ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 1 - 2026

Exploring the Intelligent Path of Chinese Cultural Communication for International Students in China Driven by Artificial Intelligence Technology

Yuxiang An[1,*]

[1] Shenyang Jianzhu University, Shenyang, Liaoning, 110168, China

SUMMARY: *Due to humanity's close relationships and the quick advancement of AI technology, cultural interaction has become a focus of academic and practical study. Researchers are increasingly focusing on the cultural identity and cultural adaptability of the group of international students in China. In this sense, the paper creates a user portrait model of international students studying in China by utilizing multidimensional labels, making full use of multi-dimensional user data from brief films, and creating an extensive three-dimensional user portrait model. On the basis of the user portrait model, deep reinforcement learning, which can solve the sequential decision problem, is introduced and applied to the recommended videos of Chinese culture dissemination, and corresponding improvements are made by combining the characteristics of the scene. In the performance test of the algorithm, the average probability of users watching the recommended videos of Chinese culture dissemination based on the method of this paper is 0.76, which is higher than that of the comparison algorithm by 0.39, thus proving the superiority of the video recommendation algorithm designed in this paper. This empirical conclusion is derived from the examination of brief Chinese cultural videos created on a specific platform. The frequency of producing unique material for short films has been found to have a strong favorable impact on international students' behavioral intentions toward Chinese culture in China.*

KEYWORDS: *user profile of international students in China; video recommendation; reinforcement learning; DDPG; Chinese culture communication*

1 Introduction

Underneath the cultural dissemination lies the dissemination of fundamental values, which also constitutes the nucleus of the "soft power". In order to better "tell China's story and spread China's voice", the significance of the international students population for the dissemination of Chinese culture [1] should be thoroughly considered. Due to the growing comprehensive power and status of China in the international arena, the "Study in China Fever" phenomenon is developing rapidly; hence, the contribution of the international students becomes essential for telling the Chinese story, which becomes even more believable when told by the international students who would be telling their version of the story from a third person's perspective [2-4]. Being the witnesses of the outstanding Chinese culture development, the international students also serve as spokespersons of its dissemination. However, due to obvious limitations of the conventional method of communication regarding time and space issues, it results in the narrow audience for the Chinese culture dissemination. The advent of artificial

*15998315151@sohu.com
https://doi.org/10.65102/is2026417 Published: 30 April, 2026

intelligence allows numerous intelligent pathways to be considered within the framework of disseminating the Chinese culture among the international students in China.

One is the intelligent translation path. Artificial intelligence can easily use languages and dialects of different countries to communicate with international students in China through translation technology and voice recognition technology, breaking the communication barriers across languages, regions and cultures, and promoting Chinese cultural communication among international students [5-8]. Liang [9] emphasized that Chinese cultural translation can help to promote cultural communication, discussed the translator's subjectivity, and analyzed the translation strategies and results point to receptivity and expressiveness as the main concerns of Chinese cultural translation, and suggests suitable and effective modes of intercultural communication. In an effort to have an impact on society, Yang and Cui [10] examined the use of cutting-edge technologies to facilitate multimodal mediation in the translation and communication of Chinese culture and demonstrated how AI can help with the multimodal translation and communication of various aspects of Chinese culture.

Second, the immersion approach. Using virtual reality and augmented reality technologies to construct an immersive environment based on the theme of Chinese culture, enabling foreign students to explore cultural scenes from history [11, 12]. It helps to strengthen international students' knowledge and understanding of Chinese culture and feel the artistic charm of Chinese culture, thus improving the intensity of Chinese culture dissemination [13]. Heppner and Wang [14] discussed immersive cultural experiential learning in education and experimentally verified the role of immersive experiences in improving cultural awareness and suggested introducing cultural immersion learning environments into teaching. Shih [15] analyzed the impact of immersive virtual environments on cultural learning, and the findings based on a qualitative case study combined with a time-series design showed that immersive virtual environments help to improve students' cultural learning. Wang and Kim [16] proposed an immersive cultural interaction model based on the theory of embodied cognition and used Dwelling in the Fuchun Mountains as an example to reveal that the immersive model enhances the viewer's understanding of the landscape painting's meaning and provides new insights into the digital presentation and dissemination of traditional culture.

Third, personalized path. On social platforms, the use of AI can achieve accurate and personalized Chinese cultural content recommendation for international students based on their behavioral data and interests [17, 18]. Chinese culture is all-inclusive, and various foreign students have varied living experiences and value systems; hence, such a tailored recommendation system would serve to cater to their requirements and understanding of Chinese culture and, subsequently, further the spread of Chinese culture [19]. Wang [20] suggested a personalized recommendation system for cultural resources based on collaborative filtering methods that use preference algorithms for users; according to the experimental outcomes, the proposed recommendation approach was sufficient in satisfying the primary cultural requirements of users. Wang, Q [21] proposed a group recommendation approach based on non-negative matrix factorization, which has high accuracy and flexibility in providing different recommendations based on individual preferences, and pointed out that personalized recommendations for cultural content in an artificial intelligence environment could be considered an effective route for spreading cultures. Huang [22] examined the communication of personalized recommendations for cultural conservation with Teochew paper cuts as the case study and analyzed deeply visual communication and personalized recommendations for paper cuts with information technology like knowledge graph, multimedia, and neural networks.

The article firstly constructs the portrait of international students in China, uses Python software to write code to collect user data, preprocesses the user data, constructs the multidimensional feature label system of the user, and utilizes jieba segmentation and TF-IDF weight computation to extract the labels and compute the weights of the labels from the user's data, so as to construct the model of the user's portrait. Next, this work applies DDPG to video recommendation using the deep reinforcement learning technique. To improve the capacity to capture the sequential relation of the suggested films, the GRU network was specifically employed as the deep neural network within the DDPG framework. Lastly, the study examines the impact of the platform's short films on the spread of Chinese culture. In particular, the research dimensions of use motivation, content creation, and interaction on the short video platform are used to analyze the impact of short video use on the comprehension of Chinese culture, emotions associated with Chinese culture, and intentions of behavior in Chinese culture among the international student population in China. The research subject is the short videos created by the platform for the purpose of disseminating Chinese culture.

