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Article

Research on the Optimization Model of the Content Delivery of College Students' Civic Education in the Online and Offline Education Environment

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Abstract: In both online and offline educational environments, learning behavior data recorded by platforms can be analyzed to determine students' actual learning status, which is beneficial for optimizing educational models and improving teaching effectiveness. This paper investigates the delivery of ideological and political education content to college students, constructing an XGBoost prediction model optimized using the TPE method. Combined with the K-means algorithm and SHAP explanation method, it achieves prediction of the effectiveness of ideological and political education content delivery and analysis of influencing factors. The accuracy rate, misclassification rate, recall rate, precision, F1 score, and AUC value of the TPE-XGBoost predictive model are 91.74%, 8.96%, 93.75%, 91.22%, 0.9247, and 0.9813, respectively, enabling effective prediction of the effectiveness of ideological and political education content delivery for college students. Additionally, the K-means algorithm clustering identifies four categories of ideological and political education content delivery for college students. Additionally, the SHAP value for the feature “teacher professional competence” was the highest, followed by features such as “content timeliness and relevance” and “willingness to translate knowledge into action,” indicating that indicators such as teacher professional competence, content timeliness and relevance, and willingness to translate knowledge into action influence the effectiveness of ideological and political education content delivery. Based on this, an optimized path for the delivery of ideological and political education content for college students was designed, providing new insights for optimizing the teaching effectiveness of ideological and political education in higher education institutions.

Keywords: XGBoost; TPE optimization method; K-means algorithm; SHAP explanation method; ideological and political education

1. Introduction

Ideological and political education refers to the systematic teaching activities aimed at cultivating and guiding students to develop a correct worldview, outlook on life, and values, thereby enhancing their ideological and moral qualities and overall literacy [1-2]. Ideological and political education is an integral component of higher education, with the objective of nurturing students into well-rounded socialist builders and successors who excel in morality, intelligence, physical fitness, aesthetics, and labor [3-5]. However, with the development and widespread application of the internet, the transmission of ideological and political education content to college students faces numerous challenges, leading to issues such as ineffective teaching outcomes and lack of student interest [6-8]. With the advent of the “Internet+” era, ideological and political education has undergone significant transformation. The integration of mobile internet technology with education in blended online and offline teaching has gained prominence, presenting new opportunities for the transmission of ideological and political education content to college students [9-11].

Blended online and offline teaching is an advanced model that combines traditional teaching with online teaching resources and utilizes modern educational technology to conduct teaching activities [12-13]. College students' ideological and political education bears the significant responsibility of cultivating college students to establish a correct worldview, outlook on life, and values, and plays a foundational role in enhancing college students' ideological awareness [14-16]. Utilizing “technology-enabled innovation” to enhance the content and format of ideological and political education courses in higher education, and constructing an integrated online-offline blended teaching model, are effective measures to improve the effectiveness of such courses and the delivery of their content [17-18].

This paper first combines the TPE hyperparameter optimization method with the XGBoost model to construct a predictive model for the effectiveness of ideological and political education content delivery among college students. Then, an indicator system for evaluating the effectiveness of ideological and political education content delivery among college students is established from five dimensions: educational entities, educational content, educational methods, educational environment, and recipients. Based on the optimized indicator system, the predictive model is experimentally evaluated. Subsequently, the K-means clustering algorithm and SHAP explanation method are employed to explore the primary factors influencing the effectiveness of ideological and political education content delivery among college students. Finally, based on the research findings, an optimized path design for the delivery of ideological and political education content among college students is realized.

2. Model for Predicting the Effectiveness of Ideological and Political Education Content Delivery and Analyzing Influencing Factors

This chapter constructs a predictive model for the effectiveness of ideological and political education content delivery based on TPE and XGBoost, uses the K-means algorithm for student ideological and political behavior clustering analysis, and employs the SHAP algorithm for explanatory analysis of the model's predictive results, thereby laying the foundation for designing an optimized delivery pathway for ideological and political education content in higher education institutions.

2.1. Prediction Model Based on TPE and XGBoost

2.1.1. XGBoost model

The XGBoost model [19] is a gradient boosting tree model that supports parallel computing. It features fast parallel computing speed, high accuracy, strong flexibility, and good robustness. In recent years, it has been successfully applied in various research fields, such as finance and energy prediction. Its most basic component is classification and regression trees (CARTs). The model can be represented as:

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i) \, , \, f_k \in F \tag{1}$$

Where $i = 1, 2, ..., n$, n is the sample size, F is the set of all CARTs, and f_k is a function in F.

The objective function of the model is to minimize the error term $L(\theta)$ and the regularization term $\Omega(\theta)$, which measure the prediction error and complexity of the model, respectively, as follows:

$$f_{obj}(\theta) = L(\theta) + \Omega(\theta) \tag{2}$$

In the above equation, $L(\theta) = l(y_i, \hat{y}_i) = \sum_{i=1}^{n} (y_i - \hat{y}_i)^2$ and $\Omega(\theta) = \sum_{k=1}^{K} \Omega(f_k)$ The first term is the loss function, which evaluates the loss or error between the model's predicted values and the true values. This function must be a differentiable convex function. The second term is the regularization term, which controls the model's complexity and tends to select simpler models to avoid overfitting.

During model iteration training, a new function f that does not affect the original model is added at the t th iteration, and the objective function is observed. If the newly added f can minimize the objective function, it is added, as shown in Equation (3):

$$f_{obj}^{(t)} = \sum_{i=1}^{n} (y_i - (\hat{y}_i + f_t(x_i)))^2 + \Omega(f_t) + C \tag{3}$$

Among them, $f_t(x_i)$ represents the new function added in the t th iteration, and C represents the constant term.

The Taylor formula is introduced to expand the objective function $f_{obj}^{(t)}$ to achieve approximation and simplification. The following is the approximate objective function:

$$f_{obj}^{(t)} \approx \sum_{i=1}^{n}\left[l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i)\right] + \Omega(f_t) + C \tag{4}$$

Among these, g_i is the first-order gradient statistic of the loss function, and h_i is the second-order gradient statistic. $g_i = \partial_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$, $h_i = \partial^2_{\hat{y}^{(t-1)}} l(y_i, \hat{y}^{(t-1)})$.

