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

A Practical Study on Embedding Traditional Cultural Education Elements in One-Stop Student Communities

Qianyu Wang[1,*]

[1] Nanjing University of Industry Technology, Nanjing, Jiangsu, 230000, China

SUMMARY: *The research focuses on solving the challenges of traditional cultural educational resources in digital applications, such as dull generation effects, fragmented knowledge organization, and cold-start recommendation difficulties. Firstly, a style migration model based on adaptive instance normalization (AdaIN) is proposed. Then, we disassemble and associate cultural resources through knowledge elements to construct a structured knowledge graph containing more than 10 kinds of granularity, such as terms and events. Finally, a one-stop community learning system based on the multimodal meta-learning recommendation algorithm (UMMeLE) is designed. The statistics of 500 traditional cultural resources found that although the overall quality is fair, with most of the resources rated >70, there is a typical long-tail effect, with up to 70.4% of the resources having less than 1,000 views and only 17.2% of the resources having a download rate of more than 20%. In this paper, the multimodal meta-learning UMMeLE algorithm reduces the prediction error RMSE to as low as 0.697 on the real TCE dataset.*

KEYWORDS: *traditional culture education; adaptive instance normalization; multimodal meta-learning; one-stop communities; knowledge graphs*

1 Introduction

The 2014 circular of the Ministry of Education on the issuance of the Guidelines for Improving Education in Chinese Outstanding Traditional Culture clearly states that strengthening education in Chinese outstanding traditional culture is an important way to build a system for the transmission of Chinese outstanding traditional culture and to promote cultural inheritance and innovation, and that it is an important foundation for fostering and practicing socialist core values and for implementing the fundamental task of establishing moral character.

At present, traditional culture education faces a double dilemma. On the one hand, under the background of globalization, the multi-path infiltration of western culture makes the youth group's memory and perception of traditional culture weak; on the other hand, the marginalization of the status of traditional culture education, the incoherence of the educational content system, and the insufficient interactivity of the teaching mode lead to unsatisfactory educational effects, and students' absorption of cultural content only exists in short-term memory, and they do not have a profound experience of the cultural charm [1-5]. Ding and Lv [6] (2020) address the problem of low student satisfaction in traditional Chinese culture education courses and suggest optimizing traditional culture education courses through four stages: creating a traditional culture learning atmosphere, reshaping course content, equipping cultural resources and professional teachers, and summarizing implementation experience.

*15895820288@163.com
https://doi.org/10.65102/is2026153 Published: 30 April, 2026

Socialist core values are an important part of cultivating college students' values, and they are also a highly condensed and vivid display of contemporary Chinese spirit. Chen and Tang [7] (2024) reported that the Chinese culture to cultivate the values of college students need to optimize the classroom teaching mode, build educational practice carriers, shape the “campus culture”, enrich the social practice, and open the network classroom. Zeng et al [8] (2025) pointed out that the identity of some NHBs has shifted from skillful artisans to NHB educators, who have become curriculum designers through media integration and educational participation, linking to contemporary educational needs. Zhang et al [9] (2025) constructed an interactive platform based on digital technology for Chinese Xiannong Shentan, which transforms cultural heritage from static to dynamic, promotes the interactive teaching of traditional agricultural culture, and satisfies the interactivity of traditional cultural education. Wu et al [10] (2025) designed a virtual reality learning system for the Amis people in Taiwan using virtual reality and drone technology to integrate the Amis culture with the local environment to improve student learning while protecting the environment and passing on the national culture. This kind of regional cultural teaching participation opens up a new path for the personalization, living and diversification of traditional cultural education. In the face of the above background, the one-stop student community, as a set of students' daily life, learning and communication, organizational interaction and practice and other multiple functions, is embodying the characteristics of living, personalization and diversification, which is an appropriate solution to the dilemma of traditional culture education.

One-stop student community is an important platform and main position for teaching innovation and practice in the context of “Internet + education”, which can be used as an important carrier and intermediary to enhance the effectiveness of students' ideological and political awareness and cultural awareness, and to improve the level of students' comprehensive quality [11-14]. Integrating traditional cultural education elements into one-stop student community construction provides new ideas and new ways for one-stop student community construction on the one hand; on the other hand, it invisibly practices the relevant contents of ideological and political education and implements the important concept of “three-pronged education for all” [15-18]. Lu et al [19] (2022), in order to encourage the local community to participate in ICH preservation, developed a Craft+Make workshop to engage students from the community through creative design oriented to ICH. Chen and Chen [20] (2025), from the perspective of integrative curriculum education pathway, integrated Chinese Dragon Boat Festival culture into the practice of Dongguan universities by organizing festivals, competitions, community participation and other activities to promote students' active participation. Therefore, embedding traditional culture education elements in the one-stop student community building platform allows students to experience the charm of multi-traditional culture in the “second classroom”, stimulates national pride and identity, and strengthens national and cultural self-confidence, in order to strengthen the education of Chinese excellent traditional culture.

The research is centered on two aspects, one is the artistic generation of cultural elements and the other is the intelligent recommendation of learning resources. Firstly, based on the fast style migration network, traditional artistic styles are applied to images. By fusing batch normalization, instance normalization and conditional instance normalization, adaptive instance normalization achieves style transformation to any style image. The innovative fusion of histogram loss and improved Gram matrix loss allows the model to capture styles while preserving the inherent order and details of cultural elements. Then the knowledge meta-linking theory is introduced to organize the generated high-quality cultural resources into a knowledge graph. These knowledge meta-links are associated to form a three-dimensional interconnected knowledge network through extraction-citation-linking-characterization. Further focusing on the design of an academic support system in a one-stop student community. The system automatically analyzes students' career plans, competency shortcomings and interest trends, and from the constructed cultural resource base and knowledge network, it accurately matches their learning contents, plans their growth paths, and provides them with intelligent tutoring. Finally, the multimodal meta-learning recommendation algorithm (UMMeLE) is highlighted. The baseline model MeLU is optimized and improved by attentional feature enhancement, dynamic regularization constraints, multi-objective joint optimization and adaptive feature fusion, while dynamically fusing multimodal features such as video, audio, and text, and drawing on similar user behaviors to quickly obtain user learning preferences. It can quickly understand the user and efficiently match the resource recommendation at the same time.

2 Deep learning-based method for fusion generation of traditional cultural elements

2.1 Fast Style Migration Network

2.1.1 Batch standardized BN

Batch Normalization (BN) ensures that the data distribution is the same during the training of the network model.BN stabilizes the outputs of each layer of the filter in a certain distribution and solves the problem of vanishing gradients. The steps of BN are depicted in Fig. 1: first, the output data of a layer is gradually normalized, and then the value h_1^l calculated after activation is passed to the next layer through steps such as translation and scaling.

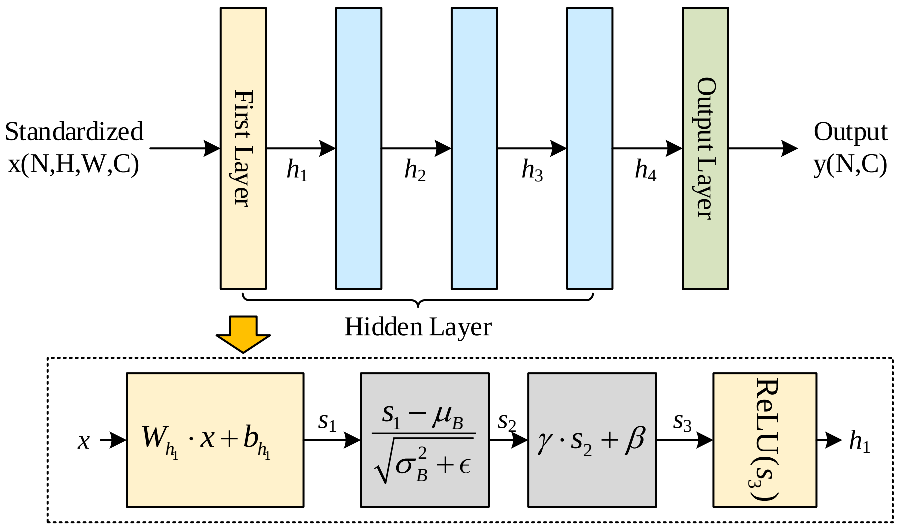

Figure 1: Specific process of batch standardization

2.1.2 Example standardization IN

Instance normalization works on a single image by finding the mean and standard deviation of all the pixels of a single image, whereas batch normalization is the batch processing of all the pixels of a set of images to compute their mean and variance. Figure 2 shows the difference between batch normalization and instance normalization.

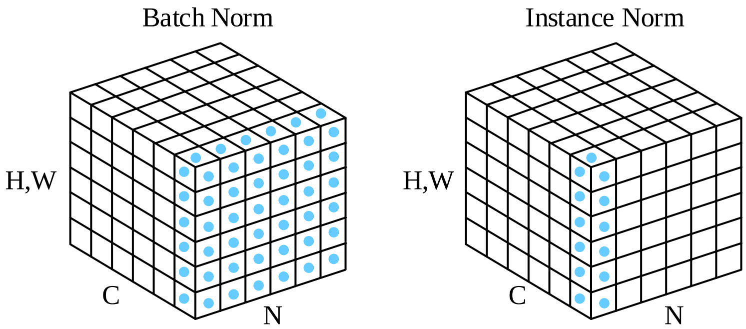

Figure 2: Difference between batch standardization and case standardization

Notate the input image as $[N, C, H, W]$, where N is the batch set size, H, W are the rows and columns, and C is the number of channels. The places marked with blue dots in the above figure are the areas where normalization is performed. Batch normalization means that a neural network uses normalization to make the distribution of data consistent during training, and exponential decay to change the mean and variance during testing.

2.1.3 Conditional Instance Normalization CIN

Both BN and IN are single style migration networks. There are some commonalities between styles, so the same parameters can be used for the shared parts between styles. Conditional Instance Normalization (CIN) is able to migrate multiple styles by changing the parameters γ and β of the instance normalization layer. m Different styles correspond to m different sets of normalization parameters, and m sets of translation and scaling parameters are calculated. The image with m different styles can be obtained by feeding forward once.

2.1.4 Fast Style Migration Network Architecture Based on Adaptive Normalization AIN

The data distribution characteristics of the network layer are closely related to the style, x and y are the values obtained from the content image and the style image after a certain layer of the network, and the distribution characteristics corresponding to this output are uniformly denoted as $(\mu(x), \sigma(x)), (\mu(y), \sigma(y))$, so that the statistical parameter of the output value of the content image tends to be the same as the value of the output statistics of the style image:

$$x' = \sigma(y)\left(\frac{x - \mu(x)}{\sigma(x)}\right) + \mu(y) \quad (1)$$

Realizing the effect of migrating different styles only requires changing the values of γ and β. The architecture of the fast style migration network proposed in the study is shown in Fig. 3.

