International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-17

https://doi.org/10.70917/ijcisim-2026-0107
Article

The Construction of Inheritance Network of Jiangsu Rural Intangible Cultural Heritage Skills Based on Knowledge Mapping and the Innovative Path of Locality

Bo Wang *

School of Design, Wuxi Institute of Technology, Wuxi 214121, Jiangsu, China; wangbo_wxit@sina.com

Abstract: This study focuses on the construction of Jiangsu rural NRM inheritance network and proposes a knowledge graph-driven systematic solution. At the technical level, the NRM ontology framework (covering 99 types of entities and 199 attributes) is constructed based on the CIDOC CRM model, the RCBC named entity recognition model integrating four modules is designed, and the RoBERTa-Effg-Adv relational extraction model is proposed, which is trained by quintuple extraction with PGD confrontation. The RCBC named entity recognition model is realized on a self-constructed dataset with a F1 value of 83.11%, an improvement of 3.87 percentage points over the optimal baseline woBERT. The RoBERTa-Effg-Adv relational extraction model achieves an F1 value of 85.88%, which is significantly better than the BERT-BiLSTM-ATT model (+1.94%). At the application level, the analysis of 20 cultural heritage digital museums found that the quality of resource integration determines the effectiveness of communication (the PR value of a website with balanced inward/outward connectivity can reach 7, and the impact factor is 13.382). The study suggests that knowledge mapping can effectively structure the temporal, spatial, person and craft associations of ICH, while digital dissemination needs to be adapted to a multi-platform content strategy to achieve localized innovation.

Keywords: intangible cultural heritage; knowledge mapping; named entity recognition; relational extraction; Jiangsu countryside

1. Introduction

Intangible cultural heritage (ICH) embodies the great wisdom of a nation, possessing profound cultural, artistic, historical, and social value. As such, the preservation and transmission of ICH have become an integral component of contemporary socio-economic and cultural development. The inheritance and development of intangible cultural heritage techniques hold significant importance for the development of Chinese culture. In recent years, the concept of “intangible cultural heritage” has gradually gained recognition, reflecting China's emphasis on its preservation. However, the development of any endeavor is not without challenges. In the process of uncovering the value of intangible cultural heritage resources and promoting rural revitalization, the development of local intangible cultural heritage resources in Jiangsu Province still faces certain obstacles.

In recent years, society's attention to intangible cultural heritage has significantly increased, but the public's understanding remains superficial, and the promotion of intangible cultural heritage often remains on the surface, failing to truly integrate into people's daily lives [1]. Therefore, how to truly integrate intangible cultural heritage into modern social life has become a critical issue that must be addressed to achieve the sustainable development of intangible cultural heritage. To this end, some scholars have proposed utilizing big data analysis technology in the internet communication era to achieve the protection and transmission of intangible cultural heritage. Li, J. argues that the transmission of intangible cultural heritage techniques must strive to adapt to the development trends of society and the times. By combining modern digital technology with internet technology, actively seeking modern strategies for the transmission of intangible cultural heritage techniques is an important path for the healthy development of the cultural industry [2]. Wan, H. and others have elucidated the advantages of big data technology in the process of intangible cultural heritage transmission, not only overcoming limitations such as geographical and temporal constraints in traditional protection efforts but also leveraging internet communication to engage more people in the protection and transmission of these valuable cultural traditions, significantly promoting the development of intangible cultural heritage [3]. He, Y. indicates that intangible cultural heritage techniques empowered by big data technology possess more detailed and diverse dissemination methods, addressing shortcomings in traditional offline dissemination forms and enabling the “living” transmission of intangible cultural heritage techniques [4]. In the face of increasingly abundant online resources for intangible cultural heritage techniques, some scholars have also explored digital resource management strategies for the transmission of intangible cultural heritage techniques. Lvping, S. emphasizes that intangible cultural heritage archive management is an important component of the protection and transmission of intangible cultural heritage techniques. By introducing blockchain technology to optimize the data storage and management system for electronic archives, the security of intangible cultural heritage archives has been effectively enhanced [5]. Liu, X. and others constructed a complete digital resource management framework for intangible cultural heritage based on distributed consensus mechanisms and blockchain deployment scenario analysis, thereby providing a secure and transparent platform for ICH inheritance activities [6].

To better showcase the rich ICH craft resources, some scholars have proposed integrating artificial intelligence knowledge graph technology into the ICH craft inheritance process. Dou, J. et al. indicate that the current stage of ICH inheritance is facing a contradiction between massive data and decentralized management, making it difficult for users to quickly grasp the key knowledge of ICH crafts. The introduction of knowledge graph technology effectively reveals the patterns and characteristics behind ICH culture, providing support for resource management [7]. Fan, T., and Wang, H. established an ICH knowledge graph based on graph neural networks, enriching the ICH database through knowledge extraction and attribute extraction methods, which helps the public gain a deeper understanding of ICH culture and thereby promotes the inheritance of ICH skills [8]. Wang, Y., et al. also utilized graph neural network knowledge extraction methods to construct an ICH knowledge graph, which serves as a visual and interconnected knowledge structure, significantly improving users' search efficiency in vast amounts of fragmented knowledge information [9]. Gu, X. et al. combined a crawler system with intelligent knowledge matching algorithms to construct an intangible cultural heritage knowledge graph, fully integrating intangible cultural heritage knowledge across different data formats. This approach demonstrates scalability and universality, providing better service support for related inheritance activities [10]. As such, knowledge graph technology demonstrates significant advantages in the systematic management, semantic association, and multi-dimensional presentation of intangible cultural heritage resources—advantages that big data and blockchain technologies cannot match.

Based on this, by conducting in-depth exploration and comprehensive organization of intangible cultural heritage craft projects in rural Jiangsu, a systematic framework for rural intangible cultural heritage in Jiangsu was successfully established [11]. This knowledge graph not only covers the basic information of intangible cultural heritage projects but also reveals the intrinsic connections and inheritance patterns between projects through association analysis, achieving the systematic and digital integration of intangible cultural heritage resources and providing robust data support for intangible cultural heritage protection [12-14]. Users can conveniently access detailed introductions, historical origins, current state of transmission, representative works, and information about inheritors for each intangible cultural heritage project with a simple tap on the screen. They can also quickly understand the intergenerational transmission, spatial distribution, and benchmark projects of Jiangsu rural intangible cultural heritage techniques [15-17]. In particular, the visualization function of the knowledge graph provides the public, experts, scholars, and management departments with a convenient tool for intuitively understanding the intergenerational transmission relationships of ICH inheritors, thereby facilitating the integration of ICH techniques with modern life [18-20].

This study focuses on the core technology system for constructing the knowledge graph of intangible skills inheritance in rural Jiangsu. Firstly, the ontology of NRL domain is constructed to provide a unified and standardized semantic framework for knowledge mapping. The CIDOC CRM model, an internationally recognized standard for cultural heritage description, is chosen as the basis. The model contains 99 classes and 199 attributes, which can effectively express the core elements of NRM knowledge such as time, place, people, connotation, process, etc. and the complex mesh relationship between them. Aiming at the characteristics of Chinese NRL texts and the deficiencies of existing models, the article proposes the RCBC named entity recognition model, which integrates the advantages of four modules. The RoBERTa module performs deep pre-training on the input Chinese utterances and generates character feature vectors with rich semantic information, and its core Transformer coding layer utilizes the self-attention mechanism to capture the contextual semantics effectively. The improved CNN module designs multi-convolutional and pooling neural networks. This module performs convolutional operations in the direction of sentence length and word embedding dimension respectively and generates combined feature vectors by combining maximum pooling and average pooling strategies. The BiLSTM module receives the features extracted by the CNN and takes advantage of its bi-directional property to consider both past and future contextual information, to better capture long-range dependencies and global features in the sequences. The CRF module serves as the output layer and considers the tag constraints between them, and globally decodes the label probability distributions output by BiLSTM to obtain the optimal entity label sequence output. Finally, to recognize the semantic relationships between extracted entities, the joint RoBERTa-Effg-Adv entity relationship extraction model is proposed.

