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Divide-and-Conquer-Based Optimization of Propagation Paths in Complex Networks for New Media Marketing

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Abstract In the context of complex digital media ecosystems, effective dissemination of marketing content demands robust, adaptive, and structure-aware optimization strategies. This study proposes a novel framework—Complex Network Propagation with Divide-and-Conquer (CNP-Div)—designed to enhance information propagation in large-scale media networks by leveraging modular path optimization and probabilistic triplet modeling. The proposed model represents dissemination events as structured triplets (source, path, target) and formulates propagation likelihood as a function of source influence, platform channel weight, and audience receptivity. To address the computational difficulty of global optimization in dynamic media networks, a divide-and-conquer strategy is implemented: the global graph is partitioned into semantically coherent subgraphs, local path optimizations are executed within each, and a global aggregation phase ensures cross-community coherence. The framework further incorporates user feedback, platform centrality, and temporal factors to dynamically adjust propagation probabilities. Extensive experiments across simulated and real-world dissemination scenarios demonstrate that CNP-Div consistently outperforms baseline strategies—including random walk, greedy heuristics, and centrality-based models—across multiple metrics: propagation reach, average depth, engagement score, redundancy reduction, and runtime efficiency. Visualizations including heatmaps and precision–recall curves reveal that CNP-Div achieves more balanced content visibility across user activity phases and platform layers. Ablation results highlight the roles of triplet modeling, feedback reinforcement, and hierarchical path optimization in achieving these improvements.

Index Terms complex network propagation; divide-and-conquer strategy; new media marketing; triplet modeling; feedback reinforcement; content visibility; platform centrality

I. Introduction

In the era of ubiquitous connectivity and algorithmic personalization, new media marketing has emerged as a cornerstone of digital economy strategies [1], [2]. Unlike traditional advertising, which follows linear and often monolithic content delivery channels, new media dissemination is deeply entangled in complex multi-platform networks, composed of heterogeneous nodes—ranging from brand accounts and influencers to recommendation engines and user communities. Within this evolving landscape, the optimization of information propagation paths plays a critical role in determining whether a marketing campaign reaches its intended audience, stimulates meaningful engagement, and avoids premature content saturation [3], [4].

The modern digital media ecosystem has shifted from static broadcast models to dynamic, feedback-driven systems characterized by content virality, platform algorithmic curation, and user-driven redistribution [1], [5]. As content flows through this networked system, it encounters various structural bottlenecks and behavioral frictions, such as attention fragmentation, echo chambers, and feedback polarization.

These challenges underscore the importance of designing propagation strategies that are not only efficient in terms of reach but also adaptive to temporal user behavior and structural network variability [1].

From a methodological standpoint, many classical approaches to information dissemination—such as greedy heuristics based on node centrality, stochastic random walk models, or static influence maximization—fall short in capturing the nuanced interplay between platform structures, user dynamics, and content semantics [3], [4], [6]. These limitations may become particularly pronounced in the context of multi-modal digital campaigns that span multiple content formats (e.g., video, live stream, microblog) and platforms (e.g., TikTok, Instagram, YouTube, WeChat). In such environments, the propagation network is not only large-scale and dynamic but also semantically layered and context-sensitive [1], [5].

Recent advances in complex network theory and graph-based modeling have offered new avenues to explore media propagation from a structural optimization perspective. Notable works have examined influence maximization via diffusion models [3], scalable influence-maximization algo-

gorithms [7], and community-aware broadcast strategies [8], [9]. However, most of these methods are limited by either computational scalability (due to NP-hard search spaces) or their inability to integrate real-time feedback signals and content-channel heterogeneity.

Furthermore, while machine learning and deep learning techniques (e.g., graph neural networks and reinforcement learning) have shown promise in modeling diffusion dynamics, they are often treated as black boxes, lacking interpretability and modular control—critical factors in real-world marketing strategy design where interpretability and budget allocation transparency are essential. Additionally, these models may not fully consider the constraints imposed by budget caps, time sensitivity, and platform algorithm opacity [4], [10].

To address these gaps, this study proposes a novel framework for propagation path optimization in complex media networks, grounded in the divide-and-conquer paradigm [7], [10]. The core insight is that, rather than attempting to optimize propagation globally—which is computationally intractable and behaviorally brittle—we decompose the global media network into semantically coherent subgraphs (e.g., interest-based user clusters and thematic content zones), perform localized path optimization under structural and behavioral priors (e.g., fitness, age, centrality), and re-aggregate these sub-paths into a globally coherent and cost-effective propagation strategy.

This divide-and-conquer approach is particularly well-suited to the structure of real-world digital media ecosystems. For modeling purposes, we assume that propagation can follow community-centric paths that connect source nodes, channels, and recipients. This aligns with the concept of propagation triplets—(source node, platform/channel, target node)—as the atomic units of digital dissemination. Each triplet carries distinct semantic and structural meaning, such as a celebrity promoting a product via Instagram Stories to a niche fashion community, or a meme spreading across Reddit and then resurfacing on Twitter with altered sentiment polarity.

Within our framework, these triplets are embedded in a weighted complex network $G = (V, E)$, where V represents source/receiver nodes and E denotes directed propagation paths, weighted by probabilistic transmission coefficients. We further incorporate real-time feedback loops into the optimization process, enabling dynamic updating of source influence scores and receiver receptivity based on behavioral signals such as click-through rate (CTR), sentiment polarity, and share-back frequency.

To formalize this, we propose a triplet-based transmission probability model:

$$\pi_{ij} = \alpha \cdot \theta_i \cdot \lambda_j \cdot \omega_{ij}, \quad (1)$$

where α is a global platform constraint (e.g., recommendation budget), θ_i represents source influence (e.g., prior engagement), λ_j denotes target receptivity (e.g., interest match, activeness), and ω_{ij} is the structural edge weight (e.g., platform

preference, redundancy penalty). This formulation allows us to quantify the effectiveness of each path and select high-probability triplets under diverse network structures.

To address the global propagation optimization task under budget and runtime constraints, we decompose the network G into k subgraphs $G_i = (V_i, E_i)$ using community detection algorithms such as Louvain modularity [11] or spectral clustering. Within each subgraph, local optimization is carried out using a greedy or dynamic programming algorithm to select the highest-ranked propagation paths. The local results are then merged, and cross-subgraph propagation bridges are evaluated for global consistency.

