Comprehensive Evaluation of Government Economic Management Performance Based on Multidimensional Data Mining

Yan Li[1*]
[1*] lecturer, College of Foreign Languages, Shanghai Jian Qiao University, Shanghai, China. Email: yanlisjqu@163.com

Abstract: Government economic management is a comprehensive discipline that consists of several disciplines, including political science, economic management, and economics. It also incorporates law, social ethics, and other elements. A government accountable to the people must ensure that its public economic management has high efficiency in resource allocation and resource utilization, i.e., it must ensure the supply of necessary variety, quantity and quality of public goods on the one hand, and minimize the occupation and consumption of resources on the other. Starting from different projects of government economic management, this paper proposes five levels of performance evaluation dimensions, namely, stakeholder satisfaction dimension, stakeholder contribution dimension, financial dimension, business process dimension and learning growth dimension, based on a comprehensive evaluation method and around internal performance management objectives. Through multi-dimensional data collection, decomposition of data objectives, analysis of key success factors, and according to the index design principles, in order to improve the scientific and rational index design, the comprehensive evaluation model is finally established, which makes a useful exploration for economic management performance evaluation.

Keywords: Data Mining, Data Processing, Government Economic Management, Performance Evaluation.

Introduction

The evaluation and audit of performance target implementation results is not only a process of verifying, accepting and confirming the performance responsibility targets of public economic management subjects at all levels during the planning period, but also a process of summarizing and analyzing the results of the performance responsibility targets accomplished by public economic management subjects at all levels. At the same time, it is also the basis for using evaluation results and implementing rewards and incentives.

The evaluation of the results of achieving performance goals usually consists of two parts: internal self-evaluation of public economic implementation agencies and evaluation by external evaluation agencies, the conclusions of which are based on the results of external evaluation. On this basis, the comprehensive authority of the public economy implementing body [1] (e.g. government planning or finance department) organizes forces or commissions third-party agencies to reevaluate the performance goals of the general public sector and makes a comprehensive evaluation report including performance, questions and recommendations to the government. External evaluation and auditing organizations specifically authorized by law or by the authorities verify, with the help of relevant information, the accomplishment of the performance objectives of the target group during the plan period by comparing the "5E" objectives [2] and their evaluation indicators, and make objective and realistic audit assessments, and make targeted recommendations on the experience gained and the problems that exist, and submit them to the competent authorities for It will be submitted to the competent authorities for consideration and announced to the society as the basic basis for the application of performance evaluation results and the realization of rewards and punishments.

The government public sector performance responsibility adopts a mixed evaluation model combining internal and external evaluation, mainly to give full play to the respective advantages of internal and external evaluation at the same time. The internal performance evaluation implemented by public sector and unit organizations includes two levels: institutional performance goal evaluation and individual job performance evaluation of civil servants [3]. The former is conducive to institutions and organizations to continuously improve their performance management level by self-summarizing and analyzing their performance management experience and identifying shortcomings, while the latter is an indispensable way for institutions and organizations to perform their performance-oriented incentive function.

For the external evaluation of the results of public sector performance objectives, a single-entity model or a two-entity model can be implemented, which should be complemented by the participation mechanisms of the press, NGOs and the public. The single-subject model refers to the fact that the public audit department is only the subject of external evaluation of the performance goals undertaken by the responsible subject. The so-called two -subject model refers to the public audit department and the government's comprehensive finance department as the subjects of external evaluation of the performance goals undertaken by the responsible subject. Both models have advantages and disadvantages. The single-discipline model has the advantage of saving evaluation costs, but it also has two disadvantages. First, it is difficult to ensure the objectivity of evaluation conclusions due to the lack of mutual confirmation. Second, the performance evaluation report given by the auditing department through performance audits generally only publicly reflects the performance results and problems that exist.

Because of this, developed countries attach great importance to the construction of performance pay and job incentive mechanisms for civil servants. As early as the middle of the 19th century, Britain established a civil service appraisal system centered on performance and talent through continuous civil service system reform, and decided to reward and promote civil servants based on individual and itemized appraisal results. 1887, the United States formally established a civil service appraisal system [4]. The appointment, salary increase and promotion of civil servants are based on the results of job evaluation and performance rewards, which is called the performance appraisal system. since the 1980s and 1990s, in the New Public Management movement pioneered in Europe and America, both the UK and the US have attached great importance to the close connection between incentive and accountability mechanisms and performance appraisal results. The application of performance appraisal results is mainly in two directions: first, performance pay or performance bonuses are determined and paid to individual civil servants based on the appraisal results; second, the appraisal results are integrated with departmental budgets, and budgetary resources are allocated based on the performance appraisal results of departments and programs [5]. Among them, the U.S. performance management and recognition system established in 1984 required each federal government agency to classify the final assessment results into five levels and to link the performance assessment levels to civil service bonuses. It was not until later that it was further reflected in the performance-based allocation of budgetary funds [6]. Together, these six elements of public economic performance management form a complete system framework (as show in Figure 1).

