International Journal for Housing Science and Its Applications
Publish August 4, 2025. Volume 46, Issue 3 Pages 2877-2888

https://doi.org/10.70517/ijhsa463241

Research on Teaching Quality Improvement Mechanism for Teachers of Marketing Majors in Higher Vocational Colleges and Universities Based on Decision Tree Modeling

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Abstract The classroom is the main battlefield of teachers' work in higher vocational colleges and universities, and good quality of classroom teaching is not only the transfer of classroom knowledge, but also an effective means of implementing the fundamental task of establishing moral character. In view of this, the article first explores the influencing factors of the teaching quality of teachers specializing in marketing in higher vocational colleges. On this basis, it constructs a predictive model of teachers' teaching quality based on the decision tree model, utilizes hypothesis testing and feature importance for feature selection, and proposes the SHAP additivity interpretation method to interpret the decision tree model by categories. The study shows that the constructed prediction model can achieve better prediction performance, while using the SHAP interpretation method, three kinds of teaching quality driving factors analysis are realized, and it is concluded that the subjectivity factor's has the greatest contribution in the improvement of teachers' teaching quality, and its SHAP value is 0.68. The relevant parts of the school can improve the teaching level of teachers of marketing majors in higher vocational colleges and universities from the aspects of improving the teaching level of teachers, stimulating the interest of students in learning and improving the teaching guarantee system.

Index Terms decision tree modeling, SHAP, teaching quality, higher vocational institutions

I. Introduction

Marketing course is a basic course to cultivate and stimulate students' interest in learning marketing [1]. With the development of society, the social demand for marketing talents is increasingly demanding, and higher vocational colleges and universities pay special attention to the training of marketing professionals, especially the teaching of marketing courses. As the teaching mode of the course lags behind the needs of social development, the higher vocational colleges and universities are also actively exploring new methods to strengthen the training of talents.

All along, higher vocational colleges and universities have always taken improving the quality of talent training as the goal of teaching reform, and the quality of talent training depends on the quality of the curriculum [2]. Teachers are the center of the whole teaching work, and the quality of the curriculum is directly reflected in the effect of teachers' "teaching" and the effect of students' "learning" [3], [4]. Therefore, the teaching supervision work should be tightly grasp the supervision of the course teaching this central link, and effectively ensure the quality of the course [5]. At present, most of the higher vocational institutions of the course quality supervision is mainly through listening to the evaluation of classes, expert group supervision, student evaluation, teaching inspection and other forms of realization [6], [7]. Due to the contradiction between the demand for marketing talents by industrial enterprises and the evaluation system of course quality, and the previous evaluation results can not be adjusted in time to the problems in teaching, the traditional teaching supervision mechanism can not practically supervise the teaching effect [8]-[10]. It is necessary to further integrate the course quality diagnosis and improvement into the daily teaching work, and effectively improve the level of construction of higher vocational marketing courses, in order to effectively improve the quality of talent cultivation in higher vocational colleges and universities [11], [12].

Decision tree is a common algorithm in machine learning, and its application to teaching evaluation in colleges and universities can fully explore the factors affecting the educational effect and their relationships, and then help teachers improve the teaching process to enhance the quality of teaching. The application of decision tree algorithm in teaching evaluation in colleges and universities has been widely studied by the academic community. For example, literature [13] establishes a teaching quality evaluation model based on the improved C4.5 decision tree algorithm, which uses an iterative analysis mechanism to analyze the personalized behavioral data generated by students in the teaching process, so as to dynamically adjust and generate reliable teaching evaluation results. Literature [14] shows that the traditional teaching evaluation method has limitations such as subjectivity, inaccuracy and ambiguity, for this reason, a multi-criteria decision tree model is constructed with the help of a cloud computing platform, and the evaluation value is transformed through the cloud model in order to assist teachers in making scientific and accurate teaching decisions. Literature [15] for the existing teaching evaluation methods can not find the problem of hidden knowledge in teaching data, put forward the teaching evaluation system based on the decision tree algorithm and association rule method, can help teachers to effectively extract students' learning characteristics, to improve teaching management, optimize the teaching configuration to provide decision-making support. Literature [16] uses the decision tree C4.5 algorithm to extract student behavioral characteristics data in the online education system and constructs an evaluation model, evaluates students' academic performance from various aspects, and at the same time proposes interventions for students' online learning behaviors, which provides reference for teachers to carry out dynamic teaching management. Literature [17] proposes a big data classification model for MOOC teaching quality evaluation, and obtains the best teaching quality evaluation indexes by introducing a decision tree model, so as to improve the informatization management capability of MOOC online evaluation. Literature [18] used the marine predator algorithm to optimize the parameter extraction process of the decision tree model, and then constructed a distance teaching quality evaluation model with robustness and high efficiency to provide accurate guidance for improving the teaching performance of colleges and universities. The above study shows that the use of decision trees and related rules to establish a teaching evaluation framework for colleges and universities can achieve the purpose of comprehensive research on teaching quality evaluation in colleges and universities. Therefore, by establishing a marketing teaching evaluation method based on the decision tree model in higher education institutions, it can effectively solve the problems of insufficient objective scientific evaluation and low accuracy in the educational process.

