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PAPER

Use of Big Data Technology for Network Classroom Teaching Quality Management

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ABSTRACT

Quality management of network classroom teaching has always been an urgent problem to be solved. Big data technology handles massive amounts of data and provides new quality management methods and means for network classroom teaching. However, data integration and fusion is a complex task and existing methods may not be able to deal with data fragmentation effectively, because data is often distributed across different systems and platforms in the network teaching environment. Therefore, this research aimed to study the quality management of network classroom teaching based on big data technology. This study provided a framework diagram of teaching quality evaluation criteria and factors affecting the teaching quality in the big data environment, explained complex relationships and effects among the factors, and described teaching quality prediction problems. The dimensionality reduction method of Least Absolute Shrinkage and Selection Operator (LASSO) was used for comprehensive status data integration of factors affecting teaching quality. An unequal-interval grey Riccati-Bernoulli model was constructed to study the internal relationships between various variable factors and network classroom teaching quality. Then the execution process of the prediction model, detailed modeling steps and teaching quality management steps were provided. The experimental results verified that the constructed model was effective.

KEYWORDS

big data analysis, network classroom, teaching environment, teaching quality management

1 INTRODUCTION

With the rapid development of information and network technology, network classroom teaching has become important in teaching [1–3]. However, network classroom teaching quality management has always been an urgent problem to be solved [4–8]. Big data technology handles massive amounts of data and provides new quality management methods and means for network classroom teaching.

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Big data technology collects and analyzes the data associated with the teaching process, including but not limited to learning behaviors of students, academic performance, teaching contents, teaching behaviors of teachers and so on [9–14]. The teaching effect can be deeply understood through data analysis, thus identifying teaching problems and providing data support for optimizing teaching design and improving teaching methods [15–18]. In addition, big data technology monitors the teaching quality in real time and enables teaching managers to adjust teaching strategies in time to improve the teaching effect. Therefore, it is significantly necessary to study the quality management of network classroom teaching based on big data technology.

A single method is usually used for current monitoring and evaluation of teaching quality, which is relatively simple and lacks verification of analysis results. Based on this, Dong [19] aimed to study the monitoring and evaluation of higher education teaching quality based on big data analysis. First, the teaching quality was monitored based on five aspects, namely, teaching level of teachers, academic performance of students, course learning effect, competence and employment of students. The time series prediction model (autoregressive composite moving average) was integrated with the differential equation model (GM (1,1)) effectively predicting the change trend of the series, which predicted and evaluated the changes of teaching quality data series. Secondly, after making conjoint analysis of the monitoring and evaluation results and the corresponding data of proposing teaching quality improvement measures and promotion frequency, a mathematical model was established through curve fitting and parameter estimation to explore the deep correlation between the two. Q. Wang and B. Wang [20] studied the blending learning quality information based on big data. Based on the initially selected evaluation indexes, expert opinions were investigated to supplement and improve the blending learning evaluation indexes, which was considered as recommended evaluation indexes. Then a questionnaire survey was conducted on students to further determine the evaluation index system. There was a significant correlation between “professional ability improvement” and “communication among students”, with a correlation coefficient of 0.55, indicating the better communication among students in blending learning, the better their professional ability improvement. The inevitable trend in future modern information technology teaching is to develop educational models using large-scale data collection and analysis methods and study the relationships between educational variables, thus providing effective support for educational reform. In the current high-level higher education system and reform, curriculum evaluation is an important tool to evaluate the classroom teaching quality and an important basis of testing the curriculum reform effect. After establishing a teaching evaluation index system based on indexes, which students participated in and accepted, and were satisfied with, Wang et al. [21] established an evaluation system at three levels, namely, curriculum micro evaluation index system, secondary college comprehensive evaluation index system, and college macro evaluation index system. Evaluation data was obtained using teaching quality evaluation. CTQ evaluation feedback system was developed by analyzing wider range of data, which improved the classroom teaching quality.

Existing quality management methods of network classroom teaching have some shortcomings. In the network teaching environment, data is often distributed on different systems and platforms, such as learning management system, online test system, discussion forum and so on. Data integration and fusion is a complex task, and existing methods may not be able to effectively deal with the data fragmentation.

So data integration is very necessary, which solves the problem of data fragmentation and improves data availability. Data cleaning and preprocessing improves data quality. Therefore, this research studied the quality management of network classroom teaching based on big data technology by taking the international trade major as an example.