2 Social Video-based Chinese Cultural Communication for International Students in China

2.1 Construction of a portrait of international students in China

2.1.1 Data collection and processing

International students' information comprises two types of data: static information data and dynamic information data. In this case, the static information data refers to the natural and social characteristics of international students, which comprise nicknames, ID numbers, gender, age, profile, geographical region, and others. On the other hand, dynamic information data refers to the behavioral information data of international students while using and browsing.

The gathered data, which is mostly separated into structured and unstructured data, has an inconsistent structure due to the complexity of the data type. To turn unstructured data into structured data, it must be processed through data screening, data concentration, data transformation, and data statute. In structured data, there are problems such as incomplete data, repeated data and synonyms. For the problem of incomplete data, it can be supplemented and improved by searching or querying. For the problem of data repetition, the uniqueness of data can be ensured by removing redundant information. For the problem of homonymy, it can be dealt with by eliminating differences. On the other hand, in the process of collecting and processing data, we aim to guarantee the security and privacy of the data of international students studying in China. In order to accomplish this task, the international students in China are anonymized and the authorization of using the data is reinforced so that only those pieces of information and data concerning the construction of the model of the portrait are collected. Furthermore, we implement centralized management of the collected data in order to reinforce the use of basic information and privacy data of international students.

2.1.2 Construction of multi-dimensional feature labeling system

A multidimensional and multilevel model of international students in China can be obtained by transforming data into labels with multiple attributes by varying the weight of each attribute of international students in China and then combining all the labels of each attribute of international students in China. In this study, using the data gathered regarding both static and dynamic information of international students in China, the labeling system for international students in China is created by employing the attributes of international students in China, which includes basic attributes, interests and preferences, and social attributes. The labeling system for international students in China is presented in Figure 1.

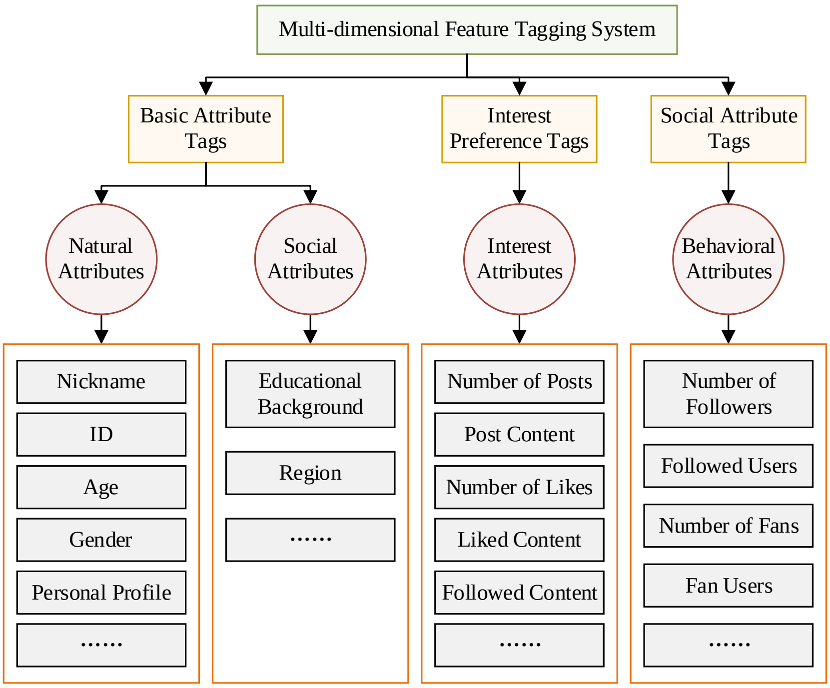

Figure 1: User tag system

The natural and social characteristics of international students in China, such as their nicknames, identification numbers, gender, age, educational background, personal information, and geographic locations, make up the core attribute tagging scheme. The interest attributes of international students in China make up the majority of the interest preferences tagging scheme. These include the titles of articles written by international students in China, the titles of articles that they like, the profiles of international students in China who follow other international students in China, and the profiles of international students in China who have other international students in China as fans. The social attribute tagging scheme primarily consists of the social attributes of international students in China. The construction of the international students in China tagging scheme is illustrated in Fig. 2.

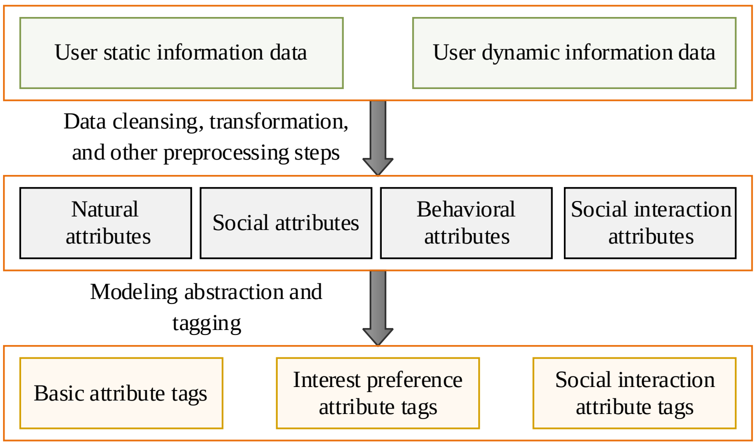

Figure 2: Construction of user profile tag system

2.1.3 Extraction of labels and weight calculation for international students in China

In this work, we have used text mining to extract labels for foreign students from various parts of the data pertaining to international students in China. The weights of the labels in this study for foreign students studying in China are calculated by multiplying the weights of the behavioral type, the quantity of behaviors, and the weights of the TF-IDF method. The TF-IDF algorithm in Chinese is known as Word Frequency-Inverse Document Frequency (WF-IDF), which is a way of counting the number of times a particular word occurs in an article, thus reflecting the significance of that word for that article. Moreover, through the log of the frequency of occurrence of the word in other documents, the weight of the word can be adjusted. With the help of the TF-IDF algorithm, the weights of the labels can be determined when the labels are extracted. The formula is shown in equation (1).

$$w_{i,j} = TF_{i,j} \times IDF \tag{1}$$

where $TF_{i,j}$ is the ratio of the number of occurrences of the word w in the text d, $count(w,d)$, and the total number of occurrences in the text d, $size(d)$. The formula is shown in equation (2). The value of IDF is the total number of texts N divided by the number of texts $docs(w,D)$ in which the word w occurs, and then the logarithm of the obtained quotient is obtained. The formula is shown in Equation (3).

