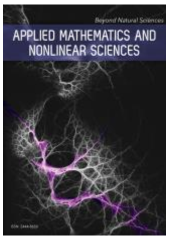
sciendo Applied Mathematics and Nonlinear Sciences, 9(1) (2024) 1-14



Applied Mathematics and Nonlinear Sciences

https://www.sciendo.com

Factors influencing communication power in new media innovation combined with multi-source data fusion analysis

Yiou Liu[1,†], Yingfei Huang[1], Haimin Huang[1], JiongZhao Chen[1], Ruomeng Liang[2]

1. Hunan International Economics University, Changsha, Hunan, 410000, China.
2. University of Leeds, Leeds, LS2 9JT, United Kingdom.

Submission Info

Communicated by Z. Sabir
Received January 29, 2023
Accepted May 15, 2023
Available online November 4, 2023

Abstract

This paper combines multi-source data and obtains effective data collection with higher value and richer knowledge connotations by cleaning, integrating, filtering, and transforming the original data. It also calculates the propagation characteristics of new media innovation, proposes the similarity of nodes, combines the propagation probability to construct the centrality degree and the near centrality expression, and analyzes the relationship of the propagation term that affects the new media innovation. The results show that when p takes 0.1, it is 13.8 and 14.15 seconds at 100 nodes and 500 nodes of new media innovations, indicating that the propagation time starts to extend gradually with the increase of p-value. The correlation between dissemination power and time in new media innovation incorporating multi-source data is demonstrated.

Keywords: Multi-source data; New media innovation; Valid data sets; Dissemination characteristics; Dissemination probability.
AMS 2010 codes: 68T05

†Corresponding author.
Email address: ninalyo610@126.com

ISSN 2444-8656
https://doi.org/10.2478/amns.2023.2.00973

1 Introduction

New media relies on Internet information technology and is supported by new technologies and ideas, including digital magazines, newspapers, radio, cell phone text messages, mobile networks, mobile media and other aspects. New media is not like traditional media forms such as newspapers, outdoor, radio, and television but is still closely connected. The distinctive feature of new media is that it dissolves the boundaries of traditional media, makes the reception and transmission of information more intelligent, and is an innovative media form based on digital technology and characterized by interactive communication, which is an inevitable trend in the degree of information dissemination [1-3]. Communication power is an affirmation based on the theory of communication science based on the developmental perspective of information dissemination. According to the statistics released by the World Creative Center for Cultural Industries, the application of digital technology has given rise to a brand new digital form, which widely plays a role in every corner of daily life and prompts the accelerated intermingling of cultures among various sectors of society [4-7].

The cohesion of communication power has become an important embodiment of the country's soft power and influence and has urgent communication value for leading the development of social opinion and media opinion form. As a form of communication, communication power can achieve the communication ability to influence the audience and society through different development paths, and at the same time, with the help of a variety of ways of communication, improve the inherent meaning of communication and realize the shaping and enhancement of new media by different communication subjects [8-10] As an information carrier with economic value, new media creates the space conditions that have the time and conditions of information transmission, as well as the space conditions that transmit the audience's psychological reaction. As a carrier of information and network technology, new media encompasses many digital media forms. Different communication elements accelerate the communication subject so that information collection, production, and integration form a new media transmission chain, bringing great changes to the communication subject [11-12].

Literature [13] comprehensively examined the impact of social media applications on the civic engagement behaviors of college and university students through a multilevel and multidimensional approach. The study looked at the use of mobile social media, the heterogeneity of communication networks, and the relationship between social capital and civic engagement and also explored the moderating role of belonging in this context. This study has significant and innovative value for gaining a deeper understanding of mobile social media use and the heterogeneity of communication networks. The study addresses a research gap concerning the most popular interactive communication medium and broadens related research topics. Literature [14], on the other hand, focuses on the political and cultural challenges local electronic music platforms face in Iran. This literature offers new perspectives and highlights the difference between these challenges and those of developed countries. This study explores the relevant issues early and in-depth through qualitative analysis, semi-structured interviews, and qualitative coding. The authors identified copyright challenges and government licensing barriers in digital music distribution as important constraints for digital music distributors to achieve lasting competitive advantage.

