Knowledge Graph-Based Design Method for the Integration of Red Cultural and Multi-Ethnic Cultural Elements

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Abstract. This paper proposes a knowledge graph-based design method for integrating red cultural and multi-ethnic cultural elements in art design. First, multi-source cultural data are collected and annotated, and a structured knowledge graph is constructed through BERT-based named entity recognition and relation extraction to represent entities and their semantic relationships. Then, a graph-driven semantic reasoning mechanism is developed to support the association and integration of cultural elements for design tasks. Furthermore, a knowledge graph-based design support approach provides intelligent recommendations and improves design efficiency. Experimental results demonstrate that the proposed method achieves higher performance in knowledge extraction and enhances design quality and efficiency. The proposed approach provides a systematic and intelligent solution for cultural integration and offers new insights for AI-assisted cultural design.

Keywords: Knowledge Graph; Cultural Integration; Red Culture; Multi-Ethnic Culture; Art Design; Semantic Reasoning.

1 Introduction

The integration of red culture and multi-ethnic culture is essential for strengthening cultural identity, yet traditional art design methods often rely on subjective experience and lack systematic approaches. Knowledge graph technology offers a structured way to organize and associate heterogeneous cultural data[2]. This study proposes a knowledge graph-based design method that extracts cultural entities and relationships, constructs a semantic graph, and supports the integration and recommendation of cultural elements in art design.

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2 Literature Review

2.1 Knowledge Graph and Cultural Data Modeling

Knowledge graphs have been widely used for cultural data modeling, enabling structured representation of entities such as historical events, artifacts, and symbols[1][3]. Existing studies focus on ontology construction and semantic retrieval, improving data organization and accessibility in cultural heritage and digital humanities[4]. However, most approaches treat knowledge graphs primarily as tools for storage and query, lacking systematic comparison in design-oriented scenarios.

More importantly, current research rarely explores how knowledge graphs can support cross-domain cultural integration. The theoretical mechanism—transforming implicit cultural knowledge into explicit semantic relations and enabling multi-hop association—is often underdeveloped. This limits their ability to support creative design tasks involving multiple cultural systems[5].

2.2 AI-Assisted Design and Cultural Integration

Artificial intelligence has been increasingly applied in art and design, particularly through recommendation systems and generative models[7]. These methods improve efficiency by analyzing user preferences and visual features. However, most existing approaches rely on pattern recognition and feature extraction, with limited capability to represent deeper cultural semantics.

As a result, they lack a structured mechanism for integrating heterogeneous cultural elements. To address this gap, this study introduces a knowledge graph-based framework that enables semantic-level reasoning and interpretable cultural integration, providing a clearer link between cultural knowledge representation and design application[6].

3 Methodology

As illustrated in Fig. 1, this study proposes a knowledge graph-based framework for integrating red cultural and multi-ethnic cultural elements in art design. It covers data acquisition, knowledge extraction, graph construction, and semantic reasoning, forming a pipeline from heterogeneous data to structured knowledge for design support.

3.1 Data Collection and Schema Definition

This study constructs a multi-source cultural dataset including textual and visual data to support the integration of red cultural and multi-ethnic cultural elements. The textual data cover historical events, figures, ethnic traditions, cultural symbols, and design-related descriptions, while the visual data include images of patterns, costumes, artifacts, and symbolic elements.

