

Analysis of the Dissemination Path of Marxist Classical Theory Based on Data Visualization Technology

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ABSTRACT This study applies data visualization technology to analyze the dissemination paths of Marxist classical theory within complex social networks. Integrating communication theory, social network analysis, and visualization techniques, the research constructs a multidimensional analytical framework to examine how Marxist theory propagates across different network structures. Based on simulation experiments involving diverse audience groups and dissemination channels, the study identifies the differentiated roles of academic, political, and mass media nodes in shaping propagation speed, coverage, and influence. The results show that scale-free networks generally exhibit faster early stage diffusion and higher overall coverage under hub-dominated conditions, while small-world networks may achieve comparable or superior early propagation speed when initial propagators are embedded in highly clustered communities. These findings highlight the conditional effects of network topology and node roles on ideological dissemination. The study demonstrates the value of data visualization in revealing structural mechanisms of theory diffusion and provides methodological reference for network propagation analysis, information-flow modeling, and signal-diffusion studies in complex communication environments.

INDEX TERMS data visualization, marxist classical theory, dissemination path, social network analysis, network propagation

I. INTRODUCTION

WITH the rapid growth of information technology, data visualization has become a powerful method for analyzing and presenting the complex data structures inherent in both digital networks and the intricate patterns of modern production. Marxist classical theory, as a profoundly influential social ideology, requires a deeper understanding of how it spreads in order to assess its impact and dissemination in today's society. Traditional methods for studying the spread of ideas often fail to effectively represent the intricate, multi-dimensional processes and relationships involved. Data visualization technology, with its ability to create clear pictures and charts, offers a new perspective on this dynamic, enabling us to trace how a theory spreads, including its speed, reach, and impact.

However, beyond merely applying general communication theory and social network analysis, it is crucial to integrate Marxist dissemination theory as a core dimension in the study of its spread. This paper not only explores the dissemination of Marxist classical theory using data visualization technology but also considers how Marxist dissemination theory can inform and guide this analysis. By integrating communication theory, social network analysis, and data visualization, this study aims to develop a

comprehensive framework for understanding the historical diffusion of Marxist ideas and exploring how these ideas can be further disseminated through contemporary technological tools [1-3].

II. THEORETICAL FRAMEWORK AND METHODOLOGY

Communication theory examines how information spreads through various channels in society, making it crucial to understand the dissemination of Marxist classical theory, which has shaped global political and social movements. Marxism, focusing on social change and class struggles, has influenced society through books, speeches, propaganda, and education. Studying its dissemination path helps us understand its historical impact and how it can be adapted for contemporary contexts. This study incorporates Marxist dissemination theory, modern communication technology, and social network structures into a multidimensional framework to analyze the spread of information. By combining data visualization with social network analysis, we gain deeper insights into how Marxist theory propagates through modern channels, identifying key influence nodes and areas where the flow of information slows or stops. This integrated approach provides a more comprehensive understanding of the dissemination process. The theoretical framework and

methodology of Marxist theory dissemination is shown in Figure 1.

A. MARXIST DISSEMINATION THEORY: HISTORICAL AND IDEOLOGICAL CONTEXT

Marxist dissemination theory emphasizes the role of mass media, political organizations, and intellectual movements in spreading Marxist ideas. Historically, Marxist theory has been disseminated through various channels, including literature, speeches, and propaganda. Key figures like Lenin proposed the importance of media as tools for ideological dissemination. Lenin famously stated that "newspapers are collective propagandists, agitators, and organizers," highlighting the significance of media in shaping public consciousness and driving social change. During the Yan'an period, the Chinese Communist Party effectively utilized grassroots communication strategies, including mass rallies, local publications, and public speeches, to promote Marxist ideas among the wider population. This historical context provides a foundation for identifying the key nodes and networks that have facilitated the dissemination of Marxist theory, as well as for understanding how modern technologies can adapt these practices to contemporary contexts [4,5].

B. MARXIST CLASSICAL THEORY AND ITS UNIQUE DISSEMINATION CHARACTERISTICS

Marxist classical theory, including seminal works such as *The Communist Manifesto* and *Das Kapital*, is marked by certain unique textual characteristics that influence its dissemination. These works are highly abstract and systematic, presenting complex ideas about class struggle, political economy, and social transformation. This makes them distinct from ordinary information that spreads through media, as their content often requires a deeper level of engagement and understanding. The abstract nature of Marxist theory means that its dissemination is not just about spreading information; it is about influencing people's understanding of the world and their actions within it.

When analyzing the spread of these texts, it is important to consider how the textual characteristics of Marxist theory—its theoretical depth, complexity, and focus on material conditions—affect the way audiences receive and interpret the information. Unlike more easily consumable forms of media, Marxist works require a more engaged and ideologically sympathetic audience, which shapes the overall dissemination path. Additionally, the dissemination of Marxist theory also relies heavily on ideological alignment. The theory often spreads more effectively in environments where there is pre-existing alignment with its core tenets—such as in left-wing political groups, intellectual circles, or labor movements. Understanding these ideological connections and their influence on the acceptance logic of the audience is essential for analyzing the path of Marxist theory in contemporary society.

