

PAPER

A Data Mining-Based Approach to Managing Intercultural Teaching Activities in Online Classrooms

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ABSTRACT

Driven by globalization and technological advances, online education is coming into its own form, opening a window for students to learn across cultural boundaries. In such a context, the intercultural teaching activities in online classrooms are particularly important, as they provide students with a good opportunity to gain a deeper understanding of different cultures and merge into different backgrounds. However, most of the currently available methods of intercultural teaching activity management focus on conventional education modes or strategies, and there isn't a deep enough analysis about the features of network environment. Aiming at these matters, this study gave an in-depth discussion on the current status of the management of intercultural teaching in online classrooms, and introduced the technology of data mining to propose a more comprehensive and systematic solution for educational issues caused by cultural differences.

KEYWORDS

online education, intercultural teaching, data mining, management of teaching activities, cultural differences

1 INTRODUCTION

Technological advances have pushed us into a digital age in which the concept of country borders has been weakened [1–4], and online education is a distinct outcome of this age. Online education brings unprecedented learning opportunities to students around the globe as it breaks geographic and cultural boundaries, allowing every student access to the best course resources in the world [5, 6]. Especially in an intercultural context, online classrooms give students and teachers a platform to learn and communicate, enabling them to know each other and merge with different cultures and knowledge systems [7–10]. But in the meantime, how to effectively manage this new intercultural teaching mode to ensure its quality and effect has become a focus of attention for world educators and researchers.

Wang, R., Zhao, X., Jiao, F., Song, J., Wu, X. (2023). A Data Mining-Based Approach to Managing Intercultural Teaching Activities in Online Classrooms. *International Journal of Emerging Technologies in Learning (iJET)*, 18(21), pp. 24–38. <https://doi.org/10.3991/ijet.v18i21.44685>

Article submitted 2023-08-03. Revision uploaded 2023-09-21. Final acceptance 2023-09-22.

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The intercultural teaching activities in online classrooms open up a window for students to know about the world, so that they can view and treat different cultures and ideas with an open mind [11, 12]. The intercultural exchanges can not only drive the personal growth of students, but also build a bridge for international educational cooperation and cultural exchange [13–15]. Systematically researching the intercultural teaching activities using scientific methods such as data mining can provide data evidences for educational administrators and decision makers, so that more accurate and efficient teaching activities can be designed and implemented [16, 17].

Previous studies on intercultural teaching generally tend to focus on theoretical discussion or conventional management strategies, and methods proposed in these works haven't fully considered the special features of education in a network environment, such as the cultural backgrounds of teachers and students, the interaction patterns in network environment, and the diversity of learning resources. As a result, previous research methods may find difficulties in actual management practice of online classrooms, and fail to solve conflicts and dilemmas caused by cultural differences.

Contents of this study are arranged as follows: at first, the current status of the management of intercultural teaching activities in online classrooms is discussed in detail, and the technology of data mining is adopted to reveal the underlying patterns and trends. Then, an exponential smoothing prediction model is built and used to predict the future management requirements, and the results could help educational institutions better plan and adjust their strategies. At last, based on these findings, a series of improvement measures are proposed, in the hopes of improving the effectiveness and satisfaction of intercultural teaching in online classrooms. Our research could fill in a blank of current research, as well as provide valuable reference and guidance for the practice of online education.

2 STATUS AND PROBLEMS OF DATA MINING-BASED INTERCULTURAL TEACHING IN ONLINE CLASSROOMS

The application scenarios of data mining in the management of intercultural teaching in online classrooms include many aspects, including student behavior analysis, course content recommendation, intercultural communication pattern analysis, teaching effect assessment, requirement prediction, cultural difference identification, risk warning, and teaching strategy optimization. By mining students' behavior patterns in online classrooms, such as their login frequency, assignment submission time, and discussion forum participation, we can figure out the learning habits and preferences of students with different cultural backgrounds. Then, based on these information, appropriate course content or learning resources could be recommended to them and they can carry out individualized learning using these materials. With the help of data mining, the communication pattern and interaction frequency of students from different cultural backgrounds in online classrooms can be analyzed, and the analysis results can be used by teachers to formulate targeted teaching strategies and recommendations. Also, data mining can dig the data of students' exam scores, homework assessment, and class participation, based on which the effect of a teaching method in different cultural backgrounds can be evaluated. According to historical data, the future requirements of intercultural teaching of online classrooms can be predicted, such as the course selection trends of students, and the requirements for teaching resources. Then, course planning and resource allocation can be conducted in a timely manner. By analyzing the data of discussion, feedback, and comments of the online class, the difference in acceptance and