2. The Key Technology for the Construction of the Knowledge Map of Intangible Skills in Jiangsu Countryside

2.1. CIDOC CRM Model-Based NRM Knowledge Ontology Construction Method for Traditional Skills Category

There are 99 classes and 199 attributes in the CIDOCCRM model, which mainly contain knowledge information such as time, place, person, connotation, process, etc. centered on NRM. The hierarchical structure and attribute relationships between classes form a complex mesh structure, which is used to completely represent the relationships between NRM knowledge elements of traditional skills. The reason why this paper chooses CIDOC CRM model to construct the ontology of traditional arts and crafts intangible is that the model provides a set of universal and complete information resource expression specifications applicable to the field of intangible, which can clearly show the vague expressions and difficult-to-understand relationships in intangible with the help of the model framework and can be widely applied to the construction of ontology of intangible. In the practical application of CIDOC CRM model, the corresponding classes can be selected according to the characteristics of intangible. At the same time, through the correspondence between the classes and attributes of NRLs, various knowledge elements of NRLs can be completely recorded, which builds a bridge for the storage and dissemination of NRL information resources.

In order to effectively realize the interconnection of intangible cultural heritage knowledge of traditional skills, this subsection combines the knowledge connotation and characteristics of intangible cultural heritage of traditional skills, and proposes a systematic knowledge ontology modeling framework from the perspective of the protection, inheritance and development of intangible cultural heritage of traditional skills, which focuses on four stages: demand analysis, ontology construction, ontology realization, and application evaluation, in order to make the knowledge organization of intangible cultural heritage of traditional skills more standardized. The specific framework is shown in Figure 1.

2.1.1. Demand Analysis

There are many types of traditional skills-based NRHs about the Jiangsu countryside, such as ancient book restoration techniques, ceramic manufacturing techniques, tie-dyeing techniques, ancient building construction techniques, sword forging techniques, etc., and different skills have different processes and technical means. When constructing the ontology model, it is necessary to consider not only the same knowledge elements of similar traditional arts and crafts NRMs, but also the differences between different arts and crafts. In order to fully understand the needs of constructing an ontology model of traditional skills NHs, the following issues should be clarified:

(1) Main purpose. The main purpose of constructing an ontology model of traditional arts and crafts NHs is to link a large number of knowledge elements to form a systematic knowledge organization system, so as to provide reference and help for the learning and inheritance of future generations.

(2) Objects of use. The ontology model is mainly oriented to groups such as traditional skills NGTs, research scholars and so on.

(3) Ontology construction tool selection. The CIDOCCRM model is first used to determine the classes and attributes of the ontology, and then the Protege tool is used for modeling, which in turn realizes the visualization of the ontology model.

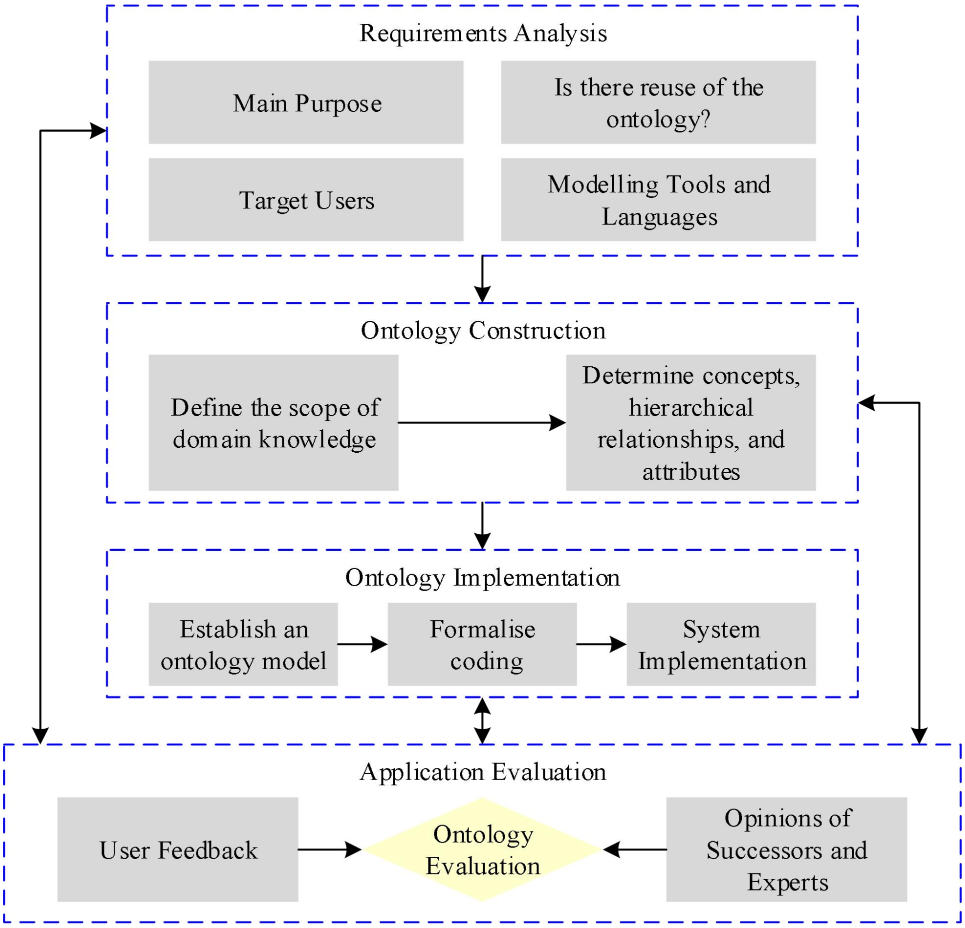

Figure 1. The modeling framework of knowledge ontology.

2.1.2. Ontology

After identifying the needs, the first step is to determine the scope of knowledge. Since the generation, development and inheritance of various traditional skills-based NRHs occurred in a certain historical period and cultural space, the scope of knowledge of traditional skills-based NRHs in rural Jiangsu can be determined from the perspectives of time, place, people, and content of skills.

In order to ensure that the constructed ontology model covers all the knowledge in the domain, it is also necessary to conduct a more in-depth study of the knowledge related to traditional skills-based NRH, so the next step is to determine the knowledge concepts, hierarchical relationships and attributes as follows:

(1) Acquire concepts and define them as classes. In the process of knowledge ontology construction, the degree of completeness and clarity of concepts directly affects the completeness and systematicity of the ontology structure. In order to integrate the knowledge framework of traditional skills-based NRH, it is necessary to organize the knowledge elements from the inheritors, recorded literature, research scholars and related NRH ontology models through different perspectives, establish a conceptual set by analyzing the concepts of the knowledge elements and abstract the modeled concepts into the most basic classes in the ontology model. A class is a collection composed of a group of individuals with certain common attributes. By analyzing the concepts of the NRH ontology in the category of traditional skills, the commonly used concepts are selected to form the core class of the ontology.

(2) Determine the hierarchical relationship and attributes of classes. Secondary and tertiary classes are divided below the core classes to determine the knowledge hierarchy of traditional skills-based NRM. Classes are distinguished from each other due to different attributes, and a class can have multiple attributes. The basic attributes of classes can be obtained from ontology-based conceptual reference models such as CIDOCCRM.

2.1.3. Average Ontology Implementation and Application

Ontology realization: After determining the classes, relations and attributes of the ontology, formal coding of the ontology is carried out to construct an ontology model of traditional skills-based NRH, which encompasses the classes and relations of attributes of the various knowledge elements of traditional skills-based NRH in the countryside of Jiangsu Province, and the ontology model is finally visualized in the form of a mapping.

