

# Supply and demand matching model of P2P sharing accommodation platforms considering fairness

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# Abstract

Due to the continuous expansion of sharing economy, the diversification of users and the heterogeneity of resources and needs on P2P platform are speeding up, which makes it difficult to match the supply and demand of P2P platform effectively. Therefore, how to achieve effective matching between service providers and customers in an increasingly complex market is a question worthy of study. In order to achieve more effective matching of heterogeneous resources and requirements, this paper focuses on P2P sharing accommodation platform, advances a theoretical framework of fair matching and builds a matching model which considering fairness. First, we analyze the transaction mode of P2P sharing accommodation platform, proposed the framework of fair matching based on preferences consistency and fairness of matching. Second, we build a matching model based on fair matching, to maximize the consistency of preference and minimize the difference between supply and demand, the fair matching framework deals with heterogeneous resources and needs by matching diversified preferences. Finally, the effectiveness and feasibility of the strategy are verified by example and sensitivity analysis. This strategy provides optimization ideas for the matching issue of P2P sharing accommodation.

Keywords P2P sharing accommodation platform  $\cdot$  Supply and demand matching  $\cdot$  Fair matching  $\cdot$  Preferences

# 1 Introduction

With the rapid development of ICT, customer preferences and consumption patterns have changed dramatically, leading to the emerging and thriving of sharing economy. The sharing economy covers a wide range of business activities, and gradually involves multiple fields such as transportation, accommodation, catering,

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manufacturing and so on. It supports the promotion of multiple types of resources and services and meets a large number of personalized requirements, promotes the full use of idle resources in the society [1, 2], stimulates economic and social development, making it a new hot business model that has attracted much attention. In China, for example, data from the China State Information Center (SIC) shows that the sharing economy market in China reached 3.28 trillion yuan in 2019, maintaining a growth rate of 11.6%. Moreover, new industry of accommodation on sharing platforms accounted for 7.3% in the industry, and coverage among netizens reached 9.7% [3]. Like the rest of the world, the Chinese government is also paying unusual attention to the sharing economy, and the incentive and regulation to it is growing. These give more confidence to the market participants, especially micro and individual investors.

Owing to its characteristics and universality, this paper focuses on P2P sharing accommodation. Based on relevant literature [4-8], we define P2P sharing economy phenomena as a business of trading for short-term access of goods, services and other resources in peers hosted by a digital platform, and P2P sharing accommodation focus on the business of lodging. Driven by the market and led by Airbnb, onehome, Xiaozhu and other successful giants, accompanied with the rapid spreading of the sharing economy, the diversification trend of P2P platforms, investors, hosts, customers and other stakeholders are accelerating. In this context, the boundary between supply and demand sides is more blurred, and the degree of heterogeneity between resources and demand is intensified, it has brought challenges to meeting diversified preferences and needs from all parties. The good news is that the growth also provides opportunities for platforms to match heterogeneous resources and heterogeneous needs better, and thus increases the benefits of both sides [7], promotes the sustainable development of the platforms. Therefore, how to match the heterogeneous assets and resources with the diverse needs effectively under the complicated market environment, to improve the liquidity of the platforms is a key problem.

P2P platforms differ from other operation modes, the subject of the transaction are peer individuals is a striking difference, which offer opportunities for both parties an in-depth understanding and offline interaction [8, 9], convenient to establish social relations. In addition, the peers can optionally switch roles on both supply and demand sides, so many of them are so-called "prosumer" [1, 7, 10–14]. Based on these differences, both sides are highly individualized and trading autonomous. In the field of P2P accommodation, the hosts of Airbnb and Xiaozhu can refuse to provide services based on features of customers, while customers can choose according to the fit of the characteristics of the houses and hosts to their own preferences. As a result, the preferences and characteristics of hosts and customers may need to be considered simultaneously when the platform matching heterogeneous resources and needs.

In the ecosystem of sharing business, there are huge positive indirect network effects on both sides of the platform [7, 15]. The user base on either side of the platform drives growth on the other side, which in turn drives overall growth, but the impact from the service provider is greater and the platform is driven more by service providers [15], therefore, the service provider's preferences cannot be ignored. Besides, in the field of digital and platform economy, price discrimination

and unequal between sellers and buyers behind the intelligent model and algorithm caused concern about the safety of machine behavior [16]. Data unfair use and transaction between different user groups challenging the corporate digital responsibility and impairing the reputation of the enterprise [17]. User's perception of unfairness harms user trust and loyalty of the P2P platform [18], and similar risks are beginning to be noticed, it provides a new perspective for supply and demand matching of P2P platforms, and puts forward new requirements.

Based on the previous analysis, this paper introduces fair matching, to consider the preferences of hosts and customers comprehensively in P2P sharing accommodation, and to achieve effective matching based on the consistency and differences of preferences. In this paper, unlike some studies that focus only on current preference and customer satisfaction [19, 20], we synthesizing HTI (historical transaction inclination) and current preference to characterize preferences of both sides. Effective matching is achieved by minimizing the consistency of preferences and maximizing differences. The two main contributions of this paper are as follows.

- 1. This paper proposes a theoretical framework of fair matching on P2P platform. Through the formal definition of preference consistency and fairness of matching, this paper puts forward the viewpoint of fair matching with maximum consistency and minimum difference.
- 2. We propose a matching model based on fair matching, to solve the matching problem of heterogeneous resources and needs of P2P sharing accommodation platforms. It lays a foundation for the research of supply and demand matching on P2P platform.
- We give the definition of user preferences consistency on the P2P sharing accommodation platform, expands the preferences to HTI and current preference, which provides a more comprehensive basis for the research of preferences analysis and matching.

This paper expects to provide a more effective matching strategy for P2P sharing accommodation platforms in the current market environment, to promote the more efficient allocation of social idle resources and a more harmonious network of social relations. According to the analysis and solution of the problem, we arrange the subsequent content of this paper as follows. Section 2 is related work of supply-demand matching of sharing economy. Section 3 is the key concept, framework of fair matching and the matching model. Section 4 shows the numerical analysis and discussion. Section 5 is the conclusion of this paper.

# 2 Related work

Matching is a core problem of platform economy, effective matching strategy can enhance the liquidity of platform, provide opportunity for platform expansion, especially for a P2P platform with a large number of heterogeneous assets and requirements. Facing the individualized peers who break the boundary of supply and demand, the research of matching of P2P sharing economy needs further development.

In recent years, due to the heterogeneity and individuation of the services and customer needs prominent increasingly, the supply and demand matching issues on sharing platforms is gradually paid attention by academia. Some studies focus on matching strategies and scenarios based on customer preferences, characteristics and the lists, such as [21-24]. They associate customer needs with a static list of services without considering the hosts behind, is a match between the customer requirements and the list, this may lead to lower supplier satisfaction, the best match for both sides is likely to be lost, or the process is complicated. Similar ideas are used in the recommendation program of Kim and Martin-Fuentes [25, 26], they optimize and sort the list of services for match and recommend. Other research focuses on the optimization of strategy and less on the development background of P2P sharing economy, or matching strategies of relatively small sharing audiences [19, 27, 28], such as sharing parking and energy sharing. And other researchers focus on the utility balance of hosts and the maximization of matching volume [29], to ensure the stability of supply-demand ratio, and thus to promote the continued participation of hosts, no trader's preference is used as the key for matching, they mainly focus on issue of the allocation of total resources.

