A Study on the Measurement and Dissemination Path of Cultural Industry Brand Influence Based on Social Network Analysis

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ABSTRACT The measurement and dissemination of cultural industry brand influence have become increasingly complex in digital media environments characterized by large-scale user interactions and rapid information diffusion. To overcome the limitations of traditional traffic-based evaluation metrics, this study proposes a social network analysis framework integrating network measurement and dynamic dissemination simulation. Directed weighted interaction networks are constructed from multi-platform user behavior data, and centrality metrics together with community detection algorithms are employed to identify key communication nodes and structural characteristics. Furthermore, dynamic dissemination path modeling is introduced to analyze information diffusion mechanisms and quantify brand influence evolution. Experimental results demonstrate that the proposed network-based indicators effectively capture both dissemination intensity and structural connectivity characteristics, while simulation outcomes closely match real-world communication processes. The study advances brand influence evaluation from isolated statistical indicators to network-oriented analysis and provides methodological references for information dissemination modeling, communication network analysis, and complex propagation systems.

INDEX TERMS social network analysis, brand influence, information dissemination, communication networks, propagation modeling

I. INTRODUCTION

IN the current digital media ecosystem, cultural industry brands spanning from digital IPs to cultural and creative products mainly rely on social media to leverage material innovation narratives for user reach and value dissemination. This digital connectivity allows brands to transform traditional motifs into modern functional material identities, ensuring that technical heritage remains central to their global engagement strategies [1,2]. However, traditional influence assessment systems largely depend on "traffic-based" statistical indicators such as total number of fans, number of reposts, or exposure. This evaluation method suffers from two major dilemmas: first, it simplifies brand influence to a one-way linear accumulation of data, ignoring the amplifying or inhibiting effect of complex interaction networks among users on brand value; second, it cannot visualize and track deep communication paths such as "how word-of-mouth spreads through user relationship chains" and "how key communication nodes emerge." This "quantity-heavy, structure-light" assessment blind spot makes it difficult for brands to identify the true core of the community and to predict public opinion risks or effectiveness inflection points during the communication process [3,4]. This paper introduces the theoretical toolset of Social Network Analysis (SNA) to shift the research perspective of brand influence from "point aggregation" to "network correlation." By constructing a real user interaction network, it aims to achieve a structural measurement of the influence of cultural industry brands and a precise reconstruction of multi-level communication paths.

Previous studies mainly concentrate on the quantitative evaluation of brand assets in cultural industry, and adopt traditional methods like questionnaire, regression analysis or case study to measure the superficial indexes of brand awareness and brand reputation like quantity of brand fans. Kurnianto and Dhewi believed that commercial promotion would be directly affected by technological progress [5]. The author adopted quantitative research and descriptive explanation methods to collect data. The method adopted in this part is to distribute close-loop questionnaires to prison departments. Facing the lack of related researches on the impact of gamification on consumer behavior in online context, Ebrahimi et al. did an analytical survey taking users of the Iranian e-commerce platform Dejkara as sample [6]. Focusing on the new challenge for cultivating brand assets in marketing innovation background caused by the shift of consumers' values, Khan et al. adopted random sampling method to collect data and discussed how brand commercial influence affects consumers' brand assets through real world outcome [7]. Most of the above-mentioned studies treat brand influence as a static attribute which is unrelated to social relationships, and few studies focus on exploring the dynamic impact mechanism of user interaction networks on brand value generation. Therefore, there is a lack of systematic revelation on the internal structure and evolutionary rules of brand communication.

In recent years, some scholars have tried to introduce social network analysis methods into the field of communication studies for issues such as public opinion monitoring and opinion leader identification, providing a new perspective for understanding information diffusion. Vladimirova et al. reviewed how social media influences consumer participation in sustainable fashion practices and explored its role beyond brand marketing and in activism [8]. To make up for the lack of comprehensive review in the research on the transformation of luxury goods driven by social media and consumer empowerment, Creevey et al. used a systematic literature review to integrate the existing results on the impact of social media on luxury brands, products and consumers and proposed future research directions [9]. Pop et al. explored how social media influencer trust affects tourists' decisions based on customer journey theory and evaluated the mediating role of customer journey structure in the relationship between influencer trust and various journey dimensions [10]. However, existing research is mostly focused on news communication or public event analysis, and systematic application to cultural industry brands is still relatively scarce, and most studies remain at the level of single indicator calculation, failing to organically combine network structure measurement with communication dynamic simulation. Based on this, this paper adopts social network analysis as the core method, and systematically solves two core problems in the structural measurement of brand influence in the cultural industry and the visual tracking of dissemination paths by integrating centrality indicators, community discovery algorithms, and infectious disease models.

