Consumption Pricing Mechanism of Scientific and Technological Resources Based on Multi-Agent Game Theory: An Interactive Analytical Model and Experimental Validation

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SUMMARY   In the context of Web 2.0, the interaction between users and resources is more and more frequent in the process of resource sharing and consumption. However, the current research on resource pricing mainly focuses on the attributes of the resource itself, and does not weigh the interests of the resource sharing participants. In order to deal with these problems, the pricing mechanism of resource-user interaction evaluation based on multi-agent game theory is established in this paper. Moreover, the user similarity, the evaluation bias based on link analysis and punishment of academic group cheating are also included in the model. Based on the data of 181 scholars and 509 articles from the Wanfang database, this paper conducts 5483 pricing experiments for 13 months, and the results show that this model is more effective than other pricing models - the pricing accuracy of resource resources is 94.2%, and the accuracy of user value evaluation is 96.4%. Besides, this model can intuitively show the relationship within users and within resources. The case study also exhibits that the user's knowledge level is not positively correlated with his or her authority. Discovering and punishing academic group cheating is conducive to objectively evaluating researchers and resources. The pricing mechanism of scientific and technological resources and the users proposed in this paper is the premise of fair trade of scientific and technological resources.

key words: *consumption pricing mechanism, scientific and technological resources, multi-agent game theory, interactive analysis, link analysis*

1.   Introduction

Scientific and technological resources refer to resources and elements that support and promote technological innovation of various forms, their typical examples include knowledge resources, human resources, data resources, hardware and software resources, and computation resources [1], [2]. With the globalization of technology and the increasingly fierce competition, technological innovation has become a new engine that reshapes the world's economic structure and international competition. Scientific and technological resources are the important foundation of scientific and technological innovation, and their open sharing and effective utilization are the key to accelerating the promotion of scientific and technological innovation and enhancing competitiveness in countries all over the world. The sharing of scientific and technological resources can greatly improve resource utilization and reduce invalid labor.

Resource pricing directly affects people's willingness and extent to share when sharing resources. Therefore, how to reasonably price resources and to evaluate contributing participants has aroused extensive discussion in academic community. Regarding the pricing of patent value, Hsieh [3] creates a framework that combines the Delphi method, fuzzy measurement, and a technology portfolio planning (TPP) model to analyze the commercialization prospects of patents. Hu et al. [4] incorporate the standard textual feature of answers and non-textual features, and proposed a multimodal deep belief network (DBN)-based learning framework to determine the value of answers in health expert question-answering (HQA). Regarding the identification of experts and influential users, Mauksch et al. [5] illustrate three epistemologies of sociological, behavioral and cognitive, and reviewed the methods for identifying experts. Neshati et al. [6] propose a learning frame-work to predict the best ranking of experts in future in Community Question Answering (CQA). In addition, the classic ranking algorithms, such as PageRank and HITS [7], [8], are often used to identify knowledge contributors and high-quality knowledge contents. The disadvantage of both algorithms is that the evaluation result is easily affected by "junk links" [7].

Table 1 shows the approaches to resource pricing and expert identification in recent researches. It is noticeable that the pricing of scientific and technological resource and the recognition of influential contributors are unrelated. In the context of Web 2.0, the interaction between users and resources is more and more frequent. It is unreasonable to establish a pricing mechanism only considering the characteristics of users or resources. Moreover, since there are many

Table 1 The approaches to resource pricing and expert identification

Contents	Factors	Researches
The pricing of scientific and technological resources	Text features	[11][12][13]
	Content features	[14]
	Index system	[15][16]
The identification methods of experts	Social acclamation	[17][18]
	Political influences	[19][20]
	Personal Involvement	[21]
	External cues	[22][23]
	Self-ratings	[24]
	Past performance	[25]
	Knowledge tests	[26]
	Psychological traits	[27]

parties involved in sharing, how to balance the interests of all parties and play a multi-agent pricing game needs to be considered. Several resource sharing communities, such as Yedda and Quora, value users' weights equally and rank resources by using likes or averages [9]. This ranking method is not the most sensible, since it is obvious that the judgment of users with high authority is more objective than the ordinary. Cheating long dwells in academia [10], but there is little targeted research or handling. Aiming at the problems of separation between users and resource, the equality of all human weights, and academic group cheating, a new pricing mechanism model is urgently needed to objectively measure the value of user and resource.

Based on link analysis algorithm, this study proposes a resource-user interactive pricing model, which combines of the evaluation data and contribution data in the interaction to achieve an objective pricing mechanism of users and resources. First, based on the follow relationship between users, users similarity, and interactions between users and resources, this study establishes user network, resource network, and resource-user bipartite network, respectively. Based on multi-agent game theory, a link analysis method for resource-user interactive evaluation is proposed. Finally, in order to correct the initial results, the group cheating is uncovered and punished accordingly. Experiments on Wanfang database prove that this model is effective, and the pricing accuracy is 94.2%.