Fairness of matching refers to the preferences of both sides are treated fairly in the matching process, and the matching goal is the minimization of differences between these preferences [30, 31], to ensure that the preferences of two sides are as close as possible and reduce differences and jealousy, which is always used as a support for the matching stability. For better matching results, the matching optimization strategies with fairness increase gradually, such as issue of matching on uncertain preference sequence [32], supply meet demand of technological knowledge [33], task match resource in cloud manufacturing [34], selection of foreign customers in B2B export cross-border e-commerce [35]. They achieve the fairness of matching mainly by setting weight coefficients for the preferences of both parties, such as (0.5, 0.5)[36, 37], or the minimization of the absolute value of preference difference [32, 34]. The difference of two numbers and the setting of two peers' preferences weight cannot reflect the similarity and difference of peer's subjective tendency. Therefore, we redefine the fairness of matching and advance the framework of fair matching in P2P sharing accommodation, to achieve a more effective match based on both sides' preferences.

In summary, there are few researches on supply-demand matching of P2P sharing economy. The specific research is embodied in the following three aspects: First, in the aspect of matching strategy, the researchers aim at maximizing customer satisfaction or transaction volume, making pairs based on customer preferences and service lists. They ignore the service provider's psychological feelings and expectations under the trend of personalized and diversified supply and demand sides, the heterogeneity of resources and needs is not fully considered. Second, the business patterns being targeted, there are three major types: sharing accommodation, parking sharing and energy sharing, research on matching issue of the representative P2P platform models such as Airbnb and Uber is weak and needs to be strengthened. Third, in terms of matching basis, researchers mainly use information such as customer

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preferences and needs, features of resources or services to conduct a matching, and transaction tendency in history between the two sides as well as the preference and satisfaction of hosts are less considered.

The ever-accelerating heterogeneity of assets, services and demands poses greater challenges to the balance of service capacity and demand [7], which requires a more comprehensive consideration of peers and their views. Therefore, our work focus on one of the most common type of sharing economy–P2P sharing accommodation; We take the preferences (including HTI and current preference) of both host and customer into consideration (Fig. 1), so that the matching strategy is more robust in the new context.

## 3 Fair matching and the model

In order to make the matching strategy clearer, we first elucidate the main transaction mode of P2P sharing accommodation represented by Airbnb, onehome and Xiaozhu, and some preliminaries, followed by the theoretical framework of fair matching, as well as the methods used in the model. Finally, we introduce the matching decision model consider fairness.

According to the needs of the conceptual description and the following model explanations, Table 1 is employed to illustrate the main variables and parameter notations.

#### 3.1 The transaction mode of P2P sharing accommodation

We focus on P2P sharing accommodation, one of the most common phenomena of sharing economy, and its transaction mode needs to be clarified here. It's a customeroriented mode that host issues short lease service on P2P platform and the platform gives a short list of optional services to customer depend on customer's preferences, after the customer make a decision, the host can accept or reject the request, Airbnb, onehome and Xiaozhu are perfect examples.

The matching process is complex, and there is not always necessarily that the willness of the two sides as close as possible in the matching results when the traditional recommendation and matching strategy used in the P2P sharing business, resulting in inefficient matching. In this mode, the heterogeneity of resources and requirements is a major challenge for matching and recommendation. We convert the transaction mode into a relatively simplified match mode based on the maximization consistency of two-sided preferences, to achieve optimal matching and



Fig. 1 The supply-demand matching idea in this paper

and parameter notations
notation interpretation
Set of hosts to be matched on P2P sharing accommodation platform
set of customers to be matched
The <i>i</i> th peer in <i>S</i> , $i = 1, 2,, m, m > 2$
The <i>j</i> th peer in <i>C</i> , $j = 1, 2,, n, n > 2$
Transaction record between $s_i$ and $d_j$
Number of transactions between the two peers $s_i$ and $c_j$ , $\theta_{ij} \ge 0$
Preference evaluation indicator set for S
Preference evaluation indicator set for $C$
Evaluation intuitionistic fuzzy set of S on P
Evaluation intuitionistic fuzzy set of $C$ on $P$
HTI vector of $s_i$ to $d_j$
HTI vector of $c_j$ to $s_i$
Preference vector of S
Preference vector of C
Matching parameter

 Table 1 Important variable and parameter notations

improve the efficiency of the matching. We change it from (1) to (2) in Fig. 2, and model the matching core modules later.

#### 3.2 Preliminaries

Because the evaluation of historical transactions have fuzzy uncertainties, and Intuitionistic Fuzzy Set (IFS) have a strong ability to express uncertain information [38–41], which can effectively describe the decision-maker's approval, negation and hesitation, reflect the actual state of decision-making objectively, so this paper uses it to describe the HTI between each peer.



Fig. 2 Transaction mode of P2P sharing accommodation

**Definition 1** (*IFS* [38]) Let *X* be an ordinary finite non-empty set, *I* is an IFS on *X* and its expression is  $I = \{\langle x, \mu_I(x), \gamma_I(x) \rangle | x \in X\}, \mu_I(x) \text{ and } \gamma_I(x) \text{ denote}$  the membership and non-membership degrees of *x* to *I*, respectively, and  $\mu_I(x)$  and  $\gamma_I(x) \in [0, 1]$ , such that for all  $x \in X$ , have  $0 \le \mu_I(x) + \gamma_I(x) \le 1$ , and  $\pi_I(x) = 1 - \mu_I(x) - \gamma_I(x)$  is the hesitation degree of *x* to *I*.

**Definition 2** (*IFS score* [41]) The score of an IFS is the degree of suitability that an alternative meets the decision-maker's needs. Assume that  $v_I$  is the score of *I*, the score function of *I* is  $v_I(x) = \mu_I(x) - \gamma_I(x)$ , where  $v_I(x) \in [-1, 1]$ .

Through IFS and IFS score, we can determine the promotion degree which historical transactions to the current transactions between  $s_i$  and  $c_j$  in the context of a fuzzy evaluation.

# 3.3 Theoretical framework of fair matching

In this part, we build the theoretical framework of fair matching on P2P platform from aspects of the heterogeneity of resources and needs, peer preferences, consistency of preferences, and fairness of matching.

## 3.3.1 The heterogeneity of resources and needs

The heterogeneity of resources and needs come from multiple aspects, in terms of resources, such as the diversity of customer groups based on multiple individuals [42], coupled with the fuzziness of the supply and demand boundary, which facilitates the differentiation of needs and makes it difficult for standardized products and services to be used. Personalized preferences of peers, e.g. the time, place and experience of customers needs are random and diverse [7], making needs differ widely. In terms of needs, a wide range of product brands in services [43], the non-standardized assets [7], different backgrounds, managerial skills, business ways, service quality and price settings of P2P service providers [5, 44, 45], and many other aspects that make the supply on a platform more heterogeneity than a traditional channel.

The causes and manifestations of heterogeneity are manifold, and there is no clear definition of it on P2P platform, most of the related researches describe it from the perspective of personalized and socialized customer demand, non-standard services and services quality. Based on the existing research, this paper advances the heterogeneity in services and needs on P2P sharing economy platform as follows.

**Definition 3** (*Heterogeneity of resources*) Assume that the sets of services from peers on P2P platform is  $S = \{s_1, s_2, ..., s_m\}$ , for all  $s_i, s_j \in S$ , if there is a large difference between  $s_i$  and  $s_j$ , embodied in but not limited to no uniform standard of

service level of the two providers, asset or service quality, and there are different individualized constraints when accessing and experiencing  $s_i$  and  $s_j$ , we define it the heterogeneity of resource of P2P platform.

**Definition 4** (*Heterogeneity of Needs*) Assume that the sets of needs from platform peers is  $C = \{c_1, c_2, ..., c_n\}$ , for every  $c_i, c_j \in C$ , if conditions  $c_i = c_j$  or  $c_i c_j$  are seldom satisfied, and standardized products and services are already difficult to meet *C*, we define *C* as the heterogeneous needs on P2P platform.