Literature [15] points out that with the growth of Internet users and the emergence of big data, organizations' workflow and subject structure have become increasingly complex. To address this challenge, the researcher used a three-way interactive research approach, combining qualitative and quantitative methods, to survey 140 media planners and explore the three dimensions of knowledge, tools, and technology. Through modern technology, these planners can skillfully utilize digital media planning tools, constantly innovate and analyze, and possess keen business insights and efficient cross-disciplinary collaboration skills. Literature [16] examines how mechanical sounds have evolved in today's pop culture and the impact of this evolution on intelligent voice assistance systems. By investigating aspects of film, television, and literature from Hollywood and other countries and incorporating previous experiences, the researcher uses existing modal roles and calling techniques to give sound social meaning to realize a positive impact on intelligent voice devices. The study proposes the smart microphone as a new media creation and influence system that relies on techno-linguistic interaction. Literature [17] explored the necessity of adopting a digital media interaction model with multi-sensory experience and interactivity to be better accepted by the general public in the new media environment. The literature uses Kinect infrared sensing to acquire motion data about Taiji culture and then blends it with Processing, a digital art creation platform, to create interactive images. An interactive feeling will be created for the audience, and, at the same time, Taijiquan culture will be promoted.

This paper combines multi-source data innovation with new media innovation to analyze the impact of communication power. Through the visualization of the data presentation, the multi-source data for the overview study can be transformed into accessible knowledge, the analysis of the influence factors of the communication power to calculate. Firstly, for the propagation characteristics of the propagation power to calculate, to solve the problem of randomness, to synthesize the structural attributes and intrinsic attributes of the nodes, and to calculate the similarity between the nodes. Secondly, the new media innovation data mining algorithm is used for identification and depth analysis, and the centrality and near-centrality calculation formula is proposed. Finally, the propagation process of communication power in new media innovation is analyzed, and the influencing factors of time and propagation transformation are calculated. And it is believed that the higher the computational complexity is, the higher the accuracy of simultaneous propagation is, and conversely, the lower the computational complexity is, the lower the accuracy of simultaneous propagation is. In the end, through parametric simulation experiments, it is verified that there is a correlation between dissemination power and marketing time in new media innovation with multi-source data.

2 Integration of data from multiple sources

2.1 Impact on dissemination

New media innovation is a communication medium for transmitting digital information relative to traditional media, based on digital technology, Internet technology, and mobile communication technology [18-19]. Under the environment of the new media digital era, the communication means, and methods of new media innovation have become more diversified, and the content of communication has become more comprehensive, which has assumed an important mission in social life and the analysis of the impact on communication power is outlined as shown in Table 1.

Table 1. Impact analysis of communication power

Opportunity analysis		Superiority Analysis	
New media innovations guarantee the possibility and enhancement of communication.	The innovative nature of new media technologies and their interaction with communication have had a positive impact on communication and have helped to strengthen it effectively.	New media innovations optimize communication.	The integration of new media technology and traditional media technology has changed the original communication path, forming a three-dimensional communication model with multiple paths and channels.
The interactive nature of new media drives the popularization and deepening of communication.	The interactive features of new media innovations can meet the needs of the general public, can be clearer and more straightforward, and the dissemination has achieved popularity.	New media innovations have enriched forms of communication.	The development of new media technology has changed the original communication environment and communication methods, and to a certain extent, it has promoted the progress of social culture.
The hyper-temporal nature of new media highlights the acceleration and broadening of communication.	Hyperspace functionality not only allows for the dissemination of scientific knowledge to the public in a very short period of time, but also greatly expands the space in which people can interact.	New media innovations have increased the efficiency of communication.	The discovery and development of new media technology is mainly combined with Internet technology, and therefore is equally characterized by convenience and speed.

2.2 Advantages of integrating data

In information science, data is defined as the result of facts or observations, a logical generalization of objective things, used to represent the raw unprocessed material of objective things, which can be in the form of text, numbers, images, video, language and other forms [20]. The DIKW model constructed by American educator Harlan Cleveland is shown in Figure 1. Specifically as follows:

1) Data is situated at the bottom level, and the three levels of information, knowledge, and wisdom progress upwards. The data will be processed in a certain way, and the information will be formed by organizing the data with logical connection, and the information will be screened, integrated, analyzed and refined. By combining experience with knowledge, people can solve more complex problems. The ability to predict the future results from the continued accumulation and application of knowledge in wisdom.

2) Data application obtains effective data before determining which data indicators to collect. And then capture these raw data through various research methods and techniques and store them in the data pre-processing of the collected raw data for cleaning and integration, filtering and transformation to improve the data quality so that it can meet the requirements of data analysis technology. With the help of graphical means, the conclusions of data analysis are transformed into an intuitive, easy-to-understand form for display, and the data can be transformed into accessible knowledge through visual data presentation. After the above layers of processing of the original data, you can get a collection of effective data that is smaller in data volume, higher in value and richer in knowledge content than the original big data.

