

PAPER

Online Sharing Mechanism of Teaching Resources from the Perspective of Knowledge Management

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With the rapid development of network technology, online sharing of teaching resources has gained widespread attention in the educational field. This sharing not only provides educators and learners with rich learning resources but also opens up new channels for knowledge innovation and dissemination. However, it remains a major challenge to efficiently manage, allocate, and evaluate these resources. Existing research methods often rely too heavily on traditional knowledge management theories and overlook the characteristics of online environments. This research aimed to study and propose a new online sharing mechanism for teaching resources from the perspective of knowledge management. This study provided a new theoretical framework and practical strategy for online sharing of teaching resources by completing the knowledge management system based on the TransCat model, introducing the online sharing algorithm of Double Deep Q-Network (DDQN), and using the resource effectiveness evaluation considering knowledge potential differences.

KEYWORDS

teaching resources, knowledge management, TransCat model, Double Deep Q-Network (DDQN) algorithm, knowledge potential difference, online sharing

1 INTRODUCTION

With the rapid development of information and network technology, online sharing of teaching resources has become an important direction of educational reform [1]. A large number of teaching resources have been disseminated and applied on the Internet, providing educators and learners with a rich and diverse range of learning materials. However, how to better manage, allocate, and utilize these online teaching resources remains an urgent issue in the educational field [2–4]. In this context, it is of great practical significance to study the online sharing mechanism of teaching resources from the perspective of knowledge management [5, 6].

Compared with traditional resource management methods, analyzing online sharing of teaching resources from the perspective of knowledge management helps

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understand the value and significance of teaching resources more deeply, as well as how to maximize their effectiveness [7–11]. Especially in the current context of the knowledge economy, teaching resources are not only carriers of information but also the key to knowledge innovation and dissemination [12–15]. Therefore, research on the new online sharing mechanism for teaching resources not only promotes innovation in educational technology but also helps improve the quality and efficiency of education.

Although research on online sharing of teaching resources has made some progress, existing research methods still have some obvious defects and shortcomings. First, most research methods rely too heavily on traditional knowledge management theories, neglecting the unique knowledge flow and interaction characteristics of online environments [16–18]. Second, existing sharing mechanisms are often too simplified to meet complex and ever-changing teaching needs. Third, the effectiveness evaluation of resources has not been studied deeply, resulting in the failure to fully utilize their true value [19, 20].

In view of the above problems, this study conducted in-depth research on the online sharing mechanism of teaching resources from the perspective of knowledge management. First, based on the TransCat model, learning resources were completed for the vulnerabilities in the knowledge management system to improve its integrity and stability. Second, a new online sharing algorithm for teaching resources was designed by introducing the Double Deep Q-Network (DDQN) algorithm, making resource allocation more reasonable and efficient. Finally, considering the potential impact of knowledge differences, the effectiveness of the teaching resource online sharing mechanism was deeply evaluated. It is expected that research on these three aspects can provide new theoretical support and practical guidance for online sharing of teaching resources, further promoting the integration and development of knowledge management and educational technology.

2 COMPLETING LEARNING RESOURCES FOR THE VULNERABILITIES IN KNOWLEDGE MANAGEMENT SYSTEM

A knowledge management system aims to provide users with complete, accurate, and timely learning resources. Vulnerabilities in the system may lead to the loss of key knowledge points, thereby affecting the learning effects of learners and the teaching plans of educators. By completing learning resources for the vulnerabilities, learners gain a more comprehensive learning experience and choose corresponding resources based on their needs and interests, thereby achieving personalized learning. In addition, systems stability can be improved, reducing the problems and risks caused by vulnerabilities. Figure 1 shows the overall idea of completing learning resources for the vulnerabilities in the knowledge management system.

This study completed learning resources for vulnerabilities in knowledge management system based on the TransCat model. Figure 2 shows the architecture of the TransCat model. The TransCat model framework was used to complete knowledge for the system vulnerabilities in the following three steps:

Step 1: The meaning and scope of the common weakness enumeration (CWE) entity were clarified to ensure that it represented key knowledge points or concepts in teaching resources. For each CWE entity, relevant texts, images, audios, or data in other forms were collected to ensure the quality and diversity of the data. Based on the word2vec word embedding model, the data of CWE entities were converted into a fixed-length semantic vector. This vector should capture the core semantics and attributes of CWE entities.