For model complexity, use q to represent the tree structure and w to represent the leaf weights, i.e.:

$$f_t(x) = w_{q(x)}, w \in R^T, q: R^T \to \{1, 2, \cdots, T\} \tag{5}$$

Define complexity as the sum of the squares of the number of nodes in each tree and the corresponding scores of its leaf nodes, as shown in Equation (6):

$$\Omega(f_t) = \gamma T + \frac{1}{2}\lambda \sum_{j=1}^{T} w_j^2 \tag{6}$$

In the equation, γ and λ are both adjustment parameters used to prevent overfitting of the model. Let $I_j = \{i \mid q(x_i) = j\}$ denote the set of leaf samples in the j th tree, and let $G_j = \sum_{i \in I_j} g_i$ and $H_j = \sum_{i \in I_j} h_i$. Then we have:

$$f_{obj}^{(t)} = \sum_{j=1}^{T}\left[G_j w_j + \frac{1}{2}(H_j + \lambda) w_j^2\right] + \gamma T \tag{7}$$

Solving equation (7), we obtain:

$$w_j^* = \frac{-G_j}{H_j + \lambda} \tag{8}$$

$$f_{obj} = -\frac{1}{2}\sum_{j=1}^{T}\frac{G_j}{H_j + \lambda} + \gamma T \tag{9}$$

In the above equation, f_{obj} is a scoring function that measures the model, and the smaller its value, the better the model.

For the CART algorithm, the computational complexity is $O(NMD)$, where N is the number of samples, M is the number of features, and D represents the depth of the decision tree. When using CART as the base classifier, XGBoost explicitly adds a regularization term to control the model's complexity, which helps prevent overfitting and improves the model's generalization. Therefore, the computational complexity of XGBoost lies between $O(N \log N)$ and $O(\log 2k)$.

2.1.2. TPE hyperparameter optimization method

Hyperparameters generally refer to a set of parameters set before training begins. They define the model structure and control the learning process, playing a crucial role in the development of machine learning models. Hyperparameter optimization refers to the process of adjusting hyperparameters to approximate optimal prediction results. Compared to other methods, automatic hyperparameter tuning can establish knowledge between parameters and models, reduce the number of tests, and improve the efficiency of the tuning process. This paper implements a variant of Bayesian optimization (BO) called the tree-structured Parzen Estimator to automatically optimize the hyperparameters of the XGBoost model.

The TPE optimization algorithm [20] is an optimization method based on a sequential model, featuring strong convergence and exploration capabilities, enabling focused and precise search within a specific optimal region. TPE transforms the hyperparameter space into a non-parametric density distribution, modeling the process of $p(x \mid y)$. This transformation can be performed in three ways: converting a uniform distribution to a truncated Gaussian mixture distribution, converting a log-uniform distribution to an exponential-phase Gaussian mixture distribution, and converting a discrete distribution to a reweighted discrete distribution.

The TPE optimization algorithm can utilize learning algorithms based on different densities by replacing different observation values $(x^1, x^2, \ldots, x^k)$ within the non-parametric density. The density is defined as:

$$p(x \mid y) = \begin{cases} l(x) & if\ y < y^* \\ g(x) & if\ y \geq y^* \end{cases} \tag{10}$$

In the equation, $l(x)$ is composed of the density of the objective function $F(x)$ being less than y^* for the observed values $\{x^t\}$, and $g(x)$ is composed of the density of the objective function $F(x)$ being greater than or equal to y^* for the observed values $\{x^t\}$. Generally, TPE uses y^* as the quantile y of the observation value y. By maintaining a sorted list of observation data in the observation domain H, the runtime of the TPE optimization algorithm scales linearly with $|H|$ and the optimized feature dimension at each iteration, where the expected improvement (EI) is:

$$EI_{y^*}(x) = \int_{-\infty}^{\infty} (y^* - y) p(y \mid x) dy = \int_{-\infty}^{y^*} (y^* - y) \frac{p(x \mid y) p(y)}{p(x)} dy \tag{11}$$

Finally, constructions $\gamma = p(y < y^*)$ and $p(x) = \int p(x \mid y) p(y) dy = \gamma l(x) + (1-\gamma) g(x)$ yield:

$$EI_{y^*}(x) = \left(r + \frac{g(x)}{l(x)} (1-\gamma) \right)^{-1} \tag{12}$$

This ensures that each iteration returns an x^* that yields the maximum EI value.

2.2. K-means clustering analysis method

2.2.1. Data preprocessing

During data preprocessing, ensuring data integrity and consistency is the foundation of analysis. Data quality directly impacts the accuracy and reliability of analysis results. Only by ensuring data integrity and consistency can in-depth analysis be conducted to draw reliable conclusions. Remove records containing null values to avoid the potential impact of data missing on analysis results and ensure data integrity. For numeric fields, use data type conversion techniques and regular expression extraction methods to process non-standard character formats in the raw data. Filter and delete duplicate records to ensure the uniqueness of the dataset and the accuracy of the analysis. Apply string processing techniques to remove invalid symbols from the data, unify character encoding, and prevent parsing errors caused by non-standard formats.

In cluster analysis, differences in feature scales can affect cluster results. Standardize the data according to Equation (13) to ensure that different features have the same scale:

$$z = \frac{x - \mu}{\sigma} \tag{13}$$

In the formula, x is the original data, μ is the mean, and σ is the standard deviation.

2.2.2. Algorithm Implementation

The K-means algorithm [21] is used to divide a dataset into K clusters, where samples within each cluster are as similar as possible, while samples between different clusters are as different as possible. The core of the algorithm is to perform clustering by minimizing the distance between each sample in a cluster and the cluster center. The algorithm steps are as follows:

Step 1: Initialization. Select K cluster centers that effectively balance clustering quality and computational efficiency.

Step 2: Assign each data point to the nearest cluster center. For each data point in the dataset, calculate its distance to the K cluster centers and assign the sample to the nearest cluster center, ensuring that each cluster has the minimum mean squared error.

Step 3: Update the cluster centers. Based on the positions of all data points in the current cluster, calculate the new center of the cluster to make the points within the cluster more closely clustered together.