#### 3.3.2 Preferences of peers on P2P platform

Preferences information is the key basis for matching decisions and often used in the research and practice of matching decision-making, such as cross-border e-commerce [35], ridesharing system [37], cloud manufacturing [34, 46], and smart intelligent technique transfer [47]. Integrating the extant studies on preferences and satisfaction in e-trading and two-sided matching [34, 37, 48, 49], we advanced the definition of preferences of P2P platform peers as follows.

**Definition 5** (*Preferences of peers on P2P platform*) Assume that  $U = \{u_1, u_2, ..., u_i, ..., u_m\}$  is a user set of a P2P platform, for  $\forall u_i, u_j \in C$ ,  $\exists P = \{p_1, p_2, ..., p_k, ...\}$ , if evaluation, pursuit or expectation of peer  $u_i$  to peer  $u_j$  and his/her services or needs are entirely dependent on *P*, then the evaluation, pursuit and expectation is the preferences of  $u_i$  to  $u_j$ , and *P* is the certain preferences indicators or characteristics of  $u_i$  and  $p_k$  is a specific indicator value. The heterogeneity of resources and needs creates diversity of peer preferences.

The preferences of peers can reflect his/her perception and expectation on product, service, attitude, character or other aspects of the interactive objects, it including past satisfaction and current expectations. Therefore, we propose that the preferences of the peers include HTI and (current) preference. We use Fig. 3 to show the preferences of each peer to be matched. Two-sided preference (TSP) is the synthesized preferences of service provider and customer in fair matching result, that is, the target function value, and each matching pair has a TSP value. The matching



Fig. 3 Preferences of peer to be matched on P2P platform

**Definition 6** (*HTI*) Assume that  $o_{ij} = (\theta_{ij}, I_S, I_C)$  is the transaction record between peer  $s_i$  and  $c_j$ , mutual transaction times  $\theta_{ij}$  is the number of transactions accumulated between  $s_i$  and  $c_j$ , the total orders of  $s_i$  is  $\theta_i$ , and  $I_S$ ,  $I_C$  denote the evaluation of  $s_i$  and  $c_j$  to these transactions, then vector  $\vec{o}_{ij}^S = (\frac{\theta_{ij}}{\theta_i}, I_S)$  is the HTI of  $s_i$  to  $c_j$ , the HTI of  $c_j$  for  $s_i$  is just the opposite.

The HTI of a peer to another is preference and satisfaction, which comes from transactions in history between the two peers, we use it to reflect the impact of historical transactions between the two sides on current decision-making, and its structure is as shown in Fig. 3.

**Definition** 7 (*Current preference*) Let  $P^S = \{p_1^S, p_2^S, \dots, p_k^S, \dots\}, P^C = \{p_1^C, p_2^C, \dots, p_l^C, \dots\}$  be the feature dimension or indicator set of *C* and *S*. Assume that  $(p_1^{S'}, p_2^{S'}, \dots, p_k^{S'}, \dots)$  is the quantization of actual level value of  $c_j$  and  $(p_1^{C'}, p_2^{C'}, \dots, p_l^{C'}, \dots)$  is the actual status of  $s_i$ , respectively, the current expectation value of  $s_i$  to *C* and  $c_j$  to *S* are  $(p_1^S, p_2^S, \dots, p_k^S, \dots)$  and  $(p_1^C, p_2^C, \dots, p_l^C, \dots)$ , respectively. Then the combination of the actual status and current expectation based on these values under  $P^S$  and  $P^C$  is the (current) preference of one peer to another on the platform. The peer's current preference reflects the current state of his or her expectation and willingness to somebody or something based on his/her actual status, and side by side with HTI. Based on this definition, the preference of  $c_j$  is  $\{p_1^C, p_2^C, \dots, p_1^{S'}, p_2^{S'}, \dots\}$ .

Comprehensive analysis of the themes of reviews on Airbnb, Xiaozhu and APP stores (Huawei, Vivo and Smartisan) in China, as well as existing research conclusions on satisfaction and preferences of sharing participants [15, 20, 26, 50, 51], we advance examples of the main indicators to shape each side's current preference and show them in Table 2. We distinguish the indicators from the general static indicator and the personalized dynamic indicator, to reflect preference of different person, different preference in different times and universal preference. Hosts can only obtain a small number of customer information before the transaction, and some information can only be obtained from temporary communication (Fig. 4, from Xiaozhu), which can easily be extracted by the platform. The asymmetry of information like this will affect the assessment of both sides and affect the final decision.

## 3.3.3 Fairness of matching

In order to consider the consistency of preferences in the matching process, the preferences balance is achieved by assigning the same weight (e.g. 0.5 and 0.5) to both sides in [36, 37], or by minimizing the difference between the two preferences as in [32, 34], or the square root of the product of the two preferences in [35]. However, the preferences of P2P platform supply and demand sides are diversified and

Table 2 Exampl	les of the main preference indicators of each	ı peer	
Set	Indicator	Type	Explanation
$p^c$	$p_1^c$ Cost performance	General	Ratio of performance to price, perception of suitable for consumption
	$p_2^c$ Service quality	General	Cleanliness of host's rooms, location and ease of travel, environmental quality
	$p_3^c$ Safety degree	General	Property and personal safety during residence
	$p_4^c$ Service availability	Personalized	Target location and available time
	$p_5^c$ Credibility	General	Authenticity of information
	$p_6^c$ Acceptance rate	Personalized	Order acceptance rate of the host
	$p_7^c$ Interaction	Personalized	Timeliness of response, provide advice and review
$p^{S}$	$p_1^S$ Identity Information	General	The integrity of validation Information such as authentic identity, photo, phone, mail, occupation, etc.
	$p_2^S$ Chargeback rate	Personalized	Cumulative orders completed
	$p_3^S$ Chargeback rate	Personalized	Rate of orders temporarily cancelled by customer
	$p_4^{\tilde{S}}$ Recovery	Personalized	Cleanliness and integrity of the facility at the end of the transaction
	$p_5^S$ Interaction	Personalized	Number of reviews and communication efficiency
	$p_6^S$ Reputation	Personalized	Comments from hosts

	房客信息		Guest information (translation)	
4位入住人: 李小淡 <u>乌</u> 张达伟 <u>오</u> 张丽娜 <u>乌</u> 王大治 <u>오</u>	验证成功,姓名和证件号匹配 尚未验证 尚未验证 尚未验证	4 occupants: Guest 1 & Guest 2 & Guest 3 & Guest 4 &	Validation successful, name matches ID numb Not verifie Not verifie Not verifie	er d d
预订人: 王大治 ♀ 联系房客	共13次入住,8次评论 >	Booker: Guest 4 & Contact	13 stays and 8 review	is >
⊘ 接受订单	☺ 拒绝订单	🛛 Acce	ept order 🛛 🕺 Reject order	

Fig. 4 Customer's main information displayed before the transaction

heterogeneous, so it is difficult to deal with them with a unified standard. Therefore, this paper gives the definition of preferences consistency based on similarity and distance.

**Definition 8** (*Consistency of preferences on P2P platform*) Let  $\alpha = \{\alpha_1, \dots, \alpha_k, \dots\}$ and  $\beta = \{\beta_1, \dots, \beta_l, \dots\}$  be the preferences value set of  $s_i$  to  $c_j$  or to *C* and  $c_j$  to  $s_i$  respectively,  $m_{ij} = S(\vec{\alpha}, \vec{\beta})$  and  $w_{ij} = D(\vec{\alpha}, \vec{\beta})$  are similarity and distance between preferences of  $s_i$  and  $c_j$ , where  $\frac{m_{ij}}{w_{ij}} \rightarrow \infty$ . Then, we call this tendency preference consistency. In the match, the consistency of preferences is realized by maximizing similarity and minimizing distance of preferences.

