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Optimizing Supplier Selection and Resource Allocation Problems in Intelligent Purchasing Systems Based on Decision Tree Algorithms

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ABSTRACT

Reasonable and scientific supplier selection and resource allocation is a prerequisite for enterprises to optimize the quality of supply chain and avoid business risks. In this paper, we select multiple supplier evaluation indexes, use decision tree algorithm to train and calculate the hierarchy of suppliers to determine the supplier options that can be selected. Then the main body of procurement resource planning decision-making is divided into three types: purchaser, database vendor, and customer, to establish a multi-objective model for optimal allocation of procurement resources, and the model is optimized by genetic algorithm to solve the optimal allocation scheme of procurement resources. The supplier selection method based on decision tree can realize the optimal selection of suppliers by constructing a decision tree and transforming it into If-then classification rules. The procurement solutions based on genetic algorithm are 10.44%, 4.31%, and 5.14% higher than B, C, and D solutions, respectively, for better allocation of procurement resources.

Keywords: decision tree, genetic algorithm, intelligent procurement system, optimal allocation of resources

1. Introduction

Supply Chain Procurement refers to the procurement activities carried out in a supply chain, including the procurement of raw materials, components, equipment or other products needed from suppliers to ensure the smooth flow of supply chain processes. Supply chain procurement is characterized by a high degree of integration, risk management, flexibility, outstanding cost-effectiveness, and continuous improvement [1-2]. Supply chain procurement requires close collaboration with suppliers to ensure timely availability of required products and services. This requires the integration of various parts of the supply chain for better management of suppliers, hence supply chain procurement is characterized by a high degree of integration. Supply chain procurement requires assessment and

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management of supplier risk [3-4]. This includes assessing the financial status, production capacity and reliability of suppliers to minimize supply chain disruptions or quality problems due to supplier problems, hence supply chain procurement is characterized by risk management [5-7].

Supply chain procurement needs to have the flexibility to adapt to changes in market demand. As market demand is constantly changing, supply chain procurement must be able to adjust to changes in demand and provide the required products and services in a timely manner, which makes supply chain procurement more flexible [8-10]. Supply chain procurement needs to pursue cost effectiveness in order to reduce procurement costs and improve supply chain effectiveness. This involves selecting suitable suppliers for effective negotiation and contract management to obtain the most favorable purchasing terms [11-12]. In addition, supply chain procurement is characterized by continuous improvement. Supply chain sourcing requires continuous improvement of sourcing processes and methods in the supply chain, including the use of advanced sourcing technologies and tools to improve sourcing efficiency and accuracy, and continuous optimization of sourcing strategies and processes in the supply chain [13-15].

The rapid development of Big Data as well as Artificial Intelligence (AI) technologies has brought unprecedented opportunities in the field of procurement decision making [16]. By collecting, storing, analyzing, and processing massive amounts of data, big data analytics and AI technologies can provide enterprises with more comprehensive and accurate market insights and decision support [17-18]. With the help of intelligent procurement decision support system based on big data analytics and artificial intelligence technology, enterprises can obtain market dynamic information in real time, effectively predict the trend of demand, further optimize the supplier selection strategy, significantly improve the efficiency of procurement work, and reduce the related costs [19-21]. This series of advantages will strongly enhance the position of enterprises in the market competition [22].

Srai, J. S et al. proposed a digitization strategy for evaluating procurement and supply chain management and confirmed the feasibility of the strategy through research feedback and practice, the study demonstrated the potential and future trends of digital development of Procurement and Supply Management (PSM) for stakeholders [23]. Allal-Chérif, O et al. reviewed the current state of research and practice of AI technologies in the field of procurement, based on real-world case studies and concluding an exploratory, inductive research methodology in order to assess the impact of AI technologies on procurement performance, redefining procurement workflows and purchasing roles, as well as supplier management policies [24]. Kehayov, M et al. elaborated that AI technology facilitates the integration of novel analytical tools in the supply chain, effectively optimizes the product production and procurement and supply management processes, and promotes the informatization and intelligence of manufacturing, procurement, and supply management (PSM) systems [25]. Bodendorf, F et al. explored the practical effects of an intelligent decision support system for procurement cost estimation by combining literature review methods and expert interviews, and noted that procurement cost analysis based on machine learning algorithms provides a great help for procurement, and accordingly its complexity also brings some potential challenges [26]. Bilinovics-Sipos, J et al. elaborated that enterprises lack the application of knowledge-based expert systems in purchasing decision-making, and thus proposed an optimized knowledge-based expert procurement support framework, which takes into full consideration of purchasing decision-maker's cognition and mind and effectively simplifies this purchasing decision-support model [27]. Artificial intelligence technology-enabled procurement and supply chain links help optimize procurement and supply chain processes and efficiency, and researchers have explored the performance of AI technology-enabled procurement and supply chain links in depth around the topics of procurement performance, cost analysis, and process optimization.

Luthra, S et al. conceptualized a sustainable supplier selection assessment model based on the Analytic Hierarchy Process (AHP) as a framework for evaluating suppliers from three dimensions: economic, environmental, and social, and demonstrated the validity and accuracy of the proposed model based on a real-world case study [28]. Rashidi, K et al. systematically reviewed journal paper studies on sustainable supplier selection, the topics of the studies were mainly related to supplier sustainability assessment, supplier assessment methodology, supplier selection methodology shift, etc., and less about sustainable supplier selection, and the most commonly used among the supplier selection tools is the analytical and mathematical approach as the core logic [29]. Kannan, D. et al. provided a decision support system for supplier selection in the Indian textile industry from the CSF theory and tested it with five real life cases to show that supplier ranking is highly correlated with the social factors in the CFS theory and conducted a sensitivity analysis by varying the weights to corroborate the impact of the social elements of the CFS on sustainable supplier selection [30]. Awasthi, A et al. designed a sustainable global supplier selection framework based on the integrated fuzzy AHP-VIKOR method, which can effectively rate supplier performance and is commonly used to assist enterprises in assessing the upstream sustainable risk of the supply chain and then make scientific decisions [31]. Scholars have tried to use AHP, CSF theory, and the integrated fuzzy AHP-VIKOR method to build a supplier selection decision-making framework, and have obtained good research results, which provides important help for the rational selection of enterprise suppliers.

