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Quantitative Study on the Communication Effectiveness of Changsha City Brand Image from “Online Star City” to “Long-term Famous City” Based on Big Data Regression Modeling

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ABSTRACT

This paper constructs an improved Changsha city brand image communication model on the basis of the traditional contagion model, and studies the communication effect of Changsha in the process of city brand image transformation from “online star city” to “long-term famous city”. By summarizing and analyzing the current situation of Changsha's city brand image communication, the evaluation index system of Changsha's city brand image communication effectiveness is constructed, and the collected evaluation index data are downscaled using principal component analysis. The support vector regression machine combined with differential evolution algorithm is used to quantitatively analyze the communication benefits of Changsha city brand image. The improved city brand image communication model in this paper has a higher accuracy compared with the traditional contagion model, and can accurately grasp the communication effect of Changsha city brand image. The average relative error of the support vector regression machine model in the quantitative analysis of communication benefits for the test samples from 2020 to 2023 is only 1.53%, which is 27.86% lower than that of the BP neural network model. It strongly demonstrates the effectiveness of the regression model selected based on the communication big data in this paper, and provides a useful reference for accurately measuring the communication benefits of Changsha's city brand image.

Keywords: city brand image, infectious disease model, principal component analysis, support vector regression machine, differential evolution, communication benefit

1. Introduction

In the 21st century, under the background of economic globalization and regional integration, in order to obtain greater economic benefits and growth potential, many Chinese cities have begun to explore the development path of city branding, and they have constructed their own city brands to disseminate

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a good city image, and the strategy of city branding has gradually become a new way of thinking for the revitalization and development of cities at all levels. Although there are many successful examples of city branding in China, there are also confusing scenes such as the convergence of brand construction, serious homogenization competition, and simple understanding concepts and strategies [1-2]. City brand is the most concentrated embodiment of the city image, how to shape and spread the city brand, so that a city's image value-added, is the city branding practice urgently need to solve the problem [3-6]. Therefore, the establishment of a scientific concept of city brand communication and the correct planning and implementation of city brand communication strategy have become a theoretical and practical issue in city brand communication.

Changsha is the capital of Hunan Province and one of the first 24 famous historical and cultural cities announced by the State Council of China. In order to implement the Hunan Provincial Party Committee and Provincial Government's goal of "developing cultural industry and building a strong cultural province", the Changsha Municipal Government has put forward the development goal of making Changsha a regional cultural center city in central China, and making Changsha an international cultural city. However, at present, the actual foundation of Changsha's soft power is better than its communication image. How to strengthen the image communication power and enhance the cultural appeal based on the full development of soft power has become the main task for Changsha to enhance its core competitiveness at present [7-9].

Existing information cycle theory shows that the evaluation of the communication effect of urban image plays a bridging role in communication activities, and can provide an important basis for new communication activities through the evaluation and reflection of existing communication activities [10-13]. However, for a long time, due to insufficient technical support and cost consumption and other factors, there is a relative lack of evaluation of the communication effect of urban image [14-15]. Nowadays, advances in database technology, network information access and big data analysis technology have been able to facilitate the quantitative analysis of communication content, which can accurately present the degree of audience attention concentration of different contents and improve the effectiveness of communication effect assessment of city brand image [16-17].

Through the statistical analysis of the NOW corpus, this paper visualizes Changsha's city brand image of "Online Star City" and "Long-term Famous City" from 2010 to 2023. Weak immunizer nodes and immunizer nodes are added to the traditional infectious disease model to construct the improved Changsha city brand image communication model in this paper. Based on the importance of social trust to the communication of city brand image, this paper integrates the audience trust mechanism in the communication model. The differential dynamics equations of the model are constructed, and the model is simulated and analyzed in Matlab platform to study the influence and role of psychological trust coefficients and other factors on Changsha city brand image communication. Construct the evaluation index system of Changsha city brand image communication benefit in line with the communication characteristics, and calculate the cumulative variance contribution rate of each index using principal component analysis. The principal components in the indicators are selected according to the criteria of eigenvalue greater than 1 and cumulative contribution rate greater than 80% to realize the dimensionality reduction of the evaluation indicators. The support vector regression machine is used to perform linear regression on the communication big data collected in this paper in the feature space, and the differential evolution algorithm is used to optimize the model of the support vector regression machine to improve the prediction accuracy of the regression model. The communication data from 2010-2019 is used as a training sample, and the data from 2020-2023 is used as a test sample to quantitatively predict the communication benefits of Changsha city brand image, and the results are compared with the BP neural network to highlight the effectiveness of the quantitative model in this paper.

2. Changsha City Brand Image Exploration

2.1. Statistics

The corpus used in this study is NOW, which contains data on 13.4 billion words originating from online newspapers and magazines from 2010 to the time of writing. The volume of data in this corpus grows by about 130 to 180 million words per month (about 250,000 new articles) and about 1.8 billion words per year. A search of the NOW corpus revealed that between January 1, 2010 and December 31, 2023, “Changsha” appeared a total of 5,471 times. Then, this study conducts a quantitative analysis, which covers the distribution of coverage time, coverage country, collocation search, coverage tendency, etc., aiming at exploring the discourse characteristics, writing style, and attitudes and evaluations towards Changsha in news reports involving Changsha, in the hope of fully recognizing and understanding Changsha's city brand image as shaped by the media, and building a solid foundation for the communication of Changsha's city brand image.

2.1.1. Frequency distribution of reports. Based on the big data regression model, the statistical distribution of the frequency of media reports about Changsha is shown in Figure 1. From the figure, it can be seen that the frequency of media reports about Changsha's city brand image increased sharply from 2012 to 2016 after a slow growth in 2010 and 2011, with the number of frequencies increasing from 102 to 525. There was a brief decline in the frequency of reports in 2016-2017, but out of the beginning of 2017 to 2023, reports about Changsha's city brand image continued to grow, and by 2023 the frequency of reports had increased to 705 times. As mentioned earlier, from 2010 to 2023, media reports on Changsha's city brand image totaled 5,471 times, and the fitted curve shows that the frequency of such reports shows a significant growth trend. In the future, there will be a higher frequency of reports about Changsha's city brand.

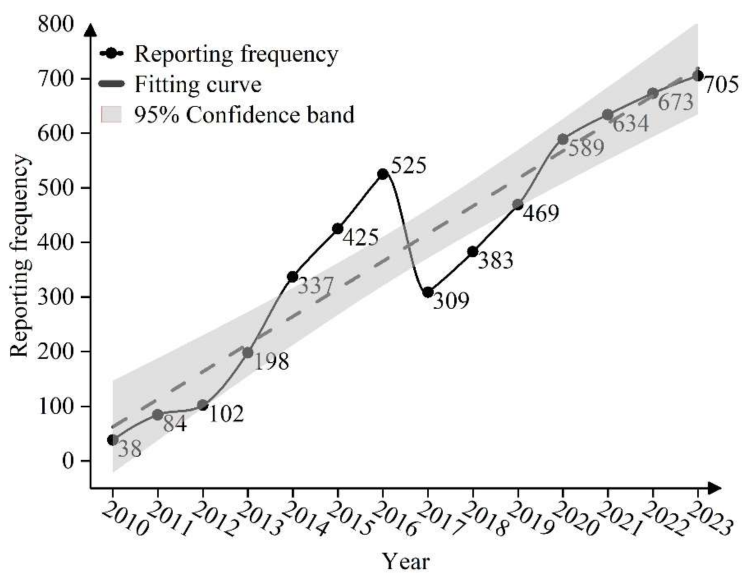


Fig. 1. Frequency distribution of reports

2.1.2. Distribution of countries covered. The geographic distribution of countries reporting on Changsha's city brand image internationally from 2010-2023 is shown in Figure 2. As can be seen from the figure, the country that reported the most about Changsha's city brand image in 14 years is Singapore, with 674 times. The second is the United States with 402 times. The Philippines came third with 349 reports. The UK and Malaysia followed with 217 and 198 reports respectively. The international coverage of Changsha will significantly benefit the communication of Changsha's city brand image and increase the effectiveness of Changsha's city brand image communication.