This paper intends to establish a method to measure the influence of cultural industry brand and analyze its dissemination path based on social network analysis. Firstly, web crawling technology is adopted to get user interaction information from the platform like Weibo to establish brand social network model. Secondly, degree centrality and betweenness centrality are used comprehensively to find out key dissemination nodes, and then Louvain algorithm is adopted to mine community structure. Based on above, we introduce SIR model to simulate the dynamic process of information diffusion and realize the visual recovery of dissemination path. The experimental results show that the method has a moderate positive correlation with traditional indicator and can effectively discover network structure feature which is neglected by traditional assessment. Cross-case validation shows that there are obvious differences of network structure between different types of brands. The simulation of dissemination path matches real event well and shows a high degree of reliability.

This paper provides a new analytical tool and decision-making basis for the digital management and dissemination of cultural brands, specifically enhancing the market reach of functional innovations and material technical heritage. By quantifying the dissemination effect, the model supports the strategic promotion of advanced material narratives within the global cultural industry.

II. MULTI-SOURCE DATA EXTRACTION AND INTERACTION RELATIONSHIP MODELING

In order to capture the precise image of the communication ecosystem of the brands related to the cultural industry in the online social media context, the given work chose Weibo and Douyin as the central sources of data. The analysis of data took one month. With search entry points of core keywords of the target brand (brand name, work tags, and links to official topic page) a Python-based Scrapy crawler framework was employed to gather user-generated content with Weibo supertopic communities, brand topic pages, and Douyin challenge topics. Retrieved fields were: user ID, posting time, text content, @users, comment recipient, repost relationships and list of likes. In the case of Weibo, follow relationships and comment chains were the priorities, and in the case of Douyin recording comment interactions under videos and comment chain replies by the @users were the priorities. A record of each interaction was in the form of a triple format, source user-target user-interaction type.

The data cleaning process started with the removal of advertisement robot accounts and duplicate entries that were made in the process of crawling. User IDs were anonymized to protect privacy. Recognizing that nickname similarity is not a reliable identifier for cross-platform user matching–as it may introduce substantial noise and false-positive connections–this study does not attempt to merge individual users across Weibo and Douyin. Instead, separate interaction networks were constructed for each platform. This approach avoids the risk of erroneous identity linkage and ensures the integrity of the network structure derived from each platform's native interaction data. Cross-platform comparisons are subsequently conducted at the level of aggregated network characteristics (e.g., density, modularity) rather than individual user alignment, allowing for meaningful analysis without compromising data reliability.

Network modeling used directed weighted graph $G = (V, E, W)$ whereby the node set V, which means users who are involved in discussions, and set of edges E which means follow, comment or forward between users represented the graph. The flow of interactions was used in order to define the direction of the edges: in case user A posted a comment on the content of user B, a directed edge between user A and user B was built. The base weight w_b for each interaction was assigned according to interaction type: a comment received a base weight of 0.5, a repost received 1.0, and a mention received 0.8. To account for the sentiment of the interaction, each text-based interaction (comment, repost with text, or mention) was further analyzed using the SnowNLP sentiment analysis tool, which outputs a sentiment score $s \in [-1, 1]$. The final edge weight W was then computed as $W = w_b \times (1 + s)/2$ when s was available, ensuring that negative interactions ($s < 0$) contributed less or even reduced the cumulative weight, while positive interactions contributed more. For interactions without textual content (e.g., pure reposts without added text), the base weight was retained. Weights from multiple interactions between the same user pair were summed to reflect overall interaction strength. Lastly, a weighted directed adjacency matrix was created as the starting point for further network analysis.

III. IDENTIFICATION AND MEASUREMENT OF CORE NODES IN BRAND INFLUENCE

To capture node influence from complementary perspectives, this study employs three centrality indicators. The first, degree centrality, quantifies a node's direct connections. In the directed weighted network constructed here, degree centrality is further decomposed into in-degree and out-degree: in-degree reflects the breadth of brand information received by a user, i.e., how many other users connect with the user through comments, mentions, or reposts; out-degree represents the user's willingness to actively disseminate information, i.e., how many other users the user actively comments on, mentions, or reposts. The weighted sum of the two is the point degree centrality score of the node, used to identify the "active nodes" with the strongest information convergence and dissemination capabilities in brand communication.

