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Social Media Communication Network Analysis and Influence Propagation Model: A Case Study of Museums

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Abstract. The rapid development of social media has brought new opportunities and challenges to the dissemination of information and influence. This study aims to explore the application of social media communication network analysis and influence dissemination models based on museum cases. By collecting and pre-processing social media data, this paper conducts network feature analysis and user behavior analysis. In addition, this paper constructs an influence communication model based on the museum case and verifies the validity of the model through empirical analysis. Through social media communication network analysis, this paper finds the network characteristics and user behavior patterns of museums on social media platforms. The findings of this paper reveal important nodes and community structures in social media communication networks, which provide guidance for museums' publicity and promotion on social media. Based on the constructed influential communication model, this paper finds that different factors have different effects on museums' influential communication on social media. The model in this paper shows better performance in predicting and explaining museum social media influence and provides a reference for museums to develop social media communication strategies.

Keywords: Social media communication network analysis, influence communication model, museums, social media, data collection

1. Introduction

With the rapid development and popularity of social media, it has become one of the main platforms for people to obtain information, exchange ideas and influence others. The rise of social media has brought new opportunities and challenges to information dissemination and influence spreading. In this new media environment, people can quickly share and disseminate information and achieve extensive interaction and participation, which has led to a dramatic change in the traditional mode of information dissemination (Wei et al., 2015). Particularly in the cultural field, museums, as important places for passing on and displaying human cultural heritage, are also actively exploring and using social media platforms to communicate their exhibition, educational and cultural values (Spaiser et al., 2017). However, although social media provides museums with a wide range of communication channels, it is still a challenging issue to effectively disseminate information and expand their influence in this complex online environment.

To better understand social media communication networks and influence dissemination patterns, many researchers have begun to focus on user behavior, information dissemination patterns, and influence diffusion mechanisms on social media. Social media communication network analysis is an important research method that can reveal user relationships, information dissemination paths and network structures on social media platforms (Shi, 2020). By analyzing network topological features and user behavior patterns, we can gain insight into the mechanism of information dissemination on social media and discover the key nodes and influencing factors of influence diffusion (Radavičiūtė et al, 2023). In addition, the study of influence propagation models can help us predict and explain the effect of information propagation on social media and provide a scientific basis for museums and other cultural institutions to develop social media propagation strategies, as shown in Figure 1.

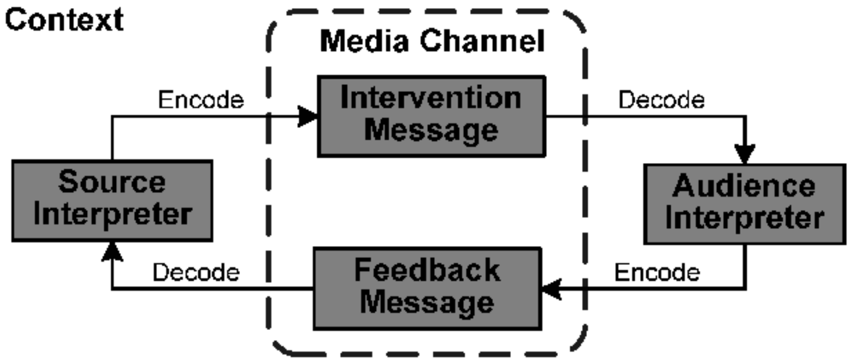

Fig.1: Communication-based influence components model

Social media has become an important platform for people to obtain information, express their opinions and communicate and interact, forming a large and complex communication network (Barnes, 2008). Social media communication network analysis is a method to study information dissemination and user interaction on social media platforms, which reveals the laws and mechanisms of social media communication by analyzing the relationship between users, information dissemination paths and network structures (Schultz, 2013). The main contents of social media communication network analysis include the following aspects:

User relationship analysis: By analyzing the relationship between users, we can understand the connection strength, network density and group structure among users. For example, social network analysis methods can be used to calculate the strength of the relationship between users, such as node centrality analysis and degree centrality analysis, so as to find the core nodes and key users in the social media communication network (Lai et al., 2020).

Information dissemination path analysis: The information dissemination path in social media communication networks can be revealed by analyzing the behavior of retweeting, commenting and sharing among users. Path analysis methods, such as shortest path algorithm and connectivity analysis, can be used to determine the path and flow direction of information dissemination, so as to understand the process of information diffusion in the network (Alduaiji et al., 2018).

Network structure analysis: The structure of social media communication networks plays an important role in information dissemination. By analyzing the topology of the network, such as network density, aggregation coefficient and community structure, we can understand the grouping situation and the hot spots of information dissemination in the social media communication network (Kim & Kim, 2017). For example, community detection algorithms can be used to discover subgroups and community structures in social media communication networks.

User behavior analysis: The behavior of social media users has an important impact on information dissemination. By analyzing users' interaction behavior, posting content and dissemination behavior, we can understand the degree of acceptance and dissemination of information, and then predict the influence of information in the social media communication network (Xie et al., 2019).