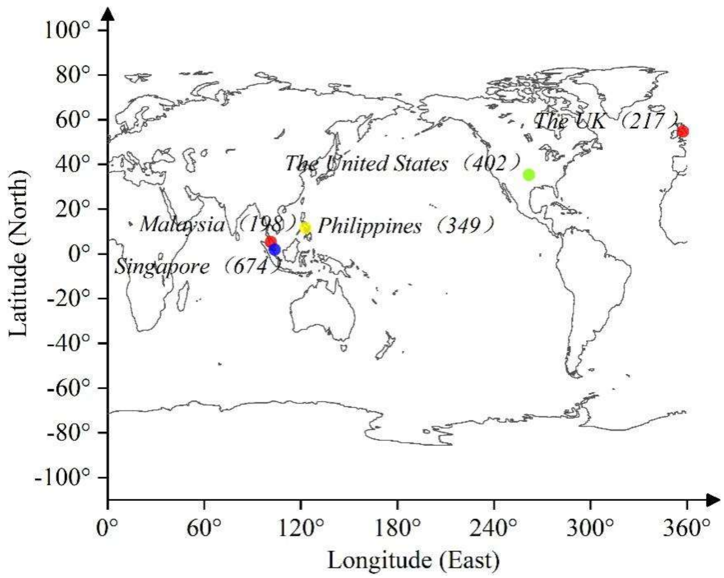


Fig. 2. International distribution of reports

2.1.3. Matching Search. In this paper, "Changsha" is used as the node word (node), and the word span is set to 5 left and 5 right, and finally the top 15 nouns with "Changsha" are counted, and the results are shown in Figure 3. The high-frequency words collocated with "Changsha" include China, Hunan, city, province, provincial capital, center, Asia, FIBA, IFC, champion and so on.

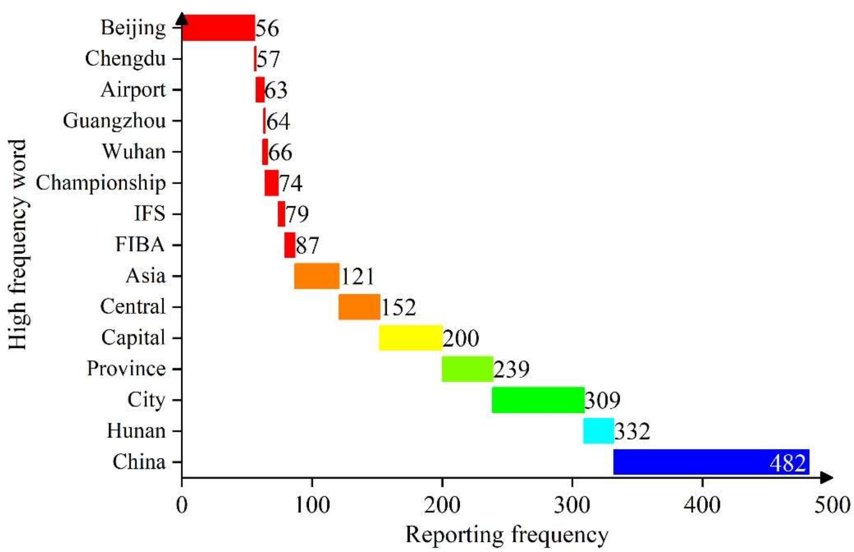


Fig. 3. High frequency words with Changsha

2.2. Theoretical analysis

In addition to data analysis, this section will adopt discourse analysis theory to conduct textual close reading, which is dedicated to digging out the ideology, value system and narrative mode behind the news reports, in order to reveal which Changsha city brand image has been shaped by the news reports, and how it has been shaped. Through the above data analysis, supplemented by textual close reading, this paper finds that the following three Changsha city brand images have been shaped by the media in recent years.

2.2.1. Active hosting of international sports events. The 2015 FIBA Asia Basketball Championship and the 2019 FIBA Triple Basketball Asia Cup were held in Changsha. According to the collocation search, FIBA is collocated with Changsha 87 times, and Championship is collocated with Changsha 74 times. A close reading of the relevant texts reveals that the overseas media reported the two international events held in Changsha in a relatively objective manner. As a result, the reports have successfully shaped Changsha's brand image as a city that "actively hosts international sports events" in the process of dissemination.

2.2.2. Online Star City. The results of the collocation search show that the frequency of collocation between IFS and Changsha is high, with a specific number of 79. The data show that Changsha and the IFS are significantly related at the level of international public opinion, which is an important direction for the media at home and abroad to shape Changsha's international image. A close reading of the texts reveals that media reports on IFS in recent years have focused on art, economy, tourism and other areas, which have significantly enhanced Changsha's attractiveness on the Internet, making Changsha a veritable "online star city".

The collocation search results also show that the high-frequency city nouns collocated with Changsha include Wuhan (66 times), Guangzhou (64 times), Chengdu (57 times), Beijing (56 times), Chongqing (53 times), Shanghai (50 times), and Shenzhen (47 times). This shows that Changsha has a more significant correlation with Wuhan, Guangzhou, Chengdu, Beijing, Chongqing, Shanghai and other major Chinese cities at the international public opinion level. This is a good indication that Changsha has relatively frequent cooperative interactions with major Chinese cities such as Wuhan, Guangzhou, Chengdu, Beijing, Chongqing, and Shanghai in the areas of trade, sports, culture, and arts. These interactions have spread Changsha's natural and humanistic landscapes, promoted Changsha's unique culture on a national and global scale, greatly enhanced Changsha's visibility in China and internationally, and successfully created Changsha's brand image as the "City of Changsha".

3. Changsha city brand image communication model

For the shaped city brand image, making it known to more people through communication is an important means to improve the communication effectiveness of Changsha's city brand image. Social trust will have a significant impact on the communication process and behavior of Changsha city image, and to a certain extent, it determines the communication coverage of the city brand image. Therefore, this section will construct a Changsha city brand image communication model integrating the audience trust mechanism to provide data support for quantifying the brand image communication benefits.

3.1. Communication of the city's brand image

The previous communication model based on the infectious disease model [18] has three kinds of audience nodes: the communicators, the healthy and the immune, but the communication model consisting of only these three kinds of nodes cannot exactly reflect the complex information dissemination pattern of the city brand image as well as the information dissemination mode and law in the model. Therefore, this paper improves the SEIR model and integrates the social trust network to propose a new communication model of city brand image - SEIRO model. In the process of city brand image dissemination, each node represents each type of audience in the platform, and the line represents the relationship between each type of audience. Audience can add friends by associating cell phone number address book, QR code scanning, associating QQ friends, etc., while friends can obtain each other's spreading message through the dynamics released by both parties' friend circle, and copy and forward it and share it to the friend circle according to psychological trust or their own willingness, so that the message will be continuously shared and spread.

3.2. Modeling

Changsha city brand image communication model belongs to the complex network structure model, based on the complex network model has a small world effect and scale-free effect, simulating the propagation of information in the complex network. The city brand image communication process is modeled, and the obtained brand image communication model is divided into five types of audience nodes (hereinafter referred to according to the type of nodes): unknown audience node S (relevant information has not yet appeared in the circle of friends of the audience node, i.e., there is a probability of contacting the brand image information), potential audience node E (relevant information has appeared in the circle of friends of the audience node, but due to the continuous updating of the information in the circle of friends, the audience node may not see this information), spreading audience node I (relevant information has appeared in the circle of friends of the audience node, but because the information is constantly updated, so that it may not see this information), dissemination audience node I (this audience node indicates that there are a number of audience nodes with dissemination ability in the potential audience node that believe in the information released from its circle of friends), immunity audience node R (this node indicates that there are a number of nodes in the potential audience node that do not believe in the brand image information), and exit audience node O (this node indicates that the dissemination audience node that has already disseminated the information has later transformed into an exit audience node). A Changsha city brand image communication system is established based on five types of audience nodes as shown in Fig. 4, and the communication model follows the following communication rules:(1) When the unknown node S comes into contact with the propagation node I with contact rate μ_1, the unknown node S is transformed into the potential node E with probability 1. (2) Potential node E has two transformation directions, one is to transform into propagation node I at infection rate μ_2. The other is to transform into immunization node R at immunization rate μ_3. (3) After propagation node I has propagated the message once, it transforms into exit node O with exit rate $\mu_6 = 1$. (4) When propagation node I comes in contact with immune node R, it transforms into immune node R with strong immunity rate $\mu_5=1$. (5) The former state is that the potential node's immune node R will not be permanently immune and will transform at an immune propagation rate μ_4 into a propagating node I. The propagating node continues to transform at an exit rate $\mu_6=1$ into an exit node O after propagating the message.

