Teaching Quality Monitoring and Evaluation in Higher Education through a Big Data Analysis

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Abstract—In the existing teaching quality monitoring and evaluation, there usually adopts only one method, which is relatively simple, lacking validation and verification in the analysis results. For this reason, this paper aims to conduct research on the teaching quality monitoring and evaluation in higher education based on big data analysis. Firstly, the teaching quality monitoring in higher education was made in five directions: teachers' teaching level, students' academic status, course learning effectiveness, students' competency, and students' employment status. Also, the time series forecasting model (Autoregressive Integrated Moving Average) and the differential equation model (GM(1,1)) model which can effectively predict the change trend of the series, are fused to make the predictive evaluation of the changes in data series of the higher education teaching quality. Next, a combined analysis was performed for both the teaching quality monitoring and evaluation results in higher education and the corresponding data on the frequency of proposing and promoting the improvement measures of teaching quality, and mathematical models were established through curve fitting and parameter estimation to explore the deep correlation between the two. Finally, the related experimental results were given to verify the fusion model. Therefore, the teaching quality monitoring and evaluation system in higher education based on big data analysis can realize the effective regulation of factors affecting teaching quality, and also provide convenience for the academic management of universities, which has certain research significance.

Keywords—big data analysis, higher education, teaching quality monitoring, teaching quality evaluation

1 Introduction

Following the increasing demand for high-quality talents in social workplaces, the reform of higher education is of great urgency [1–4]. All universities need to focus on the construction of teaching quality, especially the teaching quality evaluation [5–11]. Currently the web-based educational management system has been widely used in higher education institutions, gradually replacing the student performance-oriented traditional evaluation system. In the information-based era, it has received great attention of scholars at home and abroad on how to extract useful information from teaching quality evaluation databases in higher education [12–21]. With the help of advanced data mining technology that excels in data analysis and understanding and reveals the information embedded within the data, it's possible for the teaching quality monitoring and evaluation system in higher education based on big data analysis to effectively regulate the factors affecting teaching quality and to facilitate the academic management of universities.

To improve the reliability of higher education quality assessment, Qi et al. [22] improved the RBF neural network algorithm according to the characteristics of teaching data in higher education, and used RBF technology to build a prediction model after learning from actual teaching data samples for teaching quality assessment; the experimental results showed the effectiveness of this evaluation model based on the improved RBF. As suggested in Ref. [23], 16 evaluation indexes were determined from four aspects of teaching attitude, teaching content, teaching process and teaching results to construct an evaluation index system of higher vocational quality, while BP neural network algorithm was applied to establish the evaluation model. Finally, the empirical study was conducted in five higher vocational colleges in Henan Province. Besides, it's found that most of the current college classroom evaluations are made through qualitative analysis, lacking necessary quantitative means. Although the traditional hierarchical analysis can deal with this problem quantitatively, it is difficult to test the consistency of the judgment matrix. For this, a technique for designing a multimodal teaching quality evaluation model based on the improved particle swarm optimization algorithm was proposed in Ref. [24]. A multimodal teaching model for educational courses was developed using the augmented particle swarm optimization method. Liu et al. [25] aimed to analyze the importance of teaching process management and teaching quality monitoring, and then to design and develop an effective teaching management system for teaching practice, which can greatly adapt to the specific teaching requirements in universities. Furthermore, the data generated by the proposed system can be analyzed and mined to identify the teaching laws and bottlenecks. Considering that big data in education has the characteristics of real-time, multi-dimensionality and authenticity, etc., the study [26] analyzed the current problems of teaching quality in higher education and proposed the path of educational big data to improve teaching quality with the continuous improvement of data mining and learning analysis technologies.

The use of big data methods can capture the specific details of teaching quality monitoring data in higher education at all levels and their complex relationships, help the decision makers of higher education reform achieve comprehensive monitoring of teaching status, and further regulate the factors affecting teaching quality effectively to ensure education quality. Currently they usually adopt only one method for the existing monitoring and evaluation of teaching quality. It's relatively simple, but lacking validity and scientific verification in the analysis results. Especially for the evaluation index with large data volume and non-uniform evaluation standards, if their reliability cannot be effectively verified, it shall be difficult to obtain the ideal and usable evaluation results. In view of the above, this paper aims to study the monitoring and evaluation of teaching quality in higher education based on big data analysis. Section 2 in this paper firstly identifies five aspects of teaching quality monitoring in higher education: teachers' teaching level, students' academic status, course learning effectiveness, students' competence, and students' employment status, and fuses the two models, i.e., Autoregressive Integrated Moving Average (ARIMA) model and the GM(1,1) model, to predictively evaluate the change trend of teaching quality monitoring data series in higher education. In Section 3, the combined analysis was performed for both the teaching quality monitoring and evaluation results in higher education and the corresponding data on the frequency of proposing and promoting the improvement measures of teaching quality; the mathematical model was built by curve fitting and parameter estimation to explore the deep correlation between the two. The experimental results were given to verify the constructed model in the Section 4. Finally, the conclusions are made in Section 5.