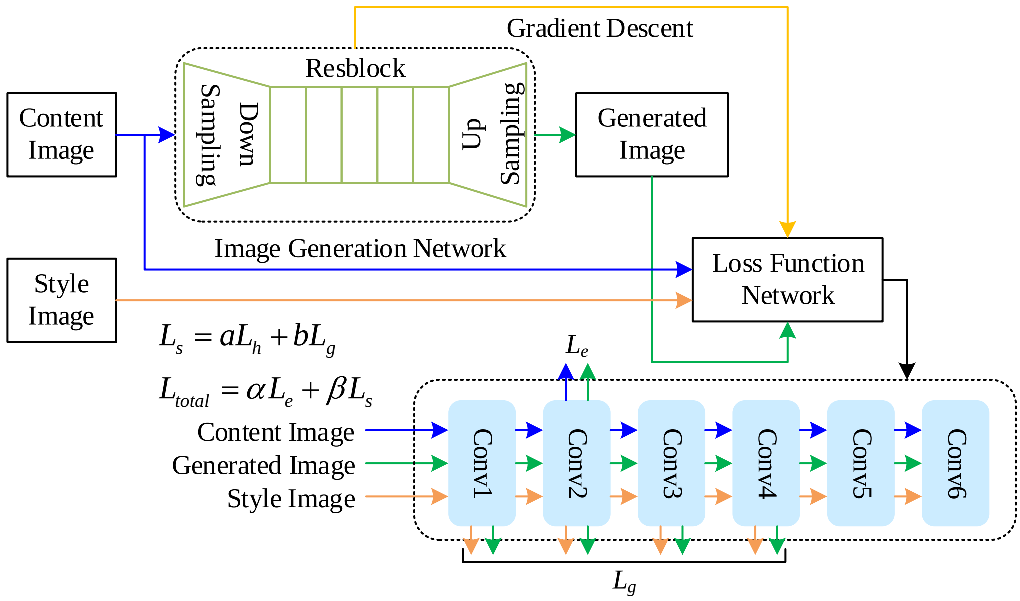

Figure 3: Fast style migration network architecture

The framework of this paper is categorized into image generation network and computational loss network. The generative network is a forward and backward network for style transformation and the loss function is used to constrain the data during training. A pre-trained partial VGG network is used to perform the downsampling operation to transfer the style image and content image from the image space to the feature space.

Normalization layers based on batch normalization and instance normalization can only be processed for single style images, while conditional instance normalization can generate several different styles at a time, but it is still limited in the number of styles it can generate. In this paper, we propose an adaptive normalization strategy to achieve style conversion for any style image.

2.2 Artistic Generation of Style Migration of Chinese Traditional Cultural Elements

On the basis of constructing a fast style migration network architecture based on adaptive normalization, this technique is applied to the artistic generation of traditional Chinese cultural elements. Because the effect of style migration is highly dependent on the design of the loss function, this section will focus on how to construct a loss function system applicable to traditional Chinese cultural elements.

2.2.1 Content Loss and Style Loss Expression

A commonality that usually exists in traditional Chinese culture is that its content semantic information is more written, and it is not easy to find its correspondence to a certain fixed expression, and the use of GRAM matrix alone is slightly lacking. Therefore, in this paper, the histogram loss is added to the loss function to match the image obtained after feature mapping with the style image, and each individual feature is matched again in the backpropagation process in the convolutional network.

S is the input stylized image, O is the output image, O_i^l is the feature mapping of the ith feature in the lth layer, the obtained feature mapping is taken to match the histogram of the stylized image, and its recombination is denoted by $R(O_i^l)$ to indicate the feature mapping obtained after recombination, the number of layers is L, and the proportion of the l th layer in which the loss of the histogram occurs is γ_l. The required histogram loss is:

$$L_h = \sum_{l=1}^{L} \gamma_l \left\| O_i^l - R(O_i^l) \right\|_F^2 \tag{2}$$

The derivatives of the reorganized feature mappings are all zero-valued in their backpropagation. With respect to the Gram matrix, the value a_{ijk}^l in each channel in the convolutional neural network denotes its output at position (i, j, k) in layer l.

$$G_{kk'}^l = \sum\nolimits_{i=1}^{n} \sum\nolimits_{j=1}^{n} a_{ijk}^l a_{ijk'}^l \tag{3}$$

G is a matrix of size $k*k$ and k is the number of channels. $G_{kk'}$ is then the value of position (k, k') in the Gram matrix. In this paper, we use the transformed Gramian to compute the inner product of a feature mapping with its spatially transformed feature mapping. The spatial transformation T is equivalent to computing the similarity between a local feature and its neighboring features, and shifting the feature mapping to the right by δ pixels in the horizontal direction yields $x_{+,\delta}$. The correlation between position (i, j) and position $(i, j+\delta)$ is computed, and the correlation of neighboring pixels in the vertical direction is also computed in addition to the horizontal direction, and the final loss value expression is as follows:

$$L_{gramian} = \frac{1}{2}\left(\left\| G_{x,\delta}^l - A_{x,\delta}^l \right\|_F^2 + \left\| G_{y,\delta}^l - A_{y,\delta}^l \right\|_F^2 \right) \tag{4}$$

$A_{x,\delta}^l$ is its Gramian matrix in the horizontal direction, and $A_{y,\delta}^l$ is its Gramian matrix in the vertical direction. The pre-trained VGG network is used to extract the features and the feature mapping is computed, which is mainly divided into content loss function and style loss function. Where the style loss function consists of two parts: histogram loss and gramian loss, a is the proportion of histogram loss in the total loss function, and b is the proportion of gramian loss in the total loss:

$$L_s = aL_h + bL_g \tag{5}$$

The content loss function does L2 loss computation on the mapping of the extracted features in the VGG network with the features extracted from the adaptive normalization layer. The style loss function mainly does L2 loss computation on the mean and variance of the style image and the original image.

2.2.2 Implementation of the gradient descent algorithm

The mean square error cost function is used as a loss function to calculate the

$$J(\Theta) = \frac{1}{2m} \sum_{i=1}^{m} \left(h_\Theta(x^{(i)}) - y^{(i)} \right)^2 \tag{6}$$

m is the total number of test data in the set; the coordinates of this data point corresponding to the y axis are noted as y;

The formula for calculating the output value is as follows:

$$h_{\Theta}(x^{(i)}) = \Theta_0 + \Theta_1 x_1^{(i)} \tag{7}$$

For the loss function different variables have to be differentiated separately to be able to calculate the value of the gradient.

$$\nabla J(\Theta) = \left\langle \frac{\partial J}{\partial \Theta_0}, \frac{\partial J}{\partial \Theta_1} \right\rangle \tag{8}$$

$$\frac{\partial J}{\partial \Theta_0} = \frac{1}{m} \sum_{i=1}^{m} \left(h_{\Theta}(x^{(i)}) - y^{(i)} \right) \tag{9}$$

$$\frac{\partial J}{\partial \Theta_1} = \frac{1}{m} \sum_{i=1}^{m} \left(h_{\Theta}(x^{(i)}) - y^{(i)} \right) x_1^{(i)} \tag{10}$$

Let the input image be x and y be the target image obtained after computation by the image generation network. The target image y is de-approximated to the content image Y^c in terms of its content, using a content loss function $L_{content}$ to represent the iterative optimization of the result obtained from the content image at the relu4_2 layer in the VGG-19 network. Next, a style loss function L_{style} is defined for the style image so that it is also iteratively optimized to get the minimum value that tends to zero, and these two loss functions are summed up to be the total loss function L_{total}, which is finally used to train the generation of the desired target migration image.

The expression of the prediction function is as follows:

$$h_{\Theta}(x^{(i)}) = \Theta_0 + \Theta_1 x_1^{(i)} \tag{11}$$

The calculation of the two variables requires adding one dimension to each point, fixed at 1, and multiplying it by Θ_0. The result of the matrixization is obtained:

$$(x_1^{(i)}, y^{(i)}) \rightarrow (x_0^{(i)}, x_1^{(i)}, y^{(i)}) \; with \; x_0^{(i)} = 1 \forall i \tag{12}$$

$$J(\Theta) = \frac{1}{2m} (X\Theta - \vec{y})^T (X\Theta - \vec{y}) \tag{13}$$

$$\nabla J(\Theta) = \frac{1}{m} X^T (X\Theta - \vec{y}) \tag{14}$$

Next the gradient descent iterations are computed using the mean square error cost function.

2.3 Knowledge service design for intermediary roles

Through the optimization experiments of the loss function in the style migration of traditional Chinese cultural elements, we found that simply relying on the image generation network alone is not enough to achieve a deeper understanding and expression of cultural connotations. In this regard, a more structured knowledge representation is introduced to support the semantic organization of cultural elements.

The core process of the study for knowledge meta-mining is extraction - citation - linking - characterization, which completes the whole process from the resource platform to the user interface. First, the knowledge elements are extracted from the existing learning content. Secondly, the extracted knowledge elements are indexed; then the knowledge element links are established through the knowledge structure dependencies between the attributes of the knowledge elements and constitute a knowledge network; finally, the knowledge elements are linked to the mobile learning resources to which they belong, and visualized and characterized.

2.3.1 Knowledge meta-extraction

Knowledge element extraction is to separate the knowledge elements in the structure of subject knowledge one by one according to the syllabus and course objectives, and to divide the knowledge elements according to their attributes. The general steps of knowledge element extraction are: firstly, all the knowledge points of the subject knowledge are determined according to the syllabus and course objectives, and then the subordinate knowledge elements are separated from the knowledge points. Secondly, the attributes of navigation information and description information are divided for each knowledge element; finally, the navigation information of the knowledge element is content analyzed to get the topology of the relationship between knowledge elements and knowledge elements. The topology of knowledge element extraction is shown in Figure 4.