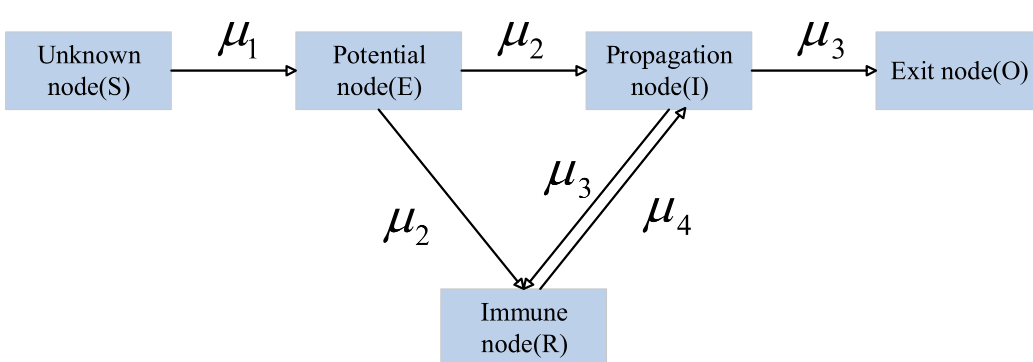


Fig. 4. Propagation model node state transformation

According to the node state transition in the Changsha city brand image communication model in the figure, set the number of audience as N, and divide the audience nodes in the moment t of the city brand image communication model into unknown node $S(t)$, potential node $E(t)$, propagation node $I(t)$, immune node $R(t)$, and exit node $O(t)$. At this time, it meets the requirements of $S(t)+E(t)+I(t)+R(t)=N$. According to the propagation principle of the communication model, the following differential dynamics equations can be constructed by integrating the psychological trust coefficients of the audience:

$$\frac{dS(t)}{dt} = -\mu_2 S(t)I(t) \tag{1}$$

$$\frac{dE(t)}{dt} = \mu_1 S(t)I(t) - (\mu_2 + \mu_3)E(t) \tag{2}$$

$$\frac{dI(t)}{dt} = \mu_2 E(t) + \mu_4 R(t) - I(t) \tag{3}$$

$$\frac{dR(t)}{dt} = (\mu_5 + \mu_6)I(t) \tag{4}$$

$$\frac{dO(t)}{dt} = \mu_6 I(t) \tag{5}$$

$$\mu_3 = a_1 - b_1 e^{-\delta_1 I(t)} \tag{6}$$

$$\mu_5 = a_2 - b_2 e^{-\delta_2 I(t)} \tag{7}$$

$$\mu_1 = \frac{\lambda S(t)}{1 + \alpha S(t)} \tag{8}$$

Where $\mu = a - be^{-\delta I(t)}$ is the interest decay, a is the maximum decay rate, and b is the adjustable decay coefficient. λ is the audience increase rate, α is the audience psychological trust coefficient.

3.3. *Model propagation threshold solving*

According to the theory of communication dynamics, there exists a communication threshold R_0, i.e., the basic regeneration number, in the corresponding system based on the communication model, which determines the communication posture of Changsha city brand image among audiences. When $R_0 \le 1$, the city brand image will gradually disappear. On the contrary, when $R_0 > 1$, the city brand image communication will persist in a certain area.

Let $X = (E, I, R, S, O)^T$, from the established differential dynamics equation:

$$\frac{dX}{dt} = F - V \tag{9}$$

Among them:

$$F = \begin{bmatrix} \varepsilon S_1 I_1 + \beta S_1 \\ (\delta + \alpha)S_1 + (\lambda + \alpha)I_1 \end{bmatrix} \tag{10}$$

$$V = \begin{bmatrix} (\lambda + \alpha + \mu_1)I_1 \\ \mu_1 R_1 \end{bmatrix} \tag{11}$$

The Jacobian matrix is obtained for F, V:

$$J_F = \begin{bmatrix} \varepsilon S_1 & 0 \\ \lambda + \alpha & 0 \end{bmatrix} \tag{12}$$

$$J_V = \begin{bmatrix} \lambda + \alpha + \mu_1 & 0 \\ 0 & \mu_1 \end{bmatrix} \tag{13}$$

So there:

$$J_V^{-1} = \frac{1}{(\lambda+\alpha+\mu_1)}\begin{bmatrix} \mu_1 & 0 \\ 0 & \lambda+\alpha+\mu_1 \end{bmatrix} \tag{14}$$

As a result, the spectral radius of the regeneration matrix $J_F J_V^{-1}$, i.e., the basic regeneration coefficient of the system, can be obtained from Eqs. (9), (12), and (13):

$$R_0 = \rho(J_F J_V^{-1}) = \frac{1}{(\lambda+\alpha+\mu_1)}\begin{bmatrix} \varepsilon S_1 \mu_1 & 0 \\ (\varepsilon+\alpha)\mu_1 & 0 \end{bmatrix} = \frac{\varepsilon S_1}{\lambda+\alpha+\mu_1} \tag{15}$$

According to the practical significance, if $R_0 \le 1$. There is a zero transmission equilibrium point M^0: $(S_1^0, 0, 0, R_1^0, 0)$ in the model, then there are only unknowns and immunizers in the model, and the communication of the city brand image will gradually disappear and will not be spread in the network. If $R_0 > 1$. There is a non-zero transmission equilibrium point M^*: $(S_1^*, E_1^*, I_1^*, R_1^*, O_1^*)$, the unknowns, potentials, transmitters, immunizers, and quitters all exist in the model, and the city brand image transmission will continue to exist in the network and reach a stable state.

4. Quantification of communication benefits based on big data regression modeling

Using the Changsha city brand image communication model established in the previous section, this paper realizes the prediction analysis of Changsha city brand image communication and lays a solid foundation for analyzing the communication benefits. Therefore, based on the research results in the previous section, this section will quantitatively analyze the communication benefits of Changsha city brand image through the big data regression model. First, based on the collation and analysis of related literature, the evaluation index system of Changsha city brand image communication benefit is established. The evaluation index data are preprocessed using principal component analysis (PCA). The processed data are used as input variables, and the support vector regression algorithm is used to construct a quantitative model of Changsha city brand image communication benefit, and quantitative prediction of communication benefit is made.

4.1. Construction of evaluation index system

On the basis of summarizing and analyzing the current situation of Changsha city's brand image communication, and combining with the prediction results of the communication model on brand image communication, the evaluation index system of Changsha city's brand image communication efficiency is constructed in line with the characteristics of communication. Therefore, the main principles for the establishment of this evaluation system are, firstly, to reflect the comprehensiveness of Changsha city's brand image communication, and secondly, to reflect the relevance and connection between individual evaluation indicators. Following the principles of scientificity, practicability and comprehensiveness, the evaluation index system of Changsha city brand image communication effectiveness constructed in this paper is shown in Table 1. In the table, media exposure (X1) indicates the number and frequency of Changsha being mentioned in all kinds of media (including newspapers, TV, network news, etc.). Social media heat (X2) indicates the number of topics about Changsha on social media platforms, the heat of discussion, and the reading volume of topics. Website Traffic (X3) indicates the number of visits to Changsha's city wide websites and websites related to tourism, culture, etc. Domestic dissemination scope (X4) refers to the breadth of dissemination of Changsha-related information in different regions of China, as reflected by geographically distributed data on media coverage, internet search heat, etc. International Scope of Communication (X5) is the exposure of Changsha on international media and social platforms, as well as the knowledge and attention of international tourists to Changsha. Audience Awareness (X6) is the degree of audience awareness of

Changsha's city brand image through questionnaires and interviews, including knowledge of Changsha's distinctive attractions, cultural heritage, and all right. Audience favorability (X7) is the degree of audience's preference for Changsha's city brand image, and whether they are willing to travel to Changsha for tourism, living, investment, and so on. Information Accuracy (X8) is to measure whether the disseminated information about Changsha city is mainly accurate, and to avoid the dissemination of false, exaggerated and other inaccurate information. Innovation of Communication Form (X9) reflects Changsha's adoption of novel communication methods, such as augmented reality, virtual reality and other experiential communication methods. Communication content innovation (X10) refers to the excavation of Changsha's unique culture, history, folklore, etc., and innovative packaging and presentation, such as Changsha's niche culture and new ways of playing with intangible cultural heritage. Duration of communication (X11) refers to the duration of Changsha's city brand image publicity activities, long-term and stable communication helps to deepen the audience's impression. Consistency of communication (X12) refers to the consistency of communication content at different stages and through different channels, forming a unified brand image perception.