Step 4: Repeat steps 2 and 3.

Step 5: Output the final cluster partitioning results, obtaining the cluster to which each data point belongs and the center of each cluster.

2.3. SHAP explanation method

SHAP (Shapley Additive Explanations) [22] can confirm the effects of global, local, and interaction factors, bridging the gap between the accuracy and interpretability of machine learning predictions. It visualizes the nonlinear relationships between independent and dependent variables. Variables with larger absolute SHAP values contribute more significantly to predicting public transportation usage indices, indicating greater importance. The XGBoost method using SHAP values can reflect nonlinear relationships and the relative contributions of independent variables to the dependent variable, as shown in Equation (14):

$$\theta_p = \sum_{S \subseteq \{x_1,\dots,x_p\} \setminus \{x_p\}} \frac{|S|!(|P|-|S|-1)!}{|P|!} \left[f(S \cup \{x_p\}) - f(S) \right] \tag{14}$$

In the equation, θ_p is the SHAP value of variable P, S is a subset of model variables, x_p is the value vector of variable P, P is the independent variable, and $f(S)$ represents the predicted value of set S.

$f(x)$ is the SHAP value linear function for variable P, as shown in Equation (15):

$$f(x) = \theta_0 + \sum_{p=1}^{P} \theta_p Z_i' \tag{15}$$

In the formula, $f(x)$ is the predicted value, and θ_0 is the expected value of the prediction. Z_i' represents a binary feature, where $Z_i' = 1$ represents the current value and $Z_i' = 0$ represents a missing value.

3. Model application experiments and results analysis

This chapter applies the constructed model for predicting the effectiveness of ideological and political education content delivery, assesses college students' ideological and political behavior, and analyzes the factors influencing the effectiveness of ideological and political education content delivery.

3.1. XGBoost prediction of the effectiveness of ideological and political education content delivery

3.1.1. Predictive Model Optimization

To avoid data redundancy that could reduce model running speed and prediction accuracy, the pruning method in TPE-optimized XGBoost (TPE-XGBoost) is used to determine the contribution of each dimension and variable in the process of ideological and political education content transmission. The selected multidimensional variables are screened to select the optimal feature subset, thereby improving model accuracy and running speed. This paper trains the model using sixteen attribute features from the five dimensions of educational subjects, educational content, educational methods, educational environment, and learners. The training accuracy of the TPE-XGBoost model is measured by the correct recognition rate in the test set, and features are screened. The specific steps are as follows:

(1) Train the TPE-XGBoost model using the selected attribute feature data, with the input variable being the indicator system and the output variable being the effectiveness of ideological and political

education content delivery.

(2) Calculate the Gini coefficient (gini) for each attribute feature and rank them by importance.

(3) Remove features with importance below 1%, then train the model using the remaining features until the model's accuracy no longer shows significant decline, thereby obtaining the optimized indicator system.

The distribution of feature importance across dimensions is shown in Figure 1, where H1–H16 represent teacher professional competence, content timeliness and relevance, willingness to translate knowledge into action, innovation in teaching methods, personal charm and approachability, purity of the online environment, proportion of practical teaching, campus cultural atmosphere, social support intensity, content depth and logical coherence, rationality of the evaluation mechanism, cognitive foundation and learning motivation, acceptance of individual differences, stability of values, content integration and hierarchical structure, and teaching ability and methods.

The five dimensions include sixteen indicators for measuring the effectiveness of ideological and political education content delivery. The importance of the dimension characteristics varies, with the three relatively higher indicators being teacher professional competence, content timeliness and relevance, and willingness to translate knowledge into action. Compared to classes with poorer effectiveness in conveying ideological and political education content, classes with better effectiveness have higher teacher professional competence, indicating that issues related to teacher professional competence are more likely to improve the effectiveness of conveying ideological and political education content, hence the feature of teacher professional competence ranks first in importance. Content timeliness and relevance more directly reflect the effectiveness of ideological and political education content, making it easier to achieve better results in conveying such content to college students, with this feature ranking second in importance. The willingness to convert knowledge into action reflects college students' subjective willingness to engage in ideological and political education practices. Under the same ideological and political education content, college students' subjective willingness has become a new requirement for measuring the effectiveness of ideological and political education content delivery, so the importance of the willingness to convert knowledge into action ranks third. The importance of the "content integration and hierarchical structure" and "teaching ability and methods" indicators is relatively low, both below 1%, so they are excluded, and the remaining items are included in the indicator system.

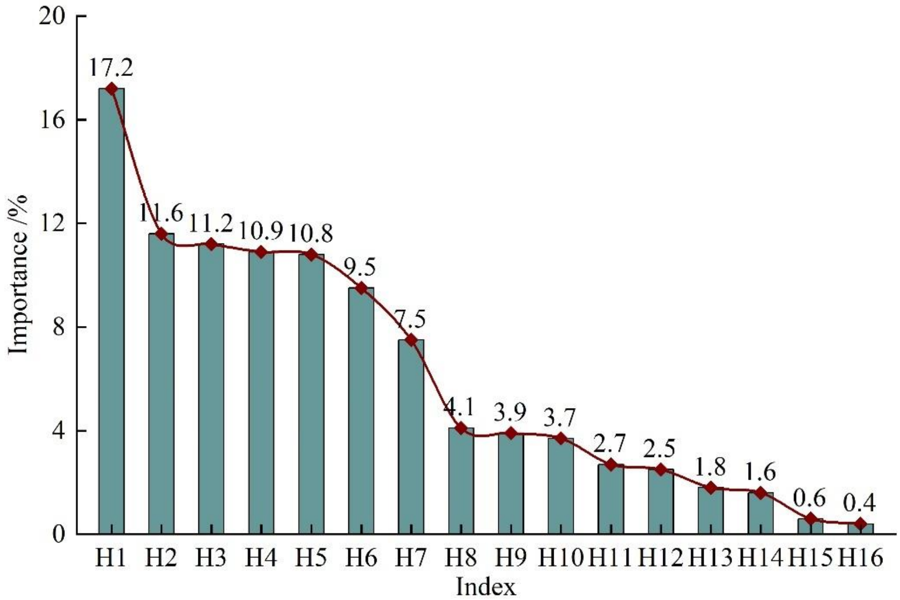

Figure 1. Importance of dimensional features.

