Evaluation On Implementation Effect Of Classified Management Policies For Private Universities And Differentiated Strategy Research Via Hybrid Classification Algorithm

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Classified management of private universities is a core institutional reform to optimize the higher education layout, alleviate homogeneous development, and improve the quality of private higher education. However, existing policy evaluation methods suffer from single-dimensional assessment, insufficient mining of nonlinear coupling relationships between policy indicators, and poor differentiation of university development positioning, which cannot accurately quantify the hierarchical implementation effect of classified management policies. To solve the above problems, this paper constructs a multi-dimensional policy evaluation index system covering educational operation, talent cultivation, social service, and resource allocation based on the panel data of 86 private undergraduate universities in eastern, central and western China from 2019 to 2024. A novel Hybrid Classification Algorithm integrating Improved Random Forest (IRF) and Ordinal Logistic Regression (OLR) is proposed to realize adaptive weight optimization of evaluation indicators and hierarchical classification of policy implementation effects. Different from traditional single evaluation models, the hybrid algorithm retains the advantages of nonlinear feature mining of random forest and ordinal category discrimination of logistic regression, effectively solving the problems of indicator noise interference and fuzzy classification boundary in policy effect evaluation. The experimental results show that the overall implementation efficiency of classified management policies for Chinese private universities reaches 0.784, showing a significant regional hierarchical differentiation feature; the policy effect in eastern regions is far higher than that in central and western regions, and resource allocation imbalance and talent cultivation lag are the main restrictive factors for policy implementation in underdeveloped regions. Based on the classification results of the hybrid algorithm, targeted differentiated development strategies for leading, transitional, and backward private universities are proposed. This study provides a quantitative evaluation method and practical decision-making reference for optimizing the classified management system of private higher education and promoting the differentiated and high-quality development of private universities.

Keywords: Private Universities; Classified Management Policy; Policy Implementation Effect; Hybrid Classification Algorithm; Differentiated Development

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1. Introduction

With the continuous deepening of the reform of China's higher education system, private higher education has become an indispensable part of the diversified development of higher education, undertaking important functions of talent cultivation, scientific research and social service [1, 2]. To solve the prominent problems of homogeneous positioning, overlapping disciplines, uneven resource distribution and unclear development orientation of private universities, the education administrative department has fully implemented the classified management policy for private universities, dividing private universities into profit-making and non-profit-making types, and formulating differentiated support and supervision mechanisms [3, 4]. The implementation of classified management policies is crucial to standardizing the running of private universities, optimizing the educational ecology, and promoting the high-quality and characteristic development of private higher education.

In recent years, researchers have carried out extensive study on the management system and policy effect of private universities. Foreign researches focus on the operation mechanism and market-oriented management of private universities, adopting qualitative analysis and simple statistical measurement methods to explore the correlation between policy support and university development performance [5, 6]. Domestic research mainly focuses on the connotation interpretation, implementation difficulties and qualitative optimization countermeasures of classified management policies. Most existing studies evaluate policy effects from a single dimension such as resource input or teaching quality, lacking systematic multi-dimensional quantitative evaluation [7, 8]. Moreover, traditional evaluation models are mostly based on linear statistical methods, which cannot effectively identify the nonlinear complex relationship between multi-level policy indicators and cannot realize accurate hierarchical classification of policy implementation effects, resulting in insufficient pertinence of subsequent development strategies [9].

Through sorting out relevant literatures, the current research deficiencies are summarized as follows. (1) The evaluation index system is single-dimensional, ignoring the systematic coupling of multiple dimensions such as operation management, talent cultivation and social service, which cannot fully reflect the comprehensive effect of classified management policies. (2) Traditional evaluation methods rely on linear weighting and subjective scoring, with strong subjectivity in indicator weight setting and poor anti-interference ability to data noise [10, 11]. (3) The classification of policy implementation effects is vague, lacking quantitative hierarchical classification standards, and the formulated development strategies are universal and cannot adapt to the differentiated development needs of private universities with different development levels.