**Definition 9** (*Fairness of matching*) Let  $\phi$  be a matching result set,  $\alpha_i$  and  $\beta_i$  be the preferences value set of  $s_i$  to  $c_j$  or to C and  $c_i$  to  $s_i$  or to S, respectively, for all  $s_e, s_l \in S$  and  $c_f, c_k \in C$ ,  $\exists (s_e, c_f) \in \phi, (s_l, c_f) \notin \phi$  and  $(s_e, c_k) \notin \phi$ , if  $\alpha, \beta$  satisfy the following conditions in the match, the nature of this match is called fairness of matching.

- (1)  $|\alpha_e \beta_f| \le |\alpha_l \beta_f|$ , and  $|\alpha_e \beta_f| \le |\alpha_e \beta_k|$ ; (2) similarity  $S(\alpha_e, \beta_f) \ge$  similarity  $S(\alpha_l, \beta_f)$ , and similarity  $S(\alpha_e, \beta_f) \ge$  similarity  $S(\alpha_{\rho},\beta_{k});$
- (3) distance  $D(\alpha_e, \beta_f) \leq \text{distance } D(\alpha_l, \beta_f)$ , and distance  $D(\alpha_e, \beta_f) \leq \text{distance } D(\alpha_e, \beta_k)$

The fairness of matching is the preferences and willingness of both sides are taken into consideration in matching process, and the preference of the two sides are as close as possible, the divergence is minimized in the matching results, to achieve an effective match based on the consistency of preferences. Because vector have directionality, we use it to describe preferences and to measure the consistency and difference of preferences.

Through these concepts advanced by this paper, we further propose a theoretical framework for fair matching of P2P platform. Fair matching of P2P platform is that under the heterogeneous resources and needs, the similarity and distance of multidimensional preferences indicator are used to maximize the consistency and reduce the difference between the two sides, to cope with the diversification and differentiation of preferences from supply and demand sides. The theoretical framework of fair matching on P2P platform is shown in Fig. 5.

## 3.4 Methods of measuring preferences

#### 3.4.1 Method for HTI

Based on Definition 1, our paper uses IFS  $I_S$  and  $I_C$  to describe the transaction evaluation of both parties, and expressed it by Eqs. (1–4).  $I_S$  and  $I_C$  are the evaluation intuitionistic fuzzy sets on non-empty evaluation set  $P^S$  and  $P^C$ . In our discussion here, we use a comprehensive score to represent the whole feeling of historical transactions between *C* and *S*.

$$I_S = \{ \langle x, \mu_{ij}^S(x), \gamma_{ij}^S(x) \rangle \mid x \in P^S \}$$
(1)

$$I_C = \{ \langle x, \mu_{ij}^C(x), \gamma_{ij}^C(x) \rangle \mid x \in P^C \}$$
<sup>(2)</sup>

$$0 \le \mu_{ij}^{S}(x) + \gamma_{ij}^{S}(x) \le 1$$
(3)

$$0 \le \mu_{ii}^{C}(x) + \gamma_{ii}^{C}(x) \le 1$$
(4)

 $\mu_{ij}^{S}(x)$  and  $\gamma_{ij}^{S}(x)$ ,  $\mu_{ij}^{C}(x)$  and  $\gamma_{ij}^{C}(x)$  are the average satisfaction (i.e. membership) and average dissatisfaction (i.e. non-membership) of history transactions between each other, is the average of all transactions. In real business, hesitation of IFS still increased the fuzzy uncertainty of the information, so we put it into the dissatisfaction. Then there's  $\mu_{ij}(x) + \gamma_{ij}(x) = 1$  or  $\mu_{ij}(x) = 1$ ,  $\gamma_{ij}(x) = 0$ .



Fig. 5 Theoretical framework of fair matching on P2P platform

On the structure of the function of transaction evaluation on IFS, for example, when Customer  $c_i$  feels good about all historical transactions with host  $s_j$ , or 80 points, we set  $\mu_{ij}^C(x)$  to 0.8, and then,  $I_C = \langle 0.8, 0.2 \rangle$ , 0.8 is the satisfaction, and the dissatisfaction is 0.2.

The IFSs can be abbreviated as  $I_S = \langle \mu_{ij}^S, \gamma_{ij}^S \rangle$  and  $I_C = \langle \mu_{ij}^C, \gamma_{ij}^C \rangle$ . Next we use vector  $\vec{o}_{ij}^S$  and  $\vec{o}_{ij}^C$  to express HTI of hosts and customers and show it in Eqs. (5–6). If  $t_{ij}^S = t_{ij}^C = 0$ , then  $\mu_{ij}^S = \gamma_{ij}^S = \mu_{ij}^C = \gamma_{ij}^C = 0$ .

$$\vec{o}_{ij}^S = (t_{ij}^S, \mu_{ij}^S, \gamma_{ij}^S) \tag{5}$$

$$\vec{o}_{ij}^C = (t_{ij}^C, \mu_{ij}^C, \gamma_{ij}^C) \tag{6}$$

Equations (7) and (8) calculate the historical transaction proportions  $t_{ij}^S$  and  $t_{ij}^C$ .  $\theta_i$  and  $\theta_j$  are the historical transaction totals of  $s_i$  and  $c_j$ .

$$t_{ij}^{S} = \begin{cases} \frac{\theta_{ij}}{\theta_{i}} = \frac{\theta_{ij}}{\sum_{j=1}^{n} \theta_{ij}}, & \theta_{ij} \neq 0\\ [3mm]0, & \theta_{ij} = 0 \end{cases}$$
(7)

$$t_{ij}^{C} = \begin{cases} \frac{\theta_{ij}}{\theta_{j}} = \frac{\theta_{ij}}{\sum_{i=1}^{m} \theta_{ij}}, & \theta_{ij} \neq 0\\ [3mm]0, & \theta_{ij} = 0 \end{cases}$$
(8)

The score of IFS mainly used to support the solution of multi-attribute decisionmaking problems [52–54], and the higher the score, the higher the fitness or approval degree. In our discussion, the IFS scores  $v_{ij}^S$  and  $v_{ij}^C$  are used as the degree of recognition of historical transactions between each other, and we use Eqs. (9–10) to get them,  $v_{ij}^S$ ,  $v_{ij}^C \in [-1, 1]$ . In addition, the comparison of the scores can reflect the lowest recognition level of the historical transactions by the two peers. Therefore, we calculate the HTI coefficient  $v_{ij}^{SC}$  by Eq. (11) and use it to show the preference of host and customer for historical transactions between them.