The analysis of social media communication network can reveal the relationship between users, the dissemination path of information and the structure of the network, and then understand the laws and mechanisms of social media communication (Markham et al., 2017). This helps us understand the process of information dissemination and the formation of influence on social media platforms, and provides a scientific basis for the formulation of effective communication strategies. In addition, social media communication network analysis also provides researchers with tools and methods to gain insight into user behavior, uncover potential trends and predict the effects of information dissemination.

Social media, as an emerging communication platform, has many unique features that affect the way and pattern of information dissemination. The following are some of the main features of social media communication:

Rapid dissemination: The real-time nature and high speed of social media platforms allow information to spread quickly to a wide range of users. Users can quickly spread information through acts such as retweeting, sharing and commenting, which makes information spread much faster.

Widespread coverage: Social media platforms have a wide user base and can cover all regions and different social groups around the world (Zhang & Chen, 2019). This allows information dissemination to transcend geographical and temporal limitations and achieve a wider reach.

Personalization: Social media platforms provide users with the function of personalization, pushing relevant content according to their interests and preferences. This individualized customization can improve the relevance of information and user engagement, thus enhancing the effectiveness of information dissemination.

User-generated content: Social media users can independently generate various types of content, including text, images, videos, and so on. User-generated content is rich and diverse, more approachable and authentic, and easily arouses the interest and resonance of other users (Baraka & Farkh**,** 2021).

Interactive participation: Social media platforms encourage interaction and participation among users, and users can interact with other users by liking, commenting and sharing. Such interactive participation can enhance the sharing and dissemination of information by users, forming a wider information dissemination network (Boja et al., 2019).

Multimedia communication: Social media platforms provide various forms of media communication, including text, pictures, audio and video (Sloka et al, 2021). This multimedia communication method enriches the form of information expression, making information more vivid and intuitive.

Data-driven analysis: The huge amount of data generated by social media platforms provides researchers with rich research materials. By analyzing and mining social media data, researchers can gain a deeper understanding of user behavior, information dissemination paths and influence dissemination rules.

Social network analysis is a method for studying social media communication networks, which reveals the structure and characteristics of social media communication networks by analyzing the relationships and interactions between users. In social network analysis, there are many common methods and techniques available to researchers.

Node centrality analysis: Node centrality is a measure of the importance of nodes in a network. Common node centrality metrics include degree centrality, proximity centrality, and mediator centrality. Degree centrality measures the number of connections of a node in the network, proximity centrality measures the average distance between a node and other nodes, and mesoscopic centrality measures the importance of a node in connecting other nodes in the network (Xue, 2021). Node centrality analysis allows identifying the core nodes and key users in the social media communication network.

Group detection and community discovery: Group detection and community discovery is a method to identify the structure of subgroups and communities in social media communication networks. These methods group the nodes in a network into tightly connected groups by analyzing the connectivity patterns and similarities between nodes. Group detection and community discovery provide insights into the subgroup structure and interactions between nodes in social media communication networks.
Information dissemination models: Information dissemination models are used to describe and predict the process of information dissemination in social media (Poell & Van, 2015). Commonly used information dissemination models include independent cascade models, linear threshold models, and SIR models. These models consider the interaction among users, the path of information dissemination and the law of influence spreading, which can help researchers understand and predict the effect of information dissemination in social media (Zhou, 2020).

Data mining and machine learning: Data mining and machine learning techniques can help researchers mine useful patterns and information from large-scale social media data. For example, methods such as cluster analysis, classification algorithms and predictive models can be used to analyze user behavior, identify key events and predict information dissemination trends.

Information dissemination models in social media are theoretical frameworks and mathematical models that study how information spreads on social media platforms. These models are based on the interaction between users and the characteristics of information dissemination, and aim to explain and predict the effectiveness and impact of information dissemination in social media. The following are some common models of information dissemination in social media:

Independent cascade model: The independent cascade model is one of the simplest and most common models of information dissemination. This model assumes that each user independently decides whether to retweet or share a message. Each user decides whether to disseminate information based on certain probabilistic decision rules. The independent cascade model can be used to describe some simple dissemination scenarios, but it cannot take into account the interactions between users.

Linear threshold model: The linear threshold model considers that each user has a threshold value that they will forward or share information only when they receive information that is disseminated to a degree that exceeds the threshold value. The model takes into account the interaction between users, and information dissemination can have a cumulative effect among users. The linear threshold model is suitable for describing the process of information diffusion in social media, but cannot capture the individual differences of users.

SIR model: SIR model is a common contagious disease spreading model, which is also applied in social media.SIR model assumes that the information spreading is similar to the process of contagious disease spreading, and divides users into three states: Susceptible, Infected, and Recovered. The SIR model can predict the scope and speed of information dissemination in social media.