2 Teaching quality monitoring data sources and predictive evaluation

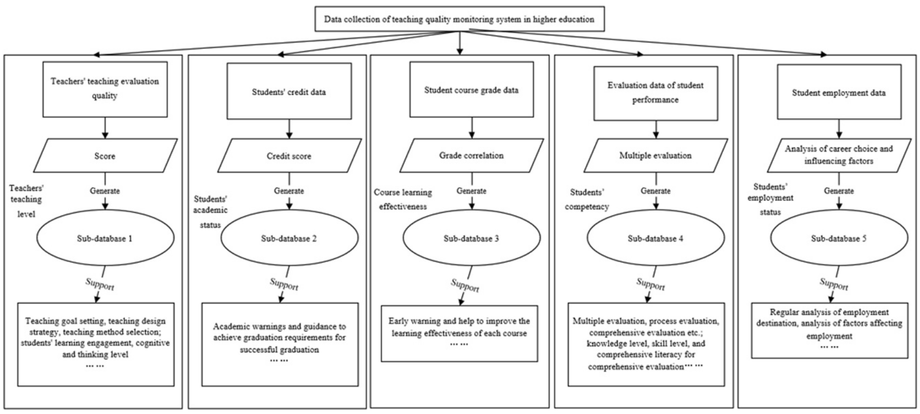

Fig. 1. Teaching quality monitoring in higher education based on big data analysis

In this paper, the teaching quality monitoring in higher education is mainly performed in terms of five aspects: teachers' teaching level, students' academic status, course learning effectiveness, students' competency, and students' employment status. Among them, the teachers' teaching level is monitored to evaluate whether teachers have achieved the teaching objectives. Various methods are used to make objective value judgments on teachers' teaching objectives, teaching design strategies, teaching methods, students' learning engagement, and cognitive and thinking level enhancement effects, and finally obtain the evaluation results. In terms of students' academic status, students' credits are monitored in stages for their real learning status, and timely academic warnings and guidance are provided to disadvantaged students based on the monitoring results to ensure that students graduate successfully. Monitoring of course learning effectiveness is to supervise and analyze the relationship between students' scores and their course learning status, to provide early warning and help to disadvantaged students in a timely manner in response to the monitoring results, and to improve the quality of students' training by improving their learning effectiveness in each course, and to generate evaluation results based on course monitoring results. Students' competency monitoring is to comprehensively evaluate students' knowledge level, skill level and comprehensive literacy by the use of multiple evaluation, process evaluation, and comprehensive evaluation etc., and achieve the evaluation results through teachers' evaluation of students' performance in different courses. To monitor students' employment status, it's divided into two steps, namely, periodic analysis of graduates' career choices, and in-depth digging of various factors affecting students' employment, specifically including professional orientation, professional ability, interpersonal skills and professionalism, etc. Specific evaluation results can be generated through the analysis and survey results. Figure 1 shows the data sources of teaching quality monitoring in higher education based on big data analysis.

Since all the monitoring and evaluation results of the above five parts are real-time data, they have valuable feature information and associated information from the perspective of time series. To ensure more accurate modeling and evaluation results for teaching quality monitoring data in higher education, the time series forecasting model ARIMA was fused with the differential equation model GM(1,1) which can effectively predict the trend of the series.

This fusion model was applied to predicatively evaluate the trend of teaching quality monitoring data series in higher education. It includes three steps: time series decomposition and reconstruction, single model modeling separately and generation of predictive evaluation results as follows:

The decomposition and reconstruction of time series refers to the singular spectrum analysis for the time series of evaluation data describing the original monitoring states of teachers' teaching level, students' academic status, course learning effectiveness, students' competency, and students' employment status, and then the extraction of the high-frequency components, low-frequency components and disorder components from them. These three components correspond to the periodic information, trend information and noise information of the time series respectively. In this paper we mainly analyzed the first two components that have a positive effect on the predictive evaluation results.

First, let a m-long time series of evaluation result data be $R = \{r_1, r_2, \dots, r_m\}$, and transform it into an $n*l$-dimensional trajectory matrix A; then $l = m-n+1$, which is expressed as:

$$A = \begin{bmatrix} r_1 & r_2 & \cdots & r_l \\ r_2 & r_3 & \cdots & r_{l+1} \\ \vdots & \vdots & & \vdots \\ r_n & r_{n+1} & \cdots & r_m \end{bmatrix} \tag{1}$$

Next, AA^T is computed and the singular value decomposition is performed, and n eigenvalues obtained are sorted in a descending order; then there are μ_1, μ, …, μ_n, and the corresponding eigenvectors are V_1, V, … V_n. Let $c = rank(A)$,