To better integrate HTI and preference, and give a full demonstration of the consistency and differences between the supply and demand sides in historical transaction and current preference, we use  $u_{ij}^{SC}$  as the coefficient of preference, and calculate it with formula (12). Because the range of preference coefficients is [-1,1], and  $v_{ii}^{SC} + u_{ii}^{SC} = 1$ , so we have  $v_{ii}^{SC} \in [0, 1]$ .

$$v_{ij}^{S} = \begin{cases} \mu_{ij}^{S} - \gamma_{ij}^{S}, & \mu_{ij}^{S} > \gamma_{ij}^{S} \\ 0, & \mu_{ij}^{S} \le \gamma_{ij}^{S} \end{cases}$$
(9)

$$v_{ij}^{C} = \begin{cases} \mu_{ij}^{C} - \gamma_{ij}^{C}, & \mu_{ij}^{C} > \gamma_{ij}^{C} \\ 0, & \mu_{ij}^{C} \le \gamma_{ij}^{C} \end{cases}$$
(10)

$$v_{ij}^{SC} = min\{v_{ij}^{S}, v_{ij}^{C}\}$$
(11)

$$u_{ij}^{SC} = 1 - v_{ij}^{SC} \tag{12}$$

#### 3.4.2 Method for current preference

Due to the platform business is driven by customer need and accommodation services, we use two vectors to depict one peer's current preference based on indicator sets  $P^{C}$  and  $P^{S}$ , i.e. the current preference of customer and host are  $\overrightarrow{PC} = \{\overrightarrow{OC}, \overrightarrow{OC'}\}$  and  $\overrightarrow{PS} = \{\overrightarrow{OS'}, \overrightarrow{OS}\}, \overrightarrow{OC'}$  and  $\overrightarrow{OS'}$  are customer and host's actual status under the indicator  $P^{S}$  and  $P^{C}$ ,  $\overrightarrow{OC}$  and  $\overrightarrow{OS}$  are the key expectations and requirements under the indicator  $P^{C}$  and  $P^{S}$ . Then the formula for the current preferences are given in Eqs. (13–18).

Due to the platform business is driven by customer need and accommodation services, we use two multidimensional vectors to depict one peer's current preference based on indicator sets  $P^C$  and  $P^S$ . Then, the current preference of customer and host are  $\overrightarrow{PC} = \{\overrightarrow{OC}, \overrightarrow{OC'}\}$  and  $\overrightarrow{PS} = \{\overrightarrow{OS'}, \overrightarrow{OS}\}$ . Among them,  $\overrightarrow{OC'}$  and  $\overrightarrow{OS'}$  are customer and host's actual status under the indicator  $P^S$  and  $P^C$ ,  $\overrightarrow{OC}$  and  $\overrightarrow{OS'}$  are the key expectations and needs under the indicator  $P^C$  and  $P^S$ . The formula for the current preferences are shown in Eqs. (13–18).

$$\overrightarrow{OC}' = (p_1^{S'}, p_2^{S'}, \dots, p_l^{S'}, \dots, p_e^{S'})$$
(13)

$$\overrightarrow{OC} = (p_1^C, p_2^C, \dots, p_k^C, \dots, p_f^C)$$
(14)

$$\overrightarrow{OS}' = (p_1^{C'}, p_2^{C'}, \dots, p_k^{C'}, \dots, p_f^{C'})$$
(15)

$$\overrightarrow{OS} = (p_1^S, p_2^S, \dots, p_l^S, \dots, p_e^S)$$
(16)

$$\overrightarrow{PS} = (p_k^{C'}, p_l^S) = (q_1^S, q_2^S, \dots, q_{e+f}^S), k = 1, 2, \dots, f; \quad l = 1, 2, \dots, e$$
(17)

$$\overrightarrow{PC} = (p_k^C, p_l^{S'}) = (q_1^C, q_2^C, \dots, q_{e+f}^C), k = 1, 2, \dots, f; \quad l = 1, 2, \dots, e$$
(18)

#### 3.4.3 Similarity and distance of preferences

Because the problem we are discussing is the comparison of two preferences vectors, it is suitable for Euclidean distance, but the traditional Euclidean distance does not take the distribution differences in the various dimensions into account, so we improved it. We subtract the average value of all peers from each peer's value on the same preferences indicator, to exclude the interference of the dimensional. Adjusted cosine similarity takes the size and direction of different dimension values into account, it can accurately measure the similarity between two multidimensional vectors, so we chose it. The formulas for distance and similarity of preferences are as follows.

The distance of HTI:

$$D(\vec{o}_{ij}^{S}, \vec{o}_{ij}^{C}) = \sqrt{\sum_{k=1}^{3} [(\rho_{ij}^{k} - \bar{\rho}_{j}^{k}) - (\sigma_{ij}^{k} - \bar{\sigma}_{i}^{k})]^{2}}$$
(19)

$$(\rho_{ij}^{1}, \rho_{ij}^{2}, \rho_{ij}^{3}) = (t_{ij}^{S}, \mu_{ij}^{S}, \gamma_{ij}^{S})$$
(20)

$$(\sigma_{ij}^{1}, \sigma_{ij}^{2}, \sigma_{ij}^{3}) = (t_{ij}^{C}, \mu_{ij}^{C}, \gamma_{ij}^{C})$$
(21)

$$\bar{\rho}_{j}^{k} = \frac{1}{m} \sum_{i=1}^{m} x_{ij}^{S}, x = t, \ \mu \ or \ \gamma$$
(22)

$$\bar{\sigma}_{i}^{k} = \frac{1}{n} \sum_{j=1}^{n} y_{ij}^{C}, y = t, \ \mu \ or \ \gamma$$
(23)

The similarity of HTI (Based on Eqs. (20, 21)):

$$S(\vec{o}_{ij}^{S}, \vec{o}_{ij}^{C}) = \frac{\sum_{k=1}^{3} (\rho_{ij}^{k} - \bar{\rho}_{i}^{k}) \cdot (\sigma_{ij}^{k} - \bar{\sigma}_{j}^{k})}{\sqrt{\sum_{k=1}^{3} (\rho_{ij}^{k} - \bar{\rho}_{i}^{k})^{2}} \cdot \sqrt{\sum_{k=1}^{3} (\sigma_{ij}^{k} - \bar{\sigma}_{j}^{k})^{2}}}$$
(24)

$$\bar{\rho}_{i}^{k} = \frac{1}{n} \sum_{j=1}^{n} \rho_{ij}^{k}$$
(25)

$$\bar{\sigma}_j^k = \frac{1}{m} \sum_{i=1}^m \sigma_{ij}^k \tag{26}$$

The distance of preference:

$$D_{ij}(\overrightarrow{PS}, \overrightarrow{PC}) = \sqrt{\sum_{l=1}^{k} [(q_{il}^{S} - \overline{q}_{l}^{S}) - (q_{jl}^{C} - \overline{q}_{l}^{C})]^{2}}$$
(27)

$$\bar{q}_{l}^{S} = \frac{1}{m} \sum_{i=1}^{m} q_{il}^{S}$$
(28)

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$$\bar{q}_{l}^{C} = \frac{1}{n} \sum_{j=1}^{n} q_{jl}^{C}$$
(29)

The similarity of preference:

$$S_{ij}(\overrightarrow{PS}, \overrightarrow{PC}) = \frac{\sum_{l=1}^{k} (q_{il}^{S} - \bar{q}_{i}^{S}) \cdot (q_{jl}^{C} - \bar{q}_{j}^{C})}{\sqrt{\sum_{l=1}^{k} (q_{il}^{S} - \bar{q}_{i}^{S})^{2}} \cdot \sqrt{\sum_{l=1}^{k} (q_{jl}^{C} - \bar{q}_{j}^{C})}}$$
(30)

$$\bar{q}_{i}^{S} = \frac{1}{k} \sum_{l=1}^{k} q_{il}^{S}$$
(31)

$$\bar{q}_{j}^{C} = \frac{1}{k} \sum_{l=1}^{k} q_{jl}^{C}$$
(32)

#### 3.5 Matching model for P2P sharing accommodation based on fair matching

According to the transaction mode of P2P sharing accommodation, we advance a theoretical framework of fair matching and build a supply-demand matching decision model based on it to achieve fairness of matching. The solution steps of supply-demand matching problem on P2P sharing accommodation platform are as follows.

*Step 1* Explicit the subject of supply and demand in transaction, in our discussion, the subject to be matched are hosts with his/her rooms and customers, i.e. *S* and *C*.