Table 1. Spread benefit evaluation system

Primary indicator	Secondary indicator
Spread influence	Media exposure(X1)
	Social media heat(X2)
	Site traffic(X3)
Spread coverage	Domestic spread range(X4)
	International spread range(X5)
Spread effectiveness	Audience awareness(X6)
	Audience preference(X7)
	Information accuracy(X8)
Spread innovation	Spread form innovation (X9)
	Spread content innovation(X10)
Spread persistence	Spread time length(X11)
	Spread coherence(X12)

4.2. Data collection and pre-processing

4.2.1. Data collection. This paper utilizes web crawler and text mining techniques to collect data related to Changsha's city brand from social media platforms (Weibo, WeChat, short video platforms, etc.), search engines (Baidu Index, etc.), and online travel platforms (Ctrip, Mabee's Nest, etc.), including the number of posts, number of likes, number of comments, search heats, and the number of tourist product bookings, etc., for the time period of 2010-2023, in order to ensure that the data can reflect the communication during the period of brand image transformation. The communication model constructed above is used to predict the number of Changsha city brand image communications, and the prediction results are also used as input data for the regression model.

4.2.2. Data pre-processing:
1) Principal component analysis. Principal component analysis is a multivariate statistical analysis method that is widely used in solving multivariate problems [19]. Usually in a comprehensive and systematic analysis of multifactorial decision-making problems, due to the need to consider the impact of a large number of indicators, each indicator reflects the information of the research problem to a different extent, in the process of indicator selection, there is inevitably a multiple correlation between the indicators, resulting in the problem of overlapping information, and too many indicators also result in the complexity of the calculation of the large workload. Principal component analysis is an effective method to solve this kind of problem. In the practical application of principal component analysis, the linear correlation between the original indicators is transformed into irrelevant through orthogonal

transformation, and the original data are transformed into new coordinates. The main aspects of principal component analysis in solving multivariate problems include the following:

(1) Correlation matrix $R=(r_{ij})$, where element r_{ij} of the matrix reflects the degree of correlation between indicators z_i and z_j. Eq. $cov(z_i, z_j)$ is the covariance of indicators z_i and z_j:

$$r_{ij} = \frac{cov(z_i, z_j)}{\sqrt{D(z_i)}\sqrt{D(z_j)}} \tag{16}$$

(2) Eigenvalues λ_i and eigenvectors of the correlation matrix r_{ij}. If R has q eigenvalues greater than 0 and the canonical orthogonal eigenvectors corresponding to the eigenvalues are $A=(a_1, a_1, \cdots, a_q)$, then the q principal components are denoted Z_i:

$$\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_q \end{bmatrix} = \begin{bmatrix} a_{11} & a_{21} & \cdots & a_{1p} \\ a_{12} & a_{22} & \cdots & a_{2p} \\ \vdots & \vdots & & \vdots \\ a_{1q} & a_{2q} & \cdots & a_{pq} \end{bmatrix} = \begin{bmatrix} Z_1 \\ Z_2 \\ \vdots \\ Z_q \end{bmatrix} \tag{17}$$

(3) The variance contribution of the g st principal component, which reflects the percentage of the original variable information carried by the w_i nd principal component:

$$w_i = \frac{\lambda_i}{\sum_{j=1}^{n} \lambda_j} \tag{18}$$

(4) Cumulative variance contribution ratio of the first m principal component p, if the cumulative variance contribution ratio P of the first m principal components reaches 80%, then the first m principal components are taken to replace the original p indicators:

$$p = \sum_{i}^{m} \lambda_i \, i \sum_{j}^{n} \lambda_j \tag{19}$$

(5) The values of each principal component and the composite value were calculated as follows using the formula:

$$F_i = U_i \cdot X_i = U_{1i} \cdot x_1 + U_{2i} \cdot x_2 +, \cdots, +U_{pi} \cdot x_p \tag{20}$$

$$F = W_i \cdot F_i \tag{21}$$

Eq:

F_i is the value of the extracted i nd principal component.

U_i is the coefficient matrix of the i th principal component.

W_i represents the overall contribution of the i th principal component.

X_i is the original data matrix. F is the sample composite evaluation value.

Through the above process, the original indicators are orthogonally transformed to obtain mutually independent principal components, which can eliminate the problem of multiple correlation between the indicators, and the stronger the correlation between the indicators, the better the effect of principal component analysis, and at the same time, solve the problem of the difficulty of selecting indicators.

2) Data Standardization. According to the evaluation index system of Changsha city brand image communication efficiency established in this paper, it is known that the evaluation indexes have the characteristics of multi-attribute and multi-outline, and there are bigger and better and smaller and

better types in many evaluation indexes. Through the dimensionless processing to eliminate the differences in the evaluation indexes, attributes:

The larger and better type indicators are:

$$x^{'}(i,j)=\frac{x^{*}(i,j)-x_{\min}(j)}{x_{\max}(j)-x_{\min}(j)} \tag{22}$$

The smaller the better type indicator is:

$$x^{'}(i,j)=\frac{x_{\max}(j)-x^{*}(i,j)}{x_{\max}(j)-x_{\min}(j)} \tag{23}$$

Eq:

$x^{'}(i,j)$ is the normalized value of the raw data for the j rd indicator in the i nd differentiation scheme.

$x^{*}(i,j)$ is the raw value of the j th indicator in the i th differentiation scheme.

$x_{max}(j)$ is the maximum of the raw values of the j th indicator.

$x_{\min}(j)$ is the minimum of the raw value of the j th indicator.

In order to standardize the range of variation in the values of the indicators, the dimensionless indicator $x^{'}(i,j)$ is normalized:

$$x_{ij}=\frac{x^{'}(i,j)-\overline{x}_j}{s_{x(j)}} \tag{24}$$

Where: $\overline{x}_j$ is the mean of the values of the j nd indicator.

$s_{x(j)}$ is the standard deviation of the j th indicator.

Where $\left\{x^{*}(i,j)\,|\,i=1,2,\cdots n; j=1,2,\cdots p\right\}$ is the set of evaluation indicators with dimensionless processing of indicator eigenvalues. The standardized indicator matrix is shown below:

$$R=\begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pn} \end{bmatrix} \tag{25}$$

4.3. Regression Modeling

4.3.1. Support vector regression machine. The support vector regression machine transforms the input space to a high-dimensional feature space by appropriate nonlinear transformations, which reduces finding the optimal hyperplane for linear regression in this feature space to solving a convex programming problem with a globally optimal solution.

When the sample set satisfies a linear relationship, the problem reduces to the following optimization problem:

$$\min\frac{1}{2}\|w\|^2+c\sum_{i}^{i}(\zeta_i+\zeta_i^{*}) \tag{26}$$

When linear regression cannot be achieved for the dataset, the original dataset is shadowed into the high-dimensional feature space by nonlinear shadowing $\varphi(x)$, and linear regression is performed in the high-dimensional feature space. The inner product operation on the high dimensional feature space can be defined as a kernel function:

$$K(x_i,x_j)=\varphi(x_i)\cdot\varphi(x_j) \tag{27}$$

It is sufficient to perform the kernel function operation on the variables in the original low-dimensional space, then the constraint expression is at this point:

$$\min \quad \frac{1}{2}\sum_{i,j=1}^{l}(a_i^*-a_i)(a_j^*-a_j)K(x_i,x_j)+\varepsilon\sum_{i=1}^{l}(a_i^*+a_i)-\sum_{i=1}^{l}y_i(a_i^*-a_i) \tag{28}$$

Obtain the optimal solution $\overline{\alpha}=(\overline{a},\overline{a}_1^*,\ldots,\overline{a}_i,\overline{a}_i^*)^T$. Compute $\overline{b}=y_i-\sum_{i=1}^{l}(\overline{a}_i^*-\overline{a}_i)K(x_i,x_j)+\varepsilon$, then the regression decision function is:

$$f(x)=\sum_{i=1}^{1}(\overline{a}_i^+-\overline{a}_i)K(x_i\cdot x)+\overline{b} \tag{29}$$

4.3.2. Differential Evolutionary Algorithms:

1) Mutation operation. Four different individuals from the population are randomly selected to generate difference vectors to the optimal individual of each generation for the mutation operation, which can improve the convergence speed of the algorithm, but also to a certain extent to maintain a high degree of population diversity. The mutation operation is performed as:

$$v_i^{g+1}=x_{isst}^{g+1}+k\left[(x_{i_1}^{g+1}-x_{i_2}^{g+1})+(x_{i_3}^{g+1}-x_{i_3}^{g+1})\right] \tag{30}$$

where v^g+1 is the mutated individual obtained by strictly performing the mutation operation on each g -generation individual x. x_{bwa}^{g+1} is the optimal individual in $g+1$. g is the current generation. $s_1,s_2,s_1,s_i\in\{1,2,\ldots,N\}$ is the random numbers that are different from each other and i; $k\in[0,1.5]$ is the scaling factor, which is the zoom-in and zoom-out control of the difference component.

