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Retraction

Retracted: Study on the Optimization of Macroeconomics Teaching Model Based on Cluster Analysis in the Context of Data

Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

References

[1] J. Wu, "Study on the Optimization of Macroeconomics Teaching Model Based on Cluster Analysis in the Context of Data," *Security and Communication Networks*, vol. 2022, Article ID 9091208, 9 pages, 2022.

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Research Article

Study on the Optimization of Macroeconomics Teaching Model Based on Cluster Analysis in the Context of Data

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Macroeconomics is a basic course among majors related to economic management. It plays a connecting role and can help students grasp economic phenomena and solve economic problems from an overall perspective. Many teachers still teach macroeconomics using the old teaching method, which ignores students' accepting abilities and preferences. It can not properly encourage pupils to take initiative in their learning, resulting in disconnect between curricular instruction and actual requirements. Teachers should correctly face the teaching reform situation, actively rely on advanced big data technology, upgrade macroeconomics teaching mode, and enhance students' ability to actively learn and solve practical problems and use teaching reform to obtain ideal teaching results. We present an optimization approach for macroeconomics teaching mode based on cluster analysis in the context of data based on this. The model's viability is confirmed through the creation of instructional situations and practical teaching. The experimental results show that students can improve their core knowledge, communication, and learning ability. The method has certain feasibility and effectiveness, which lays a foundation for the optimization of macroeconomics teaching mode.

1. Introduction

At present, big data technology has been divided into all aspects of social life and has had a profound influence on people's ideas, actual behavior, thinking mode, and habits. Nowadays, modern education and teaching have achieved great development in transformation and upgrading, and many new teaching methods have been born, which propose higher demand for the improvement of the macroeconomics teaching mode [1]. Teachers should recognize the teaching status and role of macroeconomics, grasp the significance and internal laws of curriculum teaching mode reform on the basis of the big data, recognize the necessity of education improvement, master scientific and advanced modern teaching strategies, and improve students' mastery of macroeconomic principles and practical application methods, cultivating students into applied talents in the new era [2].

Using big data to educate reform is a crucial choice for changing the macroeconomic education paradigm, raising educational levels, and speeding up education modernization [3]. In the current era, it is critical to have a clear knowledge of the relevance of macroeconomic teaching model reform in order to change teaching tactics and cultivate applied abilities. First, big data provides a huge guarantee for students to deeply understand the theoretical knowledge of macroeconomics [4]. When learning abstract and complex macroeconomics theoretical knowledge, if teachers do not take into account students' theoretical thinking and understanding ability and inculcate knowledge without taking into account students' individual learning rules, the effect will not be satisfactory. Big data can help students absorb abstract theoretical knowledge in a more vivid and intuitive way, improve their comprehension of the profession and industry's evolution, and build a solid platform for students to translate theoretical knowledge into practical skills [5]. Second, big data can expand learning resources for students and supplement macroeconomics-related materials. The advantage of the big data era is that it can provide massive information resources to make up for

the lack of information or lagging information in the past course teaching, further improve students' comprehension of macroeconomics, and perfect their theoretical knowledge system and practical learning methods [6]. Students will be able to quickly understand and apply their knowledge and accomplish their learning activities at a high level if they are exposed to a vast number of vivid and persuasive learning resources. Third, big data can help teachers change their teaching roles and improve their professional competence. In the traditional education model, teachers play the role of knowledge imparters, dominating students in the classroom [7]. The era of big data has brought changes to this teacher-student role and the traditional teaching model, especially with the sharing of resources and the popular use of modern tools. And to adapt to such a new environment, teachers need to improve their ability to master advanced technology and teaching methods, enhance their professional quality, and master professional methods to ensure the effectiveness of curriculum implementation [8]. In general, the structural block diagram of the teaching model based on big data is shown in Figure 1.

The penetration and influence of big data are expanding, affecting thoughts, behaviors, habits, thinking, etc. The big data in education and teaching is gradually increasing, and new teaching strategies have emerged. Teachers of macroeconomics should follow the trend of curriculum reform and keep pace with the development of technology [9]. They should continue to promote the reform of teaching mode, grasp the inner rules of teaching reform innovatively, and fully reflect the advantages of big data application. Based on this, we propose an optimization method of macroeconomics teaching mode based on cluster analysis. Through the design of teaching cases and practical teaching, the feasibility and effectiveness of the model are verified.