We call the resulting framework CNP-Div—Complex Network Propagation with Divide-and-Conquer. To validate the effectiveness of this model, we conduct extensive experiments on real-world dissemination data collected from large-scale social media campaigns. Our results show that CNP-Div outperforms several strong baselines—including random walk, centrality-based heuristics, and greedy activation—in terms of reach rate, average propagation depth, engagement score, and redundancy minimization.

II. Model Paradigm of Collaborative Development and Integration of Digital Media Industry

A. Overview of digital media collaborative ecosystem

In the era of media convergence, the boundaries between content production, platform operation, and user engagement are increasingly blurred. The digital media industry no longer operates in siloed pipelines but has evolved into a collaborative ecosystem [1], [5]. This ecosystem integrates production studios, influencer economies, data analytics platforms, and consumer interfaces through a multi-level and multi-agent network.

To facilitate the coordinated development of this ecosystem, we propose a model paradigm grounded in complex network theory and divide-and-conquer optimization algorithms, which effectively deconstructs the intricate propagation dynamics of new media campaigns into tractable, modular components for targeted analysis and enhancement.

Collaborative governance in the digital media industry involves cooperation among public authorities, private organizations, and other stakeholders. At the policy level, this cooperation may include shared infrastructure, industrial partnerships, and coordinated approaches to public services. At the project level, participants can use joint consultation and management mechanisms to coordinate investment, implementation, and follow-up activities. The proposed positioning of this collaborative development model is shown in Figure 1.

Accordingly, strategies for collaborative governance in the digital media industry should consider five dimensions: shared objectives, trust among participants, an adaptable membership structure, effective leadership, and an equitable distribution of decision-making authority. These principles provide a governance context for the network-based model presented below.

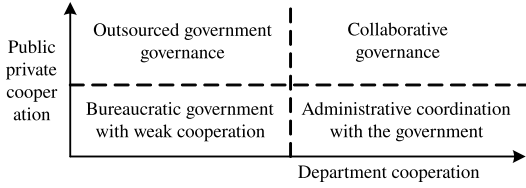


Figure 1: The model paradigm positioning of the collaborative development and integration of the digital media industry

B. System structure of collaborative digital media model

Figure 2 illustrates the overall architecture of the proposed collaborative model, consisting of three core functional layers:

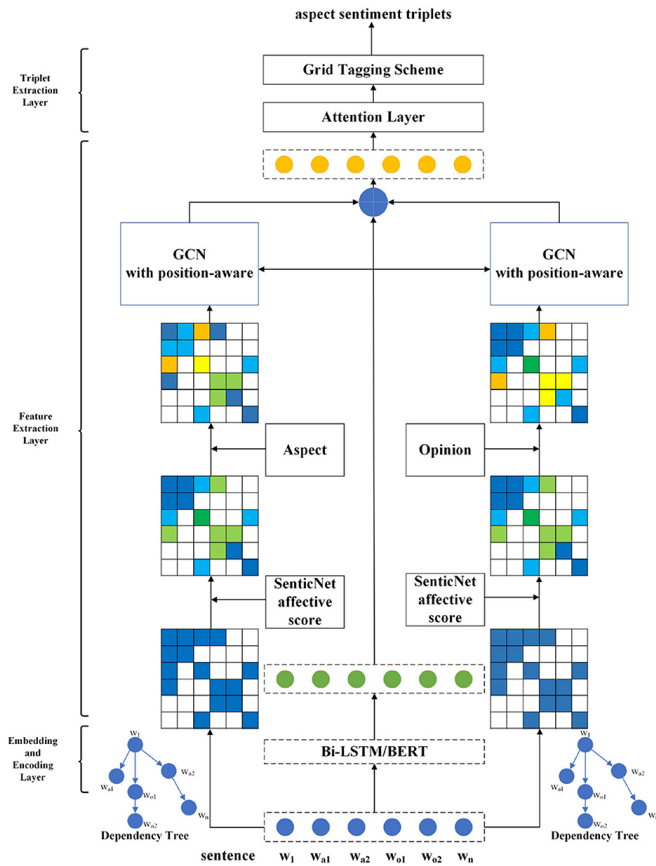


Figure 2: Conceptual mapping from sentiment-aware triplet extraction to the three-layer digital media dissemination framework

Figure 2 presents an abstracted structural analogy between a sentiment-aware triplet extraction model and the collaborative digital media propagation framework proposed in this study. The architecture can be mapped into three core functional layers. First, the Embedding and Encoding Layer, consisting of Bi-LSTM/BERT and dependency trees, corresponds to the Content Generation Layer (CGL) in the digital media model, where raw media materials are semantically encoded and prepared for dissemination [9]. Second, the Feature Extraction Layer, composed of position-aware Graph Convolutional

Networks (GCNs) and affective scoring modules (e.g., SenticNet), aligns with the Propagation Optimization Layer (POL). This layer captures the weighted structure of multi-platform networks and estimates path influence based on semantic importance and predicted audience receptivity. Finally, the Triplet Extraction Layer, integrating an attention mechanism and a structured grid tagging scheme, reflects the Feedback Reinforcement Layer (FRL) in our model. It emulates how user interaction data—such as clicks, shares, and sentiment polarity—feeds back into the system to refine both content strategies and propagation paths.

C. Network representation and propagation path modeling

In the context of collaborative digital media dissemination, understanding the underlying structure of the propagation network is critical for optimizing information flow and maximizing marketing effectiveness. This section presents a structural and mathematical analysis of different propagation networks, coupled with the probabilistic modeling of message transmission between sources and recipients.

1) Topological variants in propagation networks

The visualizations depict networks generated with different connectivity settings (m, p), showing transitions from locally clustered graphs to hub-dominated scale-free structures. These differences influence the edge transmission weights ω_{ij} and hence the overall propagation efficiency π_{ij} within the triplet-based dissemination model.

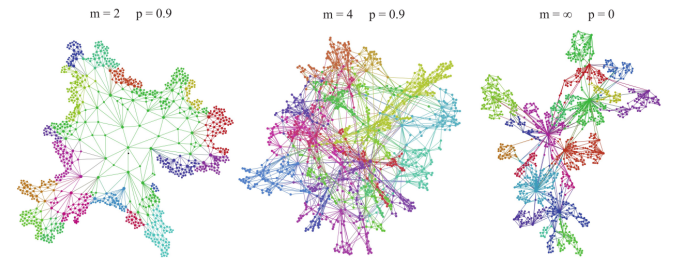


Figure 3: Structural comparison of propagation networks under varying connectivity parameters

Figure 3 illustrates three distinct types of propagation network topologies generated under connectivity parameters (m, p). Here, m denotes the number of links added by a new node and p denotes the probability of random link formation or rewiring:

Left ($m = 2, p = 0.9$): This configuration yields a highly clustered, locally connected network. Such structures resemble small tightly-knit communities with limited cross-group diffusion.