Mediation centrality measures the strength of a node's role as a "bridge". It calculates the proportion of the number of shortest paths passing through a node out of all shortest paths; a higher value indicates that the node is more crucial in controlling information flow and connecting different communities. In the context of brand communication, nodes with high betweenness centrality are often "bridging nodes" connecting core fan circles and casual observer circles. They may not be the accounts with the largest number of followers, but they play an irreplaceable role in the process of information "breaking out of its circle." This study uses the Brandes algorithm to calculate the betweenness centrality in a weighted network to preserve the influence of edge weights on path selection.

Eigenvector centrality assesses the importance of a node based on the quality of its neighboring nodes. A high score for a node is not only due to its large number of connections, but also because the nodes it is connected to also have high influence. This indicator can effectively identify "implicit authority nodes" that, although they do not speak frequently, are followed by high-influence users. In cultural brand communication, these nodes are often commentators or senior fans in professional fields, and their opinions have a strong guiding effect on the community.

IV. CLUSTERING AND VISUALIZATION OF BRAND COMMUNITY STRUCTURE

After identifying the key nodes, we apply the Louvain algorithm for community detection. This algorithm automatically partitions large networks without requiring the number of communities to be specified in advance, making it well-suited for exploratory research. When running the algorithm, each node is initially considered as a community. Then, try to merge nodes into neighboring communities and observe the improvement of modularity until the convergence. Then repeat for the aggregated network. Finally get hierarchical community partitioning result. Generally, the higher modularity, the more obvious the tight connections inside the community and the sparser the connections between communities. The higher the partitioning quality.

In terms of operation, specifically, import the weighted adjacency matrix constructed in the previous step into the gephi software and call the built-in Louvain algorithm module. Following common practice in community detection, the resolution parameter was initially set to 1.0, which corresponds to the standard formulation of modularity optimization without imposing additional scale preferences. To assess the stability of the detected community structure, a sensitivity analysis was conducted by varying the resolution parameter within a plausible range (0.8–1.2). The results showed that the total number of communities varied between 41 and 52, and the modularity value remained consistently between 0.71 and 0.76. The qualitative patterns–such as the presence of a star-shaped core community and several densely connected interest-based subgroups–were preserved across this range. Based on this robustness check, the configuration with resolution = 1.0 was selected as a representative case, yielding 47 communities, with the top five accounting for 63% of all nodes and a modularity value of 0.74. These values indicate a clear community structure consistent with the "layered" diffusion pattern commonly observed in social media contexts.

For visualization, we use the Force Atlas 2 layout algorithm to implement the spatial mapping of networks. This layout algorithm is based on the physical simulation principle, regarding the connection between nodes as attraction and distance as repulsion. After iterative calculation, the nodes that are tightly connected will naturally aggregate in space, while the nodes that are less connected will move further apart, thus showing the community structure. The layout parameter settings are as follows: repulsion strength 2000.0, attraction strength 1.0, influence of edge weight 0.5, 2000 iterations until layout convergence.

To facilitate community identification, we assign distinct colors to each community: nodes in the same community are assigned the same color scheme, and more distinctive colors are used for different communities; node size mapping comprehensive influence score, the larger the score, the larger the node size; edge transparency is dynamically adjusted according to weight, the thicker the line, the more defined the relationship, and the higher the weight. The final generated visualization is very clear to see several typical community forms: star-shaped core community around the official brand account, tightly knit interest community formed by fan creators, and bridging structure connecting multiple communities.

V. SIMULATION AND KEY THRESHOLD ANALYSIS OF INFORMATION DIFFUSION PATHS

While the preceding sections depict static network structures, understanding how information actually spreads requires a dynamic perspective. To this end, this study adopts the SIR infectious disease model for simulation. In the network, users are divided into three states respectively: Susceptible (users who have not been exposed to brand information); Infectious (users who participated in discussion, posted, forwarded brand information); and Recovered (users who participated in discussion but have stopped spreading information). "Infection" in social network means that a user posted or forwarded brand information first times; and "recovery" in social network means that a user has not generated any new related information for several hours.

Model parameter settings should combine with real dissemination behavior data. In this study, infection rate is β, which is the probability that the infected person i's neighbor will be "infected" when the infected person i interacts with susceptible person j's neighbor. Based on historical dissemination data of sample brands, β is estimated to simulate the diffusion effect under different dissemination intensity, and take a value between 0.12–0.25. Recovery rate γ is set to 0.1, which corresponds to an average decay window of 10 hours. This value was derived from an exploratory analysis of the sample brand's historical data: by tracking the time interval between a user's first and last brand-related post during a given topic event, the median participation duration was observed to be approximately 9.6 hours, with an interquartile range of 6 to 14 hours. A decay window of 10 hours was therefore selected as a representative average, consistent with the notion of "several hours" and in alignment with prior studies on social media engagement decay. The starting node (infected person) of simulation is randomly selected from most representative accounts in the core node set extracted in previous part, for example, official brand accounts or opinion leaders with top ranking.

