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Article

Analysis of Vocational Education Governance Model Innovation and Its Sustainable Development Path Based on Weighted Clustering Algorithm

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Abstract: The article conducts an in-depth study on vocational education governance and proposes weighted clustering algorithm for vocational education information fusion through clustering criterion and entropy weight method. It further proposes a dynamic weighted clustering algorithm for fusion clustering of vocational education information. Thus, the governance model and sustainable development path of vocational education are explored. The effect of the innovation of vocational education governance model in this paper is obtained through the pre- and post-test data of students' academic conditions, independent sample t-test and evaluation of governance effect. The students' academic conditions in the six dimensions have been improved substantially, and there is a significant difference after the independent sample T-test. The scores of this paper's vocational education governance model and path based on the weighted clustering algorithm on the guideline level indicators (goal planning and policy adaptability, resource guarantee and allocation efficiency, process management and operational effectiveness, result output and quality level, sustainable development and social reputation) are within the interval of [73.258, 75.768], which has a good governance effect.

Keywords: weighted clustering algorithm; entropy weight method; fusion clustering; vocational education; governance model

1. Introduction

Under the international perspective, a holistic, humanistic and sustainable development of vocational education is gradually taking shape [1]. In order to cope with the multiple challenges facing the high-quality and sustainable development of vocational education in China under the new development paradigm, digital innovation and transformation for the governance model of vocational education is an area of concern [2-3]. Digital governance is a product of expanding and innovating traditional governance theories in the context of today's digital society [4]. In the field of vocational education, the emergence of digital governance provides a more efficient means to achieve the goal of vocational education to build a lifelong skill cultivation system with dynamic precision and deep integration of industry and education, and to promote the transformation of standardized talent delivery to intelligent, personalized, and sustainable industrial innovation talent incubation paradigm [5-8]. Vocational education digital governance pursues the goal of simplified governance, strengthens the extensibility of the governance scenario by means of platformization, in order to break down the information barriers between education and industry, promotes the accurate docking of educational resources and industrial demand, and enables the main body of vocational education governance to respond to diversified governance needs in a more flexible manner [9-12].

At the same time, digital governance of vocational education also focuses on the accuracy of data, aiming to realize the accurate assessment of the educational process and results through big data analysis and mining technology, so as to improve the governance process [13-15]. In addition, the efficiency of governance effectiveness is guaranteed by using indicators as benchmarks, and effective monitoring and assessment of education quality and teaching effectiveness can be realized through the establishment of a scientific evaluation index system, so as to improve the scientific and standardized nature of governance [16-18]. Therefore, it is important to explore the effective implementation path of digital governance of vocational education, with a view to assisting the high-quality development of vocational education in the new era of China.

This paper conducts an innovative research on the current governance model of vocational education, aiming to explore the sustainable development model of vocational education governance. The entropy weight method and clustering criterion are fused, a weighted similarity matrix is constructed, and the weighted clustering algorithm is used in the fusion of vocational education information, and the vocational education information is fused and clustered through dynamic weighted clustering. Path exploration of vocational education governance model on the basis of type education, and propose vocational education governance model and path based on weighted clustering algorithm. In order to explore whether the vocational education governance model proposed in this paper is realistic and feasible, the author firstly tests the change of students' learning situation, and secondly collects students' evaluation on the governance effect of the provincial team, so as to obtain the governance effect of this vocational education innovation.

2. Vocational Education Information Fusion Based on Weighted Clustering Algorithms

2.1. Fusion of Clustering Criteria

In this paper, we use clustering metrics to measure the accuracy and variability of individual learners, and integrate the clustering validity and collective variability metrics into a new evaluation metric, by which the base clustering results are evaluated and the weights generated under this metric are calculated as the weights of their integration.

Suppose $X=\{x_n\}_{n=1}^{N}\subset R^d$ is a d -dimensional dataset, and X contains N data objects $X=\{x_1,x_2...,x_n\}$. Performing M clustering on the dataset X, the number of classes per clustering is assumed to be K_m, which yields M clustering results $P=\{p_m\}_{m=1}^{M}$, and $C_i^m(1\le i\le K)$ denotes clusters with base clustering membership P_m class labels of i. The weight of each clustering result P_m under the new evaluation criterion π is w_m^{π}, and the set of weight vectors of the base clustering matrix P is $W^{\pi}=\{w_m^{\pi}\}_{m=1}^{M}$.

According to the clustering validity and difference indicators, the new evaluation indicators are defined as follows:

$$\pi(P_m)=\pi_1(P_m)\pi_2(P_m) \tag{1}$$

where $\pi_1(P_m)$ is the evaluated value of a certain base clustering result P_m under the validity evaluation index, and $\pi_2(P_m)$ is the evaluated value of a certain base clustering result P_m under the difference evaluation index.

The clustering validity indicators used in this chapter include DBI, Hubert, DVI, CH, MB, SF, SI. The value of DBI is taken as its reciprocal in the course of the experiment because the smaller the value of DBI, the better the clustering result. The clustering variability indicators include NMI, ARI, CA, and JC, where the larger the value of NMI, ARI, CA, and JC, the more likely that the base clustering reflects the internal structural information of the given dataset.