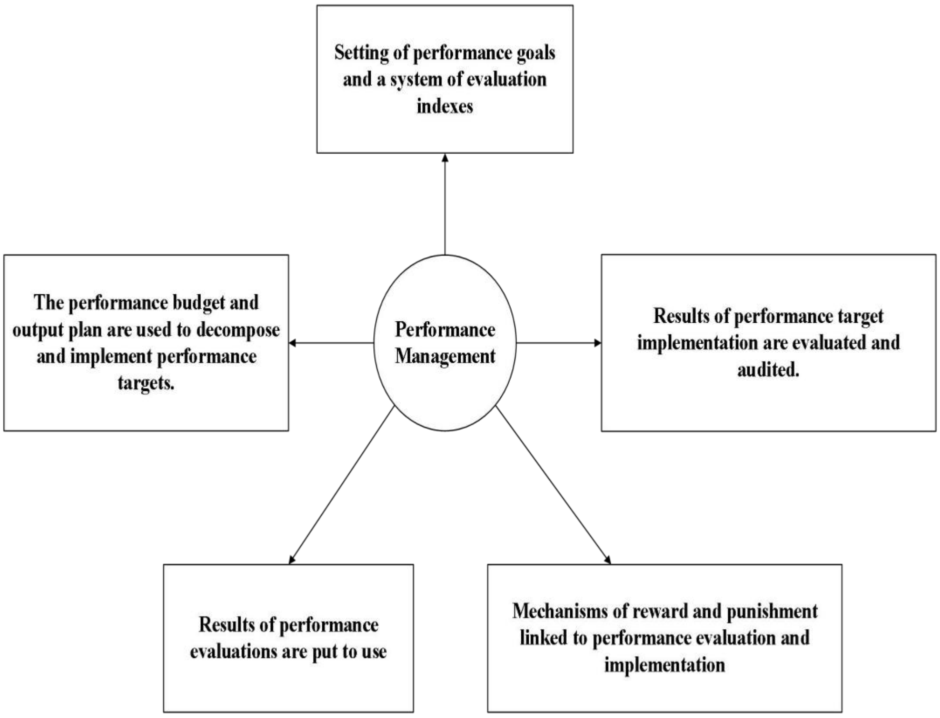

Figure 1. Diagram of Government Economic Performance Management System

As shown in the Figure 1, it is precisely the schematic diagram of the public economic performance management system

Therefore, based on multidimensional data mining, this paper first establishes the evaluation objectives of the public performance management system, based on which the performance evaluation reports given by the auditing department are collected, the incentive mechanism behind them is unearthed, and the performance incentive objectives are successfully explored, and the contributions of this paper are as follows.

Using and modifying the evaluation objectives of the government public economic performance management system, an evaluation system based on multidimensional data mining is established.

The hierarchical analysis method and fuzzy comprehensive evaluation method are elaborated, and then a comprehensive evaluation of economic management performance is conducted.

Through the construction of the evaluation model and the analysis of the comprehensive evaluation results, we illustrate the scientific and practicality of the research content of this paper, and propose policy recommendations for the existing problems.

Related Work

Problems in Performance Evaluation

There is No Unified Scientific Policy Specification

Public economic performance evaluation is mostly compelled by the requirements of higher governments or comprehensive financial departments, and reform and innovation experiments are mainly conducted by local governments spontaneously and semi-spontaneously [6]. The lack of unified policies, regulations and systems at the national level has led to the lack of clear standards, standardized procedures and scientific index systems for evaluation work, which is mostly "campaign" and "surprise" evaluation, with insufficient continuity, experience exchange and promotion. This has seriously restricted the breadth of evaluation work, the depth and intensity of performance assessment.

The Evaluation Index System is Unreasonably Set

China's current public economic performance evaluation index system has at least three problems: First, it lacks overall unity, and the quality of the evaluation index system varies. Second, the direction is biased. Some political and economic task indicators tend to ignore the actual effect of public services and the efficiency of using funds, leading to the wrong direction of work in various departments. Third, lack of objectivity [7]. Many performance evaluation indicators are set up or simply copy the indicator systems of other regions, or blindly pursue digital catch-up, which is seriously detached from the reality of regions and departments. This evaluation index system seriously restricts performance evaluation and performance audit.

The Main Body of Performance Evaluation is Hesitant and Confused

In China, government performance evaluation with the party committee, the National People's Congress, the government, enterprises, the public, scholars and third-party professional evaluation agencies as the main body has been practiced. Experience shows that the government, as the assessment subject, is influenced by power standards; citizens, as the assessment subject, are influenced by group value preferences; enterprises, as the assessment subject, are influenced by market value orientations; and third parties, as the assessment subject, are influenced by the value orientation of "customer first" [8]. Taking the government and the public as the two poles of evaluation subjects, the government knows its own operation mechanism best. However, due to organizational structure, personnel relations and performance considerations, it tends to take advantage of information asymmetry to overestimate its own administrative effects; public participation is the choice of evaluation subjects advocated by some scholars. However, the vast majority of citizens do not have the opportunity to experience first-hand the efficiency of special public services and management within the government, and only a very small number of citizens can accurately grasp the nature of public services. Especially, in the absence of a frame of reference, the determination of citizens' satisfaction is a big problem, and it is difficult to get rid of the randomness of satisfaction evaluation with limited practical effect [9]. It can be seen that it is undesirable to adopt public views in isolation.