Application evaluation: Ontology evaluation is carried out throughout the whole process of knowledge ontology construction, evaluating the scope, entities and attributes of the ontology in terms of completeness, clarity, consistency and scalability, in order to find out the deficiencies in the ontology construction process and improve them as soon as possible.

2.2. RCBC-Based Named Entity Recognition Model

Through the above systematic ontology construction process based on CIDOC CRM, a standardized semantic framework and knowledge organization system is established for the knowledge map of Jiangsu rural NRM. This section further investigates the named entity recognition technique, aiming at accurately recognizing the key entities in the NRM text.

2.2.1. RCBC Model

In this paper, we propose the RCBC model, which consists of four modules: the RoBERTa module, the CNN module, the BiLSTM module, and the CRF module.The RoBERTa module pre-trains the input text to extract the semantic features of the data, and the obtained semantic features are used as inputs to the CNN module to extract the local features and perform the outputs, which are then inputted to the LSTM module, which predicts the probability distribution of entity labels. Finally, these probability distributions of entity labels are decoded by the CRF module, and the corresponding entity labels are decoded for output.

Firstly, the Chinese utterance is input, and the text of the input utterance is decomposed into corresponding word sequences by querying the word vector table and inputted into the RoBERTa module to obtain the character feature vectors. Then the character feature vector is input to the CNN module, and the CNN is utilized to obtain the features of each character, which is then input to the BiLSTM module, and the input hidden information is computed by BiLSTM. Finally, the CRF module is used to decode and solve the output of BiLSTM module to output the Chinese utterance prediction labels. Combining CNN and BiLSTM, i.e., using CNN coding to get the embedding of each paragraph, and then sending it to LSTM to get the LSTM hidden vectors.CNN can effectively deal with the local features of the input data, and the bi-directionality of BiLSTM enables the model to consider both the past and the future information, so as to better capture the contextual information in the sequential data, which is able to learn both local and global features and can adaptively go about extracting features.

The vectors generated by RoBERTa at the input layer are summed from word vectors, sentence vectors and position vectors. The input data is transformed by querying the word vector table with word vectors. Sentence vectors represent the textual information of sentences and are used to distinguish different sentences. The input layer is shown in Fig. 2.

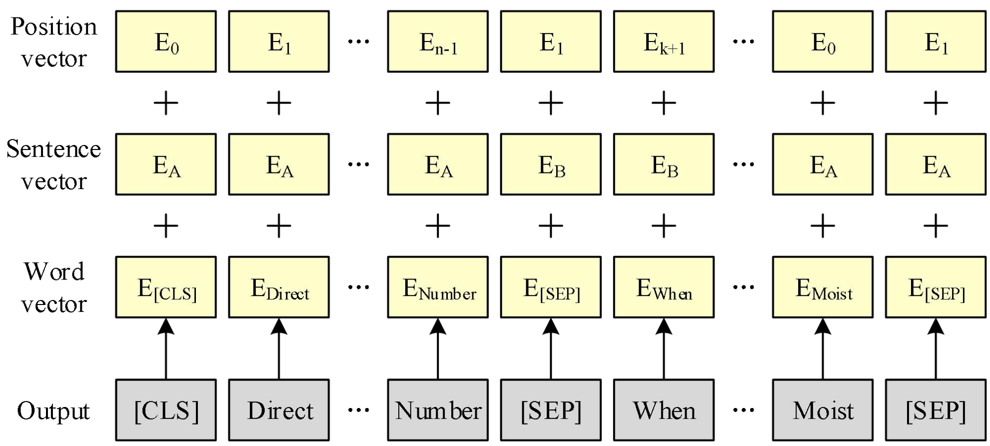

Figure 2. RoBERTa input layer diagram.

In the process of using RoBERTa model to process the data, the two-way Transformer coding layer in the model plays a key role in extracting and analyzing the features of the data.The Transformer coding layer mainly adopts Encoder feature extractor, and its structure is shown in Figure 3.

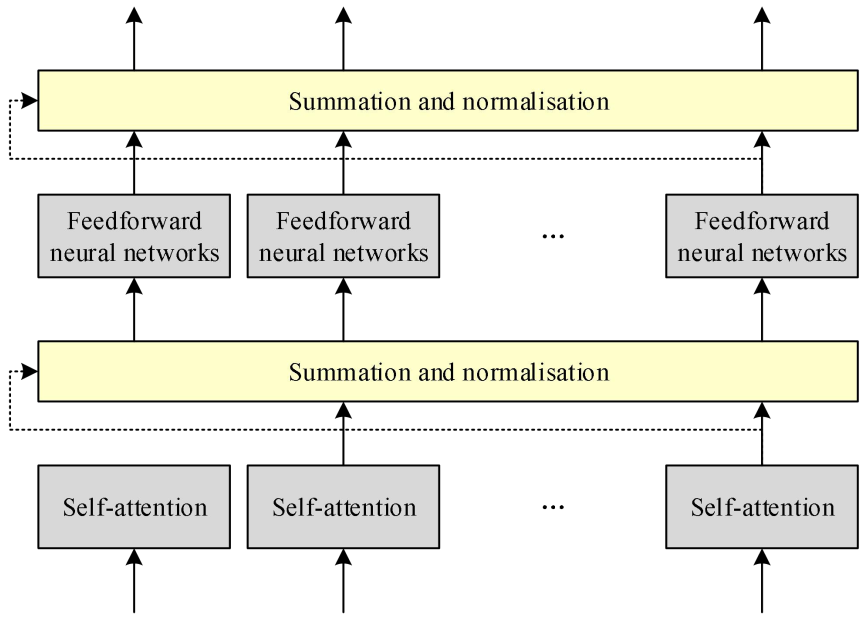

Figure 3. Transformer coding layer diagram.

Encoder mainly consists of several processing parts such as self-attention processing mechanism, summation and normalization and feed-forward neural network. One of the important parts is the self-attention mechanism, which calculates the semantic vectors by calculating the attention weights and normalizing them as shown in equations (1) and (2).

$$\begin{cases} Q = EW_Q \\ K = EW_K \\ V = EW_V \end{cases} \tag{1}$$

$$Attention(Q,K,V) = soft\max\left(\frac{QK^T}{\sqrt{d_K}}\right)V \tag{2}$$

where Q,K,V vectors are calculated for each word vector E with three parameter matrices W_Q,W_K,W_V, and d_K is the dimension of the input vector. The word vectors are processed by the coding layer to have the features to represent the contextual semantics, and then these word vectors with the contextual semantics features are used as the input vectors in the next layer.

2.2.2. Improvement of CNN

Since CNN only considers the length of the sentence while ignoring the semantic features between word vectors when extracting semantic information, and only uses maximum pooling in the pooling layer, which only considers the maximum feature value of each feature map without taking other factors into account, some important information may be lost. Therefore, this paper proposes a multi-convolutional and pooling neural network as a CNN network structure.

Assume that the length of the input sentence is n, the dimension of the word embedding is k, and the size of the convolution kernel is $n \times d$, where d is the width of the convolution kernel in the word embedding. There is no relationship between each word embedding dimension, then the convolution operation is performed separately in each word embedding dimension. The improved CNN model is shown in Fig. 4.

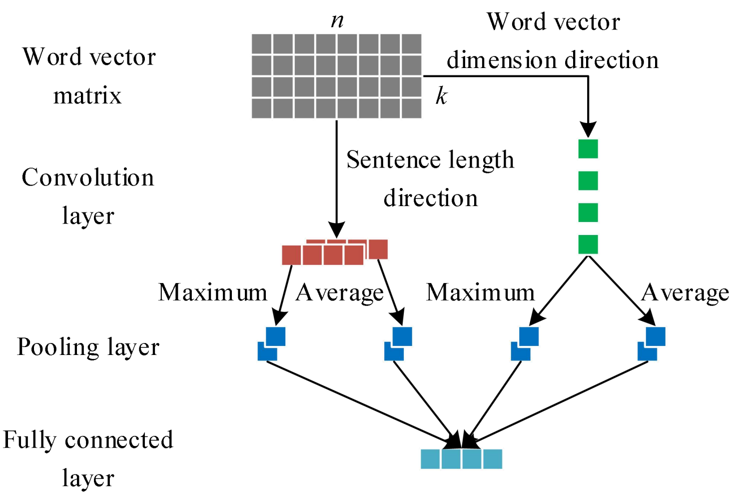

Figure 4. Improved CNN model diagram.