The paper's organization paragraph is as follows: the related work is presented in Section 2, and Section 3 analyzes the design of the model of the proposed work. Section 4 discusses the experiments and results. Finally, in Section 5, the research work is concluded.

2. Related Work

In this section, we define the current status of research on teaching macroeconomics and current status of research on clustering algorithms in detail.

2.1. Current Status of Research on Teaching Macroeconomics. To reform macroeconomics instruction, teachers must have a thorough understanding of the following principles. The guiding concept [10] is the first. Macroeconomics is a highly theoretical topic that serves as the foundation for students learning economic management courses. Its important value cannot be ignored. Since macroeconomics and learning are often set up in the basic stage of professional learning, and students have not yet started smoothly, tutors should play a guiding role in the whole process, strengthen the inspiration to students, determine the education plan according to the law of students' growth and talent cultivation needs, correctly control the whole process of students, rely on skilled big data application ability, and ensure the effect of macroeconomic reform [11]. The second is the principle of subjectivity. To truly rely on big data to innovate the macroeconomy, we must change the past one-way teaching mode, advocate two-way communication and interaction between tutors and students, and always adhere to the dominant position of students in this process [12]. Teachers should be patient in using macro data to guide students' study, and students' enthusiasm should be strengthened. Third, the principle of the times: the growth of the technology puts forward higher demand for education and teaching, so the macroeconomics teaching mode should also follow with the development trend of the big data era, reflect the spirit and requirements of the times so that students and teachers can use big data to study and solve problems in macroeconomics, and ensure the effect of curriculum system construction [13]. The schematic diagram of macroeconomics teaching mode reform is shown in Figure 2.

The epoch of big data promotes the gradual transition of research and development work in the field of social sciences from macro groups to micro individuals. By giving play to the virtues of the technology, we can get the good effect of interesting purity and eliminating the rough and refining, quickly find the required data, and see the essence through reality [14]. In order to promote the reform effect of the macroeconomics teaching mode, we should first update the teaching concept, and the support for promoting the concept renewal and reform is big data. Because big data allows for the rapid updating of various information data, the optimization of learning resources, and the provision of all-around information support to students, teachers should follow the modern teaching concept, give technology a chance in the process of using big data, and successfully complete the reform of the traditional teaching model [15]. The competent department of the school should apply and study the massive data generated in teaching, carefully sort out the relevant situation of tutors and students in teaching, and understand the problems and advantages, so as to carry out targeted reform of teaching management methods. Teachers also need to integrate massive teaching data, update and adjust the teaching process, use various macro cases of big data, enhance students' ability to integrate macroeconomic theory and actual situations, and enhance students' skills to apply what they have learned [16].

After integrating and analyzing the teaching contents of macroeconomics in the past, it is found that traditional teaching pays more attention to the knowledge and focuses on guiding students to understand abstract theoretical knowledge. The massive amount of data and information brought about by the epoch of big data has brought rich and diverse content and resources for tutors to teach activities [17]. Relying on real macroeconomic phenomena and a large number of data related to them can enrich teaching cases, enhance students' ability to deal with problems, help students master macro theoretical knowledge, and meet the demand for teaching content expansion and innovation. Tutors must promote the flexible application ability of big data technology, recognize the shortcomings existing in the