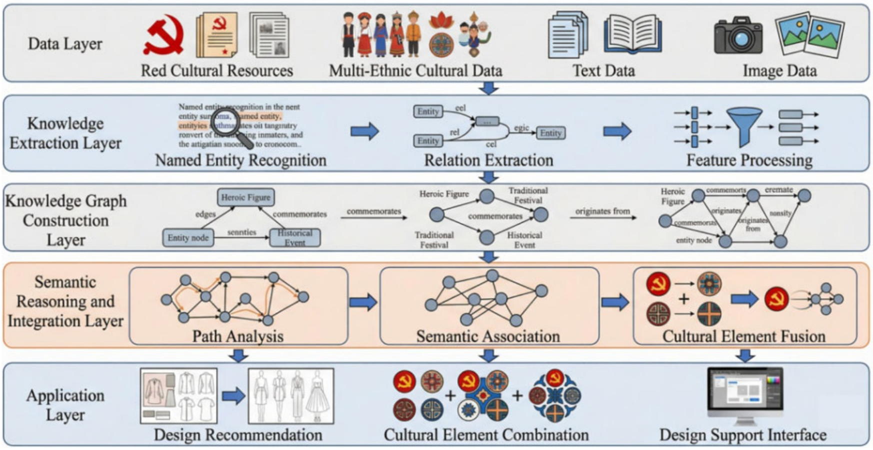

Fig. 1. Framework for Cultural Integration Based on Knowledge Graphs.

To ensure data quality, preprocessing is conducted, including text normalization, sentence segmentation, duplicate removal, and image filtering. Meanwhile, an entity–relation schema is defined to guide knowledge extraction. The entity types include Historical Event, Person, Ethnic Group, Cultural Symbol, Pattern, and Artifact, and the relation types include belongs to, symbolizes, originates from, used in, and associated with. This schema provides a structured basis for subsequent modeling.

3.2 Named Entity Recognition and Relation Extraction

To extract structured knowledge from text, a two-stage method is adopted.

For named entity recognition, a BERT-BiLSTM-CRF model is used. BERT first encodes each sentence to obtain contextual embeddings, which capture semantic information in cultural texts. Then, a BiLSTM layer models sequential dependencies to improve boundary detection. Finally, a CRF layer decodes the optimal label sequence under the BIO tagging scheme, ensuring valid label transitions. The model outputs entity spans and corresponding categories.

For relation extraction, entity pairs within the same sentence are constructed and classified using a supervised approach. The sentence containing the entity pair is encoded by BERT, and the contextual representation is used as input to a classifier. A Softmax layer predicts the relation type between entities. To reduce noise, a "no-relation" category is introduced so that unrelated pairs can be filtered out. The final output is represented as triples:

$$T=(\mathrm{h},r,t) \tag{1}$$

where h and t are entities and r is the semantic relation.

3.3 Feature Processing and Knowledge Graph Construction

To enhance knowledge representation, both textual and visual features are processed.

Textual features are obtained from BERT embeddings, which are used to represent both entities and design queries. For visual data, a convolutional neural network is applied to extract high-level features of cultural images, capturing visual characteristics such as patterns, colors, and forms. These visual features are then aligned with textual representations in a unified semantic space, allowing images to be linked to corresponding entities as attributes.

After feature extraction, entities, relations, and attributes are integrated into a knowledge graph defined as:

$$G=(E,R,T) \tag{2}$$

where E, R, and T denote entities, relations, and triples, respectively. Each node stores entity type, textual description, and optional visual features, while edges represent semantic relations. Entity alignment is performed using name normalization and semantic similarity to avoid redundancy. The graph is implemented in Neo4j for efficient storage and querying.

3.4 Semantic Reasoning and Design Support

Based on the constructed knowledge graph, a semantic reasoning mechanism is designed to support cultural element integration in art design. Given a design task, its semantic representation is generated and matched with entity embeddings to retrieve relevant cultural elements.

These elements are used as seed nodes for graph exploration. A breadth-first search strategy with limited depth is applied to discover meaningful connections between red cultural and multi-ethnic cultural elements. Paths with higher semantic relevance are prioritized to ensure interpretability and coherence.

Finally, the system outputs design support results, including recommended cultural elements, their semantic relationships, and possible integration paths. This process helps designers identify implicit cultural associations and reduces reliance on subjective experience, thereby improving the efficiency and rationality of integrated design.

