Automatic Pricing Mechanism of PWYW Based on AHP-FCE Data Value Evaluation

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Abstract: Data trading can improve data circulation and promote the development level of information technology, However, data pricing issues limit the expansion of data trading scale. In response to this issue, this study proposes pricing data products through data value assessment. This study uses the Analytic Hierarchy Process and Fuzzy Comprehensive Evaluation method to design a data value evaluation method, which combines the Pay What You Want (PWYW) mechanism with Stackelberg game to design an automated pricing method for data transactions. The results show that the designed data value evaluation method has a value evaluation error of no more than 5% for different data types. When automatically pricing data products based on the value evaluation results, the pricing result should have an error of no more than 5% compared to the market average price, and the pricing result can be automatically adjusted according to market conditions. The proposed automated pricing method for data products can automatically price products based on market conditions, effectively safeguarding the interests of both parties in the data trading market and promoting its development.

Keywords: value assessment; automatic pricing; intelligent decision; analytic hierarchy process; fuzzy comprehensive evaluation

Introduction

Driven by globalization and technological innovation, the manufacturing industry is undergoing unprecedented transformation. As a product of the integration of manufacturing and service industries, service-oriented manufacturing has become a new engine for promoting manufacturing upgrading and economic growth [1-2]. Service-oriented manufacturing not only emphasizes the production and quality of products, but also focuses on providing personalized services and overall solutions to meet the diverse needs of consumers [3]. As mobile applications and Internet of Things technology develops, the collection and utilization of data resources have become particularly important, providing intelligent decision-making support, efficiency improvement, and customer service optimization possibilities for service-oriented manufacturing [4].

However, the phenomenon of data silos seriously restricts the potential of data in service-oriented manufacturing [5]. Data trading promotes the circulation and value realization of data elements by establishing standardized and efficient data trading venues and rules, but the value of data is difficult to evaluate, making it difficult to promote data trading on a large scale [6-7]. In traditional data trading, pricing data products almost does not consider the buyer's factors and relies solely on the data owner's independent pricing. Such pricing method often leads data owners to pricing their own products beyond the actual value of the data products themselves. This practice greatly hinders the circulation and promotion of data products. The Analytic Hierarchy Process (AHP) can analyze the factors that affect the pricing of data products, considering the impact of different factors on their pricing. Combining Fuzzy Comprehensive Evaluation (FCE) can evaluate the intrinsic value of data products. Therefore, in order to improve data circulation and ensure the security to stability of data transactions, the study proposes using AHP combined with FCE to evaluate the value of data. While ensuring that the pricing of data is not lower than its own value, the buyer factor is included in the pricing consideration. Finally, the PWYW (Pay What You Want) pricing mechanism is used to automatically price the data during the data transaction process.

The innovation of the research lies in using AHP to calculate the impact of different influencing factors on the value of data products, and using FEC to automatically price data products based on the analysis results of AHP and the PWYW mechanism. At the same time, research is also considering privacy compensation for data owners in pricing.

The main contribution is to improve the scientific and rational pricing of data services, promote the effective utilization of data assets, and provide innovative solutions for the transformation and upgrading of service-oriented manufacturing. By building an intelligent trading system, it can facilitate data transactions between buyers and sellers in a secure and reliable environment, promoting the upgrading of the manufacturing service industry.

The remainder of the paper is organized in four parts. Part 1 is a literature survey on research related to data trading and automatic pricing. Part 2 is based on AHP-FCE for DVE research and automated pricing methods for data trading. Part 3 is an experimental analysis of value assessment methods and automated pricing methods to verify the feasibility of the method. Part 4 is a summary of the research content.

Related works

The pricing methods and protection of data transactions have always been the main issues in data circulation in the information age. Cui W et al. designed a blockchain-based transaction system Ecare to address privacy data management issues and achieve privacy protected data sharing. This system achieved transparency and immutability in data transactions, and it can be extended to more general big data privacy protection and data transaction scenarios [8]. Zhao B et al. proposed a reputation evaluation model with evaluation entities to address the problem of inaccurate subjective and qualitative evaluations in traditional reputation evaluation models in data transactions. This model could safely and effectively assess the reputation of the seller [9]. Yuezhou C et al. outlined the flow and

transactions of individuals and companies based on public data, and classified data factors to provide a complete picture of data flow and transactions. Data trading was complex and diverse, and the global data market was rapidly developing. The proportion of China's data market was relatively low, and relevant institutional systems needed to be improved [10]. Huang G et al. proposed the bidirectional trusted transaction protocol Bitrans to solve the problem of realizing data value in blockchain systems. This protocol utilized different asset characteristics and controls transaction status through a new consensus algorithm. Experimental results have shown that it can achieve the exchange of different assets under limited resources [11]. Bin Z et al. raised a data price dynamic evaluation model with credit game theory to address the issues of pricing inequality and credit deficiency in data trading. This model could initialize pricing mechanisms, evaluate data prices, and its price difference percentage was controllable, with a high trading success rate [12].