In this paper, we first analyze the factors affecting the quality of classroom teaching of marketing majors in higher vocational colleges and universities in terms of the level of teachers, the state of students and the role of the system, and then introduce the relevant theories according to the process of modeling, and use hypothesis testing and feature importance for feature selection. After that, the parameters in the model to cope with the unbalanced data are determined, and the SHAP interpretation method is introduced to explain the importance of the model features. Taking the teachers of marketing majors in a higher vocational college as the research object for empirical evidence, the prediction results of the three teaching quality influencing factors are explained separately using the SHAP interpretation method, and the improvement strategies of classroom teaching quality of marketing majors in higher vocational colleges and universities are proposed from the three dimensions of the improvement of the teaching level, the stimulation of the interest in learning, and the soundness of the teaching guarantee system.

II. Factors affecting the quality of classroom teaching of marketing majors in higher education institutions

II. A. Subjective factors: the level of teachers

Teachers are the designers and masters of classroom activities, and the level of teachers has a key impact on the quality of classroom teaching. Whether they can do a good job in every lesson requires that teachers must have a high degree of professionalism, which covers a wide range of knowledge systems such as morality, professional knowledge, competence, psychology, etc., and the ability to conduct superb classroom teaching activities, which involves pre-course preparations, classroom management, teaching methodology, interactive exchanges and post-course follow-up, etc. They also have a high level of teacher ethics and teacher ethics, so that teachers have a correct professional outlook and a caring attitude. It is also necessary to have a high level of teacher ethics, so that teachers have a correct view of their profession and a caring attitude towards students.

II. B. Motivational factors: students' status

Students are the main body of learning, the protagonist of the classroom teaching quality gains, high-quality classroom teaching is often teachers explicitly teach students to learn to learn to teach as a means to enable students to have the ability to independent learning behaviors, learning behaviors involved in the learning interest, learning goals, school motivation, learning status and school results. With the expansion of higher vocational colleges and universities, student management is relatively lagging behind, giving rise to a number of problems that affect the quality of classroom teaching.

II. C. Intermediary factors: the role of institutions

School-related rules and regulations for the quality of classroom teaching, directly or indirectly affect the quality of classroom teaching, the supervision of daily teaching is an important part of the quality assurance of teaching within the higher education institutions, and some colleges and universities have set up specialized supervisory departments, which play a very important role in guaranteeing the quality of classroom teaching, but the relevant systems related to teaching are still subject to deviations in the process of management and implementation.

III. Construction of a model for predicting teachers' teaching quality based on decision tree modeling

III. A. Data coding

Data preprocessing is a crucial step in machine learning, especially when we deal with data containing categorical variables. Categorical variables are those that have a limited number of possible values, such as gender, color, and animal. However, most machine learning models are based on numerical type variables. To address this problem, we first need to encode the existing categorical variables and transform them into numerical types of data that are easy for the model to understand and process. Several common methods for coding categorical variables are unique heat coding, sequence coding, frequency coding, hash coding, and target coding, respectively.

III. B. Feature selection

III. B. 1) Feature selection based on hypothesis testing

(1) Feature selection of numerical type features using the t test

The t test for the two aggregates performed in this paper is defined as follows:

Suppose that $X_1, X_2, \cdots, X_{n_1}$ is a sample from a normal population $N\left(\mu_1, \sigma^2\right)$, $Y_1, Y_2, \cdots, Y_{n_2}$ is a sample from a normal population $N\left(\mu_2, \sigma^2\right)$, the sample means of the two populations are $\bar{X}$ and $\bar{Y}$, the sample variances are S_1^2 and S_2^2, the two samples are independent of each other, and μ_1, μ_2, σ^2 are unknown. The problem to be tested is:

$$H_0 : \mu_1 - \mu_2 = \delta, H_0 : \mu_1 - \mu_2 \neq \delta \tag{1}$$

where δ is a known constant.

$$t = \frac{(\bar{X} - \bar{Y}) - \delta}{s_w \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}} \tag{2}$$

where $S_w = \sqrt{\frac{(n_1 - 1)S_1^2 + (n_2 - 1)S_2^2}{n_1 + n_2 - 2}}$ and $t \sim t(n_1 + n_2 - 2)$ when H_0 is true.

