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Identifying the Value Identity Structure of Youth in the Context of Red Culture Dissemination Using GNN

Xiaoyan Wang
School of Marxism, Henan Open University, Zhengzhou 450046, Henan, China
Corresponding author: Xiaoyan Wang (e-mail: wangxiaoyan202412@126.com)

ABSTRACT Understanding information propagation mechanisms in large-scale heterogeneous networks requires effective representation of complex relational structures and diffusion dynamics. This study proposes a graph neural network (GNN)-based framework for topology-aware identification of structural communities and propagation patterns in cross-platform information dissemination systems. A heterogeneous information graph is constructed by integrating user interactions, content transmission behaviors, and platform-level communication relationships. To capture high-order structural dependencies, a relation-aware message-passing mechanism is developed to jointly encode network topology and semantic correlations into unified node representations. Based on the learned embeddings, structural communities, influential nodes, and dominant propagation paths are quantitatively identified to characterize information-flow patterns within the network. Experimental results demonstrate that the proposed framework detects 19 core structural communities with an average degree centrality of 0.71 and an internal edge density of 0.62, outperforming conventional network-analysis approaches in structural representation capability. The proposed framework provides an effective methodology for heterogeneous network modeling, information propagation analysis, influence-path characterization, and graph-based representation learning, offering potential applications in intelligent communication systems, distributed information networks, and complex propagation-environment analysis.

INDEX TERMS graph neural network, information propagation, network topology analysis, distributed information networks

I. INTRODUCTION

IN the network era, the dissemination of red culture and the construction of youth value identity exhibit complex relational dynamics within large-scale digital communication networks. This process reflects the formation of dense relational structures in which cultural symbols circulate among interconnected social actors. It is an important theoretical problem that needs to be further explored in the field of communication studies and ideological and political education [1,2]. At the same time, it also has strong practical significance for understanding the laws of ideological dissemination and improving the accuracy and effectiveness of the guidance of main value [3].

However, existing research faces significant challenges at the methodological level. The field of red culture dissemination is essentially a complex system of heterogeneity, multimodality, and dynamic evolution [4,5]. The formation of individual youth identity is not an isolated expression of attitude, but is deeply rooted in a multidimensional interactive relationship network of "people-content-platform" [6]. Traditional methods based on questionnaire surveys or content analysis are difficult to capture the structural constraints of large-scale relational data [7]. Although classical social network analysis can describe topological connections, it cannot effectively integrate multi-source heterogeneous information such as node attributes, relational semantics, and temporal evolution, and it lacks the ability to adaptively learn higher-order structural patterns from data [8,9]. These methodological limitations often lead to superficial or fragmented portrayals of the internal network structure of youth value identity.

To address this challenge, the field of computational social science has attempted to introduce network science and machine learning methods. Representative approaches include using topic models to analyze text content to infer group focus, or applying community detection algorithms to identify clustered group structures in networks [10,11]. The core value of these methods lies in achieving quantitative processing of some structural or content features. However, their inherent limitations are equally apparent: they typically rely on the assumption of homogeneous networks or a single data modality, failing to differentiate and integrate diverse relationship types in the communication field [12,13]. More importantly, most of these methods belong to shallow feature engineering and cannot automatically extract the deep structural representations driving value identity from raw interaction data through end-to-end learning mechanisms [14]. It is precisely the shortcomings of existing methods in both "heterogeneous relationship modeling" and "deep structural learning" that have left the question of "how to automatically identify and analyze the implicit network structure of youth value identity from multi-source heterogeneous behavioral data" unanswered.

This paper aims to directly address the above issues by proposing and constructing a systematic analytical framework based on graph neural networks. The core approach of this study is as follows: first, cross-platform youth behavior data is formally defined as a heterogeneous information graph containing multiple node and relationship types. Then, a graph neural network model integrating relational semantic constraints is designed. Through multi-layered message passing and representation learning, the structure and semantic information of the propagation field are encoded into unified node embeddings. Finally, based on the learned embedding vectors and network topology, the community segmentation, key nodes, and diffusion paths of value identity are quantitatively extracted. This study demonstrates that the proposed framework effectively identifies the layered community structure of youth value identity. By revealing the structured coupling characteristics of cognitive, emotional, and behavioral dimensions, the research provides a computable and interpretable analytical paradigm for understanding the propagation mechanism of red culture.