This paper utilizes decision trees to construct a buyer selection model. Comprehensively considering the access of suppliers, product quality and other indicators, using the information gain rate as the basis for branch judgment, the model training and pruning after the output of the supplier grade value, to complete the audit and selection of suppliers. In addition, a model for optimal allocation of procurement resources is proposed based on genetic algorithm. Mathematical models are used to mathematically represent the decisions of decision-making subjects such as purchasers, database vendors and customers respectively. Genetic optimal allocation operators of three types of intelligences, namely selection, crossover and mutation, are designed to realize the optimization of the procurement resource allocation scheme. A supplier evaluation decision tree is constructed with enterprise Y as an example, and If-then classification rules are generated accordingly. The procurement resource allocation optimization scheme is validated, and the coincidence and difference analysis is carried out. Finally, the basic implementation process of the intelligent procurement resource allocation system is summarized.

2. Decision tree-based modeling of procurement vendor audits

2.1. Overview of decision trees

Decision trees are a common class of machine learning methods which can be categorized into various algorithms for generating them such as ID3, C4.5 and CART. In decision tree algorithms, a tree diagram is used to identify the logical outcome of a problem. With a decision tree, we can learn from a given training set to get a model which can classify a new dataset. A decision tree is constructed from the root node to the leaf nodes in a top-down manner, and generally a decision tree has three types of nodes: the root node, the leaf nodes, and the intermediate nodes, respectively. The root node represents the overall sample dataset, the leaf nodes correspond to the final decision results, and the intermediate nodes correspond to the different feature attributes tested. The purpose of the decision tree is to enhance the generalization ability of the classification model and its basic process uses the idea of partitioning [32].

"Information entropy" is often used as a common metric to measure the purity of a sample.

The expected entropy is denoted as:

$$H(X)=\sum_{i=1}^{n}P(x_i)\log_b p(x_i) \tag{1}$$

The concept of conditional entropy is introduced for further explanation of information gain with the following formula:

$$H\left(\frac{Y}{X}\right)=\sum_{x}p(x)H\left(\frac{Y}{X}=x\right) \tag{2}$$

In the learning process of decision tree algorithms, information gain, as an important indicator of feature selection, is usually used for attribute partition selection of decision trees. Simply put, information gain is equivalent to an indicator that is used to measure the feature variable in the decision tree algorithm. The selectivity of the variable is superior to the size of the value, and accordingly the better the selectivity the greater the information. The formula is shown in (3):

$$Gain(Y/X)=H(Y)-H(Y/X) \tag{3}$$

In fact, the information gain criterion will have a preference for feature attributes that have a high number of values that can be taken. In order to price its unfavorable effect, the information gain ratio can be used to classify the optimal attributes. Information Gain Ratio: information gain is usually suitable for selecting attributes with a relatively large number of feature values, resulting in a model that is prone to overfitting. Therefore the standard information gain ratio can also be used for classification [33]. It is calculated by the formula:

$$Gain(R)=\frac{Gain(\frac{Y}{X})}{H(\frac{Y}{X})} \tag{4}$$

The CART decision tree uses the “Gini index” to select the partition attributes, and the formula is:

$$Gini=\sum_{k=1}^{k}p_k(1-p_k)=1-\sum_{k=1}^{k}{p_k}^2 \tag{5}$$

where p_k denotes the probability of each category occurring. Intuitively, the Gini index reflects the probability that two randomly selected samples from the data set will end up with inconsistent categorization. Therefore, the smaller the Gini(D), the higher the purity of the data set.

The problem of overfitting is also often present in decision tree learning algorithms. Pruning is the main method to deal with overfitting in decision tree learning algorithms. In decision tree algorithm learning, too many decision branches are divided in order to make the result more accurate. The training set will take the attributes specific to certain cases in the training set as the basis of judgment for classification, which are actually not general. Therefore, some branches will be clipped to avoid such a situation. For pruning strategy, the basic strategies are “pre-pruning” and “post pruning”. Pre-pruning refers to the process of generating a sub-decision tree, and estimating the ability of each node to be divided to optimize the performance. If the division of the current node does not improve the generalization ability of the decision tree, the division is stopped at the current node, making it a leaf node. Post-pruning, on the other hand, judges the non-leaf nodes after a complete decision tree has been generated. If replacing the subtree corresponding to this node with a leaf node improves the generalization ability of the whole decision tree, this subtree is replaced with a leaf node.

Pre-pruning leaves many branches of the decision tree unexpanded, which only reduces the risk of overfitting and significantly reduces the training time overhead and testing time overhead of the decision tree. However, on the other hand, it may cut branches that make the subsequent performance partitioning significantly better, resulting in underfitting. Post-pruning has a small risk of underfitting and tends to generalize better than pre-pruned decision trees, but has a large training time overhead.

2.2. Procurement vendor audit modeling

Based on the C5.0 decision tree algorithm for procurement supplier audit is mainly reflected in the comprehensive consideration of the supplier's access, business status, product quality and contract fulfillment and other levels of indicator data. Decision tree algorithm is often used for classification and prediction, the idea of constructing a supplier audit model based on the decision tree algorithm is to first input the training dataset of the supplier audit, which will be set to E, the attribute dataset C, you can choose the attribute to be set as the root node or labeled as a leaf node, and then continue to select the new optimal attribute on the basis of this, as a branching criterion, and when each branch node meets the growth criterion, it can become a leaf node, otherwise it returns to the very beginning decision generation point. When all the branches have reached the leaf nodes then the decision tree is generated, enter the pruning session, and finally output the decision results.

1) Define variables. Construct A enterprise procurement supplier audit model first to determine the input and output variables, the data object that is A enterprise procurement supplier audit index data, this paper will set the training set as E, attribute set set as C, based on data collection and pre-processing after the construction of the attribute index of the 13 indicators as the input value to the supplier grade as the output value. Supplier grade is based on the professional rating of the third-party organization hired by enterprise A. The third-party rating is based on the evaluation of the main concerns of enterprise A. The output value is “1”, which indicates that the supplier grade is excellent. An output value of “2” indicates that the supplier grade is good, and an output value of “3” indicates that the supplier grade is qualified.