$T_i = (\mu_i)^{1/2} V_i U_i^T (i = 1,2, \ldots, c)$, the i-th left eigenvector and right eigenvector of AA^T are represented by V_i and U_i, respectively. The singular value decomposition of A is given as:

$$A = T_1 + T_2 + \ldots + T_c \tag{2}$$

Divide $\{T_1, T_2, \ldots, T_c\}$ in Eq. (2) above into o disjoint subsets, denoted by PU_1, $PU_2, \ldots, PU_o$, and convert Eq. (2) into Eq. (3):

$$A = A_{PU_1} + A_{PU_2} + \ldots + A_{PU_o} \tag{3}$$

The matrix obtained based on the above equation is then calculated by diagonal averaging to generate the corresponding time series. It's assumed that the elements of matrix C in order $L*K$ are $c_{ij}(1 \le i \le K, 1 \le j \le L)$, and $K^* = min\,(K,L)$, $L^* = max\,(K,L)$, $M = K + L–1$. $c^*_{ij} = c_{ij}$ if $K < L$, otherwise $c^*_{ij} = c_{ji}$. By diagonal averaging, C can be transformed into a time series, i.e., $\{c_1, c_2, \ldots, c_M\}$:

$$c_l = \begin{cases} \dfrac{1}{l} \sum\limits_{n=1}^{l} c^*_{n,l-n+1}, 1 \le l \le K^* \\ \dfrac{1}{K^*} \sum\limits_{m=1}^{L^*} c^*_{n,l-n+1}, K^* < l \le L^* \\ \dfrac{1}{M-l+1} \sum\limits_{n=l-L^*+1}^{N-K^*+1} c^*_{n,l-n+1}, L^* < l \le M \end{cases} \tag{4}$$

Following the above steps, the original time series $R = \{r_1, r_2, \ldots, r_m\}$ is decomposed and reconstructed as follows:

$$R' = \left\{ \sum_{i=u}^{v} c_{i,1}, \sum_{i=u}^{v} c_{i,2}, \ldots, \sum_{i=u}^{v} c_{i,m} \right\} \tag{5}$$

When u equals to 1 and v equals to L, the series obtained by decomposition reconstruction is the original one; the desired high-frequency components and low-frequency components can be extracted from the evaluation result data series by selecting different u and v for reconstruction.

The single model modeling of the fusion model consists of two steps: predictive evaluation of high-frequency component and low-frequency component in data series, which are completed by the ARIMA model and $GM(1,1)$ model respectively.

In the predictive evaluation of the high-frequency component, three parameters, i.e., the number of autoregressive terms o, the number of differences c, and the number of moving average terms w, are determined according to the linear characteristics of the high-frequency component in data series, where c is used to ensure the smoothness of the high-frequency component series. Assuming that the observations of the high-frequency component series are represented by r_e, the undetermined coefficients of the ARIMA model are given by $\psi_i(i = 1,2, \ldots, o)$, $\omega_i(j = 1,2, \ldots w)$, and the residuals at moment o are ρ_e. The ARIMA model is expressed as:

$$r_e = \omega_0 + \psi_1 b_{e-1} + \psi_1 b_{o-1} + \cdots + \rho_e - \omega_1 \rho_{e-1} - \omega_2 \rho_{e-2} - \cdots \omega_w \rho_{o-w} \tag{6}$$

In the predictive evaluation of low-frequency component series, the data series is given by:

$$a^{(0)} = \{a^{(0)}(1), a^{(0)}(2), \ldots, a^{(0)}(m)\} \tag{7}$$

The new time series can be obtained by accumulating the low frequency component series as follows:

$$a^{(1)} = \left\{a^{(1)}(1), a^{(1)}(2), ..., a^{(1)}(m)\right\} \tag{8}$$

where, $a^{(1)}(l) = \Sigma_{i=1}^{l} a^{(0)}(i)$. Then the nearest-neighbor mean equal-weight series of the new time series $a^{(1)}$ is generated in Eq. (9) below:

$$C^{(1)} = (c^{(1)}(2), c^{(1)}(3), \ldots, c^{(1)}(m)) \tag{9}$$

where, $c^{(1)}(l) = 1/2(a^{(1)}(l) + a^{(1)}(l-1))(l = 2,3,\ldots, m)$. The $GM(1,1)$ model is further constructed, i.e., the whitening differential equation at moment e is expressed as:

$$\frac{da^{(1)}}{de} + xa^{(1)}(e) = v \tag{10}$$

The differential equation is solved using the least squares method to obtain the undetermined parameters x and v, as shown in Eq. (11):

$$\begin{pmatrix} x \\ v \end{pmatrix} = (Y^T Y)^{-1} Y^T B \tag{11}$$

where,

$$Y = \begin{bmatrix} -c^{(1)}(2) & 1 \\ -c^{(1)}(3) & 1 \\ \vdots & \vdots \\ -c^{(1)}(m) & 1 \end{bmatrix}, Y = \begin{bmatrix} c^{(1)}(2) \\ c^{(1)}(3) \\ \vdots \\ c^{(1)}(m) \end{bmatrix} \tag{12}$$

The model calibration can be accomplished by the mean squared error ratio or small residual probability. If the model shows good performance in the predictive evaluation, the prediction can be performed for the low frequency components in data time series.