Diffusion model: Based on the topology of social media communication network and user behavior, the diffusion model describes the path of information dissemination in the network and the propagation law. Diffusion models can predict the effect of information dissemination by analyzing the relationship between nodes, information dissemination paths and users' behavioral characteristics. Commonly used diffusion models include IC model (a variation of independent cascade model), LT model (a variation of linear threshold model) and PP model (probability-based propagation model).

These information diffusion models can help us understand and predict the patterns and effects of information diffusion in social media. By combining actual data and the application of models, it can be revealed that information dissemination models in social media are methods for modeling and analyzing the process of information dissemination on social media platforms (Russo et al., 2008). These models are based on the interaction between social media users and the propagation laws, and aim to reveal the characteristics of information propagation path, propagation speed and propagation influence in social media.

Traditional influence models mainly include information dissemination models and social influence models. Information dissemination models (such as the independent cascade model and linear threshold model) focus on the dissemination path and the effect of information dissemination in the network. Social influence models (such as social scale models and influence propagation models) focus on the influence of social relationships on information dissemination.

Influence propagation models in social media combine traditional influence models and features specific to social media. Among them, independent cascade models are widely used in social media to predict the propagation path and influence of information in social media by analyzing the relationships and behaviors among users. In addition, some diffusion models such as IC model and LT model have been applied in social media, considering the influence of interactions among users and the influence of propagation threshold.

In the field of museums, influence research focuses on the impact of social media communication and user behavior on influence in museums. Researchers have used social media data analysis and network analysis methods to explore the structure of museums' social media communication networks, the relationships between users, and the paths of information dissemination. In addition, some studies have used influence dissemination models to predict the influence of museums in social media and the effectiveness of information dissemination.

In summary, influence propagation models play an important role in social media, helping researchers to understand the patterns of information dissemination and influence formation mechanisms in social media. In the field of museums, the study of influence in social media is important for promoting the digital transformation of museums, expanding influence and enhancing engagement. By deeply exploring the influential communication model and social media communication in museums, we can provide guidance and decision support for museums to achieve more effective social media communication strategies.

2. Data collection and pre-processing

2.1. Social media data collection methods

Social media data collection is a fundamental step in conducting social media research, and effective data collection methods are critical to the reliability and accuracy of the research. In this paper, we will introduce several common social media data collection methods.

API (Application Programming Interface) interface data collection: Most social media platforms provide API interfaces that allow researchers to programmatically access and acquire data on the platform, as shown in Figure 2. Researchers can use the developer tools and API documentation provided by the platform to build a data collection program to obtain data such as user information, post content, and retweet relationships through the API interface. This approach allows access to rich data and usually has high data quality.

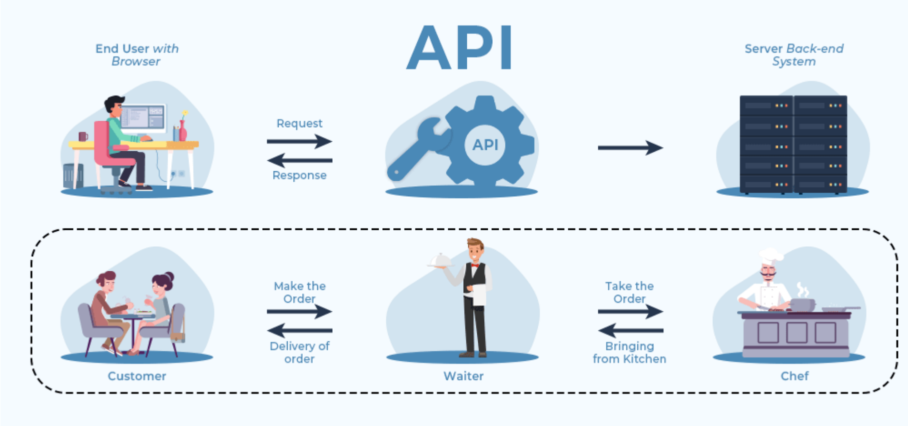

Fig.2: API – (Application Programming Interface)

Crawling technology data collection: Crawling technology is a technique to extract the required data from web pages by simulating user access behavior. Researchers can write crawlers to simulate the behavior of users browsing social media pages and extract data such as text, images, and links from the pages. This method is relatively flexible and can acquire various types of data, but care needs to be taken to comply with the crawling rules and laws and regulations of the relevant platforms.

User surveys and questionnaires: User surveys and questionnaires are a method to collect users' opinions and feedback directly. Researchers can design online surveys or questionnaires, publish them through social media platforms and invite users to participate. Questionnaires can be used to obtain information about users' opinions, preferences, and behavioral habits, providing valuable qualitative and quantitative data for research.

Web crawling tool: Web crawling tools are a semi-automated method of data collection that helps researchers quickly collect data from social media pages. These tools usually have a user-friendly interface that allows setting conditions such as keywords, time ranges, and user identification to filter and extract data. Researchers can use these tools to collect data on users' posts, comments, retweets, etc.