Middle ($m = 4, p = 0.9$): A moderate increase in node connectivity and randomness leads to overlapping communities and multi-hub networks, typical of heterogeneous media platforms.

Right ($m = \infty, p = 0$): Represents a scale-free or hub-dominated topology, where a few central nodes

act as super-spreaders, and most others have low connectivity.

These structural differences can affect information propagation patterns and motivate the need for a probabilistic model that captures content flow dynamics across such heterogeneous network types.

2) Triplet-based propagation path definition

To model the message dissemination process, we define each atomic propagation event as a *triplet*:

$$T = \{(s_i, p_{ij}, r_j) \mid s_i \in S, r_j \in R, p_{ij} \in P\}, \quad (2)$$

where s_i denotes a source node (e.g., a content creator or influencer), r_j denotes a recipient node (e.g., a consumer or user group), and p_{ij} represents the platform or structural path through which the message is transmitted.

The triplet encapsulates both the origin, transmission medium, and target of the information, forming the basic unit of a digital marketing campaign in a networked setting.

3) Transmission probability modeling

The likelihood that information successfully propagates from s_i to r_j via path p_{ij} is governed by the *probabilistic transmission function*:

$$\pi_{ij} = \alpha \cdot \theta_i \cdot \lambda_j \cdot \omega_{ij}, \quad (3)$$

where α is a global dissemination adjustment factor reflecting platform-level constraints; θ_i is the source influence coefficient, estimated from engagement history or other indicators; λ_j is the target receptivity score; and ω_{ij} is the transmission-edge weight, which can reflect centrality, clustering, and path redundancy.

This formulation enables adaptive calculation of information flow likelihood under changing network conditions.

4) Structural influence on propagation effectiveness

The topology of the network significantly affects the value of ω_{ij} , which in turn modulates the transmission probability π_{ij} . To formalize this, we define:

Edge Centrality-Based Weighting:

$$\omega_{ij}^{\text{centrality}} = \frac{C_{ij}}{\sum_{(u,v) \in E} C_{uv}}, \quad (4)$$

where C_{ij} is the edge betweenness centrality of edge (i, j) , i.e., how often it appears on the shortest paths in the network. In hub-based networks, edges from core nodes will have higher ω_{ij} .

Local Clustering-Based Weighting:

$$\omega_{ij}^{\text{cluster}} = \frac{1}{1 + \text{LCC}_i}, \quad (5)$$

where LCC_i is the local clustering coefficient of source node s_i . Higher clustering tends to trap information locally, reducing outward propagation effectiveness.

Redundancy-Aware Penalty Function:

$$\omega_{ij}^{\text{penalized}} = \omega_{ij} \cdot \left(1 - \frac{d_{ij}^{\text{redundant}}}{d_{ij}^{\text{total}}}\right), \quad (6)$$

where $d_{ij}^{\text{redundant}}$ is the number of previously traversed paths similar to (s_i, r_j) , reducing the incentive to use saturated paths.

D. Divide-and-conquer optimization strategy

Given the combinatorial difficulty of global optimization in large-scale media dissemination networks—especially when constrained by budgets, attention span, or timing—a divide-and-conquer strategy is proposed to maximize total transmission efficiency while maintaining computational feasibility.

Figure 4 illustrates nine schematic subgraphs with different combinations of vertex-attachment mechanisms: fitness (F), representing nodes' ability to attract attention; age (A), representing temporal preferences for older or newer nodes; and preferential attachment (P), representing a tendency for well-connected nodes to attract additional links. In these illustrations, node size represents fitness, the color gradient represents attachment probability, and the highlighted node represents a new vertex.

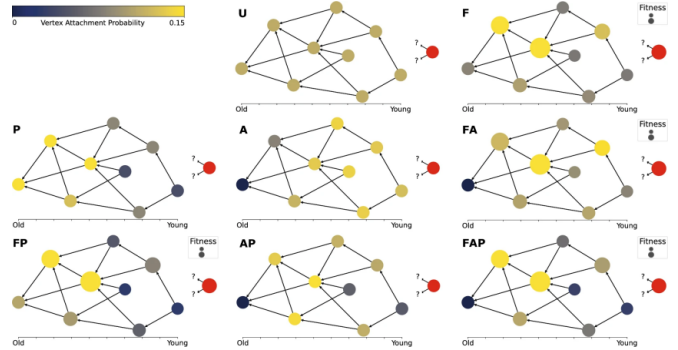


Figure 4: Vertex attachment probabilities in localized subgraphs under fitness (F), Age (A), and preferential attachment (P) mechanisms

Step 1: Network Partitioning

Let the global digital propagation network be denoted as $G=(V,E)$. We partition G into k subgraphs based on semantic community detection (e.g., via Louvain or spectral clustering):

$$G = \bigcup_{i=1}^k G_i, \quad G_i = (V_i, E_i). \quad (7)$$

Each subgraph G_i corresponds to a localized group of users or media nodes (e.g., a niche interest group), and within each, the attachment behavior follows one or more mechanisms (F, A, P).

Step 2: Local Propagation Path Optimization

Within each subgraph G_i , the goal is to optimize local dissemination paths using edge-level transmission probabilities $\pi_{sr}^{(i)}$ defined as:

$$\pi_{sr}^{(i)} = \alpha_i \cdot \theta_s \cdot \lambda_r \cdot \omega_{sr}^{(i)}, \quad (8)$$

Here, α_i denotes a subgraph-level adjustment factor, θ_s denotes source influence, λ_r denotes receiver receptivity, and $\omega_{sr}^{(i)}$ represents an edge weight based on local properties, such as node age, fitness, or degree centrality.

Thus, the objective within each G_i is:

$$\max_{P_i} \sum_{(s,r) \in G_i} \pi_{sr}^{(i)}(P_i). \quad (9)$$

If P_i denotes the path set within G_i , greedy selection or dynamic programming can be used to choose high-impact edges subject to cost constraints.