C. INTEGRATING MARXIST DISSEMINATION THEORY WITH DATA VISUALIZATION AND SOCIAL NETWORK ANALYSIS

To effectively model the dissemination of Marxist theory today, this study integrates data visualization and social network analysis with Marxist dissemination theory. Social network analysis helps identify the relationships between nodes (individuals, organizations, or media outlets) within a given network, revealing the flow of information and identifying key influence points. Data visualization techniques, such as network graphs and heat maps, can then be used to visually represent these relationships, providing an intuitive understanding of how information propagates within the network.

This combination of Marxist theory, social network analysis, and data visualization helps reveal how Marxist ideas spread across different societal groups and networks, highlighting the roles played by key nodes in the network. For example, intellectual nodes (such as Marxist scholars), political nodes (such as political organizations), and mass media nodes (such as social media influencers or public figures) each play different roles in shaping the flow of information. By analyzing these nodes and their relationships, we can better understand the mechanisms behind the dissemination of Marxist theory and the factors that affect its spread.

III. OVERVIEW OF DATA VISUALIZATION TECHNOLOGY

A. BASIC CONCEPTS AND DEVELOPMENT OF DATA VISUALIZATION

Data visualization refers to the transformation of data into visual representations such as charts, graphs, and maps, enabling more intuitive and efficient interpretation of complex datasets. It involves the systematic use of graphical elements, color schemes, and layout designs to reveal data relationships, trends, patterns, and distributions. With advances in computer science and internet technologies over recent decades, data visualization has evolved significantly, particularly in the context of big data, where it has become an essential analytical tool across fields including business, medical research, and the social sciences.

With advances in computing power and visualization tools, data visualization has evolved from static representations to dynamic and interactive forms, enabling users to explore underlying data structures and patterns with greater flexibility. Techniques such as network graphs, hierarchical tree visualizations, and heat maps effectively represent complex relational structures, facilitating deeper insights into underlying relationships and trends. These developments have significantly improved analytical efficiency and accuracy across various research fields while also reducing interpretive barriers for non-expert audiences [6-8].

B. COMMON DATA VISUALIZATION METHODS AND TECHNIQUES

In the field of data visualization, a wide range of methods and techniques are used to represent different types of

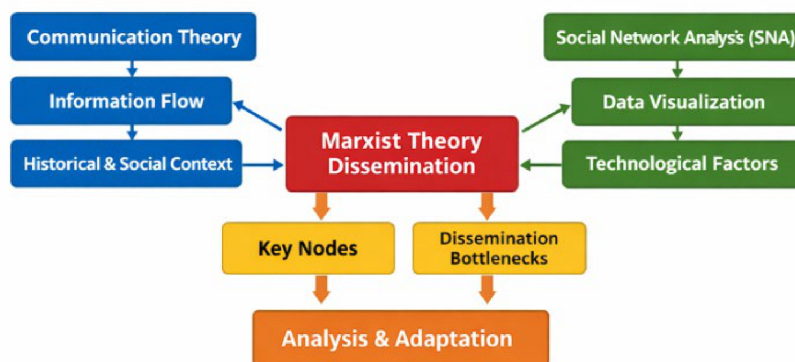


FIGURE 1. Theoretical framework and methodology of Marxist theory dissemination

data and support various analytical objectives. Common visualization methods include bar charts, line graphs, scatter plots, pie charts, heat maps, and network graphs. These visual forms facilitate understanding of data from multiple perspectives. For instance, bar charts and line graphs are primarily used to illustrate trends and temporal changes, scatter plots are suitable for analyzing data distributions and correlations, and pie charts are commonly used to represent proportional relationships within a whole. For complex network data, network graphs and force-directed layouts can effectively reveal relationships among data elements and highlight the influence of individual nodes [9-13].

With the advancement of technology, modern data visualization also involves some advanced techniques such as three-dimensional visualization, geographic information system (GIS) visualization, and time-series animations. Three-dimensional visualization helps present more complex spatial data, GIS visualization allows for intuitive display of the relationship between geographic locations and data, and time-series animations show the dynamic process of data changes over time. As shown in Figure 2, various methods and techniques are used in data visualization to represent and analyze different types of data.

C. APPLICATION OF DATA VISUALIZATION IN SOCIAL NETWORK ANALYSIS

In the analysis of social networks, data visualization plays a crucial role. Social Network Analysis focuses on examining the relationships among individuals, groups, or organizations, and visualization techniques enable these complex relational structures to be represented and analyzed more effectively. Through network graphs and other visual representations, nodes and their connecting edges can be intuitively displayed, allowing researchers to identify key actors, community structures, diffusion patterns, and directions of information flow. By transforming complex relational data into interpretable visual forms, data visualization significantly enhances analytical efficiency and interpretability [14,15].

In analyzing the dissemination pathways of Marxist clas-

sical theory, the integration of social network analysis and data visualization can effectively reveal the characteristics of different dissemination patterns and identify which nodes exert significant influence on theoretical diffusion. For example, key actors on social media platforms (such as scholars and opinion leaders) may become central nodes in information dissemination due to their high connectivity, while certain smaller communities may form dissemination “bottlenecks” or “hotspots” under specific conditions [16,17]. As shown in Figure 3, various aspects such as key nodes, group structures, information flow, and dissemination bottlenecks are explored in the analysis.

D. IMPACT NODES IN DATA VISUALIZATION: A MARXIST DISSEMINATION PERSPECTIVE

In the context of data visualization and social network analysis, impact nodes play a pivotal role in understanding the flow of information. These are specific points within a network that have a significant influence on the spread and dissemination of information. In the study of Marxist theory dissemination, identifying and analyzing these nodes is essential for understanding how Marxist ideas circulate through different social and political spheres.

