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Research Article

Multidimensional Dynamics and Forecast Models of Network Public Opinions Based on the Fusion of Smart Transportation and Big Data

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With the increase of the world's population, the means of transportation and vehicles that adapt to the times are still difficult to cope with the increase in traffic volume. The traffic problem can be said to be a worldwide problem. However, with the development of artificial intelligence, the emergence of smart transportation has brought new development to modern transportation, and the application of smart transportation and big data is inseparable. In contemporary society, the widespread use of the Internet allows the public to fully exercise their rights to participate in social management and conduct public opinion supervision, which provides a great impetus for the development of online public opinion. However, due to the huge scale of information, some false and harmful information and opinions will inevitably be mixed into it, which will make the network public opinion unable to perform its due function smoothly. Therefore, it is necessary to carry out highly effective management activities on the network public opinion. This paper studies the multidimensional dynamics and prediction model of network public opinion based on the integration of smart transportation and big data; the aim is to design a simple and effective forecasting model to provide traffic management departments with good public opinion forecasting and analysis methods so as to make better decisions. This paper analyzes the related technologies of smart transportation and network public opinion and designs a prediction model of smart transportation network public opinion. Finally, this paper uses rough set theory to optimize the model and compares the data before and after optimization. The results are as follows: the data correlation coefficient before and after optimization is 0.988, and the two-tailed significance level is 0.471, which proves that the results before and after processing are highly correlated, and the two sets of data have no significant difference, proving that the optimization of the model is effective, simplifies the analysis process, and does not change the results.

1. Introduction

With the rapid development of social informatization, the wave of the informatization era represented by the Internet is spreading all over the world, and its influence is increasing day by day. Internet public opinion is playing an increasingly important role in the formation and popularization of social public opinion. Online public opinion is a new type of public opinion generated by the Internet. As an important part of public opinion in the entire society, online public opinion has become a force that cannot be ignored and has gradually played an irreplaceable social role. The transportation department has many contacts and close relations with the masses and needs to pay attention to the problem of online public opinion. To be people-oriented, it is necessary to pay attention to the ideas of the masses and respect the masses' online public opinion. Facing the problem, investigating, analyzing, and correcting the problem are the responsibility of the traffic management department.

The intelligent transportation system integrates computer technology, mobile communication technology, image processing, transportation management, and other high-tech means and combines transportation tools, transportation channels, and management and control to play a

real-time, accurate, and efficient role. The Internet platform provides a place for different ideologies to compete, and it can reflect social public opinion in a relatively concentrated manner. If the online public opinion cannot be effectively controlled, it will easily be used by people with intentions, which will bring harm to the country and society. Therefore, the public security traffic management department must do a good job in online public opinion management, timely grasping the situation, correctly analyzing the news, making scientific and democratic decisions, promoting work, and improving people's lives. Therefore, it is very important to establish a multidimensional dynamic and predictive model of online public opinion for smart transportation.

The innovation of this paper is as follows: (1) proposing a prediction model of smart transportation network public opinion, designing each index of the model, and also designing the processing method of the index; (2) optimizing the prediction model of smart transportation network public opinion through rough set theory, simplifying the model, and comparing the data before and after optimization, and we found no significant difference, which proved that the optimization is effective. This model can help traffic control departments understand online public opinion, grasp the progress of online public opinion, and make more reasonable decisions.

2. Related Work

The rapid development of the Internet in the twenty-first century provides a platform for people to actively speak, and these speeches are mixed with many dangerous factors, so the management and control of online public opinion are very important. So far, many scholars have conducted research on online public opinion. Jiang, through a brief introduction to the connotation and characteristics of online public opinion in colleges and universities, discussed the innovation of ideological and political education in colleges and universities under the background of online public opinion from the perspectives of educational concepts, educational content, and educational methods, to ensure that this education plays a positive role in the new era. However, the study did not propose specific measures [1]. Zhu proposed an adaptive edge service placement mechanism based on online learning and a predictive edge service migration method based on a factor graph model, which solved the problem of edge computing service placement from the perspective of edge computing. The prediction model is also improved by using complex network topology. The results show that the improved model has the advantages of accuracy, rapidity, and adaptability and can be applied to other fields [2]. Based on the research results of domestic and foreign scholars, Wang and Hu analyzed the current situation of online public opinion governance and initially constructed a big data platform for online public opinion, realized the transformation from online public opinion management to governance, and strengthened the awareness of the rule of law in online public opinion. Finally, it provides development strategies for the government to create a healthy and green online public opinion ecology from three aspects. The shortcoming is the lack of experiments to verify the effectiveness of the strategy [3].

In addition to online public opinion, smart transportation is also a product of the new era, bringing new opportunities for smart transportation and the Internet of goods industry. Angshuman has established a method to evaluate the various benefits of an incident management plan. This method calculates the benefits of improved air quality brought about by driver assistance services, reduced delays, reduced fuel consumption, secondary collisions, and accident management plans. The results show that this method can save drivers 7.2 million vehicle hours of accident-related delays each year. It also calculated that the annual benefit-cost ratio was 4.4 : 1 [4]. For cities in developing countries that are less motorized and have less developed infrastructure, less financial resources, and less institutional and technical capabilities, Chen et al. suggested to benefit from smart transportation investment: involving all public and private participants in collaboration and transparent environment, developing technical capabilities for purchasing and monitoring information services, and paying attention to basic infrastructure. But these suggestions are not specifically enough [5]. Lin proposed the design of hybrid vehicle-to-infrastructure and vehicle-to-vehicle communication networks and discussed how to efficiently manage electric vehicle charging services in charging station scenarios and distributed home charging scenarios. Then, it summarizes the open research issues related to networked electric vehicle communication technology and charging services. It is also proposed that connected electric vehicles can realize a green and intelligent transportation system. However, the discussion of the study is a bit vague and not very practical [6]. Yan discussed the development and implementation of tools and methods for evaluating the benefits and costs of these systems as part of the travel demand forecasting modeling environment. He also introduced the application of the developed tools to evaluate the two most widely deployed intelligent transportation systems: incident management and advanced traveler information system. The research results show that the method developed in this research can be used to evaluate its effectiveness [7].

