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PAPER

Value Assessment of Online Educational Resources in the Context of Blended Learning

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ABSTRACT

In the context of promoting informatization education and reforming blended learning, how to accurately assess the value of online educational resources has become an important research topic. However, most existing assessment methods rely on direct data statistics and experience-based judgment, lacking scientific prediction models and comprehensive consideration of learning cycles. To solve this problem, this study constructed a hit prediction model of online educational resources based on the fusion of extreme learning machine and grey Verhulst model, and a hit-based value assessment model of the resources considering the learning cycles of students. The research results showed that the proposed model not only predicted and assessed the value of online educational resources more accurately, but also provided theoretical support and decision-making reference for the implementation of blended learning reform, thereby promoting the effective utilization of online educational resources.

KEYWORDS

blended learning reform, online educational resources, value assessment, extreme learning machine, grey verhulst model, hit prediction model, learning cycles of students

1 INTRODUCTION

With technological advancements and constant development of informatization education, blended learning, which combines traditional face-to-face teaching with online teaching, is becoming an important direction of educational reform. The blended learning reform aims to better give full play to the professional ability of teachers while providing students with more personalized and diverse learning experiences [1–18]. Therefore, one of its important topics is undoubtedly effective utilization of online educational resources, especially accurate assessment of their value. However, it is complex to some extent to assess the resource value in the context of blended learning reform [19, 20], because various factors need to be

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considered comprehensively, such as learning needs and progress of students, hits of resources, etc. [21–23].

However, current assessment methods mostly rely on direct data statistics and the experience-based judgment of teachers, lacking scientific prediction models and comprehensive consideration of learning cycles [24], which makes the resource value assessment often unable to accurately reflect the actual resource value, and may also lead to uneven distribution of teaching resources, thereby affecting the maximization of teaching effect [25–28]. Therefore, it is urgent to construct a more accurate and practical value assessment model of online educational resources [29–32].

To discuss and solve the above problems, this study focused on the value assessment of online educational resources in the context of blended learning reform, striving to provide a more scientific and reasonable assessment method. This study proposed a hit prediction model of online educational resources based on the fusion of extreme learning machine (ELM) and grey Verhulst model (GVM), and a hit-based value assessment model of the resources considering learning cycles of students. It is expected that the implementation of these methods not only improves the value assessment accuracy of online educational resources, but also provides important theoretical support and decision-making reference for the implementation of blended learning reform.

The main content of this study can be divided into two parts. In the first part, a prediction model of resource hits based on the fusion of ELM and GVM was constructed. Future hits of online educational resources were predicted by learning and analyzing historical data, thereby estimating the potential value of the resources. In the second part, a hit-based value assessment model of resources considering learning cycles of students was proposed and constructed. The resource value was assessed more accurately by analyzing and studying the learning behaviors and cycles of students. The construction of these two models aimed to assess the value of online educational resources accurately and practically, providing strong support for the implementation of blended learning reform.

2 PREDICTION OF ONLINE EDUCATIONAL RESOURCE HITS

As a basic quantitative index, the resource hits intuitively reflect the use of the resources and the participation of student users. By predicting the hits, the possible resource use and trend can be known in time, which helps make more scientific decisions on the allocation, use, and optimization of resources. At the same time, the hit prediction is also an important basis for assessing the resource value. Higher hits usually mean that the resources have higher value and popularity for student users. By predicting the hits, the potential resource value can be accurately estimated, providing basic data support for value assessment. Figure 1 shows the process of predicting the resource hits.

