq V_{CD}^{\mathrm{III}}(i, j^*) + \left[V_{GM}^{\mathrm{III}}(i, j^*) - V_{GM}^{\mathrm{III}}(i, j)\right], \tag{24}$$

$$V_{CD}^{\mathrm{III}}(i, j) \geq V_{CD}^{\mathrm{III}}(i^*, j) + \left[V_{GM}^{\mathrm{III}}(i^*, j) - V_{GM}^{\mathrm{III}}(i^*, j^*)\right], \quad \forall (i, j), (i^*, j^*) \in \mu, \mu = \left\{(i, j) \mid Z_{ij} = 1, \forall i \in I, \forall j \in J\right\}. \tag{25}$$

Equation (20) aims to maximize the total surpluses of designers and garment makers. Equations (21) and (22) represent the surplus of garment makers and designers, respectively. Equation (23) is the strategic designer's expected utility regarding the next-round task. Equations (24) and (25) are the conditions under which the robust and stable final parings can be obtained.

7. Algorithm Procedure

The classical matching problem can be solved by using Gale–Shapley algorithm. However, the proposed matching models of this paper characterize both the crowdsourcing natures and the dynamic hierarchy attributes; thus, we design an improved Gale–Shapley algorithm to adjust our garment maker-designer matching problem under the crowdsourcing environment. The algorithm procedure for the present models is described as follows (Algorithm 1).

8. Numerical Study

In this section, we present an application of garment maker-designer matching model related to the dynamical hierarchical method in the crowdsourcing context. The relevant data come from zbj.com, one of the most famous online-crowdsourcing platforms in China, providing a wide variety of crowdsourcing services including customized design for fast fashion firms. We suppose $\alpha = 0.3$, $\beta = 0.7$, $P_{N-H} = P_{B-H} = 10000$, $P_{N-L} = P_{B-L} = 8000$. In addition, two scenarios are taken into account based on the number of designers and garment makers. (i) Scenario I refers to a regular crowdsourcing case in which designers surpass garment makers in number (i.e., $n > m$), thus implying the garment maker dominates in the crowdsourcing community, whereas (ii) scenario II stands for an irregular one in which garment makers exceed designers in number (i.e., $n < m$), indicating the designers have bargaining power over garment makers. The specific parameters and attributes of garment makers and designers in two different scenarios are presented in Tables 2–5.

8.1. Scenario I: Garment Makers' Domination in Crowdsourcing.
In this subsection, considering a regular case in which the number of designers exceeds that of garment makers, we compare the pairs under three matching submodels from the hierarchical perspective, i.e., the two-sided matching model without due-date constraint (the first-level matching), that with due-date constraint (the second-level matching), and that with due-date constraint and goodwill concern (the third-level matching).

The utilities regarding the garment makers and designers are calculated according to equations (1) and (2), respectively, followed by ranking their candidates based on the

values of utilities. Then, the match between garment makers and designers proceeds by maximizing the total surplus. The first matching result of garment makers and designers can be obtained by the improved GS algorithm, and it is illustrated in Table 6, which shows that task 1 is assigned to designer 1, task 2 is assigned to designer 3, and task 3 is assigned to designer 2; while garment maker 5 chooses designer 11, and garment maker 4 chooses designer 10. Interestingly, we find that garment maker 6 does not choose anyone although three of the designers have a strong desire to match with garment maker 6, when the surpluses the designers create are under the 6th garment maker's minimum anticipation.