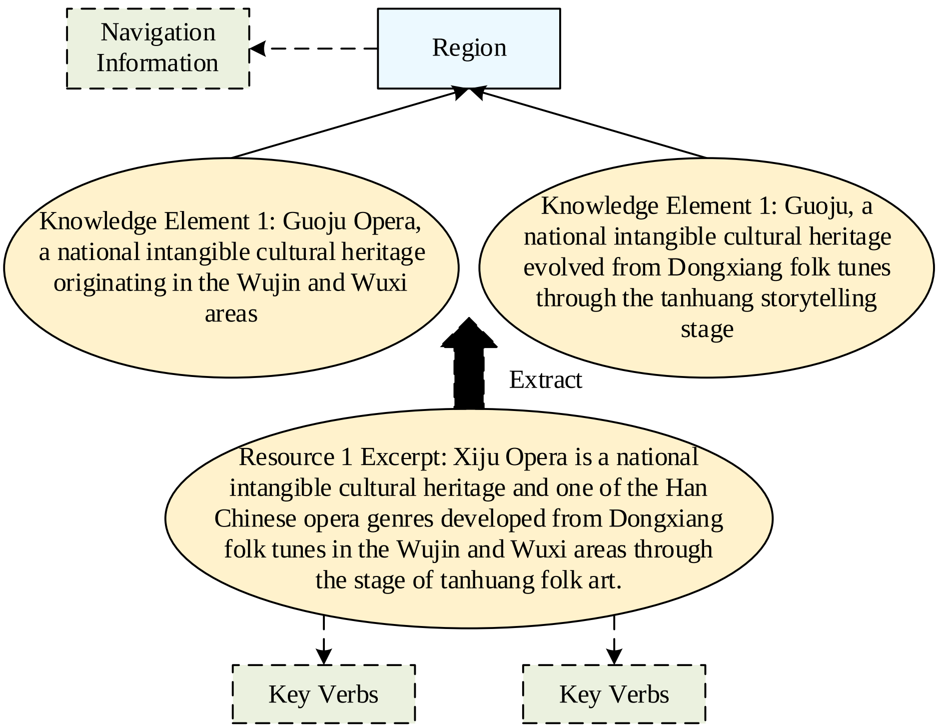

Figure 4: Knowledge element extraction decomposition

2.3.2 Knowledge meta-representation

Knowledge element labeling is the process of labeling the structural features of a knowledge element as its basic unit. Given the rules of knowledge element labeling, the external labeling of knowledge elements is superior, subordinate, related, and navigation, and the internal labeling of knowledge elements is name, attribute, law, operation, example, and source. Among them, the superordinate is the upper knowledge element of the knowledge element, the subordinate is the lower knowledge element of the knowledge element, the navigation is the link of the relationship between the knowledge elements, and the multidimensional elements are labeled dynamically for different knowledge elements.

2.3.3 Knowledge meta-links

The evolutionary structure of knowledge is the navigation transformation of knowledge elements and wizard information, $K(S)+N[K(E)+K(S)]=K[S+\Delta S]$, where $K(S)$ denotes the knowledge system, $K(E)$ denotes the knowledge elements, and N denotes the wizard information, and the structure of the knowledge element linkage is shown in Figure 5. The knowledge structure is composed of knowledge elements, and the navigation transformation of knowledge elements and wizard information causes the value-added effect of the knowledge structure. Learning is a kind of reconstruction and establishment of relationships and nodes in the knowledge network structure. Knowledge meta-link theory emphasizes that knowledge structure has evolutionary significance, and there is a value-added transformation law in the combination of wizard information and knowledge elements.

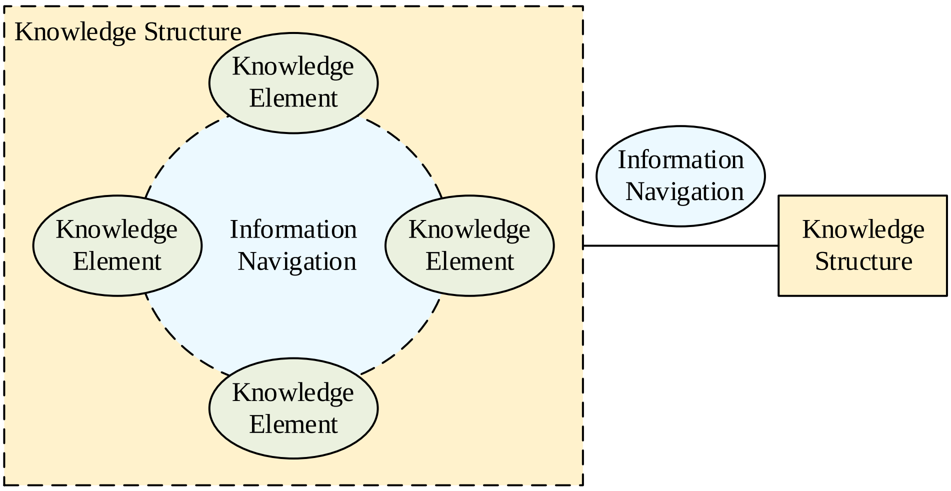

Figure 5: Knowledge element link structure

2.3.4 Knowledge meta-representation

Knowledge points and non-good questions are the smallest resource nodes in the visual representation of resources, and several knowledge element nodes can be combined to form a resource node, which is linked by the wizard information. According to the degree of relevance between resources and knowledge elements, the attributes of “original relevance”, “extended relevance” and “discovery relevance” are introduced. Taking one of the wizard information as the center, the topology of knowledge elements and resources may be composed, and the network topology of resource nodes and knowledge element nodes visualized is shown in Figure 6.

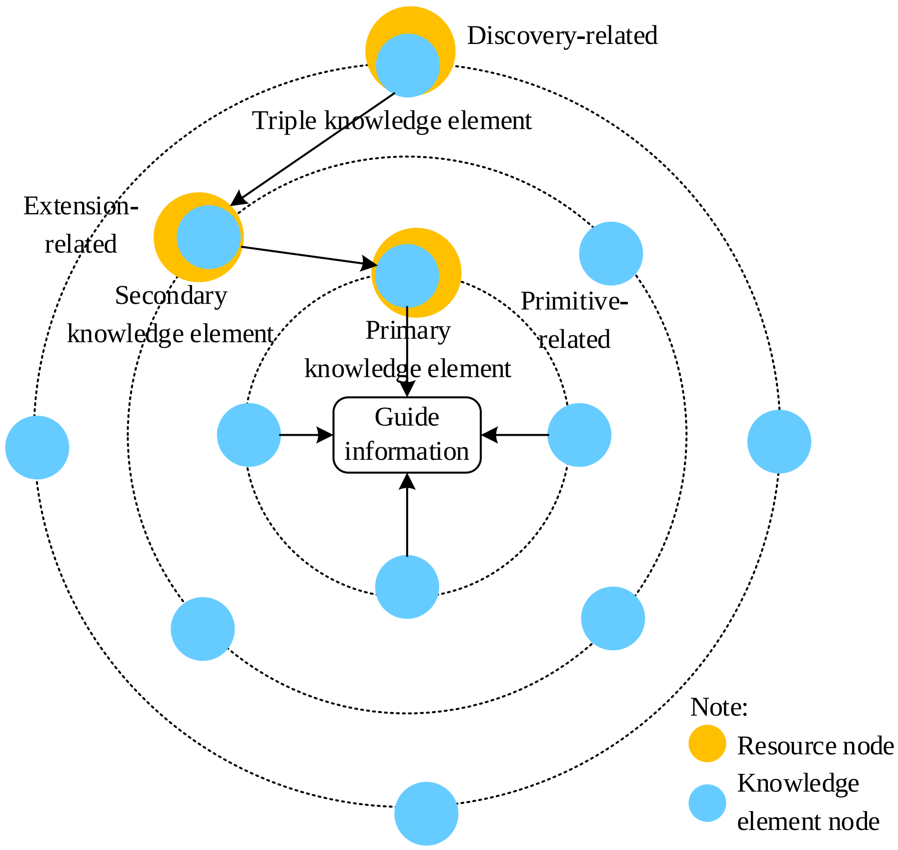

Figure 6: The network topology of resource nodes and knowledge element nodes

Among them, the knowledge element directly pointing to the wizard information is the first level knowledge element, and the resource node containing the first level knowledge element is the original relevance resource; the knowledge element directly pointing to the first level knowledge element and indirectly pointing to the wizard information is the second level knowledge element, and the resource node containing the second level knowledge element without the first level knowledge element is the extended relevance resource; by analogy, the resource node containing the third level knowledge element is the discovery relevance resource The resource nodes that contain tertiary knowledge elements are discovery-related resources.

2.4 Design of Academic Support Systems in One-Stop Student Communities

After establishing a traditional culture content organization system based on knowledge elements, this section focuses on the “one-stop student community” as an educational environment, designing a system architecture that integrates the knowledge element services and academic support functions, and realizing the application of personalized learning paths from the generation of cultural resources to the application of personalized learning paths.

2.4.1 System architecture design

In order to embed traditional culture education into the whole process of students' growth, this study designs an intelligent academic support system based on the three-layer architecture of “data layer-application layer-user layer”. The system integrates traditional cultural resources with modern academic development needs to realize the educational goal of unity of knowledge and action.

Data Layer: Construct a traditional cultural literacy database. Integrate students' behavioral data from traditional culture courses, online knowledge breakthroughs and other activities, and include their digital works such as Chinese paintings and poems.

Application layer: Deploy AI algorithm models, such as the traditional culture learning notes analysis model based on natural language processing and the comprehensive ability assessment model integrating cultural literacy, to achieve intelligent diagnosis of learning conditions and personalized resource recommendation.

User layer: design differentiated interfaces. The student side highlights traditional culture learning maps and portfolios; the teacher and counselor side strengthens the cultural literacy growth warning and home-school collaborative parenting functions, jointly guiding students' cultural identity and value shaping.

2.4.2 Functional module design

(1) Intelligent Data Collection and Analysis Module

The system automatically tracks the depth and frequency of students' participation in traditional cultural activities and builds a personal cultural literacy portrait. When it recognizes that students consistently lack records of practical sessions or have bottlenecks in creativity, it will push an alert to the tutor, prompting targeted tutoring.

(2) Personalized Learning Path Planning Module

Based on students' interests and shortcomings, the system dynamically generates growth programs that integrate cultural learning. For example, for students interested in traditional crafts, the system intelligently connects personalized progression paths and combines tasks with time management suggestions.

(3) Intelligent Tutoring and Feedback Module

Built-in intelligent assistants answer questions about traditional cultural knowledge and provide initial approval of students' learning tips or creative instructions. The system regularly generates radar charts of cultural literacy competence, visualizing students' strengths and weaknesses in knowledge understanding, skill mastery, and creative application, forming a closed loop of intelligent assessment - manual intervention - reflection and enhancement of tutoring.

(4) Collaborative Nurturing Management Module

As the core carrier of collaborative education in the community, it builds a four-way linkage platform of "counselors, cultural teachers, non-geneticists and parents". Parents can view their children's growth trajectories and portfolios of traditional cultural activities online, thus realizing the cultivation of humanistic literacy for all students, in all processes and in all aspects.

2.5 Multimodal meta-learning recommendation algorithm

The operation of academic support system relies on the accurate matching of user behavior and resource content, for which this section proposes a recommendation algorithm that integrates multimodal features and meta-learning mechanisms. In this study, a four-level optimization improvement on the meta-preference estimation model (MeLU) is carried out to further alleviate the data sparsity problem by aiding information injection with multimodal features and similar user features.

2.5.1 Meta-Learning Recommender Network Improvement

The meta-preference estimation model (MeLU) mainly consists of an input layer with user and item embeddings, a decision layer simulated by a multilayer neural network, and an output layer. It is investigated to enhance the MeLU recommendation performance through attentional feature enhancement, dynamic regularization constraints, multi-objective joint optimization and adaptive feature fusion. The model structure is shown in Fig. 7.