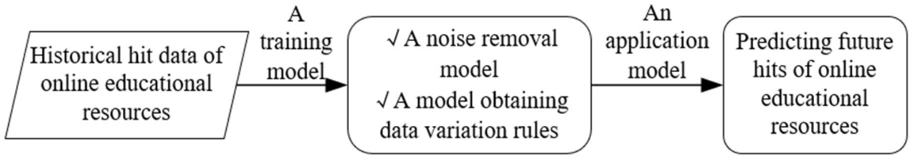

Fig. 1. Prediction process of online educational resource hits

This study constructed a prediction model of resource hits based on the fusion of ELM and GVM. ELM is a single-layer feedforward neural network, and its excellent generalization performance and fast learning speed have been widely used in many fields. Compared with traditional neural networks, ELM does not require tedious weight adjustments, greatly simplifying the learning process and saving a lot of computing resources. GVM is a famous short time series prediction model, which is based on a small amount of incomplete information for prediction, and is suitable for dealing with prediction problems with incomplete information and small-scale data, especially the prediction of online educational resource hits. When these two models were fused, their respective advantages were fully utilized. On the one hand, the fast learning ability of ELM ensured the efficient performance in the situation of large data volume. On the other hand, the small sample prediction ability of GVM improved the prediction accuracy. At the same time, this fusion model was optimized based on actual needs and data characteristics through flexible weight adjustments, further improving the prediction effect. Figure 2 shows the structure diagram of the fusion model.

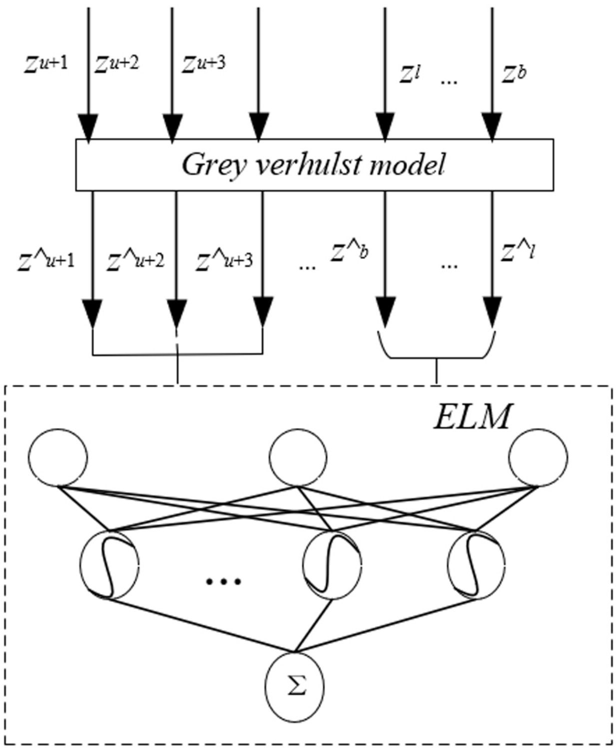

Fig. 2. Structure diagram of the fusion model

In GVM, let $Z^{(0)} = (z^{(0)}(1), z^{(0)}(2), ..., z^{(0)}(b))$ be the accumulative generated original sequence, and $Z^{(1)}$ be the one-time accumulative generated sequence of $Z^{(0)}$. The resource hits were accumulative, therefore, let $Z^{(1)}$ be the historical resource hits, and $Z^{(1)}$ satisfied the equation $Z^{(1)} = (z^{(1)}(1), z^{(1)}(2), ... , z^{(1)}(b))$, with $z^{(1)}(j) = \sum_{u=1}^{j} z^{(0)}(u)$ and $j = 1,2,...,b$. Let $x^{(1)}$ be the mean generated sequence of $x^{(0)}$, and $x^{(1)} = (x^{(1)}(1), x^{(1)}(2), ... , x^{(1)}(b))$, then $x^{(1)}(j)$ satisfied the equation $x^{(1)}(j) = 0.5z^{(1)}(j) + 0.5z^{(1)}(j-1)$.

The steps of the algorithm were described as follows:

Step 1: The original hit data were accumulated and the mean was generated, which obtained $z^{(1)}$ and $x^{(1)}$. Let s be the development coefficient, and n be the grey action quantity, then there were:

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

Step 2: The above equation was deformed, which obtained:

$$\frac{dz^{(1)}(1j)}{dy} + sx^{(1)}(j) = n(x^{(1)}(j))^2 \tag{2}$$

Let j be the time variable, then the final equation of predicting the resource hits was constructed based on the above equation:

$$1z(j+1) = \frac{sz^{(1)}(1)}{nz^{(1)}(1) + (s - nz^{(1)}(1))r^{sj}}, j = 1,2,3\ldots \tag{3}$$

By substituting s, n and $z^{(1)}$ into the above equation, the resource hits were predicted.