*Step 2* Determine the preferences of both parties, it include the HTI and preference, and build Vectors of HTI and preference based on preferences information according to Eqs. (5-6) and (17-18).

*Step 3* Calculate preference coefficients of HTI and preference based on Eqs. (11) and (12).

*Step 4* Calculate the similarity and distance of vectors by adjusted cosine similarity and improved Euclidean distance. The similarity of HTI and preference vectors can be calculated by Eqs. (24) and (30) and the distances value by applying Eqs. (19) and (27).

*Step 5* Solve the model (33) through Python platform, and the optimal matching results are obtained.

Figure 6 illustrates the matching decision process of this paper.



Fig. 6 Matching process of the model

$$\begin{cases} maxTSP = \sum_{i=1}^{m} \sum_{j=1}^{n} \left\{ \frac{v_{ij}^{SC \cdot S(\overline{O}_{ij}^{S}, \overline{O}_{ij}^{C})}}{D(\overline{O}_{ij}^{S}, \overline{O}_{ij}^{C})} \cdot \delta_{ij} + \frac{u_{ij}^{SC \cdot S_{ij}}(\overline{PS}, \overline{PC})}{D_{ij}(\overline{PS}, \overline{PC})} \cdot \delta_{ij} \right\} \\ s.t. \qquad \sum_{i=1}^{n} \delta_{ij} \leq 1, i \in \{1, 2, \dots, m\} \\ \sum_{i=1}^{m} \delta_{ij} \leq 1, j \in \{1, 2, \dots, n\} \\ \delta_{ij} \in \{0, 1\} \\ m \geq 2, n \geq 2 \end{cases}$$
(33)

In the model of Eqs. (33),  $\delta_{ij}$  is the matching parameter, the matching parameter matrix  $[\delta_{ij}]_{m \times n}$  is a 0 – 1 type numerical matrix to determine whether  $s_i$  and  $c_j$  matches each other. If the matching constraint is satisfied, the value of  $\delta_{ij}$  is 1, otherwise the value is 0, and the pair corresponding to value 1 of  $\delta_{ij}$  is a matching pair. The heterogeneity of resources and needs is reflected in the diversity of preferences, the model takes into account peers' historical transaction inclination, current preference and multidimensional preferences information to realize the diversity.

#### 4 Numerical analysis and discussion

#### 4.1 Study case design and model solving

Based on the P2P sharing accommodation transaction mode and theoretical framework of fair matching, we designed a numerical example, in which we assume that there is a host set  $S = \{s_1, s_2, ..., s_6\}$  and a customer set  $C = \{c_1, c_2, ..., c_5\}$  on a P2P platform. The data showing in Tables 3, 4 and 5 are the order numbers and HTI between hosts and customers in transaction records that generated by random numbers. Then we convert the transaction records into HTI vectors with Eqs. (5–8), and Table 4 is the value of HTI vectors from hosts to customers and Table 5 is the opposite.

ical orders and customers	$ heta_{ij}$	$c_1$	<i>c</i> <sub>2</sub>	<i>c</i> <sub>3</sub>	$c_4$	c <sub>5</sub>
	<i>s</i> <sub>1</sub>	20	26	24	7	27
	<i>s</i> <sub>2</sub>	6	16	20	24	9
	<i>s</i> <sub>3</sub>	7	17	9	15	0
	$s_4$	22	15	12	14	3
	$s_5$	25	22	24	7	19
	<i>s</i> <sub>6</sub>	14	0	13	20	15

 Table 3
 Historical orders

 between hosts and customer

Table 4 HTI data of hosts to customers

$\vec{o}_{ij}^S$	<i>c</i> <sub>1</sub>	<i>c</i> <sub>2</sub>	<i>c</i> <sub>3</sub>	$c_4$	<i>c</i> <sub>5</sub>
<i>s</i> <sub>1</sub>	(0.19, 0.05, 0.95)	(0.25, 0.20, 0.80)	(0.23, 0.82, 0.18)	(0.07, 0.84, 0.16)	(0.26, 0.82, 0.18)
<i>s</i> <sub>2</sub>	(0.08, 0.37, 0.63)	(0.21, 0.28, 0.72)	(0.27, 0.20, 0.80)	(0.32, 0.07, 0.93)	(0.12, 0.87, 0.13)
<i>s</i> <sub>3</sub>	(0.15, 0.90, 0.10)	(0.35, 0.70, 0.30)	(0.19, 0.35, 0.65)	(0.31, 0.09, 0.91)	(0, 0, 0)
$s_4$	(0.33, 0.17, 0.83)	(0.23, 0.79, 0.21)	(0.182, 0.86, 0.14)	(0.21, 0.11, 0.89)	(0.05, 0.32, 0.68)
<i>s</i> <sub>5</sub>	(0.26, 0.52, 0.48)	(0.23, 0.10, 0.90)	(0.25, 0.40, 0.60)	(0.07, 0.53, 0.47)	(0.20, 0.25, 0.75)
<i>s</i> <sub>6</sub>	(0.23, 0.14, 0.86)	(0, 0, 0)	(0.21, 0.13, 0.87)	(0.32, 0.94, 0.06)	(0.24, 0.61, 0.39)

Table 5 HTI data of customers to hosts

$\vec{o}_{ij}^C$	<i>c</i> <sub>1</sub>	<i>c</i> <sub>2</sub>	<i>c</i> <sub>3</sub>	<i>c</i> <sub>4</sub>	<i>c</i> <sub>5</sub>
<i>s</i> <sub>1</sub>	(0.21, 0.81, 0.19)	(0.27, 0.98, 0.02)	(0.24, 0.47, 0.53)	(0.08, 0.20, 0.80)	(0.37, 0.88, 0.12)
<i>s</i> <sub>2</sub>	(0.06, 0.20, 0.80)	(0.17, 0.35, 0.65)	(0.20, 0.08, 0.92)	(0.28, 0.42, 0.58)	(0.12, 0.63, 0.37)
<i>s</i> <sub>3</sub>	(0.07, 0.06, 0.94)	(0.18, 0.78, 0.22)	(0.09, 0.29, 0.71)	(0.17, 0.51, 0.49)	(0, 0, 0)
<i>s</i> <sub>4</sub>	(0.23, 0.39, 0.61)	(0.16, 0.62, 0.38)	(0.12, 0.88, 0.12)	(0.16, 0.84, 0.16)	(0.04, 0.453, 0.55)
<i>s</i> <sub>5</sub>	(0.27, 0.79, 0.21)	(0.23, 0.37, 0.63)	(0.24, 0.79, 0.21)	(0.08, 0.22, 0.78)	(0.26, 0.92, 0.08)
<i>s</i> <sub>6</sub>	(0.15, 0.39, 0.61)	(0, 0, 0)	(0.13, 0.32, 0.68)	(0.23, 0.14, 0.86)	(0.21, 0.38, 0.62)
0	(,,,	<	(,,,	(,,)	(,,

In Tables 4 and 5, the intersection of  $s_i$  and  $c_j$  is the HTI of  $s_i$  to  $c_j$  or  $c_j$  to  $s_i$ . As an example of Table 4, the position of the cross in row 1 and column 1 of the table is the HTI of  $s_1$  to  $c_1$ , that is,  $\vec{o}_{11}^S = (0.19, 0.05, 0.95)$ .

The preference vectors of hosts and customers related to the actual situation and expectation of both sides. Tables 6 and 7 show actual status and expectation data in current preference based on the preference indicators in Table 2 and Eqs. (12-17).