However, garment maker 2 finds that matching with designer 2 can help him get, $V_{GM}(2, 2) - V_{GM}(2, 3) = 500$, more surpluses. Therefore, with intention to change his ranking, garment maker 2 transfers no more than 500 surpluses to designer 2. But designer 2 prefers garment maker 3, such that designer 2 may lose, $V_{CD}(3, 2) - V_{CD}(2, 2) = 400$, surpluses if he matches with designer 2. Thereby, only if garment maker 2 compensates designer 2 at least 400 surpluses, can he change the ranking. Meanwhile, garment maker 3, which is now assigned to designer 2 will give up at most, $V_{GM}(3, 2) - V_{GM}(3, 3) = 500$, to resist garment maker 2's matching behavior, avoiding being assigned to designer 3 at the loss of 500 surpluses. So $V_{CD}(3, 2) - V_{CD}(2, 2) < V_{GM}(2, 2) - V_{GM}(2, 3) < [V_{CD}(3, 2) - V_{CD}(2, 2)] + [V_{GM}(3, 2) - V_{GM}(3, 3)]$ indicates that garment maker 3 can retain his status by transferring the surplus of $[V_{GM}(2, 2) - V_{GM}(2, 3)] - [V_{CD}(3, 2) - V_{CD}(2, 2)]$ to garment maker 2. Therefore, we can obtain the following observation.

Observation 1. (necessary condition for crowdsourcing participation). If $V_{CD}(i^*, j^*) - V_{CD}(i, j^*) < V_{GM}(i, j^*) - V_{GM}(i, j) < [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$, $\forall (i, j), (i^*, j^*) \in \mu$ holds, a garment maker i^* has to increase his reward to a designer j^* to eliminate the possibility of the designer j^* being assigned to a garment maker i.

Observation 1 implies if the rewards announced by garment makers are below a certain threshold, thus leading to crowdsourcing matching failure. Even worse, the crowdsourcing platform cannot be sustainable to operate due to being unable to attract sufficient designers' participation. The proof of Observation 1 is showed in Appendix.

Meanwhile, garment maker 1 matching with designer 1 also prefers designer 2, with $V_{GM}(1, 2) - V_{GM}(1, 1) = 3000$, whereas designer 2 whose best choice is garment maker 3 will reduce his surpluses of $V_{CD}'(3, 2) - V_{CD}(1, 2) = 2100$. To keep his surpluses, garment maker 3 is willing to transfer no more than $V_{GM}'(3, 2) - V_{GM}(3, 3) = 400$ to designer 2, thus eliminating the possibility of being assigned to designer 3. However, $V_{GM}(1, 2) - V_{GM}(1, 1) > [V_{CD}'(3, 2) - V_{CD}$

```
(1)  $\mu^0 \longleftarrow \Phi$; $U_{ij}^{M(0)} \longleftarrow E(\underline{U}_{ij}^D, \underline{U}_{ij}^M)$; $n \longleftarrow 0$
(2)  do
(3)    $n \longleftarrow n + 1$
(4)    $U_{ij}^{M(n)} \longleftarrow E(\underline{U}_{ij}^D, \underline{U}_{ij}^M)$; $x_j \longleftarrow$ rank $V_{CD}(k, j)$ in descending order;
(5)    $a \longleftarrow 0$; $b \longleftarrow 0$;
(6)    while $(a < n)$ do
(7)      $a \longleftarrow a + 1$; $b \longleftarrow 0$;
(8)      while $(b < H_j)$ do
(9)        $b \longleftarrow b + 1$; $j \longleftarrow a$; $y \longleftarrow b$; $i^* \longleftarrow x_j^y$
(10)       if (not $(V_{CD}(i^*, j^*) \geq V_{CD}(i, j^*) + [V_{GM}(i, j^*) - V_{GM}(i, j)])$) then
(11)         if $(V_{GM}(i, j^*) - V_{GM}(i, j) > V_{CD}(i^*, j^*) - V_{CD}(i, j^*)$ (option)) then
(12)  $U_{i*j*}^{M(n+1)} = U_{i*j*}^{M(n)} - [V_{GM}(i, j^*) - V_{GM}(i, j)] + [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)]$;
(13)         else
(14)  $U_{ij*}^{M(n+1)} = U_{ij*}^{M(n)} - [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] - [V_{GM}(i, j^*) - V_{GM}(i^*, j)]$;
(15)         end if
(16)       end if
(17)     end while
(18)   end while
(19)   $\mu^{(n+1)} \longleftarrow$ GS algorithm;
(20) while (not $(\mu^{(n-1)} == \mu^{(n)}$ and $U_{ij}^{M(n-1)} == U_{ij}^{M(n)})$)
(21) Output results
```

ALGORITHM 1: The solution procedure of the matching models.