Step 3: The values of s and n were calculated based on the following equation:

$$[s,n]^Y = (N^Y N)^{-1} N^Y T \tag{4}$$

N and T were calculated using the following equation:

$$N = \begin{pmatrix} -x^{(1)}(2) & x^2(2) \\ -x^{(1)}(3) & x^2(3) \\ \vdots & \vdots \\ -x^{(1)}(l) & x^2(l) \end{pmatrix}, T = \begin{bmatrix} z^{(1)}(2) \\ z^{(1)}(3) \\ \vdots \\ z^{(1)}(l) \end{bmatrix} \tag{5}$$

The steps of ELM were described as follows:

Step 1: The input of the prediction model was clarified. Let $\{z_u, z_y\}_{y=1}^{B} \subset E^b \times E^l$ be the training set with a given sample size of B, $\{t_u\}_{u=1}^{L}$ be the testing set with a sample size of L, $d(z)$ be the activation function, M be the number of hidden-layer nodes, (q_1, n_1), $u = 1, 2, \ldots, M$ be the weight between the randomly generated input and output layers, and n_1 be the bias of the hidden-layer nodes.

Step 2: Let α be the connection weight between the hidden and output layers of ELM, and G be the output matrix of the hidden layer, then there were:

$$G = \begin{bmatrix} d(\mu_1, n_1, z_1) & & d(\mu_M, n_M, z_1) \\ \vdots & \cdots & \vdots \\ d(\mu_1, n_1, z_B) & & d(\mu_M, n_M, z_B) \end{bmatrix}_{B\times M} \tag{6}$$

The true output Y of the training set was calculated using the following equation:

$$Y = \begin{bmatrix} y_1 \\ \vdots \\ y_B \end{bmatrix}_{B\times 1} \tag{7}$$

Then there were $G\alpha = Y$. The following equation was obtained in accordance with the calculation of pseudo inverse:

$$\alpha = (G^Y G)^{-1} G^Y Y \tag{8}$$

Step 3: Let $\{t_u\}_{u=1}^{L}$ be the testing set, (μ_u, n_u) be the weight of the input layer, and α be the weight from the hidden layer to the output layer. The output value was calculated and obtained based on $\{t_u\}_{u=1}^{L}$, (μ_u, n_u) and $\boldsymbol{\alpha}$.

Based on the constructed fusion model of ELM and GVM, the prediction steps of online educational resource hits were described in detail below.

The sequence data of resource hits were divided first. The historical resource hit data were collected, and divided into training and testing sets. The training set was used to train the fusion model, and the testing set was used to verify the model's prediction performance. Under the assumption that a hit sequence of online educational resources containing b pieces of data was collected, let $\{z_u\}_{iu=1}^{l}$ be the training set composed of l pieces of data, which was used to train the fusion model and determine unknown parameters. Let $\{z_u\}_{u=l+1}^{b}$ be the testing set composed of $b - l$ pieces of data, which was used to compare with the predicted value of the model.

The actual resource hit data may contain various noises, such as abnormal hits, system errors, etc., which may interfere with the prediction results. Therefore, the noises of original data should be filtered before prediction. According to the model calculation, the hit value $\{z_u^{\wedge}\}_{u=1}^{b}$ without noises was initially obtained, which retained the distribution pattern of original hit data.

After data division and noise filtering, the fusion model of ELM and GVM was used to predict the hit data without noises. The training set data were used to train the model, which obtained model parameters. Then these parameters were applied to the testing set data for prediction. The prediction results were directly used for assessing the resource value, and were also compared with actual hits to verify the prediction accuracy and robustness of the model. The hit value $\{z_u^{\wedge}\}_{u=1}^{b}$ of online educational resources without noises was obtained, with $\{z_u\}_{u=l+1}^{b}$ actually being the predicted value of resource hits obtained through model calculation, but the accuracy was not high.