2) Crossover operation. In order to improve the diversity of the population, the crossover operation mode is:

$$y_i^{g+1}=\begin{cases}v_{i,j}^{g+1} & rand(j)\le CR\\ x_{i,j}^{g} & rand(j)>CR\end{cases} \tag{31}$$

where y_f^{g+1} is and the test individual obtained by performing a crossover operation on x_{ij}^g and the generated variant individual. $rand(j)$ is a uniformly distributed random number between [0, 1]. $CR\in[0,1]$ is the crossover probability.

3) Selection operation. Adopting a "greedy" search strategy, test individuals y_i^{g+1} and x_i^g generated after compilation and crossover operations compete with each other. Only if the fitness of y_i^{g+1} is better than that of x_i^g, it will be selected as the offspring. Otherwise, x_i^p is directly selected as the offspring. The selection operation was performed as follows.

$$x_i^{g+1}=\begin{cases}y_i^{g+1} & f(y_i^{g+1})<f(x_i^g)\\ x_i^g & f(y_i^{g+1})\ge f(x_i^g)\end{cases} \tag{32}$$

4.3.3. Quantitative regression modeling. The SVR parameters are first optimized using the DE algorithm. The RBF kernel is selected as the SVR kernel function. The penalty parameter c is a compromise between the proportion of control misclassified samples and the complexity of the algorithm. The Gaussian kernel parameter δ is the width of the RBF kernel, the change of which actually changes the mapping function implicitly. Parameter optimization of the support vector machine refers to the selection of the optimal penalty parameter C and Gaussian kernel function δ, which further improves the SVR learning and generalization capabilities. Define the fitness function as:

$$\min \sum (\hat{y}_i - yi)^2 \tag{33}$$

where y_i is the statistically observed value for period t. $\hat{y}_i$ is the corresponding predicted value of period t, $t = 1, 2, \ldots, m$.

The specific steps of the DE algorithm to optimize the SVR parameters are as follows:

Step1: Initialize the population size N, evolutionary generation g_a, scaling factor k, crossover probability CR, termination threshold, and the upper and lower limit values of SVR penalty parameter C and kernel parameter δ, so as to randomly generate (C, δ).

Step2: Take the current (C, δ)-parameter combination value as the parameter of SVR, use SVR to train and test the sample data, and get the test result, i.e. the quantized prediction result of the sample.

Step3: Compare the prediction result obtained according to Step2 with the actual value, calculate the value of the objective function, and judge whether its value reaches the predetermined accuracy or satisfies $g = g_m$, i.e., reaches the maximum number of evolutionary generations, if any of them is satisfied, then go to Step9, otherwise proceed to the next step.

Step4: $g = g + 1$, i.e., enter the next generation of evolution.

Step5: Randomly select 4 different individuals x_i^s from the current g-generation population and perform the mutation operation using Eq. to generate $g+1$ mutated individual v_i^{g+1}.

Step6: Perform crossover operation on $g+1$ generation variant individual v_i^{g+1} according to equation (31) to generate $g+1$ test individual y_i^{g+1}.

Step7: Perform selection operation on $g+1$ generation test individual y_i^{q+1} according to equation (32) to generate $g+1$ individual x_i^{g+1}.

Step8: In the $g+1$-generation population, compute to generate a new (C, δ), and then go to Step2.

Step9: Obtain the SVR optimal parameters (C, δ) and quantify them by training and testing the sample data using SVR.

Then train and test the SVR on the sample set and quantitatively predict the new sample data using the trained robust SVR.

5. Results and analysis

5.1. Analysis of communication models

5.1.1. Model steady state analysis. The numerical equilibrium point solutions of the SEIRO model equations in this paper are solved in the Matlab simulation platform to analyze the overall effect of the equilibrium point changes on the model. Taking μ_2 as an example, the variation of equilibrium points for E nodes, I nodes and R nodes is analyzed for different values, and the results are shown in Fig. 5. The analysis of E the number of nodes over time shows that the position of the model equilibrium point is at the highest point of the graph, where the latents, weak immunizers and propagators are each in a relatively balanced state. From the information in the graph, it can be seen that with the increasing of μ_2 from 0 to 1, the equilibrium point of the number of lurker nodes shows the trend of increasing and then decreasing, that is to say, when the probability of a lurker node turning into a propagator node gradually increases, the extreme value of the lurker node increases and then decreases, instead of continuing to grow all the time. Therefore, in the actual brand image communication for the publicity and exposure of specific topics, it is not the higher the exposure the better, but should grasp the optimal value in advance, in the cost of appropriate publicity at the same time, so that the communication efficiency to achieve the best.

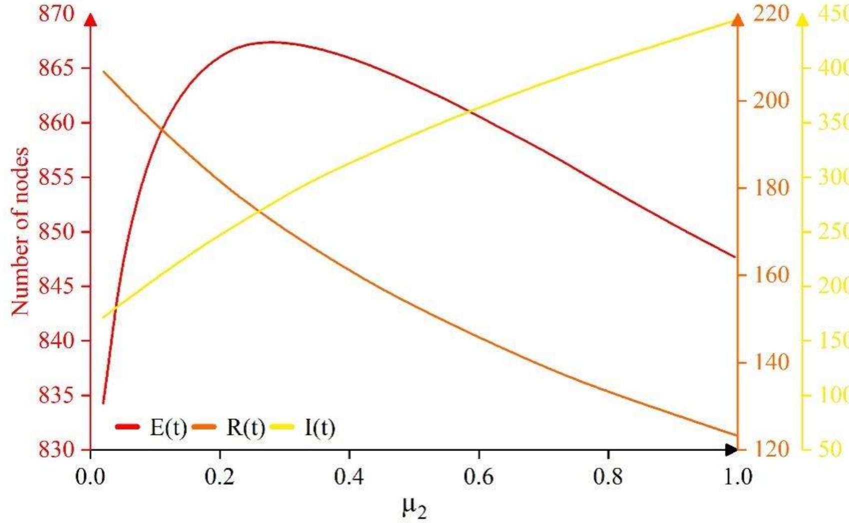
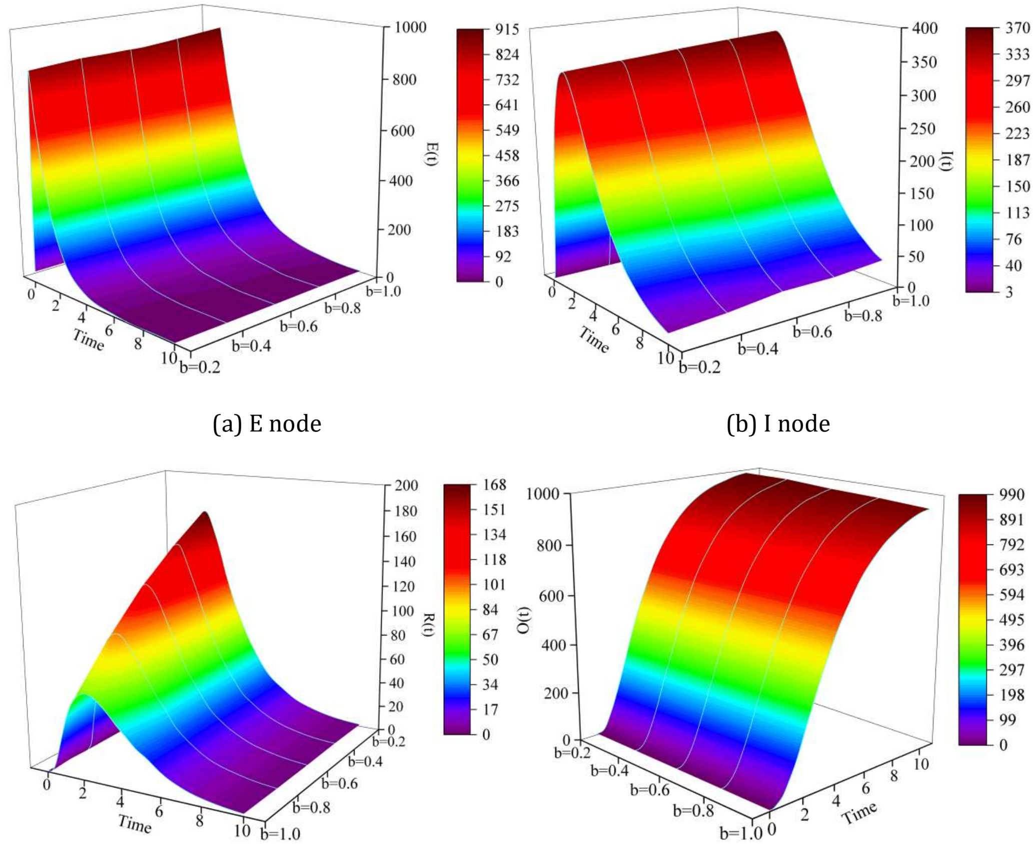