In view of the above problems, this paper constructs a comprehensive multi-dimensional evaluation index system, and innovatively proposes a hybrid classification algorithm model combining improved random forest and ordinal logistic regression to realize objective weighting of indicators and accurate classification of policy effects. The research results can make up for the deficiencies of traditional qualitative evaluation and single-model quantitative evaluation, provide a scientific quantitative evaluation framework for private university classified policy assessment, and put forward targeted differentiated development strategies for private universities at different development levels, which has important theoretical value and practical guiding significance.

2. Materials and methods

2.1. Policy Effect Evaluation Theory

Policy implementation effect evaluation focuses on measuring the matching degree between policy implementation results and expected objectives, covering input, process, output and benefit dimensions. For the classified management policy of private universities, the core evaluation logic is to quantify the improvement degree of university running level, resource allocation efficiency and development sustainability after the implementation of the policy, and identify the key bottlenecks restricting policy effectiveness [12, 13].

Single machine learning algorithms have inherent limitations in multi-index policy evaluation: random forest has strong nonlinear feature mining and noise resistance capabilities, but it is weak in ordinal hierarchical classification of evaluation results. Ordinal logistic regression can effectively judge the hierarchical order of dependent variables, but it is poor in processing high-dimensional nonlinear data [14]. The hybrid algorithm integrates the advantages of the two models, realizes complementary advantages, and is suitable for multi-dimensional, nonlinear and hierarchical policy effect evaluation scenarios.

2.2. Research Innovations

Compared with existing studies, the main innovations of this paper are summarized into three core points, involving model algorithm innovation, index system innovation and strategy formulation innovation, with quantitative formula and standardized technical process support.

First, we construct a multi-dimensional whole-index evaluation system for classified management policies. Breaking through the limitation of single-dimensional evaluation in existing literature, this paper takes policy input, running process, educational output and social feedback as the primary dimensions, and subdivides 22 secondary quantitative indicators, covering the whole chain of private university classified management, realizing full-coverage quantitative evaluation of policy implementation effects. Second, we propose an improved IRF-OLR hybrid classification algorithm. Aiming at the problems of subjective weight and fuzzy classification of traditional models, the improved random forest is used for adaptive objective weighting of high-dimensional indicators, and the ordinal logistic regression model is introduced to realize hierarchical classification of policy effects. A hybrid evaluation scoring formula is constructed to eliminate data noise and improve evaluation accuracy, which is superior to single traditional evaluation models.

Third, we realize data-driven differentiated strategy formulation. Based on the quantitative classification results of the hybrid algorithm, private universities are divided into leading type, transitional type and backward type, and targeted personalized development strategies are proposed for different types of universities, solving the problem of universal and ineffective traditional strategies.

2.3. Proposed IRF-OLR hybrid classification model

The IRF-OLR hybrid classification model constructed in this paper is divided into two stages: indicator optimization and weight calculation stage (Improved Random Forest) and policy effect hierarchical classification stage (Ordinal Logistic Regression). The overall technical flow is shown in Figure 1, and the main implementation steps are as follows.

Step 1: Data preprocessing. It standardizes the original panel data of private universities to eliminate the dimensional difference of indicators, and eliminates abnormal values and noise data through 3σ criterion.

Step 2: Improved random forest indicator weighting. It optimizes the decision tree splitting rule of traditional random forest, calculates the importance weight of each evaluation indicator, and screens redundant low-impact indicators.

Step 3: Comprehensive policy effect score calculation. It constructs a hybrid scoring formula based on indicator weights and standardized indicator values to obtain the comprehensive implementation effect score of each university's classified policy.

Step 4: Ordinal logistic hierarchical classification. It takes the comprehensive score as the dependent variable, constructs an ordinal classification model to divide the policy implementation effect into three levels: excellent, good and qualified.