The contribution of this work is threefold. First, different from the traditional method of pricing mechanism of users and resources separately [28], [29], this paper fully considers the interaction between users and resources, and accurately determines the values of both users and resources. Second, different from the current resource sharing community where the weight of users is equal, this paper balances the interests of all users based on the multi-agent game theory, and endows users with different weights that are assigned by the objectivity of pricing and sharing contribution. Third, the pricing mechanism proposed by this study considers the user similarity and punishes the behavior of academic cheating, which is common in academia and can lead to bias in the evaluation of resources value [10].

The article proceeds as follows. In Sect. 2, we review the related works on user similarity and link analysis. In Sect. 3, we introduce the resource-user interactive evaluation model by considering the similarity within users as well as within resource and their interaction. In Sect. 4, a case study is conducted to prove the effectiveness of the pricing mechanism based on multi-agent game theory. The conclusion is conducted in Sect. 5.

2. Related Works

The consumption pricing mechanism based on multi-agent game theory proposed in this paper belongs to typical link analysis. Besides, the establishment of user network and resource network is based on their similarity. We review the related works of user similarity and link analysis and present it below.

2.1 User Similarity

Discovering user similarities from social media can create the basis for user evaluation, user targeting and product recommendation [30], [31]. Hu et al. [32] propose a method of collaborative clustering in social network based on time, location and Point-of-Interest (POI) to measure user similarity. Wang et al. [33] propose a new user similarity scheme by a hybrid method, which considers the influence of all possible rated items, the non-linear relationship between variables, the asymmetry between users, and the rating preference of users. Yue et al. [30] hold a view that user similarities could be obtained by analyzing their behavioral interactions since the similarities reflect users' behavioral manner when concerned in social activities. The category of locations visited by users have been used by researchers to reveal their interests [34]–[36] since user movements are generally driven by their interests and mining these mobility patterns can reveal commonalities between a pair of users. Mazumdar et al. [37] present a framework for mining the published trajectories to identify patterns in user mobility. Lv et al. [38] propose a two-stage approach to measure user similarity based on routine activity. Through the above resource, we found that the existing research commonly used time, location, interest, user interaction behavior, daily activities to measure user similarity. In the resource sharing community, user's research field, interest and label can be used as the measure of user similarity, and then establish user network. There are currently three main methods for measuring the similarity between users, i.e., Cosine, Correlation, and Adjusted Cosine [39]. Studies have shown that choosing different similarity measures has minimal impact on the results [39].

2.2 Link Analysis

Link analysis is the process of looking for and establishing links between entities within a data set as well as characterizing the weight associated with any link between two entities [40]. Link analysis is essentially a

kind of knowledge discovery, which can be used to visualize data for better analysis, especially in the context of links, whether it is a web link or a relationship link between people or between different entities. Link analysis can be done manually with spreadsheets or with software designed specifically to organize data into something meaningful and easy to understand. One of the fuller featured analysis tools is IBM's i2 Analyst's Notebook (www-03.ibm.com/software/products/en/analysts-notebook) [41].

Link analysis can be applied to the construction of network structure, the determination of important nodes and risk control. The main role is to find the key nodes and connections between nodes. The PageRank algorithm and the HITS algorithm are extremely basic and important algorithms in link analysis, and many scholars use these two algorithms to evaluate the relationships or connections between network nodes [42]–[44]. The disadvantages of the traditional PageRank algorithm and the HITS algorithm are that the old node rank is higher than the new node, and the evaluation result is easily affected by "junk links" [7]. Thus, in order to improve the effectiveness of the results, scholars often need to modify them or combine multiple algorithms when using them.

3. Scientific and Technical Resource-User Interactive Pricing Model Based on Multi-Agent Game Theory

When a user quotes for a resource, he or she does not know what others are quoting for the resource. The process is similar to a sealed auction game. The user's game goal is to gain a greater degree of authority. When users quote prices for resources, they should not only consider their own evaluation of the value of the resources, but also consider the possible evaluation of most users for the resources, since the deviation of the rating will affect their authority. Because the grading process determines the user's authority and the real level of resources at the same time, and the two influence each other, the traditional game model is not applicable to this situation. Therefore, this model adds a link analysis method on the basis of multi-agent game theory, so that users' authority and resource pricing can interact.