II. FRAMEWORK FOR GRAPH MODELING AND VALUE IDENTITY STRUCTURE OF THE RED CULTURE DISSEMINATION FIELD BASED ON GNN

In the field of red culture dissemination, the generation of youth value identity does not originate from a single information contact, but rather evolves gradually under the combined influence of cross-platform interactive relationships, content semantic orientation, and media structural constraints. Around this networked generation mechanism, this research starts with the objective recording of dissemination behavior, unifying youth individuals, red culture content, and dissemination carriers into a heterogeneous relationship system. Structured modeling is used to characterize the connection states and evolutionary trajectories among multiple subjects. Based on this, graph neural networks are introduced to learn the high-order structural information carried by the dissemination relationships, transforming the youth's interactive positions, content contact paths, and media embedding methods in the dissemination field into computable structural representations. Therefore, the dissemination field is transformed from an empirically descriptive object into a computational structure with clear mathematical constraints, and youth value identity enters a quantifiable and analytical research framework. Based on the above research path, the overall technical and theoretical framework of Chapter 2 is constructed, as shown in Figure 1.

Figure 1, starting from the structural modeling of the dissemination field, transforms cross-platform interactive data into a heterogeneous information graph constrained by multiple nodes and relationships. This allows the interaction between individual youths, red culture content, and dissemination carriers to move beyond discrete behavioral levels and be uniformly embedded within the network structure. The construction of the heterogeneous relationship network provides structural boundaries for subsequent representation learning, ensuring that the dissemination process of the graph neural network is always limited by real interaction relationships, thereby guaranteeing the structural sensitivity of node embedding vectors to the dissemination mechanism. Community segmentation, key node identification, and dissemination path tracing, centered around the embedded representation, transform the identity associations originally implicit in the complex network into observable structural patterns. This process transforms value identity from subjective judgment into a stable association result induced by network evolution. As community aggregation states, node structural positions, and path flow patterns form corresponding relationships within the same analytical framework, cognitive triggering, emotional resonance, and behavioral manifestation can be uniformly explained as networked results under the influence of the dissemination field structure. This indicates that youth value identity in the process of red culture dissemination exhibits multi-layered coupling characteristics endogenously shaped by the relationship structure.

A. CONSTRUCTION OF HETEROGENEOUS INFOGRAPHICS FROM MULTI-SOURCE HETEROGENEOUS DATA

This study defines the generation process of youth value identity in the field of red culture dissemination as a relational system composed of multiple types of behavioral subjects and dissemination elements, and formally models this system through a heterogeneous Infographic [15,16]. The data relied upon for modeling is limited to objective behavioral records that have occurred and can be traced back in the cross-platform digital dissemination environment. These behavioral records originate from public interaction activities on the social media platforms Weibo, Bilibili, and Douyin, which constitute the platform carrier nodes within the heterogeneous dissemination graph. The data content covers social connections between young individuals, interactive behaviors between young people and red culture content, and the carrying relationships of content in different dissemination carriers [17,18]. The above information, at the semantic level, corresponds to the relational basis, cognitive trigger, and behavioral manifestation dimensions in the value identity formation process, and is therefore uniformly

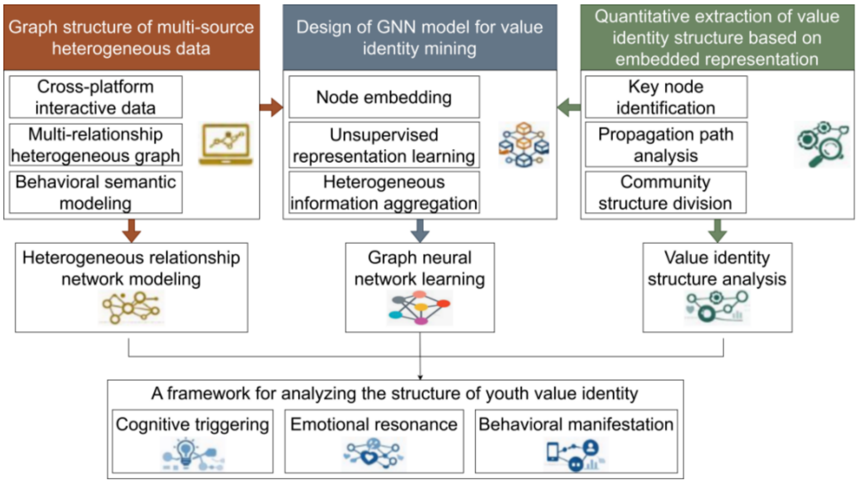

FIGURE 1. Framework for modeling the dissemination field of red culture and analyzing the structure of youth value identity based on graph neural networks

incorporated into the same computational framework for constraint during the structural modeling stage.