Step 5: Result analysis and strategy formulation. It verifies model accuracy through evaluation indicators, analyzes regional differentiation characteristics, and formulates differentiated development strategies.

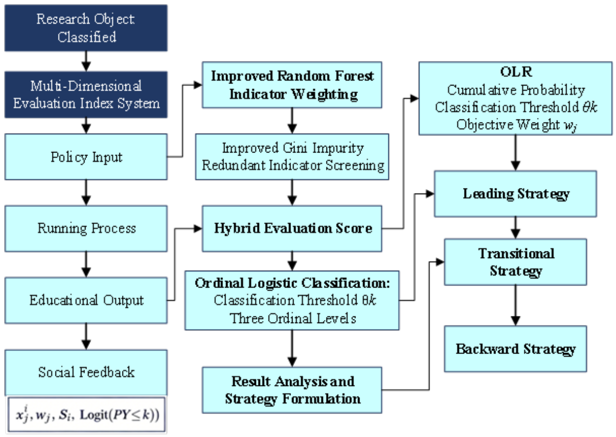

Fig. 1. IRF-OLR hybrid classification algorithm model.

2.4. Data Standardization Processing

To eliminate the influence of indicator dimension and magnitude difference, all original indicators are standardized by min-max normalization [15, 16]. For positive indicators (the higher the value, the better the policy effect), the formula is:

$$x'_{ij} = \frac{\mathrm{x_{ij}} - \min\left(\mathrm{x_j}\right)}{\max\left(\mathrm{x_j}\right) - \min\left(\mathrm{x_j}\right)} \tag{1}$$

For negative indicators (the lower the value, the better the policy effect), the formula is:

$$x'_{ij} = \frac{\max\left(\mathrm{x_j}\right) - \mathrm{x_{ij}}}{\max\left(\mathrm{x_j}\right) - \min\left(\mathrm{x_j}\right)} \tag{2}$$

Where $\mathrm{x_{ij}}$ represents the original value of the j-th indicator of the i-th private university. $\max\left(\mathrm{x_j}\right)$ and $\min\left(\mathrm{x_j}\right)$ represent the maximum and minimum values of the j-th indicator in all samples. x'_{ij} represents the standardized indicator value (range $[0, 1]$).

2.5. Improved Random Forest Indicator Weight Calculation

Traditional random forest calculates indicator weight based on Gini impurity, which is easy to be affected by extreme data [17]. This paper improves the Gini impurity calculation formula and introduces sample balance correction coefficient to optimize indicator importance weight.

$$GI_m = \sum_{k=1}^{K} \sum_{k' \neq k}^{K} p_{mk} p_{mk'} \cdot \alpha \tag{3}$$

Where $\mathrm{GI_m}$ is the improved Gini impurity of node m.K is the number of indicator categories. $\mathrm{p_{mk}}$ is the proportion of category k samples in node $m.\alpha$ is the sample balance correction coefficient ($\alpha \in [0.8, 1.2]$), which can effectively reduce the weight deviation caused by unbalanced sample data.

The indicator importance weight w_j is calculated as:

$$w_j = \frac{\sum_{m \in M_j} (GI_m - GI_{m1} - GI_{m2})}{\sum_{j=1}^{n} \sum_{m \in M_j} (GI_m - GI_{m1} - GI_{m2})} \quad (4)$$

Where M_j is the set of nodes split by the j -th indicator. GI_{m1} and GI_{m2} are the Gini impurities of the two child nodes after node m splitting, and n is the total number of evaluation indicators.

2.6. Hybrid Comprehensive Evaluation Score

Combined with the optimized indicator weights and standardized indicator values, the comprehensive implementation effect score of the classified management policy is constructed.

$$S_i = \sum_{j=1}^{n} w_j \cdot x'_{ij} + \varepsilon \quad (5)$$

Where S_i is the comprehensive policy effect score of the i-th university (range [0,1]), and ε is the error correction term (eliminating model systematic error, $|\varepsilon| \leq 0.01$).