Based on link analysis, the interactive pricing model of scientific and technical resource-user is conducted. The idea of this interactive evaluation model is as follows. Users in the resource sharing community could contribute and evaluate resource. The knowledge level of users is determined by the level of resource he or she contribute. Different users have different evaluation weights when evaluating the resources. If the user's evaluation score of the resource has a larger deviation than the final score of the resource, the user's evaluation weight will be affected. The flow chart of this model is shown in Fig. 1. First, we establish bipartite network of users and resource according to the information of users' contribution and pricing of resources; next we establish user network and resource network according to the similarity and the interaction of bipartite network. Then the pricing model is established according to the link analysis method. Finally, the pricing result is corrected by correcting cheating. Definitions of each measure are explained below.

3.1 Bipartite Network of Users and Resources

There are multiple ways of interaction between users and resources: browsing, reading, commenting and downloading. Based on these interactions, a bipartite network of users and resources can be established. The bipartite network $G(U, K, R)$ contains two types of nodes, user U and resource R, as well as the relationship E, R between them, which can be expressed as $E, R = R_1 \circ R_2 \circ \cdots \circ R_l$. For $\forall u_i \in U$ and $\forall r_j \in R$, the relationship between them can generate any number of edge $e_{ijr} \in E_{ij}$ based on the interaction between the system users and the resource knowledge. Different interaction actions are given different weights, and the weight-based summation method can be used to synthesize multiple associations between u_i and r_j into one weighted edge, that is,
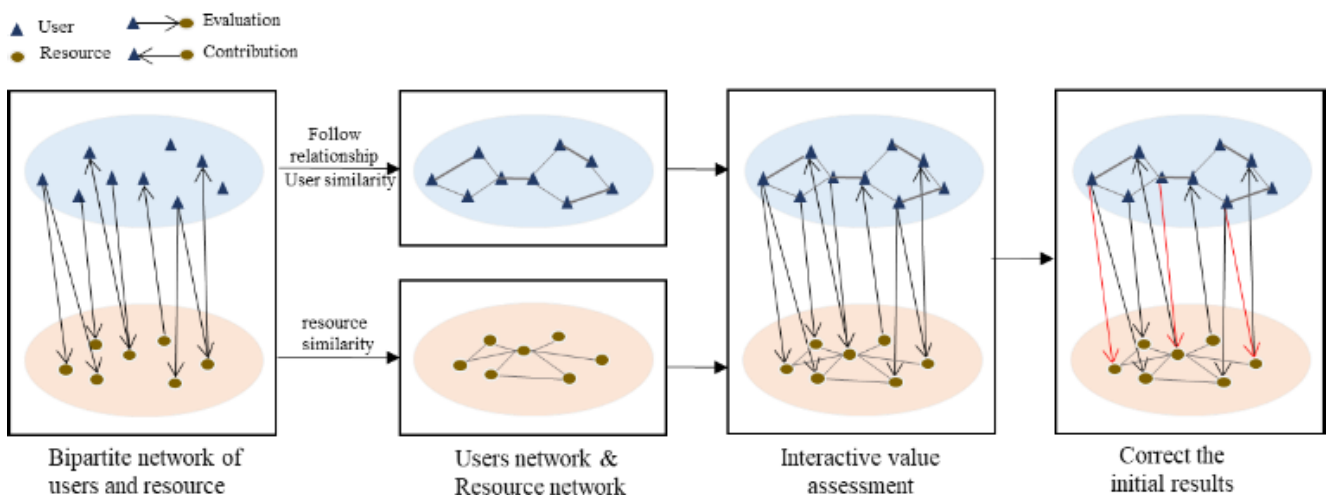

Fig. 1 The flow chart of the resource-user interactive evaluation model.

$$E_{i \to j} = \alpha * Br + \beta * Ra + \gamma * Co + \delta * Do. \tag{1}$$

where $E_{i \to j}$ represents the comprehensive evaluation result of user i to resource j; α represents the weight of browsing; Br indicates whether user i has viewed resource j, Br can take 0 or 1, Br takes to indicate user i has viewed resource j, and Br takes 0 to indicate the opposite; β represents the weight of ratings; Ra represents the direct score of resource j by user i. γ represents the weight of comments; Co represents the degree of approval of user i when commenting on resource j, its value is calculated after natural language processing; δ represents the weight of downloading; Do indicates whether resource j has been downloaded by user i, Do can take 0 or 1, Do takes 1 to indicate that it has been downloaded, and Do takes 0 to indicate the opposite.