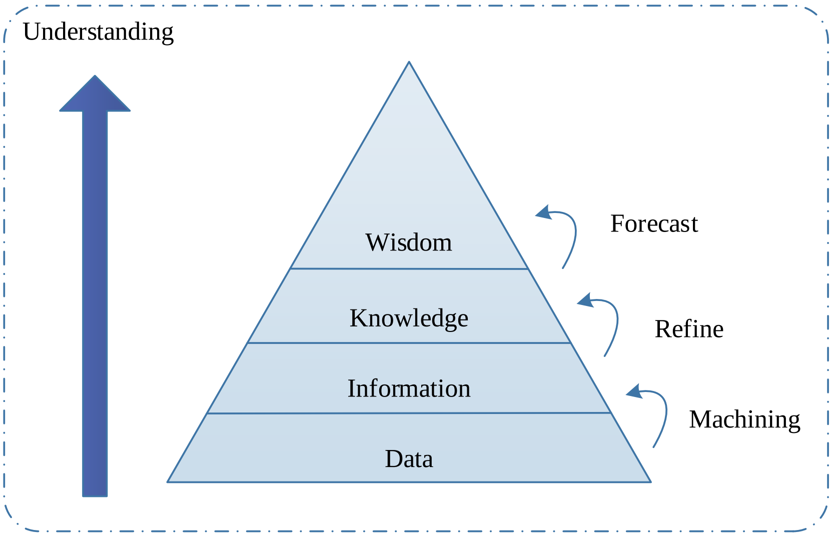


Figure 1. DIKW model

3 Communication power of new media innovations

3.1 Calculation of propagation characteristics

While the current algorithm considers the propagation characteristics of new media innovations by assuming that nodes are directly labeled by their neighboring nodes, this does not hold true in a real new media innovation network. Each node has both the ability to propagate labels and receive labels, and it is generally assumed that nodes with more influence have a stronger ability to propagate labels. Since influential nodes are less likely to receive influence, the receiving ability of influential nodes is weaker, so the formula is as follows:

$$k_{i\leftarrow j} = \frac{log\left(1+Inf_j\right)}{log\left(\left(1+Inf_i\right)\times\left(1+Inf_j\right)\right)} \tag{1}$$

Where the propagation characteristics k, $k_{i\leftarrow j}$ are the propagation characteristic metrics of the label from node j to node i.

is determined by the influence of nodes i and j, and in general $k_{i\leftarrow j} \neq k_{j\leftarrow i}$, when Inf_i is much smaller than Inf_j, $k_{i\leftarrow j} \approx 1$, suggesting that node i is highly likely to accept j 's label due to j greater influence. Conversely, when Inf_i is much larger than Inf_j, $k_{i\leftarrow j} \approx 0$, it means that i is more influential and node i is less likely to accept j 's label.

Realistic new media innovation networks not only have topological structure features, but also the intrinsic attributes of nodes in new media are easily accessible, so the attribute feature S of nodes contains two parts, which are structural attribute St and node intrinsic attribute In.

Therefore, in order to solve the randomness problem, the structural attributes and intrinsic attributes of the nodes are combined to jointly calculate the similarity between nodes, i.e., the similarity between i and j, which is calculated as follows:

$$S_{i,j} = St_{i,j} + In_{i,j} \tag{2}$$

Calculate the structural similarity of nodes i and j:

$$St_{i,j} = \frac{\left|\Gamma(i) \cap \Gamma(j)\right|}{\sqrt{\left|\Gamma(i)\right| \times \left|\Gamma(j)\right|}} \tag{3}$$

Where $\Gamma(i)$ denotes the set of all neighbors of node i with node i. $In_i = \{in_{i1}, in_{i2}, ..., in_{in}\}$ is the set of intrinsic attributes of node i, in_{ik} is the k th attribute value of node i, and N is the number of intrinsic attributes. Then the similarity $In_{i,j}$ of intrinsic attributes of nodes i and j is calculated as:

$$In_{i+j} = \frac{1}{N} \sum_{k=1}^{N} \zeta\left(in_{ik}, in_{jk}\right) \tag{4}$$

$$\zeta\left(in_{ik}, in_{jk}\right) = \begin{cases} 1, in_{ik} = in_{jk} \\ 0, in_{ik} \neq in_{jk} \end{cases} \tag{5}$$

The problem of misclassification can be avoided by extending the similarity between nodes to the similarity between nodes and communities, i.e., the similarity between node i and community A is calculated as follows:

$$S_{t,A} = \frac{1}{M} \sum_{j \in A} S_{t,j} = \frac{1}{M} \sum_{j \in A} \frac{\Gamma(i) \cap \Gamma(j)}{\sqrt{\left|\Gamma(i)\right| \times \left|\Gamma(j)\right|}} + \frac{1}{M \times N} \sum_{j \in A} \sum_{k=1}^{N} \zeta\left(in_{ik}, in_{jk}\right) \tag{6}$$

Where, M the total number of nodes in community A. During the label selection process, nodes always choose the community with the greatest similarity to themselves as their label.