feedback of students coming from different cultural backgrounds for course content and teaching method could be figured out. Using the data mining technology, we can also sound early warning of the possible risks of cultural conflicts and student loss, thereby providing evidences for administrators to make timely decisions. At last, by analyzing students' learning results and feedback, the teaching strategies can be optimized continuously to adapt to students from different cultural backgrounds.

Now most online education platforms have the function of recording students' behaviors and they have collected massive data of this kind. By mining these data, educational institutions can discover students' learning patterns and habits. For example, students from a certain cultural background may prefer to study in the evening, while others may like to discuss with their peers. Analysis of these information provides references for course design and time planning. In the meantime, some advanced online education platforms have already begun to provide the function of personalized recommendation, that is, to recommend suitable course content based on students' learning history and cultural background, and recommendation systems of this kind can increase students' interest and participation in learning.

3 REQUIREMENT PREDICTION OF INTERCULTURAL TEACHING MANAGEMENT OF ONLINE CLASSROOMS

As the trend of globalization has extended into the field of education, now more and more students are coming from different cultural backgrounds, which creates diversity while posing certain challenges. The accurate prediction of such cross-cultural requirements can help educators better meet the needs of students with different backgrounds and improve their learning experiences and outcomes. Also, it can instruct educational institutions to make wiser choices in terms of human, material, and financial resources. Based on the prediction results, teachers can adjust their teaching strategies to make sure that the teaching method can match with students' anticipation and needs, thereby improving the teaching quality and effect. Moreover, accurate requirement prediction can instruct the preparation of teaching content, create more chances of communication for students coming from different cultural backgrounds, and promote cultural exchange and integration.

Different requirements of intercultural teaching management of online classrooms have different features, some requirements are short term and seasonal, while some are long term and lasting; some requirements might be stable, while some may fluctuate significantly; also, some requirements could show obvious periodicity, and some would exhibit an upward or downward trend. Based on above features, in this study, different prediction methods were adopted to make predictions on the requirements of intercultural teaching management of online classrooms.

3.1 Prediction of requirements for intercultural teaching resources based on moving averages

The moving average prediction method predicts future requirements based on the average value of historical data. It is particularly suitable for scenarios with stable and non-obvious trends or seasonal fluctuations, or there is no apparent upward or downward trend in the sustained requirement for a particular teaching material or tool. Specific steps of requirement prediction of intercultural teaching resources based on the moving average method are given below.

At first, an appropriate time frame (such as 12 months or 24 months in the past) is selected. On the premise that the selected data are accurate and complete, the number of historical data points is determined to calculate the average value. The size of the window is determined by data fluctuations. For stable data, a smaller window size could be selected; while for fluctuated data, a larger window could be selected to ensure smooth fluctuation. Further, for each period, the average value of data points in the selected window size is calculated. Assuming: $\{t_y\}$ represents a time series, b represents the number of moving averages, t_y represents the actual value of the y -th period, then the predicted value of the $y+1$ -th period is:

$$\hat{t}_{y+1} = L_y^{(1)} = \frac{t_y + t_{y-1} + \dots + t_{y-b+1}}{b} = \frac{1}{b} \sum_{k=1}^b t_{y-b+k} \quad (1)$$

When b is relatively large, assuming: $L_y^{(1)}$ represents the primary moving average of the y -th period, \hat{t}_{y+1} represents the predicted value of the $y+1$ -th period ($y \geq b$); then the most recent moving average is taken as the predicted value of the next period, and the predicted value can be calculated by the following formula:

$$\hat{t}_{y+1} = L_y^{(1)} = L_{y-1}^{(1)} + \frac{t_y - t_{y-b}}{b} \quad (2)$$

Assuming: B represents the number of raw data in time series $\{t_y\}$, by comparing with the actual requirements, the prediction error can be calculated:

$$A = \sqrt{\frac{\sum (t_{y+1} - \hat{t}_{y+1})^2}{B - b}} \quad (3)$$

Based on the prediction error, questions such as whether the window size needs to be adjusted or other prediction methods need to be adopted were considered. Then reviews and updates should be conducted regularly to make sure that the prediction method is consistent with the actual situation. Predicting the requirements for intercultural teaching resources based on moving averages is a continuous and iterative process that requires to collect new data, evaluate prediction effect, and make optimizations and adjustments constantly, thereby improving the prediction accuracy.

