International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 6087-6098

https://doi.org/10.70517/ijhsa463523

Research on the Accuracy of Enterprise Market Forecasting and Strategic Decision-Making Driven by Business Data Analysis

Tian Luo[1], Guangmao Wei[2] and Fan Zhang[2,*]
[1] Faculty of Business Administration, University of Macau, Macau, 999078, China
[2] School of Logistics and Finance, Guangxi Logistics Vocational and Technical College, Guigang, Guangxi, 531007, China
Corresponding authors: (e-mail: HRBZHANGFAN@163.com).

Abstract Market forecasting capability, as an important ability for enterprises to gain insight into changes in the external environment, directly affects the quality of strategic decisions. However, existing studies have not explored enough the mechanism of how market forecasting capability specifically affects the accuracy of strategic decisions, and lack a systematic quantitative analysis method. In this study, the ACO-MPSO association rule mining algorithm is designed by combining the ant colony optimization algorithm and particle swarm optimization algorithm and introducing the Metropolis mechanism. 1640 data of A-share listed companies in the manufacturing industry from 2016 to 2023 are selected, a decision table containing 25 conditional attributes is constructed, and the new algorithm is applied to mine the association rules of market forecasting ability and strategic decision precision. The results show that: when the enterprise market prediction ability is strong, 12 high strategic decision precision rules are mined, with an average accuracy of 90.4%; compared with the traditional Apriori algorithm, the ACO-MPSO algorithm completes the mining in only 15.84 seconds under the 45% support threshold, which is a 42% improvement in the efficiency; and the validation of the test set shows that the overall classification accuracy of the rules is 84.2%. Among them, the classification accuracy for high-precision samples reaches 93.16%. It is found that policy sensitivity, data accuracy, and resource endowment fulfillment are the key factors to promote high strategic decision-making accuracy, and the improvement of enterprise market forecasting ability can significantly enhance strategic decision-making accuracy.

Index Terms Association rule mining, market forecasting capability, strategic decision precision, ant colony optimization algorithm, particle swarm optimization algorithm, listed manufacturing companies

I. Introduction

An enterprise is not an “island”, but an open system [1]. Changes in the external environment are also a great challenge to its own development, especially with the arrival of economic globalization, the technological revolution and the knowledge-based economy, which inevitably face a variety of environmental stimuli [2]-[4]. In a highly uncertain and turbulent environment, enterprises rely heavily on forecasting ability when making strategic decisions, and their performance is also affected by their attention and resource allocation to environmental forecasts, enterprises underestimate the environmental stimuli make them unable to keep up with the changes in the external environment, and ultimately lose their competitive advantage [5]-[7]. In addition to this, the reality of such a large amount of information will lead to companies feel a lack of predictive ability [8]. It has been pointed out that whether enterprises are able to make predictions about the environment in advance must be seriously thought about their learning ability. Behavioral learning theory suggests that enterprises can avoid repeated mistakes in time through the act of organizational learning so that their predictive ability can be steadily improved [9], [10].

In a relatively stable environment, management theories are mainly based on industrial economics, and traditional strategic decision-making issues mainly focus on how enterprises can maintain their competitive advantages, and leaders make strategic decisions mainly based on their past experiences [11], [12]. With the development of science and technology and the deep integration of the global economy, the environment in which enterprises are located is complex and changing, and the requirements for leaders are higher, leaders must make predictions about the environment in which enterprises are located, conform to the trend of the environment, make strategic decisions, and seize the strategic high ground, so that they can fully grasp the opportunities, give full play to their strengths, cope with the threats, and promote the continuous development of enterprises [13]-[15]. Based on this, it puts higher requirements on leaders themselves, who must break through experience and rely more on their own cognition to make strategic decisions. However, although existing studies have explored the relationship between cognitive flexibility, cognitive complexity, attentional focus, meaning construction and strategic decision-making, they have not further revealed the intrinsic mechanism of the role of corporate market forecasting ability and strategic decision-making [16], [17]. Therefore, selecting a representative enterprise as the research object and investigating the mechanism of the role of enterprise market forecasting ability on strategic decision-making has important inspiration and reference significance for other enterprises and leaders.

Enterprise strategic decision-making is the core link of enterprise development, and its accuracy directly determines the enterprise's market competitiveness and long-term development prospects. In the current complex and changing market environment, enterprises must have keen market insight and accurate forecasting ability in order to make strategic decisions in line with the market development trend. Market forecasting ability, as an important ability for enterprises to perceive changes in the external environment and grasp market opportunities, has become a key factor affecting the quality of strategic decisions. However, traditional research mostly analyzes the impact of market forecasting on strategic decisions from a qualitative perspective, lacking in-depth quantitative analysis and mechanism exploration. Meanwhile, the existing research methods are inefficient and lack of precision when dealing with the massive data generated in the operation of enterprises, and it is difficult to accurately mine the complex association relationship between market forecasting ability and the precision of strategic decision-making. As an important technique of data mining, association rule mining can discover the implicit relationship between variables from large-scale data, which provides a new research path to explore the influence mechanism of market forecasting ability on strategic decision precision. Based on the theory of association rule mining, this study designs a new mining algorithm integrating ant colony optimization algorithm and particle swarm optimization algorithm, and enhances the global search capability of the algorithm by introducing Metropolis mechanism to improve the efficiency and accuracy of rule mining. The study selects listed companies in the manufacturing industry as samples, constructs a multi-dimensional evaluation index system covering the enterprise's market forecasting ability, data information quality, decision-making process scientificity, external environment insight, and internal resource matching, and utilizes the proposed algorithms to deeply explore the influence of each factor on the accuracy of strategic decision-making. The superiority of the new algorithm is verified through comparative experiments, and the mechanism of market forecasting ability in improving the accuracy of strategic decision-making is revealed through empirical analysis, which provides scientific basis for enterprises to optimize the decision-making process and improve the quality of decision-making.