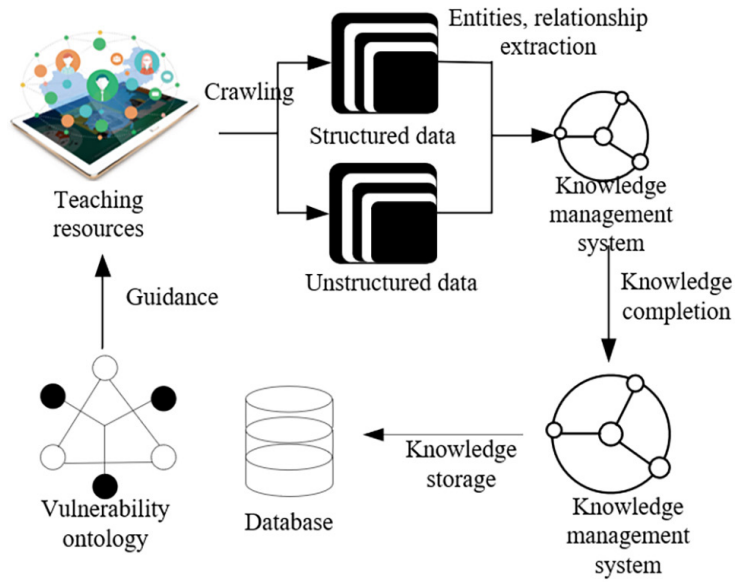


Fig. 1. Overall idea of completing learning resources for vulnerabilities in knowledge management system

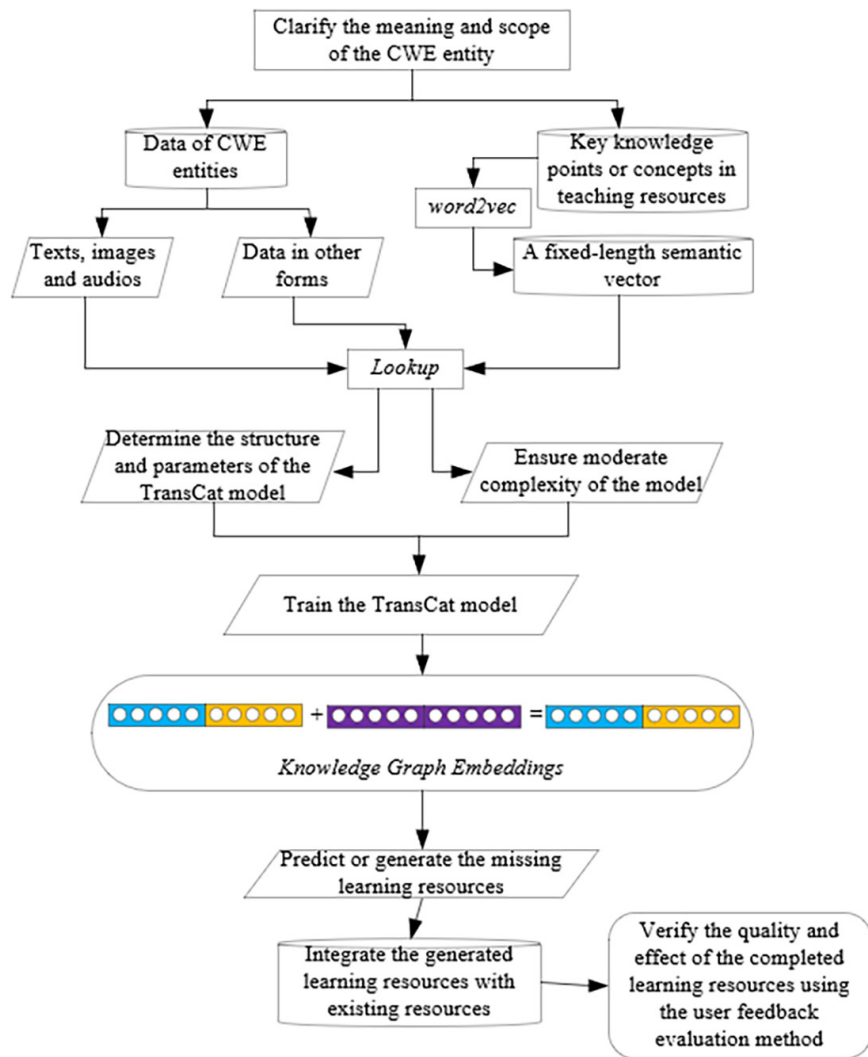


Fig. 2. Architecture of the TransCat model

Step 2: The collected data were cleaned to eliminate noise and redundancy, thereby being prepared for training the model. The structure and parameters of the TransCat model were determined, such as the number of layers and nodes, thereby ensuring that the model had moderate complexity to capture data characteristics without overfitting. The semantic representations of CWE entities were used as the input to train the TransCat model, making it accurately predict or complete learning resources for vulnerabilities. Let g_f and y_f be the semantic representations of the obtained head and tail entities, respectively, g_a and y_a be the trainable structural representations of the head and tail entities, respectively, then there were relational expressions:

$$g = g_f \oplus g_a \quad (1)$$

$$y = y_f \oplus y_a \quad (2)$$

The energy function of TransCat was given by the following equation:

$$R = \|g + e - y\| \quad (3)$$

Let R be the above defined energy function, Y be the true triple set, Y' be the false triple set generated through negative sampling, and ε be the marginal parameter. The loss function, which was used to learn the relationship between CWE entities and the energy function of TransCat, was given by the following equation:

$$LOSS = \sum_{(g,e,y) \in Y} \sum_{(g',e',y') \in Y'} MAX(\varepsilon + R(g,e,y) - R(g',e',y'), 0) \quad (4)$$

Step 3: The learning resources in the knowledge management system were analyzed to determine vulnerabilities and the content that needed to be completed. Along with the semantic representations of CWE entities, the trained TransCat model was used to predict or generate the missing learning resources. The generated learning resources were integrated with existing resources to ensure their coherence and consistency. The user feedback evaluation method was used to verify the quality and effect of the completed learning resources.