The dissemination field is formally represented as a heterogeneous graph $G = (V, E, T)$ with a time mapping. Here, V is the set of nodes, consisting of youth user nodes, red culture content nodes, and dissemination carrier nodes. E is the set of edges, the semantics of which are determined by user-to-user relationships, user-to-content interactions, and content-to-carrier carrying relationships. T is a time mapping function used to describe the changes in node state and edge weight in the time dimension. Different types of nodes are explicitly distinguished during the modeling stage to ensure that different propagation mechanisms remain identifiable at the structural level [19]. The youth user node may carry a feature vector that reflects the significant accumulation of their historical behavior, which can be used to constrain their structural position in the propagation system. Moreover, the content node might use semantic representation as the core state variable to express the cognitive orientation of red culture information. Furthermore, the propagation carrier node is used to characterize structural restrictions imposed on information flow by institutional propagation channels. Given that these nodes interact within the system, the feature vector may demonstrate patterns of user engagement. However, carrier nodes indicate constraints on information dissemination.

Any edge is defined as a directed weighted relation, and its weight is determined by the interaction strength and time decay. The edge weight of node i pointing to node j at time t is defined as:

$$w_{ij}(t) = f_{ij} \cdot \exp(-\lambda \Delta t) \tag{1}$$

In Formula (1), f_{ij} represents the normalized interaction frequency from node i to node j within the observation window; Δt represents the time difference between the occurrence of this interaction and the current moment; λ is the time decay coefficient, used to limit the influence range of historical behavior on the current structural state. This definition uniformly constrains the strength of propagation relationships in the time dimension, thereby ensuring the inherent consistency of the graph structure evolution process. To adapt to the multi-relation propagation mechanism, heterogeneous graphs are represented as a set of adjacency matrices $\{A^{(r)}\}$ with restricted relation types, where r represents the semantic type of the edge. The initial feature vector of node i is denoted as x_i, and its composition is determined by the node type and aligned within a unified feature space. Carrier nodes do not function as independent information producers in the propagation process. Their role in the graph structure is limited to constraining the adjacency relations between user nodes and content nodes through platform-level connection patterns. During message passing, carrier nodes transmit structural constraints rather than semantic information, which means that their feature states remain fixed while the propagation process only updates the representations of user and content nodes. Through this representation, different node types are processed within a unified computational interface while preserving their distinct functional roles in the propagation structure in subsequent graph neural network computations, while their information aggregation paths are strictly limited by relation types, In heterogeneous propagation graphs, semantic aliasing refers to the situation in which nodes representing different social roles become indistinguishable during representation learning due to the aggregation of incompatible relational contexts, structurally avoiding semantic aliasing [20,21].

The above modeling process relies solely on the propagation behavior and its structural constraints, without introducing external labels or prior hierarchical assumptions. Instead, it transforms the field of red culture propagation into a computational object with clear mathematical boundaries through the formal definition of nodes, relationships, and time weights [22].

B. DESIGN OF GNN MODEL INTEGRATING RELATIONAL SEMANTICS

Based on heterogeneous propagation field graphs, this study transforms the structural mining task of youth value identity into a node representation learning problem, and employs a graph neural network model adapted to heterogeneous relational constraints to uniformly learn the latent representations of nodes [23,24]. The model design uses the propagation relation itself as the sole information transmission path. Through a multi-relational message passing mechanism, the interaction positions, content contact trajectories, and media constraints of youth individuals in the propagation network are jointly encoded into a low-dimensional embedding space, thus providing a computable representation for subsequent structural analysis [25,26].