$$TF_{i,j} = \frac{count(w,d)}{size(d)} \tag{2}$$

$$IDF = \log\left(\frac{N}{docs(w,D)}\right) \tag{3}$$

Since the following, liking, and posting behaviors of international students in China on the short video application are among the most prevalent, observable, and simple to collect, the frequency of these three behaviors is selected and used as an indicator to measure the weight of the action types, which will subsequently be ascertained using the information entropy method. First, the standardization process is carried out, and the standardization formula is shown in equation (4).

$$x'_{i,j} = \frac{x_{ij} - \min\{x_{ij},...,x_{nj}\}}{\max\{x_{ij},...,x_{nj}\} - \min\{x_{ij},...,x_{nj}\}} \tag{4}$$

where x_{ij} is the number of times i international students in China have committed behavior j, and x'_{ij} is the value after processing. The information entropy calculation formula of behavior j is shown in equation (5).

$$E_j = \sum_{i=1}^{n} P_{ij} \log_2(P_{ij}), P_{ij} = \frac{x'_{ij}}{\sum_{i=1}^{n} x'_{ij}} \tag{5}$$

where E_j is the information entropy of behavior j. P_{ij} is the size of the proportion of the i th international student in China under the j th attribute in this attribute. Then, the formula of weight V_j corresponding to behavior j is shown in equation (6).

$$V_j = \frac{1-E_j}{\sum_j^m \left(1-E_j\right)} \tag{6}$$

2.1.4 Generate a portrait of international students in China

The development of the labeling system for foreign students in China is followed by an analysis of the characteristics of these students based on the characteristics from the labeling system of various characteristics of international students in China. Then, we match the attribute features with the labels and return the corresponding labels to the corresponding attribute features of the international students to realize the labeling of various attribute data of the international students and construct the model of the portrait of the international students. After the construction of the portrait of international students in China is realized, all kinds of tags in the tag system are then visualized by applying wordCloud, Wordle, Tagul, etc., which are more comprehensive at present, according to their weights, so as to generate the portrait of international students in China. After the visualization analysis, semantic analysis technology can also be used to explore the potential relationship between international students in China and the information content. Then, we can aggregate the international students with similar label contents to form a collection of international students with similar attributes and characteristics, so as to obtain different groups of international students' portrait models.

2.2 Deep Reinforcement Learning-based Video Recommendation Algorithm for Chinese Culture

2.2.1 Deep reinforcement learning

Deep Q Network (DQN) is produced by fusing Convolutional Neural Network (CNN) and Q-Learning. The CNN network's ability to extract the spatial connection between pixels and learn the appropriate action from the data obtained from the raw picture is its advantage. Equation (7) proposes the objective function computation for the DQN method.

$$y_j = \begin{cases} R_j & is\_end_j = true \\ R_j + \gamma \max_{a'} Q'(\phi(S'_j), A'_j, w) & is\_end_j = false \end{cases} \tag{7}$$

Among them, the target Q value is calculated using the parameters of the currently trained Q network, but in practical applications, we prefer to update the parameters of the Q network through y_j. From the above, it can be seen that there is a very high level of interdependence between the two. In the process of iteration, it is difficult for an algorithm to converge when the correlation is high. The iterative process of DQN is given by equation (8).

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha \left[R_{t+1} + \gamma \max Q(S_{t+1}, a) - Q(S_t, A_t)\right] \tag{8}$$

There are two problems with this iterative process. One, the Q function puts the state S_t and the action A_t together for learning optimization, which makes there is action-independent bias between different states. Second, max easily leads to the overestimation problem, which makes the model's Q value deviate greatly from the true value.

To address the first problem mentioned above, the researchers have solved the problem by splitting the Q function into a state function V and a state-based action function A, as shown in Equation (9). As a result, the researchers proposed the DuelingDQN network, and the main improvement is that the Q value is obtained by adding the state value V and the action value A.

$$Q(S_t, A_t; \theta, \alpha, \beta) = V(S_t; \theta, \alpha) + A(A_t; \theta, \beta) \tag{9}$$

For the second problem, the problem of overestimation is substantially eliminated by decoupling the two steps of calculation of the target Q value and selection of the action. As shown in equation (10).

$$\begin{gathered} Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha\left[R_{t+1} + \gamma \max Q'(S_{t+1}, a) - Q(S_t, A_t)\right] \\ \theta^Q \leftarrow (1-\alpha)\theta^Q + \alpha\theta^{Q'} \end{gathered} \tag{10}$$

From this, the DoubleDQN algorithm was derived. The main difference is that it is divided into two parts: the main network and the target network. The main network is responsible for action selection and the target network performs the fitting of Q values.

2.2.2 Application of DDPG to Video Recommendations

(1) DDPG structure

The DQN model based on Q network and its improved model are mainly based on single-step update of TD algorithm, which has fast convergence speed, but can only deal with discrete action space, with poor action characterization ability and high computational complexity of optimal action. The reinforcement learning algorithm based on policy network can deal with continuous action space, has strong action characterization ability, and can learn the optimal action directly based on the state, with low decision complexity, but its updating mechanism is round updating, and the model convergence is slow. However, a more effective approach would be to leverage the benefits of both Fusion Q and Policy Networks through Generative Adversarial Learning, which takes the form of the Deep Deterministic Policy Gradient (DDPG).

"Deep" refers to the usage of deep neural networks in Deep Deterministic Policy Gradient (DDPG). Stochastic Policy Gradient and Deterministic Policy Gradient are connected. Both continuous and high-dimensional discrete values can be included in the reinforcement learning action space. For the case where the dimension of the action space is extremely large, using a stochastic policy to compute all the possible actions with extremely large values requires a large enough sample size and brings about a huge computational consumption at the same time. So some scholars proposed to use deterministic strategy.

When it comes to stochastic policy, the probability distribution determines the action that is selected in the same state of the same strategy. As a result, it is necessary to sample the stochastic probability gradient throughout the whole action space. The gradient may be calculated using the Q value as shown in (11):

$$\nabla_\theta J(\pi_\theta) = E_{s\sim p^\pi, a\sim\pi_\theta}\left[\nabla_\theta log\pi_\theta(s,a) Q^\pi(s,a)\right] \tag{11}$$

where p^π is the state sampling space and $\nabla_\theta log\pi_\theta(s,a)$ is the score function.