The formula for calculating the weights w_m^{π} generated under the membership of the new evaluation index π is defined as follows:

$$w_m^{\pi}=\frac{\pi(P_m)-\min(\pi(P_m))}{\max(\pi(P_m))-\min(\pi(P_m))} \tag{2}$$

Substituting equation (1) into equation (2) yields the weight w_m^{π} corresponding to the base clustering member P_m, and the larger w_m^{π} indicates the larger weight of the base clustering member P_m. The weight design method proposed in this chapter is formed by ensuring the validity of the base clustering members while considering the variability between different clustering results. Therefore, the weights designed according to this method can be more favorable to the base clusters that contribute more to the integration, which ultimately helps to obtain better cluster integration results.

2.2. Research on the Entropy Law

Entropy is often used to measure the disorder of a system, the greater the entropy, the more disordered it indicates, i.e., the less amount of information carried in that system, and vice versa, the more ordered it indicates.

The main role of information entropy is to describe the size of the amount of information contained in an event [19], therefore, the information entropy is the expectation of the amount of information contained in a certain event, according to the definition of expectation in mathematics, it can be known that the information entropy of the formula is:

$$\begin{aligned}&\text{Information entropy} = \sum \text{The probability of each possible event}\\&\text{*The amount of information contained in each possible event}\end{aligned} \tag{3}$$

The amount of information contained in each possible event is related to the probability of the event occurring, the higher the probability the smaller the amount of information. The amount of information contained in each possible event is calculated using the uncertainty function f :

$$f = \log(\frac{1}{P}) = -\log P \tag{4}$$

Substituting the uncertainty function into Eq. (3) yields the formula for entropy mentioned in the previous section:

$$H(X) = -\sum_{i=1}^{n} P_i \log P_i \tag{5}$$

where H is the entropy and X is the set of all possible events with n values: $X_1,\cdots X_i,\cdots,X_n$ corresponding to the probabilities $P_1,\cdots,P_i,\cdots,P_n$, with logarithmic base is typically 2.

The entropy weight method is to target a certain feature in an event [20], and then determine its discrete degree by calculating the magnitude of information entropy. According to the analysis of information entropy above, we can know that the smaller the value of information entropy is, the more discrete the feature is, i.e., the greater its influence on the comprehensive evaluation, and therefore the greater the weight is; if the entropy values of a feature are all equal, it means that the selected feature does not work for the comprehensive evaluation of the event.

The calculation steps of entropy weight method are as follows:

(1) Determine the index system.

(2) Data pre-processing.

(3) Data normalization.

There are two common approaches to normalization: 0-1 normalization and Z-score normalization.

0-1 normalization is also called the critical value method, for example, the j th indicator of the i th user is x_{ij}, which is normalized to $x_{ij}^{'}$, and there are two formulas as follows:

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \text{ or } x_{ij}^{'} = \frac{\max(x_j) - x_{ij}}{\max(x_j) - \min(x_j)} \tag{6}$$

The first formula is used if the indicator is positive and the second formula is used if the indicator is negative.

The Z-score normalization is shown in equation (7):

$$x_{ij}^{'} = \frac{x_{ij} - \overline{x}_j}{S} \tag{7}$$

(4) Calculate the entropy and weight of indicators

First, the weight of the j th indicator for the i th user is calculated: $y_{ij} = \frac{x_{ij}^{'}}{\sum_{i=1}^{m} x_{ij}^{''}}$.

Calculation of the information entropy of the j th indicator: $e_j = -K\sum_{i=1}^{m} y_{ij} \ln y_{ij}$, with K in the formula being a constant, $K = \frac{1}{\ln m}$.

Calculation of the weight of the j th indicator: $w_j = \frac{1-e_j}{\Sigma_j 1-e_j}$.

(5) Weighting of indicators to calculate the score

Calculation of evaluation value: $S = \Sigma_j 100 * y_{ij} w_j$, where S is the composite score and w_j is the weight of the j th indicator.

2.3. Weighted Similarity Matrix

For each base clustering member P_m corresponds to an affiliation matrix $H_m = \{0,1\}^{N\times Km}$, where K_m is the number of classes in which the base clustering member P_m is clustered into. The row vectors in this affiliation matrix H_m represent the data objects, and the column vectors represent whether the data objects belong to the class cluster represented by the column. If and when the data object belongs to this cluster, it is represented by 1. Otherwise it is represented by 0. Based on the matrix H_m it is possible to generate the similarity matrix $S_m = \{0,1\}^{N\times N}$ between the data objects, defined as shown below:

$$S_m = H_m H_m^T \tag{8}$$

Each element $(S_m)_{ij}$ in S_m indicates whether the data objects in rows i and j of the matrix H_m belong to the same cluster.

If the element $(S_m)_{ij} = 1$, it means that data object i and data object j are classified into the same cluster.