Table 1 shows the optimized evaluation index system for the transmission effect of ideological and political education content. It can be seen that the difference in the importance of the characteristics of the education recipient dimension is small, and the *V* value is obtained by adding the importance of the indicator characteristics in the five dimensions for comparison, among which the dimension with the largest *V* value is the dimension of education subject, followed by the dimension of education method, educational environment, education recipient and educational content, and the corresponding *V* values are 0.280, 0.211, 0.175, 0.171 and 0.153, respectively. It can be seen that the subject dimension of education is still the core dimension for judging the content delivery effect of college students' ideological and political education, and the index of teachers' professional quality is still the core basis for judging the content transmission effect of ideological and political education, which is the core dimension for constructing the prediction model of ideological and political education content transmission effect.

Table 1. The optimized evaluation index system.

Dimension	Serial number	Indicator	Feature importance
Educational subject	1	Professional quality of teachers	0.172
	2	Personal charm and affinity	0.108
Educational content	3	The timeliness and pertinence of the content	0.116
	4	Content depth and logic	0.037
Educational methods	5	Innovative teaching methods	0.109
	6	The proportion of practical teaching	0.075
	7	The rationality of the evaluation mechanism	0.027
Educational environment	8	Campus cultural atmosphere	0.041
	9	Social support intensity	0.039
	10	The purification degree of the network environment	0.095
Educated	11	Cognitive foundation and learning motivation	0.025
	12	Stability of values	0.016
	13	Individual differences in acceptance	0.018
	14	The willingness to transform knowledge into action	0.112

3.1.2. Evaluation of predictive models

The TPE-XGBoost model for predicting the effectiveness of ideological and political education content delivery, constructed using MATLAB, has had its optimized indicator system validated. However, the predictive capability of the TPE-XGBoost model still needs to be analyzed. By examining the confusion matrix of the training dataset within the TPE-XGBoost model, we can assess its predictive capability. The validation metrics calculated from the confusion matrix are shown in Table 2.

The accuracy rate of the TPE-XGBoost prediction model is 91.74%, meaning that the ratio of students identified as having good or poor effectiveness in the delivery of ideological and political education content in the established TPE-XGBoost model to the total number of students is 91.74%. The misclassification rate of the TPE-XGBoost model is only 8.96%, indicating that the classification error of the TPE-XGBoost model is relatively small. The sensitivity of the TPE-XGBoost model, i.e., the recall rate, is 93.75%, indicating that the model can correctly identify the effectiveness of ideological and political education content transmission for 93.75% of students. The precision of the TPE-XGBoost model is 91.22%, meaning that the model's classification accuracy is relatively high. The F1 score of the TPE-XGBoost model is relatively high, reaching 0.9247, indicating that the TPE-XGBoost model performs better in classifying the effectiveness of ideological and political education content delivery. The AUC value is 0.9813, indicating that the area under the ROC curve is relatively large, suggesting that the TPE-XGBoost model has excellent classification performance.

Table 2. Classification test index of TPE-XGBoost algorithm.

Classification test index	Numerical value
Accuracy	0.9174
Eror Rate	0.0896
Sensitivity / recall	0.9375
Precision	0.9122
F1 score	0.9247
AUC	0.9813

3.2. Cluster analysis of the effectiveness of ideological and political education for college students

Using the TPE-XGBoost-based model established above to predict the effectiveness of ideological and political education content delivery, we conducted an effectiveness prediction of the current state of ideological and political education content delivery for the undergraduate student dataset at H University.

Subsequently, the prediction results were subjected to further clustering analysis using a clustering analysis model, and the clustering analysis results were output to identify the differences in feature values across five dimensions and sixteen attributes among university students at H University, thereby determining the primary dimensions influencing the effectiveness of ideological and political education content delivery. Using the TPE-XGBoost prediction model established in the preceding text to predict the university student dataset at H University, 124 students with relatively high effectiveness in ideological and political education content delivery were identified.

Based on the key indicators selected by the predictive model, the optimized objective function value of the K-means algorithm was selected as the metric. The number of clusters K was set to vary from 1 to 16, with 120 simulation runs, and the average value of the metrics was taken. The decision diagram is shown in Figure 2.

After comprehensively considering the impact of the number of clusters on the decline in the metric, 4 was selected as the critical point for K. Cluster analysis was then performed on students with better effectiveness in the transmission of ideological and political education content. The clustering results for each metric are shown in Figure 3.

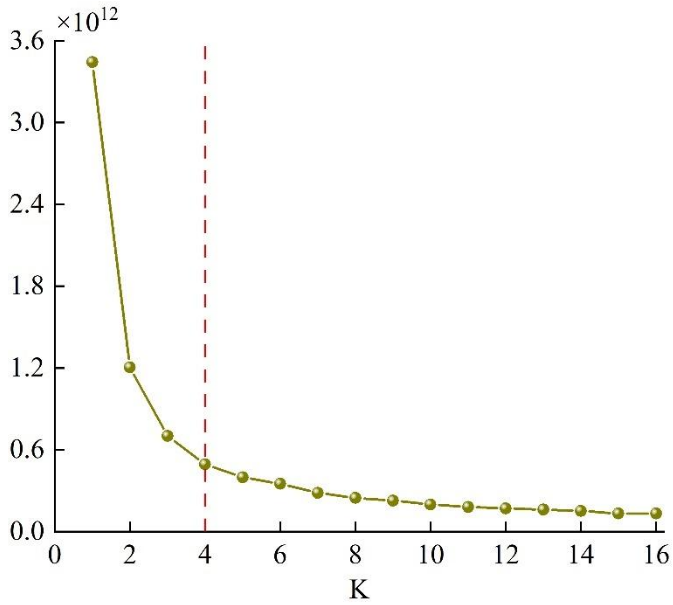

Figure 2. Decision diagram.