Li B et al. proposed an improved subscription scheme to address the increasing demand for data and the instability and no arbitrage issues of existing subscription schemes, which includes two parts: computation and specific validity. This scheme could stabilize pricing and maximize seller profits, while giving the plan more rationality [13]. Xu Y et al. proposed a data collection market and iterative bilateral auction mechanism for the Internet of Vehicles to maximize social welfare. They constructed a data energy trading ecosystem based on bilateral auctions. The system was economically feasible, operated efficiently, and converged quickly [14]. Jiang W et al. raised a blockchain data repair

technology based on data migration to ensure the security of data in data transactions, and they established a multi-party data migration on chain repair system. This technology used chameleon hash algorithm combined with controlled data restoration strategy for data restoration. Compared with traditional algorithms, this algorithm could reduce data repair costs by 10% [15]. Saba T et al. proposed a secure blockchain model to address the security issues of heterogeneous services and financial transactions in the big data environment. This model could protect intelligent service financial interactions, improve network throughput, reduce computational overhead, data latency, response time, and minimize packet loss [16]. Liu Z et al. raised a secure electricity data trading scheme to address privacy protection, transaction security, and data reliability issues in electricity data trading. This scheme could achieve privacy protection, transaction security, and data reliability, and the privacy protection attributes have been verified in real cases [17].

In summary, existing studies mostly focus on a single data type, lacking extensive applicability studies for evaluating the value of multiple types of data. Many studies have failed to fully consider the need for user privacy protection in data pricing, especially in the context of increasing risks of data breaches, and they lack effective privacy compensation mechanisms. In addition, existing technologies have shown insufficient performance in dealing with the dynamic and real-time issues in data trading, making it difficult to adapt to rapidly changing market environments. Finally, although some studies have proposed data transaction models that combine blockchain and other technologies, further exploration and

solutions are needed to balance efficiency and security, to achieve cross platform data interoperability in practical applications. The circulation of important data relies on data transactions. In the current data trading market, the intangibility and replicability of data make it difficult to clearly define its ownership. The rights and obligations between data suppliers, demanders, and trading platforms are unclear, and the legal effectiveness of data trading contracts is uncertain. The value of data is influenced by various factors, including data integrity, accuracy, real-time performance, etc. In a complex market structure, there are issues of information asymmetry and uneven bargaining power among multiple stakeholders, Unreasonable pricing results are also detrimental to the growth of the data trading market. At present, the lack of unified DVE standards and pricing mechanisms has led to difficulties in data pricing. Therefore, this study proposes combining AHP and FCE evaluation methods to construct an evaluation method for data value and designing an automatic pricing algorithm for data trading based on the PWYW mechanism and Stackelberg game theory.

DVE and Automatic Pricing Methods

DVE method based on AHP-FCE

The value of data is directly related to its data type. The main circulating data in the current data trading market is manufacturing service data [18]. This study takes manufacturing data as an example to analyze its value evaluation. Manufacturing service-related industries not only need to provide products in the market, but also need to provide other services related to products. When evaluating the value of data, it needs to consider the basic characteristics of the data, focus on its specific applications, and take into account the impact of market factors [19-20]. According to the above requirements, this study constructs a DVE index system, as denoted in Table 1.

Table 1. Data value evaluation index system

Dimension	Indicator Name	Dimension	Indicator Name
Quality dimension	Data integrity	Application dimension	Data scarcity
	Data correctness		Data timeliness
	Consistency		Scenario economy
	Data repeatability		Data correlation
	Obtain difficulty level		Multidimensional data

The DVE indicator system constructed is divided into two dimensions, with the quality dimension including data integrity, correctness, consistency, repeatability, and ease of acquisition, and the application dimension including data scarcity, timeliness, correlation, scenario economy, and multi-dimensionality. This study uses AHP to determine the weights of indicators, including the construction of judgment matrices, consistency checks, and weight calculations. When constructing the judgment matrix, this study constructs it from two dimensions. The quality dimension judgment matrix is shown in equation (1) [21-22].

$$Q = \begin{bmatrix} a & b & b & b & b \\ 1/b & a & a & b & c \\ 1/b & a & a & b & b \\ 1/b & 1/b & 1/b & a & b \\ 1/b & 1/c & 1/b & 1/b & a \end{bmatrix}$$

（1）

In equation (1), Q is the quality dimension judgment matrix. c is of equal importance for two factors. *a, b, 1/b*, and *1/c* indicate that the importance of one factor is slightly, significantly, strongly, and absolutely superior to another factor. The judgment matrix of the application dimension is shown in equation (2).

