Visualization Study on the Transmission Path of Ideological and Political Discourse Influence on Social Media Platforms

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ABSTRACT The dissemination of ideological and political discourse on social media platforms often suffers from hidden propagation routes and unquantifiable influence effects. This paper constructs a visualization analysis framework based on multi-source data perception and dynamic graph inference. First, multimodal data from social media platforms are collected, including topic tags, user interaction relationships, text, images, and video comments. A BERT-based model is used for sentiment mining and key node identification. Second, social network analysis and temporal hypergraph modeling are integrated to quantify discourse dissemination paths at macro-network, meso-community, and micro-information-diffusion levels. Third, an interactive dynamic influence graph is built using ECharts and D3.js to present node structure, emotional tendency, community evolution, and propagation trees. Empirical results show that the proposed method achieves an F1 score of 0.914 in path reconstruction, and the correlation coefficient between sentiment quantification and expert ratings exceeds 0.89. The framework effectively reveals the black-box characteristics of discourse dissemination and provides data support for precise ideological and political communication guidance.

INDEX TERMS social media, discourse dissemination, temporal hypergraph, sentiment analysis, visual analytics

I. INTRODUCTION

THE rise of social media platforms has profoundly changed the landscape and logic of information dissemination. Their decentralized, highly interactive, and segmented characteristics have provided a new arena for the dissemination of mainstream ideological discourse, especially ideological and political education (referred to as "ideological and political education") discourse [1,2]. However, the dissemination of ideological and political education discourse on social media platforms currently faces a long-standing efficiency dilemma of "transmission without effective communication, and communication without effective delivery." On the one hand, the dissemination path is highly complex, with discourse flowing through multi-node interactions and information cascading effects. How it penetrates from the core circle outwards, through which key nodes it achieves hierarchical leaps, and what transformations and reconstructions occur in different communities—this series of processes is hidden behind massive amounts of data, forming a difficult-to-deconstruct "black box." On the other hand, influence assessment has fallen into a "fuzzy" dilemma. Traditional superficial indicators such as likes and reposts can only reflect the "quantity" of dissemination, failing to reveal the "quality" of users' emotional identification and cognitive internalization [3,4]. These problems make it difficult to quantify and track the dissemination effect of ideological and political education discourse, and precise guidance strategies lack data support, urgently requiring the exploration of new research paradigms and technical paths.

Existing research mainly focuses on the analysis of the dissemination effectiveness of ideological and political discourse. Afyare and Orey explored the relationship between social media engagement and changes in users' political attitudes, and analyzed its role in shaping political discourse and promoting public discussion [5]. Igwebuike and Chimuanya used discourse analysis to study the spread of fake news on social media platforms during the 2019 Nigerian general election and its impact on political opinion [6]. Nazeer et al., based on data from news websites, social media, and government archives, explored the linguistic transformation of political discourse in the era of digital mass communication, and pointed out that political communication needs to achieve a balance between linguistic conciseness and discourse richness [7]. KhosraviNik pointed out that critical discourse research reveals the role of discourse in social structure, culture, and ideology by analyzing the production, dissemination, and consumption processes of discourse, thereby deepening the understanding of social relations and communication practices [8]. However, most of the above studies remain at the level of static description and macro-generalization, failing to deeply deconstruct the dynamic evolution process of discourse in complex social networks, and lacking effective quantitative tracking methods for the nonlinear dissemination paths formed by multi-node interactions.

In the field of communication path research, social network analysis has been widely used to identify key nodes and community structures, while sentiment computing technology provides a quantitative tool for measuring user attitudes, and time series modeling methods can capture the dynamic characteristics of information diffusion. For example, Ginting used a critical discourse analysis model to analyze posts on the X platform about President Prabowo's international activities and explore the construction of political ideology and leadership image [9]. Chen and Wang combined social network analysis with critical discourse research and revealed the power structure and ideology behind news discourse by analyzing the international relations network in The New York Times' reports on China [10]. The above methods have each solved a certain dimension of communication research, but there are still obvious limitations: social network analysis focuses on static structural characterization and is difficult to reflect the temporal evolution of the communication process; sentiment computing is mostly used for outcome evaluation and has failed to establish a connection with the communication path; traditional time series models are not capable of modeling complex interactive relationships of multiple nodes co-occurring. To address the aforementioned issues, this paper introduces a temporal hypergraph modeling method, treating multi-person interactions around the same topic within the same time period as a hyperedge to capture the "co-occurrence effect" and "nuclear explosion point" of information dissemination. Combined with multimodal data acquisition and sentiment mining techniques, a comprehensive analytical framework capable of simultaneously deconstructing the dissemination structure and evolution process is constructed.