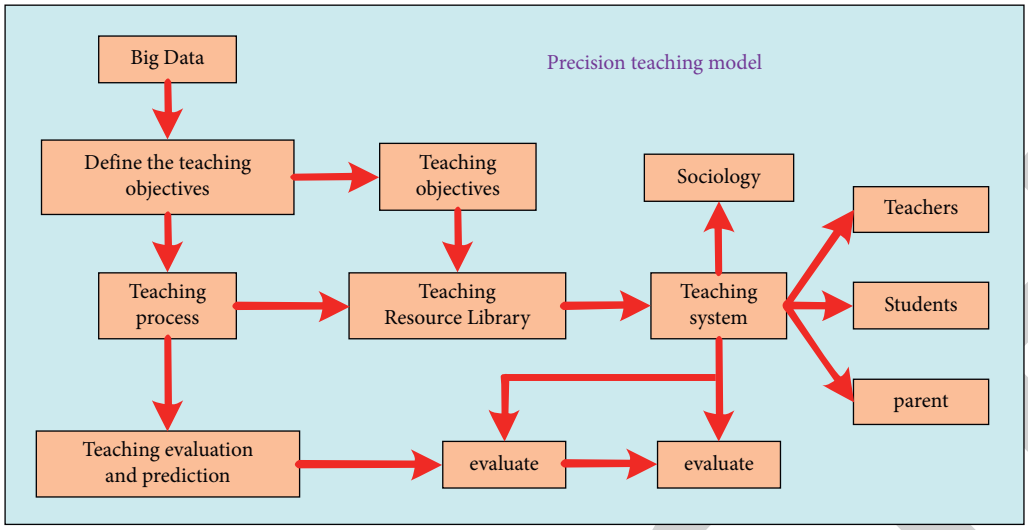

Figure 1: Precision teaching model based on big data.

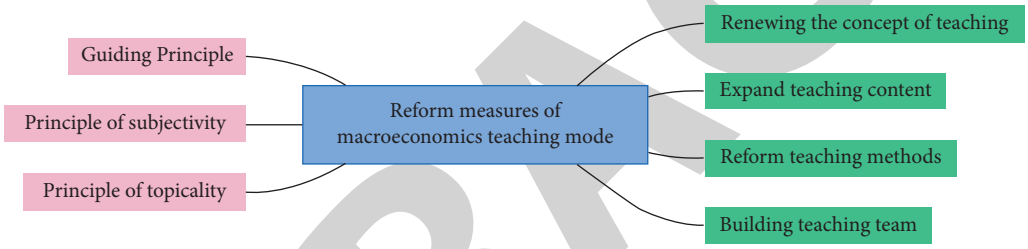

Figure 2: Schematic diagram of macroeconomics teaching mode reform.

application of current teaching resources, and make use of the advantages of information resources brought by big data to enrich teaching achievements [18]. For example, when teaching the consumer price index, tutors can first guide them to get basic theoretical knowledge and then use the technology to collect relevant cases, such as the detailed explanation of case resources such as web search data and Google trend prediction consumer price index. At the same time, it provides students with access to information resources and self-study ways to enrich teaching content and broaden students' knowledge [19]. For example, students can rely on the financial times, Mu class platform, and intelligent learning tools to obtain diversified course information to meet their diversified learning needs.

2.2. Current Status of Research on Clustering Algorithms. Clustering algorithms have been studied for quite a long time, dating back as far as 1954, when data clustering first appeared in the title of an article on processing anthropological data. In the following decades, researchers and scholars have blossomed, proposing more than a thousand different clustering algorithms and applying them to a wide range of fields [20].

There are two types of clustering algorithms: hierarchical clustering and split clustering [21]. Using aggregation or splitting patterns, hierarchical clustering algorithms recursively discover clusters. The aggregation model is to form a hierarchy of clusters by iteratively merging neighboring clusters by treating each data point as an initial cluster [22]. The splitting model is to form a hierarchy of clusters by iteratively splitting all data points into smaller clusters as one large cluster. In contrast to hierarchical clustering algorithms, partitioned clustering algorithms simultaneously find all clusters as part of the data without the need to form a hierarchy [23]. It optimizes the objective function by constructing an iterative process, and when optimized to the minimum or minimal value of the objective function, some disjoint subsets of the data set can be obtained, and it is usually considered that each subset obtained at this time is a cluster [24]. Because the division clustering algorithm is simple and efficient and easy to implement, researchers have conducted many application studies in-depth, and the most widely known method is the K-means algorithm. The process of clustering is shown in Figure 3.

The K-means algorithm has a rich and diverse history, and its related scholars have been proposed in different fields separately since 1956 [25]. Until 1976, scholars gave the detailed steps of the K-means algorithm and used the sum of squared distances as a measure of clustering quality [26]. The traditional K-means algorithm has some drawbacks: the clustering is easy to fall into the local optimal solution, the clustering result depends on the selection of the initial clustering center, and the selection of the K-value does not

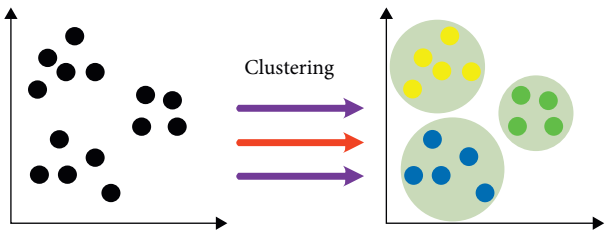

Figure 3: Schematic diagram of the clustering process.