Suppose the input matrix of the convolutional layer is $x \in R^{n \times d}$, where n denotes the length of the input sentence and k denotes the dimension of the word vector. In the direction of sentence length, x_i denotes the i th word vector and $x_{i:j}$ denotes the link from the i th word vector to the j th word vector. The input matrix x can be represented as a link of k -dimensional n word vectors, where $\oplus$ denotes a vector link, as shown in equation (3).

$$x_{1:n} = x_1 \oplus x_2 \oplus \cdots \oplus x_n \tag{3}$$

In the direction of the word embedding dimension, x^i denotes the sentence vector of the i th word in the word vector dimension, and $x^{i:j}$ denotes the link from the i th word to the sentence vector of the j th word. The input matrix x can be represented as a link of k sentence vectors in the n th dimension, where $\oplus$ denotes a vector link, as shown in equation (4).

$$x^{1:k} = x^1 \oplus x^2 \oplus \cdots \oplus x^k \tag{4}$$

The convolutional layer of the CNN generates the feature c_{req} for the i th word sequence $x_{i:j+d-1}$, and the width of the convolutional kernel $w_{req} \in R^{n \times d}$ is d as shown in equation (5).

$$c_{req}^l = f\left(w_{req} \cdot x_{i:j+d-1} + b_{req}\right) \tag{5}$$

where $b_{req} \in R$ is a deviation, f is a nonlinear function, and - denotes matrix multiplication. The convolution kernel w_{req} is then applied to all possible windows $\{x_{1:d}, x_{1:d+1}, \cdots, x_{n:d+n-1}\}$ in the sentence to generate the corresponding feature maps as shown in equation (6).

$$c_{req} = \left[c_{req}^1, c_{req}^2, \cdots, c_{req}^{n-d+1}\right] \tag{6}$$

where c_{req} denotes the convolution result in the sentence length direction.

Since each word embedding dimension corresponds to its own convolution kernel, there are k convolution kernels, each of size $n \times 1$. Suppose the convolutional kernel for the i th word embedding dimension is $w_{emd}^i \in R^{n \times 1}$, and n denotes the length of the input sentence. The feature c_{emd}^i is obtained by using the convolution w_{emd}^i on the sentence vector $x^i \in R^{n \times 1}$ in the i th word-embedding dimension of the input matrix as shown in equation (7).

$$c_{emd}^i = f\left(w_{emd}^i \cdot x^i + b_{emd}^i\right) \tag{7}$$

where $b_{emd}^i \in R$ is a deviation and f is a nonlinear function. The convolution kernel w_{emd}^i is then applied to the i th word embedding dimension to generate the final feature mapping as shown in equation (8).

$$c_{emd} = \left[c_{emd}^1, c_{emd}^2, \cdots, c_{emd}^k \right] \tag{8}$$

In the pooling layer, two types of pooling (max-pooling and average-pooling) are performed on the convolutional output vectors $c_{req} \in R^{n-d+1}$ in the direction of sentence length and c_{emd} in the direction of word embedding dimensions, and then four feature values are obtained, as shown in equations (9), (10), (11), and (12)) shown.

$$\hat{c}_{req} = \max\left(c_{req}\right) \tag{9}$$

$$\overline{c}_{req} = mean\left(c_{req}\right) \tag{10}$$

$$\hat{c}_{emd} = \max\left(c_{emd}\right) \tag{11}$$

$$\overline{c}_{emd} = mean\left(c_{emd}\right) \tag{12}$$

For the above four output features, combining the maximum pooling and average pooling results of the two convolutions yields two combinations: $(\hat{c}_{req}, \overline{c}_{req})$ and $(\hat{c}_{emd}, \overline{c}_{emd})$. A combination (c_1, c_2) has three different combinations as shown in equations (13), (14) and (15).

$$c_{add} = c_1 + c_2 \tag{13}$$

$$c_{sub} = c_1 - c_2 \tag{14}$$

$$c_{Abs\_Sub} = \left|c_1 - c_2\right| \tag{15}$$

where + means add by bit, - means subtract by bit, and $||$ means subtract to take the absolute value.

After combining the two combinations, two eigenvalues are obtained and connected as shown in equation (16).

$$v = v_1 \oplus v_2 \tag{16}$$

where $\oplus$ denotes the connection and v is the final output vector of the pooling layer.

2.3. Relationship Extraction Model

The relationship extraction task on the field of intangible skills inheritance in rural Jiangsu is to extract the relationship information between predefined entities in the named entity recognition task. This study proposes a joint RoBERTa-Effg-Adv entity-relationship extraction model, which adopts the idea of entity-relationship quintuple extraction, uses multiple heads to recognize nested entities, can effectively extract overlapping triples in Chinese text, and combines with the PGD adversarial training algorithm, which effectively improves the model's perturbation-resistant capability.

2.3.1. Relationship Extraction Module

The relationship extraction process is shown in Fig. 5, where the relationship extraction task is split into a quintuple processing, which is subdivided into header relationship extraction, tail relationship extraction, and subject and object identification. Where Equation (17) is the scoring function for the entity-relationship quintet.

$$\begin{gathered} S(s_h, s_t, p, o_h, o_t) = S(s_h, s_t) + S(o_h, o_t) \\ + S(s_h, o_h \mid p) + S(s_t, o_t \mid p) \end{gathered} \tag{17}$$

During model training, for the labeled quintet let $S(s_h, s_t)$, $S(o_h, o_t)$, $S(s_h, o_h \mid p)$, and $S(s_t, o_t \mid p)$ in Eq. (17) be greater than 0, and for the rest of the quintet let all four terms be less than 0. When model prediction is done, enumerate all the possible quintets to find out the values of $S(s_h, s_t) > 0$, $S(o_h, o_t) > 0$, $S(s_h, o_h \mid p) > 0$, and $S(s_t, o_t \mid p) > 0$, and take their intersection as the final output.

The functions $S(s_h, s_t)$ and $S(o_h, o_t)$ are the first and last scoring functions for subject entities and object entities, respectively, and all of them are obtained by $S(s_h, s_t) > 0$ and $S(o_h, o_t) > 0$. As for the functions $S(s_h, o_h \mid p)$ and $S(s_t, o_t \mid p)$, the matching of the predicted relations, $S(s_h, o_h \mid p)$ indicates that the first feature of the subject and object as its own representation is matched once, and considering the existence of the nested named entities, the tails of the entities need to be matched once more with the function $S(s_t, o_t \mid p)$ denotes. Since $S(s_h, s_t)$, $S(o_h, o_t)$ are used to identify subject and object entities, it is done with an Efficient Global Pointer. As for $S(s_h, o_h \mid p)$ it is used to identify (S_h, O_h) pairs whose relation is P, which can also be done with an Efficient Global Pointer, and finally for the item $S(s_t, o_t \mid p)$ the treatment is the same as the principle of $S(s_h, o_h \mid p)$.