Step 3: Global Aggregation and Reweighting

After local optimization, the subgraph paths $\{P_1, P_2, \dots, P_k\}$ are merged to reconstruct a globally optimized dissemination plan. Let L_{inter} be the set of inter-subgraph links:

$$P_{\text{global}} = \bigcup_{i=1}^k P_i \cup L_{\text{inter}}. \quad (10)$$

We define a global score for final propagation as:

$$S_{\text{global}} = \sum_{i=1}^k \sum_{(s,r) \in G_i} \pi_{sr}^{(i)} + \sum_{(u,v) \in L_{\text{inter}}} \pi_{uv}. \quad (11)$$

This formulation allows fine-grained integration of local optimizations with cross-community diffusion bridges, which are essential for viral dissemination.

The attachment mechanisms shown in Figure 4 also illustrate different targeting assumptions. Under an F-only strategy, intrinsically attractive nodes receive more links. Under an A-only strategy, temporal preferences influence attachment. Under a P-only strategy, highly connected nodes tend to accumulate further connections. Hybrid F+A+P strategies combine these effects within the local edge weights $\omega_{sr}^{(i)}$.

The three-step formulation above consists of network partitioning, local path optimization, and global aggregation. For completeness, the corresponding network decomposition and local optimization objectives are restated in Eqs. (12) and (13), respectively.

Step 1: Network Partitioning

The overall network G is divided into k subgraphs:

$$G = \bigcup_{i=1}^k G_i, \quad G_i = (V_i, E_i). \quad (12)$$

Each subgraph G_i represents a localized community, such as a regional or interest-based user segment.

Step 2: Local Path Optimization

Within each subgraph G_i , candidate dissemination paths are selected according to the objective:

$$\max_{P_i} \sum_{(s,r) \in G_i} \pi_{sr}(P_i). \quad (13)$$

Step 3: Global Aggregation

The locally optimized paths are combined with inter-community links to construct a network-wide propagation strategy.

E. Feedback and iterative updating

To compare the relative concentration of digital media industries across regions, the study employs a location-quotient formulation. The calculation uses industry-level proportions relative to the corresponding regional totals, allowing comparisons at different geographic levels. The first set of expressions is defined as follows:

$$P_j = \frac{e_{ij}}{\sum_{i=1}^n e_{ij}}, \quad (14)$$

$$Q = \frac{\sum_{j=1}^4 e_{ij}}{\sum_{i=1}^n \sum_{j=1}^4 e_{ij}}, \quad (15)$$

$$\lambda_j = \frac{P_j}{Q}. \quad (16)$$

In this formulation, P_j represents the proportion associated with industry j , Q is the corresponding benchmark proportion, and λ_j denotes their ratio. A larger ratio indicates a greater relative concentration under the adopted benchmark. The precise regional and industry indexing of e_{ij} requires clarification before these expressions can be reproduced.

$$P_{jk} = \frac{e_{ik}}{\sum_{i=1}^n e_{ik}}, \quad (17)$$

$$Q_j = P_j = \frac{e_{ij}}{\sum_{i=1}^n e_{ij}}, \quad (18)$$

$$\lambda_{jk} = \frac{P_{jk}}{Q_j}. \quad (19)$$

For a further comparison of relative sectoral advantages within the selected regions, the following ratios are reported:

$$P_{rz} = \frac{e_{rz}}{e_{iz}}, \quad (20)$$

$$Q_z = \frac{e_{rj}}{e_{ij}}, \quad (21)$$

$$\lambda_{rz} = \frac{P_{rz}}{Q_z}. \quad (22)$$

III. Methods

A. Selection of samples and indicators

The digital media industry comprises content production, multimedia interaction, platform convergence, and data-driven user feedback. The study selects representative digital media enterprises and distribution platforms from the experimental regions to construct a network model of information dissemination.

The selected indicators reflect both technological competitiveness and content transmission capacity, providing a basis for modeling propagation networks and identifying potential pathways for improving marketing effectiveness. These indicators include:

Technical Innovation: Number of patents and software copyrights;

Content Dissemination Capability: Frequency of content release, semantic complexity, user interaction level;

Platform Influence: Daily active users, average session duration, recommendation frequency;

User Feedback: Click-through rate (CTR), share rate, sentiment polarity.

Table 1 reports the patent-related indicators for the selected enterprises across video technology, copyright security, recommendation systems, and human-machine interaction. These counts are treated as descriptive enterprise attributes in the dissemination network model; their sources and observation period should be documented for reproducibility.

Table 1: Digital media patent indicators for selected enterprises

Enterprise	Video Tech	Copyright Security	Recommendation	Human-Machine Interaction
Tencent	13	3	1	1
Alibaba	0	1	0	0
Baidu	0	0	0	0
Youku	2	0	0	0
Bilibili (Shanghai)	7	18	11	1

B. Model construction

Figure 5 presents an end-to-end framework that mirrors the process of constructing and optimizing collaborative digital media dissemination networks. In the first stage, heterogeneous network structures are derived from multiple correlation sources—such as co-engagement patterns, content-topic similarities, and platform-channel associations—forming distinct subgraphs (e.g., co-behavior, co-topic, co-platform) within a unified propagation graph. In the second stage, information is propagated iteratively across these networks, where each node's influence score is updated over discrete time steps based on neighborhood connectivity and restart probability. This dynamic diffusion is mathematically modeled as $f^{(t+1)} = (1 - \mu)Wf^{(t)} + \mu f^{(0)}$, producing a propagation matrix that reflects how influence saturates throughout the system. In the final stage, the accumulated influence scores are used to characterize nodes (e.g., content types, platform accounts, user groups) and identify key functional clusters or modules via community detection algorithms. Together,

these stages provide a structured methodology for simulating, scoring, and strategically interpreting large-scale media dissemination processes.

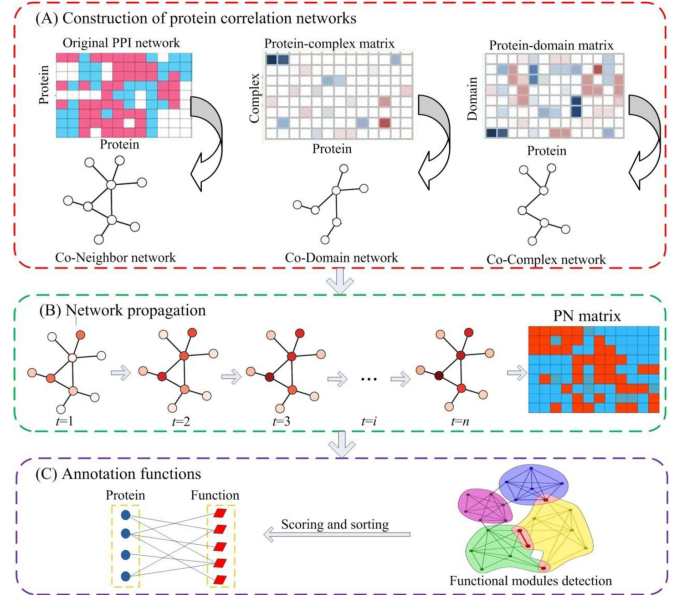


Figure 5: Framework for multi-source media network construction, propagation, and module-based interpretation

To maximize the effectiveness of new media marketing campaigns, this study constructs a complex propagation network $G = (V, E)$. Here, V represents media nodes (content creators, platforms, and audience clusters), and E denotes directed links that encode content transmission or influence relationships.