In the model initialization phase, the input representation of node i is given by its initial feature vector x_i in the heterogeneous graph, which has already undergone cross-type alignment. The core computational process of the graph neural network unfolds conditionally based on relational types. For any node i, its hidden representation $h_i^{(l+1)}$ in layer $l+1$ is jointly determined by its neighborhood information in different relational subgraphs, defined as:

$$h_i^{(l+1)} = \sigma\left(\sum_r \sum_{j \in N_i^{(r)}} A_{ij}^{(r)} W^{(r)} h_j^{(l)}\right) \tag{2}$$

In Formula (2), $N_i^{(r)}$ represents the set of neighboring nodes of node i under relation type r; $A_{ij}^{(r)}$ is the weighted connection strength of node j pointing to node i in the adjacency matrix of relation type r; $W^{(r)}$ is the learnable transformation matrix of the corresponding relation type; $\sigma(\cdot)$ represents the nonlinear activation function. This propagation mechanism keeps different semantic relations independently constrained in the parameter space, while achieving structural fusion of multi-relation information through weighted summation [27].

After multi-layer propagation, the final embedding vector of node i is denoted as $z_i = h_i^{(L)}$, where L represents the number of network layers. This embedding vector is defined as the latent representation of the node under the structural constraints of the propagation field, and its value is determined only by the graph structure and the interaction relationship between nodes, without relying on external identification labels or manual classification results [28]. To ensure the sensitivity of the embedding results to the real propagation structure, an unsupervised learning objective based on structural consistency is introduced during the model training stage. By constraining the structural similarity between node pairs, the distance relationship in the embedding space is kept consistent with the connection relationship in the graph [29,30]. Specifically, the model uses the inner product between node embeddings as an estimate of the structural association strength, and learns the parameters by minimizing the following loss function:

$$L = -\sum_{(i,j)\in E} \log \sigma(z_i^\top z_j) - \sum_{(i,k)\notin E} \log \sigma(-z_i^\top z_k) \tag{3}$$

In Formula (3), $(i,j) \in E$ represents a pair of nodes connected in the propagation field graph; $(i,k) \notin E$ represents a pair of nodes that are not structurally connected; $\sigma(\cdot)$ is the Sigmoid function. This objective function, by simultaneously constraining the representation relationships of positively and negatively connected node pairs, allows the model to retain the value-based association information implicit in the propagation structure within the embedding space.

Through the above model design, the structural positions of young individuals, red culture content, and propagation carriers in heterogeneous propagation fields are uniformly mapped to the same representation space. Without introducing external judgment criteria, the node embedding vectors intrinsically encode the network structural conditions upon which the formation and diffusion of value-based identity depend, providing direct input for the subsequent quantitative extraction of value-based identity structures.

C. MULTIDIMENSIONAL QUANTITATIVE EXTRACTION STRATEGY OF VALUE IDENTITY STRUCTURE

After completing the representation learning of the propagation field graph, this study limits the structural analysis of youth value identity to a quantitative characterization of the correspondence between node embedding distribution and the original graph structure. In communication studies, value identity refers to the relatively stable orientation formed through repeated exposure to symbolic content, interaction experience, and interpretive alignment within a social environment. This orientation exists prior to computational modeling and is traditionally examined through discourse interpretation and behavioral observation. In this study, the computational task does not attempt to redefine the concept itself, but operationalizes value identity as the observable structural alignment among individuals who interact with similar symbolic content and relational environments in the dissemination network. Therefore, its extraction process is entirely based on the geometric relationships in the embedding space and their mapping results to the graph structure [31]. The results obtained from this computational process should be interpreted as structural alignment patterns derived from interaction networks rather than direct psychological measurements of individual value identity. The model captures similarities in relational environments and symbolic exposure among users in the dissemination field, and these similarities serve as observable structural proxies associated with the formation of collective value identity within the network.

The node embedding vector z_i is considered as the structural representation of node i in the heterogeneous propagation field. This representation simultaneously encodes its relational connection state, information contact path, and media constraints. Based on the relative distance relationships in the embedding space, the representations of youth user nodes are aggregated unsupervised to obtain a set of nodes that are structurally relatively close. This set is defined as a value identity community, formed solely based on the structural similarity induced by the propagation relationship, rather than any external semantic labels or artificial division criteria, thus ensuring the consistency between the community division results and the internal structure of the propagation network [32,33].