2 DESCRIPTION OF TEACHING QUALITY PREDICTION PROBLEMS

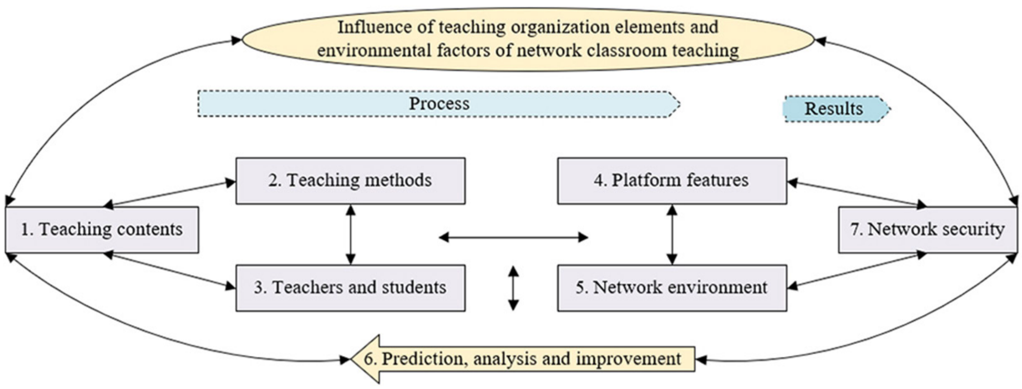

Fig. 1. Framework of quality evaluation criteria

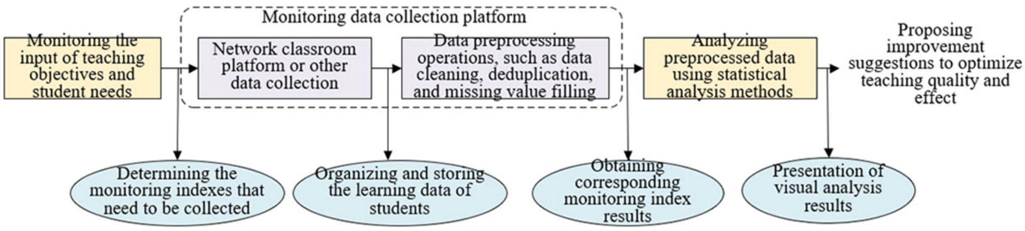

Fig. 2. Sources of quality management data

Figure 1 shows the quality evaluation criteria framework of international trade network classroom teaching. As shown in the figure, the factors affecting teaching quality in the big data environment were mainly divided into two types: teaching organization elements and teaching environmental factors. The former includes teaching contents and methods, quality of teachers, and participation degree of students. The latter includes stability, usability, functionality and data management of network platform, stability and speed of network environment, and network security. Figure 2 shows the sources of quality management data.

Complex relationships and effects existed among the above factors in the big data environment. Teaching content design and teaching method selection influenced each other. Teaching contents should adapt to the needs of teaching methods, and the teaching methods should fully display and convey the teaching contents. For example, if the teaching contents involved complex problem-solving or innovative thinking, a project-based teaching method needed to be adopted. Professional quality and technical ability of teachers affected the participation degree of students. If teachers used various network teaching tools proficiently and stimulated the interest of students to learn, it was possible to increase their participation degree. In terms of technology platform and data management, the stability, usability, and functionality of technology platform affected the data management effect. An excellent technical platform should provide convenient data collection, storage and analysis functions, and support teachers and students to apply data effectively. Stability and speed of network environment affected network security. If the network environment was unstable, it may increase the risk of data loss or attack. In addition, excellent network security facilities improved the stability and reliability of network environment. How to integrate the information of influencing factor variables containing these effects and then quantify the teaching quality state were of great significance for the teaching quality management.

The basic principle of predicting network classroom teaching quality was to establish a teaching quality prediction model, with key factors affecting teaching quality as input indexes and teaching effect characteristics as output indexes. Let A be the teaching effect sample space, $z^{(0)}(j)$ be the quality index of sample $j(j\in A)$, q_j be the teaching organization element of sample j, and y_j be the comprehensive network classroom teaching environment of sample j, then the teaching effect index $z^{(0)}(j)$ was considered as the comprehensive results of the teaching organization element q_j in the network classroom teaching environment y_j. The specific relationships were as follows:

$$q_j \overset{y_j}{\Rightarrow} z^{(0)}(y_j) \tag{1}$$

It can be seen from the above equation that the main reasons for the teaching effect difference are the difference in both teaching organization elements and teaching environment. Let $i_u(j)$ be the value of the u-th variable factor of sample j of the above two aspects. For a single sample j, the effect difference state of comprehensive network classroom teaching was regarded as the clustering of all variable factors in the variable space L. Let α_u be the clustering coefficient of $i_u(j)$, then there were:

$$y_j = \sum_{u\in L} i_u(j)\alpha_u \tag{2}$$

3 QUANTIFICATION OF TEACHING EFFECT DIFFERENCE STATE

The LASSO dimensionality reduction method was used for comprehensive state data integration of factors affecting teaching quality, which was of great significance to construct a teaching quality prediction model based on big data technology. In the network classroom teaching process, many factors affected teaching quality, and complex relationships may exist among them. If all factors were directly used to construct the prediction model, the problem of "dimensionality curse" may occur, i.e., a model with too high complexity, high training difficulty and poor generalization performance. However, when the LASSO method was used for dimensionality reduction, the factors affecting teaching quality the most were selected, which reduced the model complexity and improved the prediction accuracy. Figure 3 shows the LASSO-based state data integration principle.