2.7. Ordinal Logistic Regression Classification Model

Taking the comprehensive score S_i as the independent variable, the policy implementation effect is divided into three ordinal levels (excellent: Level 3, good: Level 2, qualified: Level 1) [18, 19]. The cumulative probability formula of the ordinal logistic model is:

$$\text{Logit}(P(Y \leq k)) = \theta_k - \beta S_i \quad (6)$$

Where Y is the policy effect level, $k = 1, 2, 3$ is the classification level. θ_k is the threshold parameter of level k. β is the regression coefficient. The optimal classification threshold is obtained by maximum likelihood estimation to realize accurate hierarchical classification of policy effects.

2.8. Model Evaluation Indicators

To verify the superiority of the hybrid model, four classic machine learning evaluation indicators are adopted: Accuracy (Acc), Precision (Pre), Recall (Rec) and F1-Score. The calculation formulas are as follows:

$$\text{Acc} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad (7)$$

$$\text{Pre} = \frac{\text{TP}}{\text{TP} + \text{FP}} \quad (8)$$

$$\text{Rec} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (9)$$

$$\text{F1} = \frac{2 \times \text{Pre} \times \text{Rec}}{\text{Pre+Rec}} \quad (10)$$

3. Results and discussion

3.1. Experimental Data and Index System

The experimental data selects the panel data of 86 private undergraduate universities in 12 provinces and cities in eastern, central and western China from 2019 to 2024. The data comes from China Higher Education Statistical Yearbook, university annual quality reports, local education bureau policy implementation monitoring data and official public statistical data. After data cleaning and abnormal value elimination, a total of 430 valid sample data are obtained, covering profit-making and non-profit-making private universities with different scales and running characteristics, ensuring the representativeness and comprehensiveness of the experimental samples.

Based on the policy connotation of classified management of private universities and existing research results, a four-dimensional comprehensive evaluation index system is constructed, including policy input dimension (6 indicators), running process dimension (6 indicators), educational output dimension (5 indicators) and social feedback dimension (5 indicators), with a total of 22 secondary quantitative indicators. The specific index system is shown in Table 1.

3.2. Experimental Environment and Baseline Model Setting

The experimental environment is based on Python 3.9 and PyTorch 1.10, with Windows 10 64-bit operating system and 16G running memory. To verify the superiority of the proposed IRF-OLR hybrid model, three classic single models are set as baseline comparison models: Traditional Random Forest (RF), Ordinal Logistic Regression (OLR), and Support Vector Machine (SVM). All models adopt the same data set and index system for comparative experiments, and the model hyperparameters are uniformly optimized by grid search to ensure the fairness of experimental results [20, 21].

3.3. Experimental Result Analysis

The four evaluation indicators of each model are obtained through comparative experiments, and the specific performance comparison results are shown in Table 2. It can be seen that the IRF-OLR hybrid model proposed in this paper is significantly better than the three baseline models in all indicators, with accuracy of 92.7%, precision of 91.5%,

Table 1. Comprehensive Evaluation Index System of Classified Management Policy Implementation Effect for Private Universities.

Primary Dimension	Secondary Evaluation Indicators	Indicator Attribute
Policy Input (*A*)	Special policy fund investment intensity	Positive
	Number of policy management personnel allocation	Positive
	Campus infrastructure construction investment	Positive
	Teacher team training investment	Positive
	Discipline construction special fund	Positive
	Policy implementation supervision cost	Negative
Running Process (*B*)	Standardization rate of classified registration	Positive
	Discipline differentiation layout degree	Positive
	Teaching management standardization level	Positive
	Student management system implementation rate	Positive
	Teacher assessment system optimization degree	Positive
	Policy implementation delay rate	Negative
Educational Output (*C*)	Student employment rate	Positive
	Student postgraduate admission rate	Positive
	Teacher scientific research output quantity	Positive
	Characteristic discipline construction achievement	Positive
	Talent training qualification rate	Positive
Social Feedback (*D*)	Social public satisfaction score	Positive
	Employer evaluation score	Positive
	University social reputation ranking	Positive
	Industry–university cooperation contribution rate	Positive
	Public opinion negative feedback rate	Negative