However, the t test requires that both totals obeying a normal distribution have equal variances, so it is necessary to test whether the two totals have equal variances before conducting the t test. The F test is usually used:

$$H_0 : \sigma_1^2 = \sigma_2^2, H_0 : \sigma_1^2 \neq \sigma_2^2 \tag{3}$$

$$F = \frac{S_1^2}{S_2^2} \tag{4}$$

If the two overall variances are considered to be the same, the t test is done directly, and if the two overall variances are different, the Welch modified t test is performed, and this method is a better way to do the t test when the overall variances are different.The Welch approximation of the t test assumes that, when δ is taken to be zero in the test problem for the t test, the test statistic t can be approximated to obey the t distribution when H_0 holds. H_0 holds can be approximated to obey the t distribution with degrees of freedom:

$$\frac{\left(\frac{S_1^2}{n_1} + \frac{S_2^2}{n_2}\right)^2}{\frac{S_1^4}{n_1^2(n_1 - 1)} + \frac{S_2^4}{n_2^2(n_2 - 1)}} \tag{5}$$

(2) Feature selection of subtype features using the Lev-Level Table chi-square test

In this paper, we study a dichotomous problem where the target variable is a sub-type of feature, and we can use the column-linked table chi-square test to calculate whether there is a significant difference between two sub-type variables.

The column-linked table chi-square test is a statistical method used to analyze the independence between two or more categorical variables. It does this mainly by looking at the degree of agreement or deviation between the actual number of observations and the theoretical frequency. The results of its test can help us determine whether there is a correlation between these variables.

In conducting the test, the original and alternative hypotheses are first established, with the original hypothesis H_0 being that the two variables are not independent and the alternative hypothesis H_1 being that the two variables are independent of each other. Next, the theoretical frequencies are calculated and the degrees of freedom are computed by the formula $df = (R-1)(C-1)$, where R is the number of rows in a list of columns and C is the number of columns in a list of columns. In turn, the chi-square statistic can be calculated:

$$\chi^2 = \sum \frac{(f_0 - f_e)^2}{f_e} \tag{6}$$

where f_0 is the frequency of observations and f_e is the frequency of expectations.

Eventually, the corresponding critical values are found in the chi-square distribution table based on the degree of freedom and significance level. If the calculated chi-square statistic is greater than the critical value, the null hypothesis is rejected and the variables are considered not independent. If the calculated chi-square statistic is less than or equal to the critical value, the null hypothesis is not rejected and the variables are considered independent.

III. B. 2) Feature selection based on model feature importance

In the feature selection process, the trained model can be used to evaluate the extent to which each feature contributes to the model's performance, so that the most important subset of features can be selected.

First, a baseline model is trained using the full set of features, which can be of any type, e.g., linear regression, decision trees, support vector machines, etc. Then, evaluate the impact of each feature in the model on the predictive ability of the model. Some models allow direct querying of feature importance, and for models that do not support direct querying of feature importance, feature importance can be indirectly evaluated by observing the change in the model's performance after removing a feature. Second, based on the results of the feature importance assessment, the most important features are selected, which can be done using different strategies such as selecting the top k most important features or using a threshold to filter out less important features. Finally, the performance is evaluated on a validation set using the model trained on the dataset obtained after feature selection to ensure that the feature selection process has not compromised the predictive ability of the model.

III. C. Imbalance data processing

III. C. 1) Sampling

In machine learning algorithms, oversampling is a strategy to address the uneven data distribution of the target variable. Oversampling means increasing the amount of data for a few categories of samples, so that the proportion of positive and negative samples in the dataset is as expected, thus achieving the purpose of improving the prediction accuracy of the model for a few categories. Commonly used oversampling methods include random oversampling, SMOTE sampling, and so on.

(1) Random oversampling

Random oversampling by randomly selecting samples in a few categories, and then these samples are simply copied many times until the state of balance between the number of positive and negative samples is reached, and the sample gap between the few categories and the majority category determines the number of samples copied from the few categories in the oversampling process.

(2) SMOTE sampling

SMOTE is an oversampling technique specifically designed to address the problem of categorical data imbalance.SMOTE works on the principle that for each sample of the minority class, the algorithm randomly selects samples among its k nearest neighbors, and then interpolates between the original samples and the selected nearest neighbors to generate new synthetic samples, which can be linear, quadratic, or in other forms depending on the characteristics and distribution of the data.

III. C. 2) Adjustment of model parameters

When dealing with unbalanced categorical datasets, LightGBM and XGBoost provide the scale_pos_weight parameter, while Random Forest uses the class_weight parameter, both of which are designed to alleviate the class imbalance problem, but they differ in their mechanism of action and usage. scale_pos_weight parameter is a tool in LightGBM and XGBoost for adjusting the weights of positive and negative samples to solve the problem of sample size imbalance. By increasing the weight of the minority class, this parameter enables the model to pay more attention to the minority class during training, which improves the accuracy of the minority class during prediction. scale_pos_weight's value should be set according to the ratio of positive and negative samples in the dataset. If the ratio of positive and negative samples is close to 1:1, it can be set to 1. If the minority class has fewer samples, a value greater than 1 can be set to increase the relative weight of the minority sample.