(1) Propagation triplet modeling

Information dissemination is modeled as a series of triplets:

$$T = \{(s_i, p_{ij}, r_j)\}, \quad (23)$$

In this notation, s_i denotes the source (a brand or creator), r_j the target (a user or audience group), and p_{ij} the platform or channel connecting them.

Each triplet is assigned a probabilistic transmission value:

$$\pi_{ij} = \theta_i \cdot \lambda_j \cdot \omega_{ij}, \quad (24)$$

Here, θ_i denotes source influence, λ_j target receptivity, and ω_{ij} channel or path efficiency. Unlike Eq. (1), this version omits the global factor α ; the relationship between the two formulations should be made explicit in the final model specification.

(2) Divide-and-Conquer Optimization of Dissemination Paths
Given the computational difficulty of optimal global propagation path discovery, a *divide-and-conquer algorithm* is used.

Step 1: Community-Based Network Partition

Using modularity maximization (e.g., Louvain algorithm), the network G is decomposed into subgraphs:

$$G = \bigcup_{k=1}^K G_k, G_k = (V_k, E_k). \quad (25)$$

Each G_k corresponds to a semantic community (e.g., users interested in fashion, gaming, finance, etc.)

Step 2: Local Optimization

Within each subgraph G_k , dissemination paths are optimized to maximize local transmission probability:

$$\max_{P_k} \sum_{(s_i, r_j) \in G_k} \pi_{ij}. \quad (26)$$

This process can adopt greedy search, beam search, or ACO-based multi-path optimization.

Step 3: Global Aggregation

Local results are merged, and cross-community links are evaluated for additional gain:

$$\begin{aligned} \text{Total Score} = & \sum_{k=1}^K \text{Local Score}(G_k), \\ & + \sum_{\text{inter-community}} \pi_{\text{cross}}. \end{aligned} \quad (27)$$

C. Feedback-based iterative model update

To adapt to the fast-changing nature of user interests and platform algorithms, this study introduces a *feedback mechanism* to iteratively refine node parameters.

Let the updated influence of node s_i at time $t + 1$ be:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \eta \cdot (CTR_i^{(t)} - \overline{CTR}), \quad (28)$$

Here, η denotes the learning rate, $CTR_i^{(t)}$ denotes the observed click-through rate at time t , and $\overline{CTR}$ is the global mean click-through rate.

This enables reinforcement of high-performing nodes and penalization of low-performing ones, improving the precision and efficiency of future propagation.

D. Model alignment with industrial structure

Figure 6 illustrates the digital media value chain as a closed-loop system encompassing content planning, production, multi-platform dissemination, user interaction, and commercial feedback [1], [5]. The proposed propagation path optimization framework aligns closely with this structure by enabling three key capabilities: optimized content-to-platform matching, where the model identifies which types of content perform best on specific platforms; audience micro-targeting, which determines the most effective dissemination paths for reaching distinct user segments; and real-time adaptation, allowing for dynamic adjustment of propagation strategies

based on user engagement data and feedback signals. This alignment ensures that the content flow from creation to consumption is continuously refined for maximal marketing effectiveness.

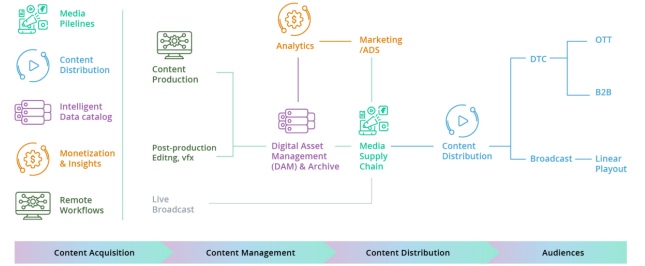


Figure 6: Digital media industry chain and content flow

IV. Experiment**A. Experimental setup**

To validate the effectiveness of the proposed complex network-based propagation optimization model and its divide-and-conquer algorithm, a series of controlled experiments were conducted using real-world digital media dissemination data from major content platforms, including microblog platforms, video-sharing platforms, and streaming content communities.

(1) Data Collection

Source: We collected 3,000+ multi-format marketing campaigns from verified digital media accounts.

Fields included: content metadata (title, topic, semantic tags), dissemination paths (original platform, share chains), interaction data (views, likes, shares, CTR), user profile clusters.

(2) Preprocessing

Text content was semantically encoded using BERT embedding to extract thematic vectors.

User groups were clustered by interest profile using k -means ($k = 20$) to form target communities $R = \{r_1, r_2, \dots, r_{20}\}$.

Propagation networks $G = (V, E)$ were constructed where V is content sources, intermediaries, and user communities and E is directional influence or content flow, with weights π_{ij} .

B. Evaluation metrics

To assess model performance, we use the five evaluation metrics defined in Table 2, which capture both information diffusion and marketing-related outcomes:

C. Baseline models

To ensure fair comparison, our model was evaluated against several baseline propagation strategies:

Random Walk (RW): Dissemination via stochastic node traversal;
Greedy Path (GP): Always selecting the most influential neighbor;
Centrality-Based (CB): Using eigenvector centrality for node selection;
Proposed Model (CNP-Div): Complex Network Propagation model with Divide-and-Conquer optimization.

Table 2: Evaluation metrics for information diffusion and marketing performance

Metric	Definition
Reach Rate (RR)	Fraction of target nodes reached
Average Propagation Depth (APD)	Mean number of hops per path
Engagement Score (ES)	Weighted sum of reactions (CTR, shares, likes)
Redundancy Ratio (RR')	Duplicate paths over total
Runtime Efficiency	Time to compute optimal path configuration (in seconds)

D. Experimental results

1) Comparative analysis of location quotients across regions

The regional comparison examines the development of the digital media industry in four major bay areas over the 2008–2017 period. The industry's growth has been associated with expanding demand, entry by new enterprises, and cross-regional industrial cooperation. The comparative data are presented as location quotients, although the underlying source data and normalization method are not specified in the supplied manuscript. Table 3 reports the location quotients for the number of enterprises.