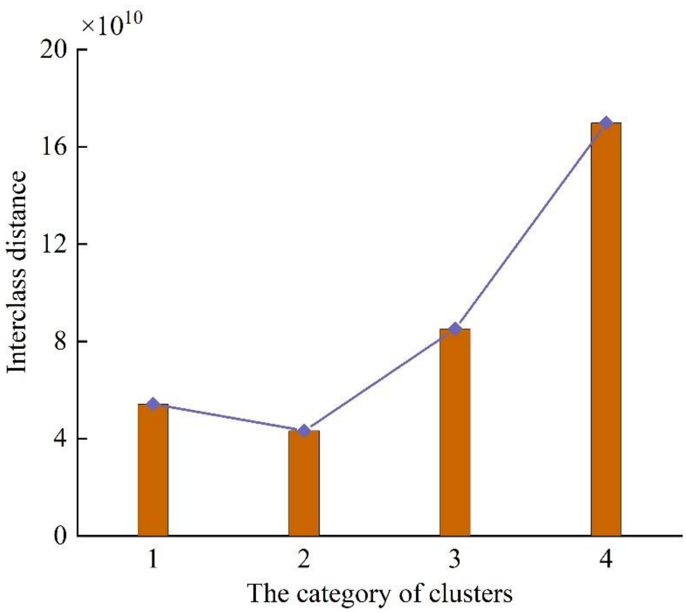

Figure 3. Clustering results.

When N ≥ 4, direct visualization is not possible, so each pair of dimensions is visualized separately. The visualization of the clustering results for the selected dimensions of campus cultural atmosphere and willingness to convert knowledge into action is shown in Figure 4.

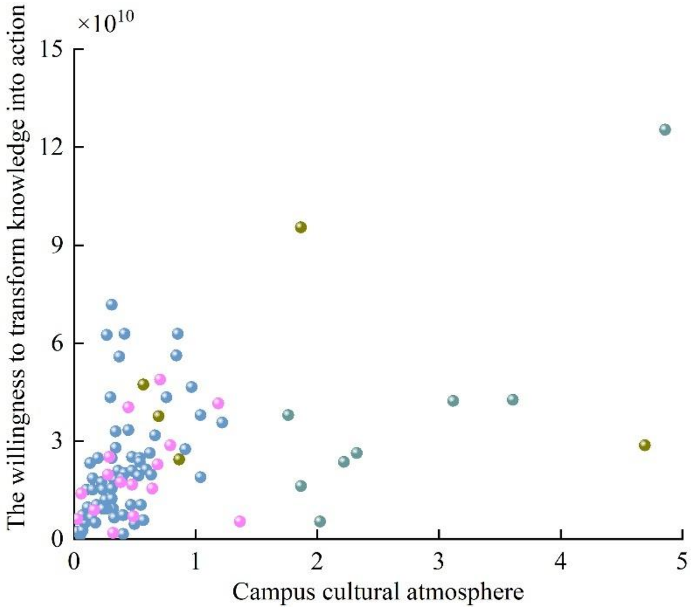

Figure 4. Visualization diagram.

Due to the complexity of the visualized data, a comparison analysis of the mean or variance of the indicators for the output results of the cluster analysis of the transmission of ideological and political education content for college students was conducted. The results indicate that the cluster results of the four categories exhibit differences in several indicators, including teachers' professional competence, willingness to translate knowledge into action, innovation in teaching methods, rationality of evaluation mechanisms, cognitive foundation and learning motivation, and stability of values. These differences generally categorize the four categories of ideological and political education content transmission into the following types:

(1) Category one exhibits significant differences from other categories in terms of teaching method innovation, personal charm and approachability, and the proportion of practical teaching. It also differs from other categories in terms of value stability. This may be attributed to the unique teaching methods of ideological and political education, the strong personal charm of teachers, and a teaching approach that emphasizes practicality. Additionally, the teaching audience consists of first-year university students, who possess strong value malleability, thereby achieving superior teaching outcomes.

(2) Category Two outperforms other categories in terms of teacher professional competence, content timeliness, and relevance. This suggests that enhancing teacher professional competence, ensuring the timeliness and relevance of core content, can significantly improve the effectiveness of ideological and political education.

(3) When comparing the indicators of category 3 with other categories, it is found that the ideological and political education of college students in this category is quite different from other types in terms of willingness to transform knowledge and action, campus cultural atmosphere and social support, which enlightens us: when transmitting the content of ideological and political education, we should pay attention to the main position of students, create a good cultural atmosphere, and increase the support of ideological and political education, so as to enhance students' enthusiasm and participation, and then achieve excellent teaching results.

(4) Category Four outperforms the other three categories in terms of content depth and logical coherence, and also leads in teaching ability and methods, as well as the rationality of evaluation mechanisms. This indicates that the transmission of ideological and political education content requires teachers to enhance their teaching capabilities, improve teaching methods, optimize the depth and logical coherence of teaching content, and complement these efforts with reasonable evaluation mechanisms to continuously optimize the effectiveness of ideological and political education content transmission.

3.3. Feature selection visualization analysis based on the SHAP method

Table 3 shows the ranking of the importance of the features of college students' ideological and political behavior selected in this paper after model training, and the SHAP value of the features decreases in descending order. It can be seen that the SHAP value of characteristic teachers' professional quality is the highest, followed by the timeliness and pertinence of content, and the willingness to transform knowledge and action, and the acceptance of individual differences and the stability of values are the lowest, close to 0.01.

Table 3. Ranking of feature importance.