In contrast, the class_weight parameter is used in Random Forests to deal with class imbalance, which allows the user to manually specify weights for each class or have the algorithm automatically calculate weights based on the frequency of classes. Random Forest's class_weight defaults to a "balanced" strategy, which assigns weights to each category based on its frequency, thus ensuring that the importance of each category in model training matches its proportion in the dataset.

The adjustment of these two parameters can improve the performance of the model when dealing with unbalanced datasets to a certain extent, but we need to determine the optimal parameter values according to the specific data and problems.

III. D. Machine learning models

III. D. 1) Decision tree model

Decision tree model is a widely used machine learning model for classification, and its principle comes from the tree structure. Specifically, the algorithm learns information from the training data in the order of "root node - leaf node", and arrives at the final prediction result based on a series of progressive classification decisions. The fitting process of the decision tree model is relatively simple, and the model results are relatively less dependent on parameter assumptions, which is more suitable for high-dimensional data. In the decision tree model, the commonly used classification criteria are the information gain criterion, Gini index criterion [19]. In this paper, we will construct a classification and regression tree (CART) based on the Gini coefficient, and the specific framework is as follows.

First, take the root node as the starting point, for the dataset D here, calculate the Gini coefficient under the binary classification problem:

$$Gini(D) = 2p(1-p) \tag{7}$$

where p denotes the probability that a randomly drawn sample from the data set D belongs to the default sample. $(1-p)$, on the other hand, denotes the probability that a randomly drawn sample from the dataset D belongs to the normal sample.

Second, for the current node, the Gini coefficient of the influence variable is computed for all values taken on the data set D:

$$Gini\left(D,a\right) = \frac{D_1}{D}Gini\left(D_1\right) + \frac{D_2}{D}Gini\left(D_2\right) \tag{8}$$

where a denotes some value of the influence variable A. D_1 and D_2 denote the classification results of the data set D according to the influence variables and their values, respectively.

Third, for all the influence variables and their corresponding values, the optimal influence variables and optimal values corresponding to the smallest Gini coefficient are determined according to the Gini coefficient minimization criterion:

$$a^* = \underset{a \in A}{\arg\min}\, Gini\left(D,a\right) \tag{9}$$

Fourth, the left and right leaf nodes are divided, and the data set D is divided into two parts, D_1^* and D_2^*, based on the values of the optimal influence variables, where D_1^* is the data set at the left leaf node and D_2^* is the data set at the right leaf node.

Repeat the above steps for the generated leaf nodes until the Gini coefficient or the total amount of data in the dataset at the leaf node is below the threshold, and the decision tree model construction is completed.

III. D. 2) Random Forest Model

The Random Forest model is derived from integrated learning and is a synthesis of the Bagging algorithm and decision trees. In the construction process, the model randomly extracts datasets, influence variables to generate multiple decision trees, and summarizes the classification prediction results of all the decision trees. The random forest model is easy to implement and learns faster. At the same time, the use of random sampling method gives it better generalization performance, remains robust in the case of more outliers, and the overall accuracy of the model is high [20]. Specifically, the generation of the random forest model is analyzed as follows.

First, the dataset D is sampled randomly and with putback using Bootstrap method to generate k training sets $\{D_1, D_2, \cdots, D_k\}$.

Second, for each training set, m randomly selected $(m < x)$ from all x influence variables, and the decision tree model is built by applying complete splitting without pruning.

Finally, the random forest model consists of the fitted k decision tree models $\{T_1(x), T_2(x), \cdots, T_k(x)\}$. During the prediction process, each decision tree model will produce classification results, and the final result is determined by the majority voting principle:

$$\begin{aligned} H(x) &= \arg\max \sum_{i=1}^{k} I\left(T_i(x) = y\right) \\ I\left(T_i(x) = y\right) &= \begin{cases} 1, T_i(x) = y \\ 0, T_i(x) \neq y \end{cases} \end{aligned} \tag{10}$$

where $H(\cdot)$ denotes the result obtained from the integrated post random forest model. $T_i(\cdot)$ denotes the fitting result of the i th decision tree model. $I(\cdot)$ is a schematic function that serves to statistically predict the categorical results of the decision tree model.

III. E. SHAP Interpretation Methods

Model interpretability is a major challenge in the application of machine learning methods, and model interpretation has not been given enough attention in the research field of using machine learning for educational big data prediction. In order to improve the interpretability of machine learning models, this paper adopts the SHAP method, which assigns a value to each input variable reflecting its importance to the prediction results.