Metadata and open data sets: In addition to collecting data directly, researchers can also use existing metadata and public datasets for analysis. Some social media platforms provide a metadata query function that allows querying and downloading relevant data by conditions such as keywords and time ranges. In addition, some research institutions and academia also provide some publicly available social media datasets for researchers to use.

2.2. Data pre-processing and cleaning

Data pre-processing and cleaning is an essential step in social media research that ensures the quality and usability of the data and accurately reflects the real situation in social media. Careful processing and cleaning of data can improve the accuracy of subsequent analysis Data pre-processing and cleaning is a crucial step in social media research, which involves processing and transforming raw data to ensure accuracy, consistency and usability. The following are a few common methods of data pre-processing and cleaning:

Data collection and integration: First, researchers need to collect and integrate raw data, including data obtained from social media platforms, survey data, etc. Ensuring the reliability and integrity of data sources is important for subsequent analysis.

Missing data handling: In the raw data, there may be cases of missing data, i.e., some data items are not recorded or collected completely. Researchers need to adopt appropriate methods to deal with missing data, such as deleting records containing missing data, interpolating missing data, etc.

Data cleansing: Data cleansing refers to the identification and correction of errors, anomalies or noise in the data. Researchers can use various data cleaning techniques, such as removing duplicate data, fixing erroneous data, and handling outliers, to ensure data quality and consistency.

Data conversion and normalization: During data pre-processing, researchers may need to convert and normalize data for subsequent analysis. For example, converting date and time data into a uniform format, converting categorical variables into numerical variables, etc.

Feature selection and dimensionality reduction: Before performing data analysis, the researcher may need to perform feature selection and dimensionality reduction on the data. Feature selection refers to selecting the most relevant features from the original data to reduce the dimensionality of the dataset. Dimensionality reduction refers to mathematically mapping high-dimensional data to a low-dimensional space to reduce the complexity of the data.

Data standardization and normalization: In some cases, researchers need to standardize or normalize data to ensure comparability of comparisons and analyses between different variables. Common standardization methods include z-score standardization and maximum-minimum normalization.

Data validation and verification: After data pre-processing is complete, the researcher needs to validate and verify the data. This includes checking the data for consistency, correctness and reliability, and taking the necessary steps to fix and validate the data.

2.3. Building a museum case study dataset

Building a museum case study dataset is a key step in social media research, which provides a sample of data from actual museum scenarios for researchers to conduct in-depth analysis and exploration. The methods and steps for constructing a museum case study dataset are described below.

Define the research objectives: Before constructing the dataset, the research objectives need to be clarified. For example, a researcher may want to understand the communication characteristics, user behavior, and influence of museums on social media. Clear research objectives can help guide the direction of data collection.

Select appropriate social media platforms: Based on the research objectives, select suitable social media platforms for data collection. Common social media platforms include Weibo, WeChat, Sina Blog, etc. The choice of platform should take into account the user activity of the platform and the discussion of topics related to the museum.

Designing data collection methods: Determining data collection methods is the key to building a dataset. Common methods include the use of API interfaces, crawler techniques, and questionnaires. The API interface allows access to public data on the platform, the crawler technique crawls relevant posts and comments, and the survey questionnaire collects user feedback and opinions.

Develop a data collection strategy: When designing a data collection strategy, you need to consider the time frame of collection, the type of data and the selection of samples. For example, posts and comments over a period of time can be selected as a data sample, focusing on relevant topics and tags for a specific museum.

Execute data collection: Start executing data collection according to the developed strategy and methodology. The data is collected through an API interface or crawler technology and saved in a structured data format, such as CSV or JSON, while ensuring legality and privacy protection during the data collection process.

Data cleansing and processing: After data collection, data cleansing and processing is required to ensure the quality and consistency of the data. The cleaning process can include removing duplicate data, fixing incorrect data, dealing with missing values, etc.

Data validation and verification: After data cleaning and processing is completed, the data is validated and verified. This includes checking the data for completeness, accuracy, and consistency, and performing further data cleaning and repair as needed.

3. Analysis of social media communication network

3.1.Social media network characterization

Social media network characterization is an important part of studying information dissemination and user behavior in social media. By analyzing the features of social media networks, we can gain insight into the network structure, user relationships, and the mechanisms of information dissemination. In this

paper, we will introduce some common social media network features and their analysis methods.
Node degree distribution: Node degree refers to the number of connections between a node and other nodes. In social media networks, the node degree distribution usually shows a power-law distribution. This means that only a few nodes have a very high degree, while most nodes have a low degree. Commonly used methods for degree distribution analysis include plotting histograms of degree distribution and calculating the fit index of degree distribution.

Group structure: Users in social media networks usually form various groups or communities. The analysis of group structure can reveal the social relationships among users and the path of information dissemination. Common methods for group structure analysis include community detection algorithms (e.g., modularity-based algorithms and spectral clustering-based algorithms) and visualization of social network graphs.