Impact nodes can be categorized into different types, each playing distinct roles in the dissemination process. In the Marxist dissemination context, we can primarily distinguish between three types of impact nodes: academic nodes, political nodes, and mass media nodes. Each of these nodes represents a different source of influence and contributes to the propagation of Marxist theory in unique ways.

1) Academic Nodes

These are scholars, intellectuals, and educators who contribute to the spread of Marxist theory through publications, lectures, and academic discussions. They often serve as the theoretical foundation for the dissemination of ideas, making their impact particularly strong among those with a similar ideological alignment or those seeking to understand Marxism at a deeper, more academic level. Academic nodes are essential for ensuring the intellectual rigor of Marxist

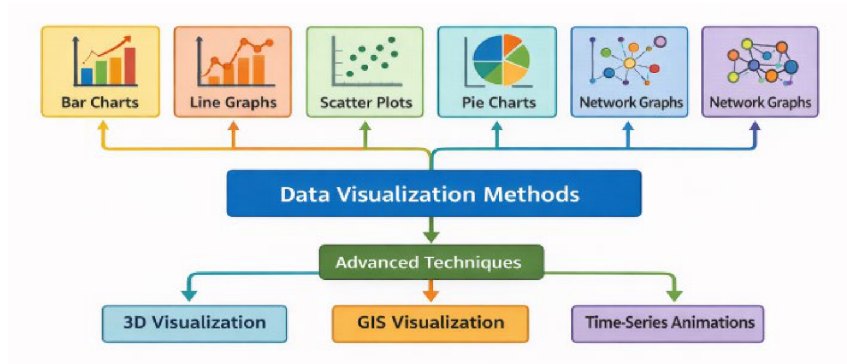


FIGURE 2. Common Data Visualization Methods and Techniques

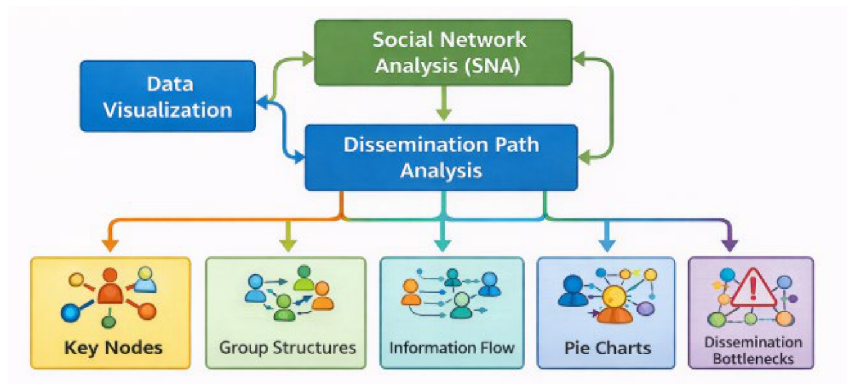


FIGURE 3. Application of Data Visualization in Social Network Analysis

theory, and their role in network visualization is typically represented as key influencers with high centrality and strong connections to other intellectual circles.

2) Political Nodes

These nodes include political organizations, government institutions, and ideological leaders. In the context of Marxist theory, political nodes are central to institutionalizing and spreading Marxist ideas. Their influence can extend to large groups of followers, shaping public policy, ideological shifts, and collective action. In the context of data visualization, political nodes may be represented by nodes with high connectivity and influence over decision-making processes within social and political networks. These nodes are key drivers of mass dissemination, particularly in political and revolutionary contexts.

IV. DISSEMINATION PATH ANALYSIS MODELS

A. APPLICATION OF THE SIR MODEL IN INFORMATION PROPAGATION

The SIR model (Susceptible–Infected–Recovered model) was originally developed to simulate the spread of infectious diseases. With the expansion of its theoretical applications, it has been widely adopted in the study of information diffusion and social communication processes. In the context of information dissemination, the SIR model categorizes individuals into three states: susceptible *S*, infected *I*, and removed *R*. Susceptible individuals are those who have not

yet been exposed to the information. Infected individuals refer to actors who have received the information and are actively participating in its dissemination. In the context of ideological dissemination, the Removed *R* state does not indicate ideological rejection or opposition. Instead, it represents individuals who have ceased active propagation behavior, while potentially retaining cognitive or attitudinal acceptance of the ideology. This distinction is particularly important for ideological communication, where belief retention and transmission behavior do not always coincide. Accordingly, the transition from the infected *I* state to the removed *R* state reflects a shift in propagation behavior rather than a change in ideological stance. Individuals in the *R* state may stop sharing content due to saturation, declining attention, contextual constraints, or institutional boundaries, even though they may continue to accept or support the ideological content internally.