$$A = \begin{bmatrix} a & a & b & b & b \\ a & a & b & b & c \\ 1/b & 1/b & a & b & b \\ 1/b & 1/b & 1/b & a & b \\ 1/b & 1/c & 1/b & 1/b & a \end{bmatrix}$$

（2）

Consistency testing requires first calculating the consistency index, as shown in equation (3).

$$CI = \frac{\lambda_{max} - n}{n - 1}$$

（3）

In equation (3), CI is the consistency indicator. λ_{max} means the maximum eigenvalue of the maximum judgment matrix. n means the order of the judgment matrix. The consistency ratio can be calculated by combining the consistency index with the random consistency index, as shown in equation (4).

$$CR = \frac{CI}{RI}$$

（4）

In equation (4), CR means the consistency ratio. RI means a random consistency indicator. Comparing the consistency ratio results with the set threshold can determine whether the quality dimension and application dimension indicators meet the consistency requirements. After confirming that the consistency of the indicators meets the requirements, the judgment matrices of the quality dimension and application dimension are subjected to eigenvalue decomposition to obtain the eigenvectors of the two judgment matrices. After normalizing it, the sum of indicator weights is set to 1, and the weights of the DVE indicators can be obtained by integrating the two dimensions of indicators [23-24]. The designed data foundation value evaluation model is shown in equation (5).

$$V_R = \sum_{i=1}^{n}(a_i \times \theta_i)$$

（5）

In equation (5), V_R is the fundamental value of the data. a_i is the i-th normalized metric value. θ_i means the weight of the i-th indicator. The fundamental value of data cannot directly determine the market value of data, and the value of data assets needs to be determined based on the data application market. The constructed data asset value evaluation model is shown in equation (6).

$$V_A = V_R \times P_i + c_j$$

（6）

In equation (6), P_i is the data price of the corresponding data type in the market. c_j is the correction coefficient for the value of data in data application scenarios. In practical scenarios, the value of data will dynamically change with market conditions. To make DVE

more in line with market conditions, this study introduces three dynamic factors of satisfaction, transaction frequency, and scarcity from the perspectives of users, market, and data, and dynamically optimizes DVE [25-26]. When evaluating the dynamic impact of user satisfaction on DVE, it needs to construct a user satisfaction evaluation index system, as shown in Fig. 1.
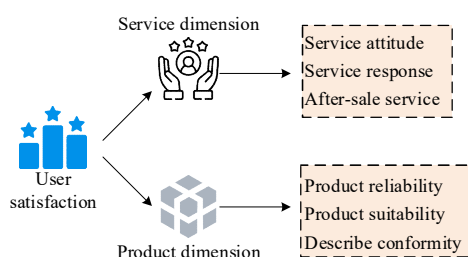
Fig. 1. User satisfaction evaluation index system

The evaluation system is divided into two dimensions: product and service. The product dimension includes reliability, suitability, and description conformity, while the service dimension includes attitude, response, and after-sales service. The evaluation of user satisfaction involves many influencing factors, and there is a fuzzy phenomenon in the evaluation indicators. This study uses FCE to process user satisfaction. FCE is a multi-factor decision-making method with fuzzy mathematics. It transforms qualitative evaluation into quantitative evaluation through fuzzy logic, which is particularly suitable for dealing with complex problems with uncertainty and fuzziness. Its operational steps are shown in Fig. 2 [27-28].
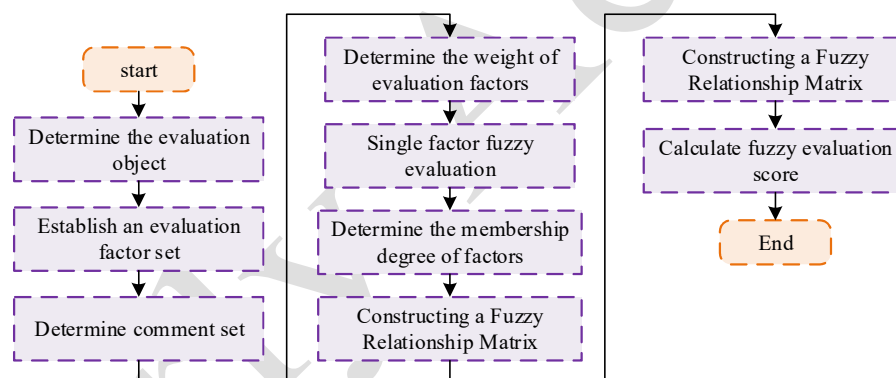
Fig. 2. The operation steps of the fuzzy comprehensive evaluation method