Fig. 5. The equilibrium balance changes at any time

5.1.2. Attenuation factor of interest. The simulation results of the interest decay factor are shown in Fig. 6, with (a)-(d) denoting E node, I nodes, R nodes and O nodes, respectively. When adjusting the value of decay factor b increases from 0.2 to 1.0, with the change of time, the latents drop to zero at a faster rate, while the final peak of the number of weak immunizer nodes increases significantly, the reason is that the latents are transformed into weak immunizers at a faster rate, the maximum value of the number of propagators decreases dramatically with the increase of the decay factor, and the decay rate becomes faster after reaching the maximum value, obviously with the forgetting Obviously, as the role of the forgetting mechanism increases, the audience's interest in the message decreases faster, and the number of quitters increases relatively faster.

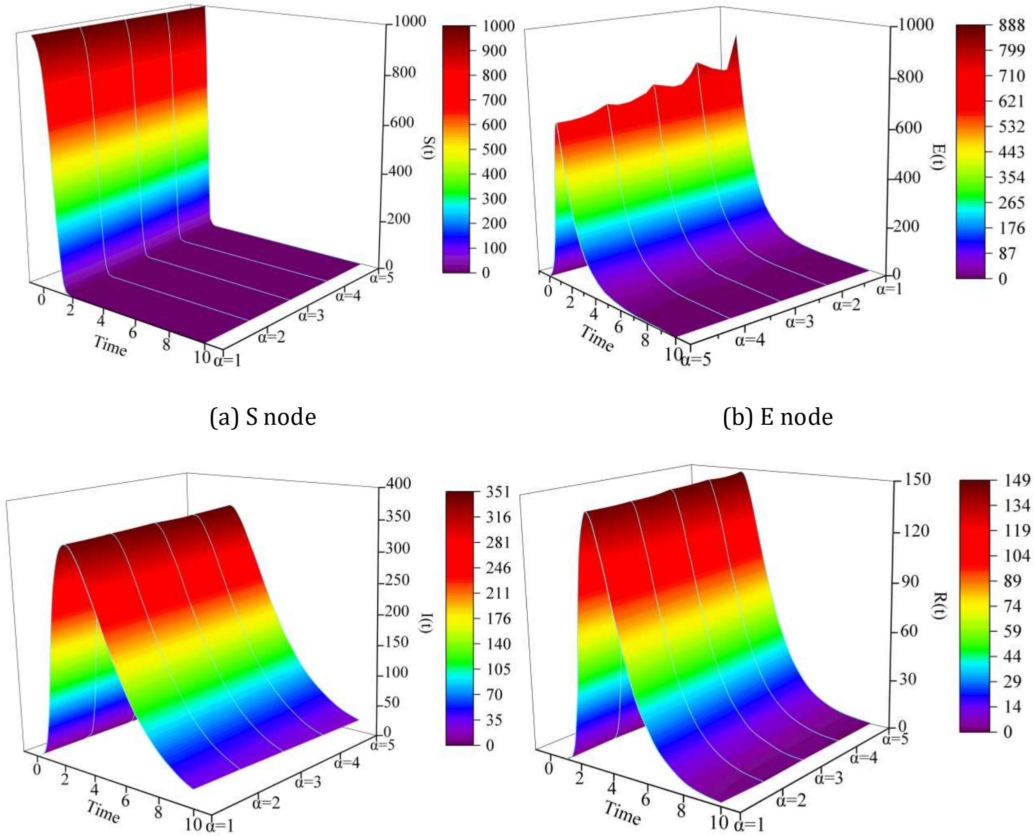


(a) E node (b) I node

(c) R node (d) O node

Fig. 6. Changes in variation of the nodes when attenuation coefficient changes

5.1.3. Psychological trust factor. The changes of each node when the psychological trust coefficient changes are shown in Fig. 7, (a)-(d) denote S node, E nodes, I nodes and R nodes respectively. When the psychological effect coefficient increases, the speed of the unknown node converted into the latent node becomes much slower, because there is a greater psychological effect of the unknown on the communicator resulting in a lower degree of trust in the information so that many unknowns are converted into latents at a slower speed, and the latents, communicators and weak immunizers are all increased at a slower speed and the peak value is also smaller. That is to say, in the process of Changsha city brand image communication, if there is a big trust problem between the audience, then the whole process of information dissemination will be slowed down, and the efficiency will be significantly reduced.

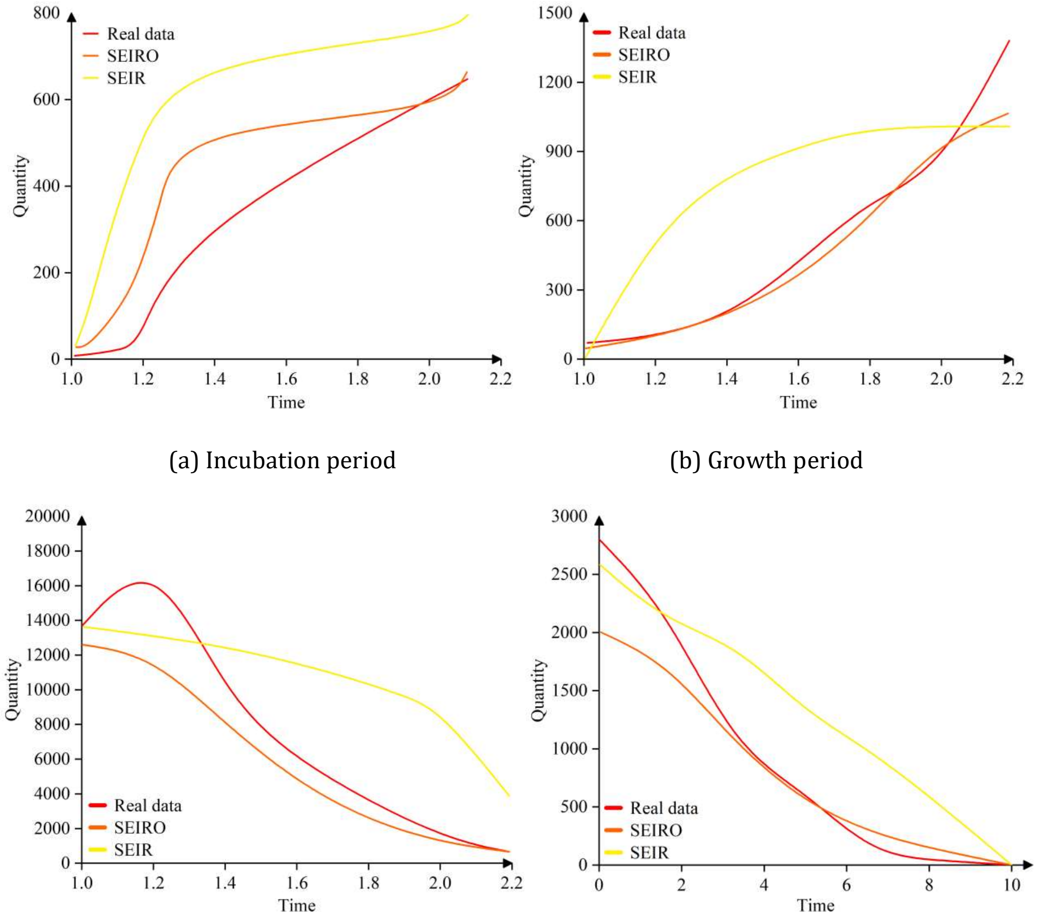


(a) S node (b) E node

(c) I node (d) R node

Fig. 7. Changes in the nodes of trust when the coefficient of trust changes

5.1.4. Comparative analysis of experiments. This paper takes the microblogging platform as an example, firstly, it grabs the microblogging data in the hot topics about Changsha city brand image in 2023, including likes, retweets, etc., and takes this as the communication data of Changsha city image in the microblogging platform. Then the microblog data from January to December 2023 are categorized into latency, growth, maturity and decline according to the characteristics of the microblog data. 4 stages of the model fitting situation and the actual data are shown in Figure 8. From the overall view of the 4 stages, the SEIRO model is more similar to the SEIR model compared to the actual data. The fit of both SEIRO and SEIR models in the latency stage is greater than the actual data due to less data disseminated in the latency stage. The simulation results of SEIRO in the growth and decline phases are similar to the actual situation, while the results of SEIR are higher than the actual. The reason that the results of SEIRO in the maturity stage are lower than the actual while the results of SEIR are still higher than the actual is that the former takes into account the presence of quitters in the complete propagation process, which makes the number of propagators lower but also more in line with the actual situation. In summary, the communication model constructed in this paper can effectively analyze the communication effect of Changsha city brand image in various platforms, and can predict the communication data of the brand image more accurately, laying a solid foundation for the quantitative analysis of the communication benefit.



