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Article

Exploring the Path of Cultivating and Managing Graduate Students' Innovative Ability Based on Decision Tree Modeling

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Abstract: Graduate students' innovation ability is the main driving force to promote academic research and scientific and technological progress, but at present there are still many difficulties and obstacles in the cultivation and management path. In this paper, we firstly collected the relevant information of the students in the School of Information Science and Technology of X University of Science and Technology, and constructed the evaluation index system of graduate students' innovation ability from the three aspects of comprehensive innovation thinking ability, innovation quality characteristics and innovation practice ability. Based on the random forest to predict the innovation ability of graduate students, then quantitatively analyze the characteristic importance of the factors influencing the innovation ability of graduate students under different grades by SHAP model. Then the partial dependency diagram was used to further reveal the relationship existing between the influencing factors and graduate students' innovation ability. The prediction accuracy, precision, recall and F1 value of the model are all above 80%, and the importance of the influencing factors varies with different grades of graduate student innovation ability. Finally, this paper proposes a path for the cultivation and management of graduate students' innovation ability at three levels, namely, innovation of interdisciplinary knowledge system, adoption of interactive teaching methods and enrichment of practical programs for innovation ability cultivation, in order to promote the high-quality development of graduate education.

Keywords: Random Forest Model; SHAP Model; Partial Dependency Graph; Feature Importance; Graduate Student Innovation Ability Evaluation

1. Introduction

With the proposal and further improvement of “Talent Power Strategy” and “Innovation-driven Development Strategy”, we have formed the consensus that talent is the first resource, innovation is the first power, and innovation depends on talent [1-2]. The ability to innovate is the soul of national progress and the driving force of national prosperity [3]. “The core of graduate education is to cultivate innovation ability”, this view has been recognized by many education experts and scholars [4]. In the cultivation specification of human resources education, graduate education is at the highest level, and graduate education is the main channel to cultivate high-level innovative talents, and with the expansion of the scale of graduate education, the implementation of the “Graduate Education Innovation Project”, and in the process of the construction of innovative countries, more and more people recognize the importance of cultivating innovative ability of graduate students, and the innovative ability of graduate students is the most important thing. With the expansion of graduate education training scale, the implementation of “Graduate Education Innovation Project”, in the process of building an innovative country, more and more people recognize the importance of cultivating graduate students' innovation ability, and the cultivation of graduate students' innovation ability has gradually become a hot topic [5-7].

Graduate education is different from undergraduate education, which focuses on basic theories and methods, while graduate education mainly focuses on the cultivation of practical innovation and scientific research ability [8]. Therefore, from the perspective of both the goal of graduate education and the process of its realization, scientific research ability and knowledge innovation have become the focus and key of graduate education. In terms of the cultivation mode of graduate students' innovation ability, there have been many discussions in the academic circles on the issue of "graduate students' innovation ability", mainly the use of industry-university-research cooperation, the construction of training platforms, the adoption of multiple systems, curriculum development, academic lectures, and the diversified integration of various resources, and the adoption of the "manager education model" to cultivate the ability of comprehensive thinking [9-13].

Take China as an example, since 1978, the number of its graduate students in school has risen from 10,000 to more than 4.09 million, compared with the yearly rising trend of the number, the quality of graduate students is relatively slow to improve, especially in terms of innovation ability, and there is still a big gap with developed countries [14-16]. The reason is that the training mode and management mechanism of graduate students have constraints on the cultivation of innovation ability. On the one hand, most of the postgraduates' training and management modes are based on the linear form of “course + research + dissertation”, with credit system as the completion system, and there is less than 20% of individual innovation, which is difficult to adapt to the personalized needs and innovation needs of students nowadays [17-18]. On the other hand, the evaluation of students' innovation ability almost only relies on the results of thesis publication as the basis, ignoring the evaluation of students' innovation process, and the tutor is highly subjective, which is not conducive to the observation of students' innovation ability [19-20].

With the digital transformation of education, a variety of analysis models have been introduced. Decision tree model is a decision analysis method based on tree structure, which finds the optimal solution by decomposing the decision problem into a series of choices and judgments. It can realize the interpretation of nonlinear relationships and visualized decision-making, can dynamically predict the expected effect of time, and can promote the efficiency of students' innovation output, which is conducive to students' innovation training and management decision-making [21-23]. The model and management mechanism of postgraduate innovation ability cultivation is the institutional basis for the improvement of postgraduate innovation ability, which has positive theoretical and practical significance.

Aiming at the educational status quo that the process of postgraduate innovation ability cultivation is complex and susceptible to the interaction of various factors, this paper proposes a postgraduate innovation ability assessment model based on the random forest model, which processes high-dimensional postgraduate student data and identifies postgraduate students' innovation ability. Meanwhile, the SHAP method and partial dependency graph method are utilized to further explain the prediction results of the random forest model, and visually reveal the influence paths and influence strengths of the factors influencing graduate students' innovative ability under different grades. The practicality of this paper's inquiry method is verified through comparative experiments and case application experiments, thus constructing a scientific and effective path for the cultivation and management of graduate students' innovation ability.

2. Subjects of Study and Sources of Data

2.1. Overview of the Study Population

This paper is based on graduate student data collected by the College of Information Science and Technology of X University of Science and Technology in the National Engineering Education Accreditation. The data consists of various aspects such as college archival records, questionnaires, and comprehensive assessment of innovation ability, and the data is based on the information of students majoring in computer science, information engineering, and software engineering in the College of Information Science and Technology of X University of Science and Technology.

2.2. Data Sampling and Data Processing

2.2.1. Data Acquisition

Take X University of Science and Technology as an example, the student evaluation of the university is based on comprehensive assessment, which includes students' academic innovation ability and moral innovation ability. Among them, the academic innovation ability corresponds to the professional and technical ability, which is the student's academic performance; the moral performance includes the student's performance in school, which corresponds to the four abilities of innovation creation, knowledge learning, management practice and comprehensive development. In the traditional statistics, it is just a simple weighted sum of the four ability scores without differentiation, therefore, when collecting evaluation indexes, it is necessary to separate the students' school performance, and all the usual performance innovation ability in the unified student evaluation method is uniformly calculated, although this calculation method is simple, but there is no scientific research on the index points in the process of calculating, and all the weighted calculation is All the weighted calculations are determined artificially according to experience, so its results are too much influenced by human beings, and its results are not closely enough related to the future development of students, and therefore its results are not able to reflect the real students' abilities. For the above reasons, this paper reclassifies and calculates the moral innovation ability according to the division of ability in the process of data collection.