3.2 User Network

The establishment process of the user network is based on the following information:

- The follow relationship between users;
- Transformation of similarity. First, the user's similarity between the tags and the research areas is established according to the Correlation, and then it is converted into a user network.
- Transformation of resource-user bipartite network. The resource-user dichotomy network can be regarded as a general network with resource as the association relationship, so that the user relationship network becomes a network with the user U as the vertex and the resource-user conversion relationship E as the edge. In this process, we need to synthesize the association weight between the user and the user on the basis of balancing the association weight between the resource as the intermediary node and the upper and lower users. The weight transformation is shown in Eq. (2).

$$pw_{U_{12}} = f(pw_{u_1 r}, pw_{u_2 r}). \tag{2}$$

3.3 Resource Network

The establishment process of the resource network is based on the following information:

- Transformation of resource similarity. First, the resource's research areas similarity is established according to the Cosine, and then it is converted into a resource network.
- Transformation of resource-user bipartite network. Similar to Eq. (2), the weight transformation is shown in Eq. (3).

$$pw_{r_{12}} = f(pw_{ur_1}, pw_{ur_2}). \tag{3}$$

3.4 Interactive Value Assessment

First of all, for the resource-user network, the following assumptions are put forward: (1) Due to the existence of swarm intelligence, a single evaluator is always no better than the evaluation group; (2) The authoritative evaluator evaluates the resource more accurately than the general evaluator.

According to the hypothesis, for the bipartite network $G(U, P, R)$, a represents the evaluation authority of user nodes, and s represents the value of resource nodes. Users with higher a value can have a greater impact on the final score s when pricing resource. For users whose price are close to the final score s, the value of a will increase. Conversely, if the user's evaluation differs too much from s, the value of a will decrease.

Let the value of a for all initial users u_i be $a_0(u_i) = 1$. Since this method does not converge in the calculation of user weights, the iterative increase and decrease limits of $\overline{a}$ and $\underline{a}$ are given for the value of a. For u_i, the evaluated resource set is R_i. At the $t-1$ iteration, the weight of u_i is shown in Eq. (4).

$$a_t(u_i) = a_{t-1}(u_i) + \sum_{R_p \in R_i} \left(\frac{1}{\lambda} - \frac{|s_{t-1}(r_p) - s_{u_i}(r_p)|}{\lambda s_{max}} \right). \tag{4}$$

where $a_t(u_i)$ represents the authority of user i at time t, s_{max} represents the maximum pricing that can be obtained for a resource given by the system, $s_{u_i}(r_p)$ represents the evaluation score given by u_i to r_p, and λ is a boundary constant used to determine the user rating $s_{u_i}(r_p)$ and the degree of deviation of the actual patent pricing $s_{t-1}(r_p)$. When the user's score deviates from the average and exceeds $\frac{1}{\lambda}$, the user's evaluation of the resource will have a negative impact on his own authority.

For the resource node r_i, the set of users who evaluate it is U_i. At the t iteration, the score of r_i is as shown in Eq. (5). Obviously, the score of r_i is a weighted average of the ratings of all users who are evaluated.

$$s_t(r_i) = \frac{\sum_{u_p \in U_i} a_{t-1}(u_p) s_{u_p}(r_i)}{\sum_{u_p \in U_i} a_{t-1}(u_p)}. \tag{5}$$

where $s_t(r_i)$ represents the weighted score of resource i at time t. $a_{t-1}(u_p)$ represents the authority value of user u_p at time $t-1$. $s_{u_p}(r_i)$ represents the evaluation score given by u_p to r_i.

The method cannot converge, so the upper and lower limits of iteration of $a_t(u_i)$ are defined as the termination condition of traversal. Iterations are repeated until $\exists u_i$, $a_t(u_i) \le \underline{a} \lor a_t(u_i) \ge \overline{a}$.

In the resource-user pricing process, the upper and lower limits of a value can control the degree of separation of weights between users, and the rate of decline is determined by λ. After a limited number of iterations, it can be considered that the weights of all users have been basically determined. With the continuous occurrence of evaluation behavior, the algorithm should be re-run at regular intervals or when a sufficient number of new evaluation interactions have occurred in the system. Update the actual weights of

users in the system to maintain the accuracy of users' evaluation behaviors in the system.

For u_i, the set of contributed resource is PU_i. After the iteration, the knowledge level $l(U_i)$ of u_i is calculated as follows:

$$l(u_i) = \frac{\sum_{PU_r \in PU_i} s_t(p_i)}{crad(PU_i)}. \tag{6}$$

where $crad(PU_i)$ represents the number of elements in the set PU_i. $l(U_i)$ represents the user's knowledge level, obviously this value is the average of the weighted score of the resource contributed by the user.

According to Eq. (4) and Eq. (6), each user has an authority level $a_t(u_i)$ and a knowledge level $l(u_i)$. Different weights are given to these two capabilities to obtain the equation of the user's overall value $V(u_i)$:

$$V(u_i) = \alpha * a_t(u_i) + \beta * l(u_i). \tag{7}$$

where $V(u_i)$ represents the overall value of u_i; α represents the weight of the user's authority; β represents the weight of the user's knowledge level.