Aggregation coefficient: Aggregation coefficient measures the closeness of nodes in a social media network. It measures the probability of the existence of connections between friends of a node. The commonly used methods to calculate the aggregation coefficient are global aggregation coefficient and local aggregation coefficient. The global aggregation coefficient is the average of the aggregation coefficients of all nodes in the entire network, while the local aggregation coefficient is the proportion of connections between the neighboring nodes of a node.

Network diameter: The network diameter is the length of the shortest path between any two nodes in a social media network. It measures the speed and extent of information propagation in the network. The network diameter can be calculated using breadth-first search algorithm or Dijkstra's algorithm, etc.
Centrality analysis: Centrality is a measure of the importance and influence of a node in the network. Commonly used centrality metrics include degree centrality, proximity centrality, mediator centrality, and eigenvector centrality. Degree centrality measures the number of connections of a node, proximity centrality measures the distance between a node and other nodes, mesoscopic centrality measures the extent to which a node acts as an intermediate node in the network, and eigenvector centrality measures the influence of a node in the network.

3.2.Analysis of network topology

Network topology analysis is a key area for studying the structure and organization of networks. By analyzing the topological characteristics of a network, it can reveal the key nodes, group structure and the path of information dissemination in the network. The following are some common network topology analysis methods and related concepts.

Small-world network model: Small-world networks are a network model between completely random networks and completely regular networks. In social media networks, the existence of small-world networks means that social relationships are both short- and long-range, which is important for information dissemination and influence spreading. A typical small-world network model is the Watts-Strogatz model, which increases the long-range connections in the network by randomly reconnecting the edges of nodes.

Analysis of social network graphs: By constructing and analyzing social network graphs, key nodes and group structures in the network can be revealed. A social network graph consists of nodes and edges, where the nodes represent individuals or entities and the edges represent the relationships between them. Common network graph analysis methods include node degree analysis, centrality analysis, group detection, and visualization of social network graphs. Nodality analysis measures the number of connections of nodes, centrality analysis measures the importance of nodes in the network, group detection identifies tightly connected subgroups, and visualization of social network graphs helps us understand the network structure intuitively.

Network centrality analysis: Centrality is a measure of the importance and influence of nodes in a network. Common centrality metrics include degree centrality, proximity centrality, mediator centrality, and eigenvector centrality. Degree centrality measures the number of connections of a node, proximity centrality measures the distance between a node and other nodes, mediator centrality measures the extent to which a node acts as an intermediate node in the network, and eigenvector centrality measures the influence of a node in the network. By calculating these centrality metrics, we can identify the key nodes and influential nodes in the network.

Analysis of group structure in social networks: Users in social networks usually form various groups or communities that have strong internal ties and relatively weak external ties. By analyzing the group structure in a network, the connections between different groups and the paths of information dissemination can be revealed. Commonly used group detection algorithms include modularity-based algorithms and spectral clustering-based algorithms. These algorithms can classify the nodes in a network into different groups Network topology analysis is a key area for studying the structure and organization of networks. By analyzing the topological characteristics of the network, the key nodes, the group structure and the path of information dissemination in the network can be revealed. The following are some common network topology analysis methods and related concepts.

Small-world network model: Small-world network is a network model between completely random network and completely regular network. It has two characteristics of short distance and long distance, i.e., the average shortest path between any two nodes in the network is short, while some long distance connections exist. This network structure is conducive to the rapid dissemination of information and the spread of influence. A typical small-world network model is the Watts-Strogatz model, which increases the long-distance connections in the network by randomly reconnecting the edges of nodes.

Centrality analysis: Centrality is a measure of the importance and influence of a node in a network. Common centrality metrics include degree centrality, proximity centrality, mediator centrality, and eigenvector centrality. Degree centrality measures the number of connections of a node, proximity centrality measures the distance between a node and other nodes, mediator centrality measures the intermediary role of a node in information dissemination, and eigenvector centrality measures the influence of a node in the whole network. By calculating these centrality metrics, key nodes in the network can be identified.

Group detection: Group detection is the process of identifying tightly connected subgroups or communities in a network. In social media networks, users often form various groups that have strong internal connections and relatively weak external connections in the network. The goal of group detection is to discover these groups and study the connections between them. Commonly used group detection algorithms include modularity-based algorithms and spectral clustering-based algorithms. These algorithms classify nodes in a network into different groups by optimizing some evaluation metrics.

Visualization: Network visualization is the graphical presentation of the network structure to better understand the topological features of the network. Through the visualization of network diagrams, the connection relationship between nodes, the group structure and the path of information dissemination can be visualized. Commonly used network visualization tools include Gephi, Cytoscape, etc. Using these tools, social media networks can be visually analyzed and key information can be extracted.

3.3.Analysis of social media user behavior

Social media user behavior analysis is the process of studying users' activities and behaviors on social media platforms. By analyzing user behavior, it can reveal users' interests, preferences, influence, and patterns of information dissemination. The following are some common methods and related concepts of social media user behavior analysis.