In the training stage of ELM, consecutive j hit values $\{z_u^{\wedge}, z_{u+1}^{\wedge}, z_{u+2}^{\wedge}\}$ $(u = 1, 2, 3, \ldots, l-3)$ were selected as the input, and $\{z_{u+3}^{\wedge}\}$ $(u = 1, 2, 3, \ldots, l-3)$ as the output.

Figure 3 shows the experimental flowchart. The algorithm process of the model was detailed as follows:

Step 1: The collected resource hit data $\{z_u\}_{u=1}^{l}$ were used as the input of GVM;
Step 2: The unknown parameters s and n were calculated during the denoising stage of GVM;
Step 3: The output value $\{z_u^{\wedge}\}_{u=1}^{b}$ of GVM was calculated and obtained;
Step 4: In the training stage of ELM, $\{z_u^{\wedge}, z_{u+1}^{\wedge}, z_{u+2}^{\wedge}\}$ $(u = 1, 2, 3, \ldots, l-3)$ was used as the input, and $\{z_{u+3}^{\wedge}\}$ $(u = 1, 2, 3, \ldots, l-3)$ as the output to solve the unknown parameters of the model;
Step 5: In the testing stage of ELM, the input was $\{z_u^{\wedge}, z_{u+1}^{\wedge}, z_{u+2}^{\wedge}\}$ $(u = l-2, l-1, l)$, and the output was the predicted resource hits.

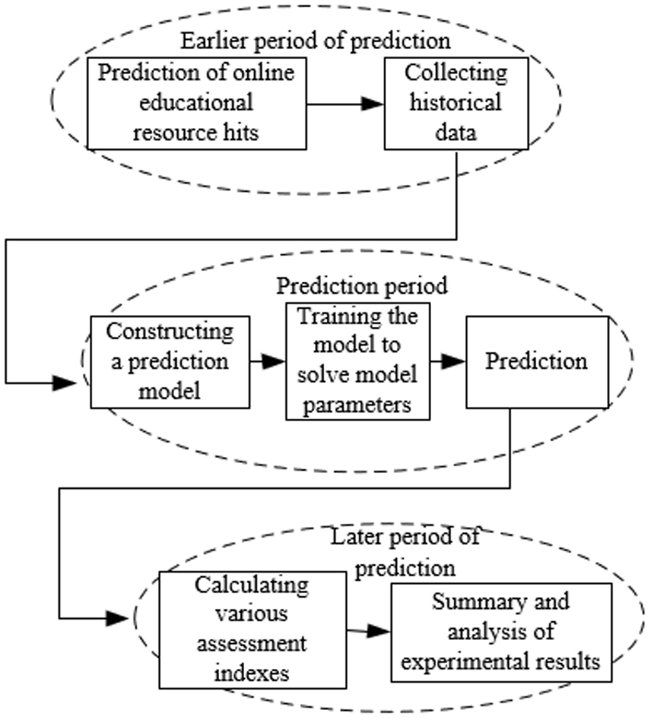

Fig. 3. Experimental flowchart

3 HIT-BASED VALUE ASSESSMENT OF ONLINE EDUCATIONAL RESOURCES

The hit-based resource value assessment model considering learning cycles of students mainly associated the resource hits of students with the value they brought to the blended learning platforms during their learning cycles. The learning cycle value of students was the quantitative result of the contribution and impact arising from their participation in blended learning activities within a certain period of time, which included not only the learning effect and progress of students, but also their activity level and degree of participation in blended learning platforms and the participation and learning of other students that might arise. At the same time, the online educational resource hits of students were used as an important index to measure the use of resources, which directly reflected their degree of participation and learning enthusiasm in blended learning activities. In general, educational resources with higher hits have greater appeal and influence for students. Therefore, it was considered that these resources also contributed more to the learning cycle value of students.