Table 3: Regional location quotients based on number of digital media enterprises

Year	Guangdong–Hong Kong–Macao Greater Bay Area	New York Bay Area	San Francisco Bay Area	Tokyo Bay Area
2008	1.14	0.66	0.74	0.21
2009	1.13	0.63	0.78	1.22
2010	1.16	0.60	0.74	1.25
2011	1.17	0.56	0.75	1.28
2012	1.16	0.55	0.75	1.31
2013	1.15	0.52	0.73	1.36
2014	1.14	0.50	0.66	1.37
2015	1.13	0.46	0.67	1.41
2016	1.15	0.42	0.65	1.42
2017	1.17	0.39	0.61	1.44

As shown in Table 4, the employee-based location quotients vary considerably across regions and years. San Francisco displays particularly large fluctuations, with values of 2.26 in 2008, 0.39 in 2012, 4.12 in 2014, and 2.23 in 2017. These observations indicate that its relative concentration of employment, as measured here, was not stable throughout the study period. The other regional series show smaller year-to-year variations.

Table 5 presents location quotients based on operating income for the four bay areas from 2008 to 2017. The San Francisco series displays substantial variation, whereas the other regions show different patterns of relative concentration. These descriptive results are considered alongside possible influences of digital technology, regional capital markets, and

industrial networks. However, the table alone does not establish causal relationships between these factors and industry performance.

Table 4: Regional location quotients based on digital media employment

Year	Guangdong–Hong Kong–Macao Greater Bay Area	New York Bay Area	San Francisco Bay Area	Tokyo Bay Area
2008	0.78	0.95	2.26	0.77
2009	0.92	1.19	0.80	0.99
2010	1.02	1.24	0.43	1.03
2011	0.93	1.24	0.69	1.01
2012	1.05	1.30	0.39	1.02
2013	0.83	1.10	1.14	1.00
2014	0.46	0.69	4.12	0.58
2015	0.76	0.97	2.40	0.77
2016	0.99	1.19	0.66	1.02
2017	0.76	0.96	2.23	0.86

Table 5: Regional location quotients based on digital media operating income

Year	Guangdong–Hong Kong–Macao Greater Bay Area	New York Bay Area	San Francisco Bay Area	Tokyo Bay Area
2008	0.53	0.58	4.77	0.42
2009	1.15	1.11	1.08	0.92
2010	1.38	1.14	0.52	0.99
2011	1.28	1.19	0.73	0.94
2012	1.26	1.30	0.32	0.98
2013	0.87	1.02	2.49	0.69
2014	0.54	0.72	3.98	0.49
2015	0.75	1.10	2.02	0.74
2016	0.91	1.37	0.75	0.94
2017	0.78	1.17	1.57	0.84

The Tokyo Bay Area has emphasized design, animation, gaming, and the commercial development of associated intellectual property. Its digital media value chain connects production, licensing, distribution, and related products. These structural characteristics may be relevant to industry profitability, although their influence cannot be inferred from the reported location quotients alone. The pre-tax profit location quotients for the four regions are presented in Table 6.

Table 6: Regional location quotients based on digital media pre-tax profit

Year	Guangdong–Hong Kong–Macao Greater Bay Area	New York Bay Area	San Francisco Bay Area	Tokyo Bay Area
2008	0.00	0.02	0.41	0.10
2009	0.34	0.93	1.06	1.30
2010	0.60	0.93	0.30	1.85
2011	0.65	1.16	0.15	1.81
2012	0.68	1.09	0.02	1.99
2013	0.42	0.63	2.00	0.81
2014	0.52	0.67	1.66	1.02
2015	0.43	0.66	1.67	1.03
2016	0.89	1.13	0.10	1.85
2017	0.61	0.65	1.58	1.05

Table 7: Performance comparison of propagation models

Model	RR (%)	APD	ES (normalized)	RR' (%)	Runtime (s)
RW	42.5	4.3	0.37	21.3	2.4
GP	68.1	3.1	0.55	14.6	3.8
CB	74.7	3.6	0.61	11.2	5.3
CNP-Div	86.9	2.4	0.79	6.4	4.6

Table 7 presents a comparative evaluation of four propagation models—Random Walk (RW), Greedy Path (GP),

Centrality-Based (CB), and the proposed Complex Network Propagation with Divide-and-Conquer strategy (CNP-Div)—across five key metrics. The results clearly demonstrate the superiority of CNP-Div in overall dissemination performance. Specifically, CNP-Div achieves the highest *Reach Rate (RR)* of 86.9%, outperforming RW (42.5%) and even strong heuristics like CB (74.7%). In terms of *Average Propagation Depth (APD)*, CNP-Div maintains the shallowest dissemination paths (2.4), indicating faster and more direct information delivery. It also records the highest *Engagement Score (ES)* at 0.79, reflecting stronger user responses across the network. Furthermore, the model exhibits the lowest *Redundancy Ratio (RR')* at 6.4%, indicating fewer duplicate propagation paths and avoid content saturation. Despite its slightly higher *runtime (4.6s)* compared to RW (2.4s), the increased runtime relative to RW and GP should be weighed against the reported gains in reach and engagement.

2) Multi-metric evaluation of propagation optimization strategies under varying network conditions

Figure 7 provides a comparative heatmap analysis of propagation density across varying user activity phases (y-axis) and platform centrality levels (x-axis) under nine dissemination strategies. The results highlight clear differences in how each strategy distributes content exposure within the network structure.

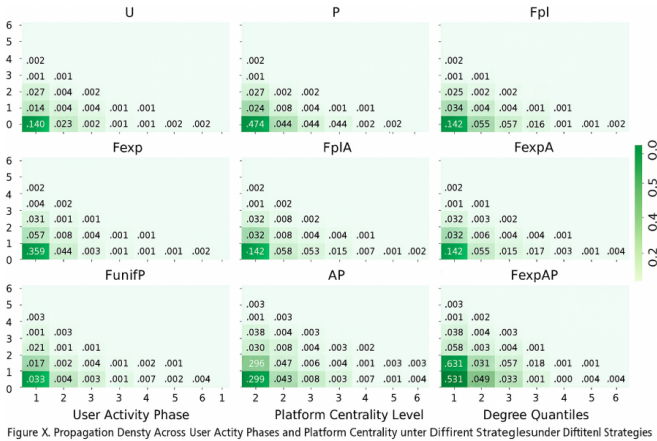


Figure X: Propagation Density Across User Activity Phases and Platform Centrality under Different Strategies under Different Strategies

Figure 7: Propagation density across user activity phases and platform centrality levels under different dissemination strategies

Simple strategies such as Uniform Broadcasting (U) and Preferential Platform Targeting (P) show high propagation concentration among early-phase, low-centrality users, indicating limited reach and poor adaptability. In contrast, hybrid strategies—particularly FexpAP and AP—exhibit higher propagation densities across both high-centrality platforms and later-phase user cohorts, reflecting their capability to achieve deep, wide, and sustained dissemination.