When using FCE to evaluate user satisfaction, it is necessary to first determine the evaluation factors and comments. The evaluation factors for user satisfaction evaluation are six evaluation indicators. This study will set the comments into five levels: very satisfied, dissatisfied, average, relatively satisfied, and satisfied. After determining the evaluation factors and comments, it is necessary to determine the weights of the relevant evaluation indicators. This study uses the AHP method to determine the weight of rating indicators, and the

operation steps are consistent with the calculation steps of the DVE indicator system weight. After determining the weights of the indicator system, a single factor fuzzy evaluation is used to evaluate each factor and determine its membership degree to each comment, constructing a fuzzy relationship matrix. The evaluation score is obtained by performing fuzzy operations using weight vectors and fuzzy relationship matrices. The calculation of transaction frequency is shown in equation (7).

$$F_i = \frac{T_i}{N} \qquad (7)$$

In equation (7), F_i is the historical transaction count of the data. T_i is the number of transactions per unit time for data. N means the number of transactions during the current time period. The calculation of data scarcity is shown in equation (8).

$$D_i = m \cdot p_i + (1-m) \cdot S_i \qquad (8)$$

In equation (8), D_i is the scarcity of data. p_i is the frequency of occurrence of the data in the corresponding field. S_i is the expert's assessment of the scarcity of the data. m is a scarcity evaluation parameter. After adding the three dynamic influencing factors mentioned above, the DVE model is shown in equation (9).

$$V_n = V_{n-1} \times [1 + \Sigma(\Delta\alpha_k \times \mu_k)] \qquad (9)$$

In equation (9), V_n and V_{n-1} are the DVE results after and before dynamic optimization. $\Delta\alpha_k$ is the variable of dynamic influencing factors. μ_k is the weight of dynamic influencing factors.

Automatic pricing method for data trading based on PWYW mechanism and Stackelberg game

After evaluating the value of the data, transaction pricing can be determined based on the evaluation results and the specific circumstances of both parties involved in the transaction. PWYW is a non-traditional pricing mechanism that grants consumers maximum pricing autonomy. In this mode, consumers are free to decide the price they are willing to pay for a product or service, including paying zero price. The PWYW pricing strategy is becoming increasingly popular in the service industry and digital products. When pricing data products based on the PWYW mechanism, it is necessary to consider the basic logic of user payment and external influencing factors. The conceptual model of the constructed data product PWYW is shown in Fig. 3.
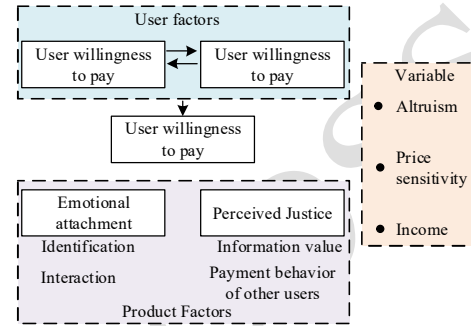
Fig. 3. Data product PWYW conceptual model

The willingness of users to pay for data products can be broken into data product factors and user factors. The factors of data products include emotional attachment and perceived fairness. Emotional attachment mainly refers to the user's identification and interactivity with the data product. Perceived fairness mainly refers to the actual value of the data product and the payment value of other users for the product. User factors include the type of data product and impulse buying tendency. The types of data products can be roughly classified as hedonic and practical. Impulsive buying tends to be directly related to the user's own situation and has no other potential influencing factors. The control variables for user payment include altruism, price sensitivity, and user income [29-30]. Based on this conceptual model, this study proposes using Stackelberg game theory for automated pricing of data products. Stackelberg game is a non-cooperative sequential game model. The mechanism of the automated pricing

method for the designed data product is shown in Fig. 4.
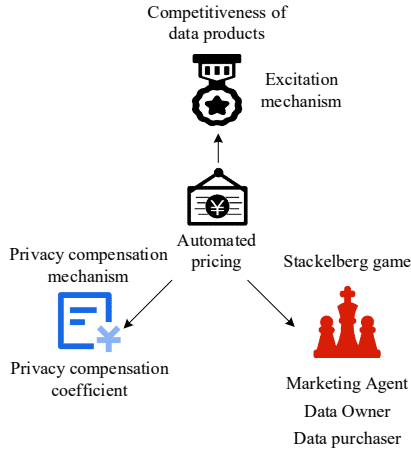
Fig. 4. Automatic pricing mechanism of data products based on the Starkerburg game

The mechanism of automated pricing method for data products based on Stackelberg game includes three-stage game mechanism, incentive competition mechanism, and privacy compensation mechanism. When users pay for data products, their willingness to pay is strongly correlated with data prices. When pricing data products, the owners of the data products will interact with each other. The stronger the competitiveness of data product owners, the higher the willingness of users to pay for their products. The competitiveness calculation of data owners is shown in equation (10).