In this model, the resource hits of students were first predicted using the prediction model, which was based on the fusion of ELM and GVM. Then the predicted hits were associated with the learning cycle value of students, which obtained the value that the students brought to the blended learning platforms in their own learning cycles. Let Y be the duration of using the platforms by students now, XJ_y be the resource hits within the time period y, and f be the equal-value conversion value corresponding to the hits. The basic model expression for calculation was given as follows:

$$MX = \sum_{y=0}^{Y} \frac{XJ_y}{(1+f)^y} \tag{9}$$

Although the calculation process of the above equal-value conversion model was relatively simple, it easily demonstrated the calculation method of current student value. However, the actual calculation process also needed to fully consider the number of students and how many of them being converted into stable student users. The impact factor *j* was introduced to assess the resource value of blended learning platforms, because the learning degree and repeated resource hits during the learning process of students should be fully considered. The expression was as follows:

$$MX = \sum_{y=0}^{Y} \frac{j \times XJ_y}{(1+f)^y} \tag{10}$$

In this way, the overall value of the platforms was represented by the sum of student value, and the expression of the specific model was as follows:

$$MX = \sum_{u=1}^{b} \sum_{y=0}^{Yu} \frac{j \times XJ_y}{(1+f)^y} \tag{11}$$

If a hit-based resource value assessment model is used to assess the value of blended learning platforms, it has some shortcomings. First, the current model mainly focuses on the connection between the hits and the learning cycle value of students, but does not consider the changes in the number of students in the future. The increase or decrease in the number of students directly affects the activity level of the platforms and the use of educational resources, thereby affecting the overall value of the platforms. If the number of future students is not predicted and analyzed, the model may not be able to accurately predict the value of future online educational resources. Second, each blended learning platform has its unique characteristics, such as the types and quality of educational resources, educational patterns, target groups, etc., which should be taken into consideration by the model, because they affect the hits of students. If these characteristics are ignored, it may cause the prediction results of the model to deviate from the actual situation. Finally, the model mainly relies on historical hit data for prediction, which, to some extent, overlooks the growth and creativity of the platforms. For the platforms in their growth or start-up stages, their hits may rapidly increase in the short term. If the prediction is solely based on historical data, it may not accurately reflect their future value.

Therefore, based on the original model, this study made the following specific adjustments by combining with the characteristics of different assessment objects:

First, total number of students. When considering the total number of students, the emphasis was placed on stable student users, i.e., students who were active on the platforms for a long time and continued to use online educational resources, because they had a significant impact on the activity level, frequency of use, and long-term development of the platforms. This adjustment made the model focus more on the value of stable students, instead of just hits. The definition of stable students is crucial. They were defined as students who completed at least a certain number of courses within a specific time period (e.g. one semester, one year, etc.) and had a certain frequency of activities on the platforms. To accurately track and record these data, behavior analysis tools of student users may need to be introduced into the platforms, which aimed to track their behaviors on the platforms, such as visit frequency, duration of stay, completed courses, etc., and to generate relevant reports for analysis.

Second, activity index of students. This study used Bass diffusion model to predict the activity index of the platforms. The model describes the diffusion of products or new technologies in society, and is suitable for describing the trend of the number of student users over time. The Bass diffusion model was used to predict the activity level of students, i.e. the use of the platforms in this study. An intuitive index DAU/MAU was introduced, which is usually used to measure the activity level and stickiness of student users. The higher this ratio, the better the stickiness of student users towards the platforms, and the stronger the attractiveness of the platforms to student users. By introducing the DAU/MAU index into the resource value assessment model, the activity level of student users towards the platforms was reflected. If the DAU/MAU ratio was high, it indicated that student users accessed and used the platforms frequently within a certain time range, which often meant that the platforms had high-quality educational resources and student users were strongly dependent on the platforms, indicating that the platforms had great development potential. At the same time, the DAU/MAU ratio also reflected the stickiness of student users towards the platforms. If this ratio was high, it indicated that student users frequently accessed and used the platforms within a certain time range, i.e. they had strong stickiness to the platforms. The strong stickiness often led to higher retention rates of student users, which was also more conducive to the long-term stable development of the platforms. The DAU/MAU ratio also provided a dynamic perspective to observe the use of resources. By observing the changes in this ratio, the dynamic changes in the resource use of student users were understood, thereby better understanding the value changes of resources, that is,

$$MX = \sum_{u=0}^{b} \sum_{y=0}^{Yu} \frac{DAU}{MAU} \times \frac{XJ_{u,y}}{(1+f)^{y}} \tag{12}$$