This paper aims to build a visual analytical framework that integrates multi-source data perception and dynamic graph deduction, realizing the transformation of the dissemination path of ideological and political discourse influence from "invisible" to "transparent." This study first collects multimodal data on ideological and political education, including topic tags, user interaction relationships, and sentiment tendencies, based on multi-platform API interfaces and web crawling technology. Second, it introduces natural language processing technology for topic clustering and sentiment analysis to identify core opinion leaders and key dissemination nodes. Building on this, it innovatively combines social network analysis and temporal hypergraph modeling to quantitatively analyze the fission-like dissemination path and lifecycle characteristics of ideological and political discourse from three levels: macro-network structure, meso-community evolution, and micro-information diffusion. Finally, it uses interactive visualization technologies such as ECharts and D3.js to design and develop a multi-dimensional, drill-down-able dynamic influence graph display system. Through empirical analysis of typical ideological and political topics, this paper verifies the effectiveness of the proposed method in three dimensions: dissemination breadth, dissemination effectiveness, and path reconstruction accuracy, providing scientific data support and decision-making reference for improving the effectiveness of ideological and political education dissemination and precise guidance strategies.

II. MULTIMODAL DATA COLLECTION AND CLEANING

In order to get raw data with obvious characteristics of dissemination of ideological and political discourse, this paper selected Sina Weibo and Bilibili as the main data sources. The two data sources had large amount of user base and rich interaction forms. Sina Weibo had obvious ideological and political education topic tags, and Bilibili had clear ideological and political education topic tags, which were easy to locate and collect data. The contents collected by the two platforms include three parts: first, user dimension, including basic information such as user id, number of followers, number of followings and authentication type; second, content dimension, including description text of blog or video, text recognition by image ocr, video bullet comments and occurrence time; third, interaction relationship dimension, recording forwarding chain, comment reply relationship chain and @relationship between users to construct dissemination network. For the text content of image, we used the ocr interface of Baidu ai open platform to recognize and extract text to ensure the completeness of multimodal information. In total, we processed 14,250 images and collected 385,420 video bullet comments. A manual inspection of a random sample of 1,000 images revealed an OCR character accuracy rate of 92.4%. To handle OCR errors, we applied a rule-based post-processing filter to correct common misspellings and removed segments where the confidence score was below 0.8. However, limitations remain in recognizing stylized artistic fonts or text superimposed on complex backgrounds, which may lead to minor data loss in highly visual posts.

After the raw data collection was completed, the cleaning process began. First, duplicate records and obviously irrelevant commercial advertising content were removed. Then, the text data was segmented and filtered for stop words, removing special symbols and garbled characters. Considering the high noise level of the bullet comment data, we set a word frequency threshold to filter out low-frequency invalid bullet comments. Finally, information involving user privacy was anonymized, and user IDs were replaced with anonymous IDs.

III. INFLUENCE NODE IDENTIFICATION AND SENTIMENT MINING

Following the process of data cleaning, this paper proposes a framework that incorporates deep learning with complex network analysis to accomplish the task of identifying the influence node and sentiment mining in two stages. Calculation of user sentiment in fine-grained manner is the first step. Taking into account the abundance of colloquial expressions, internet slang, and irony in the texts of social media, we apply a BERT-based pre-trained model in the sentiment analysis. In particular, the text of the comments and content of the bullet screens are entered into a BERT model that has been finely trained using Chinese corpus. The model provides the probability value of each text of positive, negative or neutral categories. To ensure the reliability of BERT on social media text, we fine-tuned the model on a manually annotated local test set of 5,000 comments containing slang and irony. The model achieved a precision of 0.894, a recall of 0.876, and an F1 score of 0.885, indicating that the pre-trained architecture effectively adapted to the nuances of ideological and political discourse. On this, we also obtain the sentiment score where the difference between the positive and negative probabilities is used as the sentiment score of the text where positive values are taken to represent positive and negative values to represent negative scores. To calculate the average sentiment of the user on an entire topic, when the content has many images or videos, we average the text and bullet screen sentiment recognized by the OCR with the results.