(a) Incubation period (b) Growth period

(c) Maturation period (d) Decline period

Fig. 8. Comparison of the number of propagation in each phase

5.2. PCA downscaling analysis

5.2.1. Correlation analysis. According to the evaluation index system of Changsha city brand image communication benefit constructed in this paper, the correlation coefficient matrix calculated by combining the PCA algorithm is shown in Figure 9. From the figure, it can be seen that the correlation coefficient between the sample indicators is overwhelmingly greater than 0.5, indicating that there is a strong correlation between these indicators, which suggests that the data can be downscaled using principal component analysis.

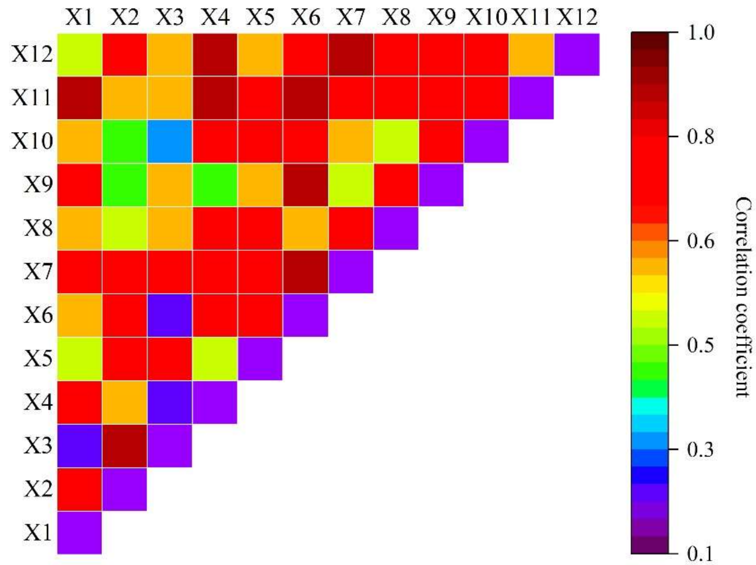


Fig. 9. Correlation coefficient matrix

5.2.2. Principal component extraction. The result of calculating the cumulative contribution of each principal component is shown in Figure 10. From the figure, it can be seen that the study extracted five principal components from the original sample data, and the cumulative contribution rate of the first five principal components reached 93.48%, which is greater than 80%, therefore, these five principal components are able to explain most of the original data information.

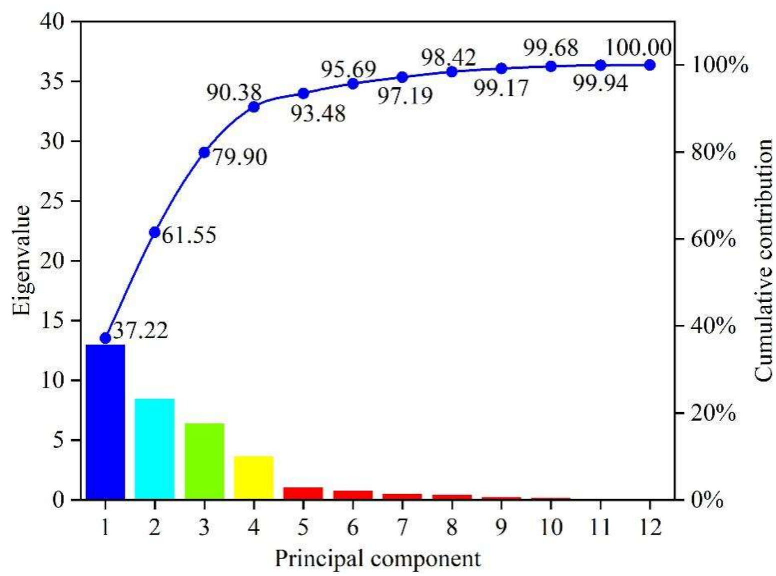


Fig. 10. Cumulative contribution of principal component

By calculating the correlation coefficients between the principal components and indicators, the relationship between each principal component and the original indicators can be derived, and the results are shown in Table 2. From the table, it can be seen that the principal component F1 focuses on the communication influence of Changsha city brand image, so F1 can be named as “communication influence”. F2 reflects the communication coverage of the brand image, so F2 is named “communication coverage”. Principal component F3 highlights the communication effectiveness of Changsha city brand image, so F3 is named as “communication effectiveness”. F4 and F5 focus on the communication innovativeness and continuity of the city brand image, so the main components F4 and

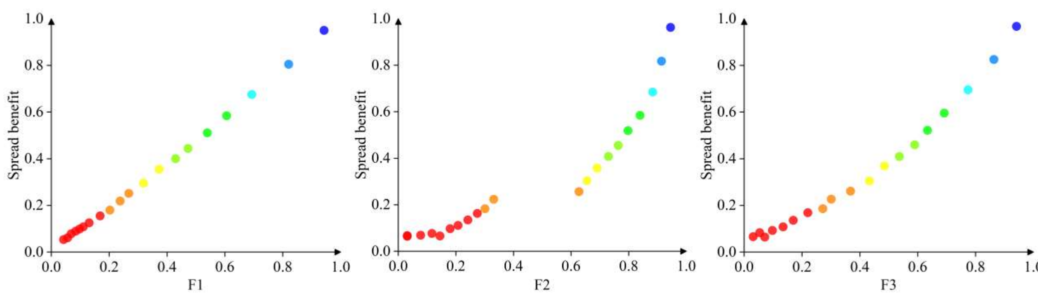
F5 are named as "communication innovativeness" and "communication continuity" respectively. So far, this paper replaced the original 12 evaluation indexes with 5 principal components and successfully realized the data dimensionality reduction operation.

Table 2. The relationship between principal component and original index

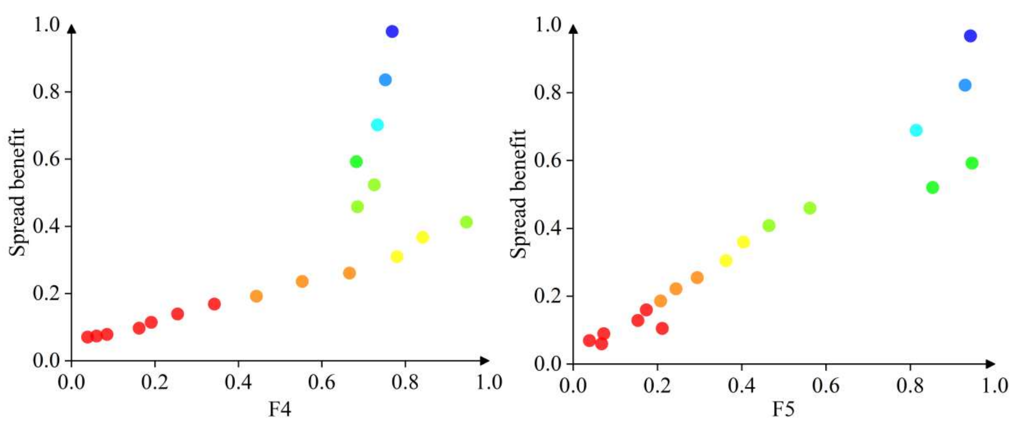
Principal component	Primary indicator
F1	X1, X2, X3
F2	X4, X5
F3	X6, X7, X8
F4	X9, X10
F5	X11, X12

5.3. Quantitative analysis of communication benefits

After the dimensionality reduction of the evaluation indexes of Changsha city brand image communication benefits, it is necessary to study the relationship between each principal component and the communication benefits, which can be analyzed by drawing scatter plots, and the three scatter plots between the variables are obtained as shown in Figure 11. Through the data in the figure, it can be seen that there is a correlation between the communication benefits of Changsha city brand image and each principal component, so the communication benefits can be quantitatively analyzed according to the principal components.