3. Network Public Opinion Based on the Integration of Smart Transportation and Big Data

3.1. Data Analysis Technology in Smart Transportation

3.1.1. Data Mining Task. Data mining is also translated into data exploration and data mining. It is a method of analyzing a large amount of data stored in an enterprise through mathematical models to find different customers or market segments and to analyze consumer preferences and behaviors. Data mining tasks can be divided into statistical data mining, knowledge data mining, and unstructured data mining. According to the realized functions, data mining tasks can be divided into four types: predictive modeling, association analysis, cluster analysis, and anomaly detection.

(1) Predictive Modeling. According to the discreteness and continuity of target variables, predictive modeling can be divided into classification mining and regression mining. Classification mining is based on the analysis of the training data set to derive the corresponding prediction model. Sometimes people may wish to predict some unknown or missing data values. This situation is called regression. Regression is to evaluate unlabeled samples by establishing a model, or to evaluate the value interval that a sample may have [8].

(2) Association Analysis. Correlation characterizes the dependency between various attributes and events. Association rules are implicit expressions of the form $A \Rightarrow B$ [support, confidence]. Support reflects the usefulness of the discovered association rules, and confidence reflects the certainty of the discovered association rules.

Let I be a collection of items and D a collection of database transactions T. The association rule is an implicit formula of the form $A \Rightarrow B$, $A \subset I$, $B \subset I$, and $A \cap B = \varnothing$, and the support of the rule $A \Rightarrow B$ in the transaction set D is as follows:

$$\text{support}(A \Rightarrow B) = P(A \cap B). \tag{1}$$

Rule $A \Rightarrow B$'s confidence in transaction set D refers to the ratio of the transaction containing A and B to the transaction containing A, as follows:

$$\text{confidence}(A \Rightarrow B) = P(B \cap A). \tag{2}$$

(3) Cluster Analysis. The definition of clustering determines the need for a standard to characterize the similarity between data objects, so the key to clustering is the measurement of object similarity. Usually, using distance to measure the similarity of objects is the method we most often think of. The smaller the distance between two objects is, the more similar they are [9]. Cluster analysis itself is not a specific algorithm, but a task that needs to be solved in general. It can be implemented by different algorithms, which are very different in understanding the composition of clusters and how to find them effectively.

(4) Anomaly Detection. In general, data mining methods will try to minimize the impact of abnormal points or outliers, such as treating abnormal points as noise or discarding or repairing incorrect data. But in some special applications, it is these abnormal points that will help a lot. Data mining for these abnormal points is called anomaly detection.

3.1.2. Data Mining Algorithm. There are some very classic mining algorithms in data mining technology, some of which will be introduced.

(1) Bayesian Classification. Bayesian classification is a statistical classification method. Its analysis method is characterized by the use of probability to represent all forms of uncertainty, and learning or reasoning must be implemented by probability rules. Bayesian classification is a classification method of predictive modeling, which can predict the possibility of a certain attribute, such as the probability that a given sample belongs to a certain class. Let X be a data sample of unknown class attributes, and A a certain assumption: the data sample X belongs to class C. The classification problem is to obtain the probability that hypothesis A holds for a given sample of observation data X, that is, the conditional probability $P(A \mid X)$. Bayes' theorem provides a method for calculating $P(H \mid A)$ when $P(X)$, $P(A)$ and $P(X \mid A)$ are known. The formula is as follows:

$$P(A \mid X) = \frac{P(X \mid A)P(A)}{P(X)}. \tag{3}$$

Naive Bayes classification has a smaller error rate than other classification algorithms and is widely used in text classification and other fields. The steps of naive Bayes classification are as follows: the first step is to use an n-dimensional feature vector X to characterize each data sample, describing n metrics of n attributes to the sample. The second step, for a given unknown data sample X, assumes that there are m classes of $C_1, C_2, \ldots, C_m$, and the Bayesian classification algorithm classifies X into the class with the highest posterior probability [10]. That is, when the following conditions are met,

$$P(C_i \mid X) > (C_i \mid X), \quad 1 \le j \le m, j \ne i. \tag{4}$$

Naive Bayes classification assigns unknown samples to class C_i and then maximizes $P(C_i \mid X)$. Among them, $P(C_i \mid X)$ of the largest C_i is called the largest posterior hypothesis. According to Bayes' theorem,

$$P(C_i \mid X) = \frac{P(X \mid C_i)P(C_i)}{P(X)}. \tag{5}$$

In the third step, you only need $P(X \mid C_i)P(C_i))$ to be the largest. If the prior probability of the class cannot be obtained, it can be assumed that these classes are of equal probability. That is, $P(C_1) = P(C_2) = \ldots = P(C_m)$, According to this, $P(C_i \mid X)$ is maximized.