For the subset of student features $S \subseteq F$ (where F represents the set of all features), two separate models are trained to extract the influence of feature i. The first model $f_{S\cup\{i\}}(x_{S\cup\{i\}})$ is trained with feature i as an input, while the other model $f_S(x_S)$ is trained without feature i as an input, where $x_{S\cup\{i\}}$ is the input feature with x_S. Then, for each possible subset $S \subseteq F \setminus \{i\}$, $f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)$ is computed to obtain the Shapley value for each feature i:

$$\phi_i = \sum_{S \subseteq F\setminus\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!}(f_{S\cup\{i\}}(x_{S\cup\{i\}}) - f_S(x_S)) \tag{11}$$

However, a major limitation of Eq. (11) is that the computational cost will increase exponentially as the number of features increases. To address this issue, an easy to handle computational tree model interpretation method i.e. TreeExplainer is proposed.The TreeExplainer method makes it more efficient to compute the SHAP values for both local and global eigenfactors.

SHAP combines optimal assignment and local interpretation using classical Shapley values. It will help the user to trust the predictive model, not only what the predictions are, but also why and how the predictions are made. Thus, the SHAP interaction value can be calculated as the difference between the Shapley values with factor i and without factor j in Eq:

$$\begin{aligned} \phi_{i,j} = \sum_{S \subseteq F\setminus\{i,j\}} \frac{|S|!\left(|F|-|S|-2\right)!}{|F|!} &\left(f_{S\cup\{i,j\}}\left(x_{S\cup\{i,j\}}\right)\right. \\ &\left. - f_{S\cup\{i\}}\left(x_{S\cup\{i\}}\right) - f_{S\cup\{j\}}\left(x_{S\cup\{j\}}\right) - f_S\left(x_S\right)\right) \end{aligned} \tag{12}$$

Based on this advantage, it is used in this part to explain the decision tree-based XGBoost model with a view to discovering the predictive impact of different features of students on their final destination. Thus, SHAP not only ranks the importance of features but also shows the positivity and negativity of the results of the influence of the features in order to improve the interpretation of the model output compared to the existing methods [21].

IV. Empirical studies

IV. A. Sample Selection and Data Sources

In this paper, the teachers of marketing majors in a higher vocational college are studied, and the data set of 2010-2020 students' academic performance is selected as the test sample. The three main factors measuring teachers' teaching quality in this paper mainly include subjectivity factor, dynamism factor and mediation factor.

IV. B. Selection of indicators

(1) Indicators based on subjectivity factors

The indicators of teachers' influence on the quality of classroom teaching mainly include: faculty structure, teaching methods, professional attitudes, and classroom interaction.

(2) Indicators based on motivational factors

Indicators based on motivational factors mainly include individual characteristics, knowledge reserve, self-control level and learning interest.

(3) Indicators based on mediating factors

Indicators based on mediating factors mainly include teacher training system, student evaluation, and incentive mechanism.

IV. C. Test of teaching quality prediction model based on decision tree modeling

IV. C. 1) Optimization of model parameters

During the empirical modeling process, it was found that different parameter settings affect the classification performance of the decision tree model. Among them, three hyperparameters, n_estimators, max_depth and min_samples_split, have an important impact on the performance and complexity of the decision tree model, which can effectively control the overfitting and underfitting situations of the model. Next, the parameter optimization effect is evaluated through the training set to obtain the best model parameters.

First, the GridSearchCV function in the Scikit-learn library was called using Python3, and ROC_AUC was chosen as the evaluation criterion during the model training process because it can well reflect the model's ability to differentiate between positive and negative samples when evaluating the model's performance without being affected by the sample imbalance. Then, the input data are divided into training and validation sets using five-fold cross-validation, and the score of the model on the validation set is calculated under each parameter combination, and the combination with the highest score is regarded as the best model parameter combination. The specific process is as follows:

(1) n_estimators

Set the range of n_estimators between 10 and 200 and add 10 base learners each time. The learning curve of the number of subclassifiers in the decision tree model is shown in Figure 1. As can be seen from the figure, the score of the model increases as the number of base learners increases. When n_estimators is 110, the model reaches the optimum and the number of base learners in the decision tree model is finally set to 110.