Based on the weights w_m^{π} evaluated by the base clustering members P_m, adding it on top of the similarity matrix S_m will produce a weighted similarity matrix S^{π} defined as follows:

$$S^{\pi} = \sum_{m=1}^{M} w_m^{\pi} S_m \tag{9}$$

The weighted similarity matrix S^{π} portrays the relationship between the base clustering members P_m under the new evaluation criterion π, which treats different base clustering members differently, and thus tends to be an accumulation of evidence for the evaluation of a series of clustering results.

2.4. Algorithm Description

In this chapter, the idea of clustering criterion fusion is used to address the impact of low-quality cluster membership, and the steps of the weighted clustering integration algorithm are as follows:

Step 1: Perform the K-Means clustering algorithm multiple times on the dataset to randomly generate a series of base clustering results to form the base clustering matrix P.

Step 2: Evaluate the validity of the base clustering matrix P using the fused evaluation criterion π and use it as a weight to a fused weighted similarity matrix S^{π}.

Step 3: Cluster the fused weighted similarity matrix S^{π} with Average-link clustering algorithm to get the final clustering result.

The framework of the algorithm is schematically shown in Fig. 1.

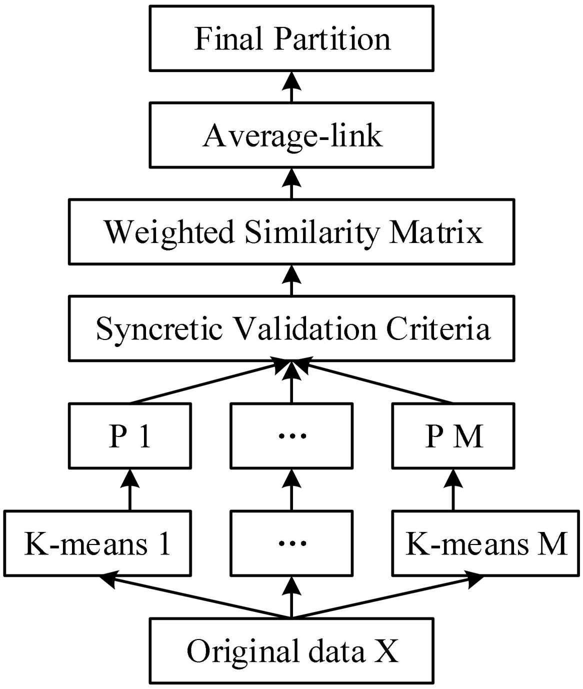

Figure 1. Algorithm framework.

2.5. Vocational Education Information Fusion Clustering

Analyzed from the perspective of fusion, depending on how each type of information source is used, there are currently three different levels of multi-perspective learning algorithms: feature-level, semantic-level, and kernel-level fusion. Each of these three fusions operates on the data of each information source, and then fuses each information source at all three levels. The drawback of this is that it ignores the helpful guidance and possible permeability between information sources.

To complete the clustering of educational information, the premise is to analyze the feasibility of cross-reference and reference between different information sources, for this reason, in the multimedia information fusion, this paper proposes a new clustering algorithm - dynamic weighted clustering algorithm. The algorithm is based on the traditional clustering algorithm, which assumes that different features of the information have different levels of importance for the expression of the content, and dynamically determines the weight of each feature. Especially in the semantic representation of information, the information like features that play an important role in the expression of the content occupy a larger weight, so that it will play a pivotal role in the similarity degree calculation. This approach is called weighted similarity metric criterion. The similarity between information pairs is measured based on this criterion, and after the measurement, a weighted similarity matrix is formed between the information pairs, which is decomposed, and by the method of symmetric non-negative matrix decomposition (SN-MF) [21], better clustering results can be obtained in general. The framework and steps of the algorithm are described below.

2.5.1. Framework for Dynamically Weighted Clustering

The general process is like this: firstly, it is assumed that the network multimedia target is determined, and the text and information features are available in the attributes, and these two features are extracted respectively. Then according to the content importance of the text features, based on the dynamic weighting scheme, different information features are dynamically assigned corresponding weights, and after obtaining the weight of each information feature, the weighted similarity criterion is used to measure and calculate the weighted similarity between the information pairs, and by substituting each similarity into the algorithm, a weighted similarity matrix based on the information pairs is established. Finally, a symmetric non-negative matrix decomposition is applied to this weighted similarity matrix to obtain clustering results.