The dynamics of the SIR model are expressed as follows:

$$\begin{aligned}\frac{dS}{dt} &= -\beta SI \\ \frac{dI}{dt} &= \beta SI - \gamma I \\ \frac{dR}{dt} &= \gamma I\end{aligned}\quad (1)$$

In Equation (1), *S*, *I*, and *R* denote the number of susceptible, infected, and removed individuals, respectively. The parameter β represents the transmission rate, indicating

the probability that information is passed from an infected individual to a susceptible one. The parameter γ denotes the rate at which individuals exit the active propagation process. Importantly, γ is interpreted in this study as a behavioral attenuation rate rather than a measure of ideological abandonment. This modeling choice is intended to focus on observable dissemination dynamics, such as transmission frequency, propagation duration, and network reach, rather than latent belief states, which are difficult to quantify without large-scale survey data or ethnographic investigation. By adopting this interpretation, the SIR framework remains suitable for analyzing the speed, range, and structural characteristics of Marxist theory dissemination within social networks. While the present study does not explicitly model ideological rejection or silent belief retention as separate states, future research may extend the framework by introducing additional categories (e.g., silent believers or ideological opposition) to capture more nuanced belief dynamics in ideological communication.

B. SOCIAL NETWORK ANALYSIS MODEL AND DISSEMINATION PATH CONSTRUCTION

Social Network Analysis (SNA) provides a structural framework for examining how information flows among individuals or groups within a network. In this study, the dissemination network is modeled as a graph composed of nodes and edges, where nodes represent actors involved in the dissemination of Marxist classical theory, and edges represent potential communication or influence relationships between them. The importance of a node in the dissemination process is evaluated using node centrality measures. A simplified form of degree-based centrality is expressed as:

$$C_i = \frac{1}{N} \sum_{j=1}^N A_{ij} \quad (2)$$

In formula (2), C_i represents the centrality of node i , A_{ij} represents the connection between node i and node j , and N is the total number of nodes in the network. High-centrality nodes are typically the core of information dissemination and have greater potential to propagate information. Social network propagation path analysis can also include calculating path length, group density, propagation efficiency, and other indicators to further understand the characteristics of information spread within the network.

In this model, academic, political, and mass media nodes are not represented by separate mathematical formulations. Instead, node types are incorporated through type-specific parameter weights, which influence their connectivity patterns, transmission probabilities, and persistence in the propagation process. For example, political nodes are assigned higher probabilities of cross-community connections, while academic nodes tend to form denser links within intellectually aligned sub-networks.

By encoding node heterogeneity through parameter differentiation rather than structural separation, the model

preserves mathematical simplicity while capturing functional diversity among node types. This approach allows the analysis to focus on how network structure and node role differentiation jointly shape dissemination paths, rather than on micro-level belief modeling at the individual node level.

C. SIMULATION AND DESIGN OF DISSEMINATION PATHS

The simulation and design of dissemination paths rely on computational modeling of information diffusion processes in complex networks. These simulations aim to predict how Marxist classical theory propagates under different network structures and node-role configurations. When designing propagation simulations, multiple factors are considered, including network topology, node heterogeneity, propagation rules, and termination conditions. Together, these factors determine both the trajectory and efficiency of dissemination. In early modeling stages, propagation speed is often expressed in a simplified form as:

$$V = \frac{D}{T} \quad (3)$$

where V denotes propagation speed, T represents the elapsed simulation time, and D denotes the propagation distance. It should be emphasized that D does not represent physical distance, but rather a network-based distance metric. In the context of this study, D is defined as the average shortest-path distance (measured in hop counts) from the initial seed nodes to newly infected nodes within the network at a given time step. This definition reflects the topological reach of information diffusion rather than spatial displacement.

However, due to the heterogeneous and non-linear nature of information diffusion in social networks—particularly under SIR-type dynamics—the formulation $V=D/T$ serves only as an intuitive illustration and is insufficient as a primary evaluation metric. To ensure mathematical transparency and analytical rigor, this study adopts coverage- and threshold-based diffusion indicators, which are more commonly used in network propagation research and better aligned with empirical interpretation. Accordingly, propagation speed and efficiency are evaluated using the following indicators:

Coverage-based propagation speed

$$V_c = \frac{\Delta C}{\Delta t} \quad (4)$$

where C denotes the proportion of infected nodes in the network. This indicator measures the growth rate of dissemination coverage per unit time.

Threshold-based propagation time T_{50} , T_{80} , where T_{50} and T_{80} represent the time required for information to reach 50% and 80% of the total reachable nodes, respectively. These metrics are used as the primary indicators of early- and mid-stage propagation speed in subsequent experimental analysis.

Peak diffusion rate

$$\max_t \frac{dI(t)}{dt} \quad (5)$$

which captures the maximum rate of increase in infected nodes during the simulation and reflects the intensity of dissemination bursts.

By employing these indicators, dissemination paths become directly comparable across different network configurations and parameter settings. Moreover, the selected metrics correspond explicitly to the propagation speed, coverage, efficiency, and average propagation time reported in Section “Experimental Results of Propagation Speed, Breadth, and Influence”, ensuring consistency between the mathematical modeling framework and the empirical results.

D. DATA SOURCE AND PREPROCESSING

To clarify the empirical basis of the dissemination analysis and address potential ambiguity regarding data provenance, this study explicitly adopts a simulation-driven and synthetic data approach rather than relying on direct data scraping from real-world platforms or historical archives.

The dissemination data used in this research are generated through computational simulations based on classical network generation models, including small-world networks, scale-free networks, and random networks. These models are widely recognized in social network analysis for their ability to approximate key structural characteristics of real-world communication systems, such as clustering, degree heterogeneity, and path efficiency. The use of synthetic networks allows for controlled experimentation and systematic comparison across different structural conditions.