In the fourth step, the complexity of calculating $P(X \mid C_i)$ may be very large. In order to reduce the cost of calculating $P(X \mid C_i)$, assume that the class conditions are independent. That is, assume that the attribute value conditions are independent of each other. This is Bayesian classification. Get

$$P(X|C_i) = \prod_{k=1}^{n} p(x_k|C_i). \tag{6}$$

(2) K-Means Algorithm. K-Means algorithm is by far the most widely used clustering technique. The K-Means algorithm essentially implements the basic idea of clustering: the closer the data points within the class, the better, and the farther the data points between the classes, the better the algorithm. For large-scale and massive data, the scalability and operating efficiency of the algorithm are very high. The K-Means algorithm first specifies the number k value of the clusters to be divided. During initialization, k objects are

randomly selected from n data objects, representing k average values or centers. For the remaining (n-k) objects, measure the distance between each of the k cluster centers, assign them to the nearest clusters, and then recalculate the centroid of each cluster. Repeat the above process cyclically until the criterion function converges; that is, the center of mass no longer changes [11]. The criterion function is shown in the following formula:

$$E = \sum_{i=1}^{k} \sum_{x \in C_i} \left| x - \overline{x}_i \right|^2. \tag{7}$$

3.1.3. Hadoop Technology. Hadoop is a framework for applications running on large server clusters. It is good at complex analysis of large data sets. Hadoop contains two key technologies: reliable data storage using Hadoop distributed file system (HDFS), and high-performance parallel data processing using MapReduce technology. Figure 1 shows the structure of the Hadoop distributed file system.

HDFS breaks up the input data into blocks and stores them redundantly across server clusters. In this way, it can be ensured that even if multiple nodes fail, data will not be lost. HDFS is a master/slave architecture. HDFS includes a master server client and many data servers. The NameNode is the core of the HDFS file system. It keeps a directory tree of all files in the file system and tracks where the file data of the server cluster is saved.

MapReduce is mainly used to write various distributed applications. MapReduce is a method of dividing huge tasks into discrete tasks that can be executed in parallel [12, 13]. After analyzing each discrete task, the results will be integrated into a single output. This method can eliminate the processing bottleneck of a monolithic storage system.

3.2. Internet Public Opinion Related Theories

3.2.1. Complex Social Network Theory. If you only use traditional social networks to analyze data, it is often very limited. Therefore, it is necessary to make full use of the relevant theories and analysis methods of complex networks in social network analysis. From the history of complex network research, it can be roughly divided into three stages, namely, the regular network stage, the random network stage, and the complex network stage. Generally speaking, a complex network consists of many nodes and complex connections between these nodes. The structural characteristics of the network do not depend on specific node positions or connection forms, which are the topological characteristics of complex networks. In this regard, the average path length, clustering coefficient, and degree distribution of the network are the three most basic concepts used to describe the topological properties of complex networks [14].

From the point of view of graph theory, a specific network can be abstracted as a two-tuple $G = (V, E)$, where the set V is the electric set, E is the edge set, and each edge in set E has a point pair in set V corresponding to it. The

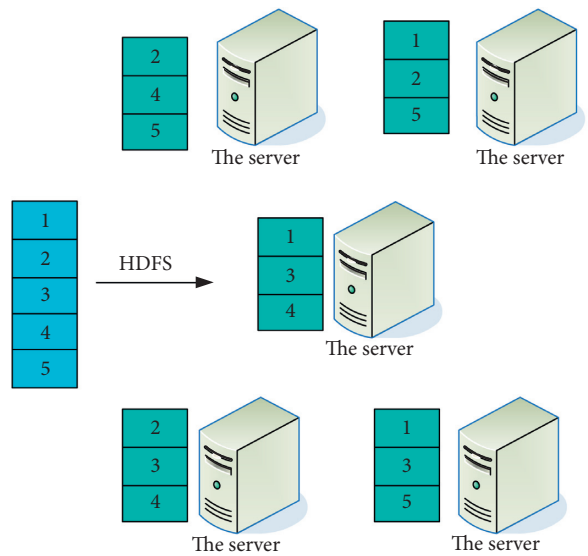

Figure 1: Hadoop distributed file system.

distance between nodes I and J, d_{ij}, is usually defined as the number of edges on the shortest path connecting these two nodes. The average path length D of the network is the average value of the distance between any two nodes. In a social network, it represents the number of individuals in the shortest relationship chain of two individuals, and its calculation formula is as follows:

$$D = \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} d_{ij}}{N^2}. \tag{8}$$

N represents the number of nodes, for an undirected network, $d_{ij} = d_{ji}$, so it can be simplified to the following formula:

$$D = \frac{2\sum_{i \geq j} d_{ij}}{N(N-1)}. \tag{9}$$

What the agglomeration coefficient wants to reveal is the agglomeration characteristics of the network. The so-called agglomeration characteristic means that two nodes in the network that are connected to a node by an edge are likely to be connected to each other by an edge. Suppose that node i has k edges connecting it to other nodes, and these k nodes are neighboring nodes of node i [15]. If the actual number of neighboring nodes of node i is R, then the agglomeration coefficient of node i is

$$C_i = \frac{2R}{k(k-1)}. \tag{10}$$

The clustering coefficient of the entire network is the mean value of the clustering coefficients of all nodes, which is

$$C = \frac{\sum_{i=1}^{N} C_i}{N}. \tag{11}$$

When $C = 0$, all nodes in the network are isolated nodes without any connecting edges; when $C = 1$, the network is completely coupled, and any two nodes are directly connected.

Degree is an important concept to describe the attributes of a single node in the network. The number of neighboring nodes of a node is the degree of the node.

In a directed network, degrees are divided into out-degree and in-degree, where out-degree refers to the number of edges from node i to other nodes in the network, and the in-degree is the number of edges pointing to node i from other nodes in the network. By averaging the degrees of all nodes in the network, the average degree of the network can be obtained, usually denoted as $\langle k \rangle$.

$$\langle k \rangle = \frac{\sum_{i=1}^{N} k}{N}. \tag{12}$$

For a regular network, since all nodes have the same degree, its degree distribution is concentrated on a single peak, which is the Delta distribution. For a completely random network, its degree distribution approximately satisfies the Poisson distribution. However, a large number of studies in recent years have shown that the degree distribution of real networks does not show a Poisson distribution like random networks. Especially when the network scale is large, their degree distribution can be better described in the form of approximate power-law distribution. A network whose degree distribution conforms to a power-law distribution is usually called a scale-free network [16,17]. The images of these degree distributions are shown in Figure 2.