With the preference data prepared, the similarity and difference of preferences can be solved according to the formula of similarity degree and distance, then the model can be solved and the matching parameters  $\delta_{ij}$  can be obtained. The solution matrix for the matching parameter  $\delta_{ij}$  can be found in Table 8.

$\overrightarrow{PS}$	$q_1$	$q_2$	$q_3$	$q_4$	$q_5$	$q_6$	$q_7$	$q_8$	$q_9$	$q_{10}$	$q_{11}$	<i>q</i> <sub>12</sub>	<i>q</i> <sub>13</sub>
<i>s</i> <sub>1</sub>	3.2	2.6	0.0	0.4	4.0	4.6	3.9	3.0	3.7	0.6	1.6	3.8	2.8
<i>s</i> <sub>2</sub>	2.3	1.7	4.0	5.0	3.3	1.4	0.8	4.4	2.4	3.3	0.9	4.5	3.8
<i>s</i> <sub>3</sub>	2.6	4.3	0.9	0.4	0.2	3.0	2.9	3.8	3.7	2.5	1.3	1.4	0.7
<i>s</i> <sub>4</sub>	3.5	4.6	4.4	3.2	3.6	1.3	1.4	0.3	3.1	1.3	3.5	1.4	3.9
<i>s</i> <sub>5</sub>	4.4	1.2	2.2	0.5	4.3	0.1	1.1	0.8	4.7	0.8	0.9	1.6	1.0
<i>s</i> <sub>6</sub>	4.2	4.3	1.7	4.6	2.7	2.2	3.8	3.4	2.2	0.1	1.3	3.4	4.6

Table 6 Preference data of hosts

 Table 7
 Preference data of customers

$\overrightarrow{PC}$	$q_1$	$q_2$	$q_3$	$q_4$	$q_5$	$q_6$	$q_7$	$q_8$	$q_9$	$q_{10}$	$q_{11}$	$q_{12}$	$q_{13}$
<i>c</i> <sub>1</sub>	2.1	2.1	3.4	2.4	0.1	2.5	4.1	0.2	0.2	0.6	3.8	2.0	2.2
$c_2$	0.8	0.9	4.3	4.0	2.3	1.5	4.6	4.7	2.7	0.2	0.5	1.5	2.8
$c_3$	4.2	3.0	1.2	3.5	3.8	4.5	3.2	3.8	3.5	0.6	0.3	2.0	0.3
$c_4$	3.2	1.8	1.5	4.8	1.0	2.6	0.9	2.0	2.9	1.6	4.1	3.7	1.3
c <sub>5</sub>	4.6	4.1	2.0	3.5	0.4	2.5	0.9	3.6	3.0	4.0	2.7	4.4	3.4

Table 8	Matching parameter
matrix	

Table 9 Matching results

$\delta_{ij}$	$c_1$	<i>c</i> <sub>2</sub>	<i>c</i> <sub>3</sub>	$c_4$	<i>c</i> <sub>5</sub>
<i>s</i> <sub>1</sub>	0	0	0	0	1
<i>s</i> <sub>2</sub>	0	0	0	1	0
<i>s</i> <sub>3</sub>	0	1	0	0	0
<i>s</i> <sub>4</sub>	0	0	1	0	0
<i>s</i> <sub>5</sub>	1	0	0	0	0
<i>s</i> <sub>6</sub>	0	0	0	0	0

The bold numbers are the value of the matching parameter  $\delta_{ij}$  corresponding to  $s_i$  and  $c_i$ , indicating that  $s_i$  and  $c_i$  match each other

TSP	Optimal matching pair	TSP of each pair
22.49	$(s_1, c_5)$	15.26
	$(s_2, c_4)$	0.03
	$(s_3, c_2)$	2.08
	$(s_4, c_3)$	3.24
	$(s_5, c_1)$	1.88

Table 8 shows the matching result of maximizing the TSP based on preferences consistency, in which the supply-demand corresponding to 0 is a non-matching pair. Combining the data in Tables 8 and 9 presents the best matching pair as follows.

Table 9 shows 5 pairs based on preferences consistency, which shows that the model implements matching hosts and customers under fair matching. The TSP value of the matching scheme is 22.49. For host  $s_1$ , 1 customer  $c_5$  who with the similar preferences is matched, for  $s_2$ , customer  $c_4$  is matched, and so on, the matching strategy helps both sides find the trading partners with their HTI and current preference.

#### 4.2 Discussion

The experiment of the example uses  $6 \times 5$  group simulation data of hosts and customers to test the supply-demand matching decision model based on preference consistency. The experimental results show that the model can obtain satisfactory results. To illustrate the feasibility and rationality of the matching strategy proposed in this paper, we use different data sets to detect the model and analyze the sensitivity. In our model, the preferences data include HTI and current preference are randomly generated, different matching results should be produced according to different preferences data. In addition,  $v_{ij}^{SC}$  and  $u_{ij}^{SC}$  are the weight coefficients of historical preference and preference, which used to determine the extent that historical transaction and current preferences can produce different match pairs and the effect of the change in weight on the result. We design the sensitivity analysis based on several different sets of data and the constraints on the weights.

We designed a calculation method for the proportion of similar matching pairs (similarity rate) between two different data sets and the average similarity rate of matching results between these data sets, and expressed with Eqs. (34) and (35). In the equation,  $NS_{ij}$  and  $NT_i$  represent the number of similar matching pairs between *dataseti* and *datasetj*, and the number of matching pairs of each data set, respectively. Based on Eqs. (34) and (35), we design an algorithm to calculate the similarity rate of matching results (Algorithm 1).

$$r_i = \frac{1}{m-1} \sum_{j=1}^m \frac{1}{2} \left( \frac{NS_{ij}}{NT_i} + \frac{NS_{ij}}{NT_j} \right), \quad i, j = 1, 2, \dots, m; \quad i \neq j$$
(34)

$$as = \frac{1}{m \cdot (m-1)} \sum_{j=1}^{m} \sum_{i=1}^{m} \frac{NS_{ij}}{NT_i}, \quad i, j = 1, 2, \dots, m; \quad i \neq j$$
(35)

**Algorithm 1** Algorithm for similarity rate of matching results

```
input: Set of matching results sets: M
output: Similarity rate of each set: r.average similarity rate of M: as
 1: m = length(M)
 2: C = []_{m \times m}, l = []_{1 \times m}, r = []_{1 \times m}, as = 0
 3: for 0 \le i < m do
 4:
        l[i] = length(M[i])
 5: end for
 6: for 0 \le i < m, 0 \le j < m do
 7 \cdot
      for 0 \le k < l[i], 0 \le l < l[j] do
 8:
            if M[i][k] == M[j][l] then
 9:
                C[i][j] = C[i][j] + 1
10:
            end if
11:
        end for
12: end for
13: for 0 \le i < l[i] do
14:
        for 0 \le j \le l[j] do
15:
            if i != j then
                r[i] = \frac{1}{2} * (C[i][j]/C[i][i] + C[j][i]/C[j][j])
16 \cdot
17:
                as = a\overline{s} + C[i][j]/C[i][i]
18:
            end if
19:
        end for
        r[i] = \frac{1}{m-1} * r[i]
20:
21: end for
22: as = \frac{1}{m(m-1)} * as
23: return r, as
```

#### 4.2.1 Comparison between different preferences data sets

First, we fixed the coefficient of preferences and change preferences data to test the change of the matching results. We have designed three use cases, which are the random numbers that obey the normal distribution, beta distribution and exponential distribution, to represent three different sets of preferences. Figure 7 shows the distribution of the three data sets, to present the use case data in a concise way. Since satisfaction is a key variable in HTI, we only adjust it in part HTI. In Fig. 7, the four subgraphs on the left are preferences data distribution, which obeys the beta distribution. In addition, the four subgraphs on the right are the distribution of data set that under exponential distribution. We named them *dataset*1, *dataset*2 and *dataset*3, respectively.