follow the criterion and needs to be determined in advance [27]. In 1981, mathematicians proposed the FCM algorithm, which uses fuzzy mathematical methods for cluster analysis to determine the degree to which each data point belongs to a certain cluster in terms of affiliation, making an improvement on the traditional hard clustering [28]. The K-medoids algorithm selects the centroid of clusters instead of the mean value of data objects in the algorithm as the reference point, which can effectively handle abnormal data and enhance the robustness of the algorithm. Since then, mathematicians have proposed the PAM algorithm, the CLARA algorithm, and the CLARANS algorithm, which are a series of improvements and extensions of the K-medoids algorithm [29]. The PAM algorithm selects K points with the smallest average dissimilarity as the centroids for clustering. The CLARA algorithm handles large data application clustering based on the PAM. The CLARANS algorithm combines the sampling technique of the PAM algorithm to search for local optimum by randomly selecting nodes [30,31].

For the K-means algorithm, the random initialization of the clustering centers is likely to lead to the phenomenon that the clustering centers fall into local optima, which reduces the accuracy of clustering. As a result, selecting an acceptable set of initial clustering centers in the K-means algorithm is critical. Although the recently proposed better technique improves the initial clustering center selection and the stability of clustering outcomes to some level, this single selection approach still has flaws. In addition, the improved algorithm should have better execution efficiency and stability than the original algorithm, with better clustering quality.

3. Design of the Model

Data clustering is widely utilized not only in computer science and many related fields, but also in everyday life, addressing a variety of practical problems and developing a variety of famous techniques. This section discusses the concepts and principles of basic clustering algorithms, followed by a detailed discussion of improved clustering algorithms.

3.1. Basic Concepts and Principles of Clustering. Clustering analysis is a widely used multivariate mathematical statistics method. With the continuous improvement and optimization of clustering models, the scope and application fields are gradually expanding, such as data mining, image processing, machine learning, information security, and quality testing. The clustering algorithm has gradually changed from an awareness model to a decision-making tool. In addition, the clustering model is no longer just an abstract mathematical model but has even been gradually applied to business operations and marketing decisions, classifying users according to their portraits.

As the application area of clustering algorithms continues to expand, the selection of clustering algorithms and the evaluation of the results become particularly important. The explosive growth of data brought by the rapid development of the Internet is also constantly providing pressure on algorithm optimization, and the challenges faced by the development of clustering algorithms are gradually increasing in the face of the increasing scale and dimensionality of data, and under the heavy pressure, more and more scholars have started to invest in research. As the application area of clustering algorithms continues to expand, the selection of clustering algorithms and the evaluation of the results become particularly important. The explosive growth of data due to the rapid development of the Internet is also providing pressure on algorithm optimization. A good clustering algorithm can maximize the similarity between the same type of data and expand the difference between different data sets. Ultimately, the variability between different cluster classes and the level of similarity between the same cluster classes reflect the performance of the algorithm to some extent.

It divides the dataset into partitions, each representing a cluster. The hierarchy-based clustering algorithm is a method to achieve clustering by forming hierarchical classification trees based on the hierarchical relationships among data objects. There are mainly two types of division: top-down splitting mode and bottom-up aggregation mode. Hierarchy-based clustering algorithm does not depend on the form of the data set and does not need to set parameters in advance, which is simple and easy to implement. Based on the distribution density of data items, the density-based clustering algorithm finds dense regions divided by sparse regions to achieve clustering. It can identify clusters with arbitrary shapes and effectively handle anomalous data such as noise and isolated points and is applicable to spatial data sets. The model-based clustering algorithm is a method to achieve clustering by finding the best fit between data and model based on the statistical model. There are two main clustering methods based on statistical methods and neural network-based methods. The improvement of the clustering algorithm aims to discover clusters of the highest possible quality in little time. The algorithm should ensure that its validity does not change with the size of the data set. Table 1 compares the performance of representative algorithms from the above types of traditional clustering algorithms.

The introduction of regular terms ensures that the subspace representation matrix obtained by the model is blocked sparse under the condition of subspace independence, which is conducive to subspace partitioning and improves clustering accuracy and is experimentally verified and analytically illustrated. Sparsity and grouping ability are the two key factors considered for subspace structure

Table 1: Performance comparison of some traditional clustering algorithms.