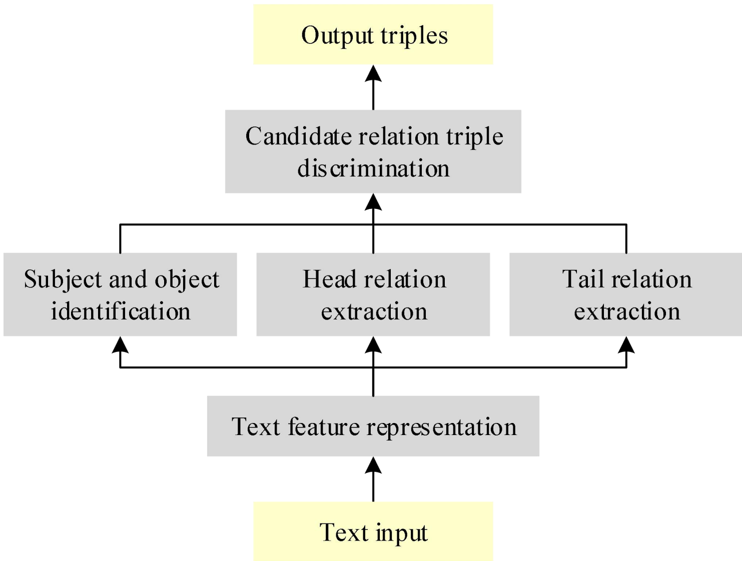

Figure 5. Relationship extraction process.

2.3.2. Confrontation Training

Adversarial training is a type of training that introduces noise and can regularize the parameters to improve the robustness and generalization of the model. Some smaller perturbations are added to the word vectors of the embedding layer to generate adversarial samples, and the obtained adversarial samples are then fed back to the model to improve the model's perturbation resistance. The PGD adversarial training algorithm is used in this study. The algorithm finds the optimal strategy through multiple iterations with the strategy of "small steps, many times", and prevents the perturbation from being too large by setting the perturbation radius. The perturbation term radv is calculated as follows:

$$r_{adv} = \varepsilon \cdot g(x) / \| g(x) \|_2 \tag{18}$$

$$g(x) = \nabla_x L(\theta, x, y) \tag{19}$$

where x denotes the input, y denotes the label, θ denotes the model parameters, ε denotes the perturbation radius, and $L(\theta, x, y)$ denotes the individual sample loss.

The steps of the PGD algorithm are shown below:

(1) Compute the x forward loss, then backpropagate to compute the gradient and back up;

(2) For each step t: according to the gradient of the embedding layer, compute its norm, then compute the radv according to the formula, and then accumulate the radv to the original embedded samples, i.e., $x + radv$, to get the antagonistic samples;

(3) If t is not the last step, normalize the gradient to 0, calculate the forward and backward directions according to $x + radv$ and get the gradient;

(4) If t is the last step, recover the gradient value at step (1), compute the last $x + radv$ and

accumulate the gradient to step (1), and jump out of the loop;

(5) Restore the modified embedding to the value at step (1);

(6) Update the model parameters based on the gradient at step (4).

2.3.3. Loss Function

The loss function uses a sparse version of the cross-entropy loss function for multi-label classification, as shown in Equation (20). P , N are sets of positive and negative classes, $A = P \cup N$, and S is the corresponding score, respectively.

$$\log\left(1+\sum_{i\in N} e^{S_i}\right) = \log\left(1+\sum_{i\in A} e^{S_i}\right) + \log\left(1-\left(\sum_{i\in P} e^{S_i}\right)\Big/\left(1+\sum_{i\in A} e^{S_i}\right)\right) \tag{20}$$

Let $a = \log\left(1+\sum_{i\in A} e^{S_i}\right)$, $b = \log\left(\sum_{i\in P} e^{S_i}\right)$, then Eq. (20) can be simplified to Eq. (21).

$$\log\left(1+\sum_{i\in N} e^{S_i}\right) = a + \log\left(1-e^{b-a}\right) \tag{21}$$

3. Empirical Evaluation of Entity Recognition and Relationship Extraction for the Knowledge Graph of Jiangsu Rural Intangible Cultural Heritage Skills

After completing the construction of knowledge ontology and the design of RCBC named entity recognition model based on CIDOC CRM, it is necessary to verify its technical effectiveness through empirical evidence. In this chapter, the performance of the named entity recognition and entity relationship extraction model is systematically evaluated using the Jiangsu rural intangible text dataset as a benchmark.

3.1. Named Entity Recognition Methods for the Inheritance of Intangible Cultural Heritage Skills in Jiangsu Countryside

3.1.1. Data Sets and Data Pre-Processing

The dataset constructed in this study focuses on traditional skills-based NH projects in rural Jiangsu, covering ancient book restoration, ceramics manufacturing, tie-dyeing, ancient building construction, sword forging and other skills texts.

The data types include structured data: the list of intangible items, inheritor files, and geographic distribution information (obtained from the intangible database of the Jiangsu Provincial Department of Culture and Tourism); and unstructured texts: local history documents, records of the process of the skills, and oral texts of the inheritors (collected from the archives of the cultural centers and field surveys).

A total of 7492 text fragments are included, each with an average length of 120 characters and about 48235 labeled entities. The training set, validation set and test set are divided by 8:1:1.

The preprocessing process includes

(1) Text cleaning: remove irrelevant symbols, HTML tags, advertisement text; merge sentence breaks (e.g., “ceramic.../...manufacturing technology” → “ceramic manufacturing technology”).

(2) Segmentation and lexical annotation: use THULAC tool to segment words and retain noun/verb phrases.

(3) Entity Boundary Calibration: Manual calibration of automatic labeling results (e.g., “Suzhou Woof” needs to be fully labeled rather than split into “Suzhou” + “Woof”).

3.1.2. Experimental Environment and Evaluation Indicators

All experiments in this chapter use RTX3090 graphics card for training, testing and validation, and Pytorch, a deep learning framework, is used to construct the models. The specific parameters of the experimental environment are as follows: CPU: Inter(R) i7 12700F, 64GB of RAM, and GPU: Nvidia RTX3090 24GB.

The RCBC model was trained on a training round size of 300, a training batch size of 32, a learning rate of 0.001, an optimizer of Adam, and a maximum sequence length of 512.

The recognition accuracy of the model as well as the impact of different parameters on the performance of the model need to be reflected using accurate evaluation metrics. The Chinese named entity recognition task is essentially a classification task, so this paper adopts three evaluation metrics that are widely used in classification tasks to evaluate the model, which are Precision, Recall, and F1-score.

3.1.3. Comparison of Baseline Models

This chapter compares a variety of models, including models that do not introduce pre-training such as LSTM-CRF, BiLSTM-CRF. It also compares models that use BERT pre-training, and the BERT models compared in this chapter have introduced the full word coverage mechanism. The ALBERT model introduces the embedding parameter decomposition and cross-layer parameter sharing compared to the original BERT model, which effectively reduces the number of parameters. The ALBERT-att model is based on the ALBERT model by modifying the inter-layer parameter sharing scheme to only share the Attention layer parameters.The RoBERTa model employs a dynamic masking mechanism, which results in different Mask results for each sentence when it is fed into the model. Also, this chapter compares the vocabulary-based Chinese pre-training model woBERT.

3.1.4. Analysis of Model Comparison Results

The named entity recognition results for the eight models are shown in Table 1.

Table 1. The named entity recognition results of 8 models.

Model	Precision/%	Recall/%	F1/%
LSTM-CRF	57.49	53.87	55.62
BiLSTM-CRF	58.73	54.11	56.33
BERT	70.79	67.96	69.35
ALBERT	75.07	69.39	72.12
ALBERT-att	79.81	75.34	77.51
RoBERTa	80.69	69.49	74.67
woBERT	80.99	77.57	79.24
RCBC	86.05	80.37	83.11

As can be seen from the results in the table, the models without introducing pre-training (LSTM-CRF, BiLSTM-CRF) have the weakest performance (F1 ≤ 56.33%), while the pre-trained model significantly improves the performance (F1 ≥ 69.35% for the models of BERT and above), which confirms the effectiveness of pre-training for the NER task. The RCBC model proposed in this paper significantly outperforms the other models in terms of precision (86.05%), recall (80.37%), and F1 value (83.11%), and improves the F1 value of the second-place woBERT by 3.87 percentage points. The vocabulary-based pre-training of woBERT improves significantly on BERT, with F1 improving from 69.35% to 79.24%, indicating that the vocabulary granularity is more suitable for Chinese NER.