II. Design of association rule mining algorithm based on ACO-MPSO

In order to use association rule mining to explore the mechanism of the influence of enterprise market forecasting ability on the accuracy of strategic decision-making, this paper combines the ant colony optimization (ACO) algorithm [18] and particle swarm optimization (PSO) algorithm [19], and introduces the Metropolis mechanism to design the association rule mining algorithm ACO-MPSO.

II. A.Association Rule Mining

II. A. 1) Basic theory of association rules

Let $I=\{i_1,i_2,...,i_m\}$ be a set containing all items, where $i_j(1\le j\le m)$ is the unique identifier of Item and j is the serial number of the item. Let transaction database $M=\{t_1,t_2,...,t_n\}$ be a collection of transactions, each transaction $t_i(1\le i\le n)$ corresponds to a subset on I, where t_i is the unique identification of the transaction, and i represents the serial number of the transaction. In order to elaborate the basic theory of association in detail, this paper exemplifies a small commodity trading database as shown in Table 1 for illustration.

Table 1: Data on small commodity transactions

TID	List of purchased goods	TID	List of purchased goods
t1	Beer, bread, biscuits	t6	Bread, diapers
t2	Bread, milk	t7	Beer, diapers
t3	Diapers, milk	t8	Beer, bread, diapers, biscuits
t4	Beer, bread, milk	t9	Beer, bread, diapers
t5	Beer, diapers		

In order to reduce the computation amount when mining association rules at a later stage, then the commodities beer, bread, diapers, milk and cookies in the above can be specifically expressed as follows: i_1,i_2,i_3,i_4,i_5 .

Association rule: Formally, the association rule can be divided into two parts, i.e., the antecedent of the rule and the consequent of the rule, which can be expressed by the formula like $X \to Y$, where X, Y is the set of disjoint items, i.e., $X \cap Y = \phi$, respectively, and X is expressed as the antecedent of the rule, and Y is expressed as the consequent of the rule.

In general, the strength and credibility of association rules can be evaluated by two indicators: support and confidence.

Support: In the global item set I and transaction database M, the support of item set $I_1 \subseteq I$ on M, which can be expressed as the proportion of transactions i containing I_1 in M, that is:

$$support = \frac{|\{t_i \mid I_1 \subseteq t_i, t_i \in M\,|}{|M|} \tag{1}$$

where $|\cdot|$ denotes the count of the set $\cdot$, i.e., the number of elements in it, which can be defined colloquially as:

$$support(X \to Y) = \frac{M \text{ contains the number of transactions of } X \cup Y}{\text{The total number of transactions in } M} \tag{2}$$

Using the form of probability can be expressed as:

$$support(X \to Y) = P(X \cup Y) \tag{3}$$

where $P(X \cup Y)$ denotes the probability of a $X \cup Y$ -term set.

Clearly, $support(X \to Y)$ and $support(Y \to X)$ are of equal size.

Confidence: In the global itemset I and the transaction database M, an association rule of the form $X \to Y$ on I and M, where $X, Y \in I$, and $X \cap Y = \phi$, then its confidence is the ratio of the number of transactions containing X and Y to the number of transactions containing X, i.e.:

$$confidence(X \to Y) = \frac{M \text{ contains the number of transactions of } X \cup Y}{M \text{ the only contains } X \text{ number of transactions}} \tag{4}$$

In the form of probability it can be expressed as:

$$confidence(XarrowY) = P(X \mid Y) \tag{5}$$

where $P(X \mid Y)$ denotes the conditional probability of Y given X. For rule $X \to Y$, the larger the value of $confidence(X \to Y) = P(X \mid Y)$, the greater the probability that Y is included in the transaction in which X occurs. Obviously, $confidence(X \to Y)$ and $confidence(Y \to X)$ are not necessarily equal in size.

In association rule $X \to Y$, $support(X \to Y) \le confidence(X \to Y)$ always holds Based on the above description, the conditions for association rule $X \to Y$ to hold can be defined as follows:

(1) It means that the frequency of all items in the rule occurring simultaneously in transaction database M is at least greater than or equal to $S\%$, where S is its support.

(2) In transaction database M, at least $C\%$ of the transactions containing X also contain Y, where C is its confidence level.

Frequent itemsets: given a global itemset I and a transaction database M, I_1 is said to be a frequent itemset if its support is greater than or equal to min_sup for a non-empty subset I_1 of I.

Association rule mining process: association rule mining, the essence of which is to find out the eligible rules in the database according to the user's requirements, can be divided into the following two steps:

(1) Finding frequent itemsets: By setting the minimum support threshold: min_sup, find out the frequent itemsets in the transaction database, i.e., keep only the itemsets which are greater than or equal to min_sup.

(2) Mining association rules: by setting the minimum confidence threshold: min_conf, mining association rules in the frequent itemsets, i.e., deleting the rules that do not satisfy min_conf.