3 DDQN-BASED ONLINE SHARING ALGORITHM OF TEACHING RESOURCES

Double Deep Q-Network is an important branch of deep reinforcement learning. The core idea of reinforcement learning is to learn the optimal strategy through interaction with the resource sharing process, which is highly similar to the dynamic decision-making and resource allocation in teaching resource online sharing. The DDQN algorithm provides real-time decision-making support for online sharing, including resource matching, recommendation, and allocation, while easily responding to large-scale teaching resources and user needs. DDQN processes high-dimensional inputs to meet the complexity and diversity of teaching resource online sharing because its structure is based on deep neural networks.

This study proposes a teaching resource online sharing algorithm based on the DDQN algorithm. A simulation environment was first constructed for online

sharing, including defining all available teaching resources, possible user requests, sharing strategies, etc. Two neural networks were built, with one as the current Q network and the other as the target Q network. Both networks were the same at the beginning, but they became different over time. Experience replay was used to stabilize learning, which involved storing a memory pool for keeping previous transitions (states, actions, rewards, and new states). Figure 3 shows a schematic diagram of the interaction between each DDQN unit and the resource sharing process.

When the current status of teaching resource sharing process was input into the Q network, the network output the expected rewards for each possible action. The ϵ -greedy strategy was used to select an action. The action s_y corresponded to the Q value $Q_{\epsilon\text{-greedy}}(a_y, s_y)$ in the output layer of Q network. After executing the selected action in the teaching resource sharing environment, the state transitioned to a_{y+1} . The current state, selected action, observed rewards, and new state were stored in the experience replay storage. At the same time, the reward value e_{y+1} was calculated based on feedback, and the sample was stored in the experience pool R in the form of $[a_y, e_y, s_y, a_{y+1}]$.

A small batch of samples was randomly selected from the stored transformation. For each sample, the target Q network was used to calculate the maximum expected reward value for the next state. This value was combined with the rewards observed from the environment, which formed the target Q value for updating the Q network. Let Z be the number of small batch samples, and $SA_z = [a_y^z, e_y^z, s_y^z, a_{y+1}^z]$ be the samples.

With a_y^z as the input of the current Q network, the corresponding Q value (i.e., the current Q value) of s_y^z was obtained using the current neural network. With a_{y+1}^z as the input of the current Q network, the action corresponding to the maximum Q value was obtained using the current neural network:

$$s_{MAX}(a_{y+1}^z, \phi) = ARG MAX_{s_{y+1} \in S} W_V(a_{y+1}^z, s_{y+1}, \phi) \quad (5)$$

With a_{y+1}^z as the input of the target Q network, the action strategy $s_{MAX}(a_{y+1}^z, \phi)$ was used to obtain the Q value. The target Q value y_x was further calculated:

$$t_z = e_{y+1}^z + \epsilon MAX_{s_{y+1} \in S} W_V(a_{y+1}^z, s_{y+1}, \phi) \quad (6)$$

The mean square error (MSE) loss function was used to compare the Q value predicted by the Q network with the target Q value. The weight of the Q network was updated through backpropagation.

$$LOSS = \frac{1}{Z} \sum_z (t_z - W(a_y^z, s_y^z, \phi_y^z))^2 \quad (7)$$

The weight of the Q network was copied to the target Q network in every fixed step, aiming to ensure that the target Q network did not change too frequently. Through these steps, the DDON algorithm learned how to make the best decision in an online sharing environment of teaching resources, thereby ensuring the best matching between resources and needs while providing a high-quality user experience.

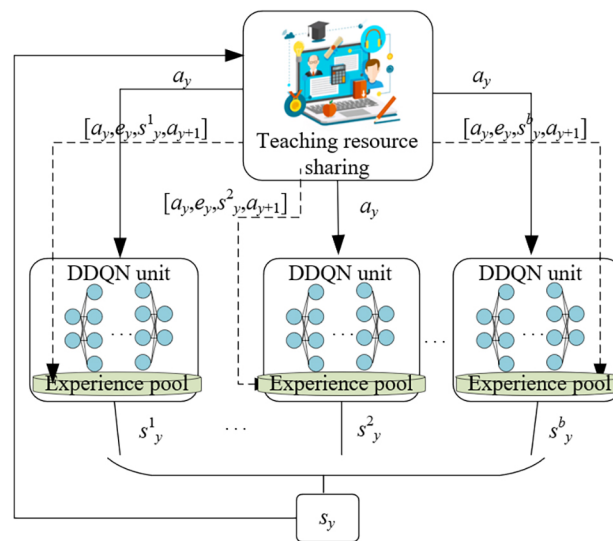


Fig. 3. Schematic diagram of interaction between each DDQN unit and resource sharing process

The basic idea of the DDQN-based teaching resource online sharing algorithm is: First, knowledge management systems play a key role in the entire online sharing process of teaching resources. It not only perceives the current “situation” (i.e., real-time information on teaching resource status, needs, etc.), but is also responsible for processing the information to ensure that all relevant information is up-to-date, thereby ensuring real-time and accurate decision-making.