2.5.2. Dynamic Weight Assignment

Let $m_i = (f_i, t_i)$ represent the i th image in the dataset, and the variables t_i and f_i represent the text features and image features of the i th image, respectively. $S_f(f_i, f_j, w) = \sum_i f_{i,l} f_{j,l}$ represents that when establishing the parameter weight v, variable f_u represents the l th dimension of the image feature f_i and $f_{j\mu}$ represents the l th dimension of the image feature f_j in view of the similarity measurement criterion between the i rd and j th images of the image feature. $S_i(t_i, t_j) = \sum_k t_{i,k} t_{j,k}$ represents the similarity metric criterion between the i th and the j th image in view of the text features. In addition, for each k, $t_{i,k}$ represents whether or not the textual introduction inside the image contains the k th word for the i th image. Based on the image feature, in order to get the appropriate weight vector v for it, the above similarity measure criterion based on text and image respectively, i.e., the consistency between $S_j(f_i, f_j; w)$ and $S_i(t_i, t_j)$, needs to be used. In short, it can be understood as solving an optimization problem:

$$w^* = \arg\min \sum_{i \neq j} (S_j(f_i, f_j; w) - S_i(t_i, t_j))^2, s.t. w \geq 0 \tag{10}$$

The dimensions in the image features are represented by P and Eq. (10) can be rewritten in the following form:

$$\begin{aligned}
&\sum_{i \neq j} (S_f(f_i, f_j; w) - S_d(t_i, t_j))^2 \\
&= \sum_{i \neq j} (f_{i,1} f_{j,1} w_1 + \cdots + f_{i,p} f_{j,p} w_p - \sum_i t_{i,k} t_{j,k})^2 \\
&= \sum_{i \neq j} (f_{i,1} f_{j,1} w_1 + \cdots + f_{i,p} f_{j,p} w_p)^2 - 2(f_{i,1} f_{j,1} w_1 + \cdots + f_{i,p} f_{j,p} w_p) \\
&\times (\sum_i t_{i,k} t_{j,k}) + (\sum_i t_{i,k} t_{j,k})^2
\end{aligned} \tag{11}$$

The number of images in the dataset is represented by n and let:

$$F = \begin{bmatrix} f_{1,1} f_{2,1} & f_{1,2} f_{2,2} & \cdots & f_{1,g} f_{2,g} \\ \cdots & \cdots & \cdots & \cdots \\ f_{n-1,1} f_{n,1} & f_{n-1,2} f_{n,2} & \cdots & f_{n-1,g} f_{n,g} \end{bmatrix} \tag{12}$$

$$T = \begin{bmatrix} \sum_{i \neq j} f_{i,1} f_{j,1} (\sum_i t_{i,2} t_{j,2}) \\ \vdots \\ \sum_{i \neq j} f_{i,s} f_{j,s} (\sum_i t_{i,s} t_{j,s}) \end{bmatrix} \tag{13}$$

Here, F is a $\left(\binom{n}{2} \times p\right)$-dimensional matrix, and T is a $(p \times 1)$-dimensional column vector. Therefore, Eq. (11) is equivalent:

$$\begin{aligned} w^* &= \arg\min\left[\frac{1}{2}\times 2(Fw)^T(Fw) - T^T w\right] \\ &= \arg\min\left[\frac{1}{2}(w^\tau(2F^\tau F)w) + (-2T^\tau)w\right], s.t. w \geq 0 \end{aligned} \tag{14}$$

The above optimization problem can be solved by quadratic programming techniques to obtain the optimal solution with dynamic weights.

2.5.3. Weighted Similarity Matrix

Two images are known, the image features are f_i and f_j, and w^* is the optimal dynamic weight for f_i and f_j, then the weighted similarity between these two images can be written as:

$$Sim(f_i, f_j) = 1 - \sqrt{\sum_i w_i^* \times (f_{i,i} - f_{j,i})^2} \tag{15}$$

Here, the l -dimension in the image feature f_i is represented by $f_{i,l}$ and the l -dimension in the image feature f_j is represented by $f_{i,l}$. The image features f_i and f_i and the weights w' are processed to keep them uniformly canonical and the dynamic weights v' are in accordance with $\sum_l w_l^* = 1$. So the weighted similarity in Eq. (15) takes values between [0, 1]. The similarity metric criterion here takes the Euclidean distance as the reference standard.

According to the weighted similarity degree in Eq. (6), a weighted similarity matrix M can be obtained in view of the full image dataset, and each element M_{ij} in M represents the weighted similarity between the i th and the j th image. Obviously, this matrix M is symmetric and all elements on the diagonal are 1. Finally, a symmetric non-negative matrix decomposition is unfolded on this matrix to obtain the clustering results.

2.5.4. Symmetric Nonnegative Matrix Factorization

After obtaining the weighted similarity matrix of the information pairs, it is necessary to cluster these information using a clustering algorithm. In this paper, symmetric nonnegative matrix factorization algorithm is used to cluster the information into some different clusters.