Third, hits generated by unit student. The original model mainly relies on historical data, but each platform has its unique operational strategies and characteristics, such as the characteristics of course resources, teaching methods, composition of student users and so on, which all affect the use and hits of platform resources. Sole reliance on historical data and negligence of the uniqueness of platforms may lead to deviation in the value assessment results. At the same time, each platform has its own development strategy, which determines its long-term development paths and goals. The model improvement should take this into account so that the value assessment results can be consistent with the platforms' development strategies, providing a more accurate basis for their strategic decisions. Moreover, the learning habits and activity level of students may change along with other factors over time, and the presence of unstable student users affects the prediction of hits. The improved model should consider these factors so that the assessment results can more realistically reflect the resource value. Different learning cycles may also affect the activity level of students and the use of resources. The model improvement should take into account the impact of learning cycles to make the assessment results more accurate. Therefore, the existing model was further improved in this study. Let *SEEOI* be the contribution of various student users to the assessment of platform resources, then there were:

$$\begin{aligned} & MX \sum_{u=0}^{b} \sum_{y=0}^{Yu} \frac{DAU}{MAU} \times \frac{XJ_{u,y}}{(1+f)^{y}} \\ & = \sum_{u=0}^{b} \sum_{y=0}^{Yu} \frac{DAU}{MAU} \times \frac{j \times XJ_{y}}{(1+f)^{y}} \\ & = \frac{DAU}{MAU} \times \sum_{u=1}^{b} \sum_{y=0}^{Yu} \frac{SEEOI_{u,y}}{(1+f)^{y}} \end{aligned} \tag{13}$$

The new model formed a more comprehensive analysis framework after multiple optimizations. Instead of relying on historical data only, the new model integrated multiple factors, such as the characteristics and development strategies of blended learning platforms, learning habits and activity level of students, thereby providing a more comprehensive analytical framework for the value assessment of online educational resources. By introducing new indicators, such as the total number and activity index of students, and the hits generated by unit student, the new model assessed the resource value more accurately, and provided more reliable results.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1 shows the performance of five models, namely, ensemble neural network (ENN), random forest ensemble learning (RFEL), gradient boosting machine (GBM), ensemble deep learning model (EDLM) and the proposed model in this study, in terms of three assessment indexes, namely, mean absolute percentage error (MAPE), mean absolute error (MAE) and mean square error (MSE). First, in terms of the MAPE values, the proposed model in this study has the best performance, with a MAPE value of only 2.82%, indicating that the mean percentage error between the prediction result of the proposed model and the true value is the smallest, and the proposed model has a relatively high prediction accuracy. The MAPE value of RFEL is 2.85%, which has the second best performance. The MAPE values of ENN, GBM, and EDLM are 6.75%, 4.56%, and 3.87%, respectively, indicating relatively low prediction accuracy. Second, in terms of the MAE values, the proposed model also has the best performance, with a MAE value of only 5.86, which means that the mean absolute error between the prediction result of the proposed model and the true value is the smallest, and the proposed model has a relatively high prediction accuracy. RFEL has a MAE value of 6.15, which has the second best performance. The MAE values of ENN, GBM, and EDLM are 15.26, 11.58, and 8.93, respectively, indicating relatively low prediction accuracy. Finally, in terms of the MSE values, the proposed model also has the best performance, with an MSE value of 3725.58, meaning that the mean square error between the prediction result of the proposed model and the true value is the smallest, and the proposed model has a relatively high prediction accuracy. The MSE value of RFEL is 5012.69, which has the second best performance. The MSE values of ENN, GBM and EDLM are 2285.12, 10529.68 and 7868.68, respectively, possibly meaning that these models have large errors in some predictions, because MSE is sensitive to abnormal values. In summary, compared with the other four models, the proposed model has superior performance in predicting the hits of online educational resources, and has high prediction accuracy and stability.