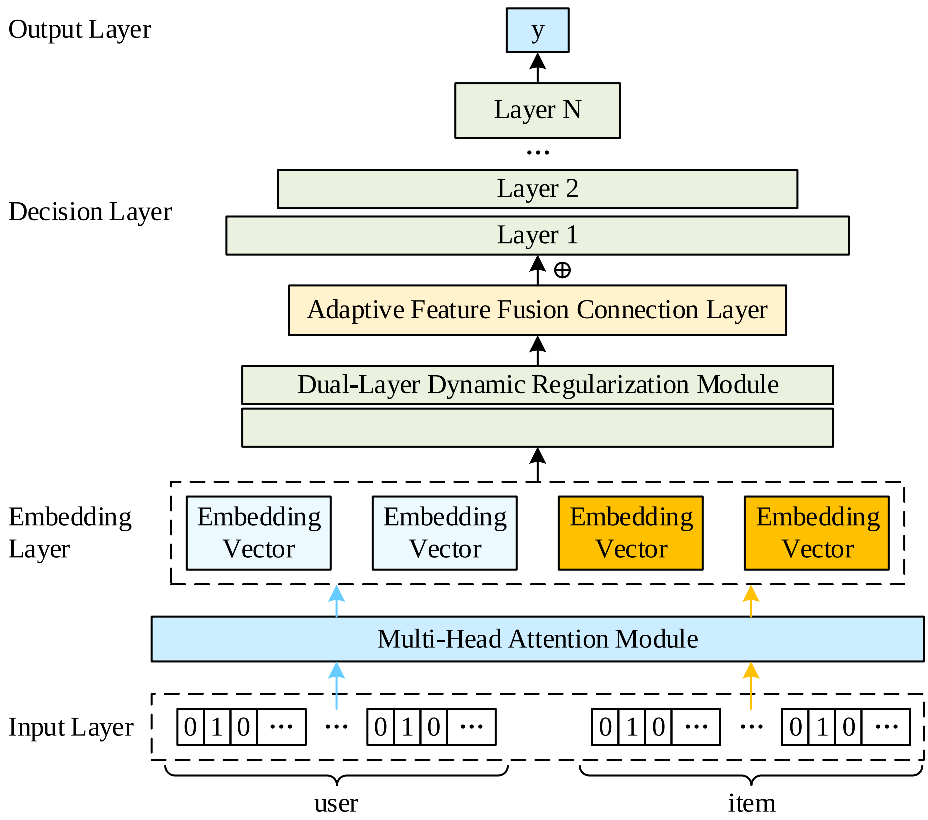

Figure 7: Improved meta-learning recommendation network

(1) Enhanced multi-head attention characteristics

Introduce an improved multi-head attention mechanism. Define the query matrix $Q = UW^{Q}$, the key matrix $K = IW^{K}$, and the value matrix $V = IW^{V}$, where $U \in R^{n\times d_v}$, and $I \in R^{m\times d_i}$ are the user and item embedding matrices, respectively. The attention score matrix is calculated as

$$A = soft\max\left(\frac{QK^{T}}{\sqrt{d_K}} + M\right) \tag{15}$$

where $M \in R^{n\times m}$ is a learnable relative position encoding matrix capturing the temporal properties of user-item interactions.

Multiple heads of attention are used for parallel computation, and the outputs of each head are spliced and then projected through the learnable matrix $W^{O} \in R^{sd_v \times d}$

$$MultiHead = Concat\left(head_1, \ldots, head_s\right)W^{O} \tag{16}$$

Constructing Feature Enhancement Modules via Residual Joining and Layer Normalization

$$X' = LayerNorm\left(X + MultiHead\left(X, X, X\right)\right) \tag{17}$$

The design inherits the core idea of Transformer, so that the model dynamically focuses on key feature dimensions.

(2) Dynamic regularization constraint system

In order to prevent model overfitting, a two-layer regularization mechanism is established:

1) Parameter regularization: introduce the L2 weight decay term in the Adam optimizer, and the loss function is expanded as

$$L_{total} = L_{task} + \frac{\lambda}{2}\sum_{l=1}^{L}\left\|W^{[l]}\right\|_F^2 \tag{18}$$

where λ is the decay coefficient, and $\|\cdot\|_F$ denotes the Frobenius paradigm, which is designed to enhance the generalization ability by constraining the parameter space smoothness.

2) Feature regularization: the Dropout mechanism is applied in the embedding layer to adjust the dropout probability according to the activation strength of neurons

$$p_i = p_{base} \cdot \frac{E\left[\|e_i\|\right]}{\max_j E\left[\|e_j\|\right]} \tag{19}$$

Add Gaussian noise to the embedding layer $\epsilon \sim \mathcal{N}(0, \sigma^2)$

$$\tilde{e} = e + \epsilon \cdot \text{sign}(\nabla_e \mathcal{L}) \tag{20}$$

(3) Multi-objective joint optimization function

The alignment loss forces potential features to remain linearly correlated with the label space, and the smoothing loss constrains the continuity of feature evolution; this multi-objective design draws on the joint optimization idea of cross-modal hash learning.

1) Prediction loss: using Huber loss to enhance outlier robustness

$$\mathcal{L}_{pred} = \frac{1}{n}\sum_{i=1}^{n}\begin{cases}\frac{1}{2}(y_i - \hat{y}_i)^2 & |y_i - \hat{y}_i| \le \delta \\ \delta|y_i - \hat{y}_i| - \frac{1}{2}\delta^2 & otherwise\end{cases} \tag{21}$$

where $\delta = 1.5$ is the threshold parameter.

2) Alignment Loss: Introducing Maximum Mean Difference (MMD) constraints on the consistency of the distribution of the hidden space and the label space

$$\mathcal{L}_{align} = MMD^2\left(\{X_i\}, \{y_i \cdot 1_d\}\right) \tag{22}$$

where the kernel function is chosen as Gaussian kernel $k(a,b) = \exp\left(-\|a-b\|^2 / (2\sigma^2)\right)$.

3) Smoothing loss: design second-order difference constraints to ensure feature evolution continuity

$$\mathcal{L}_{smooth} = \frac{1}{T-2}\sum_{t=1}^{T-2}\left\| X_{t+2} - 2X_{t+1} + X_t \right\|_2 \tag{23}$$

Finally, the loss weights are automatically adjusted by the homoskedasticity uncertainty principle

$$\mathcal{L}_{total} = \sum_{k=1}^{3}\frac{1}{2\sigma_k^2}\mathcal{L}_k + \log\sigma_k^2 \tag{24}$$

where σ_k^2 is the learnable noise variance parameter, reflecting the uncertainty of each loss term.

4) Adaptive feature fusion

Determine the optimal fusion position through micro-searchable $[s, e]$

$$s = sigmoid\left(w_s^T f\right) \tag{25}$$

$$e = s + softplus\left(w_e^T f\right) \tag{26}$$

where w_s, w_e are learnable parameters ensuring $0 \le s \le e \le d$.

The dynamic weighting coefficient γ is calculated by the gating network to achieve fine-grained control of feature importance. The formula is as follows

$$\gamma = MLP\left(\left[f_{user}; f_{item}; f_{fused} \right]\right) \tag{27}$$

2.5.2 Potential embedding optimization

The MAML algorithm is trained through two levels, the inner loop is started by a random initialization of θ and updated for each task to get a parameter $\theta_{i'}$, the update process is as follows

$$\theta_{i'} = \theta - \alpha\nabla_\theta\mathcal{L}_{\mathcal{T}_i}\left(f_\theta\right) \tag{28}$$

After completing an inner loop, the model parameters $\theta_{i'}$ corresponding to a number of tasks can be obtained, and then the initialization parameters θ are updated as follows

$$\theta \leftarrow \theta - \beta\nabla_\theta \sum_{\mathcal{T}_i \sim p(\mathcal{T})} \mathcal{L}_{\mathcal{T}_i}\left(f_{\theta_{i'}}\right) \tag{29}$$

The final model parameters θ are obtained. The improvement of the potential embedding optimization method is the introduction of a low-dimensional hidden space. The flowchart of the algorithm is shown in Fig. 8.

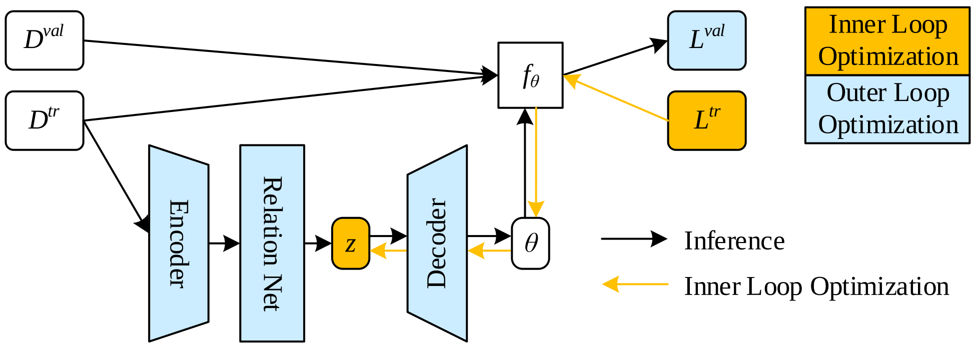

Figure 8: Potential Embedding Optimization Process

Firstly, an encoder ϕ_e and a relational network ϕ_r are used to project the samples X_n^t in the meta-training set into a low-dimensional hidden space Z to get the hidden vector Z' corresponding to each task, and then the hidden vectors Z' are transformed into the high-dimensional model parameters $\theta_{i'}$ using a decoder ϕ_d. The hidden vector Z' is updated in the inner loop as follows

$$Z' \leftarrow Z' - \alpha \nabla_{Z'} \mathcal{L}_{\mathcal{T}_i}^{tr}\left(f_{\theta_{i'}}\right) \tag{30}$$

In the outer loop, parameters such as encoder, relational network, decoder and learning rate are updated

$$\varnothing \leftarrow \varnothing - \eta \nabla_{\varnothing} \sum_{\mathcal{T}_i} \mathcal{L}_{\mathcal{T}_i}^{val}\left(f_{\theta_{i'}}\right) \tag{31}$$

2.5.3 Incorporating multimodal and user-feature enhancement

The multimodal meta-learning recommendation model (UMMeLE) is constructed in the improved meta-learning recommendation network by dynamically fusing multimodal features such as video, audio, and text, and enhancing the user representations by combining the similar user behavior information. The model mainly contains the following modules: multimodal feature extraction and dynamic fusion module, similar user group feature enhancement module and improved meta-learning recommendation network.

The prediction process of the model can be formalized as

$$\hat{y}_{ui} = \Phi_{UMMeLE}\left(e_u^{enhanced}, f_i^{fused}, r\right) \cdot C(u,i) \tag{32}$$

where $e_u^{enhanced}$ is the enhanced user embedding, f_i^{fused} is the dynamically fused multimodal item features, r is the user's rating of the video, Φ_{UMMeLE} is the meta-learning recommender network, and $C(u,i)$ is the hard prior knowledge point constraints that force filtering of offending items based on user learning progress.