2) Split rules. Purchasing supplier audit test, the need to divide it into three data sets, the division of the split method will affect the final classification prediction effect. The C5.0 chosen in this paper adopts the information gain rate as the basis for branching judgment, and the information gain rate is obtained on the basis of calculating the information entropy and information gain under a certain attribute. Information entropy represents the certainty of the data, and the larger the information entropy is, the more chaotic the data is, and the more information can be obtained, and vice versa is less. The formula for calculating information entropy is as follows:

$$Ent(E) = -\sum_{k=1}^{|m|} P_k \times \log_2(P_k) \tag{6}$$

Information gain indicates the extent to which information uncertainty can be reduced, and the formula for information gain is as follows:

$$SplitInfo_A(E) = \sum_{j=1}^{m} \frac{|T_j|}{|T|} \log_2 \frac{|T_j|}{|T|} \tag{7}$$

The division of subsets is carried out according to the information gain, and as the number of subsets increases, the information entropy will be smaller, which will reduce the purity of the data information in the subsets to a certain extent.C5.0 Decision Tree algorithm adopts the gain rate to determine whether classification is needed or not, which avoids the situation of too much classification. The formula for the information gain rate is as follows:

$$GainRatio(A) = \frac{Cain(A)}{Split \ln fo(A)} \tag{8}$$

3) Decision tree pruning. The decision tree generation process may result in abnormal branches due to the presence of outlier data in the dataset, therefore, pruning the decision tree generated by the model run is very necessary. Pruning can be a good way to deal with overfitting, usually using statistical methods to remove the most unreliable branches.

4) Model Application. Organize the relevant data of procurement supplier indicators, according to the process of the decision tree algorithm, input the indicator data through the IBMSPSSModerler tool, carry out the model training and pruning operation, and finally output different supplier grade values.

Supplier Intelligent Audit is to consider the supplier qualification, business status, product quality, contract fulfillment and other indicator values, and train in the model as a whole to find the law. Through the data training analysis to find out the possible risks in supplier selection, to help Enterprise A in the standardization, rationalization and intelligent management of procurement suppliers to put forward the opinion, according to the problems found by the auditors to put forward solutions.

3. Genetic algorithm-based model for optimal allocation of procurement resources

The framework of the optimal allocation model of procurement resources based on multi-intelligence system and genetic algorithm is shown in Fig. 1, the multi-intelligence system is used to simulate the decision-making subjects involved in procurement resource planning and procurement, and the genetic algorithm calculates the Pareto-optimal procurement resource allocation scheme with the assistance of multi-intelligence bodies.

The algorithm uses two-dimensional coding to characterize the procurement resources, chromosomes correspond to the procurement resource allocation scheme, and genes characterize a specific database system. The genetic algorithm provides computational results for decision-making in the multi-intelligence body system, and the database system characterized by the chromosome obtains comprehensive analysis and evaluation results through the multi-objective synergistic system and a variety of constraints, and they are analyzed and perceived by the multi-intelligence body of procurement resource planning. The opinions and decision-making behaviors of the subjects in the multi-intelligence system also affect the chromosome, and an interaction relationship is formed between the two. The multi-intelligence body initializes the chromosome through procurement resource planning, and its decision-making behavior acts in the genetic optimal allocation operator to optimize the procurement resource allocation scheme. The goals and constraints of the multi-intelligence body constitute the goal system and constraint system of the model, and are transformed into the fitness function of the genetic algorithm to guide the algorithm to generate the optimal procurement resource allocation scheme, and to realize the Pareto-optimal allocation scheme of the procurement resources under the synergistic collaboration of the multi-objectives of the types and quantities of the resources, the function of the retrieval system, the cost and value of the procurement resources, the quality of the database vendor's service, and the comprehensive revenue of the procurement resources.

3.1. Procurement resource planning multi-intelligence

Based on the basic process of Purchasing Resource Planning (PRP) and procurement, the subjects of PRP decision-making are categorized into three types of Agents: purchasers, databases, and customers.

3.1.1. Procuring Agent. The purchaser Agent obtains the requests and feedback from the database vendor and the customer Agent and uses Equation (9) to coordinate their conflicts:

$$C_t(i,j)=U_d(i,j,t)+\alpha\cdot U_p(i,j,t)+P_t \tag{9}$$

Equation (9), $C_t(i,j)$ represents unit (i,j) on the t types of procurement resources.

Competitiveness of the database, $U_d(i,j,t)$ and $U_p(i,j,t)$ represent the utility function of the t class of electronic databases to the database vendor Agent and customer Agent, respectively, and α represents the degree of customer participation [0, 1], the higher the degree of customer participation in the database the more competitive it is. When the value of the utility function of the Database Vendor Agent or the Customer Agent is larger, the probability that the purchaser Agent purchases the database (i,j) in the t procurement resources will be larger to reflect the purchaser's willingness to give full consideration to the database vendors and customers. The model simulates this process by adjusting the degree of competition to realize the feedback effect among multiple intelligences:

$$C_t^{'}(i,j) = C_t(i,j) + n_d \cdot \Delta P_d + n_p \cdot \Delta P_p \tag{10}$$

In Equation (10), $\dot{C}_t(i,j)$ represents the adjusted competitiveness, n_d is the number of times the database vendor has marketed database (i,j,t), and ΔP_d is the size of the increase in competitiveness each time it is marketed. n_p is the number of customer recommendations for database (i,j,t), and ΔP_p is the size of the increased competition for each recommendation.

3.1.2. Database vendor Agents. Database vendor Agents represent or sell a variety of electronic databases, and they market a variety of purchasing resources to purchaser Agents, and under the unified coordination of purchaser Agents, they advertise to their customers in a variety of ways to form a competitive marketing. The study adopts stochastic dynamic model and discrete choice model to simulate the competitive behavior among Database Vendor Agents, and the probability of choosing the electronic database (i,j) marketed by Database Vendor Agent for a certain type of resource t is expressed as Equation (11):

$$P(i,j,t) = \frac{\exp(U_d(i,j,t))}{\sum \exp(U_d(i,j,t))} = \frac{\exp(R_{neigs} \cdot S_{ijt})}{\sum \exp(R_{neigss} \cdot S_{ijt})} \tag{11}$$

In formula (11), R_{neigh} represents the number of databases competing for resources in category t, and S_{ijt} represents the suitability (competitiveness) of procurement resource (i,j) in category t.