Table 1. Prediction results of online educational resource hits using different prediction models

Models	*MAPE* (%)	*MAE* (10^4%)	*MSE* (10^6%)
ENN	6.75(5)	15.26(5)	2285.12(5)
RFEL	2.85(2)	6.15(2)	5012.69(2)
GBM	4.56(4)	11.58(4)	10529.68(4)
EDLM	3.87(3)	8.93(3)	7868.68(3)
The proposed model in this study	2.82(1)	5.86(1)	3725.58(1)

Table 2. Number of student users and hits of online educational resources in ten historical learning cycles

Learning Cycles	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Number of student users (10,000)	211.58	265.86	284.26	234.52	298
Resource hits (million)	265.68	335.19	365.29	335.86	436.28
Learning Cycles	**Cycle 6**	**Cycle 7**	**Cycle 8**	**Cycle 9**	**Cycle 10**
Number of student users (10,000)	352.06	356.34	326.30	342.06	399.01
Resource hits (million)	485.26	452.36	485.36	486.32	465.19

Table 3. Predicted number of student users and hits of online educational resources in five future learning cycles

Learning Cycles	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Number of student users (10,000)	397.26	415.36	439.58	436.39	486.35
Resource hits (million)	495.58	523.65	544.98	568.97	586.17

It can be seen from Tables 2 and 3 that the number of student users and the resource hits show an upward trend as the learning cycle progresses, indicating that the activity level of student users and the usage of resources on blended learning platforms are continuously increasing. In addition, by comparing the predicted values with the true ones, it can be found that the prediction results of the prediction model proposed in this study are close to the actual data, which indicates that the model has a high prediction accuracy. It can be seen from the data in Table 2 that there is a significant positive correlation between the number of student users and the resource hits, that is, the increase in the number of student users leads to an increase in the resource hits. This is in line with common sense, because more student users bring more hits. This positive correlation has also been validated in the prediction model proposed in this study. The predicted data in Table 3 show that the number of student users and the resource hits will continue to increase in the future learning cycles.

At the same time, the proposed prediction model took into account the platform characteristics, and combined with factors, such as learning cycles and activity index of students, thereby making the proposed model more complex and scientific. In addition, by analyzing historical data, the model more accurately predicted the number of student users and the resource hits in the future learning cycles, indicating its high prediction accuracy. Therefore, the prediction model proposed in this study is scientific. In summary, the proposed prediction model not only has a high prediction accuracy, but also takes into account the platform characteristics and the behaviors of student users, making it a scientific prediction method. This model can provide important references for the future development of blended learning platforms, and provide references for prediction models of other similar online platforms.

Table 4. Value estimation and growth rate of blended learning platforms and their resources in five historical learning cycles

Resource Types	Cycle 6	Cycle 7	Cycle 8	Cycle 9	Cycle 10
Content resources	325.68	289.36	289.36	324.87	364.25
Interactive resources	184.36	185.34	189.37	181.99	181.65
Assessment resources	121.58	136.25	135.25	102.55	121.99
Growth rate	6.98%	–0.84%	3.14%	–3.58%	11.25%

Table 5. Value estimation prediction of blended learning platforms and their resources in five future learning cycles

Resource Types	Cycle 1	Cycle 2	Cycle 3	Cycle 4	Cycle 5
Content resources	385.25	389.25	418.35	426.58	435.11
Interactive resources	189.32	197.32	201.36	214.25	223.02
Assessment resources	121.54	124.23	126.36	139.25	135.4
Growth rate	3.35%	3.35%	3.35%	3.35%	3.35%

It can be seen from the data in Tables 4 and 5 that the value estimation of platforms and their resources changes in each learning cycle, indicating that the value of platforms and their resources constantly changes. In addition, by comparing the predicted values with the true ones, it can be found that the prediction results of the assessment and prediction models proposed in this study are close to the actual data, indicating that these two models have high prediction accuracy. It can be seen from the data in Tables 4 and 5 that the value estimation of different types of resources varies in each learning cycle, with content resources having the highest value estimation, which is followed by interactive and assessment resources, maybe because different types of resources have different roles and influences on the platforms. Content resources are usually the main learning materials for students, which leads to their relatively high value. Interactive resources also have high value, because they enhance the learning interest and participation of students. Assessment resources are mainly used to test the learning effect of students, and may have lower value due to their relatively low frequency of use. The proposed assessment model has a high assessment accuracy by combining with the characteristics of different assessment objects for specific model adjustments.