The deterministic strategy then picks the one with the largest action probability, i.e., the action is uniquely determined in the same strategy and state, and the strategy becomes $\pi_\theta(s) = a$. The deterministic strategy gradient is based on the Q value of the DPG gradient formula shown in (12):

$$\nabla_\theta J(\pi_\theta) = E_{s\sim p^\pi}\left[\nabla_\theta \pi_\theta(s) Q^\pi(s,a)\big|_{a=\pi_\theta(s)}\right] \tag{12}$$

Compared with Eq. (11), DPG has less integration over action and more derivatives of Q over action.

The optimization process of DPG to DDPG is very similar to that of DQN to DoubleDQN, but since the DPG itself is an Actor-Critic structure, the final DDPG possesses four networks: the Actor-main-net, the Actor-target-net, the Critic-main-net and the Critic target-net, where two Actor networks have the same structure and two Critic networks have the same structure.

DDPG can be treated as a combined algorithm of the three methods DQN, Actor-Critic and DPG. Each of the four networks has a corresponding role. the Actor-main network is responsible for iteratively updating the strategy network θ, selecting the current action A based on the current state S, which is used to interact with the environment for generating S', R. the Actor-target network is responsible for selecting the optimal next state based on the next state S' sampled from the experience playback pool. Selects the optimal next action A', with network parameters θ' periodically copied from θ. The Critic-main network is responsible for the iterative updating of the Q network parameters w, and is in charge of calculating the current Q value $Q(S,A,w)$. Target Q value $Q' = R + \gamma Q'(S', A', w')$. Critic-target network: responsible for calculating the $Q'(S', A', w')$ portion of the target Q value, with the network parameter w' copied periodically from w.

(2) Algorithm Improvement and Application

The DDPG action representation is continuous, in this scenario the Action is the relevant video and we need to set it as a continuous action. The solution we take is to design the Action as an n-dimensional vector, so that its physical meaning is a cultural communication video. Meanwhile, we will perform Pooling operation after Embedding operation on different field features of the related video, and finally generate the vector we use to characterize the action. For the sake of model unification, Pooling is also performed for user, context, and cultural communication video features, i.e., a pooling operation is added to the shared Embedding layer.

In the video recommendation scenario studied in this paper, multiple videos are recommended to the user at a time, and the location where the video is located also has a little impact on the video click. In order to utilize the sequence information between the recommendation lists, we use a recurrent neural network for the Deep part of the DDPG. After experimental validation, we finally chose to utilize GRU to further extract the hidden information between related video sequences, and GRU extracts the sequence information as shown in Fig. 3.

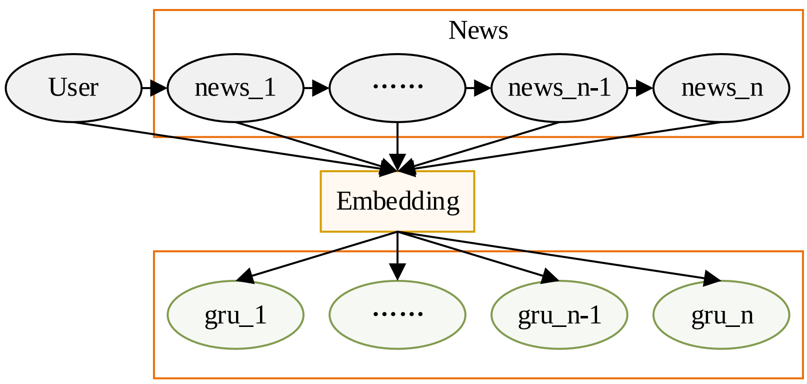

Figure 3: GRU extracts sequence information

Fig. 4 shows the architecture of the DDPG model. For simplicity, just one network is used to demonstrate the Actor and Critic designs. In this case, the pooling approach is used while the embedding layer's weights are still shared. Additionally, the Context is presented to the video's content. In the image, forward propagation is represented by the solid lines, while reverse gradient propagation is shown by the dotted ones. We can see that the Policy Gradient is propagated across the Actor and Critic networks.

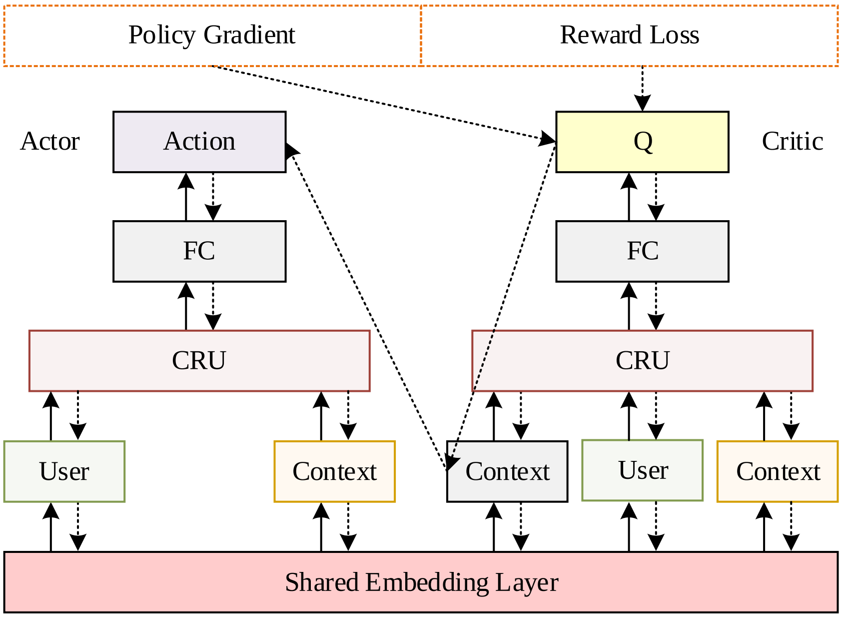

Figure 4: DDPG model

2.2.3 Experiments and analysis of results

In this section, we conduct a comparison between a DDPG-based video recommendation system and a short video recommendation system with randomly inserted Chinese culture dissemination videos.Two main aspects are considered: the probability of a user watching the recommended Chinese culture dissemination video and the situation where the user stops using the short video APP while watching the Chinese culture dissemination video. The superiority of the Chinese culture dissemination video recommendation system based on the method of this paper in improving the probability of users watching Chinese culture dissemination videos and improving the time of users using the short video APP is verified in two ways. In order to construct a prediction model for the length of time that users watch short videos, we collected half a month's short video viewing time records from volunteers, and then used a locally weighted regression model to train on the collected data, and the fitted graph of users' viewing records is shown in Fig. 5. In the locally weighted regression model, the larger the value of k, the larger the probability of underfitting,the smaller the value of k, the larger the probability of overfitting.In this experiment, k =0.6,as can be seen from the figure,the overall fitting effect of the model is good.