3.5 Correct the Initial Results

In Sect. 3.4, the boundary constant λ was introduced to determine the degree of deviation between the user's score and the actual price of resource, so as to measure the user's authority. However, some researchers may behave in groups, that is, users U_i and U_j score high on each other's resource, they are "junk links" in the network. Although the introduction of λ limits this behavior to a certain extent, it does not punish users for scoring. Thus, the scoring is revised in this section.

For user U_i and U_j, if user U_i scores all the resource contributed by user U_j above deviation $\frac{1}{\lambda}$, that is:

$$s_{u_i}(pu_r \in PU_j)$$
$$> \frac{|s_{t-1}(pu_r) - s_{u_i}(pu_r)|}{\lambda s_{max}}$$
$$\cup s_{u_j}(pu_q \in PU_i)$$
$$> \frac{|s_{t-1}(pu_q) - s_{u_j}(pu_q)|}{\lambda s_{max}} \tag{8}$$

It is considered that user U_i and user U_j have a group behavior. At this point we need to discount each other's ratings within the group, that is, $s_{u_i}(r_p) = \delta * s_{u_i}(r_p)$. Then recalculate the users' value and resource price according to the equation in Sect. 3.4.

4. Experimental Works

In order to explore the effectiveness of the above resource-user interactive pricing model, we conducted an experimental work. The case data and model results are shown below.

4.1 Case Selection and Data

We set up an online resource sharing community based
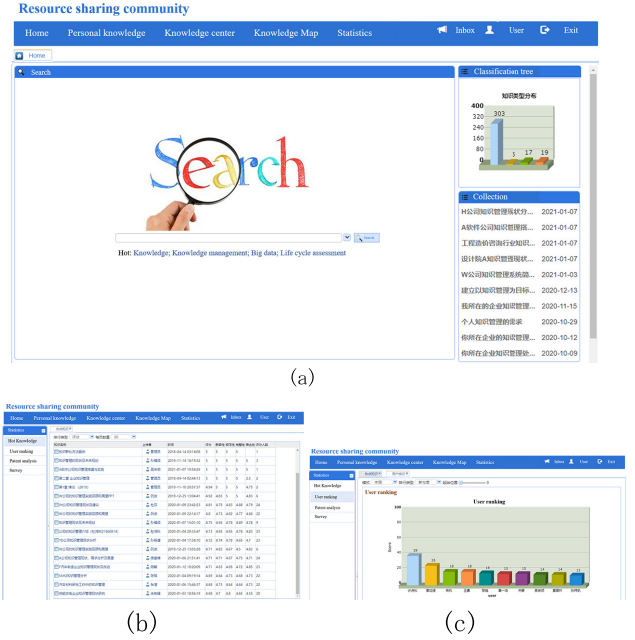
Fig. 2 The interface of the online resource sharing community (a) homepage; (b) knowledge price; (c) user ranking.

on Web 2.0 (https://ekms.zju.edu.cn/) and invite 181 researchers to import their contributed knowledge resources and recent research from the WanFang Database into the online resource sharing community for easy grading. The large number of researchers, random selection methods and anonymous evaluation guarantee the representativeness of this case. The interface of the online resource sharing community is shown in Fig. 2. The system is divided into four functional modules: personal knowledge upload module, knowledge display and evaluation module, and statistical analysis module (Fig. 2 (b) and (c)). Each researcher regularly shares his or her research gains, and prices the knowledge contributed by others, users could not see other people's pricing during the evaluation. Pricing behaviors include browsing, scoring, comments and downloading. At regular intervals, the system reuses all the data and recalculates it based on the interactive analysis method, constantly revising the pricing of all the resources and the overall value of the user. In addition to the system users, we also invite five experts in the field to price the knowledge in the system. When discrepancy happened, they would discuss to assign a final score. The average value of the experts' scores is considered to the true level of knowledge. The experts also set the weights of the four evaluation behaviors, the average result is 5% for browsing, 40% for ratings, 30% for comments, and 25% for downloads, that is, α, β, γ and δ in Eq. (1) are 5%, 40%, 30%, 25%, respectively.

The case runs for 13 months from December 1, 2018 to January 15, 2020. We invite 181 researchers in the field of knowledge management and machine learning to collect data through the online resource sharing community. These researchers contribute 509 articles introduced from WanFang database. The cumulative evaluation volume is

5483. On average, each knowledge receives 10.7 comments, and each researcher comments on 30.2 articles. The pricing ranges from 0 to 5 points. We count all the pricings and get the results shown in Fig. 3. It shows that the highest pricing is 5 points and the lowest pricing is 1 point. It is found that most of the pricings ranges from 2.5 to 5, with 3.5 to 4 scoring the most, accounting for 31% of the total. The experimental analysis is carried out from four parts: network graphics, initial results, corrected results and discussion.