In order to analyze the experimental results more intuitively, this chapter draws a double Y-axis bar-fold plot of the comparison experiments as shown in Fig. 6, where the horizontal coordinate represents the model and the vertical coordinate represents the value of the evaluation index.

3.2. Comparative Analysis of Entity Relationship Extraction Models

The high accuracy of named entity recognition lays the foundation for relationship extraction. After verifying the recognition ability of the RCBC model for Intangible Cultural Heritage entities, the extraction effect of semantic relationships between entities needs to be further evaluated. In this section, the RoBERTa-Effg-Adv entity-relationship extraction model is comparatively analyzed to verify its advantages in entity-relationship extraction.

3.2.1. Comparison of Baseline Models

The specific experimental hardware configuration and software environment settings in this chapter are exactly the same as those in the previous chapter, and the evaluation metrics are still P, R and F1 values.

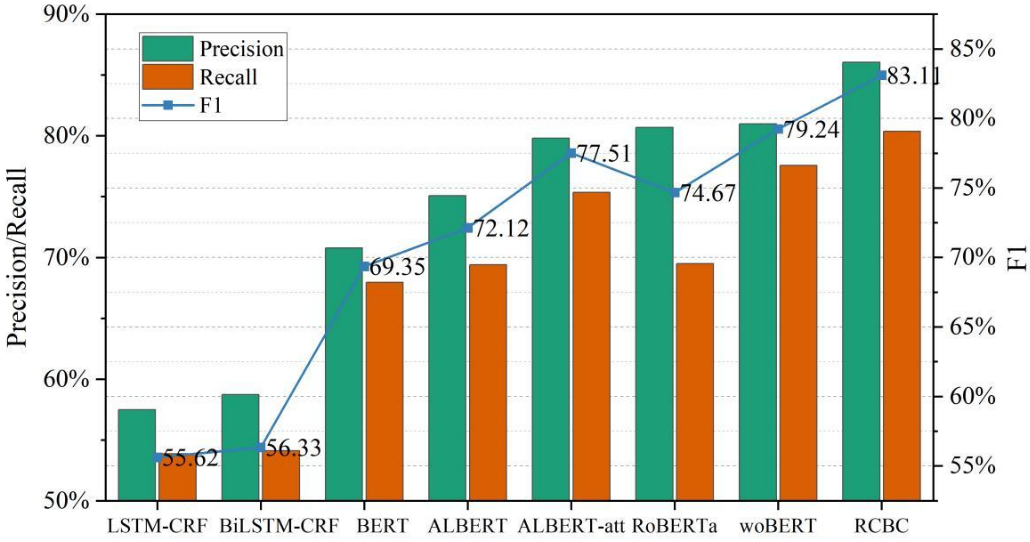

Figure 6. Comparison results of named entity recognition models.

In order to verify the performance of the RoBERTa-Effg-Adv entity-relationship joint extraction model based on PGD adversarial training, the following sets of comparison experiments are set up under the same experimental environment, including the comparison of models such as the single model and the combined model for the baseline task, and the comparison models are described as follows:

(1) BERT: A baseline model with a multilayer bi-directional Transformer encoder structure and with two pre-training tasks, which can effectively capture the contextual information and semantic relations of sentences.

(2) CBIGRU: a combined model combining CNN and BIGRU models, which can learn the local information of text utterances and also take into account the contextual information.

(3) BERT-ATT: Adding the attention mechanism, the feature vectors output from the BERT model are re-calculated for relevance.

(4) BERT-BiLSTM-ATT: Adding bi-directional LSTM network, capturing more semantic information before and after the text, and acquiring more comprehensive semantic features.

3.2.2. Analysis of Model Comparison Results

A comparison of the experimental results of entity relationship extraction for different models is shown in Table 2.

Table 2. Experimental results of entity relationship extraction for different models.

Model	Precision/%	Recall/%	F1/%
BERT	76.02	74.29	75.15
CBIGRU	72.54	71.77	72.15
BERT-ATT	79.95	77.05	78.47
BERT-BiLISM-ATT	83.33	84.55	83.94
RoBERTa-Effg-Adv	85.34	86.42	85.88

As can be seen from Table 2, the model of this paper is the overall leader, RoBERTa-Effg-Adv ranks first in precision (85.34%), recall (86.42%) and F1 value (85.88%), which is improved by 1.94 percentage points (F1 value) compared with the second-place BERT-BiLSTM-ATT. Its recall (86.42%) is the highest in the whole table, indicating that it has the strongest coverage of entity relationships, which effectively improves the model robustness in combination with adversarial training PGD. The models (BERT-ATT, BERT-BiLSTM-ATT) introducing the attention mechanism (ATT) or bidirectional LSTM (BiLSTM) significantly outperform the baseline BERT (F1 improvement ≥ 3.32 percentage points). The pure neural network model CBIGRU (CNN+BiGRU) performs the weakest (F1 = 72.15%), suggesting that the structure of the pre-trained language model is more advantageous in the relation extraction task.

In order to show the recognition effect of different models more intuitively, the data in the above table is converted into a double Y-axis bar - line graph as shown in Figure 7.

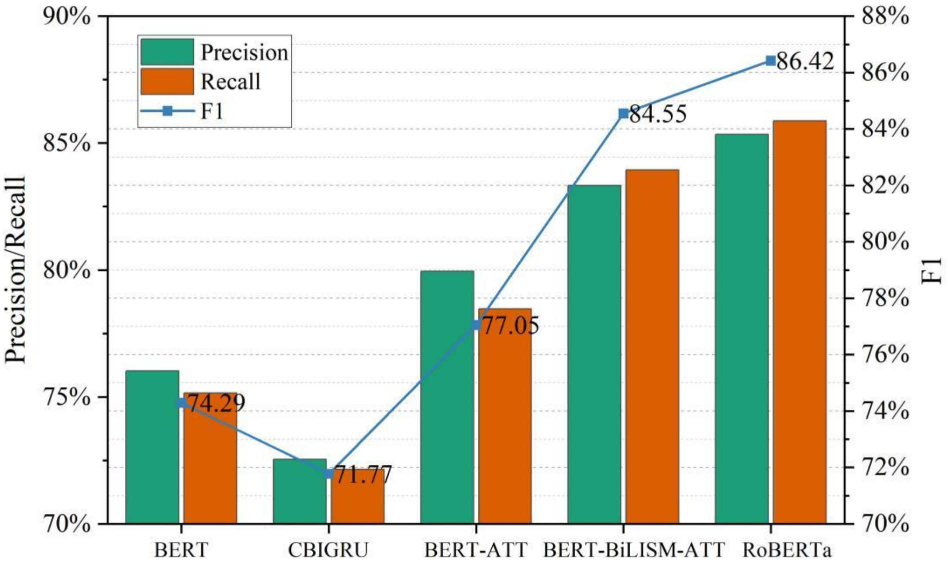

Figure 7. Comparison of Entity Relationship Extraction models.

4. Comparative Study on the Efficacy of Jiangsu's Intangible Cultural Heritage Digitized Carriers and Network Communication on Multiple Platforms

The technical validation shows that knowledge mapping can effectively structure NRL knowledge, while its practical value needs to be realized by the digital carrier. This chapter turns to the application level, firstly analyzing the influence of the website of the digital museum of NRLs, and then exploring the dissemination characteristics of the four techniques, including Suzhou embroidery, on the platforms of Baidu, WeChat and Weibo.

4.1. On the Current Status of the Construction of Intangible Digital Museums in Rural Jiangsu Province

In the positioning of the design of the intangible digital museum about intangible cultural heritage skills in the countryside of Jiangsu, 20 samples from more than 1,000 search results were retrieved with the keywords of intangible cultural heritage. Among them, the data of 20 intangible websites were organized: total connection, inner connection, outer connection, influence factor, inner factor, outer factor, and PR value. The values of the 20 ICH websites are summarized in Table 3, and the popularity of the websites is summarized according to the size of the PR value, which shows that the larger the value, the higher the level of the website, and the higher the degree of importance it receives.