In SNMF clustering algorithm, the information pairs are known and the weighted similarity matrix formed from these pairs needs to be found to satisfy the condition of equation (16):

$$\min_{H \geq 0} J = \| M - HH^\tau \|^2 \tag{16}$$

where the matrix paradigm $\| X \|^2 = \sum_{ij} X_i^2$ is the Frobenius paradigm. Since the update rule of Eq. (16) is to be introduced under the nonnegative constraint $H_{ij} \geq 0$, the Lagrange multiplier λ_{ij} is introduced here and $L = J + \sum_{ij} \lambda_{ij} H_{ij}$, the localized minimal first order Karush-Kuhn-Tuck-er (KKT) condition is:

$$\frac{\partial L}{\partial H_{ij}} = \frac{\partial J}{\partial H_{ij}} + \lambda_{ij} = 0 \tag{17}$$

And:

$$\lambda_{ij} H_{ij} = 0, \quad \forall i, j \tag{18}$$

Here we have $\frac{\partial J}{\partial H_{ij}} = -4MH + 4HH^{\tau}H$. The KKT condition above leads to the following relation:

$$(-4MH + 4HH^{\tau}H)_{ij}H_{ij} = 0 \tag{19}$$

Based on the gradient descent method, it is derived:

$$H_{ij} \to H_{ij} - \varepsilon_{ij}\frac{\partial J}{\partial H_{ij}} \tag{20}$$

Setting $\varepsilon_{ij} = \frac{H_{ij}}{(8HH^{\tau}H)_{ij}}$ again, the multiplicative update law for SNMF can be introduced:

$$H_{ij} \to \frac{1}{2}\left[H_{ij}\left(1 + \frac{(MH)_{ij}}{(HH^{\tau}H)_{ij}}\right)\right] \tag{21}$$

Under the updating law of Eq. (21), the loss function $\| M - HH^{T} \|^{2}$ is non-increasing.

Based on the above analysis, the process of the SNMF algorithm can be summarized as follows: the initial value of the matrix H is given, and then the matrix H is iteratively updated using Eq. (21) until convergence. This gradient descent statute will proceed to convergence and finally take a local minima of the solved equation.

3. Exploring the Governance Model and Path of Vocational Education Based on Type Education

The governance of vocational education is a social project, which, like natural engineering, focuses on the creation of things, but what social engineering constructs are social things, directed at solving social problems and centered on adjusting social relations. Moreover, social engineering is not the study of direct social problems, but the problems that cause social problems, with social, practical and systematic characteristics. Some scholars point out that social engineering is a process from criticism to construction. Social engineering is based on existing social problems, adjusting all kinds of social relations to meet people's expectations through system design and model creation, taking social problems as the logical starting point and model creation as the landing point. The quality of vocational education is not yet able to fully meet the requirements of the type of education is the current social problem to be solved. The causes of this problem include the national system, social culture and internal governance. This study focuses only on internal governance, which is considered an important means to improve the quality of vocational education, and constructs a model of internal governance of vocational education from the perspective of social engineering with the logic of vocational disciplines.

Pattern is a kind of practice behavior, is the carrier of the unity of objective reality and value in specific practice, and its constituent elements are structure, process and mode, in which structure is the arrangement and collocation situation of the activity subject in the pattern, which is the material foundation of the pattern. Process refers to the occurrence and development of things in the links and order and the connection of each stage. Mode is the provision of interaction relationship, usually manifested as policies, laws and systems. With the change of objective conditions, social engineering mode has the characteristics of time and space dynamics. Based on these characteristics, this study proposes the vocational education internal governance AIDS (AIDS are the initials of Aim, Implementation, Doing and Status, respectively) model as shown in Figure 2, based on the development goals of vocational education under the type of education, the principles of internal governance and the requirements of social engineering model construction.

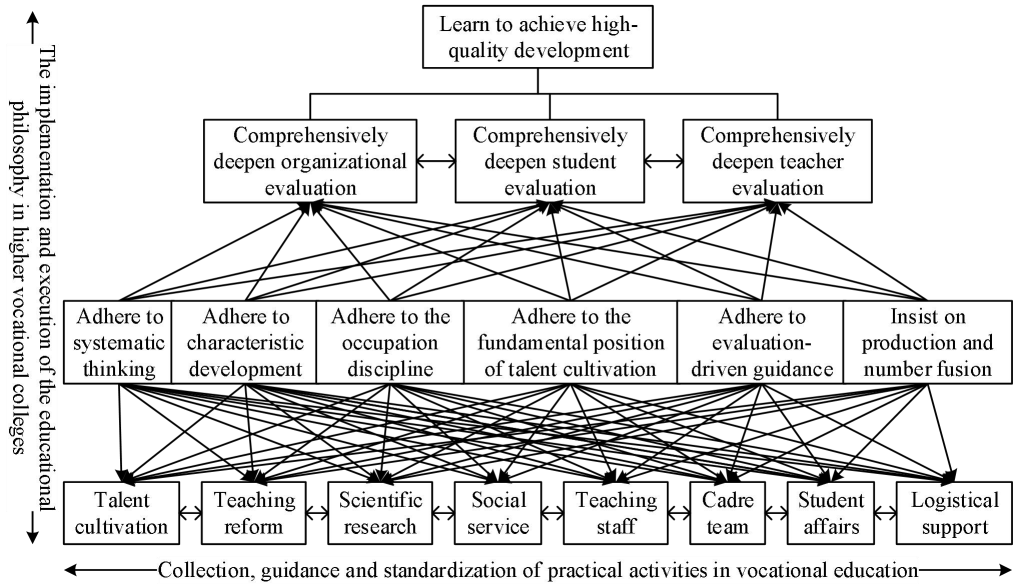

Figure 2. Vocational education management AIDS pattern.