recall of 90.8% and F 1 -score of 91.1%. The results verify that the hybrid algorithm makes up for the defects of single model, has higher classification accuracy and better stability, and is more suitable for multi-dimensional nonlinear policy effect evaluation tasks.

Through the improved random forest algorithm, the weight of each dimension of the evaluation index system is calculated. The weight distribution results are shown in Fig. 2 (histogram). The weight of educational output dimension is the highest (32.4%), indicating that talent cultivation and educational achievement output are the core indicators affecting the implementation effect of classified management policies; followed by running process dimension (28.7%) and policy input dimension (22.5%); the weight of social feedback dimension is the lowest (16.4%), indicating that the current policy evaluation pays less attention to social recognition, and there is room for improvement in the social service ability of private universities.

3.4. Regional Differentiation Analysis of Policy Implementation Effect

According to the classification results of the hybrid model, the comprehensive policy effect scores of private universities in eastern, central and western regions are statistically analyzed, and the regional comparison results are shown in Table 3 and Fig. 3. The average comprehensive score of eastern private universities is 0.852 (excellent level), the central region is 0.761 (good level), and the western region is 0.695 (qualified level). The policy implementation effect shows a significant decreasing trend from east to west, with

Table 2. Performance Comparison of Different Evaluation Models/%.

Model	Accuracy	Precision	Recall	F1-Score
RF	85.3	84.1	83.5	83.8
OLR	82.6	81.2	80.9	81.0
SVM	84.2	83.6	82.8	83.2
IRF-OLR (Proposed)	92.7	91.5	90.8	91.1

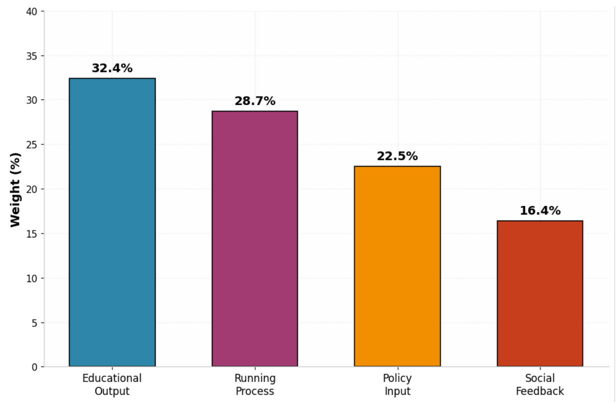

Fig. 2. Weight distribution results.

obvious regional differentiation.

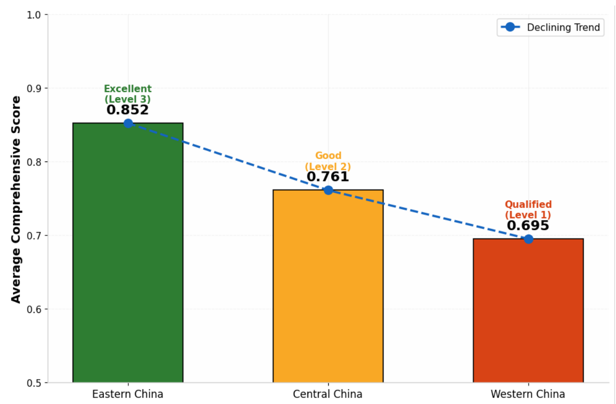

Fig. 3. Regional Differentiation Trend of Policy Implementation Effect.