At the community level, the structural characteristics of value identity are characterized by the strength of connections within the community and the connection patterns across communities. The high-density structure between nodes within a community is regarded as a stable aggregation state of identity relationships in the communication field, while the connection relationships between different communities reflect the degree of differentiation and coupling of the identity structure in the overall network [34]. The quantitative results at this level are used to characterize the layered structure of youth value identity in the communication system, without involving the value judgment of specific identity content. At the node level, the structural role of value identity is described by the positional characteristics of nodes in the propagation field. The structural influence of nodes is calculated by combining their embedding vectors with their connection patterns in the original graph G, in order to identify nodes that play a key role in the formation and diffusion of identification structures [35]. This identification process uses structural contribution as the sole basis and does not introduce the prior importance assumption of node attributes, thus avoiding the mixed interpretation of individual characteristics and structural effects.

At the path level, the propagation process of value identity is defined as a continuous structural sequence formed by the connection relationships of similar nodes in the embedding space along the original graph. By tracing the connection paths of highly similar node pairs in the graph, the main flow direction and potential structural bottlenecks of value identity in the propagation field are extracted [36]. This process uses the actual existence of propagation relationships as a constraint, ensuring that the path analysis results are always limited by the real network structure.

Through the above multi-level quantification strategy, youth value identity is analyzed as a networked structural result composed of community structure, node position, and propagation path.

III. STRUCTURAL CHARACTERISTICS OF THE RED CULTURE DISSEMINATION NETWORK AND EMPIRICAL EVIDENCE ON YOUTH VALUE IDENTITY PATTERNS

A. COMPARATIVE EXPERIMENT WITH BASELINE NETWORK ANALYSIS METHODS

To address the limitations of existing approaches discussed in the previous section and to evaluate the effectiveness of the proposed model in identifying structural characteristics of the red culture communication network, several representative baseline network analysis methods were introduced under the same network data conditions for comparison. The Louvain method performs community detection through modularity optimization. DeepWalk learns node representations through random walks over the network. Node2Vec introduces biased random walks to preserve structural relationships between nodes. The Graph Convolutional Network model propagates node features through convolution operations across adjacent nodes. The network structures obtained by different methods were evaluated using internal edge density, average degree centrality, and cross-community connection ratio. The comparison results are shown in Table 1.

TABLE 1. Comparative Analysis of Network Structural Metrics Across Different Identification Methods

Method	Internal Edge Density	Average Degree Centrality	Cross-Community Connection Ratio
Louvain Method	0.45	0.49	0.52
DeepWalk Method	0.48	0.53	0.47
Node2Vec Method	0.51	0.55	0.46
GCN Model	0.57	0.63	0.50
Proposed Model	0.62	0.71	0.55

As shown in Table 1, different methods present noticeable differences in the identification of network structural characteristics. The Louvain method produces relatively dispersed community structures when applied to communication networks containing complex interaction relations. DeepWalk and Node2Vec improve the representation of structural relationships through network embedding, but their ability to capture complex interaction structures remains limited. The GCN model improves structural representation through feature propagation across neighboring nodes. The proposed model achieves higher values in internal edge density and average degree centrality while maintaining stable cross-community connections, indicating that the identified communities present stronger internal cohesion together with clearer interaction relationships across communities within the red culture communication network.

B. OVERALL TOPOLOGICAL ATTRIBUTES OF THE DISSEMINATION NETWORK

In the process of red culture dissemination, young users do not participate in information contact and interaction as isolated individuals, but rather, through continuous communication, content contact, and platform usage, they collectively constitute a hierarchical dissemination field. Based on this understanding, this study considers young users, red culture content, and dissemination platforms as three basic subjects in the dissemination field. By integrating interaction records collected from Weibo, Bilibili, and Douyin, a network structure reflecting real dissemination relationships is constructed, and the location distribution and interconnection status of different subjects in the network are presented in a visual manner to intuitively demonstrate the overall form of information organization and flow in the dissemination field, as shown in Figure 2.

Figure 2 shows that nodes of different colors play different structural roles in the network. Blue nodes form the main connection framework of the network, indicating that the interaction between young users is the basic structure for the operation of the dissemination field. Red nodes are embedded in this framework through multiple paths, reflecting the dependency relationship of red culture content in the youth interaction network. Green nodes are mainly connected to red content nodes, reflecting the channel and hub role of the platform in aggregating and distributing red culture information. The above results show that the size difference of the nodes exists in their position difference in the global network influence structure. The sizes of larger nodes appear at the crossing of trying more important dissemination paths, occupying a more structural constraint position on the information flow, while the sizes of the smaller nodes are mainly distributed in the local connection parts and have a relatively narrow range of influence. The thickness of the edges is different from the carrying capacity of different dissemination relationship, and the above results show that the above difference comes from the product of the frequency difference of different interactions and structural position difference, which leads to the uneven dispersion of dissemination relationships in the network. Therefore, this figure reveals that the dissemination of red culture does not unfold uniformly, but rather forms a hierarchical dissemination field under structural constraints.