SHAP value ranking	Code	Feature name	SHAP value
1	X1	Professional quality of teachers	1.26
2	X2	The timeliness and pertinence of the content	1.14
3	X3	The willingness to transform knowledge into action	0.65
4	X4	Innovative teaching methods	0.57
5	X5	Personal charm and affinity	0.46
6	X6	The purification degree of the network environment	0.45
7	X7	The proportion of practical teaching	0.42
8	X8	Campus cultural atmosphere	0.35
9	X9	Social support intensity	0.33
10	X10	Content depth and logic	0.28
11	X11	The rationality of the evaluation mechanism	0.28
12	X12	Cognitive foundation and learning motivation	0.21
13	X13	Individual differences in acceptance	0.17
14	X14	Stability of values	0.08

The influence of each feature on each sample is shown in Figure 5. Each row represents a feature, and each point represents a sample. The x-axis represents the SHAP value, and the color indicates the strength of the feature value, with red and blue representing low and high values, respectively. It can be observed that higher values for features such as teacher professional competence (X1) and content timeliness and relevance (X2) increase the probability of efficient transmission of ideological and political education content to college students, while lower values for features such as content depth and logical coherence (X10), cognitive foundation and learning motivation (X12), and individual difference acceptability (X13) also increase the probability of efficient transmission of ideological and political education content to college students. Due to some students binge-watching videos at the end of the semester or cramming to complete tasks at the last minute to meet the requirements for regular performance assessments, certain characteristic values such as content depth and logical coherence, cognitive foundation and learning motivation, and individual differences in acceptance exhibit abnormally high levels during a specific period. In contrast, students with better learning habits exhibit characteristic values for ideological and political behavior that change according to certain patterns and remain relatively stable. Based on the average SHAP value importance ranking for each characteristic, it can be observed that the characteristic related to teachers' professional competence is the most important.

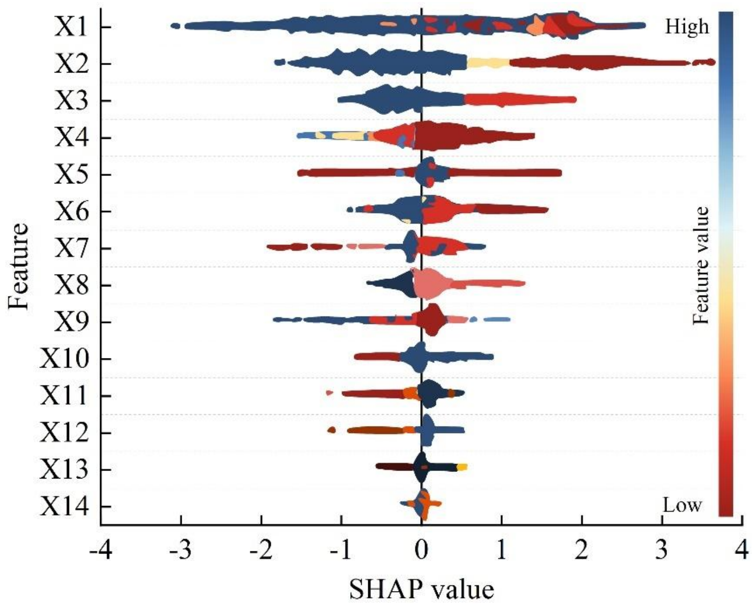

Figure 5. Scatter plot of feature influence.

To visually assess the extent to which each feature influences the sample's ability to predict whether students will achieve optimal outcomes in ideological and political education content delivery, and to demonstrate how different feature SHAP values impact the model's prediction of ideological and political education content delivery outcomes, we analyzed the contribution of each sample's feature SHAP values to the prediction results through visualization. First, we statistically analyzed the sample data as a whole. The SHAP value analysis of all features contributing to the prediction results is shown in Figure 6. Each column in the figure represents a sample, which is aggregated and arranged by similarity. The horizontal axis represents the sequence number of the samples after aggregation and sorting by similarity. The colors of the composition areas of each sample are pink and orange, respectively, and the vertical axis values corresponding to the boundaries are the model output values f(x) corresponding to the samples. The pink region consists of features that increase the output value f(x), while the orange region consists of features that suppress the increase in f(x). The distance between adjacent blue lines within the same region represents the SHAP value of a particular feature, as shown below. Figure 7 displays the sorted data of all ideological and political behavior feature data based on their contribution to predicting the effectiveness of ideological and political education content transmission.

Figure 6 shows the contribution of each feature to the prediction results for the 172nd student sample, where the values for certain features such as teacher professional competence, content timeliness and relevance, willingness to translate knowledge into action, and teaching method innovation are 53.6, 15, 36, and 67.4, respectively. The distance between adjacent blue lines in the same region in the figure represents the SHAP value for each ideological and political behavior feature, but it still does not allow for a more intuitive comparison of the impact of each ideological and political behavior feature on the model's prediction results.

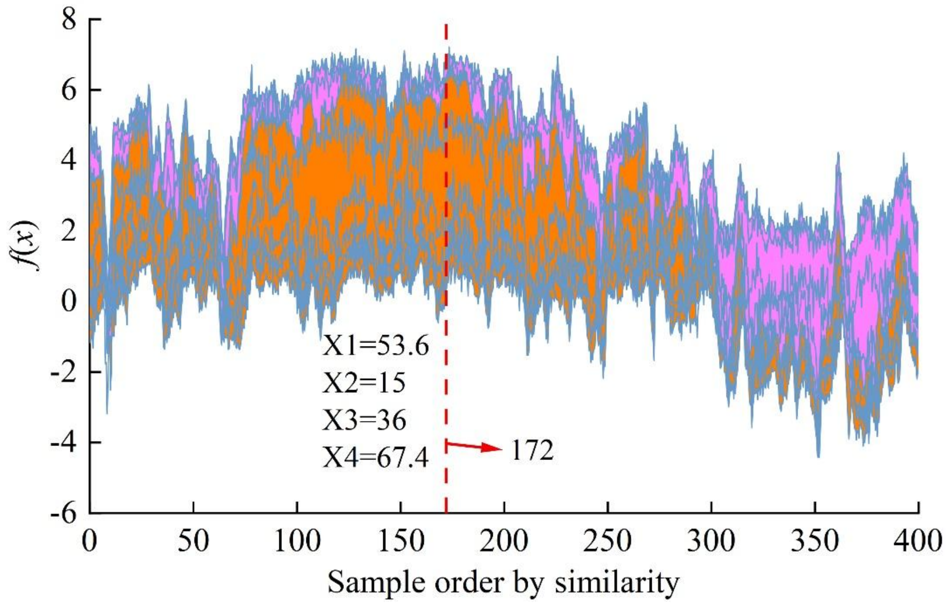

Figure 6. SHAP value analysis - sample similarity aggregation.