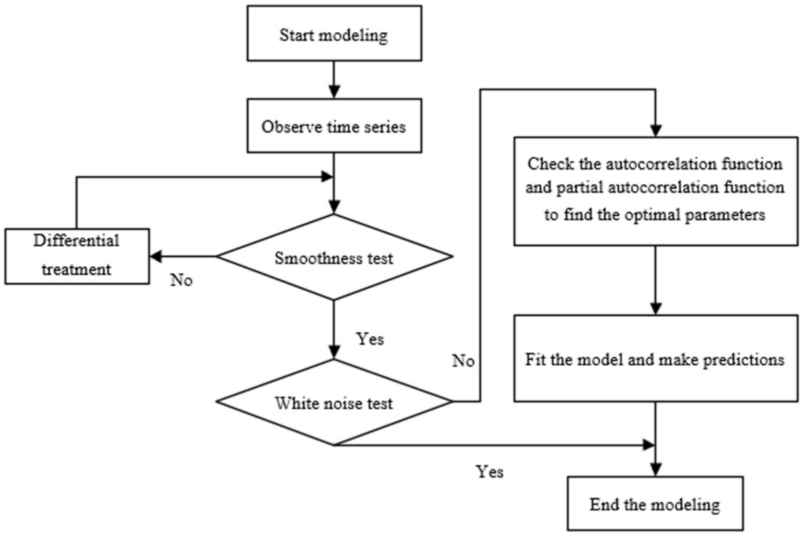

Fig. 2. ARIMA modeling process

The ARIMA model has four basic forms: autoregressive model, moving average model, moving average autoregressive model and hybrid model. The ARIMA model used in this paper is to operate the r-order difference of the series before modelling the time series of evaluation results data by the moving average autoregressive model, which is the combination of autoregressive model and moving average model. Figure 2 shows the ARIMA modeling process. It's assumed that the autoregressive coefficients are $\psi_1, \psi_2, \ldots, \psi_o$, the independent identically distributed random series is ρ_e, and ρ_e is uncorrelated with the lagged variables $a_{e-1}, a_{e-2}, \ldots, a_{e-o}$. Then, the stochastic process of the autoregressive model is given as:

$$b_e = \psi_1 a_{e-1} + \psi_2 a_{e-2} + \ldots + \psi_p a_{e-o} + \rho_e \tag{13}$$

Assuming that the moving average coefficients are represented by $\omega_1, \omega_2, \ldots, \omega_w$, the random series of white noise is denoted by ρ_e, the constant term is λ, then the stochastic process of the moving average model is expressed as:

$$b_e = \lambda + \rho_e - \omega_1 \rho_{e-1} - \omega_2 \rho_2 - \ldots - \omega_w \rho_{e-w} \tag{14}$$

Based on the Eqns. (13) and (14), the moving average autoregressive model can be expressed as:

$$b_e = \psi_1 a_{e-1} + \psi_2 a_{e-2} + \ldots + \psi_p a_{e-o} + \lambda + \rho_e - \omega_1 \rho_{e-1} - \omega_2 \rho_2 - \ldots - \omega_w \rho_{e-w} \tag{15}$$

The ARIMA model in this paper can be expressed as *ARIMA* (o, r, w). The predictive evaluation results are generated by adding the evaluation results of the two models with equal weights, so that the final predictive evaluation results are characterized by both the periodic trend of the original evaluation result data time series and the long-term trend. Figure 3 shows the equal-weighted additive fusion process of evaluation results.

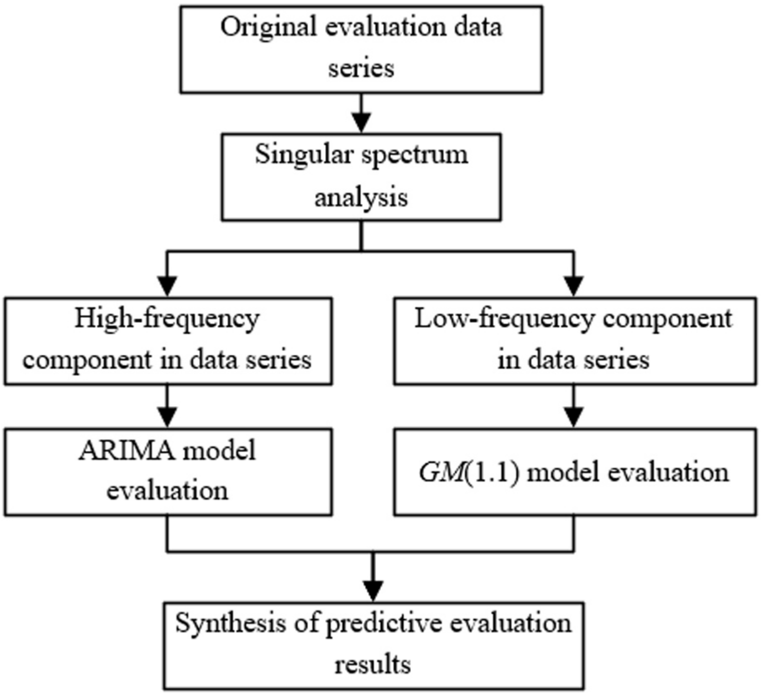

Fig. 3. Equal-weighted additive process of evaluation results

3 Analysis for correlation between teaching quality and improvement measures

Theoretically, the teaching quality monitoring and evaluation results in higher education greatly help to enhance the measures for improving the teaching quality. However, there have been few quantitative studies at home and abroad on this. Also, no study has clearly demonstrated that the monitoring and evaluation results have a direct positive impact on proposing and promoting the improvement measures of teaching quality. Therefore, this paper performs combined analysis for both the teaching quality monitoring and evaluation results and the data on the frequency of proposing and promoting the related improvement measures. Then, based on the time series data obtained from systematic observations, the series analysis was conducted for the impact of the former on the latter, Then, a mathematical model was built through curve fitting and parameter estimation to explore the deep correlation between the two.