Algorithm	TC	SC	Scalability	Dimensionality
K-means	Low	Low	Low	Low
CURE	High	Middle	High	Low
DBSCAN	Middle	Middle	Middle	Low
WaveCluster	Low	Middle	High	High
EM	High	High	Low	High

classification. The sparse subspace clustering based on one-dimensional sparsity makes the obtained representation coefficient matrix too sparse due to focusing on the sparse representation of individual data and ignoring the global structure, which leads to low clustering accuracy. The subspace clustering method based on low-rank representation guarantees the grouping of the same class of data, but the obtained subspace representation coefficient matrix may not be sparse. Improvement can usually be made by the design of regular terms. Given a data set $X = \{x_1, x_2, \ldots, x_n\}$ containing n data with k clusters whose cluster centers are $C = \{c_1, c_2, \ldots, c_k\}$, the criterion function E is defined as follows:

$$E = \sum_{i=1}^{n} \sum_{j=1}^{k} I(X) \left\| x_i - m_k \right\|^2. \tag{1}$$

If m_k is the mean value of cluster k, it is defined by the following equation:

$$m_k = \frac{1}{N_k} \sum_{x_i \in c_k} x_i, \tag{2}$$

where N_k is the number of data objects in the cluster. The basic working principle of the traditional K-means algorithm is as follows. First, each data object in the dataset is treated as a cluster, from which K data objects are randomly selected as the initial clustering centers. Next, the distance from each remaining data object to these K initial cluster centers is calculated successively, and each data object is grouped into the cluster with the closest distance. Then, the center of gravity of each cluster is recalculated to adjust the cluster centers, and the iterations are repeated until the cluster partitioning no longer changes. In addition, execution efficiency plays a crucial role among other challenging problems related to algorithms that deserve to be studied, such as execution efficiency, heterogeneity, and scalability. The traditional K-means algorithm decides which cluster to assign data objects to by iteratively traversing the entire data set. Figure 4 shows the specific illustration process of the K-means algorithm example clustering.

Of course, the K-means clustering algorithm also has some shortcomings. If the dataset contains a large number of isolated points or noisy data, to a large extent, the clustering results will be controlled by the noisy or isolated data, resulting in incorrect clustering results.

3.2. Improved Clustering Algorithm. High-dimensional data are characterized by complexity, sparsity, and diversity. Effective implementation of high-dimensional data clustering has become one of the most important tasks in the field of data mining. When facing low-dimensional datasets, traditional clustering algorithms try to find clusters in all dimensions of the dataset. However, in high-dimensional datasets, there are usually many unrelated dimensions. These irrelevant dimensions can interfere with the results of traditional clustering algorithms by hiding those clusters that are present in the noisy data, while the truly relevant data are distributed on low-dimensional structures that are representative of their features. This renders a single distance metric meaningless.

Sparse subspace clustering is a subspace clustering method based on spectral clustering. Figure 5 shows the basic framework of sparse subspace clustering.

The core idea of sparse subspace clustering is to make the constructed similarity matrix contribute to accurate subspace clustering by building the optimal sparse representation model that reveals the subspace structure. Sparse subspace clustering is a clustering method based on sparse representation. The so-called sparse representation refers to the use of the sparsity of high-dimensional data in low-dimensional space to represent the essential features of the data. If the subspaces are independent, the sparse representation is blocked sparse. Specifically, for a given set of high-dimensional data set $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \subset \mathbb{R}^m$, the data objects in it are represented as a base or dictionary $Y = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_n\}$ of linear combinations, as defined by the following equation:

$$\mathbf{x}_i = \sum_{j=1}^{n} Z_{ij} \mathbf{y}_j, \tag{3}$$

where Z_{ij} is the linear representation coefficient. Sparsity then implies that there are very few non-zero coefficients in the representation coefficients and that the positions of the non-zero coefficients correspond to the bases of the subspace to which the data belong, and the number of non-zero coefficients corresponds to the dimensionality of the subspace to which the data belong. Converting into a (3) matrix expression, the specific equation is defined as follows:

$$\mathbf{X} = \mathbf{YZ}, \tag{4}$$

where Z is called the representation coefficient matrix. If the subspace structure is known, the representation coefficient matrix Z can have a block diagonal structure under certain constraints. Sparse subspace clustering is used to construct the optimal subspace representation model by adopting different sparse constraints on the representation coefficient matrix Z. Given a set of m-dimensional data set $X = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \subset \mathbb{R}^m$ containing n data, and this set of data is distributed over k linear subspaces $\{S_l\}_{l=1}^{k}$. Represent it as a linear combination of other data in the same subspace. Therefore, the subspace representation model for sparse subspace clustering is specifically defined as follows:

$$\begin{cases} \min\limits_{Z} \|Z\|_1 \\ \text{s.t. } X = XZ, Z_{ii} = 0, \end{cases} \tag{5}$$