C. AUTOMATIC DISCOVERY AND FEATURE OF YOUTH VALUE IDENTITY COMMUNITIES

In the context of the dissemination of red culture, young individuals gradually form differentiated value identity structures under the interplay of multi-source information exposure and multiple interactive relationships. Based on the joint modeling of node semantic features and relational topology using graph neural networks, this study uniformly learns the embedding representations of youth nodes and projects the high-dimensional embedding space onto a two-dimensional plane to characterize the spatial proximity relationships of different youth groups in their identification expression and interaction patterns. Based on the clustering and labeling of the embedding results, the network structure is divided into five community types: C1 is the core identification community; C2 is the emotional resonance community; C3 is the behavioral participation community; C4 is the peripheral diffusion community; C5 is the potential identification community. The distribution of community structures in the two-dimensional embedding space based on these classifications is shown in Figure 3.

As shown in Figure 3, the five communities exhibit significant differences in spatial location and aggregation patterns. C1, located in the upper right region, has 19 nodes, with a convergent distribution of distances between nodes, indicating a highly concentrated spatial structure. This pattern suggests a high degree of consistency between the group's internal interactions and value orientations. C3, distributed in the middle of the space, has 17 nodes, with nodes stretched in multiple directions, showing a significantly higher overall dispersion than C1. This structural state reflects that the group is simultaneously embedded in multiple interaction paths. C4, located in the lower left region, has 14 nodes, with a loose distribution of nodes, indicating a lower internal correlation strength and a structural location closer to the network periphery. C2 and C5, located in the upper left and lower right regions respectively, have 16 and 15 nodes, with spatial patterns between aggregation and dispersion, reflecting an intermediate state in terms of identity stability and interaction density between the two types of communities. The differentiated distribution of different communities in the two-dimensional embedded space indicates that youth value identity exhibits a hierarchical and parallel structural characteristic within the red culture dissemination network.

Building upon the aforementioned graph neural network-based embedding representations of youth nodes, differences in structural position and interaction patterns among different youth groups within the propagation field gradually emerge. Based on the community segmentation results, the study further characterizes the structural state of communities with different value identities from a network topology perspective. By introducing average degree centrality, internal edge density, clustering coefficient, cross-community connectivity ratio, and betweenness centrality, the structural outlines and functional differentiation of communities with different identities within the overall propagation network are presented. Figure 4 shows a comparison of the network structural characteristics of communities with different value identities based on the standardized results of these indicators.

As shown in Figure 4, C1 is in a high range in terms of average degree centrality and internal edge density, with an average degree centrality of 0.71 and an internal edge density of 0.62, while maintaining a clustering coefficient of 0.58. This structural state indicates that the members of this community maintain relatively stable and high-frequency interaction relationships. C2's clustering coefficient reaches 0.61, higher than its internal edge density of 0.57, reflecting that interactions in this community are more likely to unfold around small-scale circles. C3 shows more prominent features in terms of cross-community connection ratio and average betweenness centrality, with a cross-community connection ratio of 0.55 and a betweenness centrality of 0.62, indicating that this community is more distributed in the connection channels between different communities. Its relatively low internal edge density of 0.49 and clustering coefficient of 0.46 further confirm that its structural center of gravity is not concentrated in internal aggregation. The internal edge density of C4 is 0.28, and the