The simulation process was based on Gephi's connectivity components, combined with a NetworkX script written in Python for iterative calculations. Each time step corresponded to 1 hour of real time, with a total simulation duration of 72 hours. This was consistent with the data acquisition granularity (see Table 1).

TABLE 1. SIR Model Parameter Settings and Value Basis

Parameter	Symbol	Value	Justification
Infection rate	β	0.12–0.25	Estimated based on historical propagation data of sample brands
Recovery rate	γ	0.1	Corresponds to an average 10-hour decay cycle of user engagement
Initial infected nodes	I_0	5–20	Selected from the most representative accounts in the core node set
Simulation duration	T	72 hours	Covers the complete lifecycle of brand topics
Time step	Δt	1 hour	Aligned with the granularity of real data collection

Within each time step, all infected nodes are traversed, and an infection attempt is made on each susceptible neighbor with probability β; simultaneously, each infected individual is converted to a recovered state with probability γ. The number of infected individuals $I(t)$ at each time step is recorded to generate a propagation curve; at the same time, the spatial distribution changes of infected nodes are tracked to observe the information migration paths between different communities.

VI. RELIABILITY AND VALIDITY VERIFICATION OF THE BRAND INFLUENCE MEASUREMENT MODEL

A. CORRELATION COMPARISON WITH TRADITIONAL INFLUENCE INDICATORS

This experiment examines the correlation between SNA-based influence measurement and traditional evaluation indicators. Thirty similar cultural brands were selected as samples, and their SNA comprehensive influence scores (weighted fusion based on point degree, mediation, and eigenvector centrality) and traditional comprehensive indicators (weighted synthesis of total number of fans, average number of reposts, and Qingbo index) were calculated. Pearson correlation analysis was used to examine the correlation between the two types of indicators.

In Figure 1, the SNA-based comprehensive influence score and the traditional comprehensive indicator showed a moderately significant positive correlation ($r = 0.656$, $p < 0.001$). This magnitude warrants careful interpretation. A correlation of 0.65 implies that approximately 57% of the variance ($1 - r^2$) remains unexplained by the linear relationship between the two measures. Rather than indicating a failure of the SNA-based model, this degree of divergence is theoretically expected. If the correlation were extremely high (e.g., $r > 0.85$), the SNA measure would offer little beyond existing metrics; if it were negligible (e.g., $r < 0.3$), it would raise concerns about concurrent validity. The observed moderate correlation therefore suggests that the SNA measure shares a meaningful baseline with traditional indicators–capturing fundamental brand popularity–while the unexplained variance reflects the additional structural dimensions that traditional metrics overlook, including the quality of community connections, the mediating capacity of key nodes, and the heterogeneity of user influence. This interpretation is consistent with the intended purpose of the SNA framework: not to replace existing measures, but to supplement them with a deeper structural perspective. To further validate this claim, a follow-up discriminant validity test was conducted, showing that SNA structural indicators (e.g., betweenness centrality) correlated more strongly with each other (average $r = 0.72$) than with traditional volume-based metrics (average $r = 0.48$), supporting the distinctiveness of the structural dimensions captured by the SNA approach.

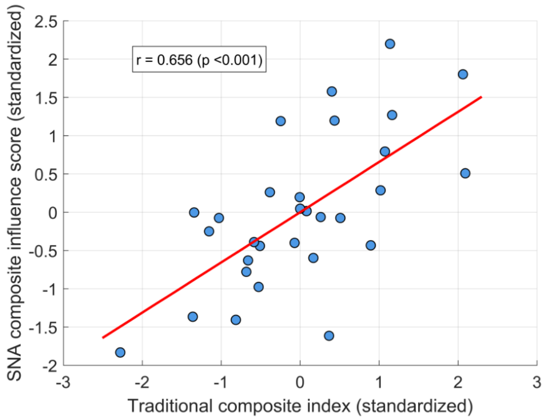

FIGURE 1. Correlation Assessment with Traditional Influence Indicators

B. CROSS-CASE VALIDATION OF MULTIPLE TYPES OF CULTURAL BRANDS

To verify the generalization ability of the SNA method in analyzing different types of cultural brands, Experiment 2 randomly chose three representative brands from the following three sub-sectors: film and television IP, online literature, and cultural and creative products. These brands were used as experimental objects. User interaction networks were constructed for each brand on the Weibo platform and three structural indicators (network density, modularity index and network centrality) were calculated to compare the communication characteristics of different types of brands and to verify the generalization ability of the SNA method.