3.1.3. Customer Agent. Customer Agent is the main user group of procurement resources, and recommends each procurement resource to the purchaser Agent according to its own needs, preferences and so on. The behavior of customer Agent recommending each procurement resource is simulated by stochastic dynamic model and discrete choice model, and the probability selection formula of procurement resource (i,j) recommended by customer in class t resource is:

$$P(i,j,t) = \frac{\exp(U_p(i,j,t))}{\sum \exp(U_p(i,j,t))} = \frac{\exp(Q_{ijt})}{\sum \exp(Q_{ijt})} \tag{12}$$

In Equation (12), Q_{ijt} represents the level of customer acceptance for the t type of resource electronic database (i,j).

3.2. Multi-objective model for optimal allocation of procurement resources

The model designs five types of objective evaluation functions for each electronic database or platform on the basis of previous and previous research.

1) Evaluation of the type and quantity of purchased resources. This objective function mainly extracts secondary indicators such as the overall situation of resource inclusion, the scope of time frame of resource inclusion, the geographical scope of resource inclusion, the coverage rate of our university disciplines, the inclusion of authoritative publications, the inclusion of full text, and the frequency of resource updating, etc., for calculation and evaluation.

2) Evaluation of resource retrieval system function. This objective function mainly extracts the secondary indicators such as system retrieval method, retrieval technology, retrieval effect, retrieval speed, system stability, interface friendliness, system scalability, concurrent users and background statistical functions for calculation and evaluation.

3) Cost and value evaluation of resources. This objective function mainly extracts the purchasing resource price, price increase, authentication cost, retrieval cost, full-text download cost, hardware and software investment cost, system update cost and other secondary indicators for calculation and evaluation.

4) Evaluation of database vendor service quality. This objective function mainly extracts secondary indicators such as resource delivery method, resource usage period, access rights, usage statistics report, publicity and training services, troubleshooting speed, customer access, etc. for calculation and evaluation.

5) Evaluation of procurement resource utilization effect. This objective function mainly extracts the number of customer system logins generated by the electronic database, the number of resource searches, the number of times per capita use, per capita full-text downloads, although other secondary indicators for calculation and evaluation.

As a result, the objective function formula F for the comprehensive evaluation of procurement resources is:

$$\mathrm{F} = \omega_a \cdot f_a + \omega_b \cdot f_b + \omega_c \cdot f_c + \omega_d \cdot f_d + \omega_e \cdot f_e \tag{13}$$

In Equation (13), f_a represents the evaluation function of the type and quantity of procurement resources, in order to f_e represents the evaluation function of the use of procurement resources, ω_a represents the weighting coefficient of f_a, and $\omega_a + \omega_b + \omega_c + \omega_d + \omega_e = 1$.

3.3. System of constraints for the optimal allocation of procurement resources

The procurement, allocation and optimization of university procurement resources are constrained by a variety of conditions, mainly including the macro policy red line and disciplinary assessment indicators, budget and actual procurement funding control, enterprise type and characteristics. The constraint system of procurement resources has both a macro guiding effect and a micro control effect on the multi-objective evaluation function of resources.

3.4. Model Optimization Configuration Operation

The operation steps of the model's optimized allocation are shown in Figure 1. First of all, database vendor Agent and customer Agent observe and analyze the current status quo of procurement resource allocation and optimization scheme, make resource allocation optimization suggestions based on random utility model and discrete choice model, and make specific suggestions to purchaser Agent. The purchaser Agent coordinates and updates the competition degree of the electronic database based on the competition degree function according to the planning. According to the characteristics of genetic algorithm, the model designs 3 types of genetic optimization configuration operators for selection, crossover and mutation of intelligences to realize the optimization of configuration scheme. The model evaluates the new generation of configuration schemes according to the procurement resource optimization objective evaluation system and constraint system, repeats the above process for iterative calculation until the conditions of program termination are met, and finally outputs a series of Pareto-optimal scheme sets for procurement resource allocation.

Among them, the model adopts two-level intelligent selection operator, the first-level selection operator uses roulette criterion to screen out chromosomes with higher adaptation as the next generation crossover after the chromosome population completes crossover and mutation, and the second-level selection algorithm compares the chromosomes before and after the crossover or mutation, and only retains the better chromosomes, which is used to improve the search efficiency of the algorithm. Intelligent crossover operator is mainly used to adjust the contradiction between the database vendor Agent and customer Agent and the current procurement resource allocation program, to avoid the contradiction between the electronic database selection and the current procurement resource planning of the purchaser. Intelligent variation operator is mainly used to solve the conflict between electronic databases with similar functions under the same kind of resources, using the competition degree function $C_t(i, j)$ to construct the electronic database selection probability function $P_t(i, j)$, and using the roulette method to solve the competition conflict [34], as shown in Equation (14):