3.2 Prediction of teaching requirements before and after special cultural festivals or events based on weighted moving averages

The weighted moving average prediction method assigns different weights to data points in the past, so that some of them have a greater influence on the prediction result. For courses or activities related to some special cultural festivals or events, the requirements may fluctuate before and after these festivals or events. At this time, recent data (such as a few weeks before the festivals or events) might be more instructive for prediction. When predicting the teaching requirements before and after special cultural festivals or events, this method can better capture changes in requirements associated with these events, and the specific steps are given below:

The first step is also to choose an appropriate time frame, which may contain data of a festival or an event in the past several years, and make sure that the adopted data are accurate and complete. Then, based on the features of historical data and the trend of expected requirements, each time point is assigned a weight. Recent

data may be given a higher weight, especially the time right before the festival or event. The sum of all weight values should be 1. For each time point, the data of this time point is multiplied by its corresponding weight, then all products are added to get the weighted moving average.

Then, the most recent weighted moving average is taken as the predicted value of future requirements. According to the nature of festivals or events and the features of historical data, the predicted value can be adjusted further. Assuming: t_y represents the actual value of the y -th period, \hat{t}_{y+1} represents the predicted value of the $y + 1$ -th period, Q_u represents the weight, b represents the number of moving averages, then there is:

$$\hat{t}_{y+1} = \frac{Q_1 t_y + Q_2 t_{y-1} + \dots + Q_b t_{y-b+1}}{Q_1 + Q_2 + \dots + Q_b} = \frac{\sum_{u=1}^b Q_u t_{y-u+1}}{\sum_{u=1}^b Q_u} \tag{4}$$

The selection of weights is re-evaluated based on the prediction error, and adjustments may be needed. Check the deviation between the actual requirements and the predicted value, if the deviation is too large, then the prediction model will be re-evaluated. Assuming Q'_u represents the first weight after adjustment, j represents the adjustment constant, t_{y-u+1} represents the predicted value of the $y - u + 1$ -th period, then there is:

$$Q'_u = Q_u + 2j \times r \times t_{y-u+1} \tag{5}$$

Based on the adjusted weights, the next-period predicted value was calculated until the prediction error reaches the prediction accuracy. Through above steps, the weighted moving average method can be used effectively to predict the requirements of intercultural teaching of online classrooms before and after certain cultural festivals or events, so as to ensure reasonable resource allocation and smooth implementation of activities.

3.3 Prediction of periodic requirements of intercultural communication activities based on exponential smoothing

The exponential smoothing prediction method is a time series prediction method that predicts future values by assigning decreasing weights to historical data. For data with periodic feature, such as the requirements of periodic cultural exchange activities, the seasonal exponential smoothing method, also called the *Holt-Winters* method, could be adopted. This method captures not only the trend of data, but also the seasonal changes. Specific steps of using exponential smoothing method to predict the requirements of periodic cultural communication activities are given below:

First, collect historical data of the requirements of cultural communication activities, and the more detailed the better; then, determine the periodicity of the data, such as annually, quarterly or monthly; next, initialize the smoothing coefficients, namely β_1 (level smoothing coefficient), β_2 (trend smoothing coefficient), and β_3 (season smoothing coefficient); and initialize components of level, trend, and season.

Use smoothing coefficients to weigh the influence of historical data and predicted value: with $s(1 - s)^u$ ($0 < s < 1$, $u = 0, 1, 2, \dots$) as the weight, perform weighted averaging on time series $\{t_y\}$. The weight of t_y is s , the weight of t_{y-1} is $s(1 - s)$, and the weight of t_{y-2} is $s(1 - s)^2 \dots$. Assuming: t_y represents the actual value of the y -th period, \hat{t}_{y+1} represents the predicted value of the $y + 1$ -th period, $A_{y-1}^{(1)}$ and $A_y^{(1)}$ respectively represent

the primary exponential smoothing predicted value of the $y - 1$ -th period and the y -th period, β_1 represents smoothing coefficient, $0 < \beta_1 < 1$, then the calculation formula is:

$$\hat{t}_{y+1} = A_y^{(1)} = \beta_1 \cdot t_y + (1 - \beta_1) \cdot A_{y-1}^{(1)} \tag{6}$$