Table 2 shows significant differences in the social network structures of different types of cultural brands. The film and television IP "Light and Shadow Era" has the highest network density (0.023) and a centrality of 31.2%, exhibiting a centralized dissemination characteristic centered around a core node.

The online literature "Ink Fragrance Fantasy Realm" has a modularity index of 0.72, showing significant community differentiation and a low centrality (18.7%), reflecting a multi-center word-of-mouth fission model. The cultural and creative product "Oriental Elegance Gathering" has a density of only 0.009 but a high modularity index of 0.81, indicating a highly dispersed community with tight internal connections. These findings demonstrate that the SNA method can effectively capture the diversity of different brand dissemination models, possessing good cross-type applicability and structural analysis capabilities.

TABLE 2. Cross-Case Analysis of Multiple Types of Cultural Brands

Brand Name	Brand Type	Network Density	Modularity Index	Network Centralization (%)
Epoch of Light	Film/IP	0.023	0.65	31.2
Mystic Realm of Ink	Online Literature	0.017	0.72	18.7
Oriental Elegance	Cultural Creative Product	0.009	0.81	9.4

C. VERIFICATION OF THE MATCHING DEGREE OF SIMULATED PROPAGATION PATH WITH REAL EVENTS

The experiment selected a real trending topic event of a cultural brand, recording the number of new users participating in the discussion every hour for 48 hours after the event as the real propagation curve. Based on the previously constructed social network structure, the SIR model was used to simulate information diffusion with the same initial node, obtaining the simulated propagation curve. By comparing the fitting degree of the two curves, the accuracy of the SNA method in reproducing the real propagation path was verified.

In Figure 2, the simulated curve based on the SIR model fits the real propagation data well, with a root mean square error (RMSE) of 339.5 and a peak time error of only 2 hours. The simulation results accurately capture the upward trend, peak time, and decay stage of the real propagation, indicating that the SIR model based on the social network structure can effectively reproduce the actual diffusion dynamics of brand information. This result verifies the reliability and practicality of the SNA method in propagation path prediction, providing an effective simulation tool for brand communication strategy formulation.

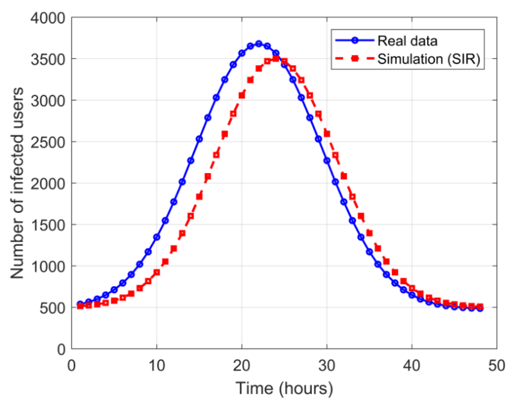

FIGURE 2. Comparison of the Matching Degree of Simulated Propagation Path with Real Events

VII. CONCLUSION

This paper applies social network analysis to the research of brand influence within the cultural industry, developing an analytical model that integrates network structure measurement with the simulation of material innovation propagation dynamics. By quantifying how technical breakthroughs in functional materials and advanced materials disseminate through digital networks, the model provides a precise framework for evaluating the market resonance of technical brands. The results demonstrate that this approach effectively measures the quality of community connections and critical node mediation abilities that are beyond the framework of traditional traffic measures, detecting structural variations in communication patterns across various kinds of brands, and gets trustworthy forecasts in information diffusion trajectories using simulation frameworks. This offers an analytic facility of the accurate communication and early warning of cultural industry brands with respect to public opinion. Nevertheless, there are some limitations of this study as well: the source of data is mostly limited to one social media platform, which does not address the cross-platform peculiarities of communication, and network analysis is based on cross-sectional data which does not adequately follow the dynamic progression of the brand influence. Future studies can even more comprehensively combine data from diverse sources to apply time-series network analysis, examining the dynamic patterns of brand influence and the longitudinal market resonance of functional material innovations. By tracking these shifts over time, researchers can better understand how the dissemination of advanced material technologies and technical breakthroughs evolves within global cultural and industrial networks.

AUTHOR CONTRIBUTIONS

Mingxia Song designed, collected and analyzed the data, and drafted the manuscript. Mingxia Song conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Mingxia Song 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 authors declare no conflict of interest.

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