3.2 Calculation of propagation probability

The label of node i propagates to node i with probability $P(i \leftarrow j)$, $P(i \leftarrow j)$ depending on nodes i and j similarity metric $S_{i,j}$, propagation characteristic metric $S_{i,j}$, and adjacency matrix $\delta(i, j)$, i.e.:

$$P\left(i \leftarrow j\right) = S_{i,j} \times k_{i \leftarrow j} \times \delta\left(i, j\right) \tag{7}$$

Where $S_{i,j} \in [0,1]$ denotes the relationship weights of nodes i and j, i.e., the attribute similarity between the nodes, and $k_{i \leftarrow j} \in [0,1]$ denotes the metric value of label propagation from node j to node i. δ is the adjacency matrix of $n \times n$, n is the total number of nodes, then $\delta(i, j)$ is represented as follows:

$$\delta\left(i, j\right) = \begin{cases} 1, \\ 0, \end{cases} \tag{8}$$

Where nodes i and j have connected edges, and $P(i \leftarrow j)$ has value in the range $[0,1]$, jointly determined by $S_{i,j}$, $k_{i \leftarrow j}$ and $\delta(i,j)$.

4 Multi-source data mining dissemination power

The set of items is $I = \{I_1, I_2, I_3, ..., I_n\}$, referred to as the itemset. When $n = k$, it is $n = k$ the item set $\{I_1, I_2, I_3, ..., I_k\}$. $T = \{t_1, t_2, t_3, ..., t_n\}$ denotes the transaction database, where any item t_i includes one or more items from the item set I.

The support of itemset X is denoted by $\sup(X)$, which is calculated as follows:

$$\sup(X) = \frac{Count(X)}{\|T\|} * 100\% \tag{9}$$

Where $Count(X)$ is the number of transactions in itemset X and $\|T\|$ is the total number of transactions. Denoting the case where events X and Y occur at the same moment as C, the confidence function $conf(\square)$ that generates the association rule $X \to Y$ is calculated as follows:

$$conf(X \to Y) = \frac{\sup(C)}{\sup(X)} = \frac{\sup(X \cap Y)}{\sup(X)} \tag{10}$$

If the support threshold minsupp and the confidence value minconf have been set beforehand, then in the transaction database T, if $\sup(X \to Y) \geq \min \sup p$ and $conf(X \to Y) \geq \min conf$, then $X \to Y$ is a strong association rule.

The data processing process based on the association rule mining algorithm mainly includes four steps: raw data acquisition, data preprocessing, data approximation and rule extraction. Among them, the data preprocessing steps include data cleaning, data integration, data transformation and data constraints. Data constraint is the process of data processing propagation using fuzzy sets, for an information system, there is at most $C_n^{n/2}$ constraint on its attributes.

The new media intelligent mining algorithm is used for identification and in-depth analysis. The degree of connectivity indicates the total number of likes, comments, and retweets received by the user's posting. The higher the degree of connectivity indicates the more popular the user's posting is, i.e., the greater the user's influence and the degree of connectivity is calculated by the number of edges pointing from one node n_i to the other nodes n_j.

Intermediary centrality refers to the number of times a node acts as a bridge for the shortest path between two other nodes. The higher the number of times a node acts as an intermediary, the greater it is intermediary centrality, i.e., the greater the influence of that user, and the intermediary centrality calculation formula is shown below:

$$C_B(n_i) = \sum_{j,k \in V} \frac{g_{jik}}{g_{jk}} \tag{11}$$

Where g_{jik} is the number of paths from point j to point k whose shortest path passes through point i, and g_{jk} is the number of shortest paths from point j to point k.

Proximity centrality refers to the average length of the shortest circuit from each node n_i to the other nodes n_j, the closer it is to the other nodes, the higher its centrality is, i.e., the greater the influence of the user, and the proximity centrality is calculated by the following formula:

$$C_c(n_i) = \sum_{j=1}^{n} \frac{1}{l(n_i, n_j)} \tag{12}$$

5 Dissemination processes in new media innovations

In a new media network, set $N(A)$ denotes the set of all individuals who receive A published messages, $TMsg(A)$ denotes the number of messages published by individual A, and $TMsg(A,B)$ denotes the number of messages forwarded by individual B to individual A. Now suppose that individual A publishes a message, which is transformed into a feature vector Msg by the generalization method of multi-source data, and then the message feature vector and individual attributes are used to calculate the message forwarding probability $Tr(A, Msg)$ as follows:

$$Tr_{local}(A, Msg) = \frac{1}{2}\left(\frac{M_{trans}(A)}{M_{local}(A)} + \frac{\sqrt{A+Msg}}{\sqrt{A^2+Msg^2}}\right) \tag{13}$$

Where $M_{trans}(A)$ denotes the number of messages posted by individual A and forwarded by other individuals, and $M_{lotal}(A)$ denotes the total number of messages posted by individual A.