4.2 Network Graphics

The researchers' contribution and pricing of the knowledge resource, as well as the correlation between users, the similarity within users as well as within resource are taken as the input of the interactive evaluation model. According to the resource-user interactive pricing model proposed in Sect. 3, the resource-user bipartite network, the user network and the knowledge network are established in turn. In order to improve the readability of the visual graph, we select 31 resource knowledge contributed by 15 researchers as an example to show three networks, as shown in Fig. 4.

Figure 4 (a) shows that U_{13} is at the center of the users' network and has the closest connection with other users, followed by U_5, U_{11} and U_2. U_4 and U_5 have less contact with other users. On average, each user has 5 closely interacting users. According to Fig. 4 (b) and the knowledge content, knowledge can be divided into two categories of knowledge management on the left and machine learning on the right, among which K_{19} and K_{21} are the topics in the overlapping fields. The overall similarity of knowledge is large. It can be seen from Fig. 4 (c) that U_1 contributes three pieces of knowledge and is the user who contributes the most knowledge; U_4, U_6, U_{11} and U_{13} offer their opinions on all knowledge. K_{30} received 14 evaluations, which is the most evaluated knowledge. On average, each researcher contributes 1.93 knowledge and prices 22.8 knowledge. On average, each knowledge is priced by 11 researchers.

4.3 Initial Results

λ in Eq. (4) takes 10, that is, when the user's score deviates from the average by more than 10%, the user's pricing of knowledge will have a negative impact on his or her own authority. The $\overline{a}$ takes 4 and the $\underline{a}$ takes 1. s_{max} takes 5. The result is shown in Fig. 5. It can be seen from Fig. 5 (a) and Fig. 5 (b) that the interactive pricing method proposed in this paper is close to the pricing of experts in terms of knowledge and user evaluation, indicating that this method is effective. However, the average knowledge level and user level are higher than the above two pricing, which may be because the weight of all people is regarded as constant when calculating the average value, while the method in this paper reduces the weight of some users due to considering the deviation between the pricing and the actual pricing, so the actual pricing of knowledge would be discounted. The average knowledge level and the average user level are far away from the results of expert ratings, which also indicates that the traditional evaluation method of evaluating knowledge by considering the weight of users as equal is flawed. As can be seen from Fig. 5 (c), there is no direct correlation between the level of knowledge and the authority of the user. Some users have a high level of knowledge and a high degree of authority, such as U_4, U_6, U_8, U_{13}. Some users have a high level of knowledge and low authority, such as U_5, U_7, U_{15}. Some users have a low level of knowledge, but a high
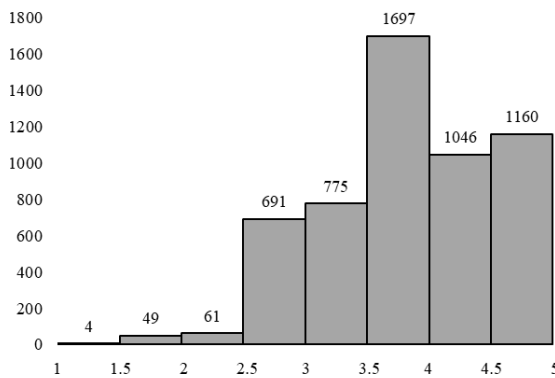