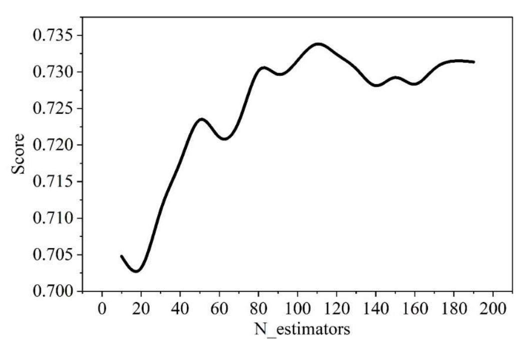

Figure 1: The learning curve of the number of neutron classifier in random forest model

(2) max_depth and min_samples_split

max_depth is the maximum depth of the control tree, increasing max_depth may lead to model overfitting as the tree becomes deeper and is able to learn detailed features of the training data. A larger max_depth may result in each leaf node containing only a small number of samples, which increases the risk of overfitting. min_samples_split is the minimum number of samples required to define a node split, increasing min_samples_split may result in the tree growth being limited as more samples are required when the node splits. A larger min_samples_split may result in slower tree growth, making the tree relatively small in depth. Therefore, a balance between the two needs to be taken care of when adjusting the parameters. The grid search method is used to traverse the values of max_depth [2,9] and min_samples_split [10,101] with a step size of 10. The optimal parameter combination is finally determined to be (max_depth: 6, min_samples_split: 30), and the statistics of model effect of some parameter combinations of the random forest are shown in Table 1 Table 1 shows the effect statistics of the random forest model. After parameter optimization, the best parameters on the training set can be determined, and the model predicts best when n_estimators is 110, max_depth is 6 and min_samples_split is 20.

Table 1: The model effect of the random forest section is calculated

min_samples_split	min_samples_split	Sroce
6	20	0.746418635
8	20	0.744987569
5	20	0.742413621
4	10	0.742387381
6	40	0.742312256
……		
2	30	0.724882846
2	50	0.724808319
2	20	0.724804769
2	90	0.724144799
2	100	0.7235896

IV. C. 2) Assessment of model effectiveness

The determined parameters are applied to the test set, and the prediction results on the test set are finally obtained. The confusion matrix for the random forest model is shown in Table 2. From the table, it can be seen that there are 62 samples that are correctly predicted to be in the "fail" category and 25 samples that belong to the "fail" category but are incorrectly classified as "passing". There were 100 samples correctly predicted to be in the "pass" category and 36 samples in the "pass" category but incorrectly classified as "failing".

Table 2: The confusion matrix of the random forest model

Real category	Prediction category	
	Inferior lattice (tag: 0)	passing (tag:1)
Inferior lattice (tag: 0)	62	25
passing (tag:1)	36	100

Performance metrics such as accuracy, precision, recall and F1-Score of the model can also be calculated based on the confusion matrix, which enables a multifaceted assessment of the model performance. The results of the decision tree model classification experiments are shown in Table 3. From an overall perspective, the accuracy of the model prediction is 0.732, indicating that the samples correctly predicted by the model account for 73.2% of the total predicted samples. From the classification index, the model's prediction performance in the passing category is slightly better than the failing category.

Table 3: Model classification experiment results

Categories	Classification index			Overall index
	Accuracy rate	Recall rate	F1-Score	Accuracy rate
Inferior lattice	0.647	0.708	0.68	0.732
passing	0.777	0.741	0.766	

In order to fully understand the performance of the classification model, the ROC curve of the model is further investigated. The ROC curve of the decision tree model is shown in Figure 2. From the figure, it can be seen that the micro-averaged AUC in the decision tree model is slightly higher than the macro-averaged AUC, indicating that the model has good classification performance in general. It can also be found that the AUC values of the two categories are equal, both being 0.779. Taken together, the AUCs of the two categories are at a high level, and the model performs well in predicting academic performance.

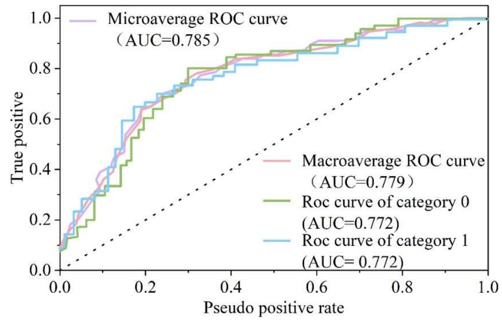

Figure 2: ROC curve of model

IV. D. Research on the quality level of teaching based on interpretable methods

The purpose of this paper is to explore the quality of teachers' teaching in marketing program in higher education institutions, therefore, this section further explores the indicators of the influence of high adaptive quality of teachers' teaching. The influence categories of teacher teaching quality are plotted on a global interpretation map, and the global interpretation map is shown in Figure 3. The SHAP value of each feature can be obtained to derive the degree of want of that feature. From the figure, it is concluded that the subjectivity factor is the main component with the largest contribution, and its SHAP value is 0.68, therefore, the original indicators that contribute more to this main component, i.e., the structure of the faculty, teaching methods, professional attitudes, and guiding classroom interactions have a greater impact on the quality of teachers' teaching of marketing majors in the higher vocational colleges and universities. This is also more consistent with the reality.