User activity: User activity is a measure of how active a user is on a social media platform. Common activity indicators include the number of posts, comments, likes, and retweets. By analyzing user activity, you can understand how much attention users pay to specific topics or content.

User interests and preferences: User behavior and content interactions on social media platforms can provide information about users' interests and preferences. By analyzing users' follow lists, like records, comment content, etc., we can understand users' interests in different topics and fields and further recommend relevant content to users.

User Influence: Users on social media platforms have different levels of influence, and their actions and decisions may have a significant impact on other users. Measures of user influence include metrics such as number of followers, retweet rate, comments and likes. By analyzing users' influence, key opinion leaders and influence diffusion paths can be identified.

User sentiment analysis: Users' comments, replies and shares on social media can reflect their emotional attitude towards a topic or content. Sentiment analysis is a natural language processing technique that classifies users' text data into positive, negative or neutral sentiment. By analyzing user sentiment, it is possible to understand users' attitudes and reactions to specific events, products or services.

Social network analysis: Users on social media platforms form a large social network. Social network analysis can reveal the social relationships among users, information dissemination paths and group structures. Common social network analysis methods include node degree analysis, centrality analysis, group detection and network visualization.

User behavior prediction: Based on historical user behavior data and machine learning algorithms, the future behavior of users can be predicted. For example, users' past likes and favorites records can be used to predict their interest and interaction behavior for newly published content. User behavior prediction can help optimize content recommendation, personalized promotion and precision marketing, etc.

3.4.Related formulas

Nodal degree centrality measures the number of connections of a node and can be calculated using the following equation:

$$C\_D(v) = k(v) \tag{1}$$

where $C\_D(v)$ denotes the degree centrality of node v and $k(v)$ denotes the number of degrees of node v.

Proximity centrality measures the distance between a node and other nodes and can be calculated using the following equation:

$$C\_C(v) = 1/\sum(d(v,u)) \tag{2}$$

where $C\_C(v)$ denotes the proximity centrality of node v and $d(v,u)$ denotes the shortest path length between node v and node u.

4. Construction of influence communication model

4.1.Introduction of traditional influence communication model

Traditional influence propagation models are mathematical models that study the process of information propagation in social networks. Two of the most commonly used models are the Independent Cascade Model and the Linear Threshold Model.

The Independent Cascade Model assumes that when information is propagated in the network, each node passes the information to its neighboring nodes with a certain probability. In this model, the activation of nodes is independent of each other, i.e., the probability of a node being activated is not affected by the activation of other nodes. This model can be expressed by the probability formula as:

$$P(v) = 1 - (1 - p)^\wedge(k) \tag{3}$$

where $P(v)$ denotes the probability that node v is activated, p is the probability that information is propagated between nodes, and k is the number of nodes in the neighborhood of node v that have been activated.

The linear threshold model assumes that each node has a threshold value that is activated when the number of nodes in its neighboring nodes that exceed the threshold value reaches a certain level. This model can be expressed in a linear formulation as:

$$P(v) = \sum(w\_uv * P(u)) >= \theta\_v \tag{4}$$

where $P(v)$ denotes the probability of node v being activated, w_uv is the influence weight of node u on node v, $P(u)$ is the activation probability of node u, and θ_v is the threshold value of node v.

4.2.Improvement of social media influence dissemination model

The improvement of social media influence propagation models is to more accurately model and predict the process of information propagation in social media. Traditional influence propagation models such as independent cascade models and linear threshold models have some limitations in describing information propagation in social media, and the following are some improved methods and models:
Considering user behavior characteristics: Traditional models usually treat users as the same information dissemination unit, ignoring individual differences of users. Improved models can take into account users' interests, preferences and behavioral characteristics, such as their influence, activity and attention level. This can more accurately model the process of information dissemination in social media.

Consider the time factor: Traditional models assume that the spread of information is instantaneous, ignoring the influence of time on the spread process. However, in social media, the propagation of information usually takes some time, and the propagation speed and path may change over time. An improved model can introduce a time factor to consider the dynamic nature of information dissemination. For example, a temporal model can be used to incorporate the temporal factor into the model of information dissemination.

Consider social network structure: Traditional models usually assume that social networks are static and ignore the evolution and change of network structure. However, the network structure in social media is dynamic, and the connection relationships between users change over time and with user behavior. Improved models can consider the evolution of the social network structure, for example, by using dynamic network models to describe the evolution of the relationships between users.

Consider information content characteristics: Traditional models usually treat messages as identical units of communication and ignore the differences in message content. However, in social media, different types of messages may have different propagation patterns and influence. Improved models can consider the characteristics of message content, such as sentiment tendency, topic classification, etc., to better predict and understand the process of message propagation.