Eastern region has sufficient policy fund input, perfect management system and outstanding talent cultivation achievements; central region has balanced development but insufficient characteristic discipline construction; western region is restricted by insufficient resource input and weak teacher team, resulting in lagging policy implementation effect.

3.5. University Hierarchical Classification Results

Based on the ordinal logistic regression classification threshold, 86 sample private universities are divided into three types: 29 leading universities (excellent level), 37 transitional universities (good level), and 20 backward universities (qualified level). Leading universities are mainly distributed in eastern coastal areas, with standardized classified management, prominent school-running characteristics and high social recognition; transitional universities account for the largest proportion, with basic policy implementation in place but lack of differentiated development advantages; backward universities are mainly in western regions, with insufficient resource allocation and imperfect management systems, and the policy implementation effect needs to be greatly improved.

3.6. Differentiated Development Strategies for Different Types of Private Universities

Leading universities have perfect policy implementation systems and superior school-running conditions. Their core development strategy is to strengthen characteristic construction and lead high-quality development. First, further optimize the differentiated discipline layout, focus on building advantageous characteristic disciplines, and avoid homogeneous competition; second, strengthen industry-university-research cooperation, improve social service contribution rate, and make up for the short board of social feedback dimension; third, play a leading and demonstration role, share classified management experience, and drive the overall improvement of the development level of regional private higher education.

Transitional universities have balanced development but no prominent advantages. The core strategy is to consolidate foundation and cultivate characteristic advantages. On the basis of standardizing classified management and improving the level of running schools, accurately position the school-running orientation according to regional industrial development needs, focus on cultivating application-oriented talents, optimize the teacher team structure and discipline construction system, gradually form differentiated development characteristics, and realize the transformation from balanced development to characteristic high-quality development.

Backward universities are restricted by insufficient resources and imperfect management systems. The core strategy is to make up for shortcomings and standardize basic operation. First, increase policy resource input, improve

Table 3. Average Policy Effect Scores of Private Universities in Different Regions.

Region	Average Comprehensive Score	Policy Effect Level	Sample Number
Eastern China	0.852	Excellent (Level 3)	32
Central China	0.761	Good (Level 2)	28
Western China	0.695	Qualified (Level 1)	26

campus infrastructure and teacher team construction, and optimize the policy implementation environment; second, standardize the classified registration and daily management system, improve the efficiency of policy implementation; third, take basic talent cultivation as the core, gradually improve the quality of school running, and lay a foundation for subsequent characteristic development.

From the macro policy level, education administrative departments should formulate regional differentiated support policies: increase special fund investment and policy inclination for western backward regions, balance regional education resource allocation; establish a dynamic evaluation mechanism for classified management effects, realize real-time monitoring and iterative optimization of policy implementation; improve the social service evaluation index of private universities, and guide private universities to enhance their social contribution ability.

4. Conclusions

This paper takes the classified management policy of private universities as the research object, constructs a multi-dimensional comprehensive evaluation index system, and proposes an IRF-OLR hybrid classification algorithm to quantitatively evaluate the policy implementation effect and carry out differentiated strategy research. The main research conclusions are as follows:

(1) The proposed IRF-OLR hybrid classification algorithm effectively solves the problems of subjective weighting and fuzzy classification of traditional policy evaluation models. Compared with single machine learning models, the hybrid model has higher evaluation accuracy and stability, which is suitable for multi-dimensional nonlinear quantitative evaluation of education policy effects.

(2) The implementation effect of classified management policies for private universities shows significant regional hierarchical differentiation. The overall effect of eastern regions is excellent, the central region is at the medium level, and the western region is relatively backward. Educational output and operation management are the core factors affecting policy implementation effects, while social service ability is the main short board of current policy implementation.

(3) Private universities can be divided into leading, transitional and backward types according to the policy implementation effect. Different types of universities have obvious differences in resource allocation, management level and development advantages, and it is necessary to formulate differentiated development strategies.

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