Assuming: b represents number of raw data contained in the time series, then the standard error of prediction can be calculated by the following formula:

$$A = \sqrt{\frac{\sum_{y=1}^{b-1} (t_{y+1} - \hat{t}_{y+1})^2}{b-1}} \tag{7}$$

Next, use the most recent trend component to predict the requirements of the next cycle. Let $s_y = 2A_y^{(1)} - A_y^{(2)}$, the primary and secondary exponential smoothing of the y -th period is respectively represented by $A_y^{(1)}$ and $A_y^{(2)}$; $n_y = \beta_2 / 1 - \beta_2 (A_y^{(1)} - A_y^{(2)})$, the smoothing coefficient is represented by β_2 , the predicted value of the $y + Y$ -th period is represented by \hat{t}_{y+Y} , then the prediction model is:

$$\hat{t}_{y+Y}^{(2)} = b_y + a_y \cdot Y \tag{8}$$

The standard error of prediction can be calculated by the following formula:

$$A = \sqrt{\frac{\sum_{y=1}^{b-1} (t_y - \hat{t}_y)^2}{b-2}} \tag{9}$$

If prediction is to be made further into the future, these components can still be used and the influence of season should be considered. Assuming: $A_y^{(1)}, A_y^{(2)}, A_y^{(3)}$ respectively represent the primary, secondary and tertiary exponential smoothing values, then the formulas of the three exponential smoothing operations are:

$$\begin{aligned} A_y^{(1)} &= \beta_3 \cdot t_y + (1 - \beta_3) A_{y-1}^{(1)} \\ A_t^{(2)} &= \beta_3 \cdot A_y^{(1)} + (1 - \beta_3) A_{y-1}^{(2)} \\ A_t^{(3)} &= \beta_3 \cdot A_y^{(2)} + (1 - \beta_3) A_{y-1}^{(3)} \end{aligned} \tag{10}$$

The prediction model can be expressed as:

$$\hat{t}_{y+Y} = s_y + n_y \cdot Y + v_y \cdot Y^2 (Y = 1, 2, 3, \dots) \tag{11}$$

where,

$$\begin{aligned} s_y &= 3A_y^{(1)} - 3A_y^{(2)} + A_y^{(3)} \\ n_y &= \frac{\beta_3}{2(1 - \beta_3)^2} \left[(6 - 5\beta_3) A_y^{(1)} - 2(5 - 4\beta_3) A_y^{(2)} + (4 - 3\beta_3) A_y^{(3)} \right] \\ v_y &= \frac{\beta_3^2}{2(1 - \beta_3)^2} \left[A_y^{(1)} - 2A_y^{(2)} + A_y^{(3)} \right] \end{aligned} \tag{12}$$

If the prediction error is large, the smoothing coefficients can be adjusted, such as using grid search or other methods, to find the optimal smoothing coefficients.

Through the above steps, the exponential smoothing prediction method can realize effective prediction of the requirements of periodic cultural exchange activities, thereby ensuring successful implementation of the events.

4 IMPROVEMENT MEASURES FOR MANAGEMENT OF INTERCULTURAL TEACHING OF ONLINE CLASSROOMS BASED ON DATA MINING

The data mining-based improvement measures for the management of intercultural teaching of online classrooms are not only a development trend of modern educational techniques and methods, but also have profound practical significance. Through data mining, educators can gain a deeper understanding of students' learning behaviors, preferences, and needs, as well as provide accurate teaching services and improve teaching effect. The data-driven decisions can optimize the allocation and utilization of teaching resources, avoiding resource waste and ensuring effective application at critical moments and locations. The purpose of intercultural teaching is to promote communication and understanding between students from different cultural backgrounds, and the strategies proposed based on data mining can better serve this goal. For instance, by analyzing the data of student interaction, the potential cultural conflicts and misunderstandings can be discovered in time, then proper measures could be taken to enhance cultural exchange and understanding.