TABLE 2: The specific attributes of garment makers in scenario I.

Garment maker	Task type	T_{ij} (day)	S_{ij} (CNY)	Goodwill	Reward (CNY)	$\underline{U}_{ij}^M$ (CNY)
1	Casual	9	1200	Normal	8000	45000
2	Casual	10	1200	Better	9600	50000
3	Casual	12	1200	Better	10000	48000
4	Sporty	10	1200	Better	12000	60000
5	Sporty	14	1200	Normal	13000	58000
6	Retro	18	1200	Better	12000	70000

TABLE 3: The relevant parameters of designers in scenario I.

Designer	Style type	C_{ij}	c_{ij} (CNY/day)	B_{ij} (CNY)
1	Casual	3600	300	62000
2	Casual	3100	250	65000
3	Casual	3300	260	64500
4	Casual	3250	320	60000
5	Casual	3350	280	61500
6	Casual	3500	300	60500
7	Casual	3200	310	61000
8	Sporty	3700	380	73000
9	Sporty	3800	400	69000
10	Sporty	3650	390	74500
11	Sporty	3850	370	75000
12	Sporty	3760	380	71000
13	Retro	4000	350	83000
14	Retro	4200	330	79000
15	Retro	4100	360	80000

$(2, 2)] + [V'_{GM}(3, 2) - V_{GM}(3, 3)]$ (i.e., garment maker 1 has more surpluses to compensate designer 2), garment maker 1 can change his ranking by transferring $[V'_{CD}(3, 2) - V_{CD}(2, 2)] + [V'_{GM}(3, 2) - V_{GM}(3, 3)]$ to designer 2. Additionally, garment maker 4 would match with designer 11 rather than designer 10, but $V_{CD}(5, 11) \geq V_{CD}(4, 11) + [V_{GM}(4, 11) - V_{GM}(4, 10)]$ satisfies the stable constraint, thus garment maker 4 does not intend to alter the current matching. Therefore, we have the following observation shown as follows.

TABLE 4: The specific attributes of garment makers in scenario II.

Garment maker	Task type	T_{ij} (day)	S_{ij} (CNY)	Goodwill	Reward (CNY)	U_{ij}^M (CNY)
1	Casual	9	1200	Normal	8000	45000
2	Casual	10	1200	Better	9600	50000
3	Casual	12	1200	Better	10000	48000
4	Casual	13	1200	Normal	10500	53000
5	Casual	11	1200	Normal	8500	52000
6	Casual	15	1200	Better	11000	53000
7	Sporty	10	1200	Better	12000	60000
8	Sporty	14	1200	Normal	13000	58000
9	Sporty	12	1200	Normal	15000	52000
10	Sporty	13	1200	Better	14500	50000
11	Retro	18	1200	Better	12000	62000
12	Retro	16	1200	Normal	15000	60000

TABLE 5: The relevant parameters of designers in scenario II.

Designer	Style type	C_{ij}	c_{ij} (CNY/day)	$B_{ij}(a)$ (CNY)
1	Casual	3600	300	62000
2	Casual	3100	250	65000
3	Casual	3300	260	64500
4	Casual	3250	320	60000
5	Casual	3350	280	61500
6	Sporty	3700	380	73000
7	Sporty	3800	400	69000
8	Sporty	3650	390	74500
9	Retro	4000	350	83000
10	Retro	4200	330	79000

TABLE 6: Scenario I: the first matching pairs in the matching submodel without due-date constraint.