II. A. 2) Classification of association rules

From different perspectives, association rules can be divided into the following categories:

(1) From the viewpoint of the attributes of the associated data, they can be divided into numerical association rules QARP and Boolean association rules. Among them, the former deals with data that are discretized variables, while in the latter it needs to deal with numerical fields, but it usually realizes the conversion from QARP to QARP by preprocessing the data.

(2) In terms of the mining level of Linked Data, it can be divided into single-layer association rules and multi-layer association rules. Among them, the former is only considered on the same level when mining, while the latter can mine strong association rules on a higher level.

(3) In terms of the dimensions of Linked Data mining, it can be divided into single-dimensional association rules and multi-dimensional association rules. Among them, the former involves only one dimension of data, while the latter needs to process data in multiple dimensions. However, multidimensional data mining can also be transformed into unidimensional data mining through attribute fusion.

(4) From other perspectives, association rules can also be divided into the following categories: transactional association rules, spatial association rules, negative association rules, sequential pattern rules, positive association rules, constraint-based association rules, and so on.

II. A. 3) Common methods for association rule mining

The commonly used mining methods for association rules can be categorized as follows:

(1) Classical association rule mining: most of the classical association rules are mined using the two methods Apriori algorithm [20] and FP-growth algorithm [21] or based on the improvement of these two methods, for example: the AprioriAll algorithm, AprioriSome algorithm, and DynamicSome algorithm in sequence pattern mining.

(2) Data flow association rule mining: the mining object of data flow is mostly massive and rapidly changing dynamic data. In view of the characteristics of data streams, sliding window technology is generally used to make regional restrictions on data streams for window query, and commonly used methods include: TDMCS algorithm, FP-stream algorithm, Ds-CFI algorithm and so on.

(3) Graph association rule mining: graph mining focuses on the mining of frequent subgraphs in graph data, and the existing algorithms on frequent subgraph mining can be roughly divided into two categories:

1) Based on Apriori nature, specifically including: algorithms such as FSG algorithm, PATH and AGM algorithm.

2) Based on pattern growth, specifically including: gSpan algorithm and FFSM algorithm and other algorithms.

(4) Other application areas: at present, the use of intelligent algorithms to realize the mining of association rules is a current research hot spot. Commonly used intelligent methods mainly include: particle swarm, genetic, simulated annealing, imperialist competition, neural network, ant colony and other algorithms.

II. B.ACO-MPSO algorithm design

II. B. 1) Data pre-processing

To match the operation of the ant colony algorithm and particle swarm algorithm in this paper, the database is transformed into a 0-1 matrix $C=(c_{ij})_{r\times h}$. where r is the number of transactions in the database and h is the number of attribute items. The transformation method is relatively simple: scan the database to find the set of attribute entries I, and sort and number the attribute entries according to some law, if $I_j \in t_i$, then $c_{ij}=1$, otherwise, $c_{ij}=0$, i.e:

$$c_{ij}=\begin{cases}1, & \text{If } I_j \in t_i \\ 0, & \text{Otherwise}\end{cases} \tag{6}$$

After the data has been processed, the database does not need to be scanned again each time the support count for itemset $\{I_1, I_2, L, I_k\}$ is calculated as shown in equation (7):

$$support\{I_1, I_2, L, I_k\}=\sum_{i=1}^{m} v_i \tag{7}$$

where $v_i=c_{i1}\Lambda c_{i2}\Lambda L\Lambda c_{ik}$ and Λ denote the logical “with”.

II. B. 2) Mining of Maximum Frequent Term Sets

The first step of the ACO-MPSO algorithm is to use the particle swarm algorithm to mine a fixed number of frequent term sets, and this design is mainly to get the initial pheromone concentration of the ant colony algorithm to improve the blindness of the AS-MFI algorithm as much as possible. Specifically, it includes the following:

(1) Initialize the particle swarm. The encoding of the PSO algorithm in the hybrid algorithm is slightly different from that of the PSO algorithm in that the particles represent only the set of attribute items, then each attribute item contains only a part of it. Since the data in the transaction database corresponds to a two-dimensional 0-1 matrix, the position of each particle is also initialized as a 0-1 vector with vector dimension equal to the number of 1-frequent itemsets. They are randomly generated, but their corresponding attribute itemsets must be frequent, otherwise they are regenerated. As for the velocity of the particles, each element of the velocity vector is restricted to be in $[-V_{\max}, V_{\max}]$ in order that the difference in its value will not be too large, and in general, $V_{\max}=10$. Their generation is also randomly generated.

(2) Fitness function. The first step of the algorithm in this paper is to mine the maximum frequent term set, and the definition method of the fitness function refers to the AS-MFI algorithm.

(3) Particle position update. the particle position and velocity update method in the ACO-MPSO algorithm is shown in Eqs. (8) to (9):

$$v^k(t+1) = w \cdot v^k(t) + c_1 r_1 (x^k_{pbest}(t) - x^k(t)) + c_2 r_2 (x_{gbest}(t) - x^k(t)) \tag{8}$$

$$x^k(t+1) = x^k(t) + v^k(t+1) \tag{9}$$

where $v^k(t)$ is the velocity of the k nd particle after t iterations, $x^k(t)$ is the position of the k th particle after t iterations, w is the inertia coefficient whose value becomes smaller as the number of iterations increases, and $c_1 = c_2 = 2$ is the learning factor. Since the particle position after the update of Eq. (9) is no longer a 0-1 vector, it needs to be transformed as shown in Eq. (10):

$$x(t)^{''}_i = \begin{cases} 1 & r_3 < Sig(x(t)^{'}_i) \\ 0 & r_3 \ge Sig(x(t)^{'}_i) \end{cases} \tag{10}$$

where r_3 is a random number uniformly distributed between [0, 1] and $Sig()$ is a sigmoid function as shown in equation (11):

$$Sig(x) = 1/(1+\exp(-x)) \tag{11}$$

(4) Output of running results.The particle swarm algorithm in ACO-MPSO algorithm will output all the optimal positions of the particles obtained in the last iteration.