The Value Orientation of Performance Evaluation is Biased

Performance evaluation should guide the public economic sector to meet the public needs of the people and improve public satisfaction with public services. However, at present, the main body of performance evaluation of public economic sectors is mostly the superior department, so the inertia of evaluating the performance of public economic sectors by "economic indicators" has been formed [10], while providing diversified public services and improving market rules are neglected, resulting in the lack of public services.

Evaluation of Economic Management Performance

Western scholars have been thinking about how to evaluate economic management performance since the early 20th century.

Yun [11] argues that it is necessary to evaluate management performance. The internal audit department must explain and demonstrate to management its value-added and contribution to improving organizational operations. Otherwise, the internal audit function is likely to be categorized by the organization's management as a consumer of organizational resources rather than a creator of organizational value. Khajavi [12] notes that audit committees play an important role in evaluating internal audit performance. Internal audit would play a greater role if the audit committee assessed the performance of internal audit. Schneider argues that the audit committee is responsible for assessing the performance of internal audit and examines and analyzes the shortcomings of the audit committee in the implementation of the assessment. The results of the study show that the audit committee charter usually does not have clear requirements for the evaluation of internal audit performance, and the audit committee's review of the internal audit function is not sufficient to measure internal audit performance. William [13] recommends improving and increasing the productivity of internal audit and advocates a performance appraisal system that includes an incentive, reward and punishment system. It includes a good incentive and punishment mechanism, scientific performance evaluation standards, objectively evaluated audit objectives and a reasonable index system. The performance evaluation indexes constructed by the author include cost effectiveness rate, audit finding unit cost, audit recommendation adoption rate, auditor turnover rate, operational audit rate, audit fee rate, audit technology progress rate, and audit value satisfaction.

Congress [14] believes that management performance should be evaluated in at least six areas: efficiency, effectiveness, quality, productivity, quality of work life, and innovation. According to the executive director of internal audit. Tone [15] identified the most useful performance indicators from the internal audit department performance indicators aggregated by the global audit information network, which can be classified into three categories based on their relevance to the internal auditor, the internal audit client, and the internal audit process. Ma [16] attempted to use the balanced scorecard to identify the key indicators that affect internal audit performance and demonstrated that using the balanced scorecard to evaluate the feasibility of internal audit performance. Also, through the study, it is noted that internal audit departments have used the balanced scorecard to explore and measure the key factors of internal audit success. Zhang [17] designed an internal audit performance assessment framework based on three principles: simplicity, practicality, and flexibility. Output, scope, and quality are performance factors, client satisfaction, number of audit plans completed, and compliance with standards are key aspects of performance evaluation, the audit charter is the basis and standard for performance, and random evaluation indicators are generated by the department, industry, or organization. To ensure that the internal audit performance evaluation framework can evolve as the audit organization evolves. However, this is a theoretical construct and does not indicate how the assessment framework works in practice.

Manny Rosenfeld devised the Best Management Performance Model as a framework for assessing internal audit performance. The model reflects progressive levels of performance and includes four stages: lagging, professional, advanced, and world-class. Of course, as new audit practices and emerging tools emerge, the Best Audit Department Model will need to be refined and developed.

Method

Multidimensional data exists mainly in the form of relational tables. Each data is considered as a row of data in the table. There are multiple attributes in the relational table, represented by columns, each column representing one attribute. By considering each attribute as a variable, the relational database becomes a multivariate database. Multidimensional data visualization treats each variable as a value of a one-dimensional variable in a multidimensional space, i.e., the attribute value of the data represents the coordinates of the data in that dimension. The data in the database are mapped to points in the multi-dimensional space. These points are also called multidimensional vectors. The vector coordinates are determined by the attribute values, so the distribution space of the data can be considered as a multidimensional space. The purpose of multidimensional data mining is to reproduce these multidimensional vectors in a two-dimensional or three-dimensional visual space and reflect their attributes in the multidimensional space, thus helping users to find patterns and information that are difficult to find in relational data tables.

The Guo [18] algorithm is a new algorithm for mining the maximum set of frequent items from transactional databases. The algorithm's search strategy combines depth-first traversal of item-set with an efficient pruning mechanism, and uses bitmaps for frequent item-set mining. The performance of the algorithm has been significantly improved [19]. K-means is a division-based classification algorithm that uses parameters to divide objects into groups; making the similarity between groups as high as possible and the similarity between groups as low as possible. Calculate the mean value of group based objects, i.e., the center of mass of the group. Calculates the mean value of the group based objects, i.e. the center of mass of the group. It is mainly used for processing numerical data. The DBSCAN algorithm is a density-based clustering algorithm [20], which is criticized for its slow convergence, sensitivity to noise and outliers, and its ability to guarantee only local optima. The DBSCAN algorithm is a density-based clustering algorithm [20], which introduces the concepts of "core objects" and "density reachability" and clusters data using spatial indexing techniques. It introduces the concepts of "core objects" and "density reachable", and uses spatial indexing techniques to search the neighborhoods of objects to form clusters of all density reachable objects. The algorithm can identify noise points and form clusters of arbitrary shape without knowing the number of clusters to be formed in advance. The disadvantage of this algorithm is that it does not reflect high-dimensional data well and clustering is only applicable to numerical data.