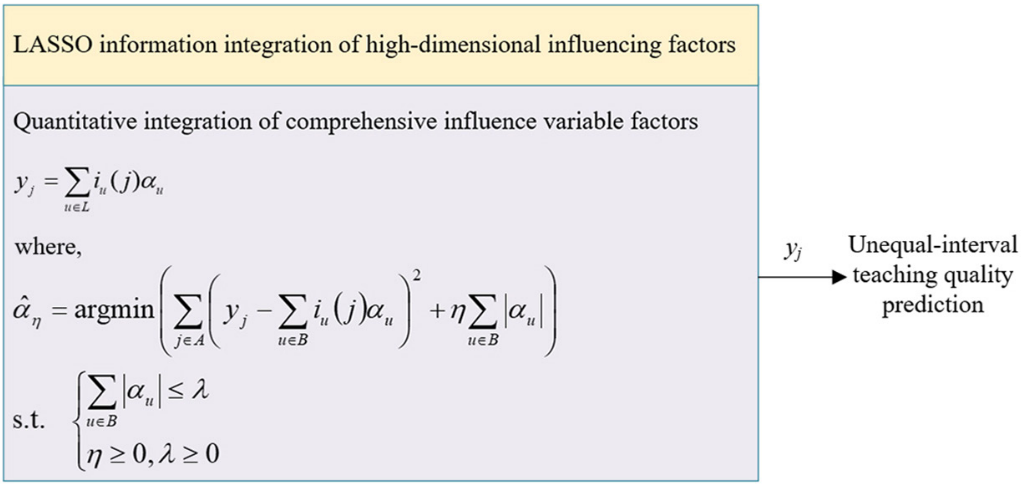

Fig. 3. LASSO-based state data integration

Compared with other dimensionality reduction methods, such as principal component analysis (PCA), the LASSO method selected features by compressing the feature coefficients affecting target variables less to 0, which not only made the model easier to interpret but also reduced its complexity. LASSO reduced the number of features by limiting the absolute values of coefficients, which helped prevent model overfitting and enhanced generalization ability of the model. That is, the LASSO-based dimensionality reduction method effectively handled the quality prediction problem of network classroom teaching in the big data environment, which made the model more accurate, stable, and easy to understand by selecting the most influential factors.

Let $\hat{\alpha}_\eta = (\alpha_1, \alpha_2, \ldots, \alpha u, \ldots)$ be the clustering coefficient parameter list to be estimated, λ be a predetermined free parameter determining the regularization degree, and η be the penalty parameter, then the LASSO regression method was expressed as:

$$\begin{aligned} &\hat{\alpha}_\eta = \text{argmin}\left(\sum_{j \in A}(y_j - \sum_{u \in B} i_u(j)\alpha_u)^2 + \eta\sum_{u \in B}|\alpha_u|\right) \\ &\text{s.t.} \quad \begin{cases} \sum_{u \in B}|\alpha_u| \le \lambda \\ \eta \ge 0, \lambda \ge 0 \end{cases} \end{aligned} \tag{3}$$

$\hat{\alpha}_\eta$ estimation was realized based on LASSO regression. The comprehensive teaching effect difference state y_j of sample j was measured by combining with Equation 2, which further obtained the following point set of sample variable factors and final teaching quality:

$$\left\{(y_1, z^{(0)}(1)), (y_2, z^{(0)}(2)), \ldots, (y_j, z^{(0)}(j)), \ldots\right\} \tag{4}$$

The above point set was further simplified as an unequal-interval teaching quality sequence, which was given by the following equation:

$$z^{(0)} = \left(z^{(0)}(y_1), z^{(0)}(y_2), \ldots, z^{(0)}(y_j), \ldots\right)^Y \tag{5}$$

Based on the quality sequence, this study constructed the relationships between various variable factors and teaching quality, and completed subsequent teaching quality prediction modeling.