In addition, there is another way to describe the degree distribution of the network, namely, the cumulative degree distribution function, which represents the probability distribution of nodes with degree not less than k. Let $P(k)$ represent the cumulative degree distribution function, and its function is as follows:

$$P(k) = \sum_{k'=k}^{\infty} p(k'). \tag{13}$$

Based on the theories and methods of complex social networks, it is not only feasible but also necessary to understand the real society from the perspective of the network, especially the individuals in the network society and their interactions with each other.

3.2.2. The Element Composition of the Network Public Opinion Model. The main body of online public opinion is the various network responders participating in the online public opinion. These network responders may be reliable network communication media, or they may be the general online public. They can play different roles in the evolution of online public opinion, but they are all important components that cannot be missed in the evolution of a complete online public opinion [18]. Figure 3 shows the spread of online public opinion.

In the evolution of online public opinion, autonomous network actors mainly include grassroots netizens, opinion leaders, and online communication media. Together, they constitute the main force in the Internet space to promote the development of online public opinion. In the evolutionary space of online public opinion, grassroots netizens constitute the largest part of the main body of online behavior; opinion leaders occupy a central position in the media information dissemination network; Internet communication media are an important actor in the evolution of online public opinion, which can quickly promote the dissemination of various online public opinion opinions and online public opinion information.

3.2.3. Construction of Online Public Opinion Aggregation Model

(1) Build Basic Rules. Without considering the increase and loss of people in the view aggregation space, set the group size as N, $\{1, 2, \ldots, n\}$ as the individual group that constitutes N, and the social network constituted by all individuals is denoted as $G(N, E)$, where E is the number of edges in the network. Let x be a random individual in the group, and his opinion value on a certain network public opinion event or issue at time t is represented by O_x^t, and $O_x^t \in [0, 1]$. Setting individual opinions in the process of aggregation of online public opinions, which independently change over time, then

$$\begin{aligned} O_x^{t+1} &\sim \left\{O_x^t, O_y^t\right\}, \quad x \neq y \text{ and } \widehat{x, y} = 1, \\ O_y^{t+1} &\sim \left\{O_y^t, O_z^t\right\}, \quad y \neq z \text{ and } \widehat{y, z} = 1. \end{aligned} \tag{14}$$

$\widehat{x, y}$ means that there is an edge that directly connects individual x and individual y; that is, y is a random node in the social network of individual x.

(2) Rules for Aggregation of Online Public Opinion in a Complex Open Space. In reality, the aggregation of group opinions also needs to consider the openness of space and its impact. In the process of the aggregation of online public opinion, the size of the virtual "discussion group" can sometimes remain the same, but more often it is constantly changing; that is, there is a flow of people in it, and at a certain moment, some individuals will be from the group, and some individuals will also join [19].

Due to the widespread celebrity effect in the Internet, it is obvious that adding edges with nonequal probability with a degree value is more in line with the actual situation of the Internet. This chapter chooses this edge addition rule to establish the relationship between newly added individuals and other individuals in the network. Figure 4 is the process of online public opinion aggregation in the open space.

Compared with a closed space where there is no increase and loss of individuals, the network structure of active groups in an open space is constantly changing. This change is reflected not only in the changes in the number of nodes and the number of nodes, but also in the changes in the connection relationship between the nodes.

3.3. Network Public Opinion Prediction Model for Smart Transportation. Smart transportation and management of network public opinion are closely related to the vital