When the particle swarm algorithm satisfies the termination condition, it turns to the execution of the ant colony algorithm. In this paper, each attribute term corresponds to a city, and the association rule mining problem corresponds to the TSP problem. Due to the shortcomings of the association rule mining method based on ACO algorithm, this paper improves the AS-MFI algorithm and adds Metropolis mechanism as follows:

(1) Pheromone initialization. The particle swarm algorithm outputs the optimal positions of all particles after the iteration is completed, calculates the number of times each attribute item i, j has been selected at the same time cu_{ij}, i.e., the support count of the 2-item set, and then carries out the pheromone determination according to Eq. (12):

$$\tau_{ij}(0) = (\tau_{\max} - \tau_{\min}) + cu_{ij} \tag{12}$$

$\tau_{\max}, \tau_{\min}$ are the upper and lower limits of the pheromone, respectively.

(2) Pheromone update. Pheromone updating mainly includes local updating and global updating, the local updating operation is executed after the ants have selected an attribute item into the set of selected attribute items, and its updating method is shown in Eqs. (13) to (15):

$$\Delta\tau_{ij}(t)^k = \begin{cases} Q & \text{If points } i \text{ and } j \text{ are included in the selected attribute item set of ant } k \\ 0 & \text{Other} \end{cases} \tag{13}$$

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{m} \Delta\tau_{ij}(t)^k \tag{14}$$

$$\tau_{ij}(t) = (1-\varepsilon)\cdot\tau_{ij}(t) + \varepsilon\cdot\Delta\tau_{ij}(t) \tag{15}$$

The global update is performed after all ants have completed one search, and its update method is shown in equations (16) to (17):

$$\tau_{ij}(t+1) = (1-\rho)\cdot\tau_{ij}(t) + \rho\cdot\Delta\tau_{ij}(t) \tag{16}$$

$$\Delta\tau_{ij}(t) = \begin{cases} \dfrac{Q}{L_{best}} & \text{If points } i \text{ and } j \text{ are included in the set of optimal solutions} \\ 0 & \text{Other} \end{cases} \tag{17}$$

L_{best} in Eq. (17) is the fitness value of the optimal frequent item set obtained after each iteration is completed. After updating the pheromone of each edge, the pheromone of the to-be-selected items is then calculated by summing and averaging the pheromone of the to-be-selected attribute items with the pheromone of the edges composed of each of the selected attribute items, i.e., Eq. (18):

$$\tau_j = \left(\sum_i \tau_{ij}\right) / c_i \mid \tag{18}$$

where $|c_i|$ is the number of items in the set of selected attribute items.

(3) Determination of heuristic information.The heuristic information determination method in the ACO-MPSO algorithm is to sum and then average the support counts of the 2-item set consisting of the to-be-selected attribute items and each of the selected attribute items after an attribute item has been selected, so that the heuristic information becomes a dynamic quantity.

(4) Attribute item selection. At the initial moment, all attribute items are taken as the first access points of different ants and numbered into their own forbidden table $tabu_k$ and the set of selected attribute items f_k. In the subsequent work of attribute item selection, the Metropolis mechanism is introduced in this paper. For any ant k, it first calculates the support count of the item set composed of all its attribute items not put into the taboo table and its own selected attribute item set, and sees whether it satisfies the condition of greater than or equal to the minimum support count. If it is satisfied, its transfer probability function is calculated according to equation (19), and if it is satisfied, it is put into the taboo table $tabu_k$:

$$p_j^k(t)=\begin{cases}\dfrac{\tau_j(t)^\alpha\eta_j(t)^\beta}{\sum_j\tau_j(t)^\alpha\eta_j(t)^\beta} & j\in allowed_k\\ 0 & j\in tabu_k\end{cases} \tag{19}$$

When all the probability functions are computed, the optional attribute term j corresponding to the maximum value of them is selected, at this point, in order to increase the diversity of the solutions and reduce the chance of the algorithm appearing premature phenomenon, the algorithm in this paper introduces the Metropolis mechanism. Assuming that f_k' is the set after f_k is put into the attribute term j, the values F and F' of f_k and f_k' are computed respectively, and then, their difference $\Delta F=F-F'$ is computed. if, $\Delta F\le 0$, then $f_k=f_k'$, otherwise, $\exp(-\Delta F/Te)$ is computed, and if $\exp(-\Delta F/Te)<Rand(0,1)$, then f_k is kept unchanged, and vice versa, there is $f_k=f_k'$. where Te represents the temperature of the annealing algorithm, and it will become smaller and smaller with the iteration of the ACO algorithm as shown in Eq. (20):

$$Te=Te_0/\ln(1+r*t) \tag{20}$$

At the same time, put j into its own taboo table.

At the end of the iteration, record the last frequent itemset sought by the ant, and remove those frequent itemsets that are unlikely to be the largest frequent itemset based on the subset relationship.

II. B. 3) Introduction of Interest Levels

Simply using the two indicators of support count and confidence as the judgment and evaluation criteria of strong association rules is not in line with the real situation, therefore, this paper will introduce the important indicator of interest degree.