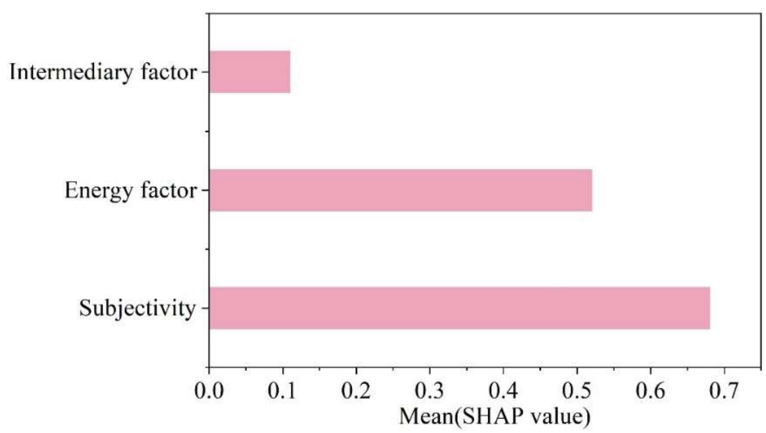

Figure 3: Global interpretation

At the same time, the feature contribution can also be analyzed by the summary graph, which is shown in Figure 4. According to the contribution degree from high to low in the y-axis from top to bottom, each point in the summary graph represents a sample, and the horizontal coordinate indicates the SHAP value of a feature of the sample. As shown in the figure, horizontal observation in the figure can be concluded that the larger the value of the principal component feature of the subjectivity factor, the larger the SHAP value, indicating that the principal component feature of the teacher's level makes a positive contribution to the quality of teaching, i.e., the original indexes of the structure of the teaching team, teaching methods, professional attitudes, and classroom interactions make a positive contribution to high quality of teaching. From this, it can be concluded that all the three factors of teacher level, student status and system are positive contributing features predicted as high teaching quality. In the following study, these principal component features are analyzed individually for interpretability so as to further explore the relationship between these principal component features and teacher teaching quality.

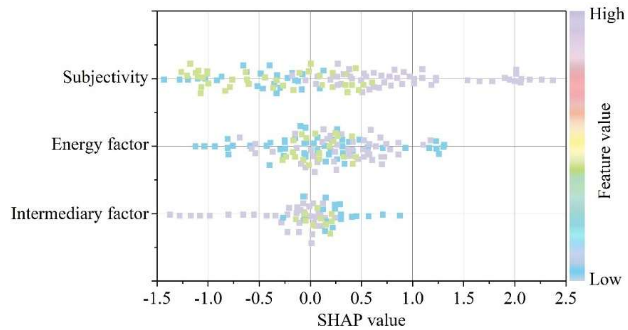

Figure 4: Feature summary

The partial dependency plot of a feature variable depicts the way in which that feature variable affects the dependent variable's characteristics, revealing how the feature variable affects the dependent variable's characteristics, starting with a single feature variable and analyzing its impact on online education fitness. Considering SHAP value as a force, each feature corresponds to a SHAP value that is either a force that increases or decreases online education fitness, if SHAP value is less than 0, it means that the feature decreases the predicted value, and if SHAPvalue is greater than 0, it means that the feature increases the predicted value, and the greater the absolute value of the SHAP value, it means that the influence on the dependent variable feature is The greater the absolute value of SHAP value, the greater the degree of influence on the characteristics of the dependent variable. In this paper, the three principal component features are studied separately. Partial dependency plots are drawn to observe the effects of their principal component features on online education adaptation. The partial dependency plots of teacher level, student status and institutional role are shown in Figures 5, 6 and 7, respectively. It can be obtained that the partial dependency plots of teacher level, student status and institutional role show an upward trend, so that teacher level, student status and institutional role are positive features of teachers' teaching quality. The information derived from the partial dependency graphs is basically consistent with the information obtained from the summary graphs of the characteristics, and this information is also more in line with the reality.