$$P_t(i,j) = \frac{C_t(i,j)}{\sum C_t \cdot (i,j)} \tag{14}$$

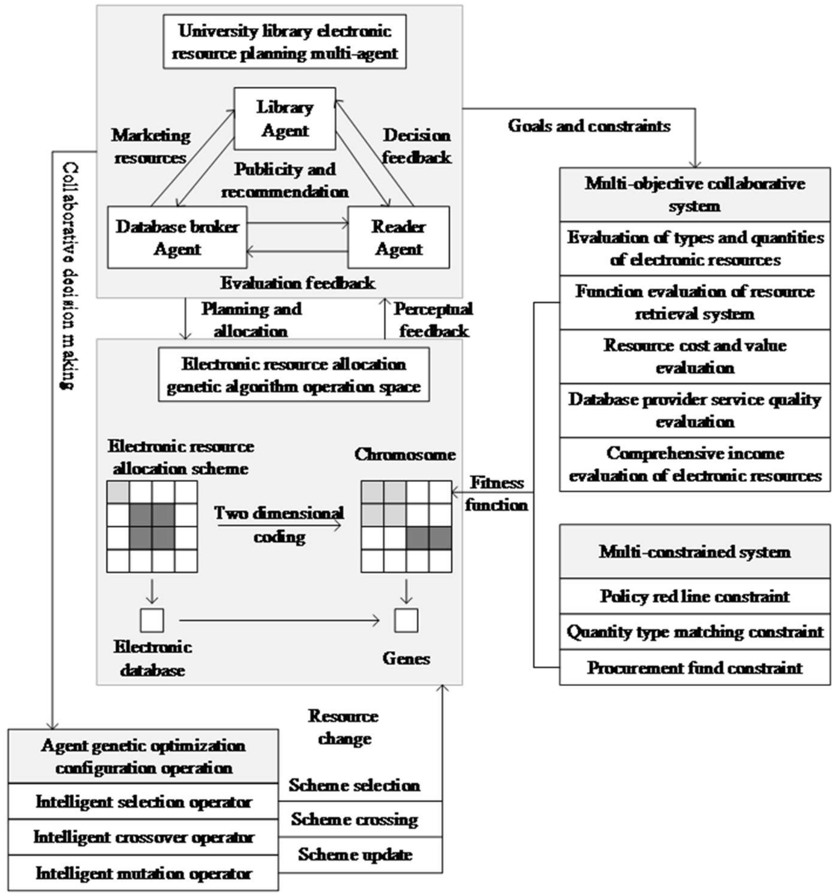

Fig. 1. Digital resource allocation model based on multi-agent genetic algorithm

4. Examples of vendor selection and procurement resourcing

4.1. *Supplier evaluation*

4.1.1. Data preparation. As the market environment changes and suppliers' own conditions continue to change, Enterprise Y wants to continuously improve supply chain competitiveness and optimize supplier quality. In order to maintain continuous competitiveness and procurement quality, supplier assessment helps eliminate unqualified suppliers, attract and maintain new suppliers, and continuously optimize the entire supply chain business process.

In the selection of indicators for supplier evaluation, it is necessary to consider all aspects of the supplier's quality, Enterprise Y has selected seven indicators as supplier evaluation indicators: supply completion rate, return rate, transportation loss rate, price, freight, other costs, and delayed delivery, as shown in Table 1, which is the relevant indicator data for the evaluation of Enterprise Y's 15 suppliers, and this paper will adopt these data as the sample data of the training set to conduct supplier evaluation example analysis.

Table 1. Supplier's supply quality data

ID	Supply quality			Quality of goods	Price(10k)	Cost(10k)	
	Supply completion rate%	Transport loss rate%	Delayed delivery (day)	Return rate%	Price	Transport fee	Other fee

1	0.851	0.0003	2	0.0035	869	206	705
2	0.828	0.0008	3	0.002	892	230	795
3	0.914	0.0016	5	0.0021	853	200	806
4	0.869	0.0006	9	0.0046	899	207	661
5	0.598	0.0007	2.5	0.0047	899	243	523
6	0.869	0.0007	7	0.0077	960	280	655
7	0.811	0.0008	5.5	0.0042	871	230	682
8	0.745	0.0013	1	0.0053	906	227	690
9	0.937	0.0004	6.5	0.0076	877	216	871
10	0.627	0.002	5	0.0027	977	254	1011
11	0.756	0.0003	3	0.0002	872	231	504
12	0.909	0.0002	1	0.0023	861	201	712
13	0.675	0.0011	3	0.0002	926	234	545
14	0.953	0.0003	8	0.0003	944	213	1190
15	0.75	0.0013	3	0.0048	923	219	782

4.1.2. Continuous Property Discretization and Approximation. The real-time data based on RosettaNet standard is extracted directly from the messages of e-commerce transactions between enterprise X and suppliers, and there is no missing data of training set samples. Because the indicator data extracted or calculated based on RosettaNet standard contains only conditional attributes, it is necessary to utilize data exchange to obtain the values of decision attributes, which are obtained according to the data exchange method based on information entropy theory.

The article uses the discretization method based on MDLP minimum description length criterion to discretize the continuous attributes. According to the result of discretization, the attribute sample data are discretized and divided into categories with letters such as 1, 2 and 3. The data mining method of rough set is used for knowledge discovery and the decision table is organized for attribute approximation in decision tree analysis. Table 2 shows the decision table based on rough set theory.

Table 2. Decision table based on rough set theory

U	a	b	c	d	e	f	g	x
1	1	1	1	2	1	1	2	2
2	1	1	1	1	1	2	2	1
3	2	3	1	1	1	2	2	1
4	2	1	2	2	2	1	1	3
5	1	2	1	2	1	3	1	3
6	2	1	2	2	2	3	1	3
7	1	2	2	1	1	2	2	2
8	2	3	1	2	2	2	1	2
9	2	1	2	2	1	1	2	2
10	1	3	2	1	2	2	2	3
11	1	1	1	1	1	2	1	1
12	2	1	1	2	1	1	2	1
13	1	3	1	1	2	2	1	2
14	2	1	2	1	2	2	2	2
15	1	2	1	2	1	2	2	2

According to the basis of rough set theory, the conditional attribute $C=\{a,b,c,d,e,f,g\}$ of the domain U and the decision attribute $D=\{x\}$. The importance of each attribute is calculated, and the attribute approximation is performed on Table 2. According to the simplification results, attribute

a,b,c,d,e has an effect on the system classification ability after omitting, so a,b,c,d,e is a nuclear attribute and cannot be omitted. Attribute f,g has no effect on the system classification ability after omission, so it is a redundant attribute and can be omitted.

4.1.3. Supplier evaluation decision tree construction. In the following, the supplier evaluation example will be presented further based on the decision tree algorithm foundation. Based on the results of the previous section, the attribute kernel value list for supplier evaluation is shown in Table 3, with U_o denoting the data sample serial number for the old domain and U_N denoting the data sample serial number for the new domain.