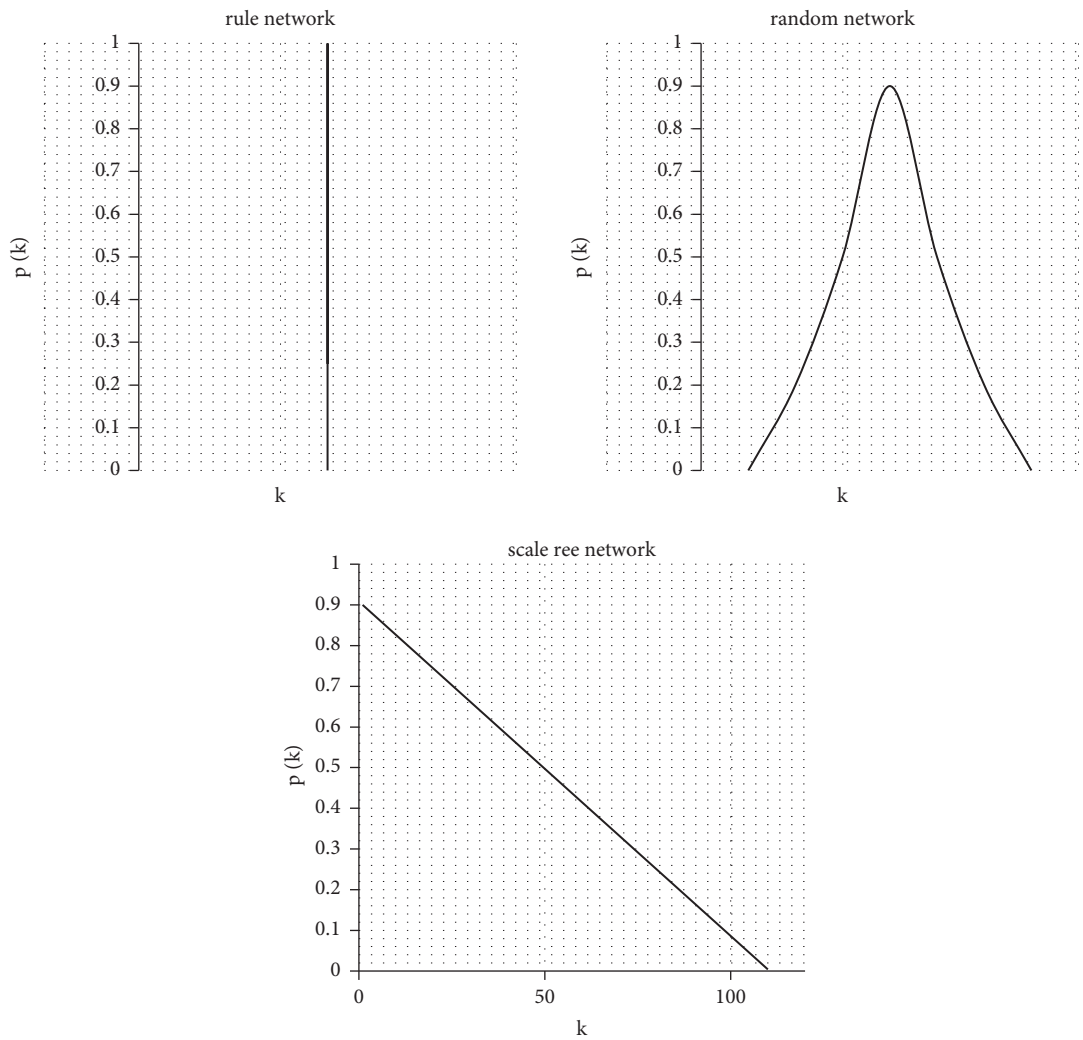

Figure 2: Degree distribution of the network.

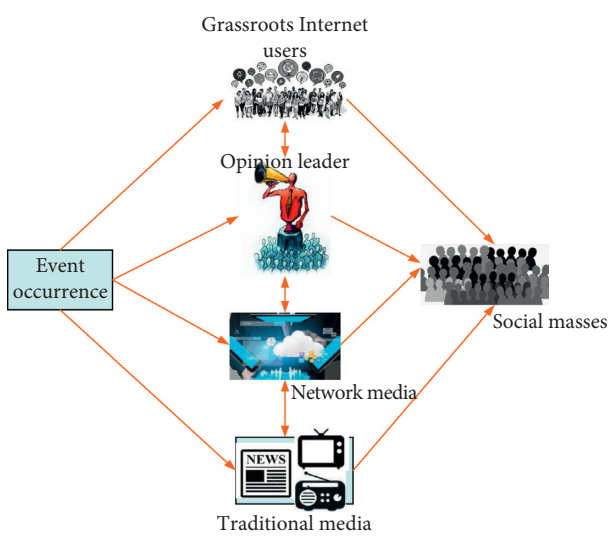

Figure 3: Ways of spreading online public opinion.

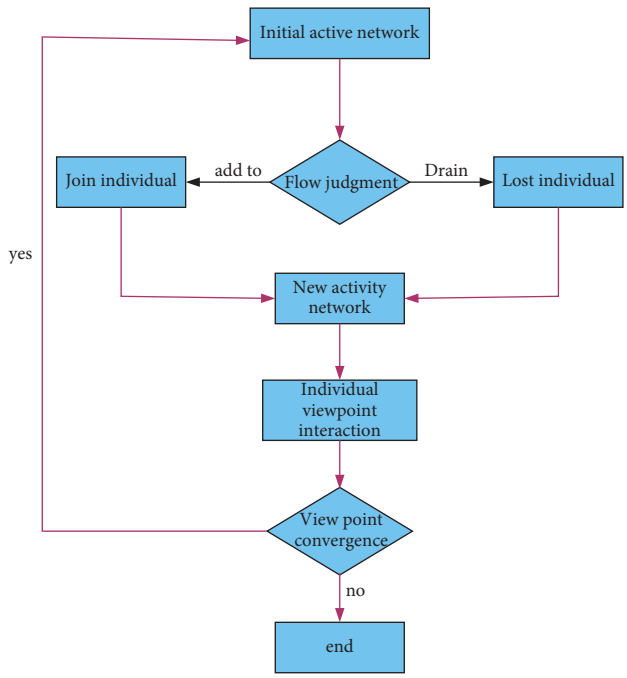

Figure 4: Network public opinion opinion aggregation process.

interests of the public and are generally concerned by the public. Therefore, network public opinion is usually manifested as a hot traffic issue that urgently needs to be improved. The core idea of Analytic Hierarchy Process is to judge the importance of indicators through the decomposition of objectives. Then, establish a judgment matrix, calculate its maximum eigenvalue and eigenvector, and get different weights, which provide a basis for decision-making. This chapter uses the analytic hierarchy process to assist in the construction of an evaluation index system for smart transportation and management network public opinion.

3.3.1. Quantitative Treatment of Evaluation Indicators

(1) Quantification of Subjective Indicators. The quantification of each indicator in the traffic safety and management network public opinion early warning evaluation index system is an important data processing task to ensure that the indicator system is scientific, comprehensive, and accurate. For the traffic safety and management network public opinion early warning evaluation index system, all indicators can be divided into two categories: subjective evaluation and objective evaluation [20–23].

The so-called subjective evaluation index refers to the evaluation made by several evaluators on the basis of their own feelings or opinions. Subjective evaluation indicators are not expressed in numerical values. They are commonly used to describe indicators such as satisfaction, authority, authenticity, scientificity, and a certain ability. The dimensionless processing of subjective data and objective data is shown in the formula. The positive indicators are as follows:

$$Y_{ij} = \frac{x_{ij} - \min(x_{ij})}{\max(x_{ij}) - \min(x_{ij})}. \tag{15}$$

The inverse index is

$$Y_{ij} = \frac{\max(x_{ij}) - x_{ij}}{\max(x_{ij}) - \min(x_{ij})}. \tag{16}$$

In the formula, $\max(x_{ij})$ represents the maximum value of the evaluation value, and $\min(x_{ij})$ represents the minimum value.