We selected the teaching quality monitoring and evaluation results data of the same time period as the proposal and promotion of improvement measures as the research data for statistical analysis. Figure 4 shows the algorithm flow. The KNN proximity algorithm was used to process the outliers for the missing data in this time period. Assuming that the feature vector in the example is $a_i \in A \subseteq R^m$, the class label is $b_i \in B = \{d_1, d_2, \ldots, d_l\}$, $i = 1, 2, \ldots, M$, then the input training dataset:

$$E = \{(a_1, b_1), (a_2, b_2), \ldots, (a_m, b_m)\} \tag{16}$$

Next, output the class b to which the instance a belongs, determine the best distance metric based on the practice, and make sure the domain $M_l(a)$ containing the l nearest instances to a in the given normal data training set E. Assuming that the target function is represented by ZB, i.e., at $b_i = d_j$, $ZB = 1$, otherwise $ZB = 0$. In $M_l(a)$, the class label b of a can be determined by the law of minority rule:

$$b = \arg\max_{t_j} \sum_{a_i \in M_l(a)} ZB(b_i = d_i), i = 1, 2 \ldots, M; j = 1, 2, \ldots, l \tag{17}$$

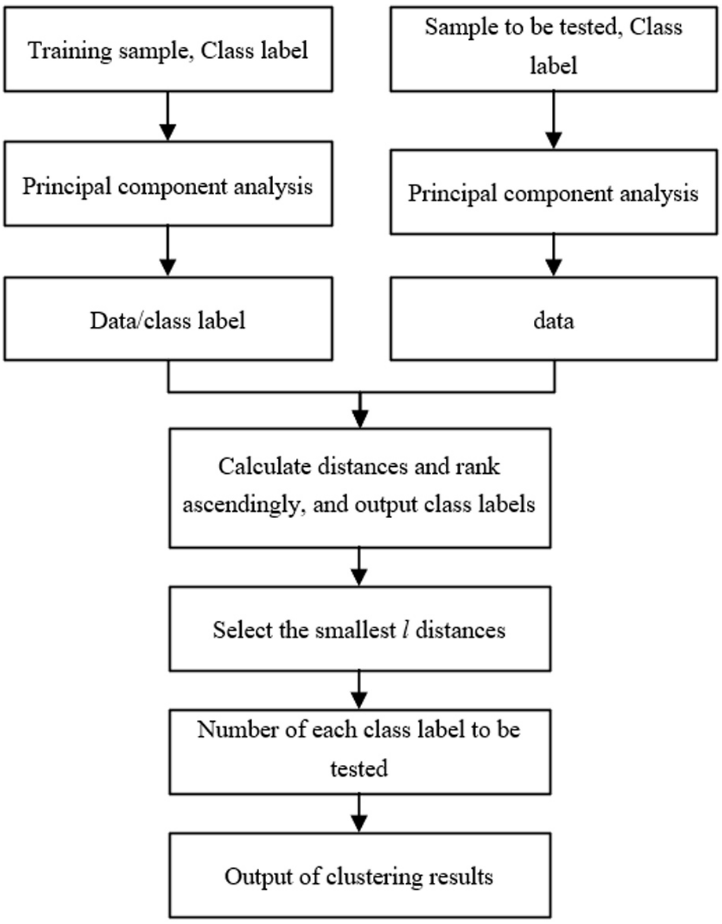

Fig. 4. Outlier processing flow

The generalized additive model was applied to perform the combined analysis between the teaching quality monitoring and evaluation results in higher education and the corresponding data on the frequency of proposing and advancing educational quality improvement measures. It's assumed that the dependent variable is b, the intercept is β, the independent variable is a_i, the expected dependent variable is $T(b)$ or λ, and the linear part is represented by $\sum_{j=1}^{l} g(a_i)$. The link function is represented by $h(.)$, to link $T(b)$ and $\sum_{j=1}^{l} g(a_i)$ in the model, making the dependent variable more consistent with the linear model conditions. The spline function is denoted by $g(.)$, to control the nonlinear relationship. Eq. (18) below gives the general form of the generalized summation function:

$$h(T(b)) = \beta + \sum_{j=1}^{l} g(a_j) \tag{18}$$

In order to control the influence of disturbing factors, this paper introduces the *Poisson* regression model into the generalized additive model and establishes the following model for the combined analysis between the two mentioned above. The frequency of proposing and proposing the improvement measures is represented by b_i, and its expected value is $T(b)$. Besides, the smoothing spline function fitting the long-term trend characteristics is denoted by $P(time, ct = 6*4)$, the natural cubic spline function that fits the impact of teaching quality monitoring and evaluation results in higher education is $ur(yrt)$, and the day of data as a dummy variable is $ya\text{-}F(xq)$, the regression coefficient is γ, the teaching quality monitoring and evaluation results with i-day lag is denoted by Q_i, and the intercept is denoted by β. Then:

$$\log\,(T(b_i)) = p(time, ct = 6*4) + ur(yrt) + ya\_F(xq) + \gamma * Q_i + \beta \tag{19}$$