Table 3. The kernel properties table after the redundant properties are removed

U_N	U_o	a	b	c	d	e	x
1	13	1	1	1	2	1	2
2	2,11	1	1	1	1	1	1
3	10	2	3	1	1	1	1
4	5,7	2	1	2	2	2	3
5	4	2	1	2	2	2	3
6	3,12	1	2	2	1	1	2
7	6	2	3	1	2	2	2
8	15	1	3	2	1	2	3
9	9	1	1	1	1	1	1
10	1	2	1	1	2	1	1
11	8	1	3	1	1	2	2
12	14	1	2	1	2	1	2

Calculate the dependency and importance of attribute a,b,c,d,e respectively. Select the attribute (b) with the largest conditional attribute importance value and the largest information gain as the root node of the decision tree. Attribute d with the largest value of attribute importance is selected as the leaf node for the branching of attribute b taking value 1. Following the decision tree algorithm, and so on, the whole decision tree obtained, as shown in Fig. 2.

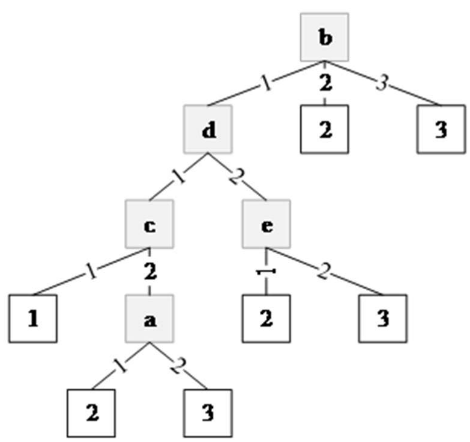

Fig. 2. Decision tree constructed by attribute dependence of rough set

4.1.4. Rule generation. According to the decision tree extraction of classification rules and discretization results, the only path from the root node to the leaf node represents a classification rule, the decision tree can be transformed into If-then classification rules, the supplier evaluation decision rules are shown in Table 4.

Based on the decision tree classification algorithm, seven classification rules from the root node to the leaf nodes are obtained, i.e., the rules used for supplier evaluation.

Table 4. Supplier assessment decision rule

Code	If	then	Evaluation result	Confidence	Support degree
1	b<0.0005 d<0.0055 c<6.0	1	Excellent	1	13.2%
2	b<0.0005 d>=0.0055 c<6.0 a<0.873	2	Passed	1	8.5%
3	b<0.0005 d>=0.0055 c<6.0 a>=0.873	1	Excellent	1	4.5%
4	b<0.0005 d>=0.0055 e<950	2	Passed	0.7	13.6%
5	b<0.0005 d>=0.0055 e>=950	3	Failed	1	11.5%
6	b>=0.0005 b<0.0009	2	Passed	0.9	15.8%
7	b>=0.0009	3	Failed	0.38	11.5%

In the application process of the real intelligent procurement system, using the decision tree classification algorithm in the paper, the supplier evaluation method is more robust, easy to understand, with high efficiency and strong scalability, and is a more commonly used supplier evaluation model in enterprise Y. It is worthwhile to promote in practice.

4.2. Procurement resourcing optimization programme

This paper takes the database procurement information of University K purchaser in 2023 as an empirical object to verify the feasibility and effectiveness of the intelligent optimization algorithm designed in this paper. The library's database procurement object for that year is divided into the renewal of historical high-quality databases, the screening procurement of trial resources, the procurement of whitelisted databases and the elimination of databases with poor usage effects, involving 75 database platforms for procurement optimization and other decision-making processes. The basic experimental method of this paper is: firstly, based on the comprehensive efficiency index system of the database, the candidate database is evaluated and scored, and used as the input of the optimization model, and then the genetic intelligence algorithm is used to obtain the optimization scheme set for the database procurement of the purchaser in the year of 2023, and the representative schemes are selected to be compared with the actual procurement scheme of the year of 2023, so as to verify the feasibility and effectiveness of the system.

4.2.1. Database composite score calculation. For the research on the comprehensive use of electronic database benefit evaluation index system, many scholars have carried out extensive exploration, formed a more scientific and comprehensive evaluation index system, and developed some more mature and feasible evaluation models and methods, such as the hierarchical analysis method, network analysis method and other methods. In view of the relatively rich and mature research results, this paper adopts the performance evaluation model of electronic resource services of university purchasers based on the network analysis method, and establishes the comprehensive benefit evaluation scoring dataset of all databases required for the study. Its calculation model is shown in Equation (15):

$$T = \sum_{i=1}^{n} w_i y_i \tag{15}$$

In the database comprehensive evaluation model, $w_i = (w_1, w_2, \ldots, w_n)$ is the full vector of the i nd evaluation index of all databases, $y_i = (y_1, y_2, \ldots, y_n)$ is the dimensionless data of the i th index of a database, T is the comprehensive evaluation score of a database, and the databases are ranked according to the magnitude of the value of T, and the larger the value of T, the higher the comprehensive evaluation of the database.

The purchase price and database usage data of the databases required for the study in this paper come from the statistical platform of electronic resource usage data purchased by the library, and the relevant data of the trial resources come from the current year or historical data provided by the data vendors. The calculation of the comprehensive database score is obtained by using SuperDecision software, which is commonly used in network analysis method. The calculation results of the scores of some databases are shown in Table 5, in which Scheme A is the scheme of this paper, and B, C and D are the comparison schemes.

Table 5. Candidate database comprehensive scoring and optimization plan(part)

Code	Type	Constrain	Score	Actual purchase	Solution A	Solution B	Solution C	Solution D
D1	Multimedia	⩾5	0.35	0	1	1	1	1
D2	Multimedia		0.53	0	0	1	0	1
D3	Multimedia		0.34	1	1	1	1	1
D4	Multimedia		0.51	1	1	0	1	1
D5	Multimedia		0.44	0	0	1	1	1
...	...	...	...	...	...	...	...	...
D71	Foreign journal	⩾4	0.66	1	0	1	1	1
D72	Foreign journal		0.73	1	1	1	0	1
D73	Foreign journal		0.55	0	1	0	0	1
D74	Foreign journal		0.53	1	1	1	1	1
D75	Foreign journal		0.75	1	0	1	1	1

The complete iterative optimization curve of the intelligent algorithm is shown in Fig. 3.