4 CONSTRUCTION OF A TEACHING QUALITY PREDICTION MODEL

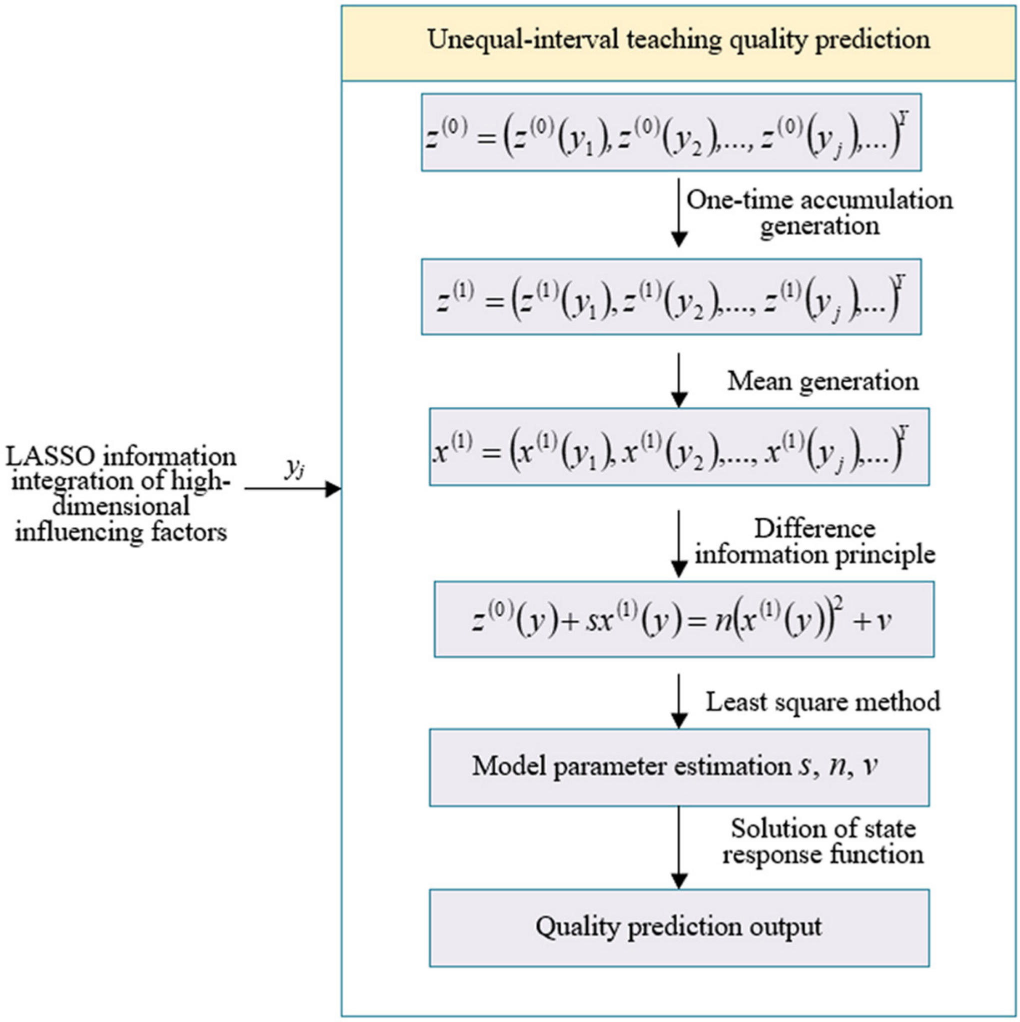

Fig. 4. Execution process of the prediction model

In actual network classroom teaching, the factors affecting teaching quality were often diverse and nonlinear, with possibly unequal-interval data. Traditional prediction models, such as linear regression models or common time series models, may not be able to effectively solve such problems. Due to its design flexibility, the unequal-interval grey Riccati-Bernoulli model handled this complex situation and better fit and predicted teaching quality. The model was constructed to study the internal relationships between various variable factors and teaching quality, because the unequal-interval teaching effect sequence $x^{(0)}$ obtained from the previous section was based on limited sample information. Figure 4 shows execution process of the prediction model.

Let $Y = \{y_1, y_2, \ldots, y_j, \ldots\}$ be the ordered teaching environment sequence, then the quality index $z^{(0)}(y_j)$ was considered as the teaching effect performance, because the implementation of network classroom teaching environment was orderly. Before y_j was reached, $z{>}(y_j)$ was regarded as the accumulation of teaching effect performance, i.e.

$$z^{(1)}(y_j) = \sum_{u=1}^{j} z^{(0)}(y_u) \ or \ z^{(1)}(y_j) = \int_{y_1}^{y_j} z^{(0)}(\pi) f \pi \tag{6}$$

It's worth noting that consideration should be given to the acceptance of students in the classroom before introducing new teaching links. According to the teaching practice theory, the acceptance $L(y_j)$ of teaching link was regarded as the monotonic increasing function of $z^{(1)}(y_j)$. Based on this, the relationships between $L(y_j)$ and $z^{(1)}(y_j)$ were expressed as follows:

$$L(y_j) = j_1 (z^{(1)}(y_j))^{\frac{1}{\beta}} + n_1, j_1 > 0, n_1 > 0, l > 0 \tag{7}$$

At the same time, the actual teaching effect performance was influenced by teaching methods and experience accumulation of teachers. Therefore, higher acceptance of teaching methods or more experience accumulation improved teaching quality, that is:

$$z^{(0)}(y_j) = j_2 L(y_j) + j_3 z^{(1)}(y_j), j_2 > 0, j_3 > 0 \tag{8}$$

Assuming $s = -j_3$, $n = j_1 j_2$, $v = j_2 n_1$, and $l = 1/\beta$, and Equations 6 and 7 were combined with Equation 8, which obtained the following differential equation:

$$\frac{dz^{(1)}(y)}{dy} + sz^{(1)}(y) = n(z^{(1)}(y))^l + v \tag{9}$$

$z^{(1)}(y)$ was a first-order continuous differentiable function in Equation 9, but the historical cumulative observation sequence $z^{(m)}$ of teaching quality was discrete. Therefore, the above equation needed to be modified and discretized to adapt to system characteristics of the grey prediction model.

Let $z^{(0)}(y_j)$ be the original observation value in state $y_j (j = 1,2,\ldots,b)$, and $z^{(0)}$ be the original observation sequence, then there were:

$$z^{(0)} = (z^{(0)}(y_1), z^{(0)}(y_2), \cdots, z^{(0)}(y_b))^T \tag{10}$$

where, $z^{(1)}(y_2), \ldots, z^{(1)}(y_b))^Y$ is the one-time accumulation generation sequence of $z^{(0)}$, then there were:

$$z^{(1)}(y_j) = \sum_{u=1}^{j} \Delta y_u z^{(0)}(y_u) \tag{11}$$

Expression of the state interval Δy_u was as follows:

$$\Delta y_u = \begin{cases} 1, u = 1 \\ y_u - y_{u-1}, u = 2,3,4,\ldots \end{cases} \tag{12}$$

For the cumulative teaching quality observation value $z^{(1)}(y)$, its change rate within the time period $[y_{j-1},y_j]$ was approximated by the following equation:

$$\frac{dz^{(1)}(y)}{dy}\bigg|_{y=y_j} \approx \frac{\Delta z^{(1)}(y)}{\Delta y}\bigg|_{y=y_j} = \frac{z^{(1)}(y_j)-z^{(1)}(y_{j-1})}{\Delta y_j} = \frac{\Delta y_j z^{(0)}(y_j)}{\Delta y_j} = z^{(0)}(y_j) \tag{13}$$