Further, we calculated the regression coefficients and standard deviations of the frequency data in teaching quality improvement measures after generating the teaching quality monitoring and evaluation results. Assuming that the natural constant is denoted by υ, the quantitative value of teaching quality monitoring and evaluation is δ, the regression coefficient is ε, and the standard deviation of the regression coefficient is represented by χ, the low-frequency prewarning degree and its 95% confidence interval are calculated as respectively:

$$\upsilon^{\delta\times\varepsilon} - 1 \tag{20}$$

$$\upsilon^{\delta\times(\varepsilon\pm1.99\times\chi)^{\varepsilon}} - 1 \tag{21}$$

4 Experimental results and analysis

Using the ARIMA model, GM(1,1) model, and the fusion model constructed in this paper, the predictive evaluation was made for the teachers' teaching level, students' academic status, course learning effectiveness, students' competency, and students' employment status. The evaluation errors are given in Table 1.

Table 1. Comparison of evaluation accuracy between different models

Evaluation Aspect	Indicator	Model		
		ARIMA	*GM*(1,1)	Fusion Model Proposed
Teachers' teaching level	*RMSE*	12.68	13.32	8.67
	MAE	9.75	11.85	7.55
Students' academic status	*RMSE*	24.92	26.42	21.63
	MAE	21.15	22.61	18.56
Course learning effectiveness	*RMSE*	14.13	15.73	9.41
	MAE	11.42	12.62	8.12
Students' competency	*RMSE*	6.87	7.57	3.98
	MAE	5.96	6.54	3.42
Students' employment status	*RMSE*	0.45	0.52	0.41
	MAE	0.37	0.43	0.36

Table 1 shows that the predictive evaluation accuracy of the fusion model constructed in this paper is significantly higher than that of the two single models, and the accuracy of predictive evaluation has been improved to different degrees in terms of the five aspects. Table 2 lists the evaluation time consumption of three models. The average time-consuming for individual index evaluation using the fusion model in this paper is about 2 seconds, which is slightly more than that of the two single models, but the increased time is within the acceptable range.

Table 2. Comparison of evaluation process time consumption

Evaluation Aspect	Time-Consumption		
	ARIMA	*GM*(1,1)	Fusion Model Proposed
Teachers' teaching level	1.36	0.13	2.21
Students' academic status	0.93	0.17	1.89
Course learning effectiveness	1.21	0.22	1.97
Students' competency	1.14	0.18	1.85
Students' employment status	0.96	0.21	2.06