Video features $v_i \in R^{d_v}$, audio features $a_i \in R^{d_a}$ and text features $t_i \in R^{d_t}$ are spliced and mapped to implicit semantic vectors z_i via a hidden space encoder. Subsequently, the multimodal features and implicit vectors are received through a meta-learner g_{meta}, which generates a modality-specific dynamic fusion weight matrix W_i^{fuse}. The multimodal features are spliced and multiplied with the dynamic weight matrix, and the final item representation f_i is obtained after fully-connected layer reduction and ReLU activation.

In each iteration, the batch task B is first sampled from the task distribution, initializing the meta-gradient accumulator $Grad_{meta}$ to zero. For the inner loop adaptation of a single task $T \in B$, the base embedding e_u of user u is extracted, the user latent representation z_u is generated by the latent encoder, and the latent relationship matrix R between the two is computed. Retrieve the set of Top-K similar users N_u^K of the target user u based on the improved similarity measure, and introduce the relationship matrix R to enhance the collaborative filtering signal. The variance-aware attention mechanism is utilized to compute the aggregation weight α_k, and the weighted summation yields the augmented user representation $\hat{e}_u$. The augmented representations are spliced with item features and fed into the prediction network to compute the support set loss $\mathcal{L}_{spt}$ and quickly update the local parameters θ'. In the latent optimization sub-loop, the hidden space gradient ∇_z and the fitness parameter θ'_{adapt} are updated by iteration.

3 Stylized image migration and evaluation of learning systems based on multimodal meta-learning recommendations

In order to verify whether the personalized recommendation-based learning system constructed in Chapter 2 efficiently serves the digital practice of traditional culture education, this chapter carries out an all-round experimental verification of this.

(1) Firstly, we test the image resource generation capability of the style migration model;

(2) Then, we analyze in-depth the pattern of students' use of traditional cultural resources;

(3) Focus on evaluating whether the newly proposed UMMeLE recommendation algorithm can accurately match resources for students;

(4) Finally, evaluate the operational efficiency of the whole academic support system.

3.1 Research on style migration of traditional cultural elements

In order to verify whether the style migration model based on adaptive instance normalization (AIN) proposed in this study has significant advantages in generating images of traditional Chinese cultural elements.

A control group comparison method is adopted, where only the normalization layer in the model is changed, using single instance normalization (IN), conditional instance normalization (CIN), and multi-fusion adaptive instance normalization (AIN), respectively, under the condition of keeping the content image, the style image, the underlying network structure, and the number of training iterations exactly the same.

In terms of evaluating the migration effect, 20 college student volunteers were invited to fill out a questionnaire about the style migration effect of traditional cultural elements, scoring from three aspects of the appearance of the generated images in terms of ornamental, satisfaction with the style simulation effect, and the degree of presentation of the national connotation, with scores ranging from integers of 1 to 5, with 1 being unsatisfactory and 5 being very satisfactory, with gradual progression in the middle.

The experimental results under the three models are shown in Fig. 9, Fig. 10 and Fig. 11, respectively.

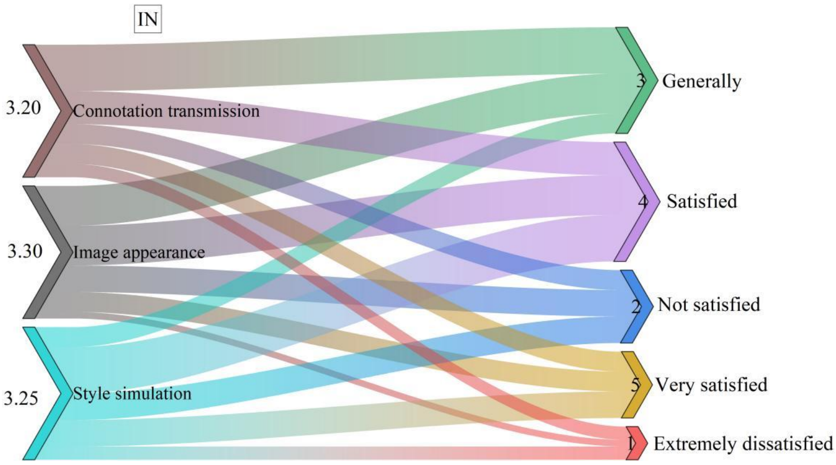

Figure 9: The results of style transfer under Instance Normalization

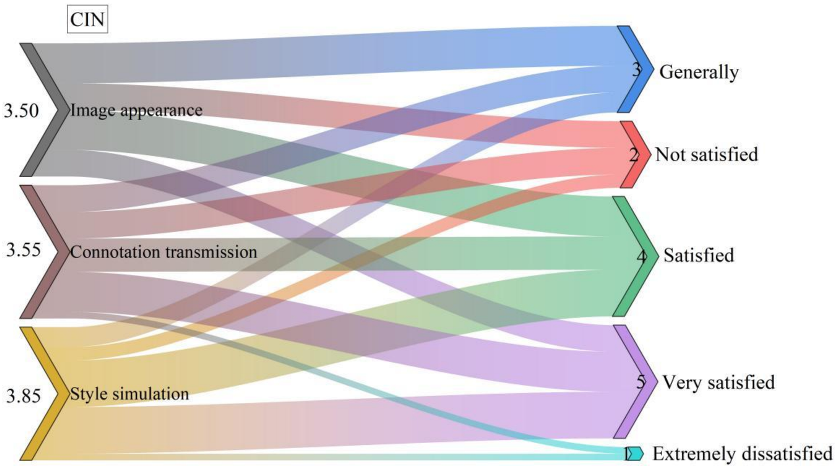

Figure 10: The results of style transfer under Condition Instances Normalization

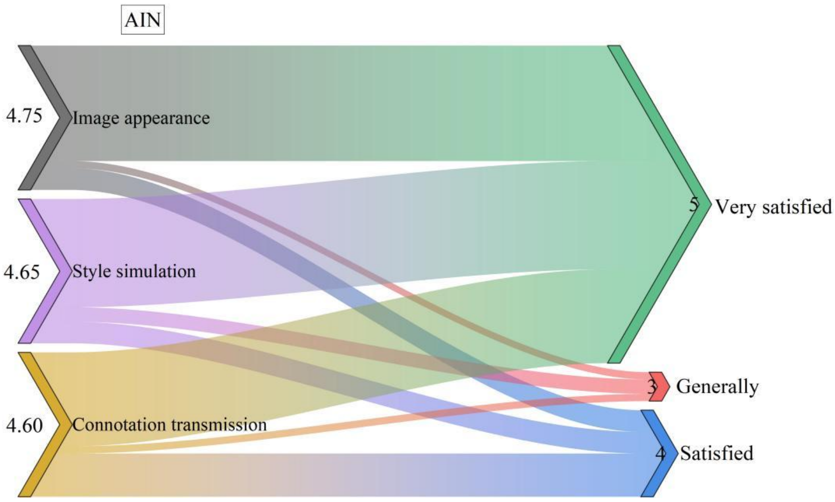

Figure 11: The results of style transfer under Adaptive Instance Normalization

The adaptive normalization layer style migration model, which integrates batch normalization, instance normalization and conditional normalization, is highly evaluated in image appearance, style simulation and connotation communication, with the three mean scores of 4.75, 4.65 and 4.60, respectively.As can be seen from the dimensionality-scoring Mulberry diagram in Figure 9, none of the volunteers rated 1 or 2 unsatisfactory, and most of the evaluations focused on the 5 “very satisfied”. flowed to 5 points “very satisfied”.

The effect of style migration image generation under a single instance normalization or conditional instance normalization layer is not ideal, and different evaluation dimensions flow to different levels of ratings. In terms of IN instance normalization, four volunteers gave a score of 1 in terms of appearance and four volunteers gave a score of 5, indicating that the generation effect is extremely unstable; in terms of connotation, most of the volunteers gave a score of 3, which is “general”, and the model is a single style under the strategy of this layer, which can only learn and generate a fixed traditional style. The model is a single style under this tier strategy, which can only learn and generate a fixed traditional style, and still lacks in conveying rich connotations.

The conditional normalized model is better at style simulation, with an average score of 3.85. More people gave the model a score of 5 (very satisfied) in both style simulation and connotation than in the lower tier, indicating that the model performs reasonably well in capturing specific style features, but some of the model's scores still flowed to a low score of 2 in the appearance tier. Although the model can generate multiple styles, the number of styles is fixed during training.

The adaptive normalization layer, AIN Style Migration, had the highest overall satisfaction and was able to consistently generate works embodying traditional cultural elements that were widely recognized for their visual aesthetics, stylistic reductions, and cultural charisma.

3.2 Analysis of data on student use of resources

The adaptive normalization model generates high-quality stylized images to provide a rich source of material for the traditional culture education resource library. In order to further explore the resource performance in depth, as well as the students' usage behavioral preferences and patterns, this section provides an in-depth analysis of the students' usage data of the resources.

3.2.1 Analysis of student use of resources

In the knowledge map of cultural resources constructed based on traditional culture knowledge elements, 500 educational resources containing traditional culture elements were selected for data analysis. The study was carried out in four aspects: resource heat, upload time, popularity and resource quality.

The distribution of the 500 resources in terms of heat, upload time, popularity and resource quality are shown in Fig. 12, Fig. 13, Fig. 14 and Fig. 15, respectively.

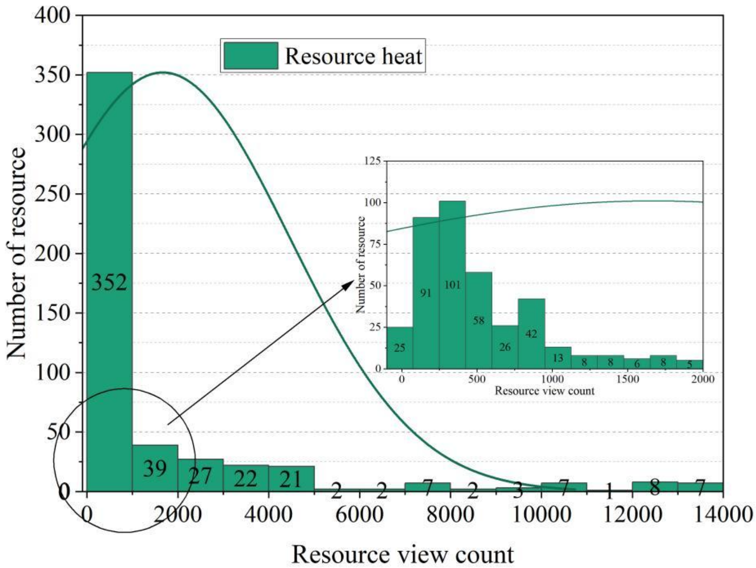

Figure 12: The distribution of the heat of 500 resources

Quantifying resource heat from resource views, it can be found that 70.4% of the resources are concentrated in the low heat range of views <1000, showing a clear long-tail distribution. Only very few resources have views above 4000, indicating that regarding traditional culture learning resources, how to activate and recommend high quality content in long-tail resources is the key to improve the overall utilization of the system.