The calculation method of interest degree is shown in equation (21):

$$inter(A\Rightarrow B)=\frac{P(A,B)-P(A)P(B)}{P(A,B)+P(A)P(B)} \tag{21}$$

The value range of the above equation is [-1, 1], in general, if the support degree and confidence degree of rule $A\Rightarrow B$ satisfy the condition, and there are $inter(A\Rightarrow B)>0$, the rule will be output as a strong association rule. In this paper, in order to enhance the effect of personalized recommendation, the reference quantity min_inter is set as the minimum degree of interest, and the degree of interest of any strong association rule shall not be smaller than this value.

II. B. 4) Generation of strong association rules

Strong association rules are generated from the maximum frequent term set, and the ACO-MPSO algorithm starts to generate all the strong association rules contained in the maximum frequent term set as soon as the ant search work is completed, as follows:

(1) Let L be any maximal frequent itemset, and find all non-empty true subsets of it.

(2) Assuming that R_1 and R_2 are any two subsets in L and the following condition is satisfied: $R_1\cap R_2=\phi, count(R_1\cup R_2)/count(R_1)\ge \min\_conf, inter(R_1\Rightarrow R_2)>\min\_inter$, then the strong association rule $R_1\Rightarrow R_2$ is obtained.

II. C.Experiments comparing ACO-MPSO with other algorithms

In order to verify the effectiveness of the proposed ACO-MPSO association rule mining algorithm, this paper uses the ACO-MPSO algorithm, Apriori algorithm, standard particle swarm algorithm, algorithm combined with Apriori algorithm (PSO-A), for association rule mining, and do the following comparative experiments with the threshold of support, threshold of confidence, and the number of particles as the parameter for mining the association rules, respectively.

(1) Association rule mining under different population sizes

Setting the dataset as 1000, learning factor C1=C2=2, and support threshold 20% for the experiment, the comparison results of the three algorithms under different groups are obtained as shown in Table 2.

From the experimental results, it can be clearly concluded that in the case of different number of particles, when the number of particles increases, the three algorithms are greatly affected by the number of particles, the algorithm execution time grows rapidly, and it is the more the number of particles the greater the impact, especially the Apriori algorithm, with the increase in the number of particles, the execution time is a lot more than the other two algorithms, and the ACO-MPSO algorithm, although it is also a great influence , but it is still better than PSO-A algorithm and much stronger than Apriori algorithm.

Table 2: Comparison of three algorithms in different groups

Number of particles	Algorithm	Average number of rules	Calculation time /s
15	Apriori	5.3	54.28
	PSO-A	5.5	36.71
	ACO-MPSO	8.4	35.34
30	Apriori	8.9	92.56
	PSO-A	9.0	86.65
	ACO-MPSO	9.2	84.19
45	Apriori	10.6	126.47
	PSO-A	10.9	115.64
	ACO-MPSO	11.2	103.83

(2) Association rule mining under different dataset sizes

Set the number of particles as 20, learning factor C1=C2=2, support threshold as 20%, conduct the experiment and get the comparison results of the three algorithms under different datasets as shown in Table 3.

Observing the data, it can be seen that when the number of particles is the same, as the number of items increases, the ACO-MPSO algorithm is significantly better than the other two algorithms, both in terms of efficiency and in terms of solving. While both particle swarm algorithms are significantly more effective than Apriori algorithm, Apriori algorithm takes a very long time when the item set is particularly large, which is completely unsuitable for association rule mining of large item sets, ACO-MPSO algorithm mines the association rules with the best efficiency, the fastest speed, and mines the largest number of association rules, and PSO-A algorithm is the second best. Compared to PSO-A algorithm, ACO-MPSO algorithm is short time consuming, has a high number of mined association rules and is highly efficient. This shows that ACO-MPSO algorithm is used to extract rules better than traditional algorithms.

Table 3: Comparison of three algorithms under different datasets

Dataset scale	Algorithm	Average number of rules	Calculation time /s
500	Apriori	5.7	46.84
	PSO-A	5.9	32.43
	ACO-MPSO	6.1	27.52
1000	Apriori	8.5	95.64
	PSO-A	8.6	56.73
	ACO-MPSO	9.0	47.85
2000	Apriori	10.3	134.52
	PSO-A	10.6	73.61
	ACO-MPSO	11.4	54.82

(3) Association rule mining under different support degrees

Set the number of particles as 20, the learning factor C1=C2=2, and the dataset as 1000 to conduct the experiment, and get the comparison results of the three algorithms under different support degrees as shown in Table 4.

It can be seen that all three algorithms have a great impact when the support is different, especially the PSO-A algorithm, the number of association rules mined decreases rapidly with the increase of support, the Apriori algorithm is relatively time-consuming and the number of rules mined is in the middle of the list, while the ACO-MPSO still has the best effect, with a short time-consumption of only 15.84s under the 45% support threshold and a significant effect of the mining of the the largest number of rules, the effect is remarkable.

Table 4: Comparison of three algorithms under different datasets

Support threshold	Algorithm	Average number of rules	Calculation time /s
15%	Apriori	10.3	62.37
	PSO-A	10.5	58.38
	ACO-MPSO	10.9	54.53
25%	Apriori	8.5	45.24
	PSO-A	7.9	42.31
	ACO-MPSO	9.2	35.68
45%	Apriori	5.4	27.34
	PSO-A	4.9	26.51
	ACO-MPSO	6.1	15.84

In summary, we can conclude that the ACO-MPSO algorithm is very effective in mining association rules, and it is the most effective relative to PSO-A algorithm and Apriori algorithm both in terms of the number of rules mined and the speed of the mining time, which meets our expectations. It proves the great superiority and feasibility of the ACO-MPSO algorithm in the utilization of rule extraction methods.