(2) Quantification of Objective Indicators. The data of objective evaluation indicators for traffic safety and management network public opinion early warning evaluation can be obtained from specialized network public opinion monitoring agencies [24]. The objective indicators are as follows: public opinion time, which is calculated as the time from when public opinion is generated to disappear. Public opinion gains and losses are the official estimated economic loss. Baidu media index is obtained from Baidu index search. The number of related news is calculated as the number of originals plus the number of reposts.

(3) Calculation of Weight Set. The index weights are determined according to the analytic hierarchy process, which has the advantages of uniformity, practicability, and simplicity. Select 40 evaluators to form a comment group consisting of public opinion workers and public opinion researchers from the traffic police department. Based on the understanding of the problem, comments on the indicators in the indicator system are made, and the comparison results are obtained according to the following principles. Take traffic police credibility B9 = {C15, C16, C17} = {legitimacy of traffic police administrative behavior, scientific traffic police administrative behavior, democratic traffic police administrative behavior} as an example, and find the weight of each indicator. The weight of the criterion layer can be obtained from the index layer calculation. Let us take the criterion layer as an example for calculation.

First find the judgment matrix, as in the following formula:

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \cdots & \cdots & \cdots & \cdots \\ a_{m1} & a_{12} & \cdots & a_{mm} \end{bmatrix}. \tag{17}$$

Then, calculating the importance weight index, assuming $n = 3$, the product of each row element is shown in the following formula:

$$M_i = a_1 \times a_{21} \times a_3, \quad i = 1, 2, 3. \tag{18}$$

Find the n-th root of M_i as follows:

$$W_i = \sqrt[3]{M_i}. \tag{19}$$

Finally, the consistency test refers to the logical consistency of judgment thinking. Here, C.I. is used for consistency check, as shown in the following formula:

$$C.I. = \frac{\lambda_{\max} - m}{m - 1}. \tag{20}$$

In the formula, m refers to the dimension of the judgment matrix A.

3.3.2. Index Weight Design. This chapter builds a model, as shown in Figure 5, to calculate the index weight. This chapter uses a graded index system for calculations. In the grading of the indicator, the red public opinion refers to the unified public opinion, and mostly negative public opinion, which needs to be solved urgently. Blue indicates that there are a large number of people participating, but a unified public opinion has not yet formed, and secondary public opinion may erupt. Green is the one that does not need attention or the public opinion event that is coming to an end.

As can be seen from the figure, the entire system is divided into three layers. The top layer is the prediction model, the second layer is layer A, and the third layer is layer B, and each element has its number.

4. Smart Transportation Network Public Opinion Prediction Model Experiment

This experiment is designed based on the network public opinion prediction model in Section 3.3. This experiment will use rough set theory to optimize the indicators in Figure 5 and evaluate the model.

4.1. Optimizing Forecast Model Indicators. The role of rough set theory is to deal with incomplete data and uncertain knowledge expression and induction. The core is to connect knowledge and classification, to equate knowledge to classification ability, and to use equivalent relations to classify and express. In this step, the rough set theory is used to process the data to make the indicators more concise without reducing the effect of the prediction model [25, 26].

4.1.1. Data Preparation. This experiment selects traffic-related Internet public opinion events in the past five years for analysis, and the way to obtain it is Baidu index, Internet public opinion report, and other websites [27–29]. Specific events and data are shown in Table 1.

Next, enter the data and perform simplified processing. The input data is shown in Table 2.

4.1.2. Data Discretization and Reduction. Rough set can only process discretized data. In view of the continuous data of the index system, the data needs to be discretized. The discretization method used in this experiment is OneRuleDiscretizer (1RD) [30]. Given a minimum value min, each discrete interval is initialized to contain min continuous attribute values, as far as possible by moving the dividing boundary to increase the observation value, until the number of objects in the main decision-making interval is greater than min.

The reduction method adopted in this experiment is attribute reduction. The attribute reduction is to remove redundant conditional attributes through algorithms and simplify the index system. The steps are as follows: (1) first, calculate the discernibility matrix of the decision table; (2) $S = \varnothing$; (3) let A be the set in the discrimination function, and $W(A)$ the weight of A. Define i as the attribute with the largest product of frequency and weight $W(A)$ in A. If the two attribute values are equal, the value is randomly selected; (4) add attribute i to set S; (5) remove items with attribute i in A; (6) if A is an empty set, then return to step (2); otherwise, return to step (3).

Table 3 shows the rules after reduction.

4.1.3. Index Analysis after Reduction. After normalizing the reduced index, the weight obtained is shown in Figure 6.

The simplified processing reduces the indicators of the B layer from the original 10 to 6 and removes some indicators that have little effect. It can be seen from Figure 6 that the event sensitivity weight in the public opinion sensitivity is the highest, reaching 0.4527. Therefore, the transportation department can focus on this content and make corresponding decisions. The media public opinion index can reflect the heat of public opinion very well and can play an early warning role in the early stage of public opinion, and its weight has reached 0.3072. Therefore, the traffic part should pay attention to the content of this part and understand the public opinion index of the event. For example, the Baidu index, the number of news, etc. are specific indicators that reflect the public opinion index, which can be used as a reference for decision-making by the transportation department.

4.2. Index Test of Network Public Opinion Prediction Model

4.2.1. Inspection Principle. The experiment uses a paired sample T test, which can be used to detect whether there is a one-to-one correspondence between two equal samples. This can be used to determine whether two samples are significantly different, and whether they come from subjects with the same normal distribution. The principle of inspection is to find the difference between each pair of corresponding observations and use the difference between the sample observations as a new single sample. The difference between the two samples is not obvious, and the difference at this time is almost zero. This is equivalent to a sample T test, which in principle is to test whether the overall mean difference is zero. Therefore, it is necessary to follow the normal distribution and obtain the judgment result according to the significance level. If the probability value of the test statistic is lower than the significance level, the null hypothesis is rejected, and the difference between the samples is significant; if it is higher, the null hypothesis is accepted, and no significant difference is considered at this time.