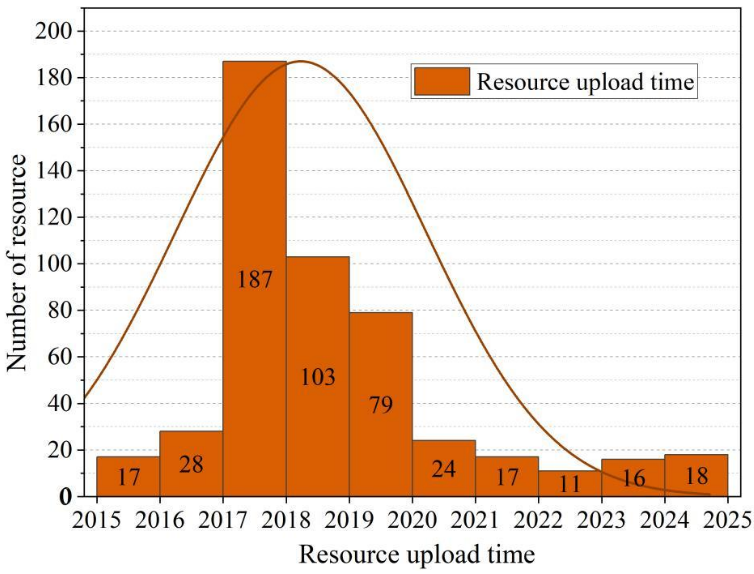

Figure 13: The distribution of the upload times for 500 resources

As for the time of resource uploading, in the early stage of the construction of the 2015-2016 system, the resource base was small, and the resources were mostly uploaded during 2017 and 2018, and the number of resources in these two years among the 500 resources extracted was 290, accounting for 58% of the total number of resources, and there is no lack of resources after 2018 in the database, which side by side reflects the continuous activity and expansion of the knowledge base.

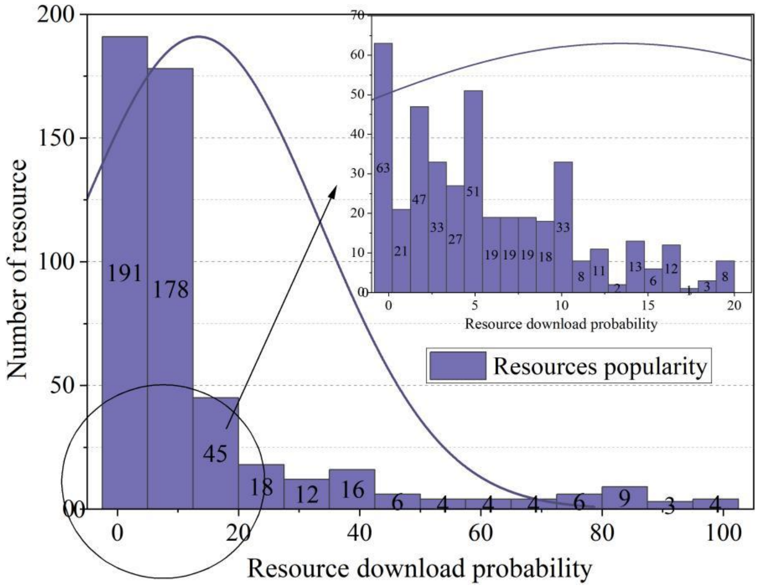

Figure 14: The distribution of the popularity for 500 resources

The popularity of resources is discounted by the download rate of resources, with 63 items, or 12.6%, having a download rate of 0. The download rate is different from the number of views, and it does not mean that the resources in this area have not been exposed accordingly, but the 0 download rate means that this part of the resources is difficult to be utilized by the students or does not attract the students, and it is a silent asset in the resource base that needs to be revitalized urgently. Most of the resources have a download probability centered between 0-20%, and only 86 resources have a download rate of more than 20%, accounting for 17.2%, indicating that high-quality traditional cultural resources widely recognized by students and willing to download and save are still relatively scarce. The vast majority of resources face the general status quo that some people look at them but few take the initiative to collect and download them, suggesting that there is still much room for improvement in enhancing the usefulness and attractiveness of resources.

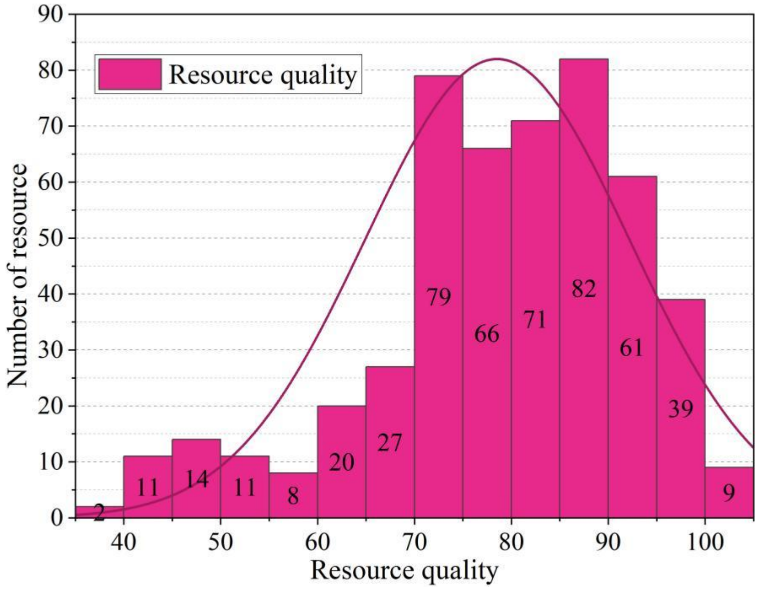

Figure 15: The distribution of the quality for 500 resources

The quality of resources presents an olive-shaped healthy structure. The quality scores of the vast majority of resources are concentrated in the good to excellent range of 70-100, indicating that the traditional culture resource base constructed has achieved solid results in basic quality construction in terms of content accuracy, form richness and metadata completeness, and the overall quality baseline is high. However, there are still 57 resources with quality scores below 60, accounting for 11.4%. They may have problems such as thin content, old forms and unclear descriptions, which directly affect students' learning experience and willingness to download, and this part of resources is exactly the marginal resources with low download rates in Figure 15.

3.2.2 Student ratings of resource use

Students were invited to rate these 500 resources (using a 5-point rating system, planning a score higher than 3 as a high rating, and ≤3 as a low rating), and finally divided them into four dimensions, namely, resource hotness, uploading time, popularity, and resource quality, to obtain the resource scores at each dimension level as shown in Fig. 16-Fig. 19.

A total of 384 of the 500 resources received a high rating, accounting for 76.8%. It shows that the constructed traditional culture resources as a whole are still widely recognized by students. The light-colored area in the following figure shows the distribution of highly rated resources.

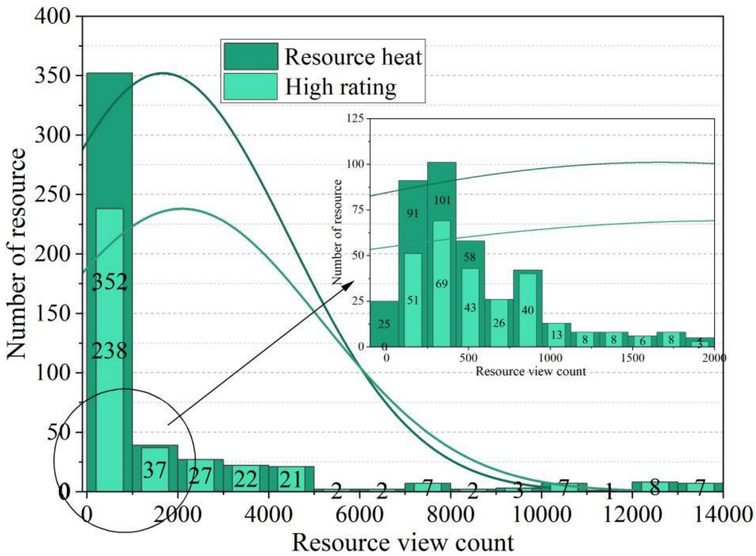

Figure 16: The distribution of resource scores classified by resource heat

In the resource heat, the resources with more than 2,000 views are all highly rated resources, while the low rated resources are all distributed in the views < 2,000. For example, among the 275 resources with <500 views, there are 112 low-scoring resources, accounting for 40.72%, but there are only 116 low-scoring resources among 500 resources, which means that 96.55% of the low-scoring resources are resources with <500 views. This fully demonstrates that students are interested in truly high-quality content that will trigger extensive clicking and browsing. The resources themselves are difficult to be well received by students due to insufficient exposure or lack of attractive content.

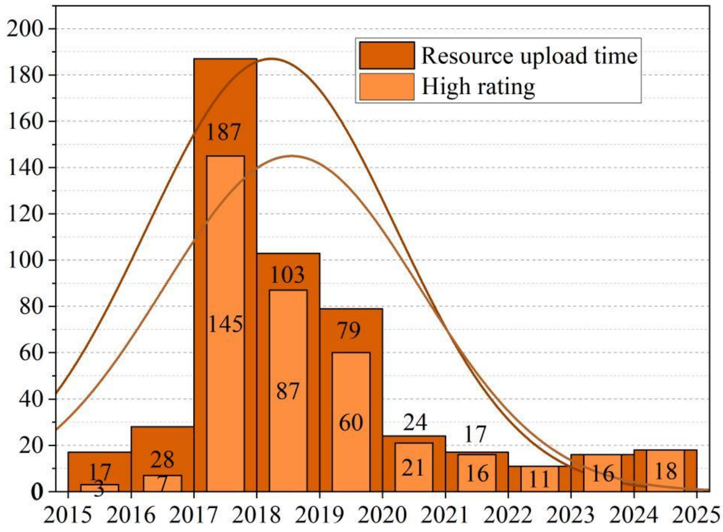

Figure 17: The distribution of resource scores classified by resource upload time

In terms of uploading time, new resources uploaded after 2018 received significantly higher percentages of high scores than earlier resources. For example, of the 17 and 28 resources uploaded in 2015 and 2016, only 3 and 7 were high-scoring resources. In contrast, all resources uploaded after 2022 were high scoring resources. This clearly reflects that it is crucial for resources to be up-to-date. The traditional culture resources uploaded in recent years covered more cutting-edge cultural topics, and thus were more likely to stimulate students' learning interest and emotional resonance, resulting in higher satisfaction ratings.