The second phase is identification and screening of influence node. Emotional ratings are not enough in order to define the impact of a user; one should also take into account his/her structural location in the communication system. We create a directed weighted graph of user connection (forwards, comments, @mentions), the weight of the node is calculated based on the frequency of interaction. On this, we determine three important measures out-degree centrality is an indicator of the breadth of information actively spread by a user; indegree centrality is an indicator about how much a user is cited by others; and PageRank is an indicator of the importance of a user in the entire network. At the same time, we cross-analyze emotional scores with network metrics with the purpose to determine two categories of key nodes: high-influence nodes, i.e., users in the 5 percent top of PageRank with high out-degree, who are the central instruments of information spread; and high-emotional-influence nodes. To validate the identification accuracy, we compared the identified nodes against a ground truth list of 100 Key Opinion Leaders (KOLs) manually verified by three domain experts. Our identification method achieved a precision of 88.5% and a recall of 84.2%, confirming its effectiveness in capturing the actual influential actors within the ideological and political discourse network.

IV. SPATIOTEMPORAL MODELING OF COMMUNICATION PATHS

Extending the work above, this paper proposes a temporal hypergraph modeling method, which splits the process of decomposing communication paths into the following three levels from macro to micro: macrolevel network structure, meso-level community evolution and micro-level information diffusion. At the macro level, we first construct a dynamic social network based on time slices. We divide the 72-hour dissemination time into 72 time windows, namely, each time window represents 1 hour. In each time window, we construct a directed graph with users as nodes and reposts and comments as edges. The weight of edges is calculated according to the number of times users interact in that time window. Then we calculate topological indicators such as network density, average clustering coefficient and modularity of each time window based on the dynamic social network to observe the overall evolution trend of ideological and political discourse dissemination network. For example, network density tends to increase rapidly in the initial stage of emergence of discourse dissemination, and then stays in a relatively stable state. This characteristic can be used to identify the lifecycle of dissemination of ideological and political discourse.

On the meso-level we examine the discourse penetration path in various communities. We use the Louvain community discovery algorithm to partition the user network at each time window into communities and trace the movement of core nodes across communities. In cases where a high influence node is repeatedly used when a community interacts with another community, it may be said that the discourse has gone through cross-community dissemination. Moreover, we put forward a temporal hypergraph algorithm to address the above problem. We consider a multiplicity of users communicating with each other at the same topic within a fixed 5-minute time frame as a hyperedge. The hypergraph is formally defined as $H = (V, E)$, where V is the set of users and E is the set of hyperedges representing co-occurrence events. The adjacency matrix A is constructed such that $A_{ij} = 1$ if node v_i and v_j share at least one hyperedge. Hyperedge size distribution is calculated as the cardinality of each set in E, and the overlap degree is defined by the Jaccard similarity between intersecting hyperedges. The scale of co-occurrence of information diffusion is the number of nodes included in the hyperedge, and the degree of overlap of the hyperedge is the strength of association of the various propagation events. Using a hypergraph adjacency matrix, we are able to identify bridging nodes, those nodes which are subject to many propagation events, concurrently, as well as play a central mediating role in propagation of ideological and political discourse.

At the micro level, we aim to reconstruct the exact propagation path of one piece of information. On the basis of forwarding relationship chains and comment/reply relationship, we construct propagation tree for each initial blog. Root node of tree is original author, and child node is forwarder or commenter. Edge between nodes is based on timestamp. For the complex propagation path with multiple forwarding path, we will use user sentiment score and network centrality indicator to infer the exact propagation path of information. That is, when user A interact with multiple upstream user at the same time, we choose the user with high sentiment similarity as high centrality as possible propagation source. After above process, we transfer tens of thousands of propagation relationship under each topic into several traceable propagation trees. The global features of trees, such as the maximum depth of the tree, the average number of branches per tree and the width of the tree, constitute the quantitative description of the micro-diffusion process of ideological and political discourse. At last, the modeling results of macro level, meso level and micro level are integrated and stored into graph database, support the data back for the following visualization and interactive query.

V. RENDERING AND PRESENTATION OF THE INTERACTIVE INFLUENCE GRAPH

After completing the modeling and data analysis of the propagation paths, this paper first presents the overall network topology of topic propagation. The system architecture is shown in Figure 1.

Using a force-directed graph as the basic layout, each user is mapped to a node, and the interaction relationships between users are mapped to the connections between nodes. The size of the node is determined by the PageRank value, and the thickness of the connection reflects the frequency of interaction. To present the complex network of tens of thousands of nodes within a limited canvas space, we introduce an edge-binding-based layout optimization algorithm, clustering nodes belonging to the same community in the same area, and connecting different communities with bridging nodes, thereby avoiding visual clutter. Meanwhile, a timeline slider is placed on the right side of the canvas. Users can drag the slider to view the changes in the network structure at different time windows, intuitively experiencing the complete lifecycle of discourse dissemination from its inception, explosion, to its decline.