Node attributes and roles are rule-based and pre-defined to reflect typical actors involved in the dissemination of Marxist classical theory. Nodes are categorized into three types—academic nodes, political nodes, and mass media nodes—according to preset proportions within each network. Each node type is assigned differentiated dissemination parameters, including transmission probability, propagation persistence, and secondary infection capacity, in order to simulate the heterogeneous influence observed in real ideological communication processes. For example, academic nodes are configured with higher theoretical engagement but lower transmission frequency, while mass media nodes emphasize broader reach with reduced depth of engagement.

Edges in the network represent potential communication or influence relationships and are generated according to the respective network model rules. No real user identities, platform-specific interaction data, or historical dissemination records are involved in the modeling process. All simulation inputs are normalized and processed to ensure comparability across network sizes and structures.

It should be emphasized that the primary objective of this study is methodological validation and mechanism exploration, namely to examine how different network topologies and node roles influence propagation speed, breadth, and

efficiency under controlled conditions. The results are therefore not intended to reproduce or predict the exact historical dissemination trajectory of Marxist theory on any specific platform. Accordingly, a limitation of this study is the absence of direct validation using real-world dissemination data from social media platforms, publication networks, or archival sources. Future research may extend the proposed framework by integrating empirical datasets to further test the external validity of the simulation findings.

V. SIMULATION EXPERIMENT DESIGN AND RESULTS ANALYSIS

A. EXPERIMENT DESIGN AND NETWORK MODEL CONSTRUCTION

In the simulation experiment analyzing how information spreads, the design of the experiment and the construction of the network model are crucial steps. The experiment design must clearly define the objectives, the hypotheses being tested, the choice of spreading models, and the data sources. To simulate the dissemination path of classical Marxist theory, this study uses a social network model, where information starts with a small number of initial spreaders, such as scholars and political groups, and then propagates to a wider audience through social media, publications, and offline activities. In the network model, nodes represent individuals or groups, and edges represent their relationships or interactions. To ensure the simulation reflects real-world dynamics, the network structure typically uses models such as small-world networks, scale-free networks, or random networks, which better capture how information spreads within society.

Several factors regarding the nodes—such as their capacity to spread information, the frequency of their interactions, and the structure of the network (including node connectivity and clustering)—are critical in determining how information flows. By adjusting parameters like the propagation rate, recovery rate, and network density, different information flows can be simulated. The simulation progresses through multiple time steps to observe how information propagates over time. To ensure the validity and reliability of the results, multiple simulations are run, allowing for the testing of consistency. Additionally, the experiment incorporates discipline-specific parameters that reflect the unique characteristics of Marxist theory dissemination. These include theoretical adaptation parameters (α) to measure how closely the content aligns with Marxist principles, audience reception parameters (β) based on ideological alignment, and organizational push parameters (γ) to simulate the influence of official entities like political organizations and educational programs. The Experiment Network Parameters and Propagation Results Statistics are shown in Table 1:

TABLE 1. Experiment Network Parameters and Propagation Results Statistics

Network Model Type	Number of Nodes (N)	Number of Edges (E)	Average Degree (K)	Propagation Rate (β)	Recovery Rate (γ)	Number of Initial Propagators	Simulation Time (T)	Propagation Coverage	Information Propagation Speed (V)
Small-World Network	1000	3000	6	0.05	0.02	5	500	70%	12
Scale-Free Network	1000	5000	10	0.03	0.01	10	500	80%	15
Random Network	1000	2000	4	0.04	0.03	8	500	60%	10
Small-World Network	500	1500	6	0.07	0.02	3	300	75%	9
Scale-Free Network	500	2500	10	0.06	0.03	6	300	85%	13

B. DATA INPUT AND EXPERIMENT PARAMETER SETTING

In the simulation experiment of information propagation paths, data input and experiment parameter setting are crucial aspects. Data input includes things like network structure, node features, propagation behaviors, and other information. Network structure serves as the foundation of the experiment, and typically, different networks are chosen to mimic information flow in various social environments, such as small-world networks or random networks. Regarding node features, these involve the node's ability to spread information, the chance of being influenced, how often they connect with others, and similar factors, which directly impact how fast and far information travels. The propagation behavior parameters in the experiment include the rate at which information spreads (β), the rate at which nodes stop spreading (γ), how attractive the information is, and other such details, which define the basic rules for how information moves through the network. In setting the experimental parameters, multiple scenarios are designed to simulate diverse propagation conditions based on established theoretical assumptions. The propagation rate determines the speed at which information is transmitted between nodes, while the recovery rate governs the likelihood that a node ceases active dissemination. In addition, varying the number of initial propagators allows the simulation to capture diffusion processes originating from different seed sizes. Differences in initial conditions and parameter configurations lead to distinct propagation outcomes. By systematically comparing these outcomes, the key factors influencing information diffusion under different network structures can be identified, thereby ensuring the scientific validity and robustness of the simulation results. The Experiment Data Input and Parameter Setting are shown in Table 2:

C. VISUALIZATION OF PROPAGATION PATHS AND RESULTS DISPLAY

Based on the simulation outputs, this study visualizes the propagation paths of Marxist classical theory by integrating node-level diffusion indicators and network-level structural characteristics. Specifically, network graphs and heat maps are generated using node centrality measures (degree centrality and betweenness centrality), node infection time (tinfect), and edge-level propagation frequency, enabling a result-oriented interpretation of dissemination dynamics

rather than a purely descriptive visualization.