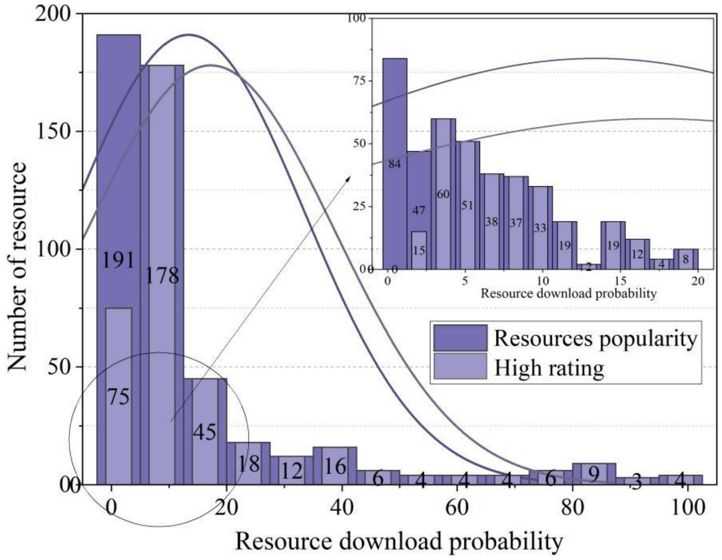

Figure 18: The distribution of resource scores classified by resource popularity

Ratings based on the popularity of the resources showed a trend consistent with the popularity of the resources, with all resources with a download rate of more than 5% having a student rating of 4 or more. This indicates that the act of “downloading” itself is a powerful five-star rating. When students think that a resource is worth saving and studying repeatedly, they will take the initiative to download it, and naturally, they will download the highly rated resources that satisfy them. Meanwhile, the graph shows that the 84 traditional culture resources with a download rate of 0 are, unsurprisingly, low-scoring resources.

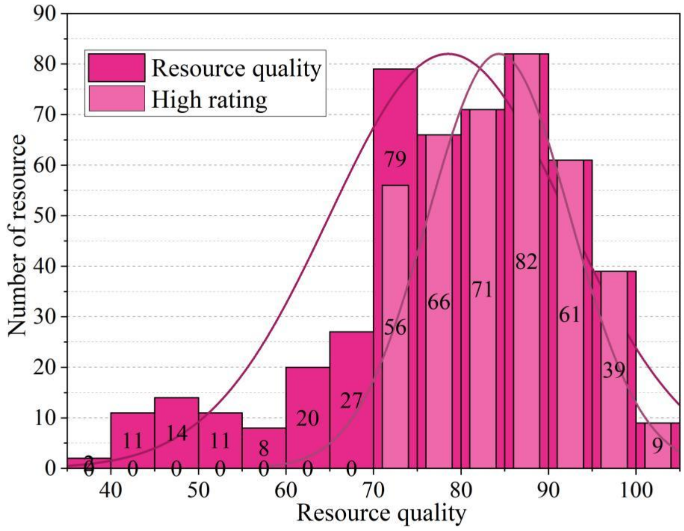

Figure 19: The distribution of resource scores classified by resource quality

Resources with quality scores of 70 or higher make up all of the high-scoring resources. Of the 79 resources with quality scores in the 70-75 score category, 56 are high scoring resources. And all cultural resources below 70 scores are low-scoring resources. It can be said that there is an absolute positive relationship between the quality of resources and students' scores, and the quality dimensions set are highly compatible with students' actual perceptions. It is just that the qualifying interval between high and low scores is not very clear, which is around 72 resource quality scores.

3.2.3 Correlation analysis of students' use of educational resources

Finally, the resource heat, upload time, popularity and resource quality were correlated, and the correlation analysis among the four is shown in Fig. 20, Fig. 21 and Fig. 22, respectively.

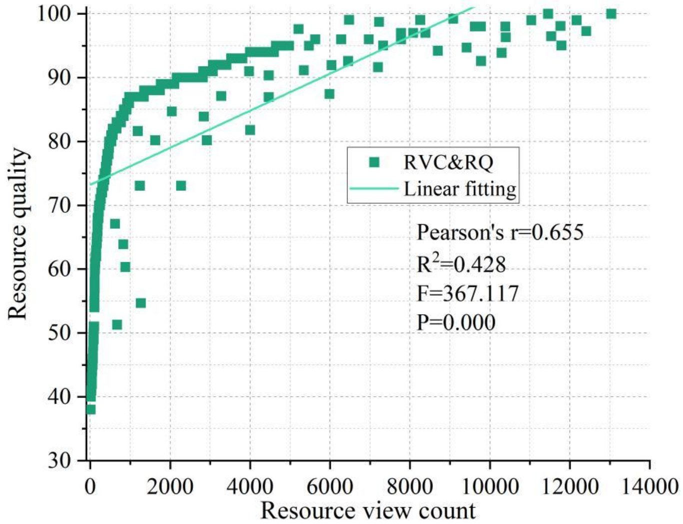

Figure 20: Correlation analysis between resource heat value and resource popularity

There was a significant positive correlation between resource quality and the number of resource views, with a Pearson correlation coefficient = 0.655. The higher the number of resource views, the higher the quality score, echoing the relationship between resource views and student ratings in section 3.2.2. Still using 2000 as the cut-off, resources with >2000 views almost always have quality scores above 80. Although there are some cases of high quality and low view counts, there are absolutely no cases of high view counts and low quality. It shows that high view count resources are necessarily of high quality, and the two are sufficiently unnecessary.

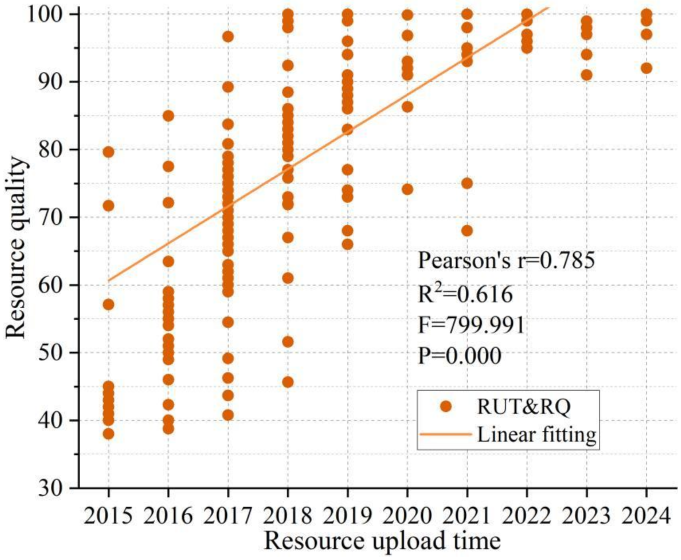

Figure 21: Correlation analysis between resource upload time and resource popularity

There is also a significant positive correlation between resource uploading time and resource quality, with the correlation coefficient even reaching 0.785. Newer resources uploaded after 2018 generally have higher average quality scores than earlier resources. From the figure, it can be seen that especially the resources uploaded after 2020 generally have quality scores above 90, and although the number of uploaded resources is small, they are absolutely refined and high quality. This clearly reflects the learning curve effect in the construction of the traditional culture resource library. As resources are updated and iterated, the later online resources are more mature in content planning and innovative applications, thus promoting the steady improvement of the overall resource library quality.

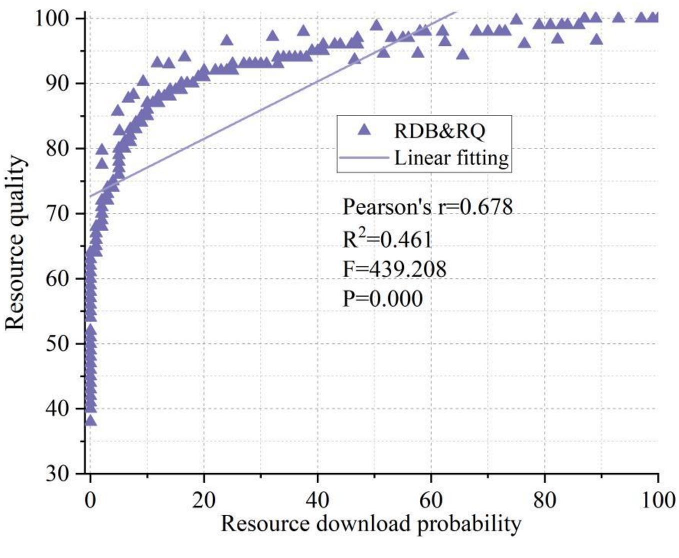

Figure 22: Correlation analysis between resource download rate and popularity

The quality of resources and the download rate also show a positive correlation. It shows that the constructed quality assessment system is highly consistent with the real needs and usage behaviors of student users, and also echoes with the student ratings in section 3.2.2. Among the 86 highly popular resources with a download rate of more than 20%, all of them have a quality score of more than 90. Those with quality scores below 60 are all 0% download rate resources without exception. There is no such thing as low quality and high download rate. However, from Figure 23, it can be found that there are some data points in the upper left corner, indicating that there are some resources with low download rate and high quality, which may be due to the fact that these high-quality resources are not commonly used by students in their daily learning, so the number of downloads is low. There is a necessary but not sufficient relationship between the download rate and the quality of resources.

3.3 Comparative Study of Personalized Recommendation Methods

In order to validate the recommendation performance of the multimodal meta-learning recommendation algorithm (UMMeLE) proposed in this paper for traditional cultural teaching resources, the original meta-preference estimation model (MeLU) and the RMeLU based on the attentional feature augmentation, dynamic regularization constraints, multi-objective co-optimization, and adaptive feature four-stage optimization are selected for the comparative study.

The study conducts experiments in an authentic traditional cultural education resource interaction dataset TCE. The dataset is derived from the real user behaviors accumulated in the one-stop student community platform, including 2,734 student users interacting with 72830 records of teaching resources.

The Root Mean Square Error (RMSE) is chosen as the evaluation metric, which measures the deviation between the predicted ratings and the actual ratings, and the smaller its value, the higher the prediction accuracy and the better the recommendation performance.

The recommendation performance of the 3 algorithms on TCE is shown in Fig. 23.