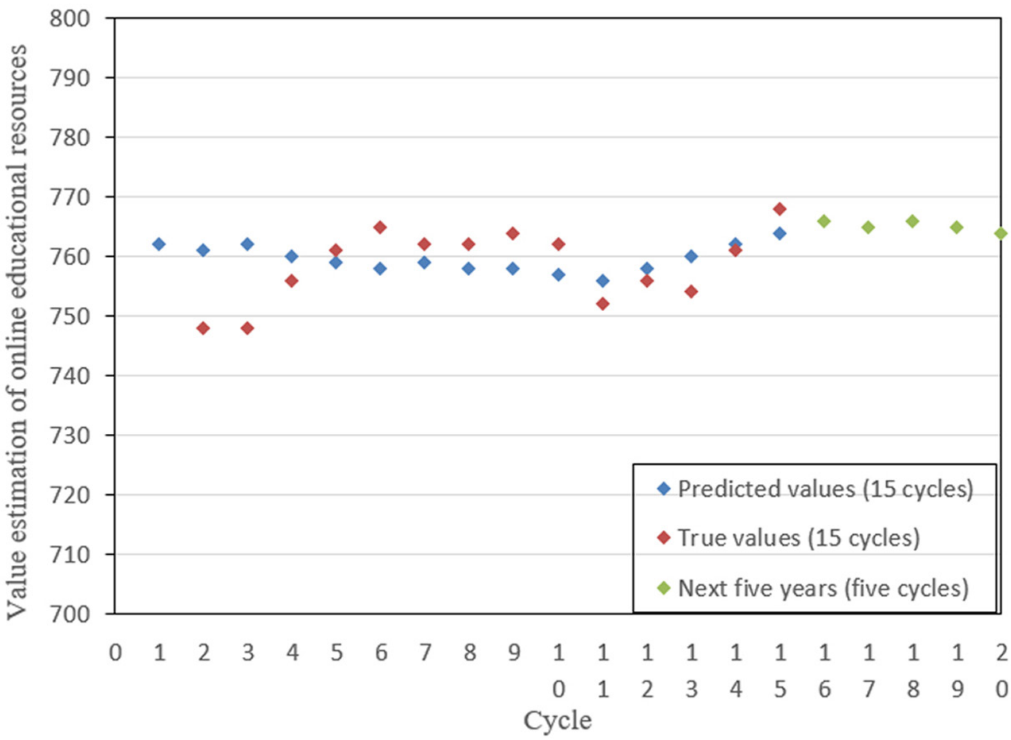

Fig. 4. Scatter diagram of comparison between true and predicted values of online educational resource value estimation

It can be seen from Figure 4 that there are some differences between the predicted and true values of resource value estimation. However, if the trend changes of both values are focused on only, it can be found that their trends are largely consistent, indicating that the prediction model has certain effect in capturing the overall trends.

5 CONCLUSION

This research mainly studied the value assessment and prediction of online educational resources, especially in the special situation of blended learning platforms. To improve the prediction accuracy, the concept of learning cycles was introduced, and the model was optimized.

Based on the learning cycle theory of blended learning platforms, student users were divided into stable and unstable students according to learning cycles, which is more in line with the actual online learning behavior pattern and helps improve the accuracy of predicting the resource hits. At the same time, the platform resources were classified to further improve the accuracy of resource value estimation.

The prediction results of the model were validated in experiment, which showed that the improved model predicted the resource hits relatively accurately, and estimated the value of platforms and their resources accurately. At the same time, the prediction results showed that the hits and value of resources would show a certain steady growth trend in the next few learning cycles.

Overall, the method proposed in this study can effectively predict and assess the value of online educational resources on blended learning platforms, which provides guidance for the optimization management and resource allocation of the platforms. However, it should be noted that although the proposed model in this study has shown certain effectiveness in prediction and assessment, it needs to be further optimized and improved to increase its accuracy and robustness.

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