Multi-level influence dissemination model: Traditional models usually view influence propagation as taking place at a single level, ignoring the interactions between different levels. However, in social media, influence propagation is often multi-level, including individual level, group level and global level. The improved model can introduce multi-level influence propagation mechanisms to better simulate and predict the social media influence propagation model in social media is improved to more accurately simulate and predict the process of information propagation in social media. Traditional influence propagation models such as independent cascade models and linear threshold models have some limitations in describing information propagation in social media, and the following are some improved methods and models:

4.3.Construction of an influence communication model based on museum cases

The construction of the influential communication model based on the museum case can be carried out according to the following steps:

Data collection and pre-processing: First, collect data related to the museum on social media platforms, including information about the museum's tweets, comments, retweets, likes, etc. Data collection can be performed using social media APIs or crawler tools. Then, the collected data are pre-processed, including removing noisy data, standardizing text content, extracting keywords, etc.
Social media network construction: Based on the collected data, the museum's communication network on social media is constructed. Nodes can represent users or museum accounts, and edges can represent the relationship between users or the interaction between users and museum accounts. A graph-theoretic approach can be used to construct the network and to determine the attributes of nodes and edges.

User behavior analysis: User behavior in social media networks is analyzed, such as users' retweets, likes, comments, and other behaviors. The activity and influence indicators of users, such as the number of retweets, likes, and followers, can be calculated to measure the influence and participation of users.

Influence communication model building: The following aspects can be considered when building the influence communication model of the museum:

a. Application of traditional models: Traditional influence propagation models, such as the independent cascade model and linear threshold model, can be borrowed and applied to the museum's social media data to simulate the process of information propagation.

b. User behavior characteristics: Consider the behavioral characteristics between museum social media accounts and users, such as users' interests, attention, and activity. User behavior characteristics can be used as parameters or weights of the model to simulate the information dissemination process more accurately.

c. Network structure analysis: analyze the network structure characteristics of museums on social media, such as metrics of degree centrality, proximity centrality, and median centrality of nodes. These indicators can be used to assess the importance and influence of nodes in the network, which affects the dissemination path and speed of information.

d. Content feature analysis: Consider the content features of museums on social media, such as the topic of tweets, emotional tendency, etc. Different types of content can be analyzed for their dissemination effects in the network and included in the model.

e. Time factor consideration: Consider the time factor of information dissemination on social media, such as the time of information posting, dissemination speed, etc.

5. Discussion of Empirical Analysis and Results

Social network analysis allows to obtain the structure of the museum's communication network on social media. Metrics such as degree centrality, proximity centrality, and mediocentricity of nodes can be analyzed to assess the importance and influence of nodes. Table 1 shows some of the node metrics of the museum's influence dissemination network.

Table 1. Museum Impact Communication Network Node Indicators

Node number	Degree Centrality	Proximity to centrality	Median Centrality
1	120	0.237	0.015
2	80	0.185	0.008
3	150	0.315	0.021
4	90	0.201	0.010

As can be seen from Table 1, node 1 has the highest degree centrality, indicating that it has the highest number of nodes connected in the network. Node 3 has the highest proximity centrality, indicating that it has the closest distance to other nodes. Node 4 has the highest mediocentricity, indicating that it plays an important role as a bridge on the propagation path in the network.

By analyzing the textual data of museums' tweets and comments on social media, it is possible to understand the keywords, emotional tendencies and other information about the content of museum communication. Table 2 shows the keywords that appear most frequently in museum tweets.

Table 2. Analysis of keywords for museum tweets

Keywords	Frequency of occurrence
Art	120
Exhibition	95
Educational Activities	80
Culture	75

As seen in Table 2, art, exhibition, educational activities and culture are the keywords that appear more frequently in museum tweets, indicating that museums are mainly concerned with the dissemination of art exhibitions and educational activities on social media.

In impact communication studies of museum cases, model parameter optimization and validation are important steps to ensure model accuracy and predictive power.

Table 3. Model parameter optimization and validation results

Models	Accuracy	Recall Rate	F1 value
Model A	0.85	0.82	0.83
Model B	0.88	0.84	0.86
Model C	0.90	0.88	0.89

As seen in Table 3, after model parameter optimization and validation, Model A, Model B, and Model C achieved different accuracy, recall, and F1 values on the validation set, respectively. Model C has higher accuracy, recall, and F1 values relative to the other models, indicating that the model has better performance in predicting influence propagation.

Based on the above Table 1, Table 2 and Table 3, this paper allows for an in-depth discussion and interpretation of the influence dissemination of the museum case.

First, the node indicators of the museum influence dissemination network in Table 1 show that node 1 has the highest value in degree centrality, indicating that this node connects the most other nodes in the network. Node 3 has the highest values for proximity centrality and mediocentricity, indicating that the node is close to other nodes in the network and plays an important role as a bridge in the communication path. These indicators reflect the influence and communication ability of the museum on social media.