3.1. Target System

Social engineering advocates value presupposition and opposes value neutrality. This study considers that school high-quality development is a key factor in optimizing the positioning of the type of higher vocational education, which is the goal and pursuit of vocational education running and governing schools, and also the value presupposition of the AIDS model. Governance logic, the ability to serve economic and social development and stakeholder evaluation have a positive correlation with school high-quality development. The competitiveness of these two indicators is positively correlated with the school's talent cultivation, vocational discipline construction and social service capacity.

3.2. Promotion Modalities

Teacher training is the core node of the entire internal governance network of vocational education, and human behavior is guided and regulated by policies. The internal governance of vocational education should be guided by evaluation reform, focusing on teacher evaluation, student evaluation and organizational evaluation, of which organizational evaluation refers to units and departments. The comprehensive deepening of evaluation reform is guided and constrained by the goal of high-quality development of schools, and these three aspects influence and constrain each other. The value goal is the direction and the way of promotion is the means, which need to be formed into specific principles to guide the construction of internal governance model. The internal governance model is essentially a kind of school governance discourse construction, and these school governance discourses are the governance principles that need to be constantly strengthened.

3.3. Principles of Action

Internal governance of vocational education is a systematic project. Systems thinking is a necessary condition for improving internal governance, and school-running characteristics are an important part of school-running orientation and an important indicator for evaluating high-quality development. Adherence to systems thinking and school-running characteristics is an action guide for improving the internal governance of vocational education. The four specific action principles of adhering to vocational discipline leadership, adhering to the fundamental position of talent cultivation, adhering to evaluation leadership and adhering to the integration of industry and education are chosen based on the position of the nodes shown in the aforementioned logical framework. Among them, vocational discipline is the leading link of internal governance, talent cultivation is the fundamental task, evaluation system is the institutional guarantee, and integration of industry and education is the basic parenting concept of higher vocational education. These six principles serve the three comprehensive ways to deepen the promotion of evaluation and are internally synergistic with each other.

3.4. State Systems

Problems of internal governance in vocational education are a social problem, and the cause of such problems is the internal governance model, specifically including internal systems, policies and behavioral culture. Internal governance of vocational education includes vocational discipline construction, personnel training and team building and many other links. The reality of these specific links is the objective condition for building internal governance model, and only through inherited innovation based on reality can the internal governance model achieve the expected results. Based on the requirements of type education for higher vocational education, this study proposes eight state systems, including talent cultivation, teaching and research, scientific research, social service, faculty, cadres, student work and logistic support, in combination with the target system, promotion method and action principles.

3.5. Philosophy

The philosophy of running schools in vocational education must be consistent in the internal governance model, which is the root and soul of running schools in vocational education. Implemented into the internal governance model, it means that the degree of achievement of school running objectives should be taken as an important assessment index for the high-quality development of vocational education, the reform of the internal evaluation system should be promoted on the basis of the philosophy of school running, and the philosophy of school running should be taken as the logic of action of the internal governance, especially in the specific implementation and safeguard links of the cultivation of talents and construction of vocational disciplines, so as to build up the internal governance mode of vocational education that combines the systematic, synergistic, holistic and distinctive features. The internal governance model of vocational education integrates systematic, synergistic, holistic and characteristic features.

4. Empirical Analysis of Governance Effectiveness

4.1. Comparison of Governance Effectiveness

In order to understand the impact of this paper's vocational education governance model and path based on the weighted clustering algorithm on vocational colleges and universities, this paper starts from the micro perspective of students' academic situation, and analyzes the governance effect produced by the innovation of vocational education governance model. Taking H vocational college as the research site, the innovative governance model proposed in this paper is implemented in this college, and students in a class of accounting majors are randomly selected as the experimental subjects to examine the changes in students' academic conditions before and after the governance. The governance effect is analyzed in six aspects: financial accounting and analysis, technology application, data processing, professional ethics, regulatory awareness, and communication and collaboration skills.

The academic status of the research subjects was tested before and after the development of vocational education governance, and the results are shown in Table 1. As can be seen from Table 1, before the reform and innovation of the governance model of vocational education, the subjects' academic performance in the six dimensions of financial accounting and analysis, technology application, data processing, professional ethics, awareness of regulations, and communication and collaboration skills were 15.28, 14.26, 12.57, 13.84, 12.15, 12.44, respectively, and after the innovation of the academic performance of the subjects were all by a relatively substantial improvement, scoring 24.06, 20.63, 21.45, 22.63, 20.46, and 23.54 on the six test dimensions.

Table 1. Studying condition before and after the vocational education management.