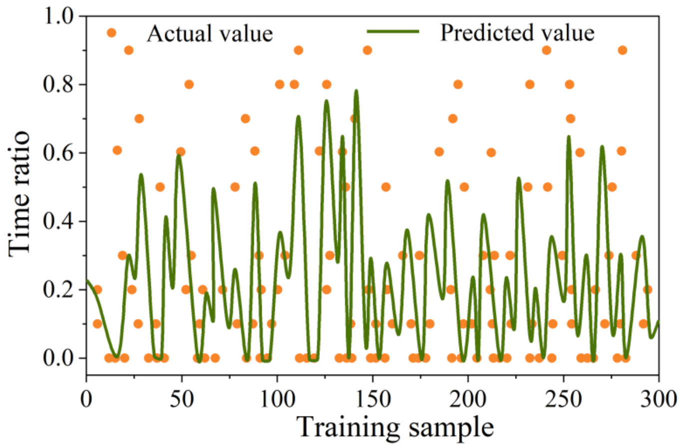

Figure 5: User viewing record fitting graph

In order to obtain the user's interest model, in this section, we collected half month's viewing records of Jitterbug from volunteers. In the data preprocessing process, the video tag, video publisher and video title of each short video are extracted. The processed data are used as inputs for training in the network, and the resulting trained model is used as the user's interest model. The loss function of the model is shown in Fig. 6. By observing the image of the loss function, it can be found that the loss function of the model has converged, so it can be considered as a valid model.

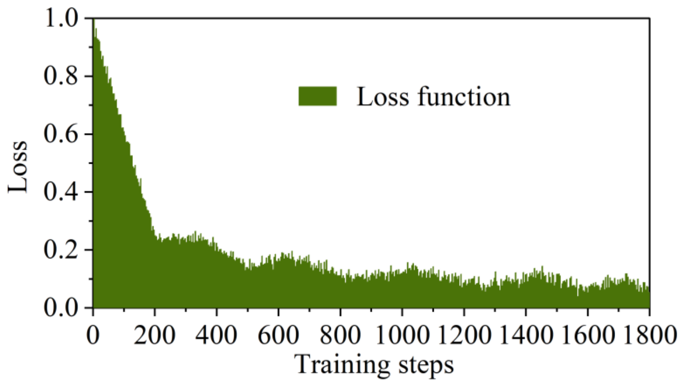

Figure 6: The loss function of the model

A comparison of system convergence is shown in Figure 7. As can be seen from the figure, the reward functions of the two models finally reach convergence. In addition, the stable reward value of the Chinese culture dissemination video recommendation system based on the method of this paper is higher than that of the short video recommendation system with randomly inserted Chinese culture dissemination videos, which is because the Chinese culture dissemination video recommendation system based on the method of this paper takes into account the influence of the time factor, and doesn't recommend the Chinese culture dissemination videos for the users when the users don't have enough time to watch the Chinese culture dissemination, so as to avoid that the users reduce their APP usage time because of being recommended the Chinese culture dissemination. In order to prevent users from decreasing the time of using APP because of being recommended Chinese culture communication. In addition, the Chinese culture dissemination video recommendation system based on the method in this paper also considers the connection between short videos and Chinese culture dissemination videos, so that the sudden insertion of Chinese culture dissemination videos will not affect the user's experience of watching short videos, but rather, it utilizes the connection between short videos and Chinese culture dissemination videos to enhance the probability of the user watching Chinese culture dissemination videos.

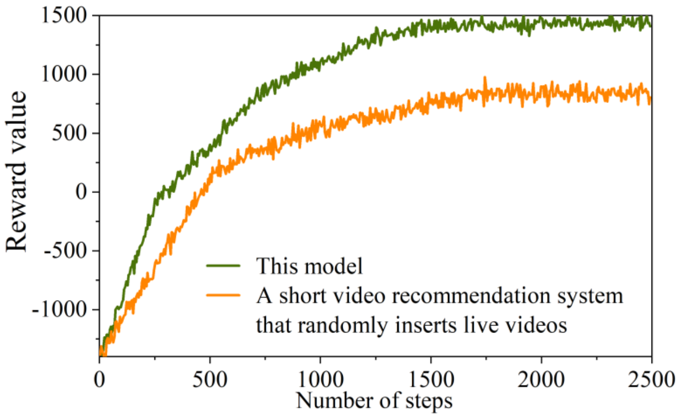

Figure 7: System convergence comparison

The frequency of users exiting APP after Chinese culture dissemination videos and the probability of clicking on recommended Chinese culture dissemination videos were obtained by continuous statistics of users' use of short video APP in one week, with 24 hours as one data statistic. The number of times users exit the APP after watching Chinese culture dissemination videos is shown in Table 1. From the table, it can be seen that the number of times users quit APP after watching Chinese culture dissemination videos is higher during the week, while the number of times users quit APP after watching Chinese culture dissemination videos decreases significantly on weekends, which is possibly because users have more time to watch Chinese culture dissemination videos on weekends. In addition, the Chinese culture dissemination video recommendation system based on the method of this paper obviously reduces the number of times users exit the APP after Chinese culture dissemination videos, which is due to the fact that the Chinese culture dissemination video recommendation system based on the method of this paper is able to recommend the Chinese culture dissemination videos to the users at the appropriate time, and it also takes into account the correlation between the Chinese culture dissemination videos and the short videos.