Second, generation of states and actions. Once the knowledge management system processes all information, it generates a so-called “global state,” which is passed to the DDQN units to make decisions based on the current state. These decisions can be seen as “actions” taken by the DDQN units.

Third, joint decisions. Although each DDQN unit independently makes decisions for its responsible resources, these decisions need coordination to form a “joint action,” which ensures that the system achieves optimal resource allocation on the whole.

Fourth, feedback and learning. After resource allocation is completed, the algorithm receives feedback based on the actual sharing effect, which is usually reflected as a “reward.” The difference between this reward and the expected reward is crucial for learning and optimization. The system uses this information to update its status, and prepares for the next decision-making cycle.

Fifth, experience replay and continuous optimization. To optimize their decisions, DDQN units not only rely on the latest feedback, but also review previous decisions and results, which are achieved by storing experience samples into the experience pool and using them in subsequent training. This method ensures that DDQN units are not only based on the latest situation, but also learn from previous experience.

Finally, convergence to the optimal solution. The entire process aims to gradually improve the decisions of DDQN units until a relatively stable and efficient resource allocation strategy (also known as a “better solution”) is found.

The steps of the DDQN-based teaching resource online sharing algorithm are as follows:

Real-time situation awareness of the online sharing process should be achieved first through the knowledge management system, involving the recognition of currently available teaching resources, resource needs, resource usage patterns, user feedback, etc. Based on the above awareness information, a state space was

designed, with each state representing a specific teaching resource sharing scenario. The state can be multidimensional to reflect various factors affecting resource sharing, such as the quantity of resource needs and used resources, etc. To be effectively used in the algorithm, each state needed to be encoded in a form accepted by the neural network.

The state correlation between the knowledge management system and the DDQN units was represented by the following equations:

$$O_{y,v}^d = U_{y,v}^d + B_{y,v} \tag{8}$$

$$O_{y,b}^d = U_{y,b}^d + B_{y,b} \tag{9}$$

Let v be the knowledge management system, b be the DDQN unit, $U_{y,v}^d$ be the quantity of resource needs of the system based on the shared need d at time slot y , $B_{y,v}$ be the quantity of used resources of the system at time slot y , $I_{t,n}^f U_{y,b}^d$ be the quantity of resource needs of b DDQN units based on the shared need d at time slot y , and $N_{t,n} B_{y,b}$ be the quantity of used resources of b DDQN units at time slot y . The state of each time slot was represented as:

$$\begin{aligned} a_{y,v} &= \{O_{y,v}^d \mid d \in D\} \\ a_{y,b} &= \{O_{y,b}^d \mid b \in B, d \in D\} \\ a_y &= \{a_{y,v}, a_{y,b}\} \end{aligned} \tag{10}$$

In teaching resource sharing, actions can be operations, such as allocating, adjusting, and optimizing resources. Each action represents a possible resource allocation strategy or decision. Actions can be classified based on their nature, impact, or other factors. For example, actions can be divided into emergency, allocation, optimized allocation, etc. Similar to states, actions also need to be encoded in a format that can be processed by the neural network. In this study, each DDQN unit used the ϵ -greedy strategy to makes decisions for actions, because the proposed algorithm adopted the framework of centralized management and distributed execution:

$$s_y^{1v} = \begin{cases} random, o = \gamma \\ ARGMAX W(a_y, s_y^{1v}, \varphi), o = 1 - \gamma \end{cases} \tag{11}$$

At time slot y , the joint action strategy of each DDQN unit represented the entire educational resource sharing scheme. Let s_y^{bv} be the teaching resource allocation scheme in the b -th DDQN unit at time y , i.e.

$$s_y = \{s_y^{1v}, s_y^{1y}, s_y^{2v}, \dots, s_y^{bv}, s_y^{by}, \dots \mid b \in B\} \tag{12}$$