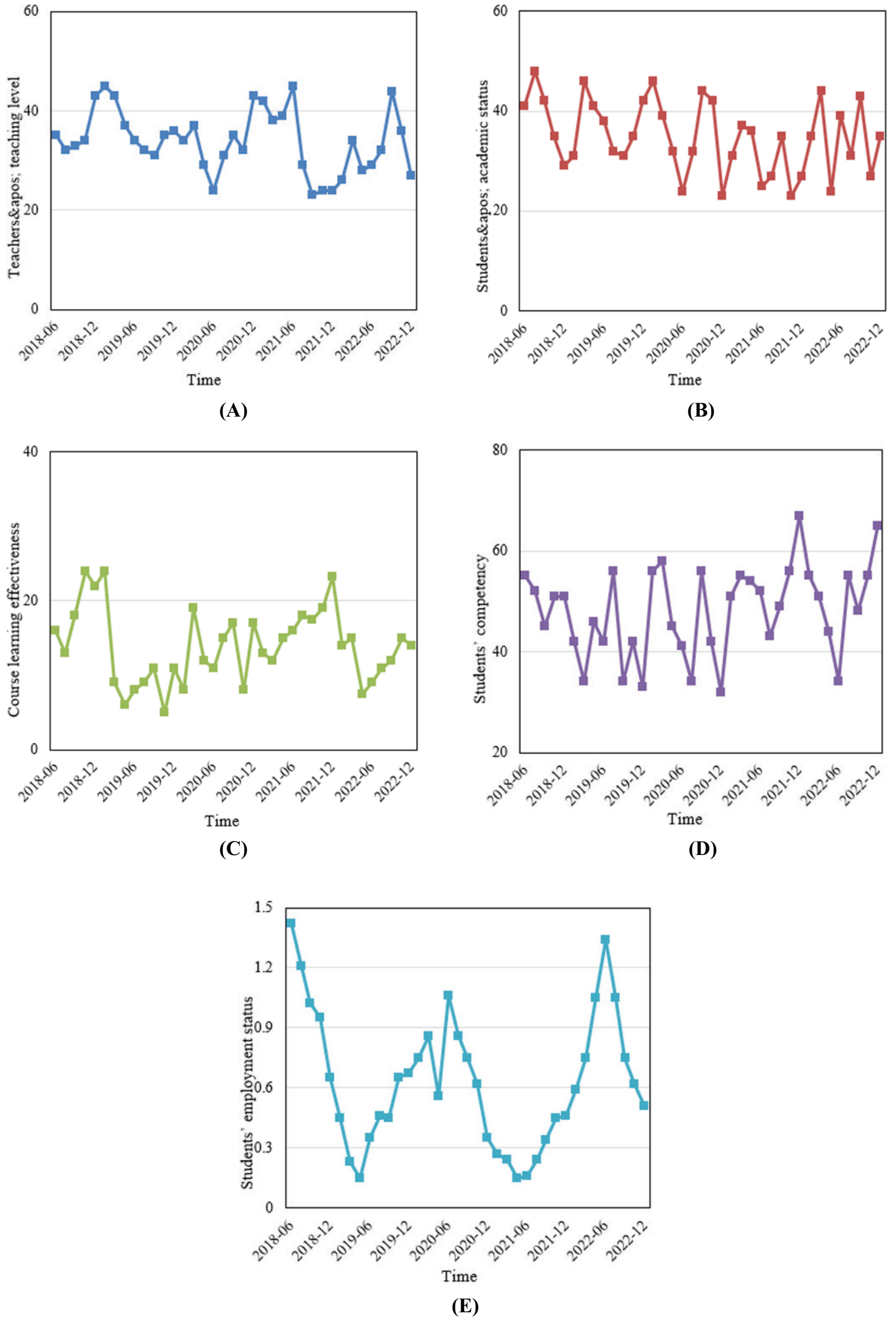

Fig. 5. Trend of semester-based mean value of higher education teaching quality evaluation

Table 3. Low-frequency prewarning degree on the frequency of proposing and promoting improvement measures in terms of teachers' teaching level at different lag weeks

Weeks of Lag	Predicted Time-Consumption (Second)			
	Low-Frequency Prewarning/%	**Lower Limit of Confidence Interval/%**	**Upper Limit of Confidence Interval/%**	***P*-Value**
1	0.5193	–0.3775	1.4223	0.0479
2	–0.0377	–0.9837	1.0726	0.9403
3	–0.2251	–1.3564	0.9186	0.7085
4	–0.2342	–1.4572	1.0049	0.7106
5	–0.0759	–1.2423	1.4125	0.9112
6	0.3342	–1.0758	1.7552	0.6438

After the outlier processing of the collected sample data, the changes in the semester mean values of the predictive evaluations in the five aspects were plotted, describing the general trend of the evaluation values, as shown in Figure 5.

Table 3 shows the model fitting analysis results of the low-frequency prewarning degree on the frequency of proposing and promoting education quality improvement measures in terms of teachers' teaching level at different lag weeks. The results show that the *P*-value between teachers' teaching level with a lag of 1 and the frequency of proposing and promoting regional education quality improvement measures is less than 0.05, while the *P*-value with a lag of 2 weeks or more is over 0.05. It can be inferred that teachers' teaching level with a lag of 1 week has a significant influence on the frequency above. At this time, the *P*-value is 0.0479 with the low frequency prewarning of 0.5193% and 95% confidence interval of –0.3775%–1.4223%.

Table 4. Low-frequency prewarning degree on the frequency of proposing and promoting the improvement measures in terms of students' academic status at different lag weeks

Weeks of Lag	Predicted Time-Consumption (Second)			
	Low-Frequency Prewarning/%	**Lower Limit of Confidence Interval/%**	**Upper Limit of Confidence Interval/%**	***P*-Value**
1	0.6871	0.0595	1.3259	0.0329
2	0.1642	–0.5842	0.9187	0.6673
3	–0.1112	–0.9512	0.7342	0.7986
4	–0.2082	–1.1284	0.7212	0.6582
5	–0.1215	–1.1153	0.8809	0.8113
6	–0.0015	–1.0623	1.0715	0.9981

Table 5. Low-frequency prewarning degree on the frequency of proposing and promoting the improvement measures in terms of course learning effectiveness at different lag weeks

Weeks of Lag	Predicted Time-Consumption (Second)			
	Low-Frequency Prewarning/%	**Lower Limit of Confidence Interval/%**	**Upper Limit of Confidence Interval/%**	***P*-Value**
1	2.4202	0.5476	4.5749	0.0017
2	2.0654	–0.2802	4.4558	0.0352
3	0.7206	–2.1651	3.6907	0.0276
4	0.1000	–3.2737	3.5889	0.0356
5	0.7882	–3.2854	4.4908	0.0485
6	2.9183	–1.3834	7.4056	0.0372

In terms of student academic status, Table 4 shows the model fitting analysis results of the low-frequency prewarning degree at different lags of weeks on the frequency of proposing and promoting educational quality improvement measures. The results show that the *P*-value between students' academic status with a lag of 1 week and the frequency of proposing and promoting regional education quality improvement measures is less than 0.05, which is statistically significant, while the *P*-value with a lag of 2 weeks or more is greater than 0.05, indicating that students' academic status with a lag of 1 week has a significant effect on the frequency mentioned. At this time, the *P*-value is 0.0329, with the low frequency prewarning degree of 0.6871, and 95% confidence interval of 0.0595 to 1.3259.