Table 1: The number of times the user exits the app after watching video

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
This model	1	1	0	1	0	0	0
A short video recommendation system that randomly inserts live videos	4	3	2	3	2	2	1

The probability of users watching the recommended Chinese cultural communication videos is shown in Table 2. As can be seen from the table, the Chinese culture dissemination video recommendation system based on the method of this paper can guide users to watch Chinese culture dissemination videos more effectively than the short video recommendation system that randomly inserts Chinese culture dissemination videos, and the average probability of users watching the recommended Chinese culture dissemination videos based on the method of this paper is 0.76. This is because the Chinese culture dissemination video recommendation system based on the method of this paper can make the inserted Chinese culture dissemination videos integrate into the recommendation list more naturally, and will not bring a sense of abruptness to the users. This is because the Chinese culture video recommendation system based on the method in this paper can make the inserted Chinese culture video integrate into the recommendation list more naturally, and will not bring a sudden feeling to the users. After the user has watched the short video, the recommended Chinese culture video is closely related to the previously watched short video, thus stimulating the user's interest and increasing the click rate and viewing rate. In addition, the Chinese culture video recommendation system based on the method in this paper can recommend Chinese culture videos when users have enough time, so the probability of users clicking to watch Chinese culture videos is significantly increased.

Table 2: The probability of users watching the recommended live video

	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
This model	0.73	0.69	0.75	0.64	0.82	0.90	0.79
A short video recommendation system that randomly inserts live videos	0.32	0.27	0.37	0.25	0.42	0.53	0.43

3 Empirical analysis of the effect of Chinese culture dissemination among international students in China

3.1 Study design

3.1.1 Sample selection

Short video texts tagged with Chinese culture and their commentary will be selected as the study object, and the short video application will be used as the target medium for texts and data sources in this work. The current study is to investigate how short video social media consumption affects Chinese cultural identity among international students in China in terms of choice, usage frequency, motivation, and readiness to use short video social media. In this study, we selected the tags with high playback volume, screened the top 1000 short videos with Chinese culture and the audience feedback indicators (the number of likes and audience comment texts), and the detailed rules and processes were as follows.

(1) Search for the keyword “Chinese culture” in the short video platform, find short videos related to Chinese culture, browse the short videos, filter out the short video tags, and click on the tags with higher playback volume to display the short video content related to Chinese culture.

(2) The publishing time range of the selected short video samples is limited to the period from January 10, 2024 to May 10, 2024)

(3) The first 1000 video samples that fall into this category are selected as the research subjects because the video texts will be arranged based on how many likes they receive. Videos with a high number of likes will more accurately represent the most popular Chinese cultural video texts among international students in China.

Based on the above sample selection rules and procedures, by May 10, 2024, the collection of short video samples for this study will be completed.

3.1.2 Class construction

This paper focuses on the interaction between audience feedback and media text content. From quantitative analysis, audience feedback indicators need to be investigated and researched around the audience and media text content. The number of audience likes represents the audience's recognition and fondness of the text content, which can intuitively reflect the audience's attitude and favorite text content, and is an important quantitative indicator of audience feedback. Within the short video platform, the number of likes is the most important factor to measure the hotness of short video works and audience's favoritism. Therefore, this study develops content coding of short video textual content from the interactive relationship between short video textual content of Chinese culture and the number of audience likes.

(1) Creative Subjects

In this paper, the identity of the Chinese culture content creators of short videos on the platform is determined by their account characteristics, content creation themes and frequency, and they are divided into four categories, namely, self-media bloggers, athletes, ordinary users, and official or institutional media.

(2) Performance Subjects

Combining the textual content and video images of short videos, this study categorizes the video subjects into five categories: political figures, athletes, the public, cultural communication workers and media workers.

(3) Video Subjects

After watching all 300 short videos, the researcher finally identified ten categories of video themes, which are Oriental wisdom, the new life of non-heritage skills, local customs and food philosophy, classical aesthetics and garden mood, from martial arts to physical culture, contemporary rituals of traditional festivals, the road of communication between ancient and modern dialogues, modern echoes of classic texts, Chinese imagination in science fiction and technology, and the modern transformation of traditional cities.

(4) Likes

The number of likes is an important indicator of audience feedback to assess the communication effect of Chinese cultural videos. On the platform, short videos with the same label are also presented in the order of the number of likes. It can be said that the number of likes is the most important indicator for assessing the dissemination effect of Chinese cultural short videos.

3.2 Analysis of Cultural Identity of International Students in China

3.2.1 Reliability and validity tests of the scale

In this study, the Cronbach a (Cronbach alpha) coefficient was used as a criterion to test the scales of international students' short-video social media use behavior and Chinese cultural identity. According to this criterion, the reliability coefficient of the total scale needs to reach more than 0.7, and the reliability coefficient of the subscales needs to be more than 0.6, or else the researcher should think about how to revise or add or subtract the scale questions. Through the reliability test conducted on the data of this questionnaire, it can be seen from the statistical data that all scales have good reliability and can be investigated with this questionnaire.

In this study, the multidimensional scales employed were submitted to factor analysis as a means of validating the validity of the instruments through KMO Test and the sphericity of Bartlett's test. The efficacy of factor analysis increases with KMO values, which range from 0 to 1. It is evident from the statistical analysis that the validity of the questionnaire scales is good. The KMO value for the three scales is 0.936, 0.755, and 0.787 respectively, and all the values being above 0.7 indicate that there exist common factors within the variables; hence, they are appropriate for factor analysis.The value of the significance of the Bartlett's test of sphericity $p=0.000 < 0.05$ shows that the items are correlated and not independent; therefore, factor analysis can be done to analyze the results obtained.

3.2.2 The state of cultural identity in China

The mean values and standard deviations of the major variables are presented in Table 3. It is evident from the data presented in the table that Chinese cultural identity among foreign students studying in China is quite high. In this respect, the mean values of Chinese cultural emotion is 4.21, while those for Chinese cultural cognition and Chinese cultural behavioral intention stand at 4.11 and 3.82 respectively. The above discussion suggests that the majority of foreign students in China exhibit higher levels of Chinese cultural emotion, Chinese cultural cognition and Chinese cultural behavioral intention.