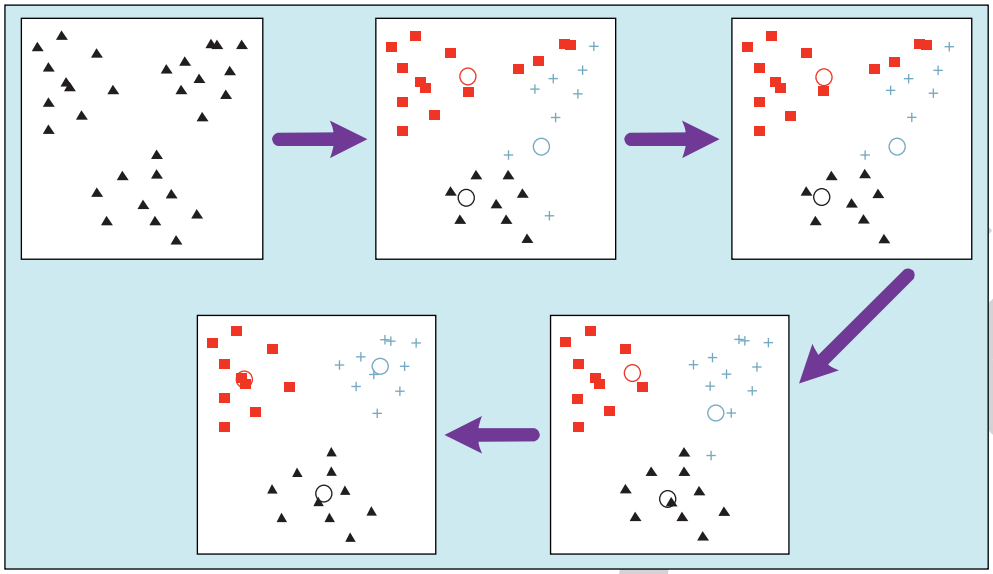

Figure 4: Example illustration of K-means algorithm.

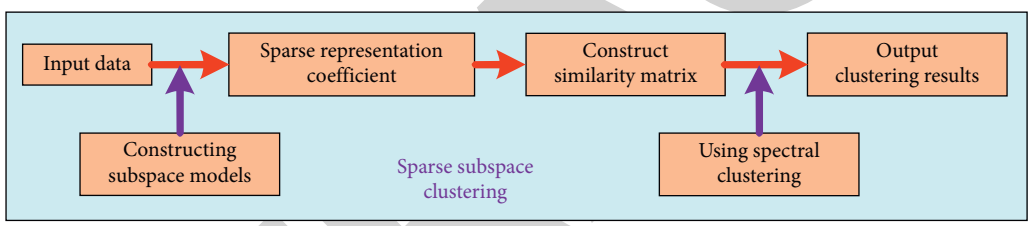

Figure 5: A basic framework for sparse subspace clustering.

where $\|\mathbf{Z}\|_1$ is the parametrization of the coefficient matrix Z. Since the actual data often contains noisy data and singularities, the dataset is usually denoted as $X = DZ + E$, where D is the dataset itself or the dictionary, and E is the noisy data and singularities. Therefore, the model expressed in (5) can be converted into the following equation:

$$\begin{cases} \min\limits_{Z,E} \|Z\|_1 + \lambda \|E\|_F^2 \\ \text{s.t. } X = XZ + E, Z_{ii} = 0, \end{cases} \tag{6}$$

where λ is the regularization parameter and $\|\mathbf{E}\|_F^2$ is the Frobenius parametrization of the matrix E, which is the regular term. The sparse representation that can be obtained from (6) constructs the similarity matrix W. To make the similarity matrix W symmetric, the specific formula is defined as follows:

$$\mathbf{W} = \frac{|\mathbf{Z}| + \left|\mathbf{Z}^T\right|}{2}, \tag{7}$$

where $|\mathbf{Z}|$ is the matrix obtained by taking absolute values of all elements of the representation coefficient matrix Z. The specific implementation flow of the algorithm is as follows.