Based on the probability that a message posted by Individual A is forwarded, combined with the trustworthiness of Individual A in the entire category, the probability that a message posted by a person with A is propagated within their category Cstr is:

$$\operatorname{Pr} o_{local}(A, Msg, Cstr) = Tr_{local}(A, Msg) Trust(A, Cstr) \tag{14}$$

Assuming that the number of individuals in category $Cster$, in which A is located, is $|Cster|$, the propagation range of the message posted by A, i.e., the number of individuals receiving the message, is the mathematical expectation:

$$\begin{aligned} Num_{local}(A, Msg, Cstr) &= |Cstr| \times \operatorname{Pr} o_{local}(A, Msg, Cstr) \\ &= |Cstr| Tr_{local}(A, Msg) Tr_{local}(A, Cstr) \end{aligned} \tag{15}$$

The entire new media innovation network can be divided into n categories based on the attributes, each category has an attribute vector of $Cstr_i\,(1 \le i \le n)$. For a message Msg category $Cstr_j$ posted by an individual A from $Cstr_i$ the similarity is:

$$Tr_j\left(Cstr_j, Msg\right) = \frac{1}{2}\left(\frac{M_{trans}\left(A, Cstr_j\right)}{M_{local}\left(A\right)} + \frac{\sqrt{Cstr_j + Msg}}{\sqrt{Cstr_j^2 + Msg^2}}\right) \tag{16}$$

Where $j \neq 1$, $M_{trans}\left(A, Cstr_j\right)$ denote the number of messages posted by A that are forwarded by individuals in $Cstr_i$. The probability that a message posted by A is propagated in $Cstr_j$ is:

$$\Pr o_{glocal}\left(A, Msg, Cstr_j\right) = Tr_j\left(Cstr_j, Msg\right) Trust\left(Cstr_i, Cstr_j\right) \tag{17}$$

Similarly, the number of individuals in $Cstr_j$ who received the message Msg from A is as follows:

$$\begin{aligned} Num_{glocal}\left(A, Msg, Cstr_j\right) &= \left|Cstr_j\right| \times \Pr o_{glocal}\left(A, Msg, Cstr_j\right) \\ &= \left|Cstr_j\right| Tr_j\left(A, Msg\right) Trust\left(Cstr_j, Cstr\right) Cstr_j \end{aligned} \tag{18}$$

Therefore the range of dissemination power in the whole new media innovation network, i.e., the sum of the number of disseminations in the individual categories, so the following formula:

$$Num\left(A, Msg\right) = \sum_{1s/sn,\{\neq\}} Num_{glocal}\left(A, Msg, Cstr_j\right) + Num_{glocal}\left(A, Msg, Cstr\right) \tag{19}$$

For each message Msg, the vector after the data statute should be selected with a specific number of options, considering both computational complexity and, at the same time, propagation accuracy. When Msg statute has more options, the computational complexity is higher, the propagation accuracy is higher at the same time, and vice versa, the computational complexity is lower, and the propagation accuracy is lower at the same time.

6 Analysis of the results of the impact of the probability of dissemination

To simulate the effect of the dissemination power of the new media innovation node-set, the top k 4 index rankings were selected for the experiment, k taking 10, 20,..., 100 and, 200, ..., 1000 nodes as new media innovation nodes, and use multi-source data analysis as new media innovation dissemination effect simulation, Figure 2 shows the new media innovation node set dissemination effect comparison results chart. As can be seen from the data, each indicator shows that with the increase of the new media innovation node-set, the scope of dissemination is gradually expanded. When the value k is below 70, the spreading effect of the four indicators shows a more obvious advantage. When the value k exceeds 70, it is gradually overtaken and then alternately leads, and when the number of new media innovation node sets increases, the spreading effect of the dataset is closer. On the contrary, the new media innovation node-set selected by the structural hole indicator has the most obvious tendency of gradually expanding the dissemination scope with the increase of the number, and the dissemination effect is gradually superior to other indicators when the value k reaches 90. Close to the centrality indicator, when the number of new media innovation node sets increases, the dissemination effect it gets is worse compared with the other three indicators.