$$\Pi_i(p_i) = \frac{l}{p_i \sum\limits_{j \in N} \frac{1}{p_j}} \quad (10)$$

In equation (10), $\Pi_i(p_i)$ is competitiveness. p_i is the data price. l is the quantity of data price. The privacy compensation mechanism is designed to compensate data owners for the risk of data leakage during data transactions, by increasing the basic pricing of relevant

data by data owners through privacy compensation coefficients. The expression for the privacy compensation coefficient is shown in equation (11).

$$k_i = -\sum_{x_j \in X} p(x_j) \log_2 p(x_j) \quad (11)$$

In equation (11), k_i is the privacy compensation coefficient. x_j is the sales record of data products. In the Stackelberg game designed based on the PWYW mechanism in this study, participants include data owners, data buyers, and market agents. The first stage of the three-stage game mechanism is the market agency game. Market agents need to utilize data price distribution to maximize their own utility, as shown in equation (12).

$$\begin{cases} \text{maximize}_P O(A, P) \\ \text{s.t.} p_i \in [c_i, p_{max}], \forall i \in N \end{cases} \quad (12)$$

In equation (12), $\text{maximize}_P O(A, P)$ maximizes the market agency utility. c_i is the unit cost of data ownership by the data owner. P is the distribution of market agency prices. A is the distribution of purchase quantities. When the game reaches Nash equilibrium, the selected party among the data owners and their data product quotes can be calculated. The second game is a data buyer game, where the data buyer needs to maximize their utility based on the amount of paid data, as shown in equation (13).

$$\begin{cases} \text{maximize}_{a_i} BU_i(a_i, p_i) \\ \text{s.t.} a_i \in [a_{min}, a_i^{max}], \forall i \in N \end{cases} \quad (13)$$

In equation (13), $\text{maximize}_{a_i} BU_i(a_i, p_i)$ maximizes the utility of the data purchaser. a_i is the quantity of data purchased. When the second game

reaches Nash equilibrium, the optimal purchase quantity for data buyers can be obtained. The third game is the data owner game, where the price obtained by the data owner is influenced by the price, purchase quantity, and privacy compensation. Therefore, data owners need to use these three influencing factors to maximize their own utility, as shown in equation (14).

$$\begin{cases} \text{maximize}_{k_i} SU_i(k_i, p_i, a_i) \\ \text{s.t.} k_i \in [k_i^{min}, k_i^{max}], \forall i \in N \end{cases}$$
（14）

In equation (14), $\text{maximize}_{k_i} SU_i(k_i, p_i, a_i)$ is maximizing the utility of the data owner. When the third game reaches Nash equilibrium, the optimal privacy compensation coefficient for the data owner can be obtained. When using this mechanism to price data products, it is necessary to solve the Nash equilibrium point. The Nash equilibrium solution algorithm designed is shown in Fig. 5.
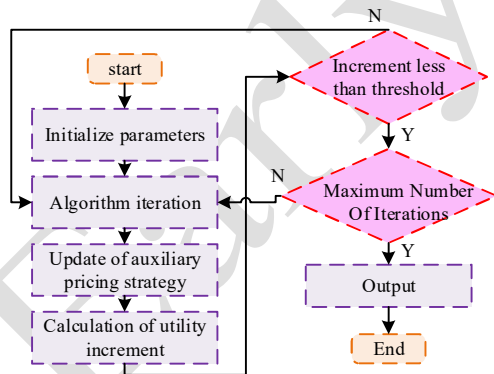
Fig. 5. Solving algorithm for Nash equilibrium based on iterative gradient update

The steps for solving the Nash equilibrium point are as follows: the first step is to initialize parameters, including price distribution, purchase quantity, privacy compensation coefficient,

auxiliary pricing strategy, iteration number, learning rate, and convergence threshold. The second step is algorithm iteration, which iteratively calculates the number of decisions for each data owner and data buyer based on the current auxiliary pricing strategy. The third step is to use gradient ascent method to update the auxiliary pricing strategy based on data owners and market agents. The fourth step is to calculate the utility increment and determine whether to stop the iteration. If the increment is less than the threshold, the algorithm is considered to have converged and the iteration is stopped. If the increment is greater than the threshold but the required number of iterations has been reached, stop iterating. The fifth step is to output the result, which is to output the final Nash equilibrium point, including price distribution, purchase quantity, privacy compensation coefficient, etc.