Dimension	Before			After		
	Mean	SD	SE	Mean	SD	SE
Financial accounting and analysis	15.28	3.445	0.685	24.06	5.562	0.274
Technical application	14.26	2.846	0.326	20.63	4.848	0.316
Data processing	12.57	3.716	0.415	21.45	5.096	0.358
Occupational ethics	13.84	4.065	0.521	22.63	4.271	0.402
Regulatory consciousness	12.15	3.623	0.413	20.46	3.899	0.234
Communication and collaboration ability	12.44	3.422	0.268	23.54	4.675	0.201

However, a rough comparison of the measurements before and after the experiment does not determine that the two results are significantly different, in order to further determine whether the significance of the test data before and after the experimental subjects is established, the two test data were subjected to an independent samples t-test, and the results of the test are shown in Table 2, in which the financial accounting and analysis, technical application, data processing, professional ethics, awareness of the rules and regulations, and communication and collaboration skills are represented respectively by FA, TA , DP, OE, RC, and CC, respectively.

Observing Table 2, it can be found that the significance of the subjects' two measures of academic affairs in the six dimensions of financial accounting and analysis, technical application, data processing, professional ethics, awareness of regulations, and communication and collaboration skills is less than 0.05, and the 95% confidence intervals of the results of the dimensions do not contain 0. It can be seen that the innovation of the governance model of vocational education has a significant impact on the optimization of students' academic affairs. The vocational education governance model based on weighted clustering algorithm in this paper has a significant positive effect on teaching effect.

Table 2. Independent sample T test results before and after the vocational education management.

		Levine variance equivalence test		Mean equivalence t test						
		F	Sig	t	df	sig(2-tailed)	MD	SED	95% CI	
									Upper	Lower
FA	Assumed	3.628	0.011	3.774	52	0.001	2.652	0.685	0.785	2.695
	Unassumed			3.774	51.035	0.001	2.652	0.685	0.785	2.695
TA	Assumed	1.896	0.015	2.543	52	0.002	2.485	0.725	0.869	3.025
	Unassumed			2.543	50.362	0.002	2.485	0.725	0.869	3.025
DP	Assumed	4.032	0.007	5.036	52	0.001	2.362	0.633	0.924	3.154
	Unassumed			5.036	51.742	0.001	2.362	0.633	0.924	3.154
OE	Assumed	4.425	0.007	5.718	52	0.001	2.845	0.548	1.065	3.854
	Unassumed			5.718	51.625	0.001	2.845	0.548	1.065	3.854
RC	Assumed	2.065	0.013	3.246	52	0.002	2.635	0.523	0.687	3.248
	Unassumed			3.246	50.725	0.002	2.635	0.523	0.687	3.248
CC	Assumed	4.984	0.003	6.155	52	0.001	2.154	0.645	0.938	3.478
	Unassumed			6.155	51.742	0.001	2.154	0.645	0.938	3.478

4.2. Evaluation of Governance Effectiveness

4.2.1. Construction of Evaluation Indicator System

In order to understand the students' feelings about the governance effect of this vocational education governance model, this paper firstly constructs the evaluation index system of vocational education governance effect as shown in Table 3. Secondly, based on this evaluation index system, a questionnaire is designed for distribution.

Table 3. Vocational education management effect evaluation index system.

Target layer	Criterion layer	Index layer
Vocational education management effect	Target planning and policy adaptability (A1)	Strategic planning clarity and foresight (A11)
		Policy execution force (A12)
		Demand response agility (A13)
		Stakeholder participation (A14)
		Fairness and inclusiveness (A15)
	Resource protection and configuration efficiency (A2)	Investment adequacy and stability (A21)
		Efficiency and transparency of funds (A22)
		Faculty size and structure (A23)
		Faculty quality and development (A24)
		Equipment advancement and utilization (A25)
	Process management and operation efficiency (A3)	Level of management system modernization (A31)
		Quality monitoring and evaluation system (A32)
		Normative teaching management (A33)
		The fusion depth of production and teaching (A34)
		Digital governance and application level (A35)
	Result output and quality (A4)	Student development (A41)
		Teaching result (A42)

		Service industry contribution (A43)
		Social training scale and quality (A44)
		Student satisfaction (A45)
	Sustainable development and social reputation (A5)	Internal development power and innovation ability (A51)
		Resource utilization sustainability (A52)
		School reputation and appeal (A53)
		International exchange and cooperation (A54)
		Student recognition and influence (A55)

The entropy value method is utilized to calculate the weights of the indicators in the above evaluation index system of the governance effect of vocational education, and the calculation results are shown in Table 4.

Table 4. Vocational education management effect evaluation index weight.