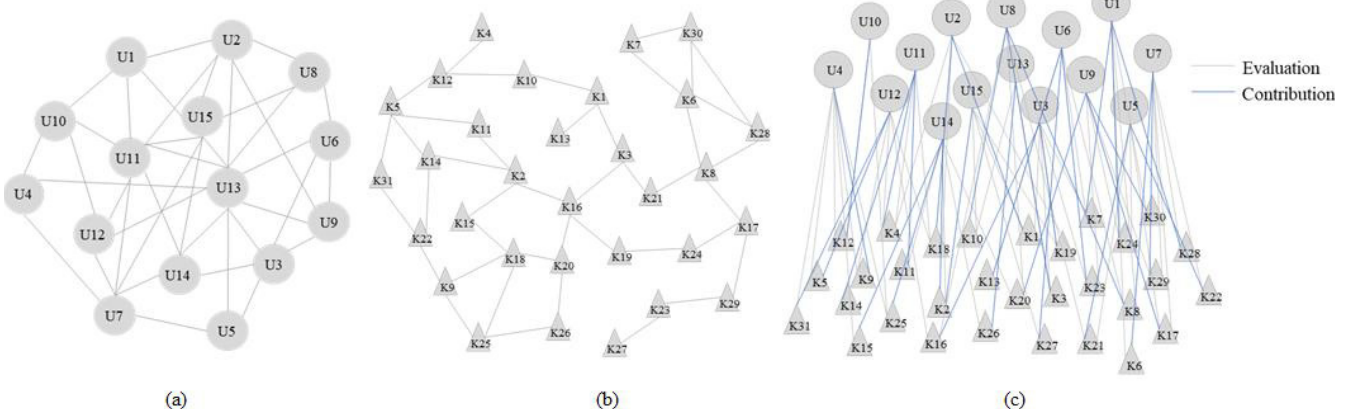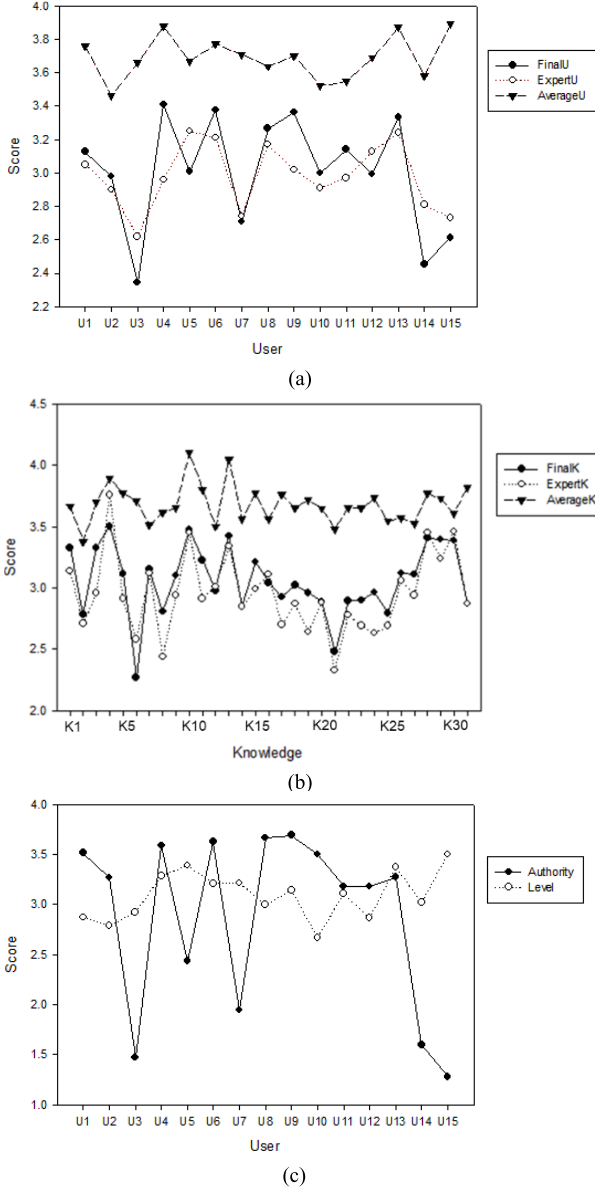**Fig. 3** Statistics of evaluation scores.

Fig. 4 (a) The user network; (b) the knowledge network; (c) the bipartite network of users and knowledge.

(a)

(b)

(c)

Fig. 5 Results contrast (a) FinalU, ExpertU and AverageU, (b) FinalK, ExpertK and AverageK, (c) Authority and Level.

degree of authority, such as U_1, U_8, U_9. These results may deviate from the traditional recognition that high-level users usually have a high degree of authority.

4.4 Corrected Results

According to Eq. (8), it can be calculated that U_4 and U_{13}, U_5 and U_{13}, U_{11} and U_{13} have group cheating behavior in the community respectively. Multiply each other's pricing by 0.9, recalculate the user value and knowledge price, we can get the contrast result shown in Fig. 6. It is calculated that the error deviation between knowledge price and real price is 5.8%, and the error deviation between user value and real value is 3.6%. In other words, the accuracy of this model for knowledge price is 94.2%, and the accuracy of

(a)