Selection and Optimization of Performance Management Data

Integrated performance data is the core of comprehensive performance assessment. It records various specific values about human resources. It essentially reflects the business status and productivity of the enterprise. However, since there are hundreds of features in the government economic management performance dataset, this paper chooses to analyze and mine these features using the Mafia algorithm in correlation analysis to identify features that are closely related to government economic management [21].

Definition 1: The standard set of performance management data is $R = (a_1, a_2, ..., a_n)$, a_i is the design value of the i eigenvalue, the upper float value is u_i , the lower float value is l_i , and n is the total number of dimensions of the engine vibration fault data.

Definition 2: The performance management data set is $D = (r_1, r_2, ..., r_n)$, where $r_i = (x_1, x_2, ..., x_n)$, denotes the first N performance management data records and x_i denotes the actual value.

In order to reflect the difference between the actual and standard data, this paper proposes a method to calculate the difference between the actual and standard values and the degree of variation of the design float, as defined below.

Definition 3: Discrete value of the degree of variation

$$t = \begin{cases} 0, & 0 \le \alpha \le 0.1 \\ 1, & 0.1 \le \alpha \le 0.3 \\ 2, & 0.3 \le \alpha \le 0.6 \\ 3, & 0.6 \le \alpha \le 1.0 \\ 4, & -0.1 \le \alpha \le 0 \\ 5, & -0.3 \le \alpha \le -0.1 \\ 6, & -0.6 \le \alpha \le -0.3 \\ 7, & -1.0 \le \alpha \le -0.6 \end{cases} \quad (1)$$

If $x - a \ge 0, \quad \alpha = \frac{x-a}{u}$

Else $x - a < 0, \quad \alpha = \frac{x-a}{l}$

Definition 4: Candidate set tree: The frequent item set mining strategy in the MAFIA algorithm uses depth-first search to complete the process of generating a candidate set, and represents the process as a candidate set tree, as shown in Figure 2 [22].

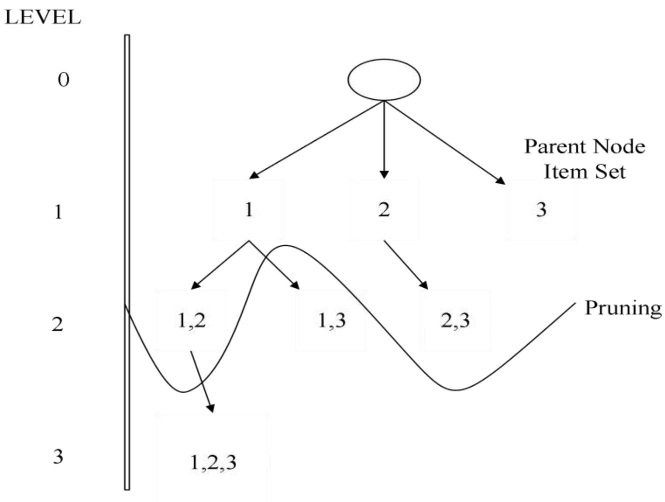

Figure 2. Option Set Tree

Each step of generating the tree expands a single item into a multi-item set. As more and more items are added to the item-set, the corresponding confidence level will become smaller and smaller. Eventually, the support will be lower than the minimum support for frequent item sets. Vertical bitmap representation Mafia stores the data as a series of vertical bitmaps, as shown in Figure 3.

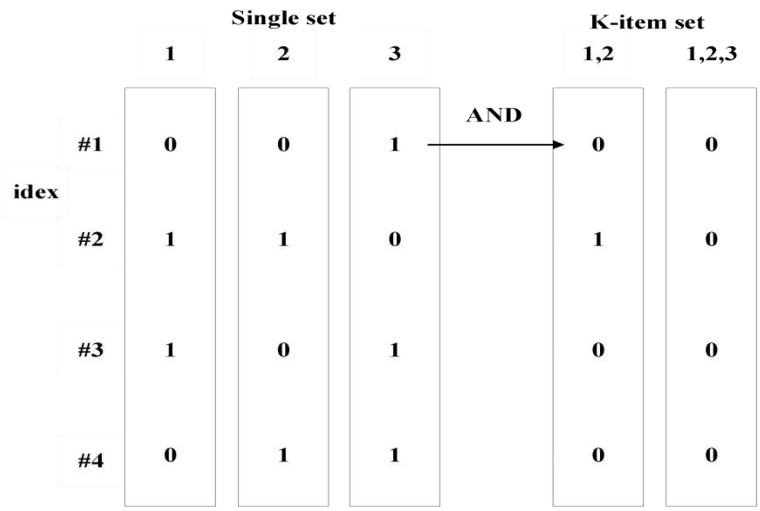

Figure 3. Vertical Bitmap

Each bitmap represents an item-set, and the bits in each bitmap indicate whether there is a pair of item-sets in the data set. Initially, each bitmap corresponds to one item-set. In order to calculate the frequency of a single item-set or multiple item-sets, a "sum" operation between bitmaps can be used.