Based on data mining, this study proposes to make improvements in the management of intercultural teaching from five aspects:

1. Improvement strategy for management of intercultural teaching of online classrooms

Analysis of mined data can reveal students' interests and preferences for different cultural topics, then the course structure and recommended content can be adjusted automatically. With the help of data mining technology and the historical data of students' learning behaviors, relevant activities or courses of intercultural teaching can be recommended. Moreover, by monitoring the participation level of activities in the catalogue, activities with low participation can be optimized or replaced.

2. Improvement strategy for management of technical specifications of online classroom platforms

By analyzing the data of students' behaviors on the platform, possible obstacles and difficulties can be found out, so that the user interface and interaction function can be optimized further. By analyzing the data of students' network equipment and environment, efforts can be made to ensure the stability and compatibility of the platform in various environments. Moreover, data mining can also identify abnormal behaviors, then measures could be taken to prevent and respond to possible security threats in a timely manner.

3. Improvement strategy for management of requirement plans of intercultural teaching

Using data mining techniques, such as moving average and exponential smoothing, the future requirements of intercultural teaching can be predicted. By automatically collecting students' feedback on teaching activities and conducting sentiment analysis and theme extraction, the students' needs and opinions can be figured out better. Then, based on the prediction results, the teaching resources, such as teachers, textbooks, and techniques, can be allocated more rationally.

4. Improvement strategy for management design of intercultural teaching

Data mining can help educators understand the unique needs and preferences of each student so that more personalized teaching content and methods can be adopted. By analyzing the data of students' interactive activities, the design of teaching activities can be optimized so as to increase student participation and satisfaction. If the data of the effect of teaching activities can be analyzed on a regular basis, such as the students' learning outcomes and their satisfaction degree, then the design of the activities can be optimized further.

5. Improvement strategy for management of activity implementation of intercultural teaching

Through real-time monitoring of the situations of teaching activities, such as students' participation and feedback, the activity implementation strategies can be adjusted dynamically based on these data. Data mining can identify possible risks and problems in advance, such as student loss or increased dissatisfaction, then corresponding measures can be adopted to deal with the situations. After an activity is finished, data analysis and activity effect evaluation can be conducted to provide reference for the implementation of the next activity.

5 EXPERIMENTAL RESULTS AND ANALYSIS

In this study, four indicators (course completion rate, number of intercultural exchanges, prediction accuracy, and cultural adaptation progress of students) had been selected and used to evaluate the effect of the intercultural teaching management system of online classes. The course completion rate counts the percentage of students who have completed the course or activity. The number of intercultural exchanges counts the number of interactions and exchanges between students from different cultural backgrounds. The prediction accuracy compares the predicted teaching requirements and the actual situations, it can measure the accuracy of the prediction model. The indicator of cultural adaptation progress of students evaluates students' understanding and adaptation of other cultures through tests or questionnaires.

Table 1. Effect of system management of different classes

Semester No.	Class	Course Completion Rate	Number of Intercultural Exchanges	Cultural Adaptation Progress of Students	Prediction Accuracy
1	Control class	85.26	923	101.28	64.26
	Test class	96.25	1214	526.04	82.22
2	Control class	86.20	992	214.25	78.23
	Test class	98.23	1208	869.36	81.11
3	Control class	89.21	536	125.06	71.45
	Test class	92.35	1231	325.04	88.36
4	Control class	87.23	568	325.07	74.26
	Test class	95.24	1102	518.03	82.05
5	Control class	86.02	864	314.08	79.26
	Test class	95.15	1102	635.02	81.02

(Continued)

Table 1. Effect of system management of different classes (*Continued*)

Semester No.	Class	Course Completion Rate	Number of Intercultural Exchanges	Cultural Adaptation Progress of Students	Prediction Accuracy
6	Control class	86.34	835	231.25	77.26
	Test class	91.20	1125	614.01	82.26
7	Control class	81.25	982	313.02	79.32
	Test class	96.02	1125	633.01	82.24
8	Control class	87.23	836	231.44	71.11
	Test class	90.21	1125	415.99	85.36

Based on the data given in Table 1, the effect of the intercultural teaching management system used in different classes (the control class and the test class) during different semesters can be observed. It's known that the course completion rate of the test class in all semesters is higher than that of the control class, especially in the second, third, and seventh semesters. The difference between the two is particularly obvious, indicating that the test class was more efficient in classroom management and teaching activity organization. During most semesters, the number of intercultural exchanges of the test class is higher than that of the control class, indicating that students in the test class were more active, or the course content or teaching method had encouraged more exchanges between students. During all semesters, the cultural adaptation progress of students in the test class is faster than the control class, indicating that the teaching method of the test class was better at helping students understand and accept different cultures. The prediction accuracy of test class is higher than that of the control class in most semesters, which means that the data mining-based intercultural teaching management strategy had been well implemented in the test class.