Let $dz^{(1)}(y)/dy$ be the grey derivative, that is, the grey derivative sequence of $z^{(1)}(y)$ was $z^{(0)}(y_j)$, which replaced $dz^{(1)}(y)/dy$ during $[j-1,j]$. In addition, it's assumed that $o\in[0,1]$, then the background value of $z^{(1)}(y)$ on $[y_{j-1},y_j]$ was obtained by the following equation:

$$z^{(1)}(y)\Big|_{[y_{j-1},y_j]} \approx oz^{(1)}(y_j)+(1-o)z^{(1)}(y_{j-1}) = x^{(1)}(y_j) \tag{14}$$

In grey modeling, the value of $z^{(1)}(y)$ on $[y_{j-1},y_j]$ was replaced with the background value $x^{(1)}(y_j)$ to define the following grey model. Let s be the development coefficient, with its size and symbol reflecting the development trend of $z^{(0)}$ and $z^{(1)}$; n be the grey action or control coefficient, reflecting the influence of $(z^{(1)})^l$ on the observed value of quality index; v be the adjustment parameter or error term, and l be the power exponent. The definition equation of the unequal-interval grey Riccati-Bernoulli model was as follows:

$$z^{(0)}(y_j)+sx^{(1)}(y_j) = n(x^{(1)}(y_j))^l + v \tag{15}$$

Its whitening differential equation was provided as follows:

$$\frac{dz^{(1)}}{dy}+sz^{(1)} = n(z^{(1)})^l + v \tag{16}$$

The special forms of the constructed model were the existing five grey models. When $l = 2$, $y_j = y$, and $\Delta y_j = 0$, the constructed model was a grey generalized Verhulst model or a nonlinear grey Riccati model, with the constant-coefficient Riccati equation as its whitening differential equation.

$$z^{(0)}(y)+sx^{(1)}(y) = n(x^{(1)}(y))^2 + v \tag{17}$$

When $l = 3$, $y_j = y$, and $\Delta y_j = 0$, the constructed model was a nonlinear grey Abel model, with the first type of Abel equation as its whitening differential equation.

$$z^{(0)}(y)+sx^{(1)}(y) = n(x^{(1)}(y))^3 + v \tag{18}$$

When $v = 0$, $y_j = y$, and $\Delta y_j = 0$, the constructed model was a nonlinear grey Bernoulli model.

$$z^{(0)}(y)+sx^{(1)}(y) = n(x^{(1)}(y))^l \tag{19}$$

When $v=0$, $l = 2$, $y_j = y$, and $\Delta y_j = 0$, the constructed model was a nonlinear grey Verhulst model.

$$z^{(0)}(y)+sx^{(1)}(y) = n(x^{(1)}(y))^2 \tag{20}$$

When $v = 0$, $l = 0$, $y_j = y$, and $\Delta y_j = 0$, the constructed model was the classical GM (1,1).

$$z^{(0)}(y)+sx^{(1)}(y) = n \tag{21}$$

5 TEACHING QUALITY PREDICTION AND MANAGEMENT

In summary, considering the high-dimensional data characteristics of factors affecting teaching quality in the big data environment, this study proposed a new combination prediction model for the network classroom teaching quality. The combination model mainly consisted of two parts. One part was an integration module based on LASSO data features of high-dimensional influencing factors, which quantified the teaching effect difference state. The other part was based on the unequal-interval grey Riccati-Bernoulli model, which constructed the relationship function of various variable factors and teaching quality, thus finally predicting the network classroom teaching effect. The detailed modeling steps were summarized as follows:

Step 1: LASSO algorithm was used for information integration of teaching effect status difference data in each teaching link, and construction of comprehensive teaching effect difference status sequence $Y = \{y_j | j = 1,2,...,b\}$.

Step 2: The teaching quality detection value $z^{(0)}(y_j)$ in certain y_j was determined to construct the unequal-interval sequence $z^{(0)}(y_j) = (z^{(0)}(y_1),z^{(0)}(y_2),...,z^{(0)}(y_b))^Y$ as the initial value sequence of teaching quality.

Step 3: For the initial sequence $z^{(0)}$, the cumulative generation sequence $z^{(1)}$ and the mean sequence $x^{(1)}$ were calculated successively; $x^{(1)}(y_j)$ and $(x^{(1)}(y_j))^l$ were used to construct data matrices N and T; the least square method was used to estimate parameters s, n, and v.

Step 4: A grey Riccati-Bernoulli model was constructed; the system response value $z^{(1)}(y_j)$ in y_j was calculated based on the actual value of l.

Step 5: The response value $z^{(1)}(y_j)$ was restored, which obtained $z^{(0)}(y_j)$, i.e. the output value of the teaching quality prediction model.

Based on the teaching quality prediction results, the scientific and reasonable quality management of network classroom teaching was achieved mainly through the following steps:

Step 1: Identifying problems. The prediction results were first used to identify key factors and problems affecting teaching quality, such as inappropriate teaching methods, incomplete functions of technical platform, low participation degree of students and so on.

Step 2: Developing an improvement plan. After identifying problems, a specific improvement plan was developed. For example, if it was found that teaching methods were inappropriate, teaching strategies may be considered to be changed, such as adopting more interactive teaching methods. If it was found that functions of the technical platform were not complete, the platform was optimized to add necessary functions.