Table 3. The various values of 20 intangible cultural heritage websites.

Website Number	Number of web pages	Total connection	Internal connection	External connection	Influence factor	Internal factor	External factor	PR value
1	19439	238400	217000	21400	11.2500	10.3607	0.8893	4
2	21930	45600	45500	131	8.5346	8.4288	0.1058	5
3	17326	45000	12500	32500	1.1777	0.4571	0.7206	5
4	15985	33700	634	33100	3.3149	0.0747	3.2402	2
5	14864	23400	18	23400	1.0142	0.0004	1.0138	3
6	13430	651	1	650	0.0838	0.0003	0.0835	3
7	10181	95	37	58	8.4453	3.1829	5.2624	2

8	9786	44000	19500	24500	13.382	0.6605	12.7215	7
9	9560	157	97	60	1.0099	0.1041	0.9058	0
10	8444	48000	46	48000	0.8385	0.0296	0.8089	2
11	7382	720	5	715	1.4441	0.0074	1.4367	4
12	6591	94500	72	94400	0.0087	0.0045	0.0042	0
13	8640	3100	96	3000	0.6461	0.0034	0.6427	4
14	7987	677	133	544	1.2255	0.0006	1.2249	5
15	5227	6300	11	6300	0.0263	0.0099	0.0164	2
16	3969	74	1	73	2.1647	0.0062	2.1585	3
17	2573	153	6	147	0.1913	0.0045	0.1868	3
18	1561	1900	36	1902	0.7164	0.0028	0.7136	4
19	1888	226	87	139	1.4103	0.9014	0.5089	4
20	2065	1800	1760	81	0.0373	0.0072	0.0301	5

Based on the analysis of the core indicators of the 20 NRM websites in Table 3, the following conclusions can be drawn.

(1) Resource integration ability is the core determinant of website influence. With a balanced structure of 19,500 internal connections and 24,500 external connections, website No. 8 achieves the highest PR value of 7 and impact factor of 13.382, which proves that internal and external resource synergy can maximize the effectiveness of communication. Although website number 12 has the highest total number of 94,500 connections in the whole table, it has only 72 internal connections (accounting for 0.08%), resulting in a PR value of 0, revealing that purely relying on external attraction cannot make up for the shortcomings of the internal structure.

(2) The quality of internal structure is significantly better than the quantity of size. High page count ≠ high influence: No.1 (19,439 pages, the highest in the whole table) was only awarded PR4 due to the high proportion of internal connections (217,000/238,400≈91%) and weak external connections (21,400); No.14 (7,987 pages) achieved PR5 with 677 total connections (133 internal connections), emphasizing the value of streamlining the structure.

4.2. Research on the Network Communication of Intangible Cultural Heritage Skills in Jiangsu Countryside

The PR values of digital museums reveal the efficacy of resource integration, and the dissemination of technology needs to rely on a wider range of online platforms. Based on the conclusions of the website analysis in the previous section, this section focuses on the multi-platform dissemination data and analyzes the distribution characteristics of content themes.

In this study, four items of intangible cultural heritage (ICH), namely, “Su embroidery”, “Nanjing paper-cutting”, “Liuching bamboo carving” and “Huishan clay figure”, are selected as samples for the research. Intangible cultural heritage as a research sample. Using the content analysis method and big data to search the relevance of these four Jiangsu intangible cultural heritage skills, the research team used the data to show the current status of the network communication of the four intangible cultural heritage handicrafts, choosing Baidu to search the pages of traditional websites, WeChat and Sina microblogging as the platforms for data collection, and then further exploring the status of the traditional artisanal skills retained on the network and the link between the inheritance.

4.2.1. Comparative Analysis of Web-Based Communication Data Platforms

The data table of network dissemination of the four NRLs in Jiangsu is shown in Figure 8.

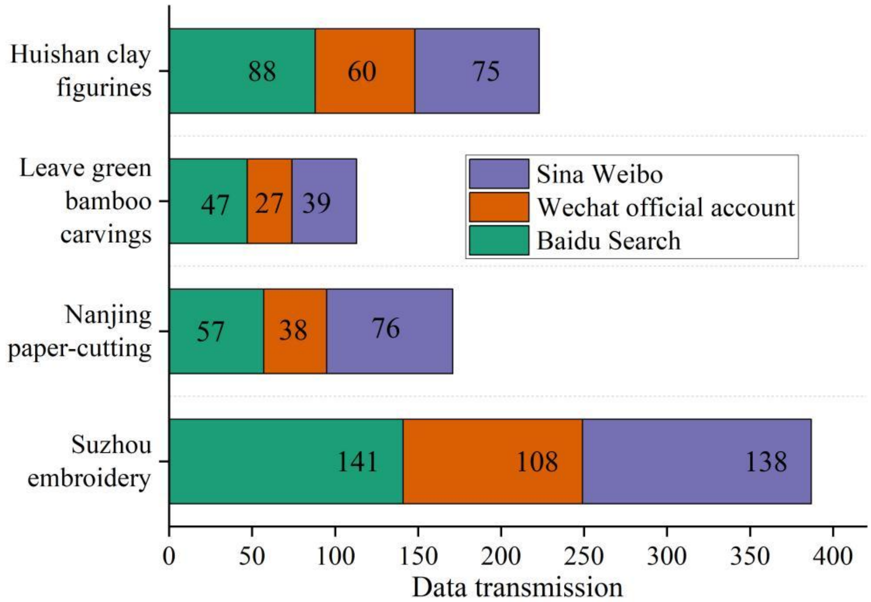

Figure 8. The online dissemination data of intangible cultural heritage skills.

The total amount of dissemination of the four Jiangsu NRHs on the three platforms shows significant differences. Among them, Suzhou embroidery has the highest total dissemination (387 articles), followed by Huishan clay figure (223 articles), Nanjing paper-cutting (171 articles), and Liucheng bamboo carving has the lowest (113 articles). In terms of platforms, in Baidu search, Suzhou embroidery (141 articles) > Huishan Clay People (88 articles) > Nanjing Paper Cutting (57 articles) > Liujing Bamboo Carving (47 articles); in WeChat, Suzhou embroidery (108 articles) > Huishan Clay People (60 articles) > Nanjing Paper Cutting (38 articles) > Liujing Bamboo Carving (27 articles); in Sina Weibo, Suzhou embroidery (138 articles) > Huishan Clay People (75 articles) > Nanjing Paper Cutting (76 articles) > Liujing Bamboo Carving (39 articles). Bamboo carving (39 articles).

The data show that Suzhou embroidery has an absolute advantage on all three platforms, while WeChat has the lowest overall dissemination (233 entries for the four techniques, which is only 53.4% of the Baidu search).

4.2.2. Network Communication Presentation of Jiangsu Rural Intangible Cultural Heritage Skills

The network communication status of these four skills was further subdivided according to the orientation of the theme of the communication content, and the data on the network communication of the four skills of the intangible cultural heritage in rural Jiangsu are shown in Table 4.

Table 4. The online dissemination of the four skills presents data.