Based on these results, it can be concluded that in terms of the four indicators, the performance of the test class is better than that of the control class, showing that the adopted data mining-based strategy can bring a positive influence on the management effect of online classrooms. So the teaching strategy and method adopted by the test class can be further explored and considered for promotion and application in a wider range in the field of education.

Table 2. Changes in the evaluation of test class students and teachers on system management

Semester No.	Student Participation	Student Satisfaction	Positive Feedback Rate of Teachers	Student Retention Rate	Training Effect of Teachers
1	1.000	0.921	1.000	1.000	0.921
2	0.923	0.842	1.000	0.921	0.784
3	0.962	0.921	1.000	0.964	0.974
4	0.987	0.975	1.000	0.985	0.977
5	0.932	0.954	1.000	0.931	0.988
6	0.954	0.995	1.000	0.982	0.924
7	0.964	0.789	0.978	0.978	0.968
8	0.975	0.931	0.987	0.985	0.989

Based on the data listed in Table 2, changes in the evaluation given by test class students and teachers on the intercultural teaching management system can be comparatively analyzed, and the results show that from the first semester to the eighth semester, the degree of student participation didn't change much, but in the fourth and eighth semesters, the participation reached a relatively high level. This might indicate that in these two semesters, the content or method of online classrooms had been optimized or the intercultural activities had attracted the students. Student satisfaction reached the highest level in the sixth semester, but declined in the seventh semester, indicating that the teaching content or method in this semester needs to be optimized further. In the first six semesters, the positive feedback rate of teachers is 1.000, indicating that teachers were very satisfied with the management and teaching activities of online classrooms. However, in the seventh and eighth semesters, the value of this indicator decreased a little, although the value is still relatively high. The student retention rate remained high throughout all semesters, suggesting that the online classrooms had a good student stickiness and satisfaction. The training effect of teachers remained high from the third semester to the eighth semester, and peaked in the fifth and eighth semesters. This may indicate that the content and method of teacher training had improved in these semesters.

The attained data suggest that the test class had performed very good in terms of all aspects in the intercultural teaching management of online classrooms. The participation and satisfaction of students, as well as the positive feedback rate of teachers all maintained at a high level, indicating that the management system had provided teachers and students with good teaching and learning experiences. Although in some semesters, such as the seventh semester, the satisfaction degree of students and the positive feedback rate of teachers declined a bit, on the whole, these indicators can prove a successful application of the intercultural teaching management system in the online classrooms.

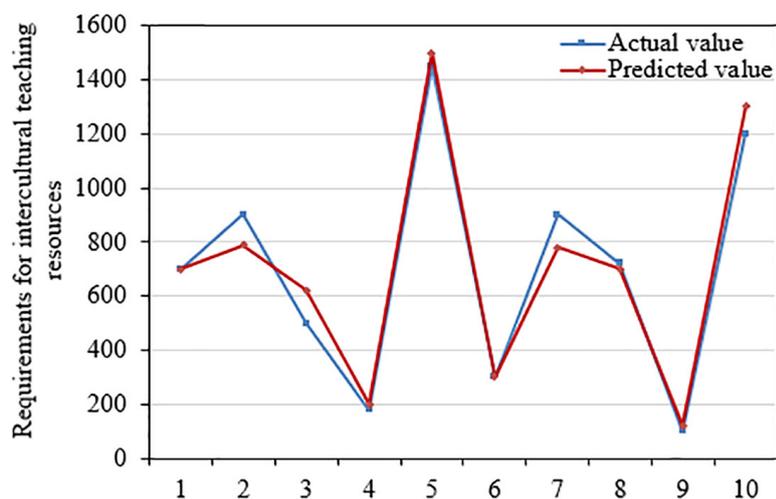


Fig. 1. Comparison of predicted value and actual value of requirements for intercultural teaching resources