The reward function aims to provide feedback for each state-action pair, thereby guiding the DDQN algorithm in finding the optimal resource allocation strategy. Rewards can be calculated based on various factors, such as the effective usage rate of resources, user satisfaction, and efficiency in resolving resource conflicts. A good reward function can balance these factors to achieve the comprehensive resource sharing effect. The reward function of this study was represented as follows:

$$e_y = \eta \sum_b \lambda_b^{CO} + (1 - \eta) \sum_b R_b^{RA} \tag{13}$$

Combined with the model setting, let $\varepsilon \in [0,1]$ be the discount coefficient, then the cumulative return was calculated using the following equation:

$$E_y = \sum_{j=0}^{Y-y-1} \varepsilon^j e_{y+j+1} \tag{14}$$

4 EFFECTIVENESS EVALUATION OF TEACHING RESOURCE ONLINE SHARING MECHANISM CONSIDERING KNOWLEDGE POTENTIAL DIFFERENCE

This study elaborates on the effectiveness of the evaluation method of the teaching resource online sharing mechanism, considering knowledge potential differences. Let D_1, D_2, \dots, D_m , be m indexes. All evaluation indexes were considered as matter elements in Extenics. Let E be the effectiveness of the teaching resource online sharing mechanism to be evaluated, and u_i be the value range of the i -th index of the object to be evaluated, then:

$$S = (E, d_i, u_i) = \begin{bmatrix} e & d_1 & u_1 \\ & d_2 & u_2 \\ & \vdots & \vdots \\ & d_m & u_m \end{bmatrix} (i = 1, 2, \dots, m) \tag{15}$$

Assuming that the effectiveness of the teaching resource online sharing mechanism was divided into n levels. Let $d_i(D_1, D_2, \dots, D_m)$ be m evaluation indexes, E_{0j} be the standard set constructed by the evaluation indexes, and $u_{0ji} = \langle x_{0ji}, y_{0ji} \rangle$ be the standard value range of E_{0j} , then the matter elements composed of E_{0j} , $d_i(D_1, D_2, \dots, D_m)$ and $u_{0ji} = \langle x_{0ji}, y_{0ji} \rangle$ were the classic domain matter elements for the effectiveness of the teaching resource online sharing mechanism. Let S_{0j} be the matter element evaluation model of the mechanism at the j -th effectiveness level, E_{0j} be the effectiveness evaluation level ($j = 1, 2, \dots, n$), and $u_{0ji} = \langle x_{0ji}, y_{0ji} \rangle$ ($i = 1, 2, \dots, m$) be the value range for the i -th index d_i at the j -th effectiveness level, then there was the following expression:

$$S_{0j} = (E_{0j}, D, U_{0ji}) = \begin{bmatrix} E_{0j} & d_1 & \langle x_{0j1}, y_{0j1} \rangle \\ & d_2 & \langle x_{0j2}, y_{0j2} \rangle \\ & \vdots & \vdots \\ & d_m & \langle x_{0jm}, y_{0jm} \rangle \end{bmatrix} \tag{16}$$

For the effectiveness evaluation of the teaching resource online sharing mechanism, the allowable value range for each index was joint domain, i.e. matter elements composed of E , d_i and $U_{ei} = \langle x_{ei}, y_{ei} \rangle$. Let S_e be the joint domain of the comprehensive evaluation matter element model for the mechanism effectiveness, E be the overall effectiveness evaluation level, $u_{e1}, u_{e2}, \dots, u_{em}$ be the value range for E regarding d_1, d_2, \dots, d_m , and U_{0ji} ($j = 1, 2, \dots, n; i = 1, 2, \dots, m$) be the range within U_{em} , then there was the following expression:

$$S_p = (E, D, U_{ei}) = \begin{bmatrix} E & d_1 & u_{e1} \\ & d_2 & u_{e2} \\ & \vdots & \vdots \\ & d_m & u_{em} \end{bmatrix} \tag{17}$$

For the teaching resource online sharing mechanism to be evaluated, let the matter element S_0 be the collected evaluation data, S_0 be the effectiveness of the sharing mechanism to be evaluated, and u_i be the specific value of the l -th index collected for the effectiveness of the sharing mechanism to be evaluated, then there were:

$$S_0 = (T_0, d_i, u_i) = \begin{bmatrix} T_0 & d_1 & u_1 \\ & d_1 & u_1 \\ & \vdots & \vdots \\ & d_m & u_m \end{bmatrix} (i = 1, 2, \dots, m) \tag{18}$$

Let β_i be the weight coefficient of the index d_p , with $\sum_{i=1}^m x_{i=1}$ and $V_i \in V_{ip}$. Let $U_i \in U_{ie}$, and $s_{ij\max}(U_i, U_j) = \max \{s_{ij}(U_i, U_j)\}$. The weight of the evaluation index, which was determined based on the simple correlation function, was calculated using the following equation:

$$s_{ij}(U_i, U_j) = \begin{cases} \frac{2(U_i - \beta_{ij})}{y_{ij} - \beta_{ij}}, U_i \leq \frac{\beta_{ij} + y_{ij}}{2} \\ \frac{2(y_{ij} - U_i)}{y_{ij} - \beta_{ij}}, U_i \geq \frac{\beta_{ij} + y_{ij}}{2} \end{cases}, (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \tag{19}$$

d_p , which fell into a higher level, was paid attention and given a greater weight, then the following was taken:

$$s_1 = \begin{cases} J_{\max} \times (1 + s_{ij\max}(U_i, U_j)), s_{ij\max}(U_i, U_j) \geq -0.5, \\ J_{\max} \times 0.5, s_{ij\max}(U_i, U_j) \leq -0.5 \end{cases} \tag{20}$$

d_p , which fell into a lower level, was given a smaller weight, then the following was taken:

$$s_i = \begin{cases} (n - J_{\max} = 1) \times [1 + s_{ij\max}(U_i, U_j)], & s_{ij\max}(U_i, U_j) \geq -0.5, \\ (n - J_{\max} = 1) \times 0.5 & s_{ij\max}(U_i, U_j) \leq -0.5. \end{cases} \tag{21}$$