The visualization results reveal clear structural differences across network types. In scale-free networks, a small number of high-degree hub nodes rapidly form the main transmission backbone during the early stages of diffusion. These hubs exhibit high centrality values and significantly earlier infection times, resulting in a shorter average propagation time and a more concentrated hotspot distribution. In contrast, small-world networks display faster diffusion within local clusters, but cross-cluster dissemination relies on a limited number of bridging edges, leading to smoother but more gradual expansion of overall propagation coverage. Hotspot areas in this case are distributed across multiple local clusters rather than concentrated around a few global hubs.

From a node-type perspective, academic nodes generally show higher betweenness centrality and earlier infection times, indicating their role as core theoretical dissemination anchors. Political nodes exhibit strong connectivity across communities, functioning as cross-group transmission bridges that expand dissemination breadth. Mass media nodes, while displaying relatively lower centrality, contribute to wider surface-level coverage through higher secondary infection counts, though with weaker depth of engagement. To ensure transparency and reproducibility, the visualization encoding rules and the corresponding statistical outcomes are reported separately. Table 3A defines the mapping between simulation indicators and visual channels, while Table 3B presents the comparative statistical results across different node types derived from the simulation outputs.

D. EXPERIMENTAL RESULTS OF PROPAGATION SPEED, BREADTH, AND INFLUENCE

In this section, we analyze the experimental results related to propagation speed, breadth, and influence across different network structures, with a focus on the roles of academic, political, and mass media nodes. To avoid ambiguity in the interpretation of propagation speed, a unified statistical definition is adopted in this study.

Specifically, propagation speed is measured using the threshold-based indicator T50, defined as the time required for the information to reach 50% of the total reachable nodes in the network. In addition, average propagation time represents the mean infection time across all infected nodes at the end of the simulation. All reported results are obtained

TABLE 2. Experiment Data Input and Parameter Setting

Network Type	Number of Nodes (N)	Number of Edges (E)	Number of Initial Propagators	Propagation Rate (β)	Recovery Rate (γ)	Information Attraction (α)	Node Propagation Capacity (θ)	Network Density (ρ)	Simulation Time (T)	Propagation Efficiency (η)
Small-World Network	1000	3000	10	0.05	0.02	0.8	0.7	0.03	500 steps	72%
Scale-Free Network	1000	5000	15	0.06	0.03	0.85	0.75	0.05	500 steps	80%
Random Network	1000	2000	8	0.04	0.03	0.75	0.6	0.02	500 steps	65%
Small-World Network	500	1500	5	0.07	0.02	0.9	0.8	0.04	300 steps	78%
Scale-Free Network	500	2500	10	0.05	0.02	0.8	0.7	0.05	300 steps	82%
Random Network	500	1000	7	0.03	0.02	0.7	0.65	0.03	300 steps	70%
Small-World Network	2000	6000	30	0.04	0.01	0.77	0.72	0.04	1000 steps	68%

TABLE 3A. A Mapping Rules Between Simulation Indicators and Visualization Channels

Visual channel	Data metric	Operational definition	Normalization method
Node size	Degree centrality / Betweenness centrality	Node connectivity strength and structural bridging role	Min–max normalization
Node color	Mean infection time (t_{infect})	Average time step when a node first enters the infected (I) state	Quantile-based binning
Edge width	Edge activation count	Number of times a given edge is involved in propagation events during simulation	Min–max normalization

TABLE 3B. Visualization Result Statistics by Node Type

Node type	Avg degree	Avg betweenness	Avg t_{infect}	Avg secondary infections	Visual interpretation
Academic nodes	High	High	Early	Moderate	Larger node size, earlier color gradient, strong core influence
Political nodes	Medium–High	High	Medium	High	Medium-to-large nodes, strong cross-community links
Mass media nodes	Medium	Low	Late	High	Smaller nodes, later color gradient, wide but shallow spread

by averaging 30 independent simulation runs under identical parameter settings, thereby reducing stochastic bias caused by initial seed placement or random transmission events. The results indicate that scale-free networks achieve shorter T50 values on average, reflecting faster early-stage diffusion driven by high-degree hub nodes. These hubs significantly accelerate information transmission and improve overall coverage. However, in certain scenarios—particularly when initial propagators are embedded within highly clustered local communities—small-world networks exhibit competitive or even superior early diffusion speed, despite a more gradual expansion in later stages. Random networks consistently perform worst in terms of both propagation speed and coverage due to limited connectivity and lack of structural hubs.

From a node-type perspective, academic nodes tend to delay early diffusion but contribute to sustained and high-quality engagement, while political and mass media nodes enhance propagation breadth and speed through higher connectivity and broader reach. The experimental results of Propagation Speed, Breadth, and Influence are shown in Table 4A, Averaged Propagation Speed Across Multiple Simulations (30 runs) is shown in Table 4B, The Analysis of

Propagation Characteristics by Impact Node Type is shown in Table 4C.

E. VISUALIZATION OF PROPAGATION PATHS AND RESULTS DISPLAY

To illustrate information propagation processes and outcomes, data visualization techniques are employed to represent diffusion pathways. Simulation results are transformed into graphical formats such as network graphs and time-series animations, enabling a clear comparison of propagation patterns across different network structures. Visual attributes, including node size and color, are used to encode node roles and relative influence, while variations in edge width or color indicate differences in propagation intensity or speed. The integration of dynamic network visualizations with heat maps further captures temporal changes in diffusion and highlights regions of concentrated information flow.