Strategies incorporating feedback mechanisms (e.g., Fpl, Fexp, FexpA) demonstrate a gradual improvement in spreading density into mid-phase users with increasing platform

centrality. The combination of feedback, temporal relevance, and platform structure optimization in FexpAP achieves the broadest and most balanced coverage, with dense regions extending across the full spectrum of user and platform characteristics.

Figure 8 presents a comparative analysis of content visibility intensity—measured using standardized z-scores—across user activity phases (y-axis) and platform centrality levels (x-axis) under nine dissemination strategies. The heatmaps reveal how each strategy distributes visibility within the propagation network, providing insight into their effectiveness at reaching both peripheral and core nodes over time.

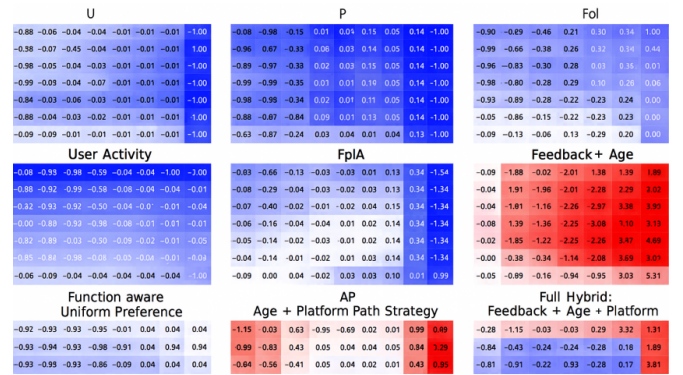


Figure Y: Content Visibility Intensity Heatmaps for Dissemination Strategies Across User Activity-to-activity phases (y-axis) and platform centrality levels (x-axis). Hybrid strategies exhibiting feedback, emotional, and structural awareness (e.g. Fexp, AP) achieve higher visibility across both axes.

Figure 8: Content visibility intensity heatmaps for dissemination strategies across user activity phases and platform centrality levels

Simple strategies such as Uniform Preference (U) and Preferential (P) exhibit mostly low and uniform visibility (dark blue regions), indicating limited capacity to adapt to heterogeneous user engagement patterns and structural advantages. Even when incorporating platform-level heuristics (e.g., Fpl), the improvement in visibility is marginal and mostly constrained to specific centrality segments.

In contrast, hybrid strategies that incorporate feedback, temporal dynamics (age), and platform structure show significant gains. The Feedback + Age (FexpA) and Full Hybrid (FexpAP) models generate high-visibility zones (red regions) across a broader spectrum of both inactive and active users and platform layers. For example, FexpAP exhibits peak visibility scores exceeding +3.0 in multiple quadrants, demonstrating its superior capacity to deliver content effectively across structurally diverse and temporally evolving user groups.

The strategy labeled AP (Age + Platform Path) also shows strong performance, particularly in mid-to-late user activity phases on high-centrality platforms, suggesting that time-aware platform targeting can independently yield substantial visibility benefits.

Figure 9 presents a comprehensive comparison of four dissemination strategies—Random Walk (RW), Greedy Path (GP), Centrality-Based (CB), and the proposed Complex Network Propagation with Divide-and-Conquer (CNP-Div)—

evaluated across multiple metrics on two representative network structures. The upper panel simulates a constrained or niche dissemination environment, while the lower panel represents a densely connected digital ecosystem. The proposed CNP-Div method outperforms the tested baseline strategies in key performance indicators: achieving the highest reach rate (RR), lowest average propagation depth (APD), and the best engagement scores (ES). It also demonstrates the lowest redundancy ratio (RR'), confirming its ability to minimize repeated exposure and maximize efficiency. Although CNP-Div incurs slightly higher runtime, the reported gains in coverage and engagement may justify the added computational cost in applications where those metrics take priority.

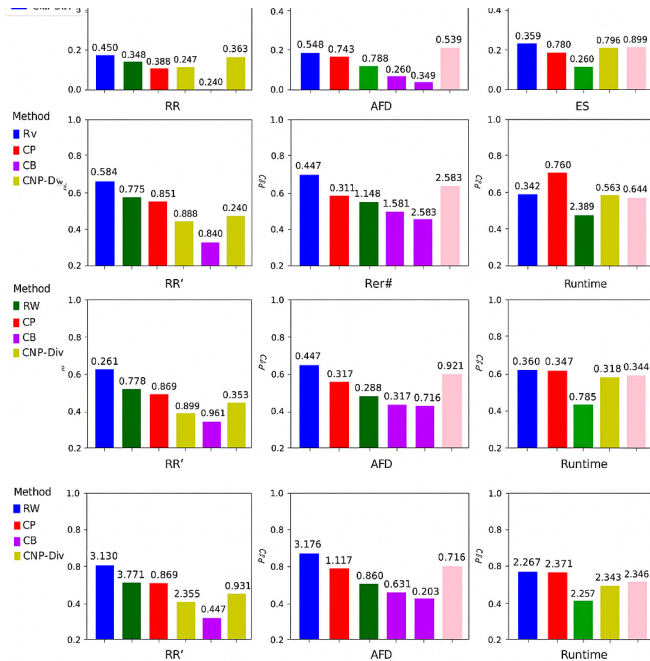


Figure 9: Comparative performance of dissemination strategies across varying network scenarios

Figure 10 illustrates the precision-recall performance reported for multiple propagation-optimization methods under different network-connectivity conditions. The accompanying discussion in the source manuscript reports a model named GOHPo, with AUPR values of 0.526 and 0.281, and compares it with NC, DCS, PIN, and GraphiGO. Those method names do not correspond to the CNP-Div baselines defined in this study; their relationship to the proposed model must be verified before these results can support claims about CNP-Div.