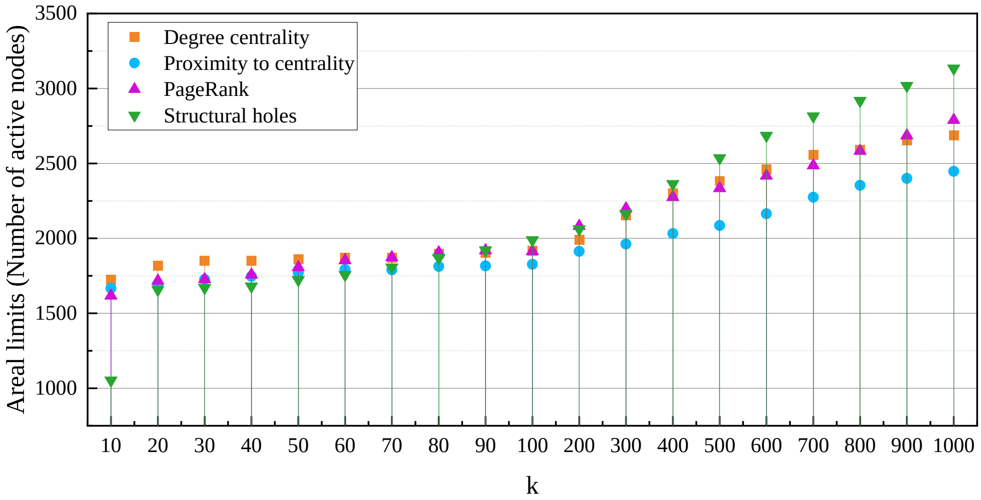
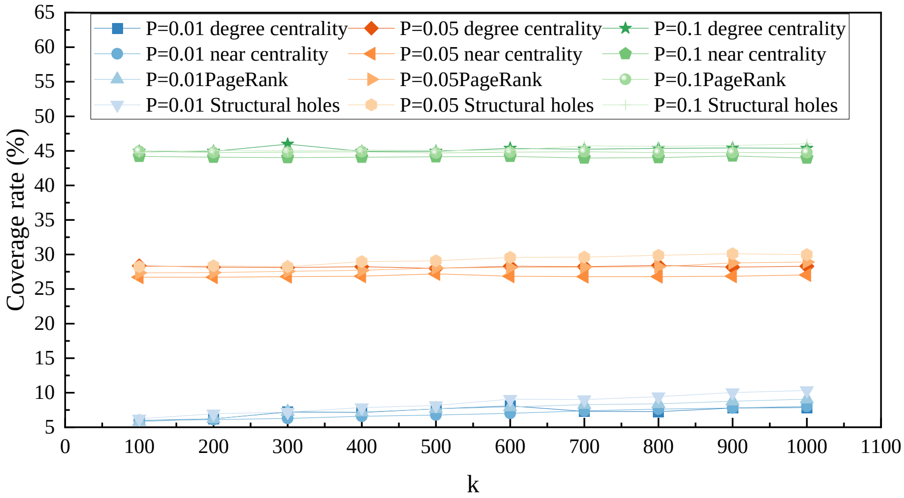


Figure 2. Comparison of the propagation effect of the seed node set of 4 indicators

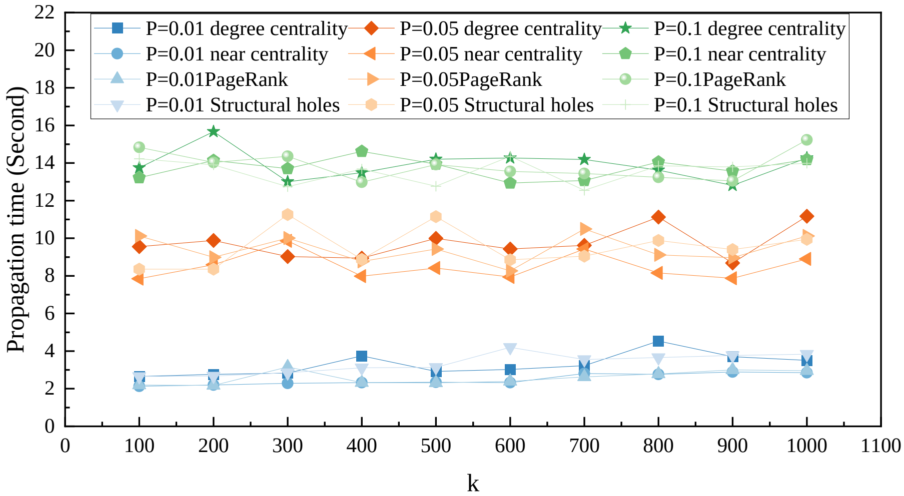
In multi-source data analysis, the value of the propagation probability p has an impact on the propagation effect, and the propagation probability between two nodes in the propagation process usually uses the random assignment method, which sets a probability set P, and then randomly selects a probability value from the set P as the propagation probability between the two nodes. To make the experimental results consistent, the above experiments use fixed propagation probability p=0.01. Therefore, the new media innovation dissemination effects of multi-source data under p=0.01, p=0.05 and p=0.1 were compared, respectively, and to make the result comparison consistent and obvious, the effect of dissemination power adopts the coverage rate as an evaluation index, i.e., the ratio of the final activated active nodes to the total number of nodes. The dissemination efficiency is also when the research of multimedia innovation dissemination power focuses on the factors to consider, the four kinds of indicators in different dissemination probability p under the dissemination time comparison can get the dissemination effect and the dissemination efficiency as shown in Figure 3.