(a) Spread benefit&F1 (b) Spread benefit&F2 (c) Spread benefit&F3



(d) Spread benefit&F4 (e) Spread benefit&F5

Fig. 11. Spread benefit and index scatter diagram

This paper selects the support vector regression (SVR) model suitable for big data, and selects the BP neural network model as a comparison model to verify the effectiveness of the regression model in this paper. The Changsha city brand image communication data from 2010-2019 and the data after dimensionality reduction are selected as the training samples, and the data from 2020-2023 are used as the test samples yet, and the accuracy of the two models in quantifying the communication benefits is derived through the comparison of the average relative errors between the real values and the predicted values in the four-year test set.

In order to make a more intuitive quantitative evaluation of the quantitative accuracy of each model, this paper chooses the average relative error (MRE) to judge the effect of the training volume of the SVR model and the BP neural network model, the formula is as follows:

$$MRE = \frac{\sum_{i=1}^{n} \left| \frac{\hat{y}_i - y_i}{y_i} \right|}{n} \times 100\% \tag{34}$$

where y_i is the original data, $\hat{y}_i$ is the predicted value of the model, and n denotes the number of training samples.

5.3.1. Quantification of SVR model dissemination benefits. In the SVR prediction, according to the research object to select the kernel function, this paper selected the more widely used radial basis function, in the kernel function needs to be tuned to three parameters C, δ, ε, the method adopted is the grid search method traversing the search for the optimal, the initial parameter settings according to the experience set, the general parameters C, $\varphi\delta$, ε of the selection of the final parameters than the range of parameters to be obtained, so as to avoid the inaccuracy due to the range of the optimal parameter missed. This can avoid omitting the optimal parameters due to the inaccuracy of the range. When parameters $C=252$, $\delta=0.13$ and $\varepsilon=0.06$ are finally obtained through the traversal optimization, the generalization ability of the SVR is better, and the average relative error obtained from the training is also the smallest, and the average relative error obtained from the training samples after the model training is %, and the overall training results look better.

When observing the relative error of each year individually, it is found that the relative error of 2019 reaches 43.86%. It is found that the relative error of 2019 reaches 43.86%, which is mainly due to the occurrence of a certain special event in this year, which has a greater impact on Changsha's city brand image, resulting in an outlier for the data of that year, and also on the other hand, it shows that the support vector regression model is more sensitive to the noise factor, in order to reduce the impact of noise, the data of 2019 is processed by linear interpolation, and after interpolation processing, the propagation benefit in 2019 is 19,996,400 yuan, at this time, when the parameters $C=192$, $\delta=0.008$, $\varepsilon=0.04$ are obtained by traversing the search for the optimal, the average relative error of the training samples is minimized to 2.36%, which is better than the prediction effect before the anomalous value processing. According to the optimal parameters obtained after interpolation, the relative error between the original sequence and the predicted value is calculated, and the results are shown in Table 3. From the table, it can be seen that after the outlier treatment, the predicted values fitted with the model are closer to the real values, and the quantitative effect on the communication benefits of Changsha city brand image is better.

Table 3. The relative error of the model training sample(SVR)

Year	True value	Predictive value	Relative error/%
2010	364.52	311.66	14.50
2011	395.09	388.2	1.74
2012	442.8	447.85	1.14
2013	544.39	547.15	0.51
2014	645.24	649.39	0.64
2015	801.51	853.57	6.50
2016	1040.9	1065.04	2.32
2017	1356.72	1366.23	0.70
2018	1596.18	1631.98	2.24
2019	1990.64	1853.28	6.90

The trained SVR model is utilized to quantitatively predict the propagation benefits from 2020 to 2023, and the relative errors of each year are calculated, and the results are shown in Table 4. The average relative error of the four years' prediction values is 1.53%, which shows that the optimal parameters found according to the grid search method also have better prediction effect when predicting the test set, and can realize the effective quantification of the communication benefits of Changsha's city brand image.

Table 4. Comparison of predictive values and true values of model(SVR)

Year	True value	Predictive value	Relative error/%
2020	2036.84	2017.65	0.94
2021	2457.92	2386.78	2.89
2022	2836.71	2836.71	0.00
2023	3029.36	3098.42	2.28

5.3.2. Quantification of BP model dissemination benefits. Neural network in the use of the need to choose the appropriate activation function, while the choice of parameters in the activation function directly determines the effect of the use of the model is good or bad, for big data, the optimization of neural network parameters to choose the method more need to be based on the law of the sample, based on experience to determine the range of neural network parameters, to determine the optimal parameters under the actual problem. In this paper, we use the batch gradient descent optimizer to continuously update the optimized network parameters to make them close to the optimal value, which can be simply understood as choosing the direction of movement with the smallest average gradient by mastering the surrounding terrain. In addition, in order to avoid the phenomenon of overfitting, this paper adopts the early stop method, that is, the number of the entire training set as a cycle, in each cycle to calculate the error of the model in the validation set, when the model in the validation set of the performance of the model began to be bad when the training is halted, so that the number of times the model training can be reduced can also be avoided to avoid continuing to train leading to the emergence of the phenomenon of overfitting.

After experiments, it is concluded that the convergence speed is the fastest when the number of nodes in the hidden layer is set to 7, and finally a 5×7×4 neural network is constructed. According to the characteristics of the data in this paper, the Relu function is chosen as the activation function, the number of training cycles is set to be 500 times, the initialization weights are set to be 0. In order to achieve better prediction results, different learning rates and weight decay parameters are set, and finally, when the two parameters are set to 0.05 and 0.05 respectively, the training effect of the model is better, and the average relative error of the training model is smaller, and the relative error between the original series and the predicted values is lower than that between the original series and the predicted values for each year. The relative errors between the original series and the predicted values are shown in Table 5. After calculation, the average relative error is 9.41%, and when we look at the relative error of each year individually, we find that the relative error of individual years' prediction is larger, while some years' prediction is smaller, and the relative errors of the nearby years are smaller, which will fall into the problem of local optimization, which is also a disadvantage of neural network in training model.

Table 5. The relative error of the model training sample(BP)

Year	True value	Predictive value	Relative error/%
2010	364.52	275.67	24.37
2011	395.09	346.79	12.23
2012	442.8	439.95	0.64
2013	544.39	571.58	4.99
2014	645.24	716.98	11.12
2015	801.51	984.27	22.8
2016	1040.9	1137.11	9.24
2017	1356.72	1353.17	0.26
2018	1596.18	1622.8	1.67
2019	1990.64	1855.29	6.8

The above trained BP model was used to quantitatively predict the communication benefits from 2020 to 2023, and the average relative error was calculated, and the results are shown in Table 6. The average relative error of the four-year prediction is calculated to be 29.39%, which is much larger than the 1.53% of the SVR model. Therefore, through quantitative calculation, it is concluded that the SVR model used in this paper has higher quantitative accuracy in the quantitative analysis of the communication benefits of Changsha's city brand image, and is able to more accurately study the benefits of Changsha's city brand image in the process of communication.

Table 6. Comparison of predictive values and true values of model (BP)

Year	True value	Predictive value	Relative error/%
2020	2036.84	1364.27	33.02
2021	2457.92	1573.49	35.98
2022	2836.71	3379.84	19.15
2023	3029.36	2138.93	29.39

6. Conclusion

Based on the research on the city brand image shaped by Changsha, this paper improves the traditional contagion model and constructs the Changsha city brand image communication model. By using the data collected by web crawler and text mining technology, combined with the number of predictions output from the contagion model, a support vector regression machine model under the optimization of differential evolution algorithm is constructed to quantify the benefits of Changsha's city brand image contagion. The results show that the regression model constructed in this paper has higher quantitative prediction accuracy compared with the BP neural network model, and the average relative error in the test set is only 1.53%, which is 27.86% lower compared with the BP neural network model. This fully demonstrates that the regression model constructed in this paper can realize the effective quantification of Changsha city brand image communication benefits.

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