(b)
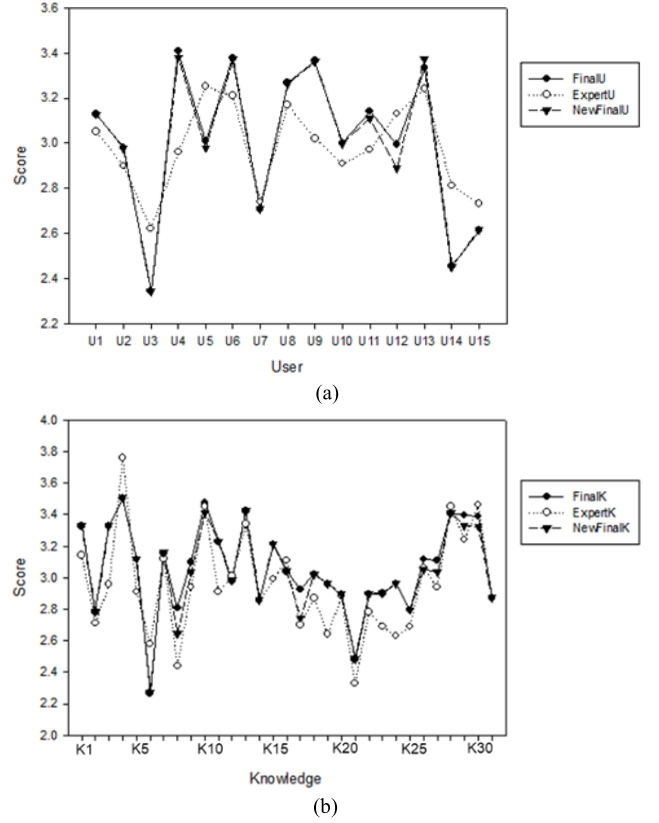
Fig. 6 Before and after correction (a) FinalU, ExpertU and NewFinalU, (b) FinalK, ExpertK and NewFinalK.

user value evaluation is 96.4%. It is found that the revised knowledge results are closer to the scores of experts, such as K_8, K_9, K_{17} and K_{29}. U_4, U_5 and U_{13} are worth less overall than they were before the correction. The corrected result is different from the initial result, which is mainly because by lowering the high scores within the cheating academia group, the price of knowledge is closer to the true level of knowledge. Therefore, the degree of deviation between the price of other users and the true level of knowledge are reduced, and the authority of other users is increased, which increases the level of knowledge accordingly. For the U_4, U_5 and U_{13} of group cheating, the gap between their scores and the true level of knowledge becomes larger, so their overall value level has dropped.

4.5 Discussion

Many studies have focused on the pricing of resource and users' value using deep learning methods based on textual features and non-textual features [4]. The selection of features may affect the accuracy of the results [45]. Besides, they do not consider the interaction data between users and resource, which is the sustainable driving force of the resource sharing community. Compared with the existing value evaluation methods which are separated from user evaluation and resource evaluation [28], [29], the advantage of this resource-user pricing model is to establish a

bipartite network between users and resources, divide user value into knowledge level and evaluation authority, consider user scoring weight and punish group cheating.

Hu and Oh [45] identify 23 user criteria (can be divided into six categories: content, cognitive, utility, information sources, extrinsic and socio-emotional) and 24 data features to assess the answer quality in social Q&A. The results show most user features (answer count, merit badges count) and review features (revision count, comment count) are positively correlated to high-quality answers. In Fig. 6 (b), the average pricing of the user's knowledge score (AverageK) is basically consistent with the trend of the true pricing of knowledge (ExpertK), which confirms the Hu and Oh' results. The pricing results of this model (FinalK) are closer to the true level of knowledge, indicating that this resource-user value evaluation is reliable.

However, the limitation of this model is that this method is mainly used in communities where users and knowledge interact frequently, that is, each user contributes more than one knowledge, and each knowledge is evaluated by many people. Less evaluation data may affect the effectiveness of value evaluation. Besides, the comprehensive evaluation method may improve the accuracy of the results [44], so the text features and user criteria can be considered in the evaluation model.

5. Conclusion

Based on link analysis and multi-agent game theory, this paper proposes a consumption pricing mechanism of scientific and technological resources to measure the value of users and resources. This method balances the interests of all users based on the multi-agent game theory, and endows users with different weights. It also makes full use of the interactive data between users and resources, considers the similarity of users, finds "junk links" and punishes cheating. Based on the data of 181 scholars and 509 articles from the Wanfang database, this paper conducts 5483 pricing experiments for 13 months, and the results show that this model is more effective than other pricing models - the pricing accuracy of resource resources is 94.2%, and the accuracy of user value evaluation is 96.4%. Through case studies, we also found that the user's knowledge level is not positively correlated with his or her authority. Discovering and punishing academic group cheating is conducive to objectively evaluating researchers and knowledge.

Future research may consider using multiple methods in combination. For example, taking into account the political influence, personal involvement, the text features and content features of knowledge when applying the interactive analysis model. In addition, the value of knowledge is constantly changing with time, so the time factor can also be considered in the measurement of the value of knowledge and users.

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