For the division of employment direction, the data contains the nature of enterprises and information on further education, so it is easy to distinguish between state-owned enterprises, institutions, graduate schools, etc. However, due to the lack of employment salary data in many employment records, the judgment of students' high-paying employment increases the difficulty, in this regard, this paper crawls the lists of companies listed on China's A-share stock market, Hong Kong stock market, and common foreign enterprises in China, etc., to match them, and approximates that the students' entry into these enterprises is High-salary employment. As for the classification of examination and research information, this paper crawls the list of 985 and 211 colleges and universities, which is used to set the classification label of examination and research. This paper also uses a questionnaire to investigate the employment information of graduates, including employment satisfaction, enterprise satisfaction and other information, and analyzes and organizes the employment data of students according to the requirements of the national engineering certification idea.

2.2.2. Data Processing

The data in this paper is collected from the information of students majoring in computer science, information engineering, and software engineering in the College of Information Science and Technology of X University of Science and Technology, which includes more than 30 fields such as institution code, name, type, graduation year, student number, name, political profile, major code, specialty, place of origin, class in which they are enrolled, code of graduation destination, type of graduation destination, accepting institution, location of accepting institution, nature of accepting institution, and more than 30 fields and More than 6000 pieces of student employment information. Here the choice of Excel tables to filter out irrelevant fields are deleted.

3. Indicators for Evaluating the Innovative Capacity of Postgraduate Students

According to the research of the existing literature, combined with the content of graduate students' innovation ability and the existing problems in the cultivation of graduate students' innovation ability, the evaluation index system of graduate students' innovation ability (A) can be preliminarily determined as follows: comprehensive innovative thinking ability (A1, subordinate indicators include observation ability, imagination ability, logical thinking ability), innovation quality characteristics (A2, openness, academic critical spirit, pioneering and innovative consciousness, tenacious perseverance, collaborative spirit), innovation practice ability (A3, The subordinate indicators include 3 first-level indicators and 11 second-level indicators of innovative competition award-winning ability, enterprise practice research ability, and innovative solution ability of practical problems. The specific evaluation index system is shown in Table 1.

Table 1. Evaluation index system.

	Primary indicator	Secondary indicator
Innovation base	Comprehensive innovative thinking ability A1	Observational ability B1
		Imagination B2
		Logical thinking B3
	Innovative quality characteristics A2	Openness B4

		Academic criticism B5
		Innovation awareness B6
		Tenacity B7
		Collaborative spirit B8
	Innovation practices ability A3	Creative competition awards B9
		The ability of enterprise to practice research B10
		Creative solutions to practical problems B11

4. Methodology for the Study of Factors Influencing Postgraduate Students' Innovative Capacity

4.1. Random Forest Principles

Random Forest [24] is composed of numerous decision trees [25]. Decision tree is named because of its tree-shaped structure and is a basic classification and regression method. Decision tree learning usually consists of three steps (1) feature selection (2) tree generation (3) tree pruning. Each decision tree consists of directed edges and nodes, and the nodes include two types of leaf nodes and internal nodes. The internal nodes represent the attributes or characteristics of the sample; when the decision tree is used for classification, the leaf nodes represent a class; when used for regression, the leaf nodes represent the predicted values.

A decision tree, when used for classification or regression, starts with the first node, tests the features contained in each sample, and, based on the results, divides the sample into its child nodes. This continues until the leaf node is reached.

Decision tree learning, assuming a given training data set:

$$D = \{(x_1, y_1), (x_2, y_2), ..., (x_N, y_N)\} \tag{1}$$

where $x_i = (x_i^{(1)}, x_i^{(2)}, ..., x_i^{(n)})^T$ is the feature vector of the sample, n is the number of feature quantities contained in the sample, and N is the number of samples. When the decision tree is used for classification, $y_i \in \{1, 2, ..., K\}$ is the category labeling; when the decision tree is used for regression is, $y_i \in R$ is the regression prediction value.

In the process of learning the sample data, the decision tree selects the best feature values in turn to split the sample data to ensure that each subtree data set reaches the optimal classification. This process is also the construction process of the decision tree. At the beginning, all the feature values are used as the features of the root node, and a best feature is selected from all the features of the root node to split the dataset, so that each subset corresponds to the best classification markers or target values, and if these subsets have been able to correspond to better target values, these subsets will be used as the leaf nodes, or else the splitting will continue to know that the optimal node is reached.

There are many ways to select the optimal features for splitting. When Decision Tree is used for classification, its features can be selected in order of optimality by information gain and its gain ratio or entropy; when used for regression analysis, mean square error and least squares are usually used as indicators for feature selection. In while in this paper, we mainly use it to do the prediction of institutional innovation ability, the target value is a continuous variable, which is a regression problem, so we only explain the regression tree.

In fact, the regression tree corresponds to the division of the feature space and its output value on the division unit. If the input space is divided into M cells $R_1, R_2, ..., R_M$ and each cell has a fixed value c_m, the decision tree regression model is:

$$f(x)=\sum_{m=1}^{M}c_m I(x\in R_m) \tag{2}$$

When the output values of each cell are well divided with feature vectors, the least squares method $\sum_{x_i\in R_w}(y_i-f(x_i))^2$ can be used to compute the prediction error on each cell, and the minimization of prediction error is used to solve for the prediction error on each cell. Output value. The output value $\hat{c}_m$ is the average of all sample predictions on cell R_m, calculated as:

$$\hat{c}_m=ave(y_i\mid x_i\in R_m) \tag{3}$$

We can choose the i th feature variable and its value s, as the cut-off variable and cut-off point, and define two regions:

$$R_1(j,s)=\{x\mid x^{(j)}\le s\}\text{ and }R_1(j,s)=\{x\mid x^{(j)}>s\} \tag{4}$$

For the optimal cut-off point and cut-off variable, it can be solved:

$$\min_{j,s}[\min_{c_1}\sum_{x_i\in R_1(j,s)}(y_i-c_1)^2+\min_{c_2}\sum_{x_i\in R_2(j,s)}(y_i-c_2)^2] \tag{5}$$

Find the optimal amount of tangent features and find the best tangent point s by fixing the variable j.

$$\hat{c}_1=ave(y_i\mid x_i\in R_1(j,s))\text{ and }\hat{c}_2=ave(y_i\mid x_i\in R_2(j,s)) \tag{6}$$

Iterate over all feature quantities to find the optimal cut-off variable j constituting (j,s). This process is repeated for each region until the stopping condition is satisfied. However, it is the fact that the decision tree is built on the basis of its arbitrary split subsets that often leads to overfitting of the completed decision tree, so pruning of the decision tree is required.

Random forests use row sampling and column sampling techniques to construct several different decision trees based on a single decision tree to improve prediction accuracy. Row sampling is used to draw m sample sets from the original N samples using the random sampling method with put-back for constructing m decision trees. The number of samples in each sample set is smaller than the number of original samples and are used to train the model, while the remaining samples are used as a test set. Column sampling is the process of randomly selecting $k(k<p)$ features among the p feature variables contained in the original samples to be used as cutoff variables in decision tree construction.

Random forests can avoid overfitting by controlling the number of internal node splits, so no further pruning is required for each decision tree constructed. Random forests are combined in the following way:

$$B=\{h(X,\theta_k)\}\quad k=1,2,\dots,p \tag{7}$$

where θ_k denotes the k th tree, X denotes the feature vector of the sample, and $h(X,\theta_k)$ is the predicted value of the k th tree.

When the generated random forest is used for regression analysis, the result is the average of all tree predictions.

4.2. Principles of the SHAP Model

SHAP [26] is an explanatory machine learning model prediction method based on the Shapley value (imputed value) in game theory, where the Shapley value is averaged by calculating the marginal contribution of each feature (player) across all potential player alignments. This involves evaluating each possible combination of features and determining the impact of each feature on the model prediction when included in those combinations. By averaging the contributions across all possible alignments, we can balance the importance of each feature in the model and make an interpretable assessment, The SHAP model is shown in Figure 1. In short, the Shapley value approach can be used to visually analyze the contribution of each feature parameter in the output model to the prediction goal.The core concept behind SHAP is to assign a specific value to each input feature that represents its specific contribution.

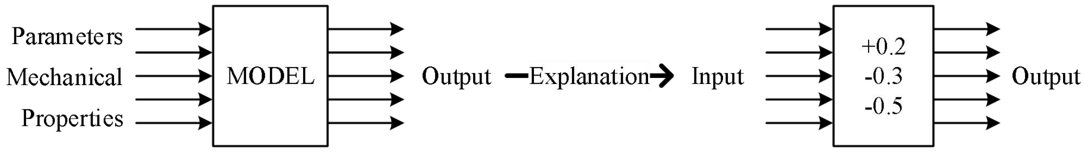

Figure 1. Schematic diagram of SHAP feature interpretation work.

In this process above, SHAP will follow three basic properties: efficiency, symmetry, and additivity.

(1) Efficiency

Efficiency means that in the case of a comprehensive analysis, the sum of the SHAP values shows the combined impact of its features on the model's predictions, and by quantifying how each feature deviates the predicted value from the average, the SHAP values help explain the model's output. For example, if the average prediction is 50 and the model's prediction is 60, the difference is 10. the sum of all SHAP values for the features should equal 10, indicating the contribution of each feature in the model to the difference. By summing all SHAP values, we can consider the full effect of the features on the prediction.

(2) Symmetry

Symmetry is the SHAP value that two features will have if they contribute equally to the prediction. This ensures fairness in attributing importance to features.

(3) Additivity

Additivity refers to the way in which SHAP values are added to show the joint contribution of multiple features to the prediction. This helps to understand the combined impact of multiple features on the model output.

It was mentioned above that SHAP values are averaged based on marginal contribution, here is the principle of marginal contribution calculation.

Taking an example of a linear model, the following is a sample prediction:

$$f(x) = \alpha_0 + \alpha_1 x_1 + \cdots \alpha_n x_n \tag{8}$$

where x is the eigenpoint we want to compute the contribution. Each x_k is an eigenvalue, where $k = 1,...,n$. α_k is the weight of the corresponding feature. Thus the contribution ϕ_k (imputed value) of the k th feature to the prediction function $f(x)$ is:

$$\phi_1(f) = \alpha_k x_k - E(\alpha_k x_k) = \alpha_k x_k - \alpha_k E(x_k) \tag{9}$$

where $E(\alpha_k x_k)$ is the predicted average effect of the feature x_k, which is the expected value. The contribution is the difference between the feature effect minus the average effect. Now we want to know exactly how much each feature contributes to the model's prediction by simply adding up the contributions of all the features in an instance. That is, the efficiency attribute we introduced above. The formula is expressed as follows:

$$\sum_{k=1}^{n} \phi_k(f) = \sum_{k=1}^{n} (\alpha_k x_k - E[\alpha_k x_k]) = f(x) - E[f(X) \mid x_1, x_2, x_3] \tag{10}$$

It is worth noting here that the result of the calculation can be negative, which also shows that the performance of the feature in the model prediction is negatively correlated.

Described above is the process of calculating the contribution of an eigenvalue and how it is calculated.The Shapley value is averaged by calculating the marginal contribution of each feature across all potential player alignments. Normally, a model cannot have only one eigenvalue, there are often multiple features a, b, c, d...etc. fed into the model at the input side. Then it can be viewed as a ranked set Z, where a, b, c, d...etc. are some elements of this set. Based on the computation of the expectation of a single feature above, then the conditional expectation of this set Z can be viewed as $E[f(x)_z]$.

4.3. Partial Dependency Diagram

Partial dependency graph [27] is a graphical presentation tool based on the results of partial dependency function calculations, which is widely used to explain and reveal the marginal effect of 1 or a small number of feature variables on the predicted results in machine learning models, partial dependency function reveals the average trend of model predictions as the values of the target features change, which helps to understand how a specific feature independently affects the predicted output of the model, the calculation is shown in Eq. (11)):

$$\hat{f}x_s(x_s) = \int \hat{f}(x_s, x_c)\mathrm{d}p(x_c) \tag{11}$$

where: $\hat{f}x_s(x_s)$ is the partial dependence function; x_s is the target feature selected for analysis, s usually has only 1~2 features; x_c is the other features of the model, and c is the complement of s .

5. Model Testing and Analysis of Results

5.1. Results of Graduate Student Innovation Capacity Prediction

The experimental data of this study is derived from the teaching data of 100 students in the third semester of Electronic Information Engineering at X University of Science and Technology.

The training and testing process of the Random Forest-based classification prediction model of students' innovation ability is as follows.

a) Divide the original dataset into training set and testing set.

b) Construct the random forest on the training set, including the steps of extracting sample subsets, constructing decision trees and integrating decision trees. In this process, special attention should be paid to the selection of the number of decision trees, by constantly adjusting the number of decision trees, observing the change of the model error, and selecting an appropriate number of decision trees to construct the model. Each decision tree is trained based on random subsamples and a random feature subset is used to segment the data.

c) The classification accuracy of the random forest model is evaluated on the test set to verify the validity and accuracy of the model. Each decision tree outputs a prediction category. Random forest uses majority voting to select the category predicted by the most decision trees as the final classification result.

Firstly, this study evaluates the effect of the number of decision trees on the error of the prediction model, the number of decision trees of the prediction model and the training error curve is shown in Fig. 2, and the error is stabilized below 0.12 when the number of decision trees is greater than 25, and the number of decision trees chosen for this experiment is 40.

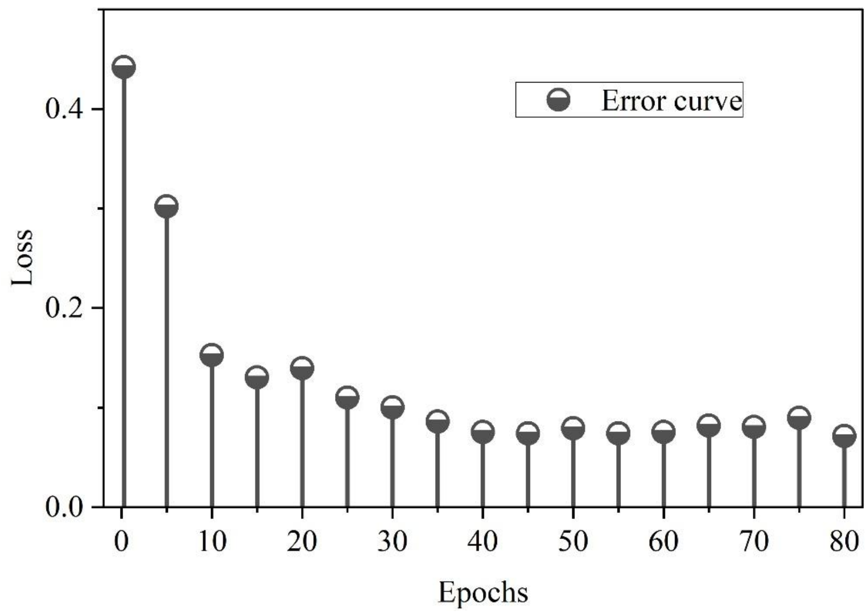

Figure 2. Prediction model decision tree number and training error curve.

Secondly, the test set is fed into the prediction model, and the prediction results of the test set of the prediction model are shown in Fig. 3, which yields a classification result accuracy of 95.00% for a particular test.

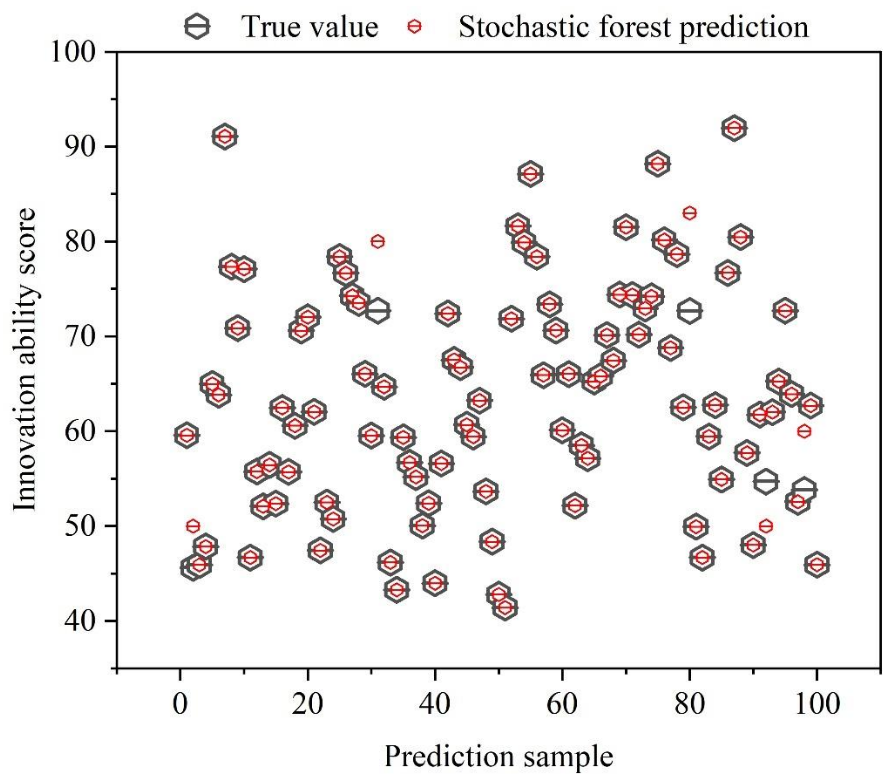

Figure 3. Prediction model test set prediction results.

Finally, the stability test of the prediction model is carried out. By repeating the experiment several times and calculating the variance and standard deviation of the model's performance indicators, the results of the stability test of the prediction model are shown in Table 2, and its accuracy, precision, recall and F1 value are above 80%, and the model's performance performance is stable and reliable, and it has good robustness.

Table 2. Prediction model stability test results.

Performance indicator	Mean	variance	Standard deviation
Accuracy	0.908	0.00015	0.012
Precision	0.889	0.00012	0.033
Recall rate	0.869	0.00013	0.039
F1-score	0.897	0.00011	0.035

5.2. Analysis of Factors Influencing Innovation Capacity Based on SHAP Analysis

5.2.1. Comparative Analysis of the Importance of Characteristics

Comparative feature importance analysis of innovation capacity assessment models. The results of the SHAP analysis were analyzed by calculating the feature importance of the Random Forest algorithm and comparing the results of the SHAP analysis. The SHAP feature importance and RF feature importance are shown in Figures 4 and 5, respectively.

The SHAP algorithm was used to analyze the innovative ability assessment model. From the figure, it can be seen that the features such as the number of days students are absent, the number of times they visit the course, the number of times they view the announcements, and the number of times they raise their hands in class have a significant effect on assessing the students' innovative ability level. On the whole, among them, the more days students are absent, the lower the innovative ability grade, while the other three features have a positive effect on the innovative ability grade, i.e. the more positive the learning performance, the higher the innovative ability grade.

Through comparison, it is found that the order of importance of the characteristics of the two algorithms is not completely consistent, and the analysis shows that the key factors affecting the students' innovation ability grade are the number of days of absence, the number of visits to the course, the number of times of checking the announcements, the number of times of raising hands in the class and the number of times of taking part in the discussion. Among them, the three features of the number of days students are absent, the number of times they visit the course, and the number of times they view announcements are ranked in the top 5 of the importance ranking of the two algorithms, which indicates that these three features are the most critical factors affecting students' innovative ability.

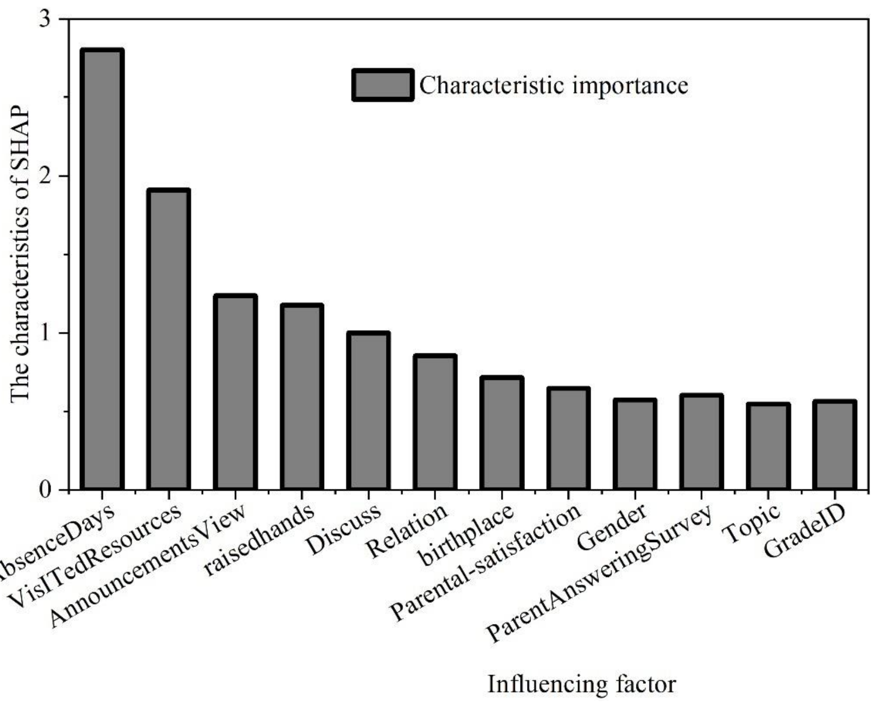

Figure 4. The characteristics of SHAP are characterized.

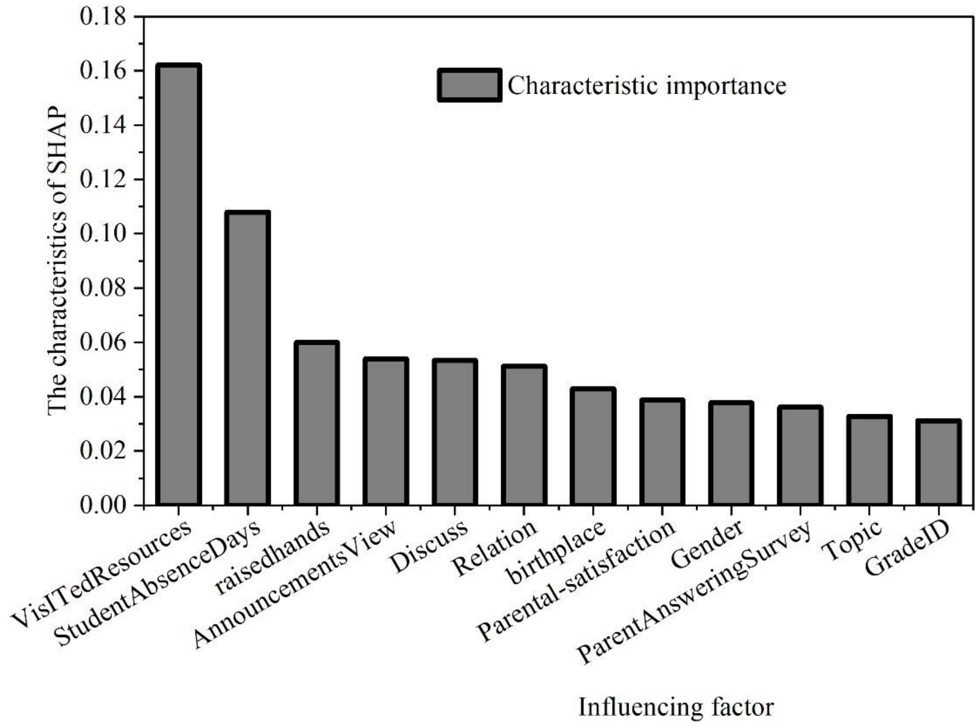

Figure 5. The characteristics of RF are characterized.

5.2.2. Analysis of Factors Affecting Different Levels of Innovative Capacity

In this paper, the students' innovative ability grade in the dataset is divided into three grades: L low, M medium and H high, and SHAP analysis is carried out on the students' innovative ability of different grades, respectively.The SHAP feature analysis summary chart combines the importance of the features and the influence of the features, and the positions on the y-axis are sorted in accordance with the importance of the features, and the x-axis is the SHAP value,and the results of the analysis are as follows.

(1) The results of the analysis of the innovative ability grade of L low grade are shown in Figure 6. From the figure, it can be seen that the more days a student is absent from school, the greater the possibility that the innovation ability grade is L low, and the more the number of visits to the course, the number of times they view announcements, the number of times they raise their hands in class, and the number of times they participate in discussions, the lower the possibility of the innovation ability grade is L low, which means that students with innovation ability grade of L low need to improve their own attendance and learning attitude in order to improve the innovation ability of the students.

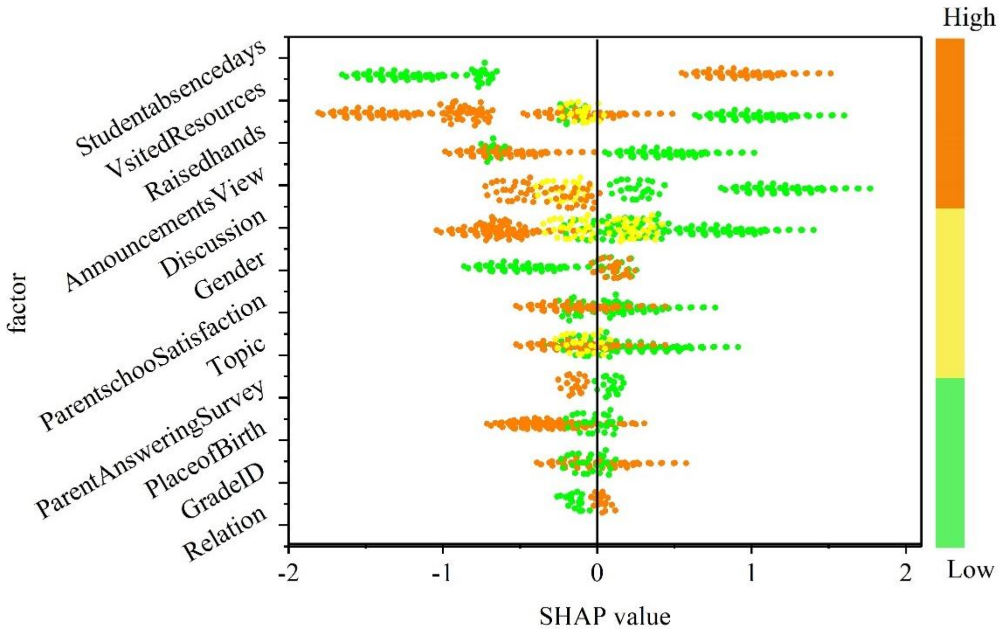

Figure 6. The results are low SHAP feature analysis abstract.

(2) The results of the analysis of the innovative ability grade of M Medium are shown in Figure 7. As can be seen from the figure, the greater the number of visits to the course, the greater the likelihood that the innovativeness level is M medium, while the number of times that one views the announcements and the number of times that one participates in the discussions do not have any particularly obvious connection with the innovativeness level being M medium. In contrast, the likelihood of having a mid-M innovativeness rating was higher when the parent responsible for the study was the father. The lower the number of days a student is absent, the higher the likelihood that the innovativeness rating is M-medium.

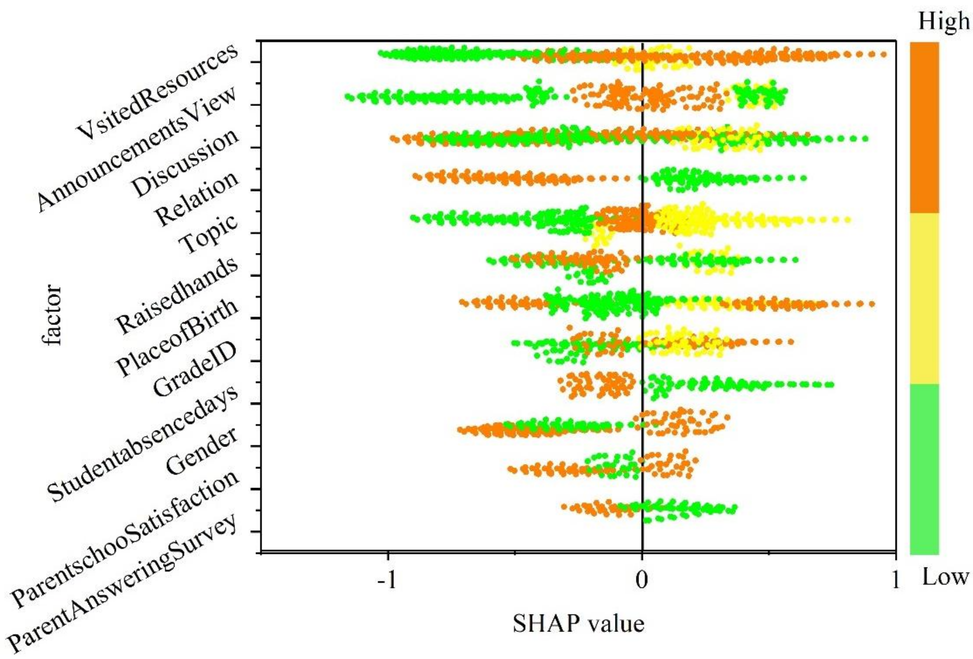

Figure 7. The results are the medium SHAP characteristics analysis abstract.

(3) The results of the analysis of the innovativeness grade of H high are shown in Figure 8. From the figure, it can be seen that the fewer days a student is absent from school, the higher the likelihood that the innovativeness grade is H high, and the number of visits to the course and the number of hands raised in class are positively correlated with the innovativeness grade being H high. And when the

parent responsible for learning is the mother, the correlation of innovativeness rating is H high is strong, and the possibility of innovativeness rating is H high is higher when whether the parent answered the survey or not, and when the parent's satisfaction with the school is positive, which shows that whether the parent is involved in the school has a positive effect on the student's innovativeness rating.

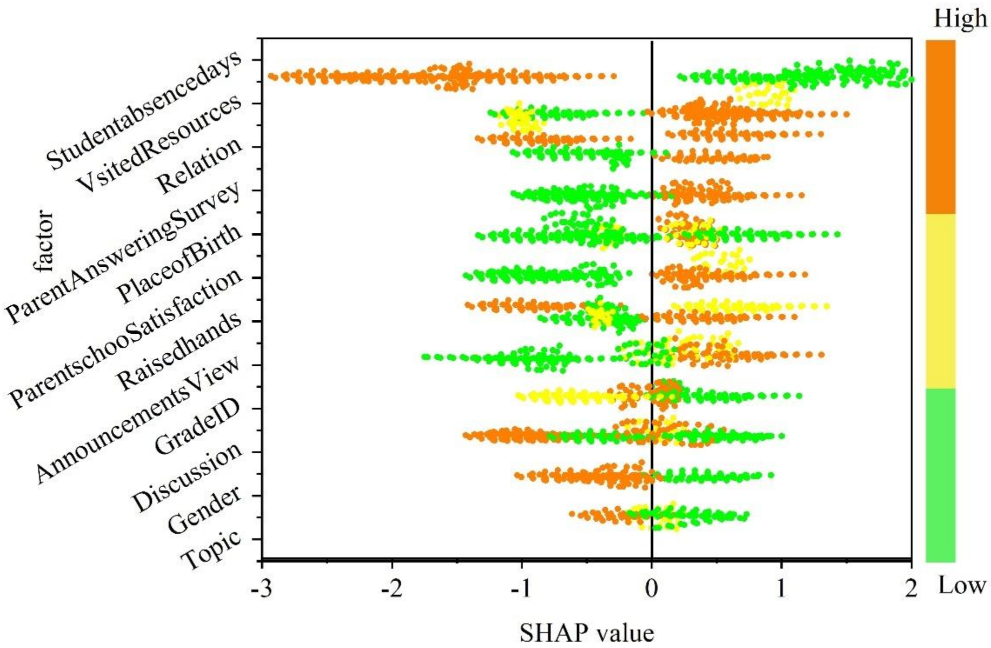

Figure 8. The analysis results of the high level of innovation ability.

5.3. Partial Dependency Graph Analysis

The bias-dependence plots are usually non-linear and have two distinct turning points: at low levels of the driver, the bias-dependence plot rises gently, and after the first turning point on the curve, the bias-dependence plot rises steeply and the slope reaches a maximum. As the driver continues to increase, the bias-dependence plot approaches a level after crossing the second turning point on the curve. The bias-dependence plot can be characterized by three key points, two turning points and a point of maximum slope, and there are clear economic implications: before the level of the driver is at the first turning point, it is too low in relation to the other drivers to exert a scale effect. After the first turning point, marginal output increases significantly, and the scale effect is gradually realized. When the slope reaches the maximum point, the marginal output reaches the maximum, at this time the scale effect is fully realized, and the combination of drivers is optimal. After the second turning point, the marginal output decreases steeply and is too high relative to the other drivers.

Figure 9 shows the bias-dependence plot for the combined innovative thinking skills. With the exception of a few students, the level of comprehensive innovative thinking ability of all grades is before the second turning point, i.e., for most students, it is possible to rapidly improve students' innovative ability by increasing the development of comprehensive innovative thinking ability. In the process of development of students of all levels, each student can choose his or her own innovative power enhancement in a targeted way by the position of his or her own driving factors.

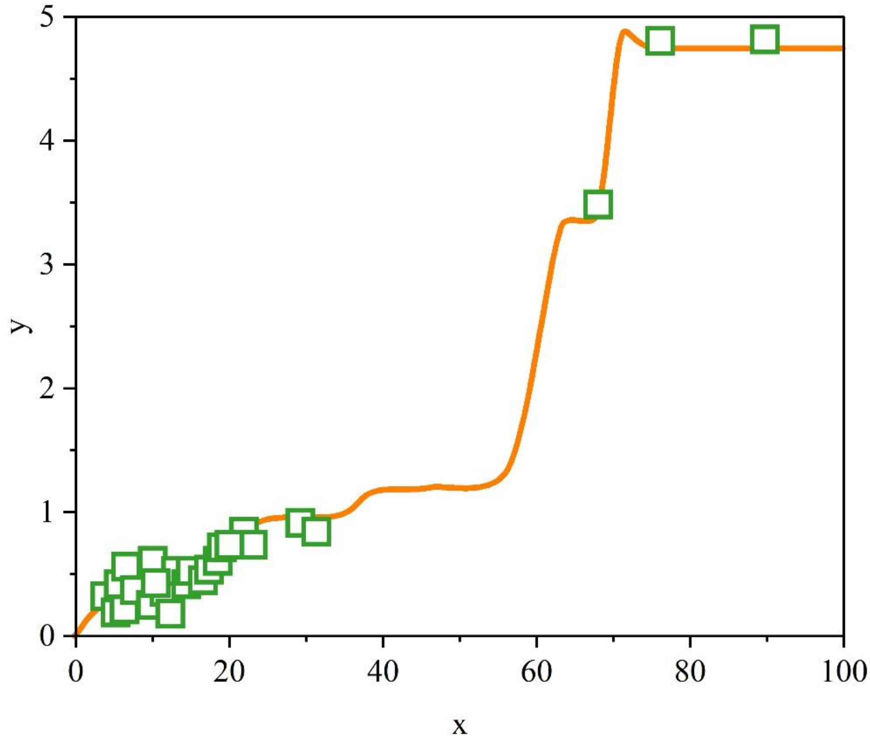

Figure 9. The dependence of comprehensive innovative thinking ability.

Figure 10 shows the bias dependence graph of innovative quality characteristics, only very few students are after the second turning point, there are no students between the point of maximum slope and the second turning point, while the vast majority of students are located around the first turning point. This indicates that for the vast majority of students, there is the problem of insufficient innovative quality characteristics, and it is urgent to increase the improvement of students' innovative quality by strengthening students' openness, improving students' academic critical spirit, etc., and prompting the innovative quality characteristics to enter the optimal combination interval or even close to the second turning point, so as to rapidly improve students' innovativeness.

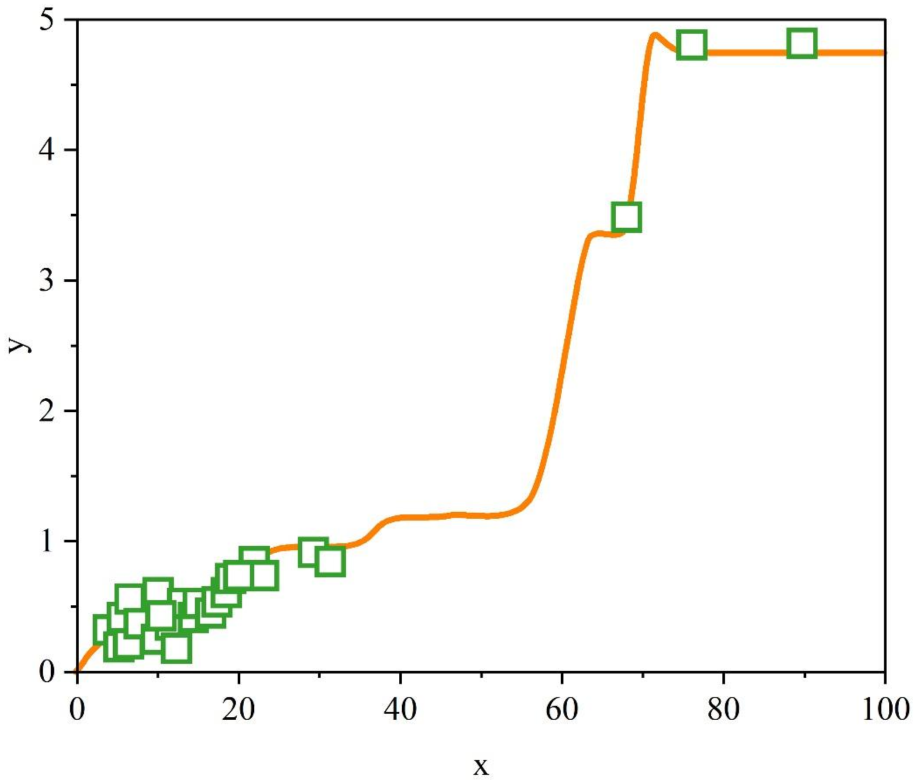

Figure 10. Biased dependence of innovative quality characteristics.

Figure 11 shows the bias dependence graph of innovative practice skills, all students did not appear after the second turning point, and only a few students were after the first turning point, while the majority of students were before the first turning point. This suggests that all students can currently contribute to student innovativeness by optimizing their innovation practice skills, and that students located before the first turning point are even more likely to focus on improving their innovation practice skills.

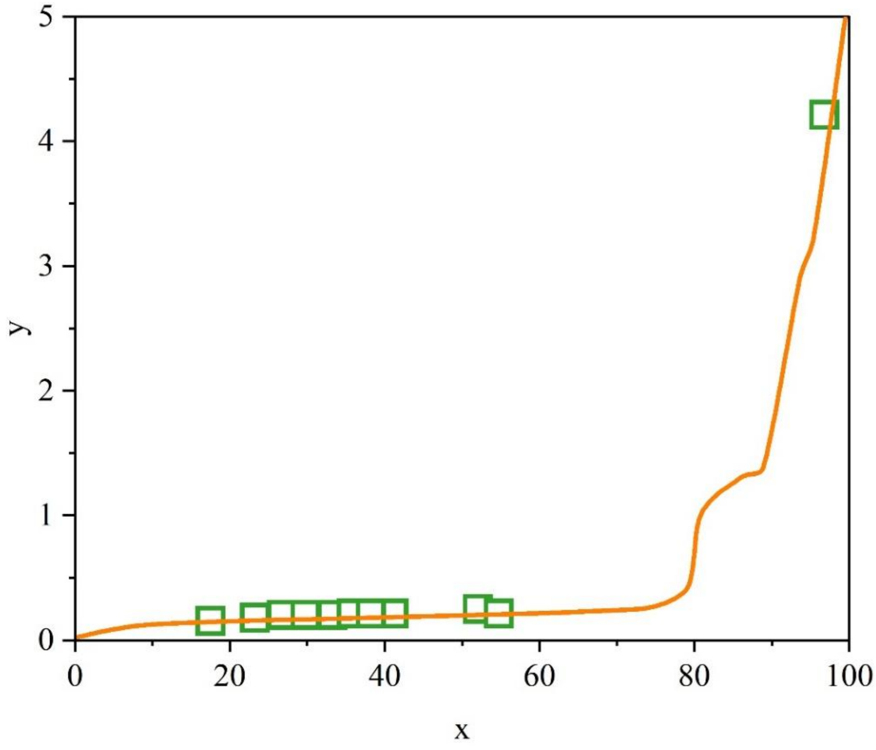

Figure 11. Biased dependence on innovative practices.

6. Pathways for the Development of Postgraduate Students' Innovative Capacities

(1) Constructing Interdisciplinary Knowledge SystemInnovation often occurs in cross-disciplinary fields. Multidisciplinary courses, faculty teams with different disciplinary backgrounds and interdisciplinary scientific research and practice projects can prompt graduate students to break through the disciplinary boundaries and the restrictions of traditional specialties, and therefore are more conducive to graduate students' acquisition of innovative thinking and the ability to solve problems from a completely new perspective.

(2) Adopting inspirational and interactive teaching methods to stimulate the enthusiasm and learning initiative of graduate students is the first step to train innovative ability. Under the traditional teaching mode, the knowledge is transmitted from teachers to graduate students in one direction, the classroom interaction time is small, and the graduate students passively accept the knowledge, lacking the teaching process of combining theory and practical application, which can't provide support for the subsequent practice and innovation ability exercise. Let postgraduates become the main body of classroom learning, comprehensively use new teaching methods and means such as case teaching, flipped classroom, enterprise classroom, etc., increase the time for postgraduates to participate in teaching interaction and active learning, and fully utilize the modern informatization teaching facilities and software to comprehensively teach the two parts of theoretical knowledge and practical application, which can help to improve postgraduates' comprehension ability, analytical ability and application ability. At the same time, the establishment of training and exchange mechanisms for classroom teachers and regular teaching exchange activities will help teachers update the teaching contents of practical and innovative classes and learn the excellent practices and experiences of others.

(3) Provide multi-kinds, multi-levels and multi-forms of practical projects for cultivating innovative ability Participating in practical projects is an important link for graduate students to digest innovative theories, apply innovative methods and exercise innovative ability. In this process, postgraduates can choose one or more of the projects under the guidance of professional teachers according to the needs of career development to form a personalized practice project group. The practical projects can be a compulsory part of the whole cultivation process or an elective course for postgraduates to choose.

7. Conclusion

This paper explores the method of evaluating the innovation ability of graduate students and exploring the influencing factors based on decision tree model, SHAP model and partial dependency graph, and the main work contains the following aspects:

(1) A method for assessing students' innovative ability based on the combination of random forest and SHAP model is proposed. Random forest is used to model the evaluation and prediction problem of graduate students' innovation ability, and the accuracy, precision, recall and F1 value of the model are above 80%, which indicates that the random forest model improves the performance and robustness of the prediction of graduate students' innovation ability and overcomes the subjectivity of the traditional evaluation method. The SHAP model is used to explain the factors influencing the grades of graduate students' innovative ability at different levels, and the degree of importance of different factors influencing the grades of graduate students' innovative ability is analyzed. For students with low innovative ability, their innovative ability can be improved by increasing the number of times they visit courses, the number of times they view announcements, the number of times they raise their hands in class, and the number of times they participate in discussions.

(2) In the partially biased dependence analysis, most of the students' comprehensive innovative thinking ability level and innovative quality characteristics are before the second turning point, and none of the students' innovative practice ability level appears after the second turning point. It shows that education work and education managers can efficiently improve students' innovation ability by increasing the cultivation of students' comprehensive innovation thinking ability and innovation quality characteristics, especially focusing on the cultivation and improvement of students' innovation practice ability. Students can also personalize their own situation and choose their own way to improve their innovative power.

(3) In summary, the interdisciplinary knowledge system innovation of graduate students is constructed in daily teaching. At the same time, inspirational and interactive teaching methods are used to stimulate the enthusiasm and learning initiative of graduate students. The university provides multiple types, levels and forms of innovation ability cultivation practice programs for students to participate.

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