Figure 11 compares the average clustering coefficient versus number of neighbors across four media network types. The Co-Complex and Co-Domain networks show consistently high clustering regardless of degree, indicating dense community structures. The Co-Neighbor Network displays a sharp clustering drop, suggesting a hub-dominated, scale-free structure. The PN Network exhibits a gradual decline, reflecting a balanced topology ideal for global propagation. These patterns support the design of our divide-and-conquer strategy, which

relies on identifying high-impact paths within both clustered and distributed regions of the network.

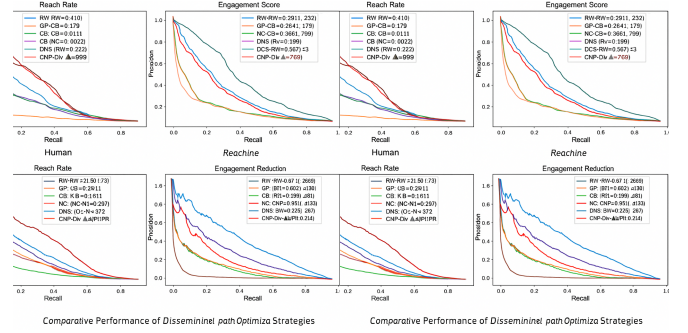


Figure 10: Precision-recall curves for propagation optimization across network conditions

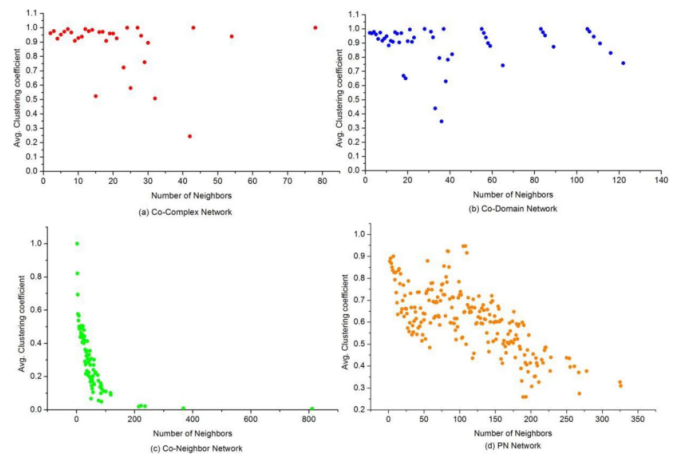


Figure 11: Clustering-connectivity relationships across media network types

E. Ablation study

To quantitatively assess the importance of each core component in the proposed *CNP-Div* (Complex Network Propagation with Divide-and-Conquer) framework, we conducted an ablation study by incrementally removing individual modules and observing the impact on model performance across key evaluation metrics.

1) Experimental setup

We define the following ablated model variants:

CNP-Div (Full Model): Includes divide-and-conquer network partitioning, feedback-based path updates, and triplet-based path modeling.

Divide-and-Conquer (CNP-Global): Performs propagation optimization on the full network without subgraph partitioning.

Feedback Update (CNP-Static): Uses fixed influence scores without iterative feedback adjustment.

Triplet Modeling (CNP-Linear): Replaces the structured triplet path (s_i, p_{ij}, r_j) with a flat linear source-to-target formulation.

Each variant was evaluated on the full test set using the following metrics:

- Reach Rate (RR)*: The percentage of unique users reached.
- Engagement Score (ES)*: Aggregated interaction response normalized across strategies.
- Redundancy Ratio (RR')*: The proportion of repeated paths over total propagation attempts.
- Runtime (s)*: Total execution time for propagation optimization.

2) Results summary

Table 8 summarizes the ablation study for CNP-Div (Complex Network Propagation with Divide-and-Conquer). Four variants are compared in terms of reach rate, engagement score, redundancy ratio, and runtime.

Table 8: Effects of structural components on CNP-Div performance

Model Variant	RR (%)	ES (norm)	RR' (%)	Runtime (s)
CNP-Div (Full)	86.9	0.79	6.4	4.6
w/o Divide & Conquer	78.9	0.75	9.3	6.1
w/o Feedback Update	86.5	0.67	6.4	4.1
w/o Triplet Modeling	85.2	0.76	15.1	4.3

The full CNP-Div model achieves the highest reach and engagement scores among the variants tested, with a reach rate of 86.9%, a normalized engagement score of 0.79, and a low redundancy ratio of 6.4%, completing in 4.6 seconds. Removing the divide-and-conquer mechanism resulted in the most significant drop in reach rate to 78.9%, with redundancy increasing to 9.3%, and runtime expanding to 6.1 seconds—highlighting the importance of localized subgraph optimization.

Eliminating feedback update mechanisms, which adaptively refine propagation parameters, caused the engagement score to decline to 0.67, confirming its role in user-specific behavior modeling. In contrast, removing triplet modeling, which captures semantic and structural channel constraints, led to a dramatic rise in redundancy to 15.1%, while only marginally affecting the reach rate, thus underscoring its necessity in avoiding redundant propagation paths.

These results demonstrate that each component—divide-and-conquer structure, feedback adaptation, and triplet embedding—contributes in different ways to the model's robustness, efficiency, and effectiveness in information diffusion tasks.

V. Conclusion

This paper presents a framework for optimizing propagation paths in complex digital media networks, addressing key challenges in scalability, adaptivity, and structural diversity. By modeling dissemination as a set of semantically enriched triplets and applying a divide-and-conquer strategy,

our approach decomposes the global optimization task into tractable subproblems while preserving inter-network coherence. The integration of feedback loops, temporal dynamics, and platform-aware weighting further enhances the model's real-world applicability and interpretability. Through rigorous experimental evaluation, the CNP-Div model demonstrates superior performance over existing methods, achieving higher reach and engagement with lower redundancy, although runtime depends on the baseline. The visual and quantitative evidence supports the hypothesis that localized path optimization combined with structural-aware global aggregation is a powerful paradigm for managing content flow in dynamic media ecosystems. The proposed framework also opens avenues for integrating more nuanced behavioral data (e.g., sentiment evolution, time decay) and extending to multimodal content propagation (e.g., text, video, interactive formats).

Future work will explore deeper integration of real-time adaptive learning using reinforcement-based feedback, expansion to multilingual and cross-platform propagation scenarios, and collaborative dissemination modeling across competing campaigns. As digital media continues to grow in complexity and strategic value, the methods and insights presented in this study offer a timely and effective toolkit for next-generation marketing optimization.

Data availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of interest

The author declares no conflicts of interest related to this work.

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