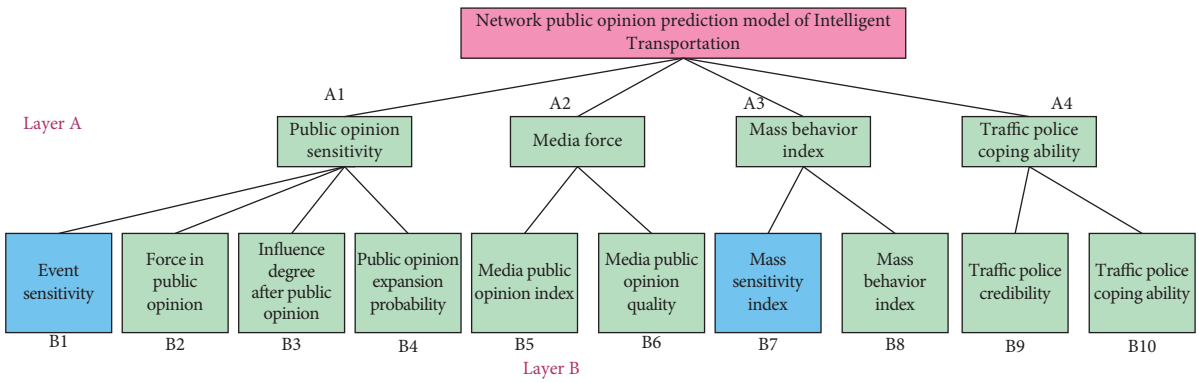

Figure 5: Indicator system.

Table 1: Events and Baidu data.

Event	Number	Baidu index (peak)	Total news
Six points will be deducted if you wear a red light	1	2510	12014
Bus falling into the river	2	3400	23095
Drunken sentence	3	2630	18319
Universal ETC payment	4	820	8915
New policy of online car Hailing	5	880	10287
Cargo Lala jumping event	6	3210	20173
Bus arson	7	190	19200

Table 2: Input data.

	1	2	3	4	5	6	7
B1	1	0.75	0.65	0.75	0.5	0.65	0.25
B2	0.5	0.25	0.75	0.5	0.65	0	0.5
B3	0.75	0.75	0.5	0.65	0	0	0.5
B4	0.25	0.5	0.75	0.25	0.5	0.25	0.75
B5	0	0.25	0.25	0.75	0	0.75	0.5
B6	1	0.5	0.25	0	0.25	0.65	0.75
B7	1	0.75	0.5	1	0.25	0.5	0

Table 3: Rules after reduction.

Arrangement	Rule
A1	B1, B2, B3
A2	B5
A3	B7
A4	B9

4.2.2. Data Comparison. Before testing the indicators, you need to multiply the values of different indicators by the corresponding weights, and the detailed operation will not be repeated. The settlement result and the comparison result of 7 public opinion events with the previous results are shown in Figure 7.

It can be seen from Figure 7 that the comprehensive data of each event before and after the reduction has not changed much. The numerical difference of each event before and after the reduction is between [0.2, 0.4], and the difference is relatively small. It can be seen that the reduction processing does not reduce the effectiveness of the predictive model while simplifying the data processing steps.

4.2.3. Data Verification of the Forecast Model Index System. First, calculate the mean, standard deviation, and standard error of the mean before and after the processing to get Figure 8 [31].

Then, calculate the correlation coefficient of the data before and after the processing, the paired test result, the two-tailed significance level, and other values, and get Figure 9.

It can be seen from Figure 8 that there is no significant difference between the standard deviation and standard error of the data before and after processing, which proves that there is no change in the structure of the model. It can be seen from Figure 9 that the correlation coefficient is 0.988, which proves that the results before and after processing are highly correlated. The paired test result is 0.712, and the two-tailed significance level is 0.471. This value is one 0.01, indicating that the null hypothesis should be accepted; that is, the two sets of data are not considered to be significantly different. In summary, there is no significant difference between the results obtained before and after processing the indicators in the model, so it is feasible to simplify and optimize the indicators of the model.

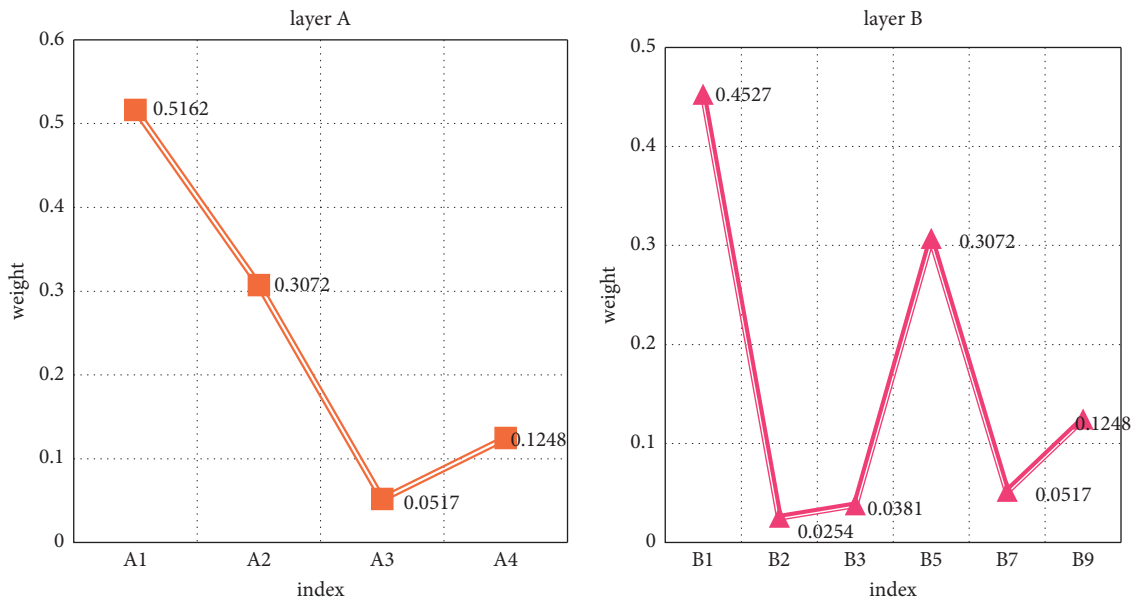

Figure 6: Index weights after reduction.