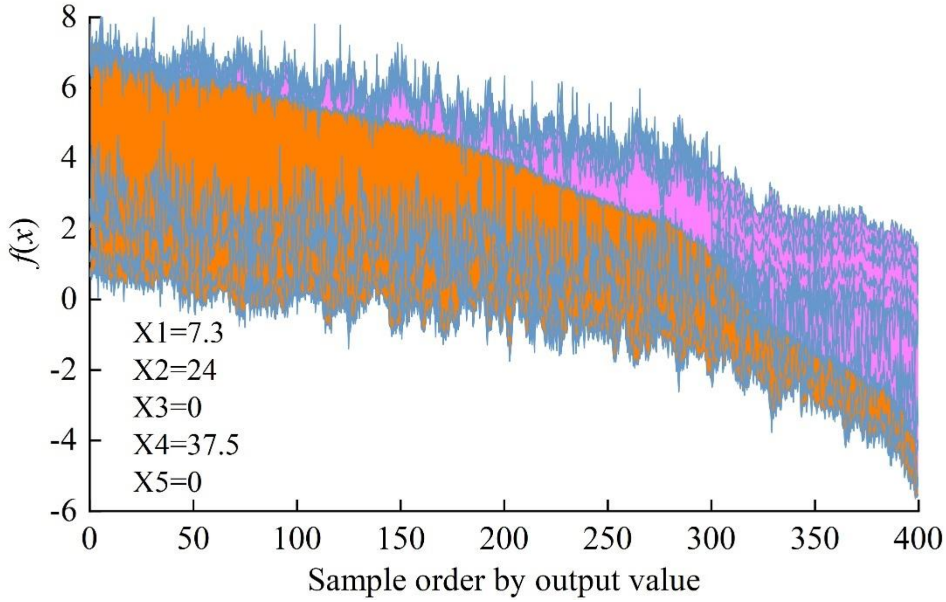

Figure 7. SHAP value analysis - ranking of contribution to model prediction.

As shown in Table 3, feature X1 has the greatest influence on the final prediction of whether students can obtain better ideological and political education content delivery effects. This paper uses feature XI as an example for visualization analysis. The SHAP value analysis of feature X1 on some student samples is shown in Figure 8, where the horizontal axis represents the value of feature X1, and the samples are arranged in ascending order according to the value of X1. It can be seen that the partial feature values of X1, X2, X3, and X4 when predicting a certain student sample are 63.5, 66, 15, and 41, respectively. From the distance between the blue lines in the figure, it can be seen that the distance between the two blue lines where feature X1 is located is the largest, indicating that the teacher's professional quality feature has the greatest influence on predicting whether most student samples can achieve optimal ideological and political education content delivery effects.

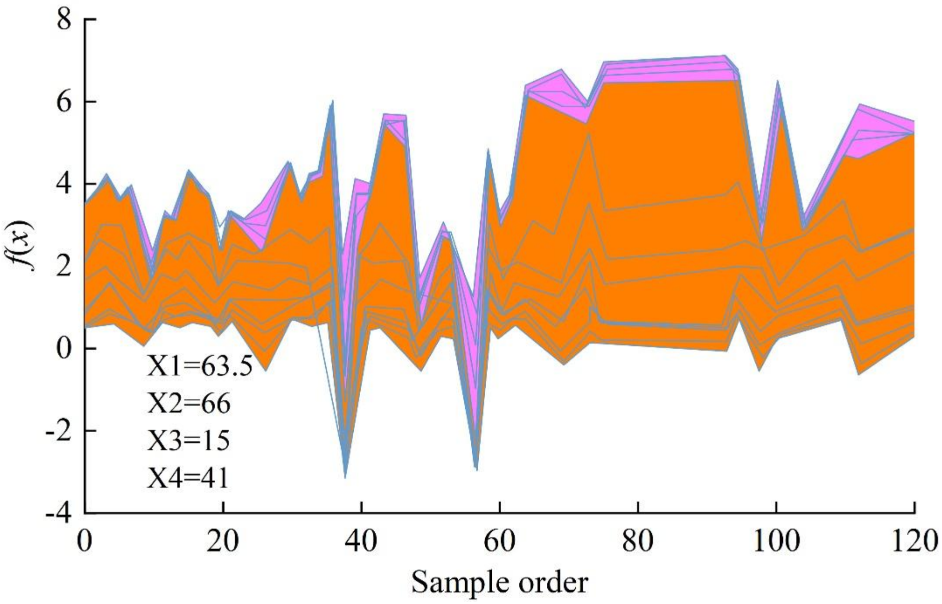

Figure 8. Analysis of X1 SHAP values.

4. Designing an optimized path for conveying ideological and political education content to college students

By evaluating the effectiveness of ideological and political education content delivery to college students and analyzing its influencing factors, this chapter designs an innovative approach to optimizing the delivery of ideological and political education content in both online and offline educational environments.

(1) Shift teaching philosophy to student-centered ideological and political education

In the context of the new media era, the traditional "teacher-centered" ideological and political education model is no longer sufficient to fully meet the demands of the times. Therefore, teaching philosophy must undergo a fundamental shift to establish the student's central role and drive innovation in ideological and political education concepts.

First, teachers should adhere to the principle of "student-centered, teacher-guided," prioritizing students' individual needs as the core consideration in instructional design. For example, at the beginning of the semester, through surveys or online feedback collection, teachers should comprehensively understand students' interests in course topics and use this as the basis for designing instructional content and activities. During the teaching process, teachers should also pay attention to student feedback, flexibly adjust course schedules and teaching methods, and ensure that instructional activities align with students' actual needs and concerns.

Second, establish a teaching philosophy that emphasizes student participation, transforming students from passive recipients to active participants in the classroom. Therefore, clearly defined classroom participation tasks can be set to encourage students to express their views and ask questions in class. At the same time, student classroom participation should be incorporated into the course evaluation system to incentivize students to actively engage in classroom activities and enhance their sense of agency.

Third, teachers should change traditional concepts and build a new type of teacher-student relationship based on equality and interaction. Teachers should abandon the one-way teaching attitude and design teaching activities as a process of joint exploration between teachers and students to create a positive interactive classroom atmosphere.