DVE and Automatic Pricing Experimental Verification

Experimental environment and parameter settings

Two experiments are designed for our research, with Experiment One being a data value evaluation experiment. In this experiment, the data products used in the study are divided into practical and hedonic types. Practical data products include test datasets, teaching courses, artificial intelligence models, software data products, etc. In order to ensure the wide applicability of the automatic pricing model designed for research, one data product was selected from each of the source dataset, online teaching courses, artificial intelligence models, software data products, and data equity combination products for model validation. Enjoyment oriented data products include music, movies, TV dramas, electronic novels, entertainment

videos, etc. The study selected one of the currently popular products from the five types of enjoyment oriented data products for model validation. Experiment 2 is an automatic pricing experiment for data trading. This experiment analyzes the hedonic products selected in Experiment 1. Table 2 shows the parameter information of experimental equipment and Experiment 2.

Table 2. Experimental equipment information and related parameter setting

Facility information		Parameter setting	
Item	Type	Name	Value
Operating system	Windows 10 64bit	Maximum price	12
GPU	NVIDIA GeForce GTX 1660Ti	Minimum purchase quantity	1
CPU	Intel(R) Core(TM) i5-12450H	Maximum purchase quantity	50
Equipped with RAM	32GB	Fitting parameter 1	5
Memory	1T	Fitting parameter 2	10
/	/	Fitting parameter 3	10

Verification of DVE experiment

This study first determines the weights of the data product value evaluation index system and the user satisfaction evaluation index system, as indicated in Table 3.

Table 3. Evaluation index system weight

Data value assessment				User satisfaction	
Index	Weight	Index	Weight	Index	Weight
Data integrity	0.2032	Data scarcity	0.1589	Product reliability	0.2494
Consistency	0.1115	Data timeliness	0.1707	Product suitability	0.3959
Data correctness	0.0996	Multidimensional data	0.0852	Describe compliance	0.1047
Obtain difficulty level	0.0322	Data correlation	0.0540	Attitude towards customers	0.0799
Data repeatability	0.0535	Scenario economy	0.0311	Service response	0.1396
/	/	/	/	After-sale service	0.0305

In the DVE indicator system, data completeness has the greatest impact on data value, and its weight reaches more than 0.2. In the user satisfaction evaluation index, product suitability has the greatest impact on user satisfaction, and its weight reaches 0.39. The value assessment results of practical data products and hedonic data products are shown in Figure 6.
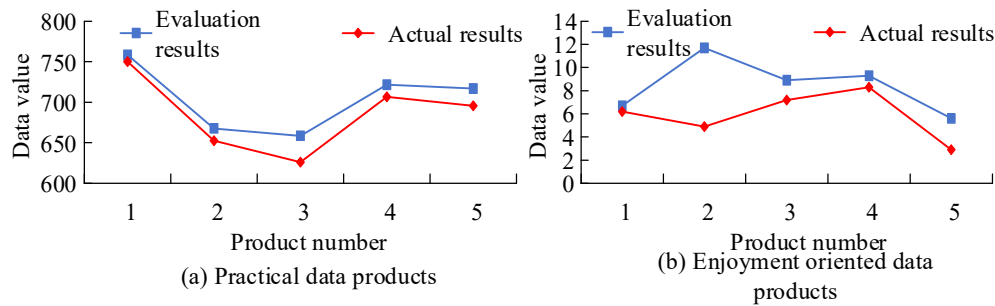
Fig. 6. Results of the data value assessment

Fig. 6 (a) shows the value evaluation results of practical data products. The evaluation results of 5 different data products are similar to the current market evaluation results. The actual value and evaluation value of product 3 have the largest error, reaching 32.6, while the actual value and evaluation value of product 1 have the smallest error, only 8.3. Fig. 6 (b) shows the value evaluation results of hedonic data products. The value evaluation results of 5 different data products are similar to those of practical data products, and the error between the evaluation results and the actual results is relatively small. Among hedonic products, the evaluation result of data product No. 2 has the largest error with the actual result, reaching 6.8, while the value evaluation error of other products is less than 3. This experiment evaluated the value of data products using the AHP-FCE method, and the results showed that there was a small error between the actual value and the evaluated value, verifying the effectiveness of the proposed method. Among practical data products, product 3 has the largest error, while product 1 has the smallest error. The evaluation error of hedonic data products is generally less than 3, indicating that the evaluation

model can accurately reflect the value of data products.

**Experimental verification of automatic pricing in data trading**

This study analyzes the convergence effect of the Nash equilibrium solving algorithm, and the results are shown in Fig. 7. Fig. 7 (a) shows the convergence effect of data volume. Owners 1, 2, 4, and 5 all completed hand convergence in the 6th iteration, with owners 1, 2, 4, and 5 having converged data volumes of 26, 28, 24, and 23, respectively. Fig. 7 (b) shows the convergence result of data prices. The data prices of all owners remain between 2 and 4 yuan after convergence. The automatic pricing experiment was analyzed using the Nash equilibrium solving algorithm, and all data owners achieved hand convergence after 6 iterations, with data prices stabilizing between 2 and 4 yuan. The iterative results of market agency utility show that the maximum utility values of different owners fluctuate between 13.2 and 15.6, indicating that the automatic pricing mechanism can effectively achieve the maximum market agency utility of different data owners and achieve a win-win situation for all parties.