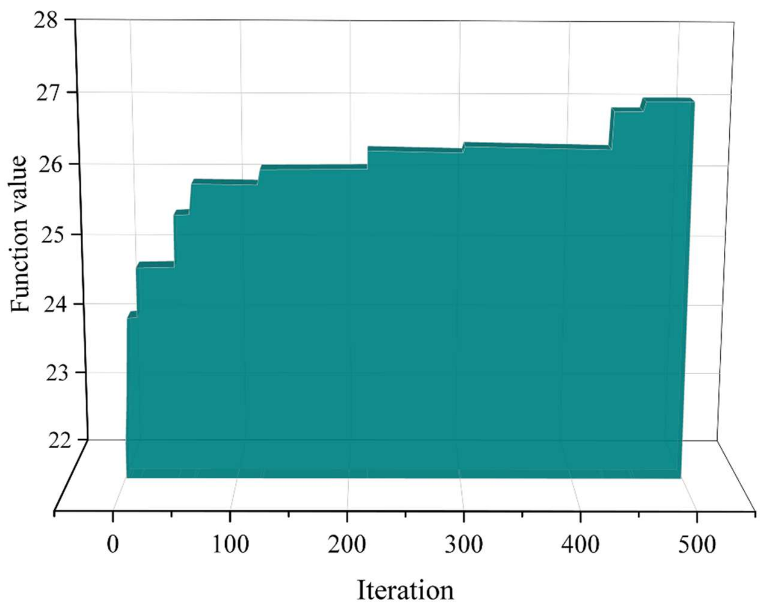

Fig. 3. Algorithm optimization process

Figure 4 shows the relationship between the number of iterations of the genetic algorithm and the convergence of the function fitness, with the increase in the number of iterations, the fitness function value of the genetic algorithm grows. However, with the increase in the number of iterations, the function value grows more and more slowly, when the number of iterations is close to 500, the function value will no longer grow, indicating that the algorithm gradually converges.

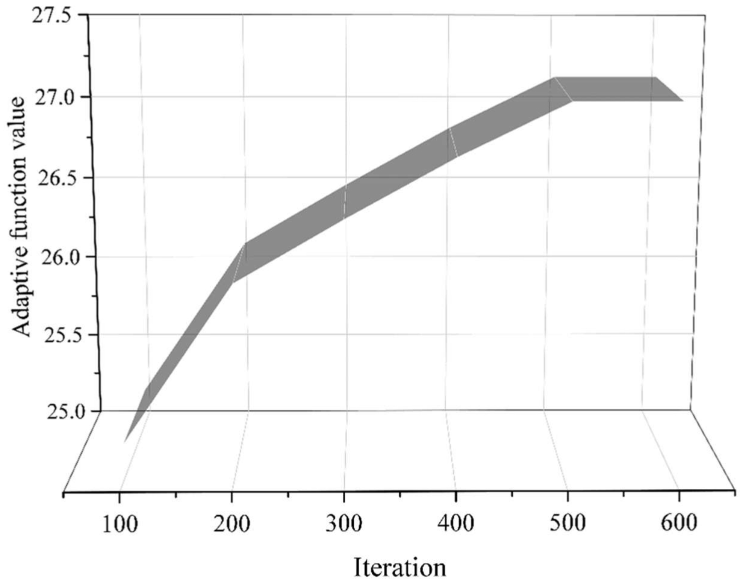

Fig. 4. The convergence of iterations and fitness

4.2.2. Validation of optimization results. The list of procurement resources actually procured by the purchaser in FY2023 is detailed in Table 6, with a total resource score of 24.55, a total procurement amount of 10928715 yuan, and a total of 55 databases in 8 categories, as shown in Table 3. According to the characteristics of genetic algorithm approximate optimization, the paper selects four optimization schemes A, B, C, D and the actual procurement scheme O for comparison and analysis. The procurement lists of the four optimization schemes are detailed in Table 2, and their total scores are all significantly higher than the total score of the actual procurement scheme, the procurement amounts are all controlled within the budget, and the total number of databases recommended to be procured is 65, 68, 70, and 64 in order. The degree of agreement between the four optimization schemes and the actual procurement scheme is 79.82%, 69.38%, 75.51%, and 74.68%, respectively. From Table 6, it can be seen that under the premise of satisfying the constraints of stable database structure type and procurement amount, the optimization scheme can get higher total procurement resource utilization scores and more databases can be procured. From the recommendation details of the optimization scheme, all the four schemes have different orientations in recommending medium and low scoring databases while keeping the high scoring databases in high segments, thus giving the decision makers a variety of Reference.

Table 6. The comparison between the actual plan and the optimization scheme

Procurement plan	Overall Score	Total purchase amount(yuan)	Total purchase amount(count)	Sim.(%)
O	24.55	10928715	55	100
A	26.32	10882571	65	79.82
B	26.82	10798148	68	69.38
C	27.18	10908237	70	75.51
D	26.68	10987381	64	74.68

4.2.3. Kissing analysis. In order to compare and analyze the database situation between the intelligent algorithm-based optimized configuration scheme and the actual procurement by the purchaser, the paper introduces the similarity coefficient Sim to calculate the degree of match between the actual resource procurement situation and the optimized configuration recommendation scheme.

From the database recommendation details of the scheme in Table 5, it is easy to get that the Count value between the four optimization schemes and the actual procurement scheme is 63, 55, 60, 59, and the number of candidate databases Sum is 75, so as to get the coincidence value as in Table 6. From Table 6, it can be seen that the highest degree of fit is optimization scheme A with a Sim value of 79.82% and the lowest degree of fit is scheme B with a Sim value of 69.38%. Overall, the coincidence degree between each optimization scheme and the actual procurement scheme is at a high level, indicating that the procurement resource optimization allocation method based on genetic algorithm can obtain a more scientific and reasonable recommendation results, and can provide decision-making argumentation reference for the procurement resource planning and procurement practice of university purchasers.