The procedure for calculating the set of frequent items in the economic management performance data using the Mafia algorithm is as follows [23].

(1) Calculate the set of discrete values of the degree of change of each performance data according to Definition 3, as shown in Table 1 below.

Table 1. The Set of Discrete Values

Idex	Feature 1	Feature 2	Feature 3	…	Feature n
#1	0	5	7	…	3
#2	2	2	2	….	5
…	…	…	…	…	…
#n	3	6	1	…	0

(2) Group the columns of the set of discrete values of the degree of change in numerical order and uniquely determine the same number in each column.

(3) Using the frequent item set mining method represented by the post-selection tree and vertical bitmap in the mafia algorithm, the minimum support degree min-support is set to obtain the frequent item set from the discrete variable value set, i.e., the feature data set f that is most closely related to the economic management performance.

Application of Clustering Algorithm

The government economic management performance dataset contains a large amount of feature information. We propose a two-layer clustering method based on DBSCAN and k-means using the idea of clustering. The method uses the two-level aggregation of DBSCAN and the k-means algorithm. The DBSCAN algorithm is used to perform initial clustering of users, remove outliers, and obtain a series of irregular clusters. These irregular clusters are then clustered bottom-up using the k-means algorithm until the desired clustering results are achieved.

DBSCAN Algorithm

The DBSCAN algorithm is a spatial data clustering method based on high connection density.

Before introducing the algorithm, the following definitions need to be understood first [24].

Definition 1 (E Neighborhood) for a given object; a spatial region of radius 6 centered at 7.

Definition 2 (Core Object) An object is said to be a core object if its E neighborhood contains at least a minimum number of MINPTS objects.

Definition 3 (boundary object) If an object's E neighborhood contains less than the number of MINPTS objects, and within the E neighborhood of the core object, the object is said to be a boundary object.

Definition 4 (Noise object) an object is said to be a noise object if it is neither a core object nor a boundary object.

Definition 5 (direct density reachable) For a set D of objects, an object p is said to be directly density reachable with respect to e and MINPTS from object q if p is within the E neighborhood of the core object q and q is a core object

Definition 6 (density reachable) If there exists a chain of objects P_1, P_2 , ..., P_n, $P_i \in D$, Q that is directly density reachable from object P1 about e and MINPTS, then object PN is density reachable from object P1 about e and MINPTS.

Definition 7 (Density connected) If there exists an object O in the set D of objects such that the object P and Q points are density reachable about e and MINPTS, then for P and Q about e and MINPTS are density connected.

The core idea of the algorithm is that for each object in the cluster, the number of data objects in the neighborhood of a given radius e must be no less than the threshold MINPTS, i.e., the neighborhood density must be no less than MINPTS, ensuring that the in-class density is much higher than the out-of-class density, and noisy objects that do not satisfy this condition will be discarded. This method defines the class as the largest set of objects connected by density, so it can exclude noisy objects and find irregularly shaped clusters, and its accuracy is related to the choice of two parameters, e and MINPTS.

Algorithm Description

(Input 1) F: dataset of government economic management performance characteristics. 2) E: neighborhood radius. 3) MINPTSE the minimum number of objects contained in the neighborhood at least.

Output preliminary clustering set T.

(1) Select a non-noise or boundary object in the economic management performance feature dataset F; 7. Execute (2) if p is a non-core object; execute (3) if the corpse is a core object.

(2) Mark p as a noisy or boundary object.

(3) Finding all density-connected data objects from this core object, grouping these objects into one class and deleting them from F, and writing these points to the set T.

(4) If there are still unscanned data points in F, repeat (1) ~ (3), and output the set T if it does not exist.

K-Means Clustering Algorithm

Algorithm description.

(Input l) / T: number of clusters.

2) T: the initial set of clusters formed by DBScan T '

The output is the set of data clustered into k class wide.

(1) Based on r, the set $M\{m_1, m_2, \ldots, m_h\}$ of prime centers of clusters is calculated

(2) Randomly select k eigenvectors $x_1, x_2, \ldots, x_k \in M$ from the middle M as the initial

clustering centers.

(3) Calculate the distance from the n-dimensional center of mass M to each initial cluster center using the normalized Euclidean distance [25] $d(i,j)=\sqrt{\sum_{t=1}^{n}\left(\frac{m_{it}-x_{jt}}{s_t}\right)^2}$ and cluster the center of mass to the cluster nearest to that point

(4) Calculate the average coordinates of all points in each cluster, and use this average as the new cluster center $x_j=\frac{\sum_{i=1}^{m}1(c_i=j)m_i}{\sum_{i=1}^{m}1(c_i=j)}$ [26].