Figure 3(a) shows the results of comparing the spreading effect of different probabilities of spreading. The overall results indicate that the spread of the new media innovation nodes increases as p increases. When p takes the value of 0.01, the average coverage of active nodes is about 8.1%. When p takes the value of 0.05, the average coverage of active nodes is about 28.2%. When p takes the value of 0.1, the average coverage of active nodes is about 44.9%. As for the specific indicators, the structural hole indicators have the best propagation effect under different propagation probabilities p, and this advantage shows a trend of gradually expanding with the increase of p-value. Degree centrality and PageRank have similar dissemination effects when p takes the values of 0.01 and 0.05, while the dissemination effect of the PageRank indicator starts to be gradually superior to that of the degree centrality indicator when p takes the value of 0.1. The set of new media innovation nodes close to the centrality index gradually increases the spreading effect as the spreading probability p increases. However, when the value of p is 0.05 and 0.1, as the number of new media innovation node sets increases, the dissemination effect it gets tends to be flat or even slightly decreases, and the dissemination effect is poor.

Figure 3(b) shows the results of the comparison of the propagation efficiency with different propagation probabilities p. It can be seen from the resultant data that, as far as the propagation time is concerned, when the value of p is small, the range of node propagation in new media innovation is small, and when the value of p is taken to be 0.01, the propagation time of proximity centrality is 2.4 seconds, and the propagation time of the structural holes is 2.45 seconds, which indicates that the propagation time is shorter. When p takes the value of 0.1, the degree centrality is 13.8 seconds at 100 nodes of new media innovations, 14.1 seconds at 500 nodes of new media innovations, and 14.15 seconds at 500 nodes of new media innovations, indicating that the propagation time starts to be gradually prolonged with the increase of p-value. However, with the increase in the number of new media innovation node sets, propagation time does not show a strong regularity, the propagation time of each indicator new media innovation node set shows a fluctuating curve, and the difference in the propagation efficiency of each indicator under the same propagation probability p is not obvious.



(a) Comparison of the propagation effects for different propagation probabilities p



(b) Comparison of propagation efficiency with different propagation probabilities p

Figure 3. Analysis of different propagation probabilities of propagation forces

7 Analysis of the impact of time on communication power

First, the effect of time on the three influence propagation terms is verified, and three influence propagation terms are proposed to optimize the probability. Firstly, the three propagation terms are verified to be inextricably linked with time, as well as the relationship between time and each influence propagation term, respectively, thus then take the relationship of verifying the parameter changes. It took five nodes to do two sets of experiments to verify the time and propagation term relationship, as shown in Table 2. The activity, propagation, and social connections are constantly changing with the change of marketing time. These two sets of experiments demonstrate that activity is not proportional to time. The 5-node parameter is 0.4, the 15-node parameter is 0.51, and the 25-node parameter is 0.45, which aligns with the life scenarios on a new media social networking site. It may be active at certain times and less active at certain times, but it will stabilize at a value after some time. The social network, on the other hand, increases with time, showing a process of growth to leveling off and then slightly decreasing, gradually converging to a value, but the total number of people does continue to increase, and we can see such a process from the experimental way. Propagation power changes constantly with time. The parameters of group A are 0.31, 0.39, 0.4, 0.62, 0.67 in order, and the parameters of group B are 0.24, 0.43, 0.54, 0.59, 0.6 in order, which is mainly related to the behavioral situation of different users, so there is not much of a trend change. Therefore, the three influencing communication terms, activity, communication power and social connection, are all inextricably linked to time. Multi-source data has shown that communication power correlates with marketing time in new media innovation.

Table 2. Time and propagation term parameter changes

Marketing time		Group A		Group B		
	Activity	Communicative power	Social Connections	Activity	Communicative power	Social Connections
5	0.40	0.31	0.21	0.20	0.24	0.10
10	0.60	0.39	0.27	0.32	0.43	0.22
15	0.51	0.40	0.42	0.43	0.54	0.32
20	0.53	0.62	0.43	0.45	0.59	0.43
25	0.45	0.67	0.41	0.42	0.60	0.41

8 Conclusion

In this paper, we analyze the impact of new media innovations on dissemination power by combining multi-source data. The raw data layers are processed to obtain an effective data set with a smaller data volume, higher value, and richer knowledge connotation. The randomness of dissemination is solved by calculating the dissemination characteristics of new media innovations, and the similarity of nodes can be calculated by combining the dissemination probability. The new media innovation data mining algorithm is used to construct the centrality degree and the near centrality calculation formula, confirming the calculation's complexity and the propagation's accuracy. Finally, through simulation experiments, the effect of the propagation power of the new media innovation node set is simulated, and the results show that the propagation effect shows a more obvious advantage when the value of k is below 70, and the propagation effect is gradually superior to the other indexes starting from when the value of k reaches 90. Then, the analysis of the influence of propagation probability on the propagation effect was carried out, and the results show that when p takes the value of 0.05, the average coverage rate of active nodes is about 28.2%, and as the value of p increases, the propagation time begins to extend gradually. The parameter change with the propagation term in the new media innovation combining multi-source data demonstrates the correlation between propagation power and time.