4.2.4. Analysis of differences. The optimized allocation results of procurement resources and the actual procurement of resources have certain differences, the main reason is: the optimized allocation of procurement resources of the genetic algorithm is strictly in accordance with the comprehensive scoring results of the database, the total budget of the procurement of resources and the constraints of resource types, etc. under the conditions of the database scoring in reverse order, and the results are obtained according to the greedy algorithm intelligent calculation. In the actual procurement process, decision makers often need to consider some other factors, for example, in the same type of resources, the ratings of database D_i and database D_j are close to each other, but when the content of the two databases is obvious, even if the ratings of databases D_i and D_j are ranked in the top of all databases, it is unlikely that two databases with significant content crossover will be procured at the same time in the actual procurement process. The intelligent algorithm selects two databases that are too close to each other in terms of their overall ratings according to random probability, while the decision-makers tend to take into account the development prospects of the database producers, the recommendations of the experts, the databases recommended for purchase by the relevant policies, and other factors that can be taken into account in a flexible manner. Overall, although the actual procurement decision-making process could not be exactly in accordance with the scheme recommended by the intelligent algorithm, there were no obvious procurement planning results that were contrary to the objective data, and the intelligent optimization scheme served as a reference for decision-making.

5. Intelligent procurement resourcing system based on procurement results

This system analyzes the method of procurement implementation based on procurement data in reverse. Based on artificial intelligence, after extracting the characteristic parameters (including but not limited to: price, technical specifications, comprehensive strength of enterprises, etc.) of the supplier samples of the old procurement projects for training, the system realizes the accurate and effective evaluation of the scores of bid evaluation/comparison of the new procurement projects by calculating the reasonable weighted value of each parameter.

The system methodology includes the following parts: procurement project data storage subsystem for training, procurement project post-assessment sample data subsystem, procurement project bid evaluation parameter extraction subsystem, artificial intelligence training subsystem, new procurement project data storage subsystem, and new procurement project bid evaluation calculation subsystem. The details are described as follows.

1) Procurement project data storage subsystem for training: according to different categories of products (e.g., switches, optical cables, power supply equipment, etc.), a large amount of past procurement project data is categorized and stored, which is used in conjunction with the procurement project post-evaluation sample data subsystem corresponding to the products of the category.

2) Post-assessment sample data subsystem for procurement items: Select items corresponding to the “procurement item data storage subsystem for training”, and obtain and store their post-assessment scores as the desired output value of the AI training subsystem.

3) Evaluation parameter extraction subsystem for procurement projects: Extract the characteristic parameters (including but not limited to: price, technical indexes, comprehensive strength of enterprises, etc.) of new/old procurement projects used for bid evaluation/comparison, and use them as input node values for the AI training subsystem.

4) Artificial Intelligence Training Subsystem: an intelligent information processing system designed to mimic the structure of the human brain and its functions, essentially a highly complex large-scale nonlinear adaptive system composed of a large number of simple processing units.

5) Bid evaluation subsystem for new procurement projects: using the characteristic parameter values extracted from the bid evaluation parameter subsystem B for procurement projects and the calculation equations given by the artificial intelligence training subsystem, it evaluates and calculates the scores for new procurement projects.

The workflow of this system is as follows.

1) "Procurement Project Bid Evaluation Parameter Extraction Subsystem A" extracts the characteristic parameters (including but not limited to: price, technical indicators, comprehensive strength of the enterprise, etc.) used for bid evaluation/comparison in the old procurement project from the "Procurement Project Data Storage Subsystem for Training" and stores them for backup.

2) “Procurement project bid evaluation parameter extraction subsystem A” inputs the extracted objective characteristic parameters into the “artificial intelligence training subsystem”.

3) The “Procurement Project Post-Assessment Sample Data Subsystem” selects project materials of a specific category from the “Procurement Project Data Storage Subsystem for Training” and extracts their post-procurement assessment result scores for backup.

4) The “Procurement Project Post-Assessment Sample Data Subsystem” transmits the extracted post-procurement assessment result scores to the “Artificial Intelligence Training Subsystem” for backup.

5) The "Artificial intelligence Training subsystem" calculates the relationship between the post-procurement evaluation results and the corresponding bid evaluation/comparison feature parameters through the "Artificial intelligence training subsystem" (actually not limited to this method) according to the characteristic parameters of the old procurement project evaluation/comparison obtained from step (2) and the corresponding post-procurement evaluation/comparison result obtained from step (4). And import "new procurement project bid evaluation subsystem".

During the AI training, the bid evaluation/selection feature parameters of these old items will be used as inputs to the neural network. The post-assessment scores of the corresponding procurement items are used as the corresponding desired output. The AI system is then trained using a learning algorithm.

6) “Procurement project bid evaluation parameter extraction subsystem B” extracts bid evaluation/selection feature parameters from the “new procurement project data storage subsystem” and stores them in the reserve.

7) “Procurement project bid evaluation parameter extraction subsystem B” inputs the extracted bid evaluation/selection feature parameters into the “new procurement project evaluation subsystem”. When the AI is well trained, the same feature extraction process is carried out for new procurement projects to obtain new bid evaluation/selection feature parameters, which are then inputted into the “Evaluation Subsystem for New Procurement Projects”.

8) The “new procurement project evaluation subsystem” calculates the bid evaluation/selection scores for new procurement projects based on the formula for calculating the weights of the characteristic parameters obtained from the artificial intelligence network training.

6. Conclusion

The article applies the decision tree algorithm to supplier evaluation and selection, and uses genetic algorithm to solve the procurement resource allocation model to improve the scientificity of supplier selection and resource allocation. Take enterprise Y as an example, use the method of this article to carry out a case study of supplier selection for it. Completion rate, return rate, transportation loss rate, price point, freight, other costs, and delayed delivery are determined as the evaluation indexes, and the number of suppliers is 15. The constructed decision tree is transformed into If-then classification rules, and the number of classification rules is obtained to be 7, which simplifies the decision-making process when the enterprise carries out supplier selection and improves the efficiency of the supplier evaluation work. Take K University Library as an example to verify the application effect of the procurement resource allocation model. The match between the resource allocation scheme of this paper and the actual procurement scheme is 79.82%, which is 10.44%, 4.31% and 5.14% higher than the B, C and D schemes, respectively, and is closer to the actual allocation scheme. It shows that the work in this paper actually facilitates the selection of suppliers and better optimizes the allocation of procurement resources.

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