Visualization enables researchers to identify key nodes, dissemination bottlenecks, and diffusion patterns more effectively, thereby supporting the optimization of propagation strategies. By visually comparing diffusion pathways and dissemination efficiency across different network structures,

TABLE 4A. Experimental Results of Propagation Speed, Breadth, and Influence

Network Type	Number of Nodes (N)	Number of Initial Propagators	Propagation Speed (hours)	Propagation Coverage (%)	Influence Nodes (I)	Propagation Breadth (%)	Propagation Efficiency (η)	Average Propagation Time (hours)	Node Connectivity (K)
Small-World Network	1000	10	12	72	20	70	0.76	15	6
Scale-Free Network	1000	15	10	80	35	80	0.82	13	10
Random Network	1000	8	15	65	15	60	0.68	17	4
Small-World Network	500	5	9	78	12	75	0.8	11	5
Scale-Free Network	500	10	13	82	25	85	0.85	14	8
Random Network	500	7	14	70	10	68	0.72	16	3
Small-World Network	2000	30	16	68	50	68	0.75	18	7

TABLE 4B. Averaged Propagation Speed Across Multiple Simulations (30 runs)

Network Type	Mean T50 (hours)	Std. Dev.	Interpretation
Small-World	12.1	± 1.9	Fast local diffusion, sensitive to seed placement
Scale-Free	10.4	± 1.3	Consistently fast early diffusion driven by hubs
Random	15.3	± 2.1	Slow and unstable diffusion pattern

TABLE 4C. Analysis of Propagation Characteristics by Impact Node Type

Node Type	Role in Propagation Process	Network Impact	Example Influence Nodes
Academic Nodes	Provide theoretical depth and spread ideas within intellectual circles	Slow spread but deep, high-quality engagement	Scholars, universities
Political Nodes	Mobilize mass support and institutionalize ideas through political structures	Fast spread, high reach, deep influence	Political organizations, leaders
Mass Media Nodes	Facilitate rapid dissemination to the general public	Fast spread but may lack depth, wide accessibility	Social media influencers, public figures

this approach provides valuable insights for refining theoretical models and improving analytical precision. The Visualization Effects of Propagation Paths and Related Indicators are shown in Table 5.

F. TARGETED EXPERIMENT SCENARIOS AND ANALYSIS

In this section, we introduce targeted experiment scenarios that reflect real-world settings in the dissemination of Marxist theory. These scenarios simulate different audience groups and dissemination channels, providing a more accurate representation of how Marxist ideas spread in various contexts. The scenarios include university students, grassroots communities, and youth on social media platforms. Each group represents a distinct target audience with specific characteristics, influencing how information is received and shared.

G. TARGET AUDIENCE GROUPINGS AND DISSEMINATION CHANNELS

1. University Student Groups:

Settings: Ideological and political theory courses, campus new media (e.g., university websites, student blogs, social media groups).

Purpose: To analyze how Marxist ideas are disseminated in an academic and intellectual setting. This group has a higher likelihood of engaging with the content deeply, especially in the classroom or through peer discussions.

2. Grassroots Communities:

Settings: Community propaganda stations, rural loud-speakers, local public meetings.

Purpose: To simulate how Marxist ideas are spread in a grassroots or rural setting, where information dissemination relies on public gatherings, word-of-mouth, and local community leaders. This represents the mass mobilization of ideas at the grassroots level.

3. Youth on Social Media Platforms:

Settings: Short video platforms (e.g., Douyin, TikTok), social media groups, online forums.

Purpose: To investigate how young people, who primarily interact through digital media, receive and share Marxist ideas. This setting emphasizes the role of digital platforms in modern communication, especially for ideologically sensitive content.

H. DISSEMINATION CHANNELS AND DIGITAL INTEGRATION

In addition to targeting different audience groups, this experiment also integrates various dissemination channels, such as digitalized Marxist classical texts, short video content related to ideological education, and online-offline integrated propaganda activities. These channels represent the diverse ways in which Marxist ideas are conveyed in modern society, from traditional forms of communication to modern digital media.

1. Digitalized Marxist Classical Texts:

Exploring the spread of works like *Das Kapital* and *The Communist Manifesto* in digital formats (e.g., eBooks, online articles, PDFs) and analyzing how digitalization affects the accessibility and reach of these texts.

2. Ideological Short Videos:

TABLE 5. Visualization Effects of Propagation Paths and Related Indicators

Network Type	Number of Nodes (N)	Number of Initial Propagators	Visualization Type	Propagation Path Display	Propagation Hotspot Area (%)	Propagation Speed (hours)	Network Density	Heatmap Color Range	Time-Series Animation Step Size
Small-World Network	1000	10	Network Graph	Edge width represents propagation speed	70	12	0.03	Red to Green	1 step/hour
Scale-Free Network	1000	15	Dynamic Graph	Node size represents influence	80	10	0.05	Blue to Orange	1 step/hour
Random Network	1000	8	Heatmap	Color represents propagation intensity	60	15	0.02	Blue to Red	2 steps/hour
Small-World Network	500	5	Dynamic Graph	Edge width represents propagation speed	75	9	0.04	Green to Yellow	1 step/hour
Scale-Free Network	500	10	Network Graph	Node color represents propagation power	85	13	0.05	Red to Green	1 step/hour
Random Network	500	7	Heatmap	Color represents propagation intensity	68	14	0.03	Blue to Red	2 steps/hour
Small-World Network	2000	30	Dynamic Graph	Edge width represents propagation speed	68	16	0.04	Green to Yellow	1 step/hour

Investigating the role of short-form video content in conveying Marxist ideas, focusing on platforms like Douyin and TikTok, where short videos can go viral and reach wide audiences, particularly the younger generation.