	GM$_1$	GM$_2$	GM$_3$	GM$_4$	GM$_5$	GM$_6$
CD$_1$	(4400, 7800)*	(6000, 1200)	(6400, 2800)	—	—	—
CD$_2$	(4900, 10800)	(6500, 4200)	(6900, 5800)*	—	—	—
CD$_3$	(4700, 10300)	(6300, 3700)*	(6700, 5300)	—	—	—
CD$_4$	(4750, 5800)	(6350, −800)	(6750, 800)	—	—	—
CD$_5$	(4650, 7300)	(6250, 700)	(6650, 2300)	—	—	—
CD$_6$	(4500, 6300)	(6100, −300)	(6500, 1300)	—	—	—
CD$_7$	(4800, 6800)	(6400, 200)	(6800, 1800)	—	—	—
CD$_8$	—	—	—	(8300, −200)	(9300, 800)	—
CD$_9$	—	—	—	(8200, −4200)	(9200, −3200)	—
CD$_{10}$	—	—	—	(8350, 1300)*	(9350, 2300)	—
CD$_{11}$	—	—	—	(8150, 1800)	(9150, 2800)*	—
CD$_{12}$	—	—	—	(8240, −2200)	(9240, −1200)	—
CD$_{13}$	—	—	—	—	—	(8000, −200)
CD$_{14}$	—	—	—	—	—	(7800, −4200)
CD$_{15}$	—	—	—	—	—	(7900, −3200)

*Indicates successful matching ones.

Observation 2. (sufficient condition for crowdsourcing participation). If $V_{GM}(i, j^*) - V_{GM}(i, j) > [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$, $\forall (i, j), (i^*, j^*) \in$ holds, a garment maker i has adequate surpluses to defeat a garment maker i^* and match with a designer j^*.

Observation 2 demonstrates that although the crowdsourcing platform attracts tremendous designers' participation, garment makers who compete against the others to win customized design solutions rely on both expected utilities and their goodwill.

In line with the stable matching rules, we summarize the results of matching shown in Tables 7 and 8. Tables 7 and 8 illustrate that the final stable pairs regarding three submodels are attained until the 3rd, 5th, and 5th matching, respectively.

Tables 7 and 8 reveal that the overall surpluses of garment makers and designers under three submodels slightly rise in the scenario I. Nonetheless, from each model aspect, the surplus of designers shows upward trend, whereas that of garment makers declines under the first two submodels.

TABLE 7: Scenario I: the multimatching results in the submodel without due-date constraint.

Matching process		Garment makers						Designers' surplus	Garment makers' surplus	Total surpluses
		1	2	3	4	5	6			
Designers	1st matching	1	3	2	10	11	—	35100	21400	56500
	2nd matching	2	1	3	10	11	—	37600	18900	56500
	3rd matching	1	2	3	10	11	—	37000	19500	56500

TABLE 8: Scenario I: The multimatching results of two extended submodels.

	Matching process		Garment makers						Designers' surplus	Garment makers' surplus	Total surpluses
			1	2	3	4	5	6			
Designers	Extended submodel with due-date constraint	1st matching	1	2	3	11	10	—	35120	21400	56520
		2nd matching	2	3	1	11	10	—	36860	19530	56390
		3rd matching	1	3	2	11	10	—	36910	19600	56510
		4th matching	1	2	3	11	10	—	36790	19730	56520
		5th matching	1	3	2	11	10	—	38080	18460	56540
	Extended submodel with goodwill concern	1st matching	1	2	3	11	10	—	80520	21400	101920
		2nd matching	3	1	2	11	10	—	83040	18750	101790
		3rd matching	1	3	2	11	10	—	81490	20450	101940
		4th matching	1	2	3	11	10	—	81370	20550	101920
		5th matching	1	3	2	11	10	—	81860	20080	101940

TABLE 9: Scenario II: multimatching results of three submodels.