Figure 1 compares the predicted and actual values of the requirements for intercultural teaching resources. Overall speaking, for the 10 semesters, the differences between the predicted and actual values are not that significant. Most of the predicted values are within an acceptable range, showing a high accuracy. As for the second, seventh, and eighth semesters, the predicted values are basically the same as the actual values, suggesting that the predictions are very close. For the third semester,

the difference between the predicted value and the actual value is 120 person-time, which may be due to changes in the requirements caused by some unpredictable factors or events. In the fourth semester, the difference between the predicted value and the actual value is only 20 person-time, showing a high prediction accuracy. The predicted value of the fifth semester is slightly higher, but the difference is within 50 person-time, which is still acceptable. The prediction of the ninth semester is 20 person-time higher, which may be due to the requirement decrease caused by some external factors. The prediction of the tenth semester is 100 person-time higher than the actual value, which may be caused by external factors or changes in the market.

The comparative analysis given above suggests that although there are some discrepancies between the predicted and actual values in some semesters, in most cases, these discrepancies are within acceptable limits, indicating that the moving average prediction method adopted in this paper is reasonable and effective in predicting the requirements for intercultural teaching resources. The moving average prediction method takes into account the actual requirements over a certain time period in the past, making the prediction more robust, thereby reducing volatility and instability in the predictions, especially in cases with random fluctuations in the requirement data. According to the attained data, even in case of large discrepancies between actual requirements and predicted values caused by certain external factors or unexpected events, the moving average prediction method can still provide decision makers with relatively accurate predictions.

In conclusion, the moving average prediction method is of high value for the practice of intercultural teaching management of online classrooms.

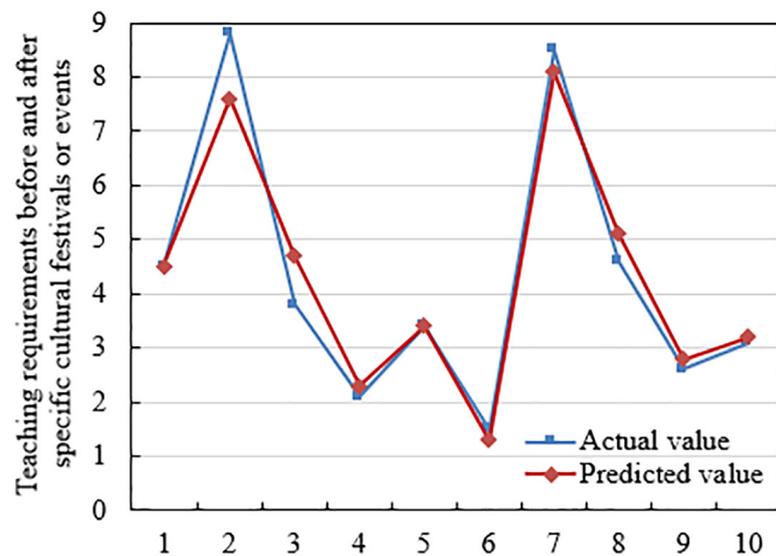


Fig. 2. Predicted values versus actual values of teaching requirements before and after specific cultural festivals or events

Figure 2 compares the predicted and actual values of teaching requirements before and after cultural festivals or events. Overall speaking, during the ten semesters, the predicted values are very close to the actual values. In most cases, there is only a small difference between the predicted and actual values, which has demonstrated the accuracy of the prediction method. The predicted value of the second semester is 761 person-time, the actual value is 885 person-time, the predicted value is bit lower but the difference is within a reasonable range. The predicted value of the third semester is slightly higher than the actual value by 95 person-time. For the

fourth, fifth, and sixth semesters, the predicted values are very close to the actual values, and the differences are tiny. The predicted value of the seventh semester has a 42 person-time difference with the actual value, but it's still very close. The prediction of the eighth semester is a bit higher, its difference with the actual value is 57 person-time. As for the ninth and tenth semesters, the differences between predicted values and actual values are also very small, showing a high accuracy.

Based on the data comparison given above, it can be seen that the weighted moving average prediction method gave a relatively high accuracy and stability in the prediction task of teaching requirements before and after cultural festivals or events. In most cases, the differences between the predicted and actual values are very small, indicating a high prediction accuracy. The effect of the weighted moving average prediction method in such prediction tasks might depend on the higher weights of recent data. In this way, it can better capture recent trends and changes. The teaching requirements before and after cultural festivals or events might be affected by recent events or changes, so it's reasonable to assign higher weights to recent data. The weighted moving average prediction method adopted in this study is reasonable and effective in predicting the said teaching requirements, and it can provide decision makers with accurate information to help them make better decisions.