III. An empirical study of the market forecasting ability of enterprises and the accuracy of strategic decision-making

Based on the validation of the proposed ACO-MPSO association rule mining algorithm, this chapter applies ACO-MPSO to the experiment of exploring the mechanism of the influence of the enterprise's market forecasting ability on the accuracy of strategic decision-making.

III. A. Data pre-processing

(1) Data sources

In this paper, A-share listed companies in the manufacturing industry from 2016 to 2023 are selected as the research sample, and all the index data are from CSMAR database. The samples with ST and data with missing values are excluded, and a total of 1640 data are obtained.

(2) Original decision table

According to the relevant literature review and analysis can get the corresponding influencing factors, so as to construct the decision table including conditional attributes and decision attributes about the accuracy of enterprise strategic decision-making according to the influencing factors. The decision table consists of 1 decision attribute variable and 25 conditional attributes. The description and division of relevant attributes are shown in Table 5.

(3) Data Completion

A total of 39 conditional attribute values are missing from the initial decision table, and the Mean/mode in ROSETTA software is applied to make up the decision table, so as to obtain a complete decision table and enhance the reliability of the final extraction rules.

(4) Attribute discretization

The samples are divided into training set and test set, and the data of all variables are converted into discrete data. The binarized discretization method is used, with the sample mean as the threshold, greater than or equal to the threshold is taken as 1, and less than the threshold is taken as 0.

III. B. Attribute variable simplification

In order to reduce the interference of redundant attributes for the classification ability of the final rule, it is necessary to simplify the conditional attributes, filter out the conditional attributes that really affect the accuracy of the enterprise's strategic decision-making, and improve the anti-interference of the indicators. In this paper, the genetic algorithm in ROSATTE software is selected to simplify the conditional attributes, and in order to improve the classification accuracy of the model, this paper eliminates some of the less influential indicators, and only retains the attribute simplification rules with a support number of more than 100, and obtains a total of 28,941 approximate simplification results.

Table 5: Explanation of decision attributes

Attribute	Classification	Variable name	Variable symbol
Conditional attribute	Enterprise market forecasting ability	Enterprise market forecasting ability	F1
	Data and information quality	Data integrity	F2
		Data accuracy	F3
		Information integration	F4
		External intelligence coverage	F5
	Scientific nature of decision-making process	Process normalization	F6
		Multisectoral participation	F7
		Risk assessment coverage	F8
		Decision time efficiency	F9
	Insight into the external environment	Accuracy rate of market trend prediction	F10
		Response speed of competitors	F11
		Policy sensitivity	F12
		Technical iteration matching degree	F13
	Internal resource matching	Satisfaction degree of resource endowment	F14
		Utilization rate of core capabilities	F15
		Cost control ability	F16
		Organizational flexibility	F17
	Decision-maker's ability	Industry experience matching degree	F18
		Cognitive bias control	F19
		Rationality of risk appetite	F20
		Team decision-making proportion	F21
	Execution and feedback	Clarity of strategic decomposition	F22
		Execution progress deviation rate	F23
		Feedback mechanism response speed	F24
		Frequency of strategic adjustment	F25
Decision attribute	Precision of strategic decision-making	Precision of strategic decision-making	D

III. C. Association rule extraction

According to the approximate rules of ROSATTE software, using ACO-MPSO algorithm for association rule mining, rules about high strategic decision precision of A-share listed companies in the manufacturing industry can be obtained, and a total of 11,204 rules are mined. Secondly, set the filtering conditions, set the credibility to be greater than 0.80, as well as the coverage rate is greater than 0.18, so that we can obtain the relevant rules that meet the filtering of 482 rules, according to this paper's research only consider the rules with the key variable of this paper, the enterprise market forecasting ability F1 in line with the high enterprise strategic decision-making precision D (1). When the enterprise market forecasting ability is strong i.e., when the conditional attribute F1 is taken as 1, there are 12 rules in total that are consistent with high strategic decision-making precision D(1). For the interpretation of the rules, for example, Rule 1, if the sample meets the enterprise market forecasting ability, data accuracy, and process standardization are higher than the average value of the industry in the current year, the probability that the enterprise achieves high strategic decision-making accuracy is 89.42%. The rule of high strategic decision-making accuracy when the enterprise market forecasting ability is strong is shown in Table 6.

When the enterprise market forecasting ability is weak i.e., when the conditional attribute F1 is taken as 0, there are four rules in line with the high enterprise strategic decision-making precision D(1), for the interpretation of Rule 1, even if the enterprise market forecasting ability of the sample is weak, as long as the policy sensitivity and resource endowment satisfaction of the representative enterprise are higher than the industry average, it still enables the enterprise to maintain a high strategic decision-making precision. The rules for high strategic decision precision when market forecasting ability is weak are shown in Table 7.