Funding:

This research was supported by the 2021 Hunan Provincial Education Research and Reform: Research and Practice on the Construction of Network and New Media Majors (HNJG-2021-1031).

Reference

[1] Yu, X. (2022). Construction of an innovative development model of intelligent media under the coverage of a wireless sensor network. Mathematical Problems in Engineering, 2022.

[2] Meisner, C., & Ledbetter, A. M. (2022). Participatory branding on social media: the affordances of live streaming for creative labor:. New Media & Society, 24(5), 1179-1195.

[3] Lee, S., & Xenos, M. (2022). Incidental news exposure via social media and political participation: evidence of reciprocal effects:. New Media & Society, 24(1), 178-201.

[4] Sujon, Z., Dyer, H. T., & Schwartz, M. (2020). Book review: transmitted wounds: media and the mediation of trauma:. New Media & Society, 22(7), 1324-1326.

[5] Morata, T. C. (2021). Expanding communication of acoustical knowledge around the globe: examples of outreach and the use of social media. The Journal of the Acoustical Society of America, 149(4), A124-A124.

[6] Guo, L., Liao, L., Li, D., & Liu, C. (2021). Understanding the highly sensitive health communication behavior in social media from the perspective of the risk perception attitude framework and perceived interactivity. International Journal of Computational Intelligence Systems, 14(1), 922.

[7] Uszczki, E., Bartosiewicz, A., Bobula, G., Kuchciak, M., & Katarzyna Dereń. (2021). New media development, sleep and lifestyle in children and adolescents. Sustainability, 13(4), 2248.

[8] Tugtekin, E. B., & Koc, M. (2020). Understanding the relationship between new media literacy, communication skills, and democratic tendency: model development and testing:. New Media & Society, 22(10), 1922-1941.

[9] Zhu, G. (2023). Scene classification based on heterogeneous features of multi-source data. Remote Sensing, 15.

[10] Schneider, J. (2018). New media pharmacology: hansen, whitehead, and worldly sensibility. Theory Culture & Society, 36(1), 026327641880699.

[11] Knox. (2020). Digital lab africa, 2016–19: emerging contours of african new media narrative publishing landscapes. Research in African Literatures, 51(1), 133.

[12] Pavlov, A. K., Meyer, A., R?Sel, A., Cohen, L., King, J., & Itkin, P., et al. (2018). Does your lab use social media? sharing three years of experience in science communication. Bulletin of the American Meteorological Society, BAMS-D-17-0195.1.

[13] Kim, Y., & Kim, B. (2022). Effects of young adults' smartphone use for social media on communication network heterogeneity, social capital and civic engagement. Online Information Review, 46(3), 616-638.

[14] Omidi, A., Zotto, C. D., Norouzi, E., & José María Valero-Pastor. (2020). Media innovation strategies for sustaining competitive advantage: evidence from music download stores in iran. Sustainability, 12.

[15] Perlado-Lamo-De-Espinosa, M., Natalia Papí Gálvez, & María Bergaz-Portolés. (2019). From media planner to media expert: the digital effect in advertising// del planificador de medios al experto en medios: el efecto digital en la publicidad. Comunicar, 2(59).

[16] Rmen, J., Helles, R., Jensen, K. B., Humphry, J., & Chesher, C. (2021). Preparing for smart voice assistants: cultural histories and media innovations: New Media & Society, 23(7), 1971-1988.

[17] Geng, L., & Cao, L. (2019). Design practice of interactive imaging art in the new media art-taking "ink-wash tai chi" as an example. MATEC Web of Conferences, 277, 02023.

[18] Taijun, J., & Jing, Y. (2020). Teaching of practice innovation of new media interactive for art design training in college. International Journal of Electrical Engineering Education, 002072092094444.

[19] Wen, Y. (2021). How to use new media technology to avoid media ethics anomie. Procedia Computer Science, 183, 833-836.

[20] Kim, H., Shin, H. H., & So, K. K. F. (2022). Actor value formation in airbnb: insight from multi-source data. International Journal of Contemporary Hospitality Management, 34(7), 2773-2797.