		Baidu Search		Wechat official account		Sina Weibo	
Content theme		Introduction to Skills and Products	Promotion of skills	Introduction to Skills and Products	Promotion of skills	Introduction to Skills and Products	Promotion of skills
Suzhou embroidery	Total	141		108		138	
	Frequency	76	65	33	75	47	91
	Proportio	53.90%	46.10%	30.56%	69.44%	34.06%	65.94%

	n						
Nanjing paper-cutting	Total	57		38		76	
	Frequency	35	22	15	23	34	42
	Proportion	61.40%	38.60%	39.47%	60.53%	44.74%	55.26%
Leave green bamboo carvings	Total	47		27		39	
	Frequency	26	21	6	21	21	18
	Proportion	55.32%	44.68%	22.22%	77.78%	53.85%	46.15%
Huishan clay figurines	Total	88		60		75	
	Frequency	47	41	24	36	32	43
	Proportion	53.41%	46.59%	40.00%	60.00%	42.67%	57.33%

The communication content themes of the four skills presented the differentiated characteristics of the platform, and the proportion of skill promotion content was: WeChat public account was the highest (69.44% for Suzhou embroidery and 77.78% for bamboo carving), followed by Weibo (65.94% for Suzhou embroidery), and the lowest for Baidu retrieval (46.10% for Suzhou embroidery); The proportion of technical product introduction: Baidu search dominated (Nanjing paper-cutting 61.40%, Suzhou embroidery 53.90%), followed by Weibo (53.85% of green bamboo carving). Among them, the proportion of product introduction (53.85%) on Weibo is abnormally higher than that of promotion (46.15%), and the proportion of promotion on WeChat public account is 77.78%, reflecting the difference in audience on the platform.

5. Conclusion

This study reveals the inheritance path and innovation mechanism of Jiangsu rural NRL skills by constructing a knowledge mapping technology system with multi-dimensional dissemination analysis.

The proposed RCBC named entity recognition model achieves an F1 value of 83.11% (Precision 86.05%/Recall 80.37%) on the Jiangsu NRL dataset (7,492 texts), which is an improvement of 3.87 percentage points compared with the woBERT baseline. the RoBERTa-Effg-Adv relational extraction model achieves the optimal value of 83.11% (Precision 85.34%/Recall 86.42%) with an F1 value of 85.88% (Precision 85.34%/Recall 86.42%) to reach the optimum, an improvement of 1.94% over BERT-BiLSTM-ATT, which proves the effectiveness of quintuple extraction and PGD adversarial training on complex semantic relations.

The influence of NRL digital museums depends on the quality of resource integration: websites with balanced internal/external connections (e.g., No. 8: internal connection 19,500/external connection 24,500) obtain the highest PR value of 7 with an impact factor of 13.382, while websites with a single reliance on external links (No. 12: external connection 94,400 accounting for 99.92%) have a PR value of 0.

There are significant differences in the content tendency of online communication platforms about Jiangsu's NRHs, with WeChat public numbers focusing on the promotion of the techniques (69.44% of Su embroidery) and Baidu searches focusing on the introduction of the products (61.40% of Nanjing paper-cutting); the total amount of dissemination is distributed in a gradient, with Su embroidery (387 articles) > Huishan mudman (223 articles) > Nanjing paper-cutting (171 articles) > Liuching bamboo carving (113 articles), reflecting the positive correlation between awareness of the techniques and online visibility. Recognition is positively correlated with network visibility.

References

1. Xi, W., Hamidon, N. A., Din, N. H., & HaiTao, D. (2024). The Interactive Path of Integrating Traditional Art Intangible Cultural Heritage into University Art Education in Jiangsu Province. Library of Progress-Library Science, Information Technology & Computer, 44(3).
2. Li, J. (2021). Digital Protection and Inheritance of Intangible Cultural Heritage in the Era of Big Data. In Cyber Security Intelligence and Analytics: 2021 International Conference on Cyber Security Intelligence and Analytics (CSIA2021), Volume 1 (pp. 24-30). Springer International Publishing.
3. Wan, H., SIKKA, S., Wang, Z., Zhang, W., & Huang, T. (2023). Protection and Inheritance of Traditional Intangible Cultural Heritage Based on Big Data Technology: A Case Study in Guangxi. Academic Journal of Humanities & Social Sciences, 6(23), 76-85.
4. He, Y. (2022, July). Research on the influencing factors of the endangered inheritance of folk intangible cultural heritage and the educational protection based on big data technology. In EAI International Conference, BigIoT-EDU (pp. 314-324). Cham: Springer Nature Switzerland.
5. Lvping, S. (2021). Blockchain technology for management of intangible cultural heritage. Scientific programming, 2021(1), 2613656.
6. Liu, X., Dong, F., Shui, W., & Geng, G. (2025). Blockchain in digital cultural heritage resources: technological integration, consensus mechanisms, and future directions. npj Heritage Science, 13(1), 1-11.
7. Dou, J., Qin, J., Jin, Z., & Li, Z. (2018). Knowledge graph based on domain ontology and natural language processing technology for Chinese intangible cultural heritage. Journal of Visual Languages & Computing, 48, 19-28.
8. Fan, T., & Wang, H. (2022). Research of Chinese intangible cultural heritage knowledge graph construction and attribute value extraction with graph attention network. Information Processing & Management, 59(1), 102753.
9. Wang, Y., Liu, J., Wang, W., Chen, J., Yang, X., Sang, L., ... & Peng, Q. (2024). Construction of Cultural Heritage Knowledge Graph Based on Graph Attention Neural Network. Applied Sciences, 14(18), 8231.
10. Gu, X., Xiao, Y., Hua, Z., Jin, H., & Wang, B. (2022, October). A novel approach for constructing intangible cultural heritage knowledge graphs. In 2022 8th International Symposium on System Security, Safety, and Reliability (ISSSR) (pp. 117-126). IEEE.
11. Liang, Y., Xie, B., Tan, W., & Zhang, Q. (2025). Ontology-based construction of embroidery intangible cultural heritage knowledge graph: A case study of Qingyang sachets. PloS one, 20(1), e0317447.
12. Huang, Y. Y., Yu, S. S., Chu, J. J., Fan, H. H., & Du, B. B. (2023). Using knowledge graphs and deep learning algorithms to enhance digital cultural heritage management. Heritage Science, 11(1), 204.
13. Lu, L., Liang, X., Yuan, G., Jing, L., Wei, C., & Cheng, C. (2023). A study on the construction of knowledge graph of Yunjin video resources under productive conservation. Heritage Science, 11(1), 83.
14. Wang, G. (2025). Development and analysis of a knowledge graph-based platform for cultural heritage protection and inheritance. Journal of Computational Methods in Sciences and Engineering, 25(1), 1039-1047.
15. Pellegrino, M. A., Scarano, V., & Spagnuolo, C. (2022). Move cultural heritage knowledge graphs in everyone's pocket. Semantic Web, 14(2), 323-359.
16. Mayr, E., Windhager, F., Liem, J., Beck, S., Koch, S., Kusnick, J., & Jänicke, S. (2022, October). The multiple faces of cultural heritage: Towards an integrated visualization platform for tangible and intangible cultural assets. In 2022 IEEE 7th Workshop on Visualization for the Digital Humanities (VIS4DH) (pp. 13-18). IEEE.
17. LIANG, Y., Ruixia, Y. A. N. G., Yihan, X. I. E., Pu, W. A. N. G., Anlin, Y. A. N. G., & Wei, L. I. (2022). Construction and analysis of global world cultural heritage knowledge graph based on big earth data. National Remote Sensing Bulletin, 25(12), 2441-2459.
18. Hyvönen, E., Boman, P., Rantala, H., Ahola, A., & Leskinen, P. (2024, December). ConfermentSampo–A Knowledge Graph, Data Service, and Semantic Portal for Intangible Academic Cultural Heritage 1643–2023 in Finland. In International Knowledge Graph and Semantic Web Conference (pp. 1-16). Cham: Springer Nature Switzerland.
19. Lu-lu, W., Mohamed, F. N., & Ze-lin, L. (2025). Lanjiefu in Wenzhou City under the Perspective of Digital Humanities: Constructing a Knowledge Graph to Empower the Cultural Resource Base. International Journal of Education and Humanities, 5(3), 404-414.
20. Maree, M. (2025). Quantifying Relational Exploration in Cultural Heritage Knowledge Graphs with LLMs: A Neuro-Symbolic Approach for Enhanced Knowledge Discovery. Data, 10(4), 52.