Finally, establish a long-term mechanism to promote changes in teachers' concepts. Colleges and universities should regularly hold teaching concept seminars, teacher-student forums, etc., to reflect on the implementation of teaching concepts and continuously optimize implementation paths.

(2) Innovate teaching content and combine the characteristics of new media to improve the relevance of education

In the era of new media, the fragmentation and diversity of information have also brought severe challenges to the content design of traditional ideological and political education. Teachers should innovate teaching content, enhance the appeal and relevance of ideological and political education, combine the characteristics of new media with educational goals, and influence students' thoughts and actions from the perspective of educational content.

First, teaching content should be dynamically adjusted to closely align with students' actual needs and areas of interest. Teachers should regularly collect information on social hot topics and news events that students are concerned about through new media platforms and incorporate the collected materials into ideological and political education courses.

Second, select specific themes and develop them in depth to enhance the timeliness and appeal of teaching content. In ideological and political education, teachers can focus on social issues with distinct contemporary characteristics and use them as entry points for ideological and political courses. At the same time, specialized courses or modules should be developed to combine such themes with Marxist theory and socialist core values, thereby demonstrating the practical application value of theory in current social development.

Third, the breadth of teaching content should be expanded to actively promote interdisciplinary integration. Teachers can attempt to combine ideological and political education with disciplines such as philosophy, sociology, and psychology to enrich the dimensions of ideological and political education content.

Finally, a distinctive teaching content system centered on school-based resources should be constructed. Schools can organize teachers and students to jointly develop ideological and political education resources with regional cultural characteristics and school characteristics, and push them to students through new media platforms.

(3) Enrich teaching methods and use new media platforms to achieve blended online and offline teaching

To meet the increasingly diversified and personalized learning needs of college students and enhance the effectiveness of ideological and political education, universities and teachers should make full use of new media platforms to promote a blended teaching model that combines online and offline teaching.

First, teachers should skillfully integrate the advantages of new media to design flexible and diverse teaching models to achieve complementary teaching effects. In course design, teachers can place theoretical and knowledge-rich content in online self-study modules for students to learn independently outside of class. At the same time, teachers can use online quizzes, group discussions, and other forms to track students' learning progress and understanding, providing data support for offline classroom interaction.

Second, online learning content should focus on enhancing students' sense of participation to stimulate their enthusiasm for active learning. On new media platforms, teachers can set up diverse teaching activities to enhance students' participation experience. To ensure the smooth implementation of online teaching, universities should build professional online learning platforms, integrate various learning resources, and provide real-time feedback and assessment mechanisms. Teachers should actively participate in platform construction and management, regularly update teaching content and interactive tasks, and ensure the richness and timeliness of platform resources.

Third, offline teaching should emphasize practicality and emotional experience to enhance students' sense of identification with ideological and political education. In classroom teaching, teachers can design group cooperation and case analysis sessions, combining materials provided by new media platforms to conduct thematic teaching and practical activities. At the same time, teachers can organize students to conduct social surveys, use new media platforms to collect relevant materials, support classroom discussions with data, and showcase learning outcomes through on-site reports.

Finally, blended online and offline teaching should fully utilize new media and new technologies to enhance the sustainability of teaching. Teachers can use multimedia, AR/VR, and other technological means in the classroom to vividly illustrate abstract theories and enhance students' immersion and learning experience.

(4) Enhance teachers' teaching abilities and improve their new media literacy and teaching skills

To adapt to the teaching needs of the new media era, universities should take effective measures to help teachers improve their teaching capabilities and ensure that ideological and political education plays a greater role in the new media environment.

First, universities should organize new media skills training and encourage teachers to improve their new media literacy through systematic learning. In addition, universities should provide teachers with ongoing support for development, offering more training and practical opportunities for young teachers, while organizing academic research and curriculum reform projects for experienced teachers to promote their continued development.

Second, teachers should continuously refine their teaching skills through ideological and political education practice. In actual teaching, teachers should actively utilize new media and technologies in instructional design, while also proactively guiding students to use new media platforms for extracurricular learning and critical thinking, thereby expanding the temporal and spatial boundaries of the classroom.

Finally, the academic literacy of teachers should be enhanced, and their interdisciplinary knowledge reserves should be enriched. Universities should encourage teachers to engage in interdisciplinary learning and organize interdisciplinary academic seminars to enhance teachers' interdisciplinary teaching abilities. Ideological and political education teachers should actively participate in academic exchanges and research activities in related fields to continuously broaden their teaching horizons and thereby enhance their teaching skills.

5. Conclusion

This paper constructs a TPE-XGBoost predictive model for the effectiveness of ideological and political education content delivery among college students. It employs the K-means clustering algorithm and SHAP explanation method to explore the primary factors influencing the effectiveness of ideological and political education content delivery among college students, and optimizes the delivery pathways for such content.

The study constructs a TPE-XGBoost attribute feature training model from five dimensions: educational subjects, educational content, educational methods, educational environment, and recipients of education. The pruning method is used to screen and obtain 14 attribute features. The TPE-XGBoost prediction model achieves optimal results in terms of accuracy, misclassification rate, recall rate, precision, F1 score, and AUC value of the TPE-XGBoost prediction model achieved optimal results, reaching 91.74%, 8.96%, 93.75%, 91.22%, 0.9247, and 0.9813, respectively, validating the effectiveness of the constructed prediction model.

Through K-means clustering analysis, four categories of ideological and political education content delivery for college students were identified. Analysis of their feature values revealed that indicators such as teaching method innovation, personal charm and approachability, practical teaching, value stability, teacher professional competence, content timeliness and relevance, willingness to translate knowledge into action, campus cultural atmosphere, social support intensity, content depth and logical coherence, teaching ability and methods, reasonableness of the evaluation mechanism, and other indicators have a significant impact on optimizing the effectiveness of ideological and political education content delivery for college students. Additionally, SHAP analysis indicates that teacher professional competence is the primary factor influencing the effectiveness of ideological and political education content delivery for college students, followed by content timeliness and relevance, and willingness to convert knowledge into action. Combining these three factors with other influencing factors, this paper designs an innovative path for optimizing ideological and political education content delivery for college students, including student-centered approaches, innovative teaching content, diverse teaching methods, and enhanced teacher teaching capabilities.

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