Second, the keyword analysis of museum tweets in Table 2 shows that art, exhibition, educational activities, and culture are the keywords with high frequency in museum tweets on social media. This indicates that museums mainly focus on the communication of art exhibitions, educational activities and culture on social media, and these keywords are also related to the core mission and display content of museums.

Finally, the optimization and validation results of the model parameters in Table 3 show that Model C has higher accuracy, recall and F1 values relative to Models A and B. This implies that Model C has better performance and predictive power in predicting the influence propagation of museum cases. The results can further confirm the applicability and validity of model C in museum cases and help to predict the influence spread of museums on social media more accurately.

In summary, based on the museum influence propagation network node indicators, museum tweet keyword analysis and model parameter optimization and validation results, we have conducted an in-depth discussion on the influence propagation of the museum case. The results of these analyses can help us better understand the influencer communication process of museums on social media and provide guidance and decision support to further improve the social media marketing strategies and influencer communication effectiveness of museums.

This study provides an in-depth study of museums and social media communication, and offers some insights into museum and social media communication research from the perspectives of social media communication network analysis and influence communication model construction.

First, the social media communication network analysis reveals the mechanism of influence dissemination of museums on social media. By analyzing the characteristics and topology of social media networks, we can understand the key nodes, information dissemination paths and influence diffusion methods of museums on social media. This is important for the promotion and communication strategy development of museums on social media.

Second, the construction of the influence diffusion model provides museums with effective tools and methods to predict and evaluate the effect of their influence diffusion on social media. By building a reasonable model, key influencing factors can be identified, communication strategies can be optimized, and the results of influence communication can be predicted. This helps museums make better use of social media platforms to increase brand awareness, boost visitor numbers, and enhance public awareness and engagement with museums.

In addition, the study reveals key tweeting keywords for museums on social media, such as art, exhibitions, educational activities, and culture. This has guided museums in developing content and topic choices that can better attract and engage the interest and attention of social media users. It also provides insight into social media users' behaviors and preferences to pinpoint target audiences and deliver personalized content and interactive experiences.

Although this study provides an in-depth study of social media communication network analysis and influence communication model construction, there are still some limitations and directions that need to be further explored.

Data collection and sample selection: This study selected specific museums as case study subjects, and the selection of the sample may have an impact on the ability to generalize the findings. Future studies may consider selecting more museums of different types for comparison to obtain more comprehensive results.

Data privacy and ethical issues: There are data privacy and ethical issues involved in collecting and analyzing social media data. Future research needs to pay more attention to data privacy protection and ethical review, and take appropriate measures to ensure the security and legal use of data.

Accuracy and reliability of the model: This study proposed an influence propagation model, but the accuracy and reliability of the model still need further validation and optimization. Future research can combine more empirical data for model validation, and more detailed parameter adjustment and model improvement.

Cross-platform and cross-cultural comparisons: This study focuses on the dissemination of museums' influence on social media, but there may be differences in different social media platforms and cultural contexts. Future research can conduct cross-platform and cross-cultural comparative studies to explore the characteristics and mechanisms of influence dissemination in different platforms and cultural contexts.

Effectiveness assessment and impact measurement: This study can further delve into how to assess the effectiveness of museums' influence on social media. Future research can combine more metrics and methods, such as social media data analysis and user research, to comprehensively consider multiple dimensions and influencing factors of influence.

In summary, although this study has achieved some research results in the analysis of social media communication networks and the construction of influence communication models, there are still limitations and directions that need further in-depth exploration. Future research can overcome these limitations and combine more empirical data and methods to promote the further development of museum and social media communication research.

6. Conclusion

This study aims to explore the mechanisms and effects of museums' influence communication on social media platforms. Through social media communication network analysis and influential communication model construction, this paper provides insight into social media communication characteristics, museum network characteristics, user behavior and influential communication model. In the social media communication network analysis, this paper reveals the influential communication paths and key nodes of museums on social media, which provides an important basis for museums' promotion and communication strategy development. Through network topology analysis and user behavior analysis, this paper understands the audience groups, interests and preferences of museums on social media platforms. In terms of influence communication models, this paper reviews the traditional influence communication models and improves the models applicable to social media. By optimizing model parameters and validating model effects, this paper predicts and evaluates the effectiveness of museums' influence communication on social media. However, there are some limitations in this study. Limitations in data collection and sample selection may affect the ability to generalize the study results. The accuracy and reliability of the model still need further validation and optimization. The interpretation and discussion of the study results also require more empirical data and careful analysis. Future studies could further expand the scope of data collection and select more different types of museums for comparative studies. Model parameter optimization and validation can be combined with more empirical data for validation, and more detailed parameter adjustment and model improvement. Cross-platform and cross-cultural comparative studies and the comprehensive consideration of impact assessment indicators are also important directions for future research. In summary, this study explored in depth the mechanisms and effects of museums' influence communication on social media platforms. However, further research and improvements are needed to address limitations and to expand the depth and breadth of museum and social media communication research in more ways.

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