Table 3: The mean and standard deviation of the main variables

Index	Mean value	Standard deviation
Chinese culture cognition	4.11	0.89
Chinese cultural emotion	4.21	0.88
Intention of Chinese cultural behavior	3.82	0.8
Entertainment motivation	3.88	1.18
Get information motivation	3.62	1.09
Culcated motive	3.45	1.08
Social interaction motivation	3.21	1.18
Self-presentation motivation	2.85	1.3
The satisfaction of the proposed social needs	3.35	1.32
User original content production	2.8	1.32
Online intensity	3.29	1.18

3.2.3 Correlation between motivation to use and cultural identity

Table 4 shows the correlation coefficient between the main variables used in this study. A-K stand for motivation for entertainment and recreation, information acquisition, connotation, socializing, self-presentation, mimesis fulfilling social need, user-generated content, online interaction intensity, culture behavior intentions, cultural emotion, and cultural cognition, respectively. ** denotes a significant relationship at the 0.01 significance level (bilaterally), while * denotes a significant relationship at the 0.05 significance level (bilaterally). From the Pearson correlation coefficients of the table, it can be seen that in terms of the motives for using short videos for international students coming to China, different motives for using short videos and the audience's personal Chinese cultural identity are all more or less correlated. Of these, the motive of entertainment has been found to be highly positively associated with the intention of engaging in Chinese cultural behavior (0.221**), Chinese cultural emotion (0.289**) and Chinese cultural awareness (0.322**). Similarly, there is high association between information access motivation and cultural behavioral intention (0.446**), cultural affect (0.196**) and cultural cognition (0.276**). It has been found that culminating motive is significantly positively associated with cultural behavior intention (0.375**), cultural emotion (0.273**) and cultural cognition (0.163*). The findings of the study suggest that with increasing entertainment motivation, information access motivation and meaning motivation for the use of short video apps, international students' perception of Chinese cultural identity will also deepen. Motivation for social interaction (0.415**), self-presentation motivation (0.453**) and mimetic social need (0.518**) have been found to be significantly positively associated with cultural behavioral intention. With increasing motivation for social interaction and self-presentation and degree of satisfaction of mimetic social needs, their level of learning, engagement and imitation of Chinese culture will increase accordingly.

Table 4: The main research focus is on the correlation matrix of variables

	A	B	C	D	E	F	G	H	I	J	K
A	1	0.312**	0.294**	0.251**	0.266**	0.163*	0.189*	0.256**	0.221**	0.289**	0.322**
B		1	0.551**	0.612**	0.573**	0.527**	0.599**	0.568**	0.446**	0.196**	0.276**
C			1	0.523**	0.389**	0.436**	0.387**	0.475**	0.375**	0.273**	0.163*
D				1	0.566**	0.622**	0.574**	0.643**	0.415**	0.142	0.13
E					1	0.643**	0.671**	0.655**	0.453**	0.012	0.119
F						1	0.657**	0.644**	0.518**	-0.088	0.089
G							1	0.785**	0.583**	-0.049	0.116
H								1	-0.088	-0.059	0.136
I									1	0.000	0.000
J										1	0.000
K											1

3.2.4 The Impact of Short Video Usage Behavior on Chinese Cultural Identity

The regression analysis between short-video social media usage and Chinese cultural identification among overseas students in China is shown in Table 5. The data is displayed as standardized regression coefficient β, *p<0.05, **p<0.01,*** p<0.001. The results of the regression analysis show that overseas students' use of short videos on social media in China has a greater capacity to explain Chinese cultural identity. Comparatively speaking, short-video social media use has the strongest explanatory power for Chinese cultural behavioral intention (adjusted R-squared = 42.1%), and the explanatory power for Chinese cultural cognition and Chinese cultural emotion is closer (adjusted R-squared = 25.3% and 26.9%, respectively). As far as the control variables are concerned, Chinese culture awareness is positively and significantly related to age (β =0.236*, p<0.05) and Chinese language proficiency (B=0.555***, p<0.001), that is to say, the older the age of the international students in China, and the higher the Chinese language proficiency of them, the higher the level of Chinese culture awareness they have. In addition, gender, whether they come from Belt and Road countries, current educational background, major and length of stay in China were not found to have a significant effect on Chinese cultural identity. When controlling for demographic variables such as gender and age, the effects of short-video social media use among international students in China on their Chinese cultural identity can be summarized as follows:

(1) Model I: Chinese cultural cognition is substantially influenced by the motivations for enjoyment (B=0.258**, p<0.01) and information (B=0.212*, p<0.05). This indicates that overseas students who are more motivated to learn and engage in leisure activities have a deeper comprehension of Chinese culture.

(2) Model II: Chinese cultural feeling is considerably favorably impacted by the number of friends on the short video (β=0.289**, p<0.01), enjoyment motive (B=0.18*, p<0.05), information acquire motive (B=0.197*, p<0.05), and conclusion motivation (B=0.177*, p<0.05). This implies that the more friends overseas students have on short video social media, the more motivated they are to watch these videos for amusement, knowledge, and significance, as well as the more deeply they love Chinese culture.

(3) Model III: The time spent on China-related short video content per day (β =0.109*, p<0.05) and the frequency of use of users' original content production of short videos (B=0.225*, p<0.05) have a significant positive effect on Chinese cultural behavioral intention. In other words, the longer international students in China watch or create China-related short videos every day, and the more frequently they engage in the use of original content production of short videos, the stronger their Chinese cultural behavioral intention is, and the deeper they

learn, participate in or imitate Chinese culture.

Table 5: Regression Analysis of Social Media Usage and Chinese Cultural Identity

Predictor variable	Cognition of Chinese Culture I	Chinese Cultural Sentiment II	Intention of Chinese Cultural Behavior III
Population variable	-0.02	0.08	0.108
Gender (whether male)	0.236*	0.046	-0.171
Age	-0.107	-0.237	0.168
From the country (whether it is a belt and road)	-0.007	0.04	0.051
Education background	-0.059	0.163	-0.104
Major (whether it is arts)	-0.025	-0.053	0.007
Hours in China	0.555***	-0.181	-0.048
Chinese level	-0.02	0.08	0.108
Adjust R^2	11.36%	5.3%	18.2%
The use of short video social media			
The number of friends on short videos	0.025	0.289**	0.006
The daily usage duration of short videos	0.007	-0.114	0.002
The daily usage duration of short videos related to China.	-0.001	0.069	0.109*
Motivation for Using Short Videos			
Entertainment motivation	0.258**	0.18*	0.108
Get information motivation	0.212*	0.197*	0.061
Culcated motive	0.052	0.177*	0.058
Social interaction motivation	-0.06	0.134	-0.054
Self-presentation motivation	-0.053	0.043	0.059
The satisfaction of the proposed social needs	0.062	-0.138	0.083
Short video content production			
The frequency of user original content production and usage	-0.015	-0.063	0.225*
Short video social relationships			
The intensity of online interaction through short videos	0.115	-0.063	0.123
Adjust R^2	25.3%	26.9%	42.1%
F	4.251***	4.395***	7.251***

In conclusion, different international students living in China would have different reasons for watching short videos, which would have varying degrees of impact on their Chinese cultural identity. While personalization frequency on audience-oriented short videos will positively affect Chinese cultural identity, entertainment, learning from content, and comprehending the deeper meaning of content will significantly positively affect Chinese cultural identity.