Figure 7 shows that there are large differences between the data sets that reflect the heterogeneity of needs and preferences. We solve the model according to Eq. (33) and show the matching results in Table 10.

The matching results of the three data sets are quite different, there are two same pairs between *dataset*1 and *dataset*2, and zero in *dataset*1 and *dataset*3, for example. It shows that different preferences data can produce different matching results by the



Fig. 7 The distribution of three preferences data sets

Table 10 Matching result based on the three preferences data sets

Dataset 1		Dataset 2		Dataset 3	
TSP	Optimal pairs	TSP	Optimal pairs	TSP	Optimal pairs
50.603	$(s_2, c_5)$	103.493	$(s_2, c_5)$	18.95	$(s_1, c_5)$
	$(s_3, c_2)$		$(s_3, c_2)$		$(s_2, c_4)$
	$(s_4, c_3)$		$(s_4, c_4)$		$(s_3, c_3)$
	$(s_5, c_4)$		$(s_5, c_3)$		$(s_5, c_1)$
	$(s_6, c_1)$				$(s_6, c_2)$

strategy in this paper. Through algorithm 1, the similarity rate of matching results between each data set and other sets can be obtained. We use Fig. 8 to show it.

We can find that the similarity rate of matching results are quite low from Fig. 8. The highest similarity rate is *dataset*1, the similarity rate is 0.225, and the lowest is *dataset*3, which is zero, and the average similarity rate of the three datasets is only 0.15. The contrast experiment is based on different preferences data, which reflects the different preferences support different matching results between hosts



Fig. 8 The similarity rate of matching results between each data set and others

and customers, which is consistent with the real business, reflecting the rationality of the model.

#### 4.2.2 Influence of different preference coefficients on the results

For the analysis of the weights of  $v_{ij}^{SC}$  and  $u_{ij}^{SC}$ , we fixed the preferences data and change the coefficient sets under normal distribution (i.e. *dataset*1), beta distribution (i.e. *dataset*2), exponential distribution (i.e. *dataset*3) and F distribution (i.e. *dataset*4). In the case of changing weight coefficient, determine whether the result is invariant. Because the HTI coefficient  $v_{ij}^{SC}$  determines the preference coefficient  $u_{ij}^{SC}$ , we use different distribution of HTI coefficient sets to test, and show the distribution of the HTI coefficients in Fig. 9 and each result based on these datasets are shown in Table 11. We name the data from Tables 3, 4, 5, 6 and 7 as *dataset*0 in Table 11.

What we can find from Fig. 9 is that these coefficients are quite different; their coverage is wider and has a strong representation. Table 11 and Fig. 10 shows that the matching results are highly consistent. *Dataset*1, *dataset*2, *dataset*3 and *dataset*4 have



Fig. 9 Distribution of HTI coefficient from 4 datasets

Dataset 0	Dataset 1	Dataset 2	Dataset 3	Dataset 4
$(s_1, c_5)$				
$(s_2, c_4)$	$(s_2, c_3)$	$(s_2, c_3)$	$(s_2, c_3)$	$(s_2, c_3)$
$(s_3, c_2)$				
$(s_4, c_3)$	$(s_5, c_1)$	$(s_5, c_1)$	$(s_5, c_1)$	$(s_5, c_1)$
$(s_5, c_1)$				

Table 11	Distribution of HTI
coefficier	nt from 4 datasets



Fig. 10 Similarity rate of matching results between each dataset and others

identical matching results, for example. *Dataset*0 has three same pairs with other data sets, and two different pairs, as a result, its similarity rate with other data sets is as low as 0.675, and the average similarity rate of all sets is as low as 0.87. The main reason is that the HTI coefficient of *dataset*0 comes from its HTI data, which makes the HTI coefficient cannot become a completely independent parameter. Otherwise, the similarity rate of each data set is 1, that is to say, different weight coefficient sets have no interference on the optimal result of the matching strategy.

Through the analysis of the above two angles, we find that the model proposed in this paper can match diversified preferences between supply and demand sides according to different preferences data, which shows that our model can obtain different matching results based on various preferences data. In terms of parameter testing, the test results show that different preferences coefficient data have no effect on the results of the model, indication the robustness of the model. However, there is still room for continuous improvement, in order to make the strategy adapt to more diversified and multidimensional preferences, to meet the matching requirements of increasingly heterogeneous resources and needs. Later we will continue to optimize the model so that it can withstand the test of practice. The sensitivity analysis shows that our model has certain applicability and rationality in the matching problem of heterogeneous resources and needs.

## 5 Conclusion

Aiming at the problem of the heterogeneous and personalized resources and needs on P2P sharing accommodation platform, this paper puts forward the theoretical framework of the fair matching based on reducing the differences and promote the maximization of consistency of diversified preferences between the two sides. Then a matching model according to fair matching is proposed. Through this strategy, the optimal combination of heterogeneous resources and needs from peers can be realized, and the rationality and certain robustness of the model are verified through experimental analysis and sensitivity analysis.

The research of this paper provides enlightenment to the study of matching problem on P2P platform, especially for match of heterogeneous and personalized resources and needs on P2P sharing accommodation platforms. We expound the transaction mode of the P2P sharing accommodation platforms, and combine the development trend of the platform, put forward the theoretical framework of fair matching, which promotes the study of matching issue on P2P sharing platform. We expand the research of supply and demand matching, redefine the preferences on P2P platform, which is taken as the basis of matching, and expand the preferences of both sides into two parts: HTI and current preference, to comprehensively describe the demands and expectations of service providers and customers. The research of matching decision is enriched by the discussion the determination and quantification of indicators and it provide new ideas for relevant researchers.

Our research provides several managerial implications for the sharing economy related industries and the public. First, this paper provides a relatively common scheme for intelligent matching of P2P platform, and provides strategic support for platform operators to match platform heterogeneous resources and needs effectively and improve the service level of the platform. Second, the analysis of the expectations and preferences of users contributes to understanding and effective evaluation between peers, providing a basis for better interaction, and giving new clues and basis for platform governance and regulation by regulators. Finally, our research on the sharing economy is helpful to people's understanding of the connotation of sharing and provides reference for investors to participate in the platform business. Our research also helps to the spread of sharing ideas and thus promote the efficient use of idle resources in society. In future research, we will conduct a more comprehensive and in-depth study of matching strategies under fair mechanism, and look for reliable mechanisms and solutions in the construction and maintenance of sharing economy platform relationship network to promote the sustainable and coordinated development of sharing economy in China.

There are still a few limitations in our study, and we extend them as follows. Because our study is based on experimental analysis and strategic exploration, its shortcomings are mainly reflected in the existence of a certain degree of deviation with the actual, which puts forward the requirements of this paper, that is, combined with the actual business scene, constantly optimize the improvement model and the corresponding strategy. In addition, there may be expectations based on the future in determining the user preferences, which may be a direction that needs to continue to expand. Then, on the selection of preference indicators, this paper is only based on platform reviews, app stores and related literature, and does not combine the actual interviews and research platform users on both sides; it is also a weak point of our work. Due to the popularity of P2P platforms, everyone may become a service provider or consumer, which makes the research of P2P sharing economy urgent to follow up, especially in intelligent life services. In the future, we will extend our current research, and focus on the evolution trend of P2P platform user network, preferences mining of service providers, platform response to unexpected disasters such as COVID-19, etc.

#### **Compliance with ethical standards**

Conflict of interest The authors declare that they have no conflict of interest.

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