Step 3: Implementing the improvement. According to the improvement plan, specific actions were taken to improve teaching quality, possibly involving training of teachers, upgrading of technology platform, reform of teaching methods and so on.

Step 4: Monitoring the effect. After implementing the improvement, teaching quality needed to be monitored continuously to see whether the improvement measures were effective, through regular quality prediction, feedback of students, teaching evaluation, and other methods.

Step 5: Continuous improvement. Necessary adjustments were made based on the monitoring results in order to further optimize the improvement plan, thus continuously improving teaching quality.

Overall, the quality management of network classroom teaching based on prediction results was a continuous and systematic process, which required scientific and reasonable planning and implementation to ensure the teaching quality improvement.

6 EXPERIMENTAL RESULTS AND ANALYSIS

Figure 5 shows the relationships between acceptance of students and experience accumulation of teachers with different clustering coefficients. The relationships depended on the size of clustering coefficients. The clustering coefficient reflected the integration degree of courses or the focus degree of teaching methods. When the clustering coefficient was low, the growth rate of student acceptance increased with the increase of teaching experience, indicating that increased experience of teachers helped them better cope with dispersed teaching environment, and provide more personalized teaching experience, thus improving the acceptance of students. When the clustering coefficient was high, the growth rate of student acceptance decreased with the increase of teaching experience, reflecting that the experience caused teachers to rely too much on fixed teaching methods or models, and ignore individual differences and new teaching methods. The above conclusions were very important for teaching management and suggested that teachers should flexibly apply their experience in practical teaching activities while paying attention to individual differences of students and new teaching methods, thus improving their acceptance. In addition, attention should be paid to clustering coefficient adjustment in order to adapt to different teaching environments and student needs.

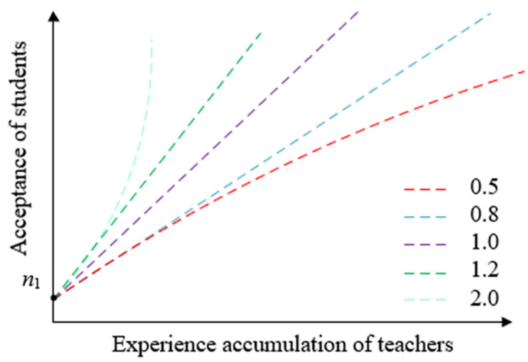

Fig. 5. Relationships between acceptance of students and experience accumulation of teachers with different clustering coefficients

Table 1. Comparative analysis of models in MSE, MAE and MAPE before and after optimization

Prediction Model	Data Sample	MSE	MAE	MAPE
Traditional grey prediction model	Training sample	23.625	1.302	26.395
	Test sample	24.152	1.625	21.520
	Full sample	26.958	1.485	23.614
Traditional grey prediction model+PCA feature selection	Training sample	1.352	0.741	15.428
	Test sample	2.518	0.762	12.103
	Full sample	2.614	0.759	16.285
Traditional grey prediction model+LASSO feature selection	Training sample	0.758	0.362	5.629
	Test sample	1.362	0.341	5.847
	Full sample	0.829	0.385	5.352
Model in this study	Training sample	0.614	0.302	5.124
	Test sample	0.425	0.215	5.017
	Full sample	0.548	0.262	5.092

The comparative analysis in Table 1 was made based on three important performance indexes of the prediction models, namely, mean square error (MSE), mean absolute error (MAE) and mean absolute percentage error (MAPE), which were widely used in prediction model evaluation to measure the difference between predicted and true values. Generally speaking, the lower the values of these indexes, the better the performance of the prediction model. It can be seen from the table that the traditional grey prediction model has high MSE, MAE and MAPE in training, test and full samples, indicating poor prediction performance. The combination model of traditional grey prediction model and PCA feature selection has significantly lower MSE, MAE and MAPE in the three samples compared with the traditional grey prediction model, indicating that PCA feature selection effectively improves prediction performance. In contrast, the combination prediction model of traditional grey prediction model and LASSO feature selection has further lower MSE, MAE and MAPE in the three samples, indicating that LASSO feature selection outperforms PCA feature selection in prediction performance. Compared with the traditional grey prediction model using LASSO feature selection, the model in this study (i.e., the unequal-interval grey Riccati-Bernoulli model+LASSO feature selection) has lower MSE, MAE and MAPE in the three samples, indicating that the model has the best prediction performance in dealing with this problem.