4 Conclusion

This paper builds a portrait model for international students in China on short video platforms, proposes a video recommendation system using deep reinforcement learning, and conducts experimental studies in order to investigate the relationship between the use of short video social media and the recognition of Chinese culture by international students in China from the perspective of the intelligent approach to the communication of Chinese culture. The experimental conclusions drawn from the article are:

(1) The average probability of users watching the recommended Chinese cultural communication videos based on this paper's method is 0.76, which is significantly higher than that of the short video recommendation system with randomly inserted Chinese cultural communication videos. The Chinese culture dissemination video recommendation algorithm proposed in this paper significantly reduces the number of times users exit the short video APP after the recommended Chinese culture dissemination video, and significantly increases the probability of users watching the recommended Chinese culture dissemination video.

(2) Through empirical research, it is found that different motives for using short videos among international students in China will have different degrees of influence on their Chinese cultural identity. For example, the motives of entertainment and recreation (B=0.258**,p<0.01) and the motive of obtaining information (B=0.212*,p<0.05) have a significant positive impact on Chinese cultural perceptions of international students in China.

References

[1] Li, X. (2015). International students in China: Cross-cultural interaction, integration, and identity construction. Journal of language, identity & education, 14(4), 237-254.

[2] Ahmad, A. B., & Shah, M. (2018). International students' choice to study in China: An exploratory study. Tertiary Education and Management, 24(4), 325-337.

[3] Zhang, W., & Li, Y. (2023). Research on Promoting the Spread of Traditional Chinese Medicine Culture at Home and Abroad through International Chinese Language Education. Academic Journal of Humanities & Social Sciences, 6(15), 19-23.

[4] Chen, X. (2024). Research on the Practice of Spreading Chinese Traditional Culture Abroad through Non-Mainstream Media. Academic Journal of Humanities & Social Sciences, 7(4), 67-72.

[5] Khasawneh, S., & Ahmad, M. (2023). The Potential Of Ai In Facilitating Cross-Cultural Communication Through Translation. Journal of Namibian Studies, 37.

[6] Shadiev, R., Sun, A., & Huang, Y. M. (2019). A study of the facilitation of cross-cultural understanding and intercultural sensitivity using speech-enabled language translation technology. British Journal of Educational Technology, 50(3), 1415-1433.

[7] Zhou, Y. (2024). Global transmission of Chinese culture from the perspective of cross-cultural communication. Philosophy and Social Science, 1(4), 10-20.

[8] Yang, C., & Mustafa, S. E. (2024). The Application and Challenges of Cross-Cultural Translation and Communication in the National Museum of China under the Perspective of Artificial Intelligence. Eurasian Journal of Applied Linguistics, 10(3), 214-229.

[9] Liang, Y. (2019). Translation of traditional Chinese culture and its modern cross-cultural communication. International Journal of Linguistics, Literature and Translation, 2(4), 290325.

[10] Yang, C., & Cui, F. (2024). Multimodal mediation in translation and communication of

Chinese museum culture in the era of artificial intelligence. Corpus-based Studies across Humanities, 1(1), 51-77.

[11] Xu, J., & Liu, Z. (2025, May). Immersive Storytelling Empowering Cultural Heritage Transmission: A Case of Xiaonan Village. In International Conference on Human-Computer Interaction (pp. 128-142). Cham: Springer Nature Switzerland.

[12] Cai, W., & Liu, Y. (2022). The value of immersive media in expanding chinese public cultural participation and its realization path from the perspective of cultural education. Frontiers in Psychology, 13, 915913.

[13] Huang, G., & Zhong, J. (2025). The Reshaping and Effect Evaluation of Immersive Communication on Museum Cultural Experience. In SHS Web of Conferences (Vol. 213, p. 02041). EDP Sciences.

[14] Heppner, P. P., & Wang, K. T. (2014). A cross-cultural immersion program: Promoting students' cultural journeys. The Counseling Psychologist, 42(8), 1159-1187.

[15] Shih, Y. C. (2015). A virtual walk through London: Culture learning through a cultural immersion experience. Computer Assisted Language Learning, 28(5), 407-428.

[16] Wang, X., & Kim, C. S. (2025, May). Research on the Reconstruction of Artistic Conception of Traditional Chinese Landscape Painting Based on VR Immersive Interaction. In International Conference on Human-Computer Interaction (pp. 341-356). Cham: Springer Nature Switzerland.

[17] Yan, L. (2024). Research on Personalized Cultural Learning Platform Based on Collaborative Filtering and Popularity Recommendation. International Journal of High Speed Electronics and Systems, 2540065.

[18] Zhan, X. (2025). Artificial Intelligence in the Cultural Industry: Applications and Challenges. Innovation in Science and Technology, 4(1), 62-68.

[19] Su, X., Sperlì, G., Moscato, V., Picariello, A., Esposito, C., & Choi, C. (2019). An edge intelligence empowered recommender system enabling cultural heritage applications. IEEE Transactions on Industrial Informatics, 15(7), 4266-4275.

[20] Wang, P. (2022, October). Personalized Intelligent Recommendation of Cultural Resources Based on User Preference Collaborative Filtering Algorithm. In 2022 IEEE 2nd International Conference on Data Science and Computer Application (ICDSCA) (pp. 1361-1365). IEEE.

[21] Wang, Q. (2022). The Application of Personalized Recommendation System in the Cross-Regional Promotion of Provincial Intangible Cultural Heritage. Advances in Multimedia, 2022(1), 5811341.

[22] Huang, W., Xie, B., & Liao, X. (2021). Personalized Information Recommendation for Chinese Paper Cutting Culture Heritage. In Fuzzy Systems and Data Mining VII (pp. 130-139). IOS Press.