(a) Convergence result of data quantity

(b) The convergence result of data prices
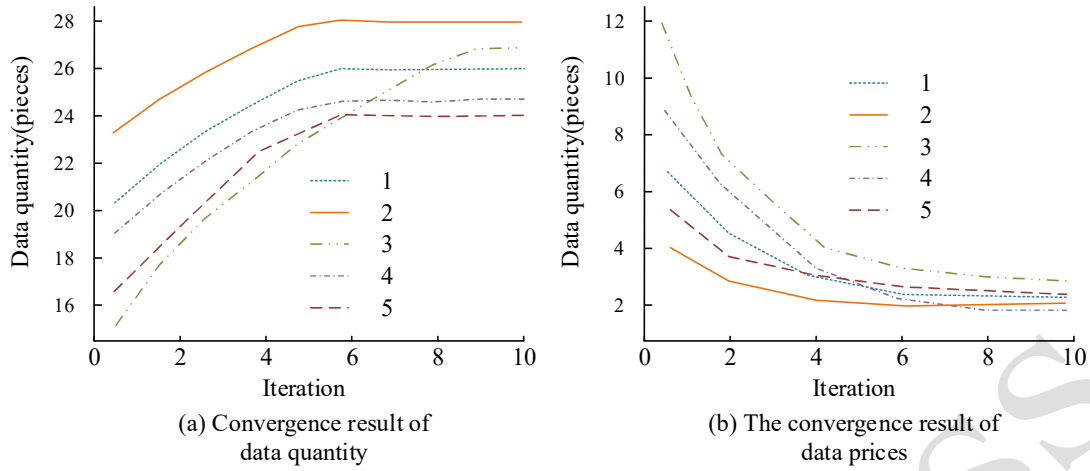
Fig. 7. Iterative effect of the Nash equilibrium solution algorithm

Fig. 8 shows the market agency utility iteration results and privacy compensation impact results of the automated pricing method for data products. Fig. 8 (a) shows the iterative results of market agency utility. The maximum utility of owners 1, 2, 3, 4, and 5 is 14.6, 13.2, 15.6, 13.5, and 14.3. Fig. 8 (b) shows the results of privacy loss compensation. As the privacy compensation coefficient increases, the winner utility will also gradually increase. When the privacy compensation coefficient is 0.6, the maximum winner utility is 9.3, and when the privacy compensation coefficient increases to 0.9, the maximum winner utility is 12.2. The experiment analyzed the impact of market agency utility and privacy compensation on automatic pricing methods. As the privacy compensation coefficient increases, the utility of the winner gradually increases. When the privacy compensation coefficient is 0.6, the maximum winner utility is 9.3. When it increases to 0.9, the maximum winner utility can reach 12.2, indicating that the privacy compensation mechanism has a positive effect on improving the utility of data owners.

(a) Market agency utility

(b) The impact of privacy compensation mechanisms
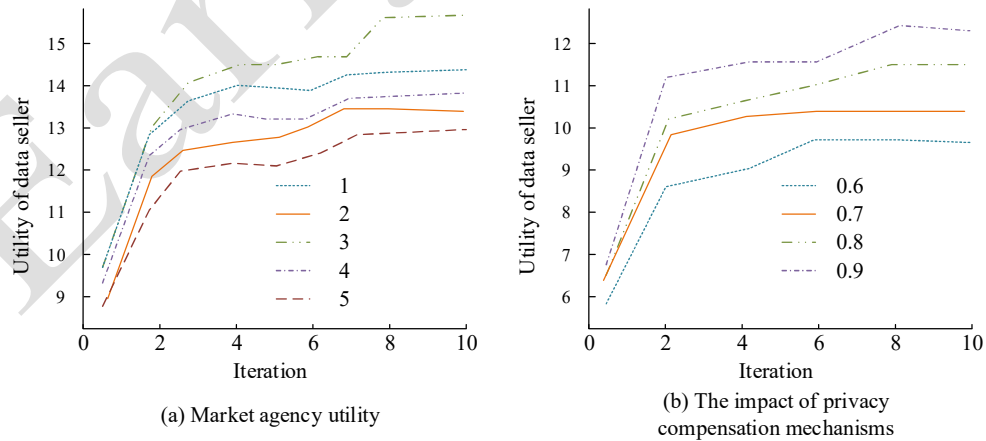
Fig. 8. The effect of market agency utility and the impact of privacy compensation