(5) Perform (3) and (4) repeatedly until the cluster centers no longer move widely to satisfy the convergence criterion function $J(c,x)=\sum_{i=1}^{m}\left\|m_i-x_{c_i}\right\|^2$

Overall Algorithm Process

The overall process of the method is divided into two main stages:

1) DBSCAN initial clustering stage: the pre-selected engine fault feature dataset is input into the DBSCAN algorithm for initial clustering, and the values of radius e and MINPTS are repeatedly adjusted so that there are a considerable number of clusters in the clustering results;

2) On the basis of the clustering results obtained in stage 1, the point with the smallest distance to each point in each column is identified and the point with the smallest sum, and form a new data set. The new distance matrix

is clustered using the k-means algorithm, and the clusters obtained in the first stage are combined into a new cluster set.

Normalization

In order to avoid affecting the analysis results of the data due to the different scales and scale units of multi-feature clustering, this paper uses data normalization to solve the problem between data indicators. The normalization process is to solve the comparability between data indicators so that the resultant values are mapped to [0, 1].

Analysis of the Algorithm

In this algorithm, the average time complexity of DBSCAN is 0 (nl0gn) and the space complexity is O (n ^ 2). The time complexity of the computational set M is O (n ^ 2). K-means has a time complexity of 0 (n*k*t), and t is the number of iterations. Due to the initial clustering of DBSCAN and the computation of set M, the number of bases for k-means clustering is effectively reduced, which speeds up the convergence of k-means, improves the overall efficiency of the algorithm, and avoids the influence of outliers on the convergence of the algorithm [27].

Experimental and Analysis

Datasets and Evaluation Indicators

Data Collection.

Performance data were collected from 600 employees at all levels of government to analyze the characteristics of performance management. The performance data are shown in Table 2.

Table 2. Performance Data

Evaluation indicators	Secondary indicators	#1001 score	#1002 score	#1003 score	…	#1599 score	#1600 score
Stakeholder Satisfaction Dimension	T1	1	1	3	…	2	3
	T2	2	1	5	…	4	3
	T3	3	4	2	…	3	1
	T4	3	3	2	…	2	4
Stakeholder Contribution Dimension	T5	1	1	4	…	1	4
	T6	2	2	3	…	2	1
	T7	4	4	3	…	2	1
Financial Dimension	T8	5	4	3	…	2	3
	T9	2	4	1	…	3	2
	T10	3	3	1	…	2	2
Business Process Dimension	T11	3	2	4	…	3	1
	T12	1	2	3	…	4	2
	T13	4	4	1	…	2	1
Learning and Growth Dimension	T14	2	4	1	…	2	3
	T15	1	3	4	…	1	2
	T16	1	1	5	…	1	2
Overall Rating	T17	92.77	84.29	90.38	…	83.61	92.60

Evaluation Indicators

In this paper, we propose five levels of performance evaluation dimensions, namely, stakeholder satisfaction dimension, stakeholder contribution dimension, financial dimension, business process dimension, and learning and growth dimension. As shown in Table 2, our evaluation indicators are presented. Our evaluation indicators are divided into "very satisfied", "satisfied", "basically satisfied", "dissatisfied" and "Very dissatisfied" five levels.

The experiments include 32 dimensions of size and stage, and the frequent item-sets are mined for 100, 300, 600 data respectively, and the mining results are shown in Table 3.

Table 3 Frequent Item-Set Mining

	Group 1	Group 2	Group 3
Sample size	100	300	600
Support	0.1	0.1	0.05
Maximum set of frequent items	(94),(284),(168),(96, 76)	(94),(96,76),(168), (284)	(96,76),(132),(168), (94)

Clustering Results

Based on the above data and analysis, it was determined that one item set (168) and two item sets (96, 76) were used as performance characteristics for clustering the performance data. The same 400 items of data were used for clustering. The experiment was divided into three groups with 100, 300, 600 records. Assuming that the clustering results in four categories, the number of engines in each category can be obtained according to the methodology of this paper, as shown in Tables 4 and 5.

Table 4 Single Set DB

Type	Group 1	Group 2	Group 3
1	35	66	90
2	21	65	42
3	20	59	112
4	34	21	97

Table 5 Binomial Set DB

Type	Group 1	Group 2	Group 3
1	34	63	96
2	20	57	121
3	43	55	135
4	54	45	89

Comparison of Clustering Methods

K-means, DBSCAN algorithm, k-means algorithm with improved centroids and the algorithm in this paper were used to cluster the above three sets of data using the same features: (168) and (96, 76), respectively, and their DB results are shown in Tables 6 and 7 [28].