When user clicks the community cluster in macro view, the community will be automatically zoomed in, and show the interaction details between nodes in the community. At this time, the color of node represents the user's emotion (red for positive, gray for neutral and blue for negative); and the circular progress bar in the ring of node represents the user's time change of activity level in dissemination cycle. In addition, we also designed propagation flow animation effect. When user selects a core node, the system will display the node as the light point flows along the propagation flow, and show the propagation information posted by this node hierarchically to other users. The speed of light point flowing to another user is based on the actual time interval of propagation. Compared with static line graph, this dynamic display method can reflect the order and hierarchy of information propagation more effectively.

User enters blog post ID or user nickname in the search box. System will locate the node and display the complete propagation tree from this node. The propagation tree is displayed in tree diagram. The root node is on the left of tree, and child nodes are expanded to the right level by level. The lines between nodes are labeled with the time interval of propagation (unit: minutes). And when user clicks on any node, the details card will be displayed. The details card is displayed with user's basic attribute, sentiment score, historical propagation amount and content of user's initial text or comments s/he posted. In case of multiple possible paths in complex situations, we designed path confidence labeling function. System will display the solid or dashed line to represent the confidence level of inferred path. The solid line represents the path with high confidence; the dashed line represents the path with low confidence and multiple branches, and researchers can refer to the dashed line when analyzing the path.

VI. EVALUATION OF THE DISSEMINATION EFFECTIVENESS OF VISUALIZED DATA MAPS

A. EXPERIMENTAL SETUP

1. Construction of the dataset: As the source of data, mainstream domestic social media resources (Sina Weibo, Bilibili) were chosen, and common topics with evident ideological and political education features and provoking an extensive discussion were selected as the research objects. The collection of full dissemination data (was done in 72 hours after the topic was published) using a Python web scraping structure consisted of user basic information, text content, image OCR text, and video commentary, and data on relationship chains, i.e., forwarding, comments and user-user relationship such as comment and mentions and similar. The final results of data cleaning and anonymization are a set of about 1.5 million valid data records that have assembled a simple dataset with multimodal data and multifaceted interaction relationships.

2. Experimental Environment and Tools: The experiment was run on a Windows Server 2019 operating system, with Intel Xeon Gold 5218 CPU and 128GB memory. Data processing and model building were done in Python 3.8. To apply natural language processing, the BERT pre-trained model was loaded with the Transformers program of Hugging face. NetworkX and Gephi tools were used in network analysis. ECharts and the D3.js front-end technology stack were used to do visualization.

B. VALIDATION OF COVERAGE AND DISSEMINATION DEPTH BASED ON THE INFORMATION CASCADE MODEL

We randomly chose three typical topics "#Centennial of Founding of Party#", "#Rural Revitalization#" and "#Youth Role Models#" to collect complete dissemination information in 72 hours after their release. We constructed