The weight for the index i was calculated using the following equation:

$$\beta_i = \frac{s_i}{\sum_{i=1}^m s_i} \tag{22}$$

5 EXPERIMENTAL RESULTS AND ANALYSIS

To make the completed teaching resources as accurate as possible, this study mainly considered the impact of the threshold on the accuracy of the positive samples completed in the knowledge management system when adjusting the model threshold. Based on Figure 4, the impact of different thresholds on the accuracy of triplet classification tasks can be analyzed. It can be seen from the figure that the classification accuracy reaches its maximum value when the threshold is in the range of 4–6, indicating that the model is extremely accurate at this time. In the threshold range of 7–10, the classification accuracy slightly fluctuates but decreases on the whole.

Especially when the threshold increases from 10 to 11, the accuracy drops sharply by 8 percentage points, which is a critical turning point. When the threshold is above 11, the accuracy continues to decrease. When the threshold reaches 15, the accuracy decreases to 0.5050, only slightly higher than random guessing. For the triplets completed into the knowledge management system, high accuracy is pursued to ensure the accuracy of the completed information. Therefore, the recommended threshold should be within the range of 4–6, because the model has the highest classification accuracy at this time.

It can be seen from Figure 5 that the loss function value of the model decreases very quickly at high learning rates, but there are also overfitting risks because the loss value decreases very quickly. At a learning rate of 0.005, the loss is 7.5 at the beginning, decreases relatively slowly to 0.1, and then slightly increases and remains low in subsequent iterations. The loss decrease rate at this learning rate is slower than 0.01, but it seems more stable. At a learning rate of 0.001, the loss is 7.4 at the beginning and then slowly decreases. As the number of iterations increases, the loss function value decreases very slowly until it significantly decreases in subsequent iterations. The model at this learning rate requires more iterations to achieve a satisfactory loss function value, but it is not easy to overfit due to its stability. Combined with the application of DDQN in teaching resource online sharing, stability and accuracy are more important than convergence speed because it is expected that optimal resources can be provided to students. Therefore, a medium to low learning rate (such as 0.005 or 0.001) should be used to ensure stable and accurate learning.

Figure 6 shows the loss function variation trends of different DDQN units. The DDQN-based teaching resource online sharing algorithm has a fast learning speed in the initial iteration and then gradually slows down and tends to stabilize. Different DDQN units have different learning speeds and stability during the training process, which is related to the characteristics of each unit and the data it processes. After approximately 40 iterations, the loss function values of most units tend to stabilize, indicating that the algorithm has found a good solution and that further training cannot bring significant improvements. For this type of task, approximately 40 iterations is a reasonable number because the loss function has no significant improvements thereafter. These conclusions provide guidance on how to optimize and adjust the performance of the DDQN algorithm for such tasks.

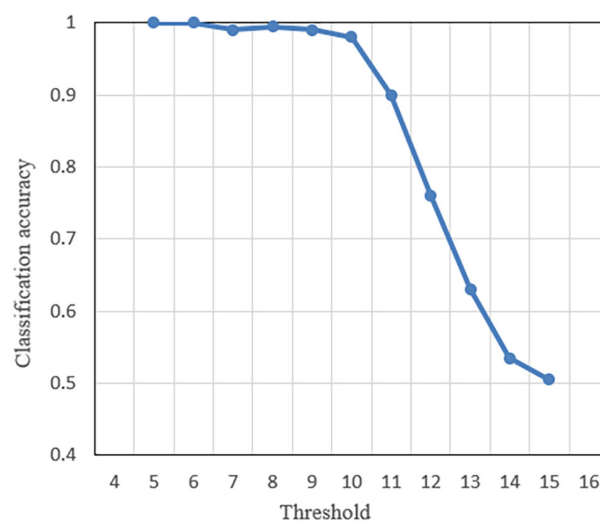


Fig. 4. Impact of different thresholds on the accuracy of triplet classification tasks