4 Experiments and Comparative Analysis

4.1 Experimental Setup

To evaluate the effectiveness of the proposed method, a multi-source cultural dataset was constructed, consisting of 1,200 textual records and 850 image samples related to red culture and multi-ethnic cultural elements. The dataset covers categories such as historical events, cultural symbols, ethnic patterns, and traditional artifacts. All data were manually annotated and verified by domain experts to ensure accuracy and consistency.

The dataset was divided into training, validation, and test sets with a ratio of 70:15:15. A BERT-BiLSTM-CRF model was used for named entity recognition, and a BERT-based classifier was adopted for relation extraction. The extracted entities and relations were used to build a knowledge graph containing 3,500 entities and 6,800 relational triples. The system was implemented using a graph database environment (Neo4j), and semantic queries were conducted to support cultural element integration.

For evaluation, Precision, Recall, and F1-score were adopted as the main metrics for both entity recognition and relation extraction tasks. In addition, a controlled experiment involving 40 design students was conducted to assess the effectiveness of the proposed method in improving cultural integration and design efficiency.

4.2 Main Experimental Results

To evaluate the performance of the proposed method, both quantitative analysis and comparative experiments were conducted. A baseline method based on keyword matching and rule-based relation identification was used for comparison.

Table 1. Performance comparison of knowledge extraction.

Method	Entity F1 (%)	Relation F1 (%)
Baseline	82.8	78.5
Proposed	91.3	88.7

Table 1 presents the performance of entity recognition and relation extraction. The proposed method achieved an Entity F1-score of 91.3% and a Relation F1-score of 88.7%, outperforming the baseline by 8.5% and 10.2%, respectively. This demonstrates that the proposed method can effectively capture contextual semantics and improve the accuracy of structured knowledge extraction.

In addition, a user study involving 40 participants was conducted to evaluate design performance. As shown in Table 2, the proposed method significantly improved both design quality and efficiency. The average design score increased from 76.4 to 86.9, while the average completion time decreased by 21.5%.

Table 2. Design performance comparison.

Method	Design Score	Completion Time (min)
Baseline	76.4	52.3
Proposed	86.9	41.1

These results indicate that the proposed knowledge graph-based method effectively enhances both cultural integration and design efficiency.

4.3 Discussion

The experimental results demonstrate that the proposed method improves both knowledge extraction performance and design application outcomes. Compared with the baseline, it achieves higher accuracy in entity and relation extraction, providing a more reliable foundation for cultural integration. The user study further confirms that the method enhances design quality while reducing completion time, indicating its practical effectiveness in supporting creative design tasks.

The effectiveness of the method can be attributed to three aspects. First, structured knowledge extraction transforms unstructured cultural data into explicit entities and relationships, improving interpretability. Second, graph-based reasoning enables multi-hop associations between heterogeneous cultural elements, facilitating cross-cultural integration. Third, the reuse of structured knowledge supports efficient retrieval and recombination of design elements.

However, several limitations remain. Some preprocessing and entity alignment procedures still rely on rule-based strategies, which may affect scalability for larger datasets. In addition, the current knowledge graph is constructed based on predefined schemas and lacks dynamic updating capability. Future work will explore more automated extraction methods and advanced reasoning mechanisms to further improve adaptability and performance.

5 Conclusion

This study proposes a knowledge graph-based method for integrating red cultural and multi-ethnic cultural elements in art design. By applying BERT-based named entity recognition and supervised relation extraction, unstructured cultural data are effectively transformed into structured knowledge and organized into a semantic knowledge graph. Based on this graph, a reasoning mechanism is further developed to discover implicit associations between heterogeneous cultural elements and provide interpretable support for design decisions.

Experimental results demonstrate that the proposed method not only improves the accuracy of knowledge extraction but also enhances design quality and efficiency in practical applications. Compared with traditional approaches, it offers a more systematic, interpretable, and efficient solution for cultural integration in art design. Future work will focus on improving the automation, scalability, and dynamic updating capabilities of the knowledge graph, as well as exploring more advanced reasoning strategies for intelligent design support.

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