	Matching process		Garment makers												Designers' surplus	Garment makers' surplus	Total surpluses
			1	2	3	4	5	6	7	8	9	10	11	12			
Designers	Two-sided matching model	1st matching	5	1	3	2	—	—	—	—	8	6	10	9	65700	37200	102900
		2nd matching	5	2	3	—	1	—	—	—	8	6	10	9	67600	36300	103900
		3rd matching	5	2	3	—	1	—	—	—	8	6	10	9	68600	35300	103900
	Extended model with due-date constraint	1st matching	5	3	1	2	—	—	—	—	8	6	10	9	61470	37200	98670
		2nd matching	2	3	1	—	—	—	—	—	8	6	10	9	57250	37640	94890
		3rd matching	1	2	3	—	—	—	—	—	8	6	10	9	58460	36560	95020
		4th matching	1	2	3	—	—	—	—	—	8	6	10	9	58490	36530	95020
	Extended model with goodwill concern	1st matching	1	2	3	—	—	—	—	—	8	6	10	9	118020	41500	159520
		2nd matching	2	3	1	—	—	—	—	—	8	6	10	9	123050	36340	159390
		3rd matching	1	3	2	—	—	—	—	—	8	6	10	9	121500	38040	159540
		4th matching	1	2	3	—	—	—	—	—	8	6	10	9	121380	38140	159520
		5th matching	1	3	2	—	—	—	—	—	8	6	10	9	121870	37670	159540

Surplus (left chart, (a)): Two-sided matching model; Extended model with due date; Extended model with goodwill concern. Categories: Designers, Garment makers, Total.

Surplus (right chart, (b)): Two-sided matching model; Extended model with due date constraint; Extended model with goodwill concern. Categories: Designers, Garment makers, Total.

(a)

(b)
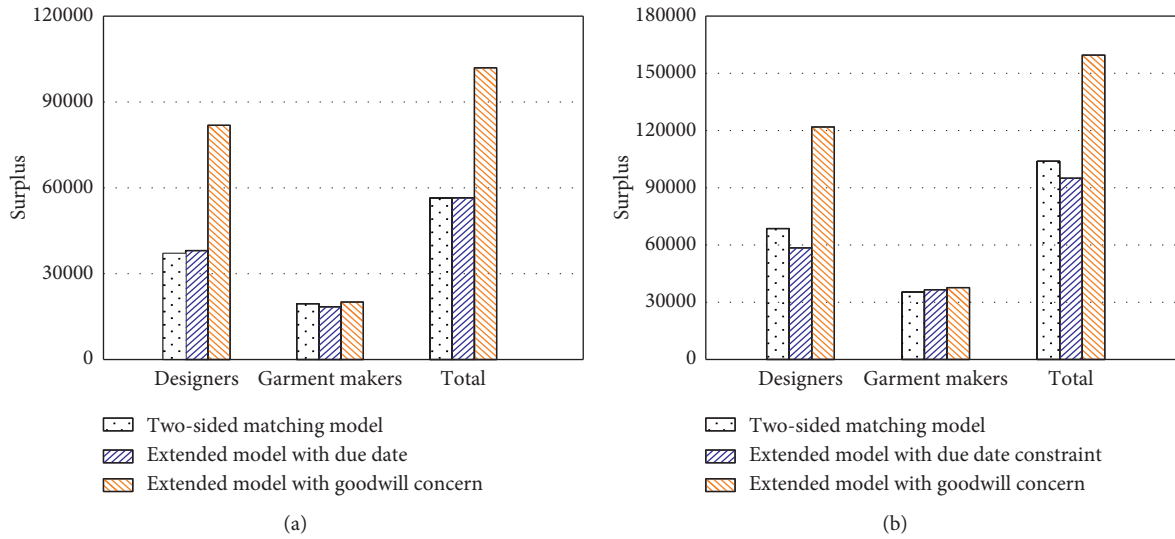
FIGURE 2: The comparison of three matching submodels in scenarios I and II. (a) Scenario I (regular case); (b) scenario II (irregular case).