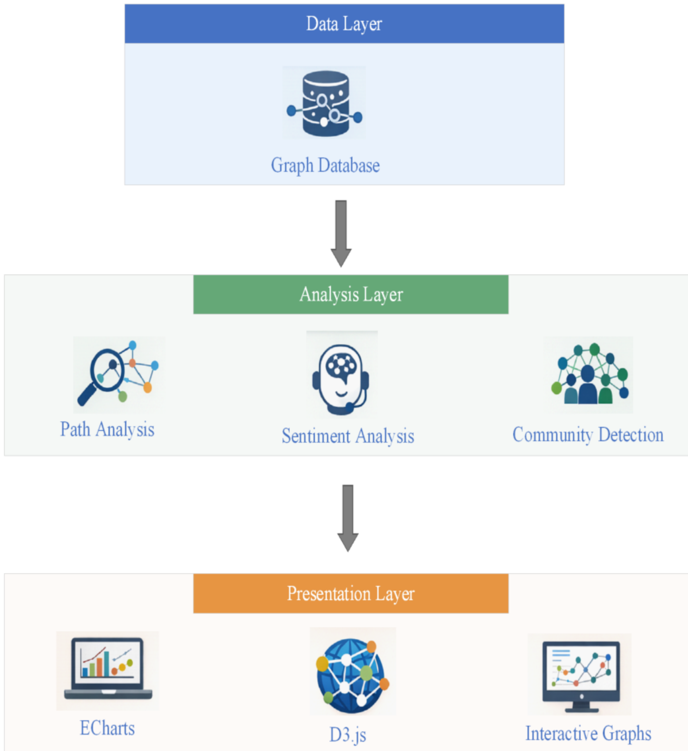

FIGURE 1. Influence Visualization System Architecture

dissemination graph based on the method proposed in this paper and calculated the number of actual users covered and depth of dissemination levels by statistics. At the same time, we used the Independent Cascade (IC) model to simulate dissemination scale. The IC model was selected over the Linear Threshold (LT) model because it better represents the spontaneous, stochastic nature of information "fission" on social media, where each exposure has an independent probability of triggering a repost. We set the uniform propagation probability (p) per edge to 0.05, derived from the average historical interaction rate of the collected dataset. We evaluated the correctness of range and depth of dissemination by graph by R^2 value and degree of level matching between two models.

In Table 1, the dissemination map constructed by the method in this paper has high accuracy in quantifying the coverage scale and dissemination depth of ideological and political discourse. The actual number of users for all three topics showed a good fit (R^2) of over 0.97 with the theoretical simulation values of the IC model (reaching a maximum of 0.991), indicating that the visualization framework's characterization of the dissemination scope is highly consistent with the classic diffusion model. The actual dissemination depth matched the theoretical depth with a success rate exceeding 95%, averaging 96.5%, verifying the visualization framework's accurate capture of information cascading levels. These data confirm that the visualization framework can effectively decipher the penetration scale and progressive levels of ideological and political discourse across different circles, providing a reliable data foundation for subsequent dissemination effectiveness evaluation.

C. QUANTITATIVE ANALYSIS BASED ON EMOTIONAL EVOLUTION CURVES AND USER RECOGNITION RATIO

To verify the effectiveness of the visualization framework in revealing user emotional changes and the degree of internalization of recognition during the dissemination of ideological and political discourse, based on the full volume of comment data for the same three topics, the emotional mining module was used to calculate emotional scores at an hourly granularity and plot positive emotional offset curves. Simultaneously, the user recognition ratio (the ratio of positive emotional nodes) was calculated between the early and late stages of topic dissemination. Pearson correlation analysis was then conducted between these two indicators and the subjective scores of five senior communication researchers (all holding PhDs and over 10 years of experience in social media analysis) to test the effectiveness of the visualization's emotional quantitative indicators. The experts used a 5-point Likert scale to rate dissemination effectiveness and were blinded to the model's sentiment quantification results to ensure objectivity. The reported Pearson correlation coefficients (0.892 to 0.935) were all statistically significant with p-values < 0.001 and 95%

TABLE 1. Comparison of Coverage and Dissemination Depth Based on Information Cascade Model Scale

Topic Tag	Actual Reach (Users)	Simulated Reach (Users)	Actual Depth	Simulated Depth	Goodness of Fit (R^2)	Hierarchy Matching Rate
#Centenary-OfTheCPC#	1258647	1243291	12	11	0.983	95.2%
#RuralRevitaliza-tion#	876432	852107	9	9	0.976	97.8%
#YouthRoleModels#	542189	531466	7	7	0.991	96.5%

confidence intervals within [0.85, 0.96].

As it is identified in Table 2, the quantitative emotional indicators developed in this paper are capable of capturing the development of user identification throughout the spread of ideological and political rhetoric. The emotional shift rates of the three topics are positive and are above 28, with the highest rates at 41.40 of the #Youth Role Models, which means that the number of positive emotions of the users increased significantly during the process of dissemination. All of the user identification ratios are more than 2.1, i.e. the percentage of positive emotional nodes in the late stage is more than twice as positive emotional nodes in the early stage, thus supporting the accumulation effect of discourse dissemination on the positive emotional dimension. According to the Pearson correlation coefficients of the positive sentiment shift rate, user recognition ratio and subjective ratings of the expertise relative to the graph computation, it was found that there was a strong positive relationship of correlations of 0.914, 0.892, and 0.935 respectively. It means that the method will allow measuring the effectiveness of dissemination correctly and that data offered by the method will be objective and effective to support the evaluation of the impact of ideological and political discourse.