Target layer	Criterion layer	Weight	Index layer	Weight
Vocational education management effect	Target planning and policy adaptability (A1)	0.2284	A11	0.2029
			A12	0.2055
			A13	0.2128
			A14	0.2105
			A15	0.1683
	Resource protection and configuration efficiency (A2)	0.2173	A21	0.1989
			A22	0.2063
			A23	0.1857
			A24	0.2097
			A25	0.1994
	Process management and operation efficiency (A3)	0.2065	A31	0.2019
			A32	0.2116
			A33	0.1956
			A34	0.1946
			A35	0.1963
	Result output and quality (A4)	0.1869	A41	0.2004
			A42	0.1919
			A43	0.2026
			A44	0.2252
			A45	0.1799
	Sustainable development and social reputation (A5)	0.1609	A51	0.2105
			A52	0.2286
			A53	0.1785
			A54	0.1925
			A55	0.1899

4.2.2. Analysis of Evaluation Results

The Fuzzy Synthesis Evaluation Method is a method based on the concept of fuzzy geometry that aims to transform complex phenomena into quantifiable results through the principle of fuzzy relational synthesis in order to better assess phenomena affected by multiple factors. It can answer difficult questions that are fuzzy and not easy to quantify, and create evaluation models that lead to a better understanding and solution of practical problems and the achievement of goals. The fuzzy evaluation matrix of the effectiveness of governance of innovation in vocational education model is calculated as shown in Table 5.

Table 5. Vocational education management effect fuzzy evaluation matrix.

	Very disagree	Disagree	Normal	Agree	Very agree
A11	0.0115	0.0553	0.2748	0.3528	0.3056
A12	0.0142	0.0881	0.2935	0.4471	0.1571
A13	0.0132	0.0525	0.3058	0.4634	0.1651
A14	0.0157	0.0377	0.2374	0.4043	0.3049
A15	0.0135	0.0875	0.3102	0.3754	0.2134

A21	0.0153	0.1353	0.2675	0.3766	0.2053
A22	0.0138	0.0779	0.2847	0.4365	0.1871
A23	0.0147	0.0438	0.3255	0.3854	0.2306
A24	0.0148	0.0926	0.2838	0.4462	0.1626
A25	0.0138	0.0669	0.3053	0.3666	0.2474
A31	0.0146	0.0767	0.2418	0.3531	0.3138
A32	0.0123	0.0859	0.2226	0.3543	0.3249
A33	0.0133	0.0456	0.3026	0.3813	0.2572
A34	0.0122	0.1322	0.3322	0.3878	0.1356
A35	0.0116	0.1034	0.2224	0.3644	0.2982
A41	0.0123	0.0508	0.2476	0.4601	0.2292
A42	0.0147	0.0451	0.2518	0.4413	0.2471
A43	0.0129	0.1388	0.3325	0.3993	0.1165
A44	0.0156	0.0885	0.2917	0.4614	0.1428
A45	0.0136	0.0957	0.3524	0.4374	0.1009
A51	0.0122	0.1019	0.2638	0.4608	0.1613
A52	0.0125	0.0531	0.2801	0.4452	0.2091
A53	0.0115	0.0642	0.3374	0.4287	0.1582
A54	0.0127	0.0729	0.2938	0.4058	0.2148
A55	0.0132	0.0932	0.3058	0.4269	0.1609

Based on the weight coefficients of each criterion layer in the index system, the evaluation index weight vector W and fuzzy evaluation matrix R are constructed, and the weight values of five comment sets are obtained through the analysis, and finally the comprehensive scores are derived from the assignment according to V=[20, 40, 60, 80, 100] as shown in Table 6. From the calculation results in Table 6, it can be seen that the vocational education governance model and path based on the weighted clustering algorithm in this paper scores above and below 75 points on the five first-level indicators of goal planning and policy adaptability (A1), resource security and allocation efficiency (A2), process management and operational effectiveness (A3), result output and quality level (A4), and sustainable development and social reputation (A5), which achieves good evaluation Results.

Table 6. Overall evaluation results of vocational education management effect.

Criterion layer	Very bad	Bad	Normal	Good	Excellent	Overall result
A1	0.0136	0.0632	0.2833	0.4104	0.2295	75.580
A2	0.0145	0.0839	0.2928	0.4032	0.2056	74.030
A3	0.0128	0.0886	0.2634	0.3678	0.2674	75.768
A4	0.0139	0.0841	0.2944	0.4404	0.1672	73.258
A5	0.0124	0.0768	0.2944	0.4345	0.1819	73.934

5. Conclusion

In this paper, the weighted clustering algorithm is used in vocational education to carry out innovative reform of the governance model of vocational education and explore the governance path of vocational education. The actual effect of the vocational education governance model based on weighted clustering algorithm is known through empirical research.

The academic performance of the subject students in the six dimensions of financial accounting and analysis, technical application, data processing, professional ethics, regulatory awareness, communication and collaboration skills improved by 8.78, 6.37, 8.88, 8.79, 8.31 and 11.10 points respectively, and in the independent sample t-test, it can be determined that the vocational education governance model of this paper has a significant effect on the improvement of students' academic performance. This paper's vocational education governance model and pathway based on the weighted clustering algorithm scores more than 70 points on the five criterion level indicators of goal planning and policy adaptability (75.580), resource security and allocation efficiency (74.030), process management and operational effectiveness (75.768), outcome output and quality level (73.258), and sustainable development and social reputation (73.934) The evaluation result is good.

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