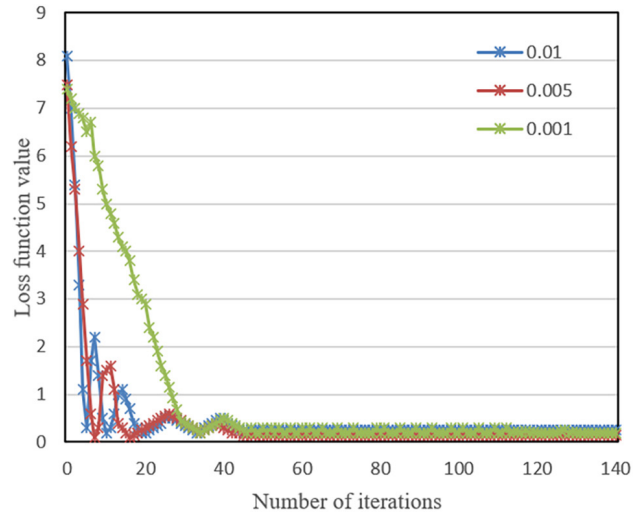


Fig. 5. Loss function curves under different learning rates

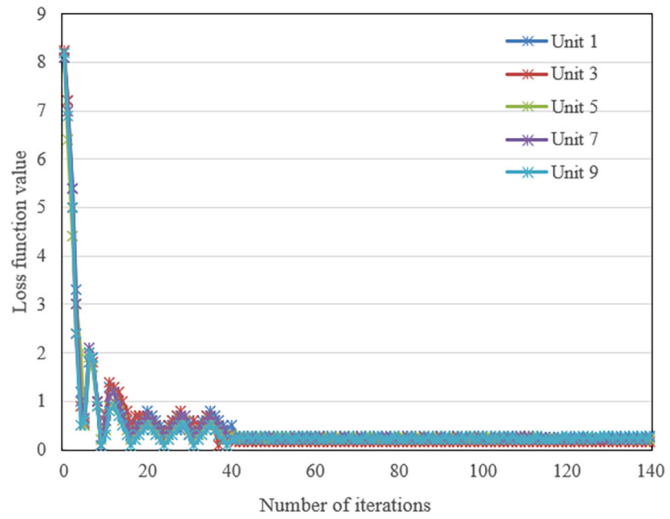


Fig. 6. Loss function variation trends of different DDQN units

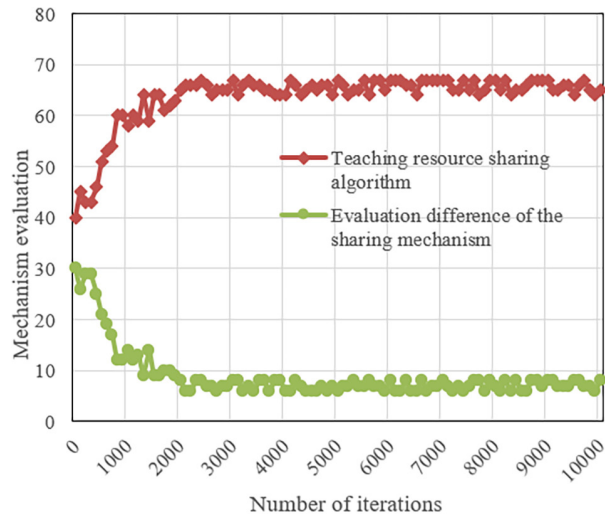


Fig. 7. Comparison of evaluation value and optimal evaluation value of the teaching resource sharing algorithm

Figure 7 shows that the evaluation value of the DDQN-based teaching resource online sharing algorithm and the evaluation difference of the sharing mechanism vary with the number of iterations. The evaluation value is an index that measures the effect of the teaching resource online sharing algorithm. The higher the value, the better the effect of the algorithm. The evaluation difference measures the gap between the actual and expected effects of the sharing mechanism. A smaller value indicates that the sharing mechanism is closer to the ideal state.

It can be seen from the data that the evaluation value of the algorithm shows an overall upward trend as the number of iterations increases. Especially in the initial stage, the evaluation value increases from 40 to 60, indicating that the algorithm has quite good results after certain learning. However, the growth of the evaluation value begins to slow down in subsequent iterations and is within the range of 65–67 very steadily. It can be seen that the evaluation difference of the sharing mechanism rapidly decreases from 30 to 12 in the early iteration stage. But then the evaluation difference begins to decrease with a smaller decrease rate and eventually stabilizes in the range of 6–8, which indicates that the sharing mechanism is close to its optimal effect after a certain number of iterations.

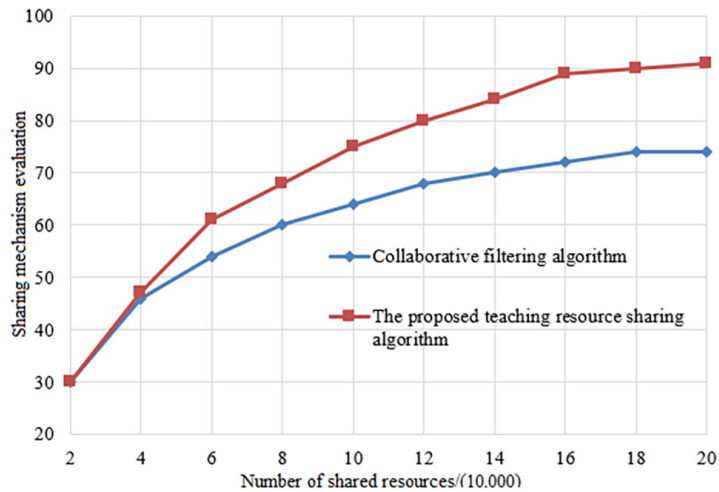


Fig. 8. Evaluation values of sharing mechanism using different algorithms vary with the number of shared resources