Input: dataset containing n data $= \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_n\} \subset \mathbb{R}^m$, number of subspaces k_1 and number of clusters k_2.

Step 1. The representation coefficient matrix Z is calculated according to the subspace representation model expressed in Equation (6).

Step 2. Using the representation coefficient matrix Z, construct the similarity matrix W according to equation (7).

Step 3. Calculate the degree matrix D and calculate the Laplace matrix L.

Step 4. Construct the normalized Laplacian matrix and calculate the eigenvectors corresponding to its first k_1 smallest eigenvalues.

Step 5. Construct a feature matrix with feature vectors, treat each row of it as a k_1 dimensional sample, and call the K-means algorithm for clustering these n samples to divide the data set into k_2 clusters.

4. Experiments and Results

In this part, we explain the experimental description, experimental results, and analysis.

4.1. Experimental Description. In this chapter, to test the feasibility and effectiveness of the teaching model of macroeconomics based on the improved clustering algorithm, teaching cases are designed, and teaching practices are carried out according to the constructed model. A deep learning measurement tool was designed to collect data on students' achievement of deep learning objectives and postclass feedback. Analyze the practice data to verify the practice effect and improve and refine the model according to the teaching practice effect. The purpose of collecting teaching data is to test the influence of students' ability improvement in education, examine students' mastery of basic knowledge, and understand students' emotional experiences during the learning process. The measurement methods mainly use work scores and questionnaires and use questionnaires to analyze the changes in students' deep learning ability. Thinking maps are used to visualize students' cognitive level and thinking level and analyze students' basic knowledge construction, using postclass feedback questionnaires to understand students' evaluation of their learning. The table of data analysis contents and data sources is shown in Table 2.

Learning ability is an important yardstick for evaluating students' learning effectiveness, so this study builds on the learning ability framework with a refined analysis of the learning ability framework. The questionnaire was developed based on the U S. deep learning competency framework, revised by drawing on well-established scales, and has good content validity. The Pearson correlations between the total scores of the six dimensions and the total scores of the scale in the pretest data were 0.855, 0.840, 0.634, 0.874, 0.685, and 0.802, respectively, and the correlation coefficients were above 0.5, which shows that the construct validity of the scale is up to standard. A total of 59 questionnaires were collected from students in this study. Some of the pupils' final mind maps were depicted in the form of drawings. This study includes various learning outcomes offered by students in the form of drawings in this evaluation, taking into account their level of comprehension of mind maps, based on the criteria designed for this study, and the statistical results are shown in Figure 6.

Twenty-five of the students' final perfected results were completed to a good degree, covering all the students' learning in the learning process, but the relationship between the knowledge points was not clear, or there was no classification between the knowledge points. Nine results had a fair level of completion, with incomplete knowledge points and no classification between knowledge points. Four other students' mind maps contained less content. Based on the overall data, it can be seen that most students process and construct knowledge at a deep structural level and achieve learning outcomes.

4.2. Experimental Results and Analysis. The materials and data of this teaching practice study include student evaluation scales, teacher evaluation scales, questionnaires, student test scores, and interview records, which are analyzed to test the experimental effects of the macroeconomics teaching model. The statistical results are shown in Table 3.

Table 2: Data analysis content and data sources table.

Analysis items	Analysis content	Data collection method
Learning objectives	Learning ability	Questionnaire
	Knowledge construction	Work analysis
Learning style	Overall evaluation	Questionnaire

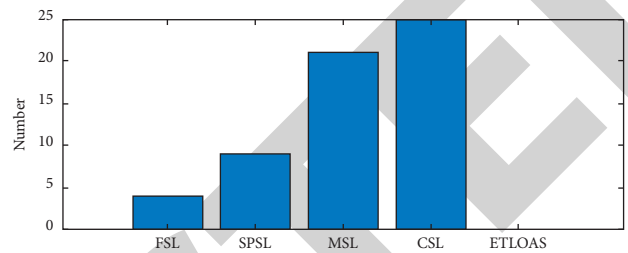

Figure 6: Statistical chart of evaluation level.