Table 6: High strategic decision-making accuracy rules (1)

Serial Number	Association rules	Number of supports	Coverage rate	Accuracy rate
1	F1(1) AND F3(1) AND F6(1) =>D(1)	168	0.2132845	0.894153
2	F1(1) AND F10(1) AND F14(1) =>D(1)	193	0.253142	0.910562
3	F1(1) AND F5(1) AND F9(1) =>D(1)	164	0.213237	0.897324
4	F1(1) AND F12(1) AND F17(1) =>D(1)	172	0.224859	0.885749
5	F1(1) AND F2(1) AND F22(1) =>D(1)	168	0.223561	0.892513
6	F1(1) AND F4(1) AND F7(1) =>D(1)	187	0.240824	0.905454
7	F1(1) AND F8(1) AND F12(1) =>D(1)	191	0.251462	0.904378
8	F1(1) AND F3(1) AND F13(1) =>D(1)	189	0.248361	0.876544
9	F1(1) AND F12(1) AND F14(1) =>D(1)	195	0.253184	0.954153
10	F1(1) AND F10(1) AND F13(1) =>D(1)	184	0.239615	0.911852
11	F1(1) AND F5(1) AND F21(1) =>D(1)	178	0.238406	0.924375
12	F1(1) AND F13(1) AND F24(1) =>D(1)	176	0.258162	0.874264

Table 7: High strategic decision-making accuracy rules (2)

Serial Number	Association rules	Number of supports	Coverage rate	Accuracy rate
1	F1(0) AND F12(1) AND F14(1) =>D(1)	179	0.233185	0.897654
2	F1(0) AND F9(1) AND F17(1) =>D(1)	224	0.302418	0.869532
3	F1(0) AND F3(1) AND F6(1) =>D(1)	221	0.298341	0.879283
4	F1(0) AND F8(1) AND F12(1) =>D(1)	178	0.226539	0.894507

Comparison of the rules with enterprise market forecasting ability at low and high levels respectively is shown in Table 8, except for the enterprise market forecasting ability variable, there are three rules with the same condition attributes, and the comparison can be made to show that the probability of obtaining high strategic decision precision for enterprises with strong enterprise market forecasting ability is greater than that for enterprises with weak enterprise market forecasting ability, all other conditions being equal.

Table 8: Comparison of rules for different enterprise market forecasting ability

Serial Number	Take F1 as 0	Accuracy rate	Take F1 as 1	Accuracy rate
1	F1(0) AND F12(1) AND F14(1) =>D(1)	0.897654	F1(1) AND F12(1) AND F14(1) =>D(1)	0.954153
2	F1(0) AND F3(1) AND F6(1) =>D(1)	0.879283	F1(1) AND F3(1) AND F6(1) =>D(1)	0.894153
3	F1(0) AND F8(1) AND F12(1) =>D(1)	0.894507	F1(1) AND F8(1) AND F12(1) =>D(1)	0.904378

III. D. Association Rule Test and Attribute Importance

After obtaining the correlation rules between the enterprise's market forecasting ability and the accuracy of strategic decision-making, the test set samples are tested to check the reliability of the rules. Firstly, the test set samples are discretized according to the breakpoints of data discretization in the training set samples, and then the test set samples are tested using the generated rule base, and the rule classification results are shown in Table 9. The classification accuracy of the samples with decision attribute 0 is 71.11%, the classification accuracy of the samples with decision attribute 1 is 93.16%, and the overall classification accuracy is 84.20%. From the results, it can be seen that the ACO-MPSO algorithm possesses good persuasive power on the ability to mine rules associated with the enterprise market forecasting ability and strategic decision accuracy, and these rules can help enterprise decision makers to make more informed decisions in different scenarios.

Table 9: Rule classification results

Result		Predict		Accuracy rate
	Decision attribute	0	1	
Actual	0	128	52	0.711111
	1	18	245	0.931558
Accuracy rate		0.876712	0.824916	0.841986

Calculating the total number of times each conditional attribute appears in the association rule of market forecasting ability and high strategic decision-making accuracy can reflect the importance of the attribute, and the more times, the greater the promotion effect for high strategic decision-making accuracy. The results of the importance ranking of each conditional attribute are shown in Table 10. It can be seen that, among the rules for market forecasting to promote high strategic decision-making accuracy in the sample enterprises, policy sensitivity has the greatest impact, followed by data accuracy indicator, resource endowment satisfaction indicator is located in the 3rd place, and technology iteration matching indicator, which represents the company's innovation ability, is located in the 4th place.

Table 10: The ranking results of the importance of each conditional attribute

Attribute	Variable name	The sum of supporting numbers	Importance ranking
F2	Data integrity	168	15
F3	Data accuracy	578	2
F4	Information integration	187	11
F5	External intelligence coverage	342	10
F6	Process normalization	389	6
F7	Multisectoral participation	187	11
F8	Risk assessment coverage	369	9
F9	Decision time efficiency	388	7
F10	Accuracy rate of market trend prediction	377	8
F12	Policy sensitivity	915	1
F13	Technical iteration matching degree	549	4
F14	Satisfaction degree of resource endowment	567	3
F17	Organizational flexibility	396	5
F21	Team decision-making proportion	178	13
F22	Clarity of strategic decomposition	168	15
F24	Feedback mechanism response speed	176	14

IV. Conclusion

The market forecasting ability of enterprises has a significant positive influence on the accuracy of strategic decision-making. When an enterprise has strong market forecasting ability, its probability of obtaining high strategic decision accuracy is 90.4% on average, which is about 3.2 percentage points higher than that of enterprises with weak market forecasting ability. Among the factors affecting strategic decision precision, policy sensitivity is the most important, with a total support of 915 in the association rule, much higher than other factors; data accuracy and resource endowment fulfillment rank second and third with 578 and 567 support, respectively, and technology iteration matching ranks fourth with 549 support. This suggests that in addition to strengthening market prediction capability, enterprises should focus on perceiving policy trends, guaranteeing data quality, optimizing resource allocation, and improving technological innovation capability when improving the accuracy of strategic decision-making.The ACO-MPSO algorithm performs well in association rule mining, and it only takes 47.85 seconds to complete the mining task under the scale of 1000 datasets, which is about 1.5 times more efficient than the traditional Apriori algorithm. The efficiency of Apriori algorithm is improved by about 50%, which provides an efficient tool for enterprises to analyze large-scale data. This study provides empirical support and methodological guidance for enterprises to optimize their decision-making system and improve the effect of strategy execution.