TABLE 10: The matching results and surplus at different α and β in scenario I.

Matching			Garment makers						Designers' surplus	Garment makers' surplus	Total surpluses
			1	2	3	4	5	6			
	α	0.1	1	2	3	11	10	–	80280	20840	101120
Robust	area	0.3	1	3	2	11	10	–	81860	20080	101940
		0.5	1	3	2	11	10	–	83460	19280	102740
		0.7	1	3	2	11	10	–	85080	18460	103540
Designers		0.9	1	3	2	11	10	–	87080	17260	104340
	β	0.1	1	3	2	11	10	–	81080	17260	98340
Robust	area	0.3	1	3	2	11	10	–	81080	18460	99540
		0.5	1	3	2	11	10	–	81460	19280	100740
		0.7	1	3	2	11	10	–	81860	20080	101940
		0.9	1	2	3	11	10	–	82170	20950	103120

TABLE 11: The matching results and surplus at different α and β in scenario II.

Matching			Garment makers													Designers' surplus	Garment makers' surplus	Total surpluses
			1	2	3	4	5	6	7	8	9	10	11	12			
	α	0.1	1	2	3	–	–	–	–	–	6	8	10	9	120060	38250	158310
Robust	area	0.3	1	3	2	–	–	–	–	–	8	6	10	9	121870	37670	159540
		0.5	1	3	2	–	–	–	–	–	8	6	10	9	123070	37670	160740
		0.7	1	3	2	–	–	–	–	–	8	6	10	9	124770	37670	161940
Designers		0.9	1	3	2	–	–	–	–	–	8	6	10	9	125570	37570	163140
	β	0.1	1	3	2	–	–	–	–	–	8	6	10	9	117170	37570	154740
Robust	area	0.3	1	3	2	–	–	–	–	–	8	6	10	9	118670	37670	156340
		0.5	1	3	2	–	–	–	–	–	8	6	10	9	120270	37620	157940
		0.7	1	3	2	–	–	–	–	–	8	6	10	9	121870	37670	159540
		0.9	1	2	3	–	–	–	–	–	6	8	10	9	122750	38360	161110

Surprisingly, for the last submodel, the surplus of designers almost remains unchanged as that of garment makers do, which implies that the final pairs of the last submodel are more stable and robust than those of the first two ones. In addition, an increase of designers' surplus in the matching process also further verifies designers' domination in a competitive fast fashion market.

8.2. Scenario II: Designers' Domination in Crowdsourcing. In this subsection, we examine an irregular case in which the designer size is smaller. Following with the same logic as scenario I, we can achieve the matching outcomes of three submodels, which are shown in Table 9. The results show that garment maker 4, garment maker 5, and garment maker 6 still remain unmatched with any crowdsourcing designers in the 1st matching, and for garment maker 7 and garment maker 8, they fail to match in the upcoming competition because they do not have enough surpluses to adjust their rewards with an aim to attract designers. Interestingly, there exist unmatchings for both garment makers and designers in such case, which to some extent reflects the real state of crowdsourcing market under the small scale of designers.

Table 9 shows that under scenario II the overall surpluses of garment makers and designers illustrate the same trend as scenario I. Parallelly, in scenario II, the surpluses of designers under the first two submodels increase in the matching process, whereas the surplus of garment makers drops. By contract, the surplus of designers under the last submodel in scenario II descend, while that of garment makers climb up, and it implies that, under an irregular case, the final pairs of the last submodel are more sensitive than the two others, which further confirms the robustness of the last submodel.