The data in the table shows that the students' group cooperation and communication in the classroom are good. Students can cooperate in groups, communicate and discuss effectively, express their own views and propose feasible opinions, and effectively complete their prescribed tasks and finally solve problems. The data collected in this teaching practice study included the test scores of 115 students in the experimental group classes and the control group classes. A total of three test scores were included, the first being the holiday test organized by the school at the beginning of the semester, and the second and third being the second monthly and final exams, respectively. The data were analyzed as shown in Table 4.

From the above table, we can see that there is no significant difference between the scores of the two classes, but there is a change in the mean difference. The mean score of the experimental class in the holiday test examination is 1.13 points higher than that of the control class, but the mean score of the experimental class in the second monthly examination is 3.12 points higher than that of the control class, which means that there is a difference arising, only that the difference is not significant. Due to the teaching material and the brief period of the teaching experiment, there was no significant difference between the scores of the two classes. To visualize the results, the three test scores are represented as line graphs, as shown in Figure 7 below.

In this teaching practice, students' improvement in this aspect of learning to learn was not obvious, and the reasons for this may be influenced by the environment and teaching time. Learning to learn is demonstrated by the fact that students will set learning goals, monitor their learning process according to the goals, and promptly reflect on what they do well and what they do not do well in the learning process to correct their learning in a timely manner. Organizing students to report results, exchange, and discussion, and allowing students to export their learning is conducive to promoting students' understanding of knowledge content and consolidating their learning; however, in specific practical teaching, too many presentations and exchanges will take up most of the teaching time.

Table 3: Data statistics of mutual evaluation table.

Evaluation options	Excellent (%)	Good (%)	Qualified (%)	Failure (%)
Cooperation	78	20	02	0
Positive	52	40	05	03
Reliable	40	45	10	05
Effective	34	52	11	03

Table 4: Score statistics and analysis table.

Class	Number	Average	Standard	Standard error of mean
Experimental class	57	63.930	08.728	1.146
Control class	58	60.810	10.609	1.405

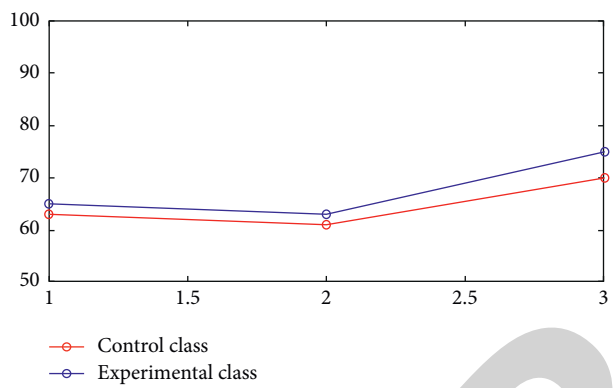

Figure 7: Comparison of the three test scores.

5. Conclusion

The advent of the big data era has brought rich and diverse teaching resources and classic cases to macroeconomics teaching and also provided strong support for the cultivation of applied and comprehensive talents. It is necessary to replace the traditional lagging teaching mode since it always follows the old lagging teaching strategy without taking into account the specific needs of students or the new educational environment. The shift is centered on conforming to the big data background, relying on big data technology to carry out curriculum teaching reform, and encouraging teaching transformation and upgrading to ensure the training quality of applied skills. In the process of reforming the teaching mode, macroeconomics teachers should flexibly use the advanced technologies and methods in the era of big data, update educational concepts, introduce diversified teaching strategies, and continuously improve students' knowledge application ability.

This research provides an optimization approach for macroeconomics teaching mode based on cluster analysis in the context of data based on this. The model's practicality and efficacy are tested through the creation of instructional situations and practical teaching. Students' core knowledge, communication, and learning capacity can all be improved, according to the results of the trial. The method proposed in this study has certain feasibility and effectiveness. The course of macroeconomics has a strong foundation and theory, which lays a foundation for students to study economic-related topics. Only after guiding students to master the course theory and relevant methods can it lay a foundation for students' in-depth learning. It can be said that macroeconomics has high requirements for teachers' educational ability and subject quality. Teachers must possess not only great communicative abilities, but also a vast breadth of information. They have the ability to incorporate macroeconomic phenomena into abstract ideas and assist pupils in resolving their learning issues. In the course implementation, teachers will have a direct impact on the teaching quality, which requires building a high-quality teaching team to provide students with good course learning guarantee in mutual communication and collaboration.

Data Availability

The datasets used during the current study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The author declares that he has no conflicts of interest.

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