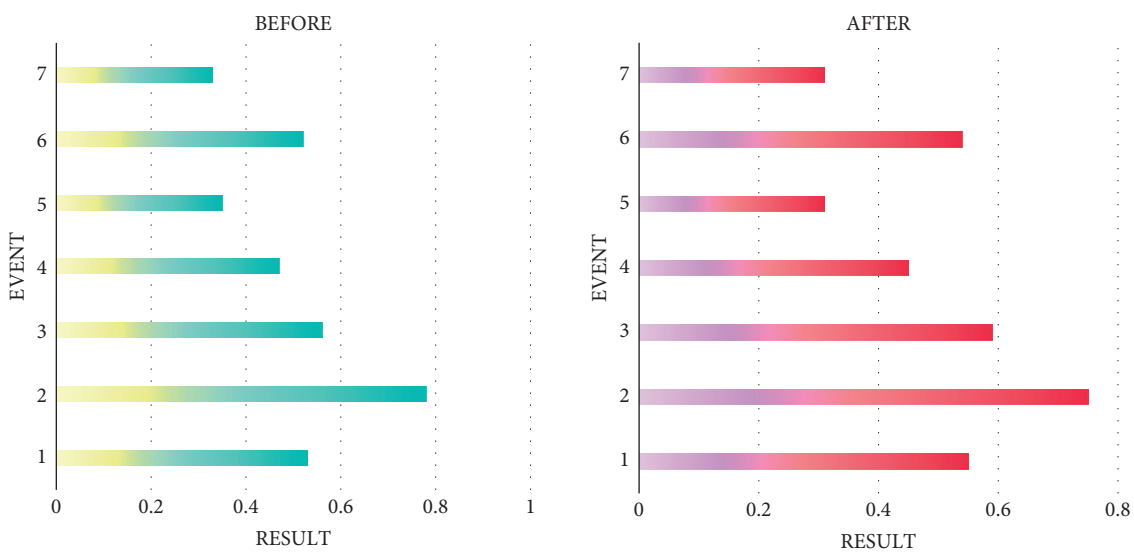

Figure 7: Comprehensive event data before and after processing.

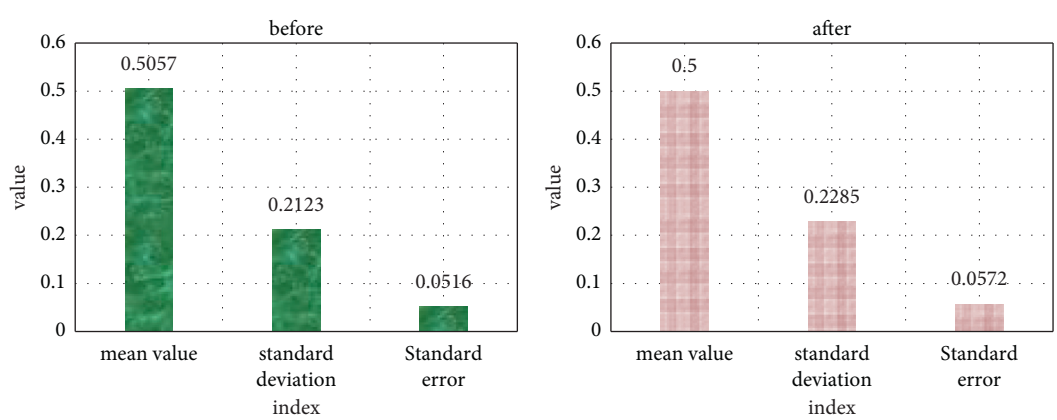

Figure 8: Sample statistics before and after processing.

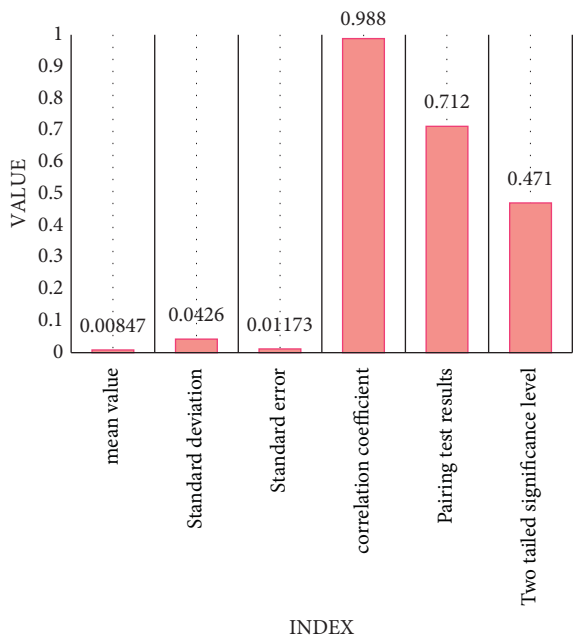

Figure 9: Sample inspection before and after processing.

5. Discussion

The network's timeliness, interactivity, and large amount of information are incomparable to traditional media such as television, newspapers, and radio. Internet public opinion plays an important role in the development of the country and society. This is the voice of netizens, and it reflects the overall situation of online public opinion and is an important reference material for traffic management departments to make decisions. The rapid development of social information has brought new challenges to the response capabilities of traffic management departments. Relevant departments should face online public opinion with an open and positive attitude and incorporate the use of public opinion into the necessary work of the