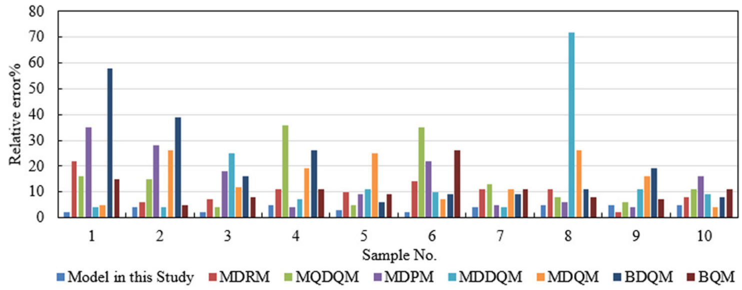

Fig. 6. RPEs of different models in Course 1

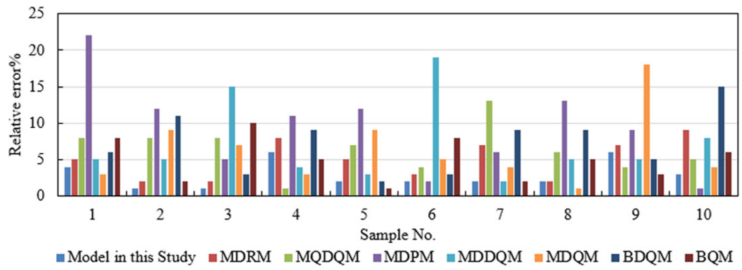

Fig. 7. RPEs of different models in Course 2

Figures 6 and 7 show the relative prediction errors (RPEs) of eight models in different teaching scenarios. The smaller the RPE, the better the predictive ability of the model. It was concluded through observation that the model in this study had relatively small RPEs in various scenarios on the whole, showing that the model had good stability and prediction accuracy. RPEs of the other seven models, namely, MDRM, MQDQM, MDPM, MDDQM, MDQM, BDQM, and BQM, varied significantly in different scenarios. For example, RPEs of MDPM in Scenarios 1 and 10 reached 22 and 12, respectively, which were very high, while the RPE was only 2 in Scenario 6, meaning that these models had significantly different predictive ability when dealing with different scenarios. Overall, except the model in this study, other models had relatively high RPEs and exhibited significant inconsistency when dealing with different scenarios, indicating that these models had big problems in their predictive ability in specific situations.

Table 2. Teaching optimization comparative analysis of different models before and after quality management

Prediction Model	Data Sample	Proportion of Amended Teaching Links	Proportion of Supplemented Teaching Contents
Traditional grey prediction model	Training sample	22.61	16.29
	Test sample	29.41	15.38
	Full sample	21.62	15.24
Traditional grey prediction model+PCA feature selection	Training sample	15.38	19.62
	Test sample	12.04	11.02
	Full sample	19.52	15.47
Traditional grey prediction model+LASSO feature selection	Training sample	16.85	13.28
	Test sample	13.41	19.42
	Full sample	18.59	16.38
Model in this study	Training sample	9.51	9.51
	Test sample	17.24	9.26
	Full sample	13.62	9.47

Table 2 presents the teaching optimization comparative analysis results of different models before and after quality management. Two indexes of "proportion of amended teaching links" and "proportion of supplemented teaching contents" were used to measure the optimization of teaching links and contents. The lower the proportions, the less the parts to be amended or supplemented, the higher the teaching quality.

The following conclusions were drawn based on the above data. The traditional grey prediction model had relatively high proportions of amended teaching links and supplemented teaching contents in the training, test and full samples, indicating that the model had poor prediction effect and required optimization of more teaching links and contents. In contrast, the combination prediction model of traditional grey prediction model+PCA feature selection had lower proportions of amended teaching links and supplemented teaching contents in the three samples, indicating that PCA feature selection effectively improved teaching quality. The combination prediction model of traditional grey prediction model+LASSO feature selection further reduced the proportions of amended teaching links and supplemented teaching contents in the three samples, indicating that LASSO feature selection was better than PCA feature selection in improving teaching quality. Overall, the feature selection methods and the model in this study effectively reduced the proportions of amended teaching links and supplemented teaching contents, thus improving teaching quality. Among all the models, the model in this study (i.e., the unequal-interval grey Riccati-Bernoulli model+LASSO feature selection) performed the best in improving teaching quality.

Compared with the traditional grey prediction model using LASSO feature selection, the model in this study had lower proportions of amended teaching links and supplemented teaching contents in training, test or full samples, indicating that the model performed the best in improving teaching quality.

7 CONCLUSION

This research studied the quality management of network classroom teaching based on big data technology. This study first provided a framework diagram of teaching quality evaluation criteria and factors affecting teaching quality in the big data environment, explained complex relationships and effects among the factors, and described teaching quality prediction problems. The LASSO dimensionality reduction method was used for comprehensive status data integration of factors affecting teaching quality. An unequal-interval grey Riccati-Bernoulli model was constructed to study the internal relationships between various variable factors and network classroom teaching quality. Then execution process of the prediction model, detailed modeling steps and teaching quality management steps were provided. Combined with experiments, the relationships between acceptance of students and experience accumulation of teachers with different clustering coefficients were analyzed and discussed, and the analysis results were provided. The comparative analysis results of different models in MSE, MAE and MAPE before and after optimization were provided, which verified that the model in this study had the optimal prediction performance when dealing with related problems. In addition, the fitting and prediction errors of eight models in six courses were compared, and the results showed that the model in this study performed well in all six courses, with low and stable prediction errors and strong robustness. RPEs of eight models in different teaching scenarios were calculated, and the results showed that all other models had high RPEs except the model in this study. Finally, the teaching optimization comparative analysis results of different models before and after quality management were provided, and the results showed that the model in this study performed the best in improving teaching quality among all models.