The abovementioned analysis focuses on each scenario; the following discussion will highlight the comparison of two scenarios. Comparing the first submodel (two-side matching model) to the second submodel (extended model with due-date constraint), it is easy to witness that the myopic designers' surpluses of the latter model are higher than those of the former in scenario I, whereas in scenario II the consequence is opposite (as shown in Figure 2). Meanwhile, the surpluses of the third submodel (extended model with goodwill concern) outperforms those of the two others in terms of garment makers and designers. This implies under the irregular case, i.e., when garment makers exceed online designers in number, crowdsourcing design tasks without due-date constraint are more attractive for designers' participation than those with due-date constraint. Particularly, in matching process, garment makers intend to share the incremental surpluses with designers so as to maximize the total surpluses of both sides. By contrast, under the regular case, i.e., when online designers surpass garment makers in number, designers are prone to choose crowdsourcing design tasks with due-date constraint than those without due date.

In addition, we find that regardless of whether under the irregular case or the regular case, the surpluses of strategic designers are obviously higher than those of myopic ones. It reminds that both crowdsourcing platforms and garment makers should emphasize the issue of goodwill concerns, for example, if the crowdsourcing platform attracts more well-known garment makers to post their name-labeled tasks online, thus making myopic designers transfer to be strategic ones, which in turn helps entice more designers' engagement in crowdsourcing activities due to the incremental surplus.

8.3. Sensitivity Analysis. In this subsection, we will examine the robustness of our approach of the current study. Tables 10 and 11 show the variance of matching results in scenario I and scenario II with the change of α and β, respectively. When α ranges from 0.3 to 0.9 and β ranges from 0.1 to 0.7, the matching pairs keep stable, which means our proposed method applied in hierarchical matching decision process on crowdsourcing design in a fast fashion market has strong robustness.

In addition, no matter what the irregular case or regular case is, the areas with respect to α and β are relatively bigger, which verifies that the extended submodel with due-date constraint and goodwill concern is more stable and more practical than the two others.

9. Conclusion

In this paper, we focus on the issue of garment maker-designer matching in the fast fashion crowdsourcing context. To handle such a problem, we propose the matching model using a dynamic hierarchical method and analyze the impact of three different matching submodels on crowdsourcing performance, including the two-sided matching model and the extended model with due-date constraint, as well as one with due-date and garment makers' goodwill concern. After that, we compare the optimal outcomes and examine the condition under which the garment makers and designers can reach stable equilibriums.

The main findings of our paper lie in several facets as follows:

(1) From the hierarchical perspective, we find that only when three key factors including surplus, due date, and goodwill are taken into account as a whole in the crowdsourcing matching context, both garment makers and designers are better off, and the whole matching system obtains the optimal result.

(2) When online designers surpass garment makers in number, dress designers prefer crowdsourcing tasks with due-date constraint to those without it. By contrast, when garment makers exceed online designers in number, crowdsourcing tasks without due-date constraint are more attractive for designers' participation than those with due-date constraint because garment makers are willing to share the incremental surpluses with designers to maximize the total surpluses.

(3) In addition, regardless of under the irregular or the regular case, more strategic designers necessarily benefit garment makers and crowdsourcing platforms than myopic ones, which implies that crowdsourcing platforms should encourage more well-known garment makers to post their name-labeled tasks, thus making myopic designers transfer to be strategic ones.

(4) Finally, sensitivity analysis reveals that no matter the irregular case or regular case, the extended submodel with goodwill concern is more stable and robust than the two others to achieve the final matching pairs.

Some limitations of this paper that should be considered in future research include the following. First, while our assumption of the crowdsourcing matching with an information symmetry could characterize most fast fashion design platforms; in practice, there is indeed a tiny portion of them which are those with an information asymmetry. Thus, future study should relax this condition. Second, for analytical convenience, we assume that the submodels proposed are the same in unit time cost of designer and due date, which could be considered differently later. Third, extension of the present study from only design sector to design-production sector could be an interesting research in the future.