Table 6. Single Set Clustering Resultsfeatures: (168)

Clustering Method	Group 1	Group 2	Group 3
K-means	0.658	0.671	0.702
DBSCAN	0.641	0.648	0.663
Improved K-means algorithm	0.612	0.628	0.636
Ours Method	0.556	0.571	0.584

Table 7. Single Set Clustering Results features (96, 76)

Clustering Method	Group 1	Group 2	Group 3
K-means	0.642	0.647	0.675
DBSCAN	0.594	0.625	0.646
Improved K-means algorithm	0.578	0.616	0.6
Ours Method	0.526	0.523	0.555

By analyzing the above two tables, the method in this paper outperforms the K-means and DBSCAN algorithms in the clustering effect of both monomial set and binomial set, and the effect of K-means algorithm with improved centroid is similar to the algorithm in this paper at 100 data. At 100 data, the effect of the improved centroid K-means algorithm is similar to that of the algorithm in this paper, but as the amount of data increases, the clustering effect of the improved centroid K-means gradually becomes worse due to the diversification of engine fault feature patterns. The method in this paper can guarantee a good effect when dealing with engine vibration fault data because of the denoising of the data.

From the comparison of Tables 6 and 7, it can be seen that the clustering effect when using one item set (168), features is not as effective as that when using the binomial set (96, 76), combined features, indicating that the performance assessment is more closely related.

Grading Results

In this paper, the Euclidean distance d from the farthest boundary point to the standard design value of the four clusters obtained by classifying 600 data is used as the grading criteria of the data, and the specific grading is shown in Table 8.

Table 8. Grading Results

Type	Group	d	level
0	90	0.003~0.004	Good
1	42	0.005~0.006	Pass
2	112	0.004~0.005	Excellent
3	97	0~0.002	Moderate

In this paper, the Euclidean distance d from the farthest boundary point to the standard design value of the four clusters obtained by classifying 600 data is used as the grading criteria of the data, and the specific grading is shown in Table 8.

According to the above conclusions, when a new set of engine assembly data is available, only the Euclidean distance from its fault characteristic value, i.e., binomial set (96, 76), to the standard value is calculated to provide a reference basis for economic performance management.

Conclusion

To address the problems of government economic management performance, on the basis of absorbing the advantages of the traditional economic management performance evaluation index system, the multidimensional data mining method is introduced into the big data research, and the evaluation objectives of the government public economic performance management system are used and modified to build a scientific, effective and operable government economic management performance evaluation index system, and the data are used for implementation and verification. The purpose of constructing evaluation indexes in this paper is to evaluate government economic management performance. However, performance evaluation is not only to get the final evaluation score, but also not limited to the analysis of "results", but to use the results to find ways to improve performance. If the evaluation results are different from the expected value, it is more necessary to analyze the causes of the problems and then make corresponding adjustments and improvements in order to promote the improvement of internal audit performance. Therefore, how to use the results of internal audit performance evaluation deserves further study.

Conflict of Interest

The authors declare that they have no conflicts of interest regarding this work.

References

[1] Jing, Y.; Zuo, L.; Peng, W., "Spatial-temporal change analysis of carbon emission from land use in Mianyang: The case study of Mianyang," Environ. Sci. Technol., vol. 44, no. 1, pp. 172-185, 2021.

[2] Han, Y.; Liu, Y.; Chen, Y.; Wang, Y.; Zhang, Z.; Chen, H.; Tan, Y., "Spatiotemporal evolution of land ecological risk in Wuhan from the perspective of carbon emission," Res. Soil Water Conserv., vol. 31, no. 2, pp. 331-341, 2024.

[3] Wei, J.; Mei, Z.; Ma, J.; Wang, X., "Spatiotemporal evolution and influencing factors of land-use carbon emissions in Guangzhou," Res. Soil Water Conserv., vol. 31, no. 3, pp. 298-307, 2024.

[4] Han, F.; Gao, F.; He, B.; Cao, Y.; Yao, X., "Exploring the spatial and temporal trajectories of land use carbon emissions and influencing factors in the Aksu River Basin from 1990 to 2020," Environ. Sci., vol. 45, no. 7, pp. 3297-3307, 2024.

[5] Zhao, X.; Peng, J.; Hu, Y.; Zhang, Z., "Spatial-temporal pattern and influence factors of county carbon emissions in Hunan Province based on nightlight data," Ecol. Sci., vol. 41, no. 2, pp. 91-99, 2022.

[6] Luo, Y.; Chen, S.; Liu, W.; Wang, X.; Qi, A., "Analysis and prediction on the spatiotemporal evolution of carbon emissions from land use in Hebei province," Chin. J. Environ. Eng., vol. 11, no. 5, pp. 3360-3373, 2024.

[7] Kang, K.; Guo, P.; Chen, J., "Research on the measurement of carbon footprint pressure and its unevenness in Chinese cities: Characteristics of differences, polarization, and spatial agglomeration," Urban Probl., vol. 10, no. 1, pp. 4-16, 2022.

[8] Tzanis, N.; Andriopoulos, N.; Magklaras, A.; Mylonas, E.; Birbas, M.; Birbas, A., "A hybrid cyber physical digital twin approach for smart grid fault prediction," in Proc. 2020 IEEE Conf. Ind. Cyberphysical Syst. (ICPS), Tampere, Finland, 10–12 June 2020, pp. 393–397.