This study randomly selects one hedonic data product from the top 20 in terms of current trading volume for pricing analysis, as denoted in Fig. 9. Fig. 9 (a) showcases the fitting result of the pricing results. Fig. 9 (b) shows the difference

between the pricing results and the average market price over the past 30 days. The pricing results of the 5 products are basically perfectly matched with the average price results of the products in the past 30 days, with a maximum error of 0.6 yuan. The automated pricing method designed for data products is in line with market conditions and can be automatically adjusted according to market conditions. This experiment compared the changes

in trading volume of data using different pricing methods over the past 30 days and found that the market using the automatic pricing scheme designed in this study reached market saturation after 25 days, with trading volume stabilizing at around 221 after saturation. This indicates that the pricing scheme designed in this study can effectively increase the trading volume of the data trading market.

(a) Pricing fitting results of data products

(b) Pricing fitting error of data products
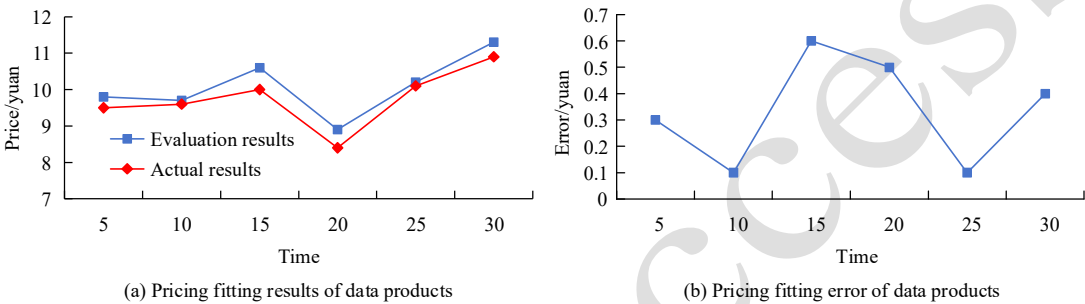
Fig. 9. Pricing and fitting results of the data products

In order to further verify the effectiveness of the data trading automatic pricing method designed in the research, a comparison is made between the data trading market using the research designed automatic pricing scheme and the data trading market using the traditional pricing scheme and the Free loading payment pricing method proposed by Wagner U et al. [27] in the past 30 days. The results are shown in Table 4.

Table 4. Data trading market volume changes for different pricing methods

Time （d）	Proposed method	Traditional method	Free loading payment pricing
5	62	31	42
10	132	48	48
15	158	56	53
20	203	55	62
25	221	72	64
30	215	68	62

From Table 4, it can be seen that the data trading market using the research design pricing scheme only reached market saturation in the past 25 days, that is, as the statistical time increased, the market trading volume did not significantly increase and began to fluctuate in a small range. The market that adopts traditional pricing schemes reaches market saturation within 20 days. The market that adopts the research design scheme has a stable trading volume of around 221 after reaching saturation, while the market that adopts the traditional pricing scheme has the highest trading volume of only 72 after reaching saturation. The research design method can promote the trading volume of the data trading market.

In summary, the self-directed pricing method for data transactions designed in this study

can accurately evaluate the value of data and adjust the pricing of data products by data owners through privacy compensation mechanisms. After using the research designed pricing scheme for data products, the trading volume in the data trading market will significantly increase, indicating that the research designed pricing scheme helps to improve data circulation.

Conclusion

To improve data circulation, ensure the rationality of data transactions, and expand the scale of data transactions, this study combined AHP and FCE to design a value evaluation method for data products. We combined PWYW mechanism and Stackelberg game to design an automated pricing method for data products. When evaluating the value of data products, it was mainly done from two dimensions: quality and application. The automated pricing method for designed data products constructed a three-stage game mechanism and added a privacy compensation coefficient. The results demonstrated that the constructed data product value evaluation method had a maximum value evaluation error of 32.6 for practical data products and 6.8 for hedonic data products. The automated pricing method designed could achieve maximum market agency utility for different data owners, achieving a win-win situation for owners, buyers, and market agents. When the privacy compensation coefficient was 0.9, the winner utility could reach its maximum value of 13.2. This pricing method had a maximum pricing error of 0.6 yuan for the product, which was close to the market price. The constructed data product value assessment method could accurately assess the value of data. The pricing results of the automated pricing method for data products were in line with market conditions and could be automatically adjusted according to

market conditions. However, the designed data trading automatic pricing method required a large amount of computation when dealing with DVE. Future research will further optimize the DVE method by combining it with machine learning algorithms to improve the computational efficiency of DVE. In addition, the future study will also explore the use of multiple game mechanisms to incorporate the game of different data owners in data product pricing considerations, in order to further expand the generalization ability and robustness of the data product pricing scheme.

Conflict of Interest

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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