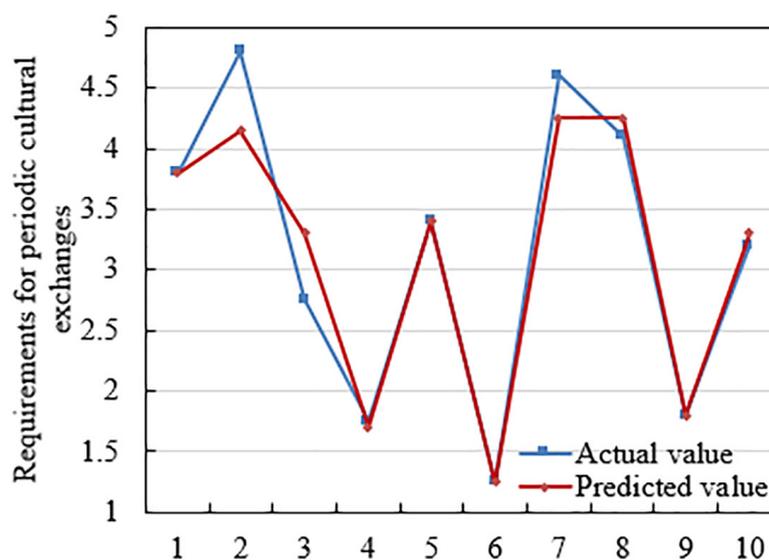


Fig. 3. Predicted values versus actual values of requirements of periodic cultural exchanges

Figure 3 compares the predicted and actual values of requirements for periodic cultural exchanges. By observing above figure, it's known that during most semesters, the predicted values and the actual values are very close, indicating that the prediction model can capture the main trend of the requirements for periodic cultural exchanges. For the second semester, the predicted value is 41,500 person-time, and the actual value is 48,000 person-time, the prediction is a bit lower but the value is within a reasonable range. The predicted value of the third semester is 33,000 person-time, the actual value is 27,500, the prediction is a bit higher than the actual situation. The predicted values of the fourth, fifth, sixth, and ninth semesters are very close to the actual values with little deviation. The predicted values of the seventh and eighth semesters are both 42,500 person-time, and the actual values are 46,000 and 41,000, the prediction of the two semesters is a bit lower and higher than the

actual situation, but the differences are acceptable. The predicted value of the tenth semester is 33,000 and the actual value is 32,000, the values are very close as well.

The above comparative analysis reveals that the exponential smoothing prediction method gives a high accuracy in the prediction task of periodic cultural exchanges. For most semesters, the differences between predicted values and actual values are small, showing the model's accuracy and stability. The exponential smoothing prediction method takes into account the influence of past observations on future forecasts and assigns higher weights to recent observations using smoothing parameter. This method is particularly suitable for data series with cyclical variations, as it is able to flexibly capture and respond to changing trends in the data. The exponential smoothing prediction method adopted in this study is reasonable and effective in prediction task of periodic cultural exchanges. It can provide useful information of decision makers, enabling them to better plan and manage the cultural exchange activities.

6 CONCLUSION

This study explored the problem of intercultural teaching management of online classrooms based on data mining. In the context of globalization, the requirement for cultural exchange and understanding is increasing, and the online classrooms can act as a main venue to promote cultural exchange through education and manage intercultural teaching activities. In this study, the moving average prediction method was adopted to predict the continuous requirements of intercultural teaching. The weighted moving average prediction method was adopted to predict the teaching requirements before and after cultural festivals or events, and the exponential smoothing prediction method was adopted to predict the requirements for periodic cultural exchanges.

Through several comparisons of actual and predicted values, it was found that the adopted methods showed good stability and accuracy in requirement prediction tasks, and measures from five aspects were proposed to improve the management of intercultural teaching of online classrooms based on data mining, including management of catalogue, platform technical specification, requirement plan, teaching activity design strategy, and teaching activity implementation. Also, several quantifiable evaluation indicators were proposed to evaluate the effectiveness of the intercultural teaching management system of online classrooms.

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