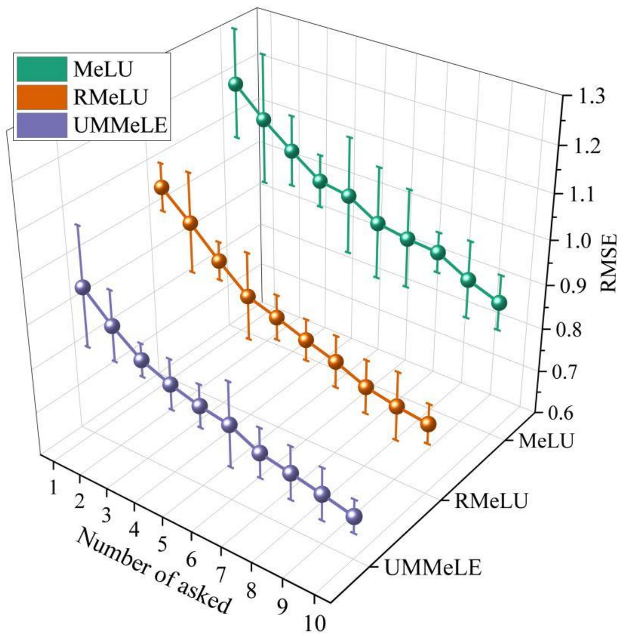

Figure 23: The recommendation performance of the algorithm on the TCE dataset

The UMMeLE model, which has been optimized four times and incorporates increased multimodal and similar user group features, achieves the optimal recommendation performance, and its RMSE reaches 0.697 as the number of questions increases, consistently maintaining the lowest prediction error throughout the learning process compared to the other two models. The RMeLU model, which has been transformed by four levels of optimization alone, also shows the same stronger learning ability. Its RMSE = 1.051 in the 1st interaction, which is 11.23% higher than the baseline model MeLU, proving that optimization strategies such as the attention mechanism and dynamic regularization effectively improve the model's ability to capture signals. However, it is still slightly inferior to UMMeLE, which consistently outperforms RMeLU by 8-11% in terms of prediction performance, and UMMeLE achieves an RMSE error of 0.785 in just 5 interactions, demonstrating its excellent ability to gain quick insights into user preferences. Once again, it proves that fusing multimodal features with similar user group information can provide the model with correlation clues in the cold-start phase and read new users faster.

3.4 Academic Support System Learning Resources Extraction Measurement

We now turn to the measurement of the one-stop student community academic support system constructed in Section 2.4, which is centered on its traditional culture learning resources extraction efficiency.

The extraction efficiency is measured using the elapsed time for a certain number of learners to customize a certain amount of learning resource information and obtain the webpage information. This elapsed time includes the time required for all stages from resource customization, resource crawling, rule generation to final page presentation. This experiment measures the time consumed when 20, 100, 500 and 1000 learners customize different modules and web pages, and measures the time consumed by the traditional server-based centralized processing strategy under the same conditions, and the time consumed at each stage under the two system architectures is shown in Table 1.

Table 1: The time consumption at each stage under the two system architectures

Number of users		20		100		500		1000	
Number of modules		200		963		3064		4471	
Number of web pages		3712		16123		39178		45189	
		Centralized				Distributed			
Number of users		20	100	500	1000	20	100	500	1000
Time consumption/s	Resource customization	42.69	229.21	406.61	615.94	56.64	98.31	134.58	161.83
	Resource crawling	302.31	2521.03	4173.37	6588.99	208.06	547.92	653.36	730.11
	Rule generation	42.69	229.21	406.61	615.94	56.64	98.31	134.58	161.83
	Page presentation	3.85	6.15	10.62	16.43	3.81	4.53	5.36	6.58
	Total	527.46	4811.62	7682.86	10273.68	472.80	842.70	1014.04	1198.97

The reason the number of modules did not increase in proportion to the number of learners is because different learners customized the same resource modules. For example, when the number of users is 100 the number of resource modules is 963, while when the number of users increases five times to 500, the resource modules only increase to 3064, indicating that there are a considerable number of overlapping modules. And the number of web pages does not increase in proportion to the number of modules because each module contains a different amount of information.

In this paper, the learning support system model architecture is distributed as “data layer-application layer-user layer”. When the number of users is small, the total time consumed by the two architectures is not much different, and the traditional architecture is even slightly faster because the process is centralized and direct. However, when the number of concurrent users increases to 1,000, the total elapsed time of the traditional architecture with centralized management strategy soars to 10273.68, which is more than 2.8h, while the total elapsed time of the academic support system with distributed management in this paper is 1,198s, which is about 20 minutes, with a performance advantage of more than 8.5 times.

Deeper into each processing stage, the core of the problem is in the resource crawling task. Under the traditional architecture, all user requests are queued and processed centrally, and with the increase of the number of users, the time consumed increases from 302.31s to 6588.99s, while the system in this paper, through intelligent scheduling and parallel processing, is only 730s even under the scale of thousands of users. The one-stop student community academic support system constructed in this paper is not only functionally integrated, but also prepared for large-scale personalized services in the underlying architecture to provide students with efficient traditional culture learning resources customization services.

4 Conclusion

Adaptive normalization technology solves the resource waste problem that the model can only learn a single style, and its generated traditional culture images get 80% full score evaluation in user evaluation and achieve stable quality output with zero bad evaluation.

Knowledge meta-mapping transforms data into interlinked knowledge by micro-labeling and associating resources. It is this structured understanding that enables the system to gain insight into the fact that 12.6% of the resources in the repository are silent assets that have not been downloaded at all, providing a semantic foundation for subsequent accurate recommendations.

The UMMeLE recommendation algorithm keeps the prediction error at a low level of 0.785 after only 5 interactions, which is conducive to the system's ability to retain new users and activate their interest in learning. Meanwhile, the distributed system of “data layer-application layer-user layer” reduces the most time-consuming resource crawling process to about 12 minutes in the face of 1,000 users through the mechanism of resource reuse and parallel processing, while the traditional centralized management takes 1.8 hours, which improves the overall efficiency by 8.5 times.

The study not only effectively revitalizes traditional culture, but also inlays it in the educational scenario of a one-stop student community to achieve personalized dissemination.

Funding

This research was supported by the:

1. 2025 Special Project of the Ministry of Education University Ideological and Political Education Innovation Development Center (Nanjing University of Industry Technology): "Research on Pathways to High-Quality Development of Digital-Empowered 'One-Stop' Student Communities in Higher Vocational Institutions" (Project No. sczxng25012);

2. 2024 Annual School-based Education Research Project "Research on the Construction of One-Stop Student Communities in Vocational Colleges" (Project No. DJYB24-03);

3. 2022 Jiangsu Provincial Philosophy and Social Sciences Research Project for Higher Education Institutions "Challenges and Coping Strategies for Labor Education in Higher

Education from the Perspective of Artificial Intelligence" (Project No. 2022SJSZ0186).

About the Author

Qianyu Wang was born in Dongtai City, Jiangsu Province, China in 1992. She obtained a Master's degree from Xi'an University of Posts and Telecommunications. She is currently employed at Nanjing University of Industry Technology. Her primary research focus is on One-Stop Student Community Management.

References

[1] Tabatabaei, S. (2020). Investigating the role of cultural globalization on youth national identity. FUNCTIONAL ASPECTS OF INTERCULTURAL COMMUNICATION. TRANSLATION AND INTERPRETING ISSUES, 57.

[2] Fang, Y. (2024). Problem-oriented Inquiry-based Teaching of China's Intangible Cultural Heritage. Int. J. New Dev. Educ., 6(9), 193-200.

[3] Xu, S. (2018). Cultivating national identity with traditional culture: China's experiences and paradoxes. Discourse: Studies in the Cultural Politics of Education, 39(4), 615-628.

[4] Li, J., Jin, M., Liu, X., & Ma, L. (2024). Bottleneck and Countermeasures of Students Learning Traditional Culture in the Information Age. International Journal of New Developments in Education, 6(5).

[5] Zhang, L. (2022). Chinese traditional culture education: Implementing the child's position and perspective in the elementary school textbook morality and law. ECNU Review of Education, 5(4), 702-719.

[6] Ding, Y., & Lv, L. (2020). Are Students Satisfied with the Current School-Based Curriculum of Chinese Traditional Culture? A Survey of 120 Elementary and Middle Schools in China. A Survey of, 120, 863-879.

[7] Chen, Y., & Tang, H. (2024). Research on the Path of Cultivating College Students' Values Through Chinese Poetry Culture. Journal of Social Science Humanities and Literature, 7(5), 44-48.

[8] Zeng, Y., Noor, H. M., Sabri, M. F., & Yao, S. (2025). From Craft to Classroom: A narrative inquiry into the cultural identity and educational roles of intangible cultural heritage inheritors. Environment-Behaviour Proceedings Journal, 10(33), 113-119.

[9] Zhang, A., Gong, Y., Chen, Q., Jin, X., Mu, Y., & Lu, Y. (2025). Driving innovation and sustainable development in cultural heritage education through digital transformation: The role of interactive technologies. Sustainability, 17(1), 314.

[10] Wu, Y. J., Ding, T. J., Hsu, J. C., Ou, K. L., & Tarng, W. (2025). Exploratory Learning of Amis Indigenous Culture and Local Environments Using Virtual Reality and Drone Technology. ISPRS International Journal of Geo-Information, 14(11), 441.

[11] Zhang, L., Zhang, B., Du, Z., & Lv, Y. (2024). Research on" one-stop" student community

education management service mode in colleges and universities. Advances in Educational Technology and Psychology, 8(4), 67-74.

[12] Power, E., Partridge, H., O’Sullivan, C., & Kek, M. Y. C. A. (2020). Integrated ‘one-stop’support for student success: Recommendations from a regional university case study. Higher Education Research & Development, 39(3), 561-576.

[13] Zhang, H. (2024). The Value Orientation, Internal Logic, and Practical Approach of Embedding Labor Education into a “One-stop” Student Community. Educational Innovation Research, 2(2), 67-73.

[14] Yang, S., Wei, G., & Yusof, M. N. B. (2024). A Study on Sustainable Development of One Stop Student Community from a Rooted Perspective—Taking Zhengde Academy of a Certain University as an Example. Frontiers in Educational Research, 7(8).

[15] Chen, Z., Hassan, A. B., & Ghazali, S. S. (2024). The Role of Community Education in China in the Transmission of Traditional Culture: A Systematic Literature Review. Int. J. Acad. Res. Bus. Soc. Sci, 14, 1-15.

[16] Zhong, W. (2020). Traditional Culture Teaching in Chinese Education Under Internet Thinking. In Data Processing Techniques and Applications for Cyber-Physical Systems (DPTA 2019) (pp. 343-350). Singapore: Springer Singapore.

[17] Li, T. (2024, December). Research on the Evaluation of One stop Student Community Education Effectiveness Based on the" Five Education" Education System. In 2024 7th International Conference on Humanities Education and Social Sciences (ICHESS 2024) (pp. 203-212). Atlantis Press.

[18] Ye, L., Liu, L., & Shao, Y. (2024). Research on the Construction of" One-stop" Student Community in Colleges and Universities under the Background of" Three-round Education". International Journal of Social Science and Education Research, 7(5), 143-147.

[19] Lu, Z., Tan, P., Ji, Y., & Ma, X. (2022, June). The crafts+ fabrication workshop: Engaging students with intangible cultural heritage-oriented creative design. In Proceedings of the 2022 ACM Designing Interactive Systems Conference (pp. 1071-1084).

[20] Chen, J., & Chen, Y. (2025). Research on the Practical Models and Effectiveness of Integrating Excellent Traditional Chinese Culture Education in Dongguan Universities via IPE Pathways: A Case Study of Dragon Boat Culture Inheritance. Frontiers in Educational Research, 8(10).