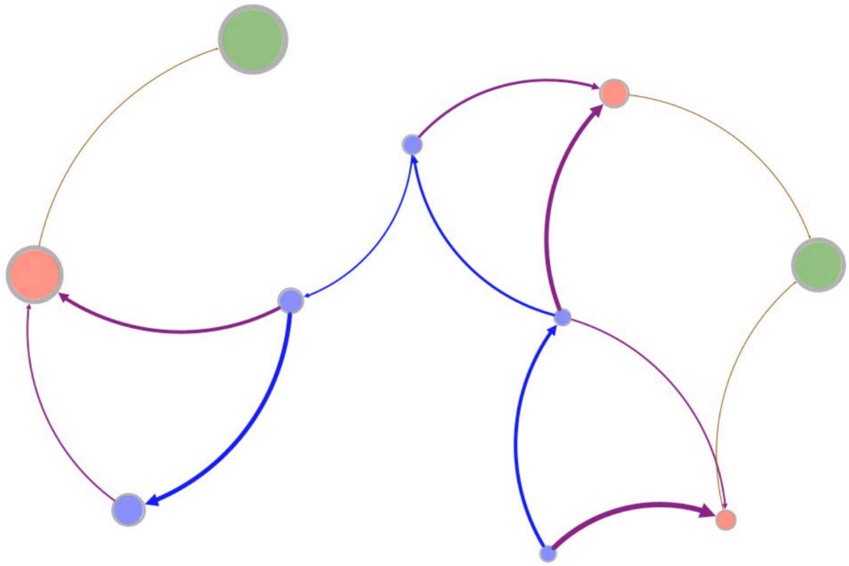

FIGURE 2. Visualization of the overall topology of the red culture dissemination field

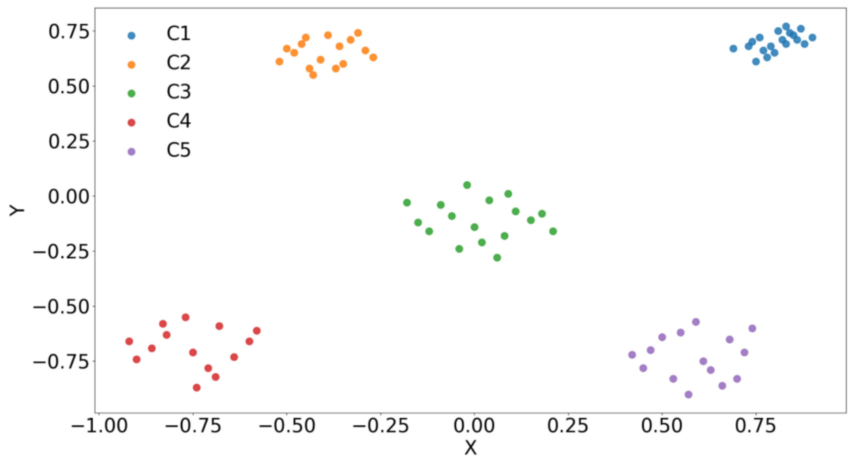

FIGURE 3. Structural distribution of youth value identity communities in a two-dimensional embedded space

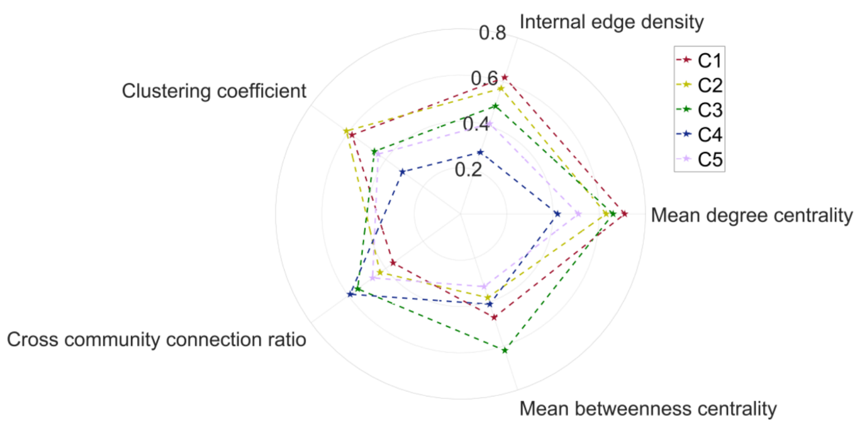

FIGURE 4. Radar chart of multidimensional network structure characteristics of communities with different value identities

average degree centrality is 0.42, but the cross-community connection ratio is 0.59. This indicates that although this community is located on the periphery of the network, it has formed a relatively active structural state in terms of external connections, which is consistent with the network law of peripheral nodes participating in diffusion and weak connection propagation. C5 is distributed in the middle range in terms of various indicators, with an average degree centrality of 0.51, an internal edge density of 0.41, and a cross-community connection ratio of 0.47, showing that its structural position has not yet converged towards high aggregation or clear bridge direction. The above structural differences indicate that youth value identity in the field of red culture dissemination presents a differentiated pattern from core cohesion, circle resonance, participation and connection to peripheral diffusion.