3. Integrated Online-Offline Propaganda Activities:

Simulating the integration of traditional face-to-face dissemination (e.g., community meetings, grassroots speeches) with online digital campaigns to study the hybrid nature of contemporary information dissemination.

I. EXPERIMENT DESIGN AND PARAMETERS

To simulate the above scenarios, the following experiment parameters and settings were defined, as shown in Table 6.

J. ANALYSIS OF RESULTS

The results from these targeted experiments reveal the strengths and weaknesses of different dissemination strategies. Below is an analysis based on the key indicators:

1. University Students:

Marxist ideas spread slowly but deeply. The intellectual engagement with the material in courses and discussion groups facilitates better understanding, but the overall spread is more contained within academic circles.

2. Grassroots Communities:

The spread is more widespread but slow, as face-to-face interactions and local media are key to reaching a broad but more traditional audience.

3. Youth on Social Media:

The speed of dissemination is high, with viral content spreading quickly among youth. However, the depth of understanding may be limited as the content is often simplified for mass consumption.

4. Digitalized Marxist Classical Texts:

This dissemination method reaches fewer people but offers greater intellectual engagement. The slow spread is due to the nature of the content, which requires deep reading and understanding.

5. Ideological Short Videos:

The use of short videos results in rapid reach across a large demographic, especially the youth, but the engagement is more superficial compared to other methods.

6. Integrated Online-Offline Propaganda:

This scenario achieves a balanced spread with good reach and moderate depth of engagement. Combining online tools with traditional methods helps leverage the strengths of both.

VI. DISCUSSION AND CONCLUSION

By integrating Marxist dissemination theory with contemporary communication models and data visualization techniques, this study provides a structured analysis of how Marxist classical theory disseminates within complex network environments. The combination of social network analysis, diffusion modeling, and visualization enables a detailed examination of dissemination paths that would be difficult to capture through traditional qualitative approaches alone. The simulation results demonstrate that dissemination outcomes are strongly conditioned by network topology and node-role differentiation. Scalefree networks, characterized by high-degree hub nodes, tend to facilitate faster early-stage diffusion and broader overall coverage. In contrast, small-world networks exhibit stronger local clustering effects, which can lead to efficient early propagation under specific initial conditions but slower expansion across the entire network. These findings underscore the importance of considering structural conditions rather than assuming a single optimal dissemination pattern.

From the perspective of node roles, academic nodes contribute to sustained and in-depth dissemination by anchoring theoretical interpretation, political nodes enhance cross-group transmission and institutional amplification, and mass media nodes expand surface-level reach through high-frequency dissemination. The interaction among these node types highlights the necessity of a differentiated dissemination strategy that balances depth, speed, and breadth. Importantly, data visualization plays a critical role in translating complex simulation outputs into interpretable analytical insights. By visualizing diffusion paths, hotspot distribu-

TABLE 6. Targeted Experiment Scenarios and Dissemination Channels

Scenario	Audience Type	Dissemination Channel	Key Characteristics	Expected Outcome
University Student Groups	University Students	Ideological courses, campus new media	Higher engagement with in-depth content, peer discussions	Deeper understanding, slower spread
Grassroots Communities	Local Communities	Propaganda stations, public meetings	Reliant on face-to-face interaction, word-of-mouth	Wider but slower spread
Youth on Social Media	Youth (18-30)	Short video platforms, social media	Rapid information spread, viral content	Fast spread, high reach
Digitalized Marxist Texts	General Public	eBooks, online articles	Easy accessibility, intellectual engagement	Slower spread, but deep engagement
Ideological Short Videos	General Public	Douyin/TikTok, YouTube	Fast, engaging, shareable content	Wide reach, less depth
Integrated Online-Offline Propaganda	General Public	Online campaigns + offline meetings	Combines digital speed with personal interaction	Balanced spread and reach

tions, and temporal dynamics, the study demonstrates how visualization can function as an analytical instrument rather than a supplementary display tool.

This research is primarily oriented toward methodological exploration and mechanism analysis based on simulation-generated data. As such, the findings should be interpreted as revealing structural tendencies rather than predicting specific real-world dissemination trajectories. Future research may extend this framework by incorporating empirical data from digital platforms, publication networks, or historical archives to further test its external validity. Overall, the study contributes to the understanding of ideological dissemination by offering a visualization-driven analytical framework that clarifies the structural mechanisms underlying the spread of Marxist classical theory in contemporary networked communication environments.

AUTHOR CONTRIBUTIONS

Conceptualization – Siqi Wang and Xukun Wu; methodology – Siqi Wang and Xukun Wu; investigation – Siqi Wang and Xukun Wu; writing-original draft preparation – Siqi Wang and Xukun Wu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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