[9] Jiang, Y.; Ortmeyer, T.H., "Propagation-based network partitioning strategies for parallel power system restoration with variable renewable generation resources," IEEE Access, vol. 9, pp. 144965–144975, 2021. [CrossRef]

[10] Damjanovic-Behrendt, V., "A digital twin-based privacy enhancement mechanism for the automotive industry," in Proc. 2018 Int. Conf. Intell. Syst. (IS), Funchal, Portugal, 25–27 Sept. 2018, pp. 272–279.

[11] Yun, H.; Park, D., "Simulation of self-driving system by implementing digital twin with GTA5," in Proc. 2021 Int. Conf. Electron., Inf., Commun. (ICEIC), Jeju, Republic of Korea, 31 Jan.–3 Feb. 2021, pp. 1–2.

[12] Khajavi, S.H.; Motlagh, N.H.; Jaribion, A.; Werner, L.C.; Holmström, J., "Digital twin: Vision, benefits, boundaries, and creation for buildings," IEEE Access, vol. 7, pp. 147406–147419, 2019. [CrossRef]

[13] Hao, Q.; Xiaoyue, L.; Qiang, T.; Liang, L., "Research progress of mechanical process system driven by digital twin," Acta Aeronaut. Et Astronaut. Sin., vol. 45, no. 8, p. 628970, 2024.

[14] Congress, S.S.C.; Puppala, A.J., "Digital twinning approach for transportation infrastructure asset management using UAV data," in Proc. Int. Conf. Transp. Dev. 2021, Virtually, 8–10 June 2021, pp. 321–331.

[15] Tone, K., " A slack-based measure of efficiency in context-dependent data envelopment analysis," Eur. J. Oper. Res., vol. 130, no. 3, pp. 498–509, 2001.

[16] Ma, D.; Zhang, J.; An, B.; Guo, Z.; Zhang, F.; Yan, Y.; Peng, G., "Research on urban land green use efficiency and influencing factors based on DEA and ESTDA models: Taking 284 cities in China as an example," Ecol. Indic., vol. 160, p. 111824, 2024.

[17] Zhang, H.; Song, Y.; Zhang, M.; Duan, Y., "Land use efficiency and energy transition in Chinese cities: A cluster-frontier super-efficiency SBM-based analytical approach," Energy, vol. 2024, p. 132049, 2024.

[18] Guo, Y.; Tong, L.; Mei, L., "The effect of industrial agglomeration on green development efficiency in Northeast China since the revitalization," J. Clean. Prod., vol. 258, p. 120584, 2020.

[19] J. C. Bezdek, and N. R. Pal, "Some new indexes of cluster validity," *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)*, vol. 28, no. 3, pp. 301-315, 1998.

[20] Banker, R.D.; Charnes, A.; Cooper, W.W., "Some models for estimating technical and scale inefficiencies in data envelopment analysis," Manage. Sci., vol. 30, no. 9, pp. 1078–1092, 1984.

[21] Tone, K., " Dealing with undesirable outputs in DEA: A slacks-based measure (SBM) approach," DEA (1), North American Productivity Workshop: Arlington, VA, USA, 2004, pp. 44–45.

[22] He, S.; Yu, S.; Li, G.; Zhang, J., " Exploring the influence of urban form on land-use efficiency from a spatiotemporal heterogeneity perspective: Evidence from 336 Chinese cities," Land Use Policy, vol. 95, p. 104576, 2020.

[23] Liu, Y.; As'arry, A.; Hassan, M.K.; Hairuddin, A.A.; Mohamad, H., "Review of the grey wolf optimisation algorithm: Variants and applications," Neural Comput. Appl., vol. 36, pp. 2713–2735, 2024.

[24] Panda, S.; Samanta, I.S.; Rout, P.K.; Sahu, B.K.; Bajaj, M.; Blazek, V.; Prokop, L.; Misak, S., " Priority-based scheduling in residential energy management systems integrated with renewable sources using adaptive Salp swarm algorithm," Results Eng., vol. 23, p. 102643, 2024.

[25] Li, P.; Wang, Z.; Wang, J.; Yang, W.; Guo, T.; Yin, Y., "Two-stage optimal operation of integrated energy system considering multiple uncertainties and integrated demand response," Energy, vol. 225, p. 120256, 2021.

[26] Karthikeyan, M.; Manimegalai, D.; RajaGopal, K., "Power control of hybrid grid-connected renewable energy system using machine learning," Energy Rep., vol. 11, pp. 1079–1087, 2024.

[27] Suyono, H.; Hasanah, R.N.; Mudjirahardjo, P.; Purnomo, M.F.E.; Uliyani, S.; Musirin, I.; Awalin, L.J., "Enhancement of the power system distribution reliability using ant colony optimisation and simulated annealing methods," Indones. J. Electr. Eng. Comput. Sci., vol. 17, pp. 877–885, 2020.

[28]D. A. Pagels, "Aviation data mining," Scholarly Horizons: University of Minnesota, Morris Undergraduate Journal, vol. 2, no. 1, p. 3. 2015.