Appendix

Proof of Observation 1

For $\forall (i, j), (i^*, j^*) \in \mu$, if garment maker i can get more surpluses when garment maker i matches with designer j^*, so garment maker i may transfer $V_{GM}(i, j^*) - V_{GM}(i, j)$, at most, to change the current ranking. However, designer j^* who prefers garment maker i^* will lose the surpluses of $V_{CD}(i^*, j^*) - V_{CD}(i, j)$ if garment maker i is assigned to garment maker i. When $V_{GM}(i, j^*) - V_{GM}(i, j) > V_{CD}(i^*, j^*) - V_{CD}(i, j^*)$, it implies that garment maker i achieves the temporary chance to change the current matching result by compensating designer j^*.

But to keep his rank regarding designer j^*, garment maker i^* who favors designer j^* should also increase his reward to guarantee his status, avoiding being assigned to designer j, thus leading to the loss of $V_{GM}(i^*, j^*) - V_{GM}(i^*, j)$. If $V_{GM}(i, j^*) - V_{GM}(i, j) < [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$, garment maker I cannot defeat garment maker i^*, and garment maker i^* just needs to give up the surpluses of $[V_{GM}(i, j^*) - V_{GM}(i, j)] - [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)]$ to designer j^* as to maintain his status. The final surpluses $V_{CD}'(i^*, j^*)$ should satisfy $[V_{GM}(i, j^*) - V_{GM}(i, j)] \le V_{CD}'(i^*, j^*) - V_{CD}(i, j^*)$ at least. Then, $V_{CD}'(i^*, j^*) \ge V_{CD}(i, j^*) + [V_{GM}(i, j^*) - V_{GM}(i, j)]$ can be deduced, which meets the stability condition. Finally, $V_{CD}'(i^*, j^*) = V_{CD}(i^*, j^*) + [V_{GM}(i, j^*) - V_{GM}(i, j)] - [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)]$ and $V_{GM}'(i^*, j^*) = V_{GM}(i^*, j^*) - [V_{GM}(i, j^*) - V_{GM}(i, j)] + [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)]$.

Proof of Observation 2

For $\forall (i, j), (i^*, j^*) \in \mu$, if garment maker i can get more surpluses when garment maker i matches with designer j^*, so garment maker i is willing to transfer at most $V_{GM}(i, j^*) - V_{GM}(i, j)$, to compensate designer j^* and thus changing the current ranking. For designer j^*, who prefers garment maker i^*, will reduce by the surpluses $V_{CD}(i^*, j^*) - V_{CD}(i, j^*)$ if designer j^* is assigned to garment maker i. When $V_{GM}(i, j^*) - V_{GM}(i, j) > V_{CD}(i^*, j^*) - V_{CD}(i, j^*)$, it implies that garment maker i achieves the temporary chance to change the current matching result.

But to keep his rank regarding designer j^*, garment maker i^* who favors designer j^* should also increase his reward to guarantee his status, avoiding being assigned to designer j, thus leading to the loss of $V_{GM}(i^*, j^*) - V_{GM}(i^*, j)$. If $V_{GM}(i, j^*) - V_{GM}(i, j) > [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$, garment i has adequate surpluses to defeat garment maker i^* by giving up the surpluses of $[V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$ to designer j^* to change his status. The final surpluses $V_{CD}'(i, j^*)$ should satisfy $V_{CD}'(i, j^*) \ge V_{CD}(i^*, j^*) + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$ at least. The new matching pairings are (i, j^*) and (i^*, j), $V_{CD}'(i, j^*) = V_{CD}(i, j^*) + [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] + [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$ and $V_{GM}'(i, j^*) = V_{GM}(i, j^*) - [V_{CD}(i^*, j^*) - V_{CD}(i, j^*)] - [V_{GM}(i^*, j^*) - V_{GM}(i^*, j)]$.

Data Availability

The data used to support the findings of this study are available within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Acknowledgments

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