D. MULTIDIMENSIONAL DIFFUSION PATH TRACKING OF VALUE IDENTITY

Based on the aforementioned representation of the dissemination field structure obtained based on graph neural networks, youth value identity is no longer only manifested as a static distribution state between communities, but further presents as a process form of continuous flow along the network structure. Based on this, by combining the cumulative access weight of community nodes and the cross-community traffic distribution, a visualization of the value recognition diffusion path is constructed, as shown in Figure 5.

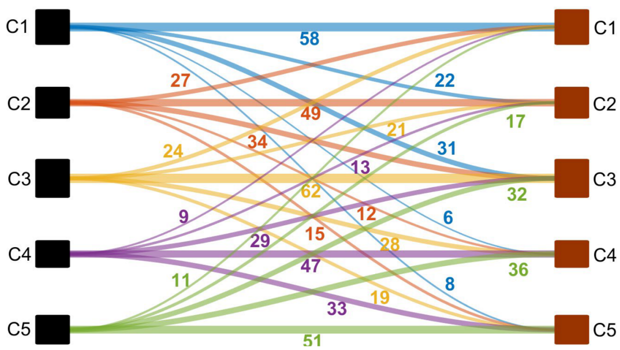

FIGURE 5. Sankey visualization of the cross-community diffusion path of youth value identity based on random walk simulation

Figure 5 presents the diffusion structure of value identity in the propagation field in the form of state transitions. The black nodes on the left correspond to the initial community state of the random walk, and the brown nodes on the right correspond to the belonging community state under steady-state conditions. The width of the connecting lines and the numerical values marked on the lines together characterize the transition strength between different states. The channels maintaining the identity within each community's own state account for the majority of the signal. The weight of the flow from black C1 to brown C1 is 58; the weight of the flow from black C3 to brown C3 is 62; the weight of the flow from black C5 to brown C5 is 51, indicating that the probability of identity remaining within the existing community structure is relatively high. In cross-state transitions, the channel pointing to brown C3 maintains a high strength in multi-source communities. The weight of the flow from black C1 to brown C3 is 31; the weight of the flow from black C2 to brown C3 is 34; the weight of the flow from black C5 to brown C3 is 32, reflecting that behavioral participation is at the convergence point of multiple paths in the overall network. Within the peripheral structure, the flow from black C4 to brown C5 is 33, and the flow from black C5 to brown C4 is 36, exhibiting a stable bidirectional flow pattern. Overall, value identity in the dissemination field forms a diffusion pattern composed of structural maintenance, hub translation, and peripheral flow.

IV. CONCLUSIONS

This study constructs a heterogeneous information graph encompassing young users, red culture content, and dissemination carriers, and employs a graph neural network model to analyze structural patterns associated with value identity formation in the dissemination network. By integrating multi-relational message passing mechanisms, the framework decodes the structured coupling of ideological dissemination. The model may encode dissemination behavior and significant network topology into these unified node embeddings, demonstrating that five distinct types of value identity communities can be identified based on the observed embedding similarity. Moreover, the experiments might suggest that the clustering coefficient of the emotional resonance type community reaches 0.61, reflecting the locally tight structure based on emotional connections. Given that the edge-diffusion type exhibits internal connection density of 0.28 and cross-community connection ratio of 0.59, structure could display weak peripheral connections but active cross-circle activity. However, structural differences may reveal synergistic effect of relationship cohesion and path dependence in formation of identity. Nevertheless, value identity appears systematically constrained by network structure in cognitive, emotional, and behavioral dimensions. Furthermore, study still has certain methodological limitations, with data sources focusing on explicit online behavior. Notwithstanding these limitations, data might fail to incorporate offline interactions and deep attitude dimensions fully. In light of the findings, model can capture static structural features. Therefore, characterization of long-term dynamic mechanisms of identity evolution may be insufficient. However, future work could introduce temporal graph neural networks and multimodal perceptual data to model generation and transformation of identity structures dynamically. Future work may explore cross-cultural and cross-community comparative perspectives to further examine how differences in communication environments influence the structural patterns of ideological dissemination networks.

AUTHOR CONTRIBUTIONS

Xiaoyan Wang designed, collected and analyzed the data, and drafted the manuscript. Xiaoyan Wang conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xiaoyan Wang participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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