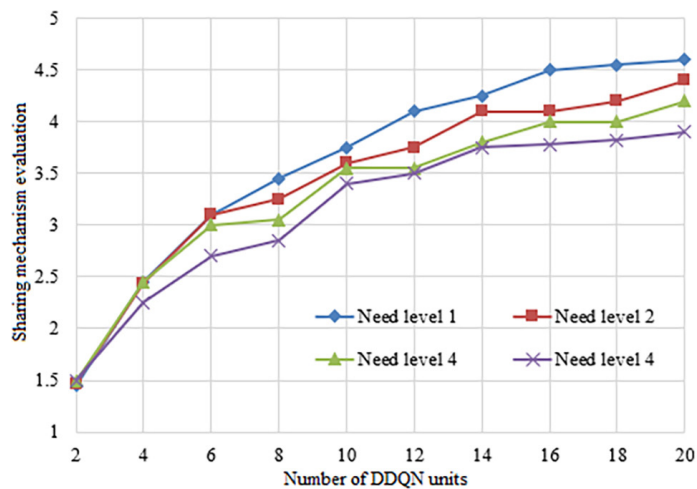


Fig. 9. Sharing mechanism evaluation of the teaching resource sharing algorithm varies with the number of DDQN units at different resource need levels

Figure 8 shows that the evaluation values of two algorithms (the collaborative filtering algorithm and the teaching resource sharing algorithm proposed in this study) vary as the number of shared resources changes from 2 to 20. As the number of shared resources increases, the evaluation values of both algorithms show an upward trend. However, the growth rate and final evaluation value of the proposed algorithm are significantly higher than those of the collaborative filtering algorithm, indicating that the proposed algorithm is more adaptable to the increase in the number of shared resources. Especially when there are a large number of resources, the proposed algorithm still continues to optimize its performance, while the performance growth of the collaborative filtering algorithm begins to saturate. When the number of shared resources is small, the performance of the two algorithms is similar. But as the number of resources increases, the advantages of the proposed algorithm gradually become apparent. In summary, the proposed algorithm shows good performance under different numbers of shared resources, and its performance advantages are more obvious, especially when the number of shared resources increases, which means that the proposed algorithm is more applicable and efficient in practical applications, especially in environments with rich resources.

Figure 9 shows the impact on the evaluation value of the teaching resource sharing algorithm at different resource need levels as the number of DDQN units increases from 2 to 20. As shown in the figure, increasing of the number of DDQN units improves the evaluation value of the algorithm, but different need levels have different responses to this. Need Level 1 shows good performance under all numbers of DDQN units. However, the performance growth of Need Level 4 tends to saturate after the number of DDQN units exceeds a fixed value. For intermediate need levels (such as Need Levels 2 and 3), although their trends are similar, their evaluation values may vary under certain specific numbers of DDQN units. In practical applications, it is necessary to select appropriate settings based on specific resource need levels and the number of available DDQN units, thereby optimizing the performance of the teaching resource sharing algorithm.

6 CONCLUSION

This study explored the teaching resource online sharing mechanism from the perspective of knowledge management. Therefore, this study emphasized the importance of knowledge, the sharing and exchange of knowledge, and the core position of knowledge in teaching resources. To manage and share teaching resources more effectively, this study adopted the TransCat model to complete the knowledge management system and proposed a new online sharing algorithm based on the DDQN algorithm. A new resource evaluation mechanism was also introduced, which took into account the knowledge potential difference, i.e., the gap between the potential value of knowledge and its value in practical applications.

Through experimentation, this study compared the DDQN-based teaching resource online sharing algorithm with the optimal evaluation value, revealing a relatively stable and gradually improving trend in the algorithm's performance. Especially under the conditions of large iterations, the algorithm showed better performance. The experimental results showed that the teaching resource sharing algorithm proposed in this study had a higher evaluation value than the collaborative filtering algorithm in most cases, especially when the number of shared resources was high, as the number of shared resources increased. As the number of DDQN units increased, the evaluation values at all need levels increased, but the evaluation value at Need Level 1 was relatively

high under all numbers of DDQN units. The experimental results showed that this new sharing mechanism not only effectively managed and shared teaching resources but also exhibited better performance than other methods at different resource need levels and under different numbers of shared resources. In addition, the study also considered the knowledge-potential difference, providing a new dimension for the effectiveness evaluation of resources. These research results provide a new idea and method for teaching resource online sharing, which have important theoretical and practical value in the fields of knowledge management and educational technology.

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