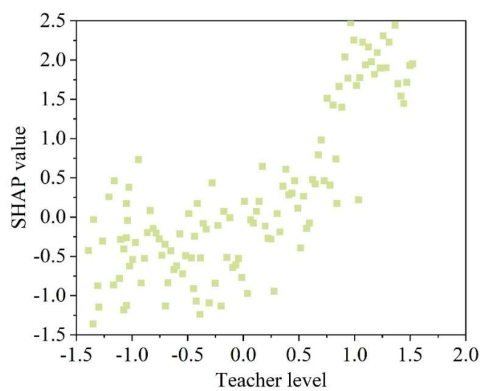

Figure 5: Part of the teacher level

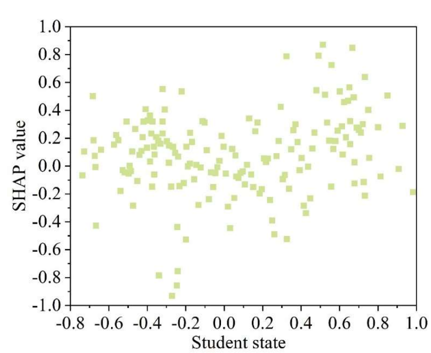

Figure 6: Part dependence of the student state

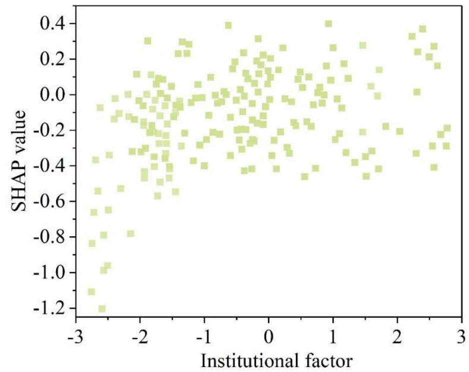

Figure 7: Part of the system's dependence diagram

V. Strategies for Improving Classroom Teaching Quality of Marketing Majors in Higher Education Institutions

V. A. Upgrading teachers' teaching skills

As the main participants in classroom teaching activities, teachers should recognize their main tasks and goals, and try their best to create conditions to attract students to the ocean of knowledge, enhance learning motivation, create a relaxed learning atmosphere, and experience the joy of teaching and learning. The university is like a small society, it is the preparatory stage before the students fully enter the society, the stage of students have strong plasticity, the words and deeds of teachers affect students, teachers should set an example, in addition to constantly improving their professional knowledge and ability, but also to establish a correct world view, outlook on life, values, improve their own ability in all aspects at the same time, increase their prestige in the hearts of students, so that students truly identify with and trust teachers from the bottom of their hearts.

V. B. Stimulating students' interest in learning

Students are the protagonists of classroom teaching activities, the quality of classroom teaching depends on the degree of student satisfaction, high-quality classroom can often stimulate students' interest in learning, to meet the learning needs of students, to enhance students' learning motivation, through the teacher's instruction to make students achieve willingness to learn, happy to learn, able to learn and insist on learning, learning in the middle of it, happy to learn, the learning ability of the students to enhance learning efficiency, learning quality has been sublimated, the development of students continue to enhance, the quality of classroom teaching can be truly improved. The quality of classroom teaching can only be truly improved when the development of students is continuously enhanced and the quality of learning is sublimated. Students are the main body of learning, how to stimulate students' subjective initiative, from the enhancement of learning efficiency, to further improve the quality of learning, the quality of classroom teaching will also be improved.

V. C. Sound teaching guarantee system

Efficient classroom teaching quality by teachers, students, environment, management and other aspects of the comprehensive impact of the school as a whole will be the organic combination of these factors, to ensure that classroom teaching and learning activities are carried out normally. First of all, it is necessary to change the concept of school teaching management. Secondly, the structure of the teacher team is optimized. The teacher team of higher vocational colleges and universities is mainly composed of young teachers as the main force, but they lack teaching experience. Colleges and universities can appropriately introduce and retain middle and senior talents, play the role of “mentorship” guidance, promote the professional growth of new teachers, improve the overall level of teachers in schools, and improve the incentive system for teachers. Schools should continue to optimize the salary level, improve the welfare benefits, pay attention to the growth of teachers in all aspects, provide teachers with learning and training platforms, cultivate excellent teachers, and strengthen the teaching force. Finally, the learning status of students is monitored. Teachers can investigate students' learning logs online, etc., and adjust the teaching method according to the results of the view, which is more helpful to tailor the teaching to the students' needs, further improve the quality of students' learning, and improve the quality of classroom teaching.

VI. Conclusion

This paper establishes a teaching quality prediction model for teachers of marketing majors in higher vocational colleges based on the decision tree model, and introduces the SHAP interpretation framework to explain the importance of the model features, and explores the strategies to improve the classroom teaching quality of marketing majors in higher vocational colleges based on the experimental results. It is concluded by the experimental article:

In the decision tree model classification experiment, the accuracy of the model prediction is 0.732, that is, the correctly predicted samples account for 73.2% of the total predicted samples. It can be concluded that the model in this paper has good prediction performance.

Based on the global interpretation graph, it can be obtained that the subjectivity factor is the main component that contributes the most, and its SHAP value is 0.68, that is, the subjectivity factor of the structure of the faculty, teaching methods, professional attitudes and guiding the classroom interaction has a more significant impact on the quality of teaching in the higher vocational colleges and universities of marketing majors teachers.

The improvement of classroom teaching quality of marketing majors in higher vocational colleges and universities can be carried out in three directions, namely, improving the teaching level of teachers, stimulating students' interest in learning and improving the teaching guarantee system.

The research results of this paper can help teachers to understand the students' performance, progress and difficulties in the learning process, and timely intervention and guidance, and can also help teachers to recognize their own teaching deficiencies, thus promoting the improvement of teachers' teaching quality.

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