In terms of the course learning effectiveness, Table 5 shows the fitting analysis results of the low-frequency prewarning degree at different lags of weeks on the frequency of proposing and promoting education quality improvement measures. The results show that the *P*-values between the course learning effectiveness with a lag of 1–6 weeks and the frequency of proposing and promoting regional education quality improvement measures is less than 0.05, especially the *P*-value with a lag of 1 week lag is less than 0.01, indicating that course learning effectiveness has a significant influence on the frequency mentioned. The *P*-value with a 1-week lag is 0.0017, less than 0.01, with the low-frequency prewarning of 2.4202%, and the 95% confidence interval of 0.5476% to 4.5749%, indicating that the increase of course learning effectiveness has a significant influence on the adjustment of teaching strategies by teachers or university administrative departments. With a lag of 6 weeks, *P*-value is 0.0372, with the low frequency prewarning of 2.9183%, and 95% confidence interval of –1.3834% to 7.4056%.

Table 6. Low-frequency prewarning degree on the frequency of proposing and promoting the improvement measures in terms of students' competence quality at different lag weeks

Weeks of Lag	Predicted Time-Consumption (Second)			
	Low-Frequency Prewarning/%	**Lower Limit of Confidence Interval/%**	**Upper Limit of Confidence Interval/%**	***P*-Value**
1	3.6954	1.7341	5.6951	0.0001
2	3.5047	1.1967	5.8239	0.0032
3	3.1381	0.5408	5.8056	0.0182
4	2.6234	0.2013	0.5163	0.0481
5	3.2368	0.2112	6.3542	0.0365
6	3.7142	0.5271	7.0019	0.0223

Table 7. Low-frequency prewarning degree on the frequency of proposing and promoting the improvement measures in terms of students' employment status at different lag weeks

Weeks of Lag	Predicted Time-Consumption (Second)			
	Low-Frequency Prewarning/%	**Lower Limit of Confidence Interval/%**	**Upper Limit of Confidence Interval/%**	***P*-Value**
1	0.6434	0.7321	1.6671	0.0001
2	0.5217	–0.1747	1.8589	0.0012
3	0.1111	–0.5338	1.8386	0.0352
4	0.6534	–0.2323	1.5433	0.0331
5	0.2218	–0.2342	1.3182	0.0343
6	–0.7852	–0.5191	1.0329	0.0213

In terms of students' competency, Table 5 shows the fitting analysis results of the low-frequency prewarning degree on the frequency of proposing and promoting education quality improvement measures at different lags of weeks. The results show that the *P*-values between students' competency and the frequency of proposing and promoting regional education quality improvement measures from 1 week lag to 6 weeks lag are less than 0.05, while their low-frequency prewarning and confidence interval are statistically significant. Especially the *P*-value from 1 week lag is less than 0.01. It can be inferred that students' competency has a significant effect on the frequency. *P*-value with a lag of 1 week is 0.0001, less than 0.01, with the low-frequency prewarning of 3.6954%, and 95% confidence interval of 1.7341% to 5.6951%, indicating that the increase in students' competency has a significant effect on the adjustment of teaching strategies implemented by teachers or university administrative departments. With a lag of 6 weeks, *P*-value is 0.0223, with the low frequency prewarning of 3.7142%, and 95% confidence interval of 0.5271%–7.0019%.

In terms of students' employment status, Table 7 shows the fitting analysis results of the low-frequency prewarning degree on the frequency of proposing and promoting education quality improvement measures at different lags of weeks. The results show that the *P*-values between student employment status and the frequency of proposing and promoting education quality improvement measures from 1 week lag to 6 weeks lag are less than 0.05, while their low-frequency prewarning and confidence intervals are statistically significant. It can be inferred that student employment status has a significant effect on the frequency. The *P*-value of 1 week lag is 0.0001, less than 0.01, with the low-frequency prewarning of 0.6434%, and the 95% confidence interval of 0.7321%–1.6671%, indicating that the improvement of students' employment status has a significant influence on the adjustment of teaching strategies by teachers or university administrative departments. With a lag of 6 weeks, the *P*-value is 0.0213 with the low frequency prewarning of –0.7852%, and 95% confidence interval of –0.5191% to 1.0329%.

5 Conclusions

This paper studies the teaching quality monitoring and evaluation in higher education based on big data analysis. Firstly, the teaching quality monitoring in higher education is identified as five directions: teachers' teaching level, students' academic status, course learning effectiveness, students' competency, and students' employment status. The ARIMA model and GM(1,1) model are fused and used to predictively evaluate the changes in the teaching quality monitoring data series in higher education. Then, the teaching quality monitoring and evaluation results in higher education were analyzed together with the data on the frequency of proposing and promoting corresponding education quality improvement measures, and mathematical models were established by curve fitting and parameter estimation, to explore the deep correlation between them. Also, the experiments were conducted to compare evaluation accuracy and evaluation time-consumption between different models, and to verify the constructed fusion model for higher education teaching quality monitoring and evaluation. For the teaching quality evaluation in higher education, the change trend of semester-based mean was plotted. Finally, the low-frequency prewarning degree on the frequency of proposing and promoting improvement measures at different lag weeks in five aspects was calculated, and the analysis results were given to verify that the teaching quality monitoring and evaluation results of higher education have a significant influence on the frequency of proposing and promoting the improvement measures of teaching quality.

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