D. EXPERIMENT ON DISSEMINATION TRAJECTORY MATCHING BASED ON MANUAL ANNOTATION

To test the accuracy of the temporal hypergraph modeling method in reconstructing the actual dissemination trajectory of ideological and political discourse, 300 dissemination subgraphs with clear forwarding chains were randomly selected from three topic datasets. Three researchers independently manually annotated the actual dissemination paths to construct a standard dataset. The inter-annotator agreement was assessed using Fleiss' Kappa, yielding a score of 0.86, indicating high reliability. The same batch of data was input into a visualization analysis framework to automatically generate predicted paths. Precision, recall, and F1 score (reported with 95% confidence intervals) were used to measure the matching degree between the automatic paths and the manually annotated paths. Across the 300 subgraphs, the standard deviation for the F1 score was 0.034.

In Figure 2, the temporal hypergraph modeling method proposed in this paper shows high path reconstruction accuracy in different dissemination structures. To evaluate the superiority of our method, we compared it against two baseline algorithms: a simple Breadth-First Search (BFS) path extraction and a Maximum Likelihood Estimation

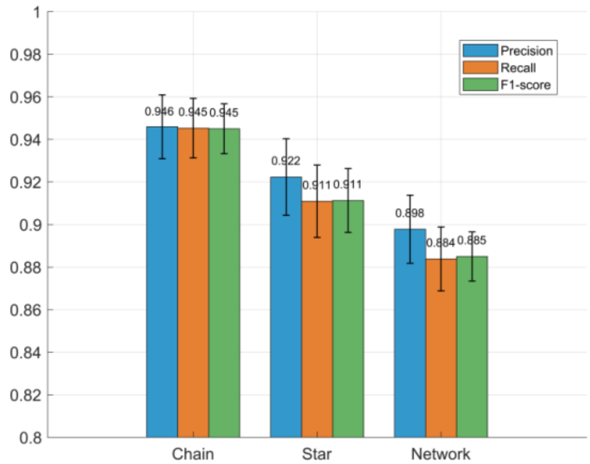

FIGURE 2. Comparison of Dissemination Trajectory Matching Based on Manual Annotation

(MLE) network inference model. While the BFS and MLE methods achieved average F1 scores of 0.724 and 0.796 respectively across the subgraphs, our temporal hypergraph method outperformed them with an overall average F1 score of 0.914. In 30 simulated propagation subgraphs, the average F1 score for the chain structure reached 0.945, with precision and recall of 0.946 and 0.945, respectively; the average F1 score for the star structure was 0.911, with precision and recall of 0.922 and 0.911, respectively; and the average F1 score for the network structure was 0.885, with precision and recall of 0.898 and 0.884, respectively. The overall average F1 score was 0.914, with the highest F1 score (0.96) appearing in the chain structure samples. The results show that this method can reconstruct the real propagation trajectory with significantly higher accuracy than traditional baselines, effectively solving the problem of the difficulty in tracing the propagation path of ideological and political discourse. By accurately mapping these trajectories, the system provides a data-driven basis for optimizing discourse guidance strategies.

VII. CONCLUSION

The actual challenges of the hidden propagation route and the impossibility of measuring the effect of ideological and political speech on social media resources are discussed in this paper by designing a scheme of visualization analysis combining the perception of multi-source data and dynamic graph inference. This paper constructively breaks down the breadth, affective validity, and path structure of ideological

TABLE 2. Quantitative Comparison Based on Emotional Evolution Curves and User Identification Ratio

Topic Tag	Positive Sentiment Shift Rate	User Recognition Ratio (Final/Initial)	Average Expert Score	Pearson Correlation Coefficient
#CentenaryOfTheCPC#	+32.6%	2.43	4.67	0.914
#RuralRevitalization#	+28.4%	2.17	4.33	0.892
#YouthRoleModels#	+41.2%	2.85	4.83	0.935

and political speech by establishing a systematic deconstruction of previously measured black box phenomenon related to dissemination process in the traditional literature of research through the introduction of temporal hypergraph modeling and social network analysis. As the results of the experiments demonstrate, the given framework is capable of correctly reconstituting the penetration path and the nature of the emotions progression that discourse undergoes within various circles, confirming the possibility of transitioning the qualitative description to the level of quantitative visualization in the context of technology-oriented research of ideological and political communication. This study is scientifically methodologically supportive and can be the source of reference in making decisions that would enhance the efficacy of mainstream ideology dispersal. One of the weaknesses is that the data collection is quite limited; in the future, the field of multi-platform data fusion will be enhanced and the concept of deep learning incentives in forecasting dissemination patterns and giving intelligent advice should be explored.

AUTHOR CONTRIBUTIONS

Yang Jing designed, collected and analyzed the data, and drafted the manuscript. Yang Jing conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Yang Jing 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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