References

[1] Panetto, H., Zdravkovic, M., Jardim-Goncalves, R., Romero, D., Cecil, J., & Mezgár, I. (2016). New perspectives for the future interoperable enterprise systems. Computers in industry, 79, 47-63.

[2] Arefieva, O. V., Miahkykh, I. M., & Shkoda, M. S. (2019). Diagnostics of external environment effects upon enterprise competitive positions in the context of its economic security. Bulletin of the Kyiv National University of Technologies and Design. Series: Economic sciences, 135(3), 8-17.

[3] Medina Munro, M., & Belanger, C. (2017). Analyzing external environment factors affecting social enterprise development. Social Enterprise Journal, 13(1), 38-52.

[4] Du, J., Peng, S., Song, W., & Peng, J. (2020). Relationship between enterprise technological diversification and technology innovation performance: Moderating role of internal resources and external environment dynamics. Transformations in Business & Economics, 19(2).

[5] Wu, Y. (2024, March). A Predictive Model for Enterprise Development Capability Based on Deep Learning. In 2024 International Conference on Distributed Computing and Optimization Techniques (ICDCOT) (pp. 1-6). IEEE.

[6] Khudyakova, T., Zhuravlyov, V., Varkova, N., Aliukov, S., Shmidt, S., & Zhuravlyov, N. (2020). Improving approaches to strategic enterprise management in the context of sustainable development. Sustainability, 12(20), 8375.

[7] Derevyanko, B., Rozhenko, O., Khailova, T., Hrudnytskyi, V., & Podskrebko, O. (2021). Strategic enterprise management based on the modeling of its economic security. Available at SSRN 3927356.

[8] Khrystyna, Z., Kateryna, P., Olha, M., & Olena, D. (2021). Strategic management of the innovative activity of the enterprise. Journal of Optimization in Industrial Engineering, 14(Special Issue), 95-103.

[9] Lorenzo, O., Kawalek, P., & Ramdani, B. (2012). Enterprise applications diffusion within organizations: A social learning perspective. Information & Management, 49(1), 47-57.

[10] Olfat, M., Ahmadi, S., Shokouhyar, S., & Bazeli, S. (2022). Linking organizational members' social-related use of enterprise social media (ESM) to their fashion behaviors: the social learning and stimulus-organism-response theories. Corporate Communications: An International Journal, 27(1), 91-109.

[11] Kniazieva, T., Kolbushkin, Y., & Smerichevskiy, S. (2017). Method of strategic planning and management decision-making considering the life cycle theory. Baltic Journal of Economic Studies, 3(5), 175-182.

[12] Papulova, Z., & Gazova, A. (2016). Role of strategic analysis in strategic decision-making. Procedia Economics and Finance, 39, 571-579.

[13] Camuffo, A., Gambardella, A., & Pignataro, A. (2024). Theory-driven strategic management decisions. Strategy science, 9(4), 382-396.

[14] Negulescu, O. H. (2014). Using a decision-making process model in strategic management. Review of General Management, 19(1), 111-123.

[15] Trigeorgis, L., & Reuer, J. J. (2017). Real options theory in strategic management. Strategic management journal, 38(1), 42-63.

[16] Laureiro‐Martínez, D., & Brusoni, S. (2018). Cognitive flexibility and adaptive decision‐making: Evidence from a laboratory study of expert decision makers. Strategic Management Journal, 39(4), 1031-1058.

[17] Fourné, S. P., Guessow, D., Margolin, M., & Schäffer, U. (2023). Controllers and strategic decision-making: The role of cognitive flexibility in controller-manager collaboration. Management accounting research, 60, 100840.

[18] Nerusupalli Dinesh Kumar Reddy, Diksha, Ashok Kumar Gupta & Anil Kumar Sahu. (2025). Improving soil liquefaction prediction: A sophisticated ensemble classifier utilizing enhanced correlation features and a metaheuristic ant colony optimization approach. Engineering Geology,351,108036-108036.

[19] Qinhao Gao, Giorgio Monti, Zhiwang Chang,Zhi Li & Fabrizio Mollaioli. (2025). An efficient method for simulating uni- and bi- directional spectrum-compatible ground motions using particle swarm optimization. Soil Dynamics and Earthquake Engineering,195,109399-109399.

[20] You Fu, Fang Ren & Jiantao Lin. (2025). Apriori algorithm based prediction of students' mental health risks in the context of artificial intelligence. Frontiers in Public Health,13,1533934-1533934.

[21] Praveen Kumar B., Padmavathy T.,Muthunagai S.U. & Paulraj D.. (2024). An optimized fuzzy based FP-growth algorithm for mining temporal data. Journal of Intelligent & Fuzzy Systems,46(1),41-51.