8 REFERENCES

[1] Ariyanto, Y., Harijanto, B., Asri, A.N. (2020). Analyzing student's learning interests in the implementation of blended learning using data mining. International Journal of Online and Biomedical Engineering, 16(11): 153–160. https://doi.org/10.3991/ijoe.v16i11.16453

[2] Gao, J., Yue, X.G., Hao, L., Crabbe, M.J.C., Manta, O., Duarte, N. (2021). Optimization analysis and implementation of online wisdom teaching mode in cloud classroom based on data mining and processing. International Journal of Emerging Technologies in Learning, 16(1): 205–218. https://doi.org/10.3991/ijet.v16i01.18233

[3] Cui, J. (2022). Mode and effect evaluation of classroom regulation under hybrid teaching mode in colleges. International Journal of Emerging Technologies in Learning, 17(10): 200–214. https://doi.org/10.3991/ijet.v17i10.31537

[4] Lakshaga Jyothi, M., Shanmugasundaram, R.S. (2021). Design and implementation of intelligent classroom framework through light-weight neural networks based on multimodal sensor data fusion approach. Revue d'Intelligence Artificielle, 35(4): 291–300. https://doi.org/10.18280/ria.350403

[5] Tan, F., Yang, P. (2023). Use of a knowledge network for management and sharing of teaching resources for building construction simulations. International Journal of Emerging Technologies in Learning, 18(8): 222–237. https://doi.org/10.3991/ijet.v18i08.39245

[6] Jing, C. (2023). Design of art teaching multimedia system based on genetic algorithms and computer network. Soft Computing, 27: 6823–6833. https://doi.org/10.1007/s00500-023-08114-y

[7] He, J., Lin, K.Y., Dai, Y. (2022). A data-driven innovation model of big data digital learning and its empirical study. Information Dynamics and Applications, 1(1): 35–43. https://doi.org/10.56578/ida010105

[8] Yang, J. (2020). An efficient scheme of network English teaching based on psycholinguistics. In 2020 12th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Phuket, Thailand, pp. 837–841. https://doi.org/10.1109/ICMTMA50254.2020.00182

[9] Cao, X., Huang, J. (2020). Analysis on the reform path of college English teaching in local engineering colleges under the background of big data. In Big Data Analytics for Cyber-Physical System in Smart City: BDCPS 2019, Shenyang, China, pp. 375–381. https://doi.org/10.1007/978-981-15-2568-1_52

[10] Eken, S. (2020). An exploratory teaching program in big data analysis for undergraduate students. Journal of Ambient Intelligence and Humanized Computing, 11(10): 4285–4304. https://doi.org/10.1007/s12652-020-02447-4

[11] Cao, Y. (2020). Teaching exploration of piano playing and singing based on big data analysis. In 2020 International Conference on Information Science and Education (ICISE-IE), Sanya, China, pp. 13–16. https://doi.org/10.1109/ICISE51755.2020.00011

[12] Xiao, J., Chen, F. (2020). Environmental art design teaching based on big data analysis. In 2020 International Conference on Computers, Information Processing and Advanced Education (CIPAE), Ottawa, ON, Canada, pp. 91–93. https://doi.org/10.1109/CIPAE51077.2020.00031

[13] Diao, A. (2020). Analysis on the evaluation model of the teaching effect of innovation and entrepreneurship course based on big data. In 2020 12th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Phuket, Thailand, pp. 848–851. https://doi.org/10.1109/ICMTMA50254.2020.00184

[14] Wang, Q. (2020). A study on the implementation path of college English classroom culture teaching based on big data analysis. In 2020 International Conference on Modern Education and Information Management (ICMEIM), Dalian, China, pp. 337–340. https://doi.org/10.1109/ICMEIM51375.2020.00084

[15] Yang, X., Zhen, L. (2023). Research on English teaching in higher vocational colleges based on big data analysis. In Application of Big Data, Blockchain, and Internet of Things for Education Informatization: Second EAI International Conference, BigIoT-EDU 2022, Virtual Event, pp. 47–52. https://doi.org/10.1007/978-3-031-23944-1_6

[16] Liu, N., Ruan, Y. (2022). Teaching design optimization and application research of college students' education evaluation data analysis based on big data. In Frontier Computing: Proceedings of FC 2021, Seoul, Korea, pp. 580–586. https://doi.org/10.1007/978-981-16-8052-6_72

[17] Jing, F. (2022). Accurate teaching data analysis of "special effects production for digital films and TV programmes" based on big data. In Business Intelligence and Information Technology: Proceedings of the International Conference on Business Intelligence and Information Technology BIIT 2021, Harbin, China, pp. 160–168. https://doi.org/10.1007/978-3-030-92632-8_16

[18] Hu, Y. (2022). English teaching method reform based on big data analysis technology. In 2022 International Symposium on Advances in Informatics, Electronics and Education (ISAIEE), Frankfurt, Germany, pp. 681–686. https://doi.org/10.1109/ISAIEE57420.2022.00144

[19] Dong, Y. (2023). Teaching quality monitoring and evaluation in higher education through a big data analysis. International Journal of Emerging Technologies in Learning (Online), 18(8): 61–78. https://doi.org/10.3991/ijet.v18i08.39247

[20] Wang, Q., Wang, B. (2022). Online and offline hybrid teaching quality information analysis under the background of big data. In Application of Intelligent Systems in Multi-modal Information Analytics: The 4th International Conference on Multi-modal Information Analytics (ICMMIA 2022), Huhehaote, China, pp. 859–866. https://doi.org/10.1007/978-3-031-05237-8_106

[21] Wang, J., Liu, C., Gao, W. (2022). Teaching quality evaluation and feedback analysis based on big data mining. Mobile Information Systems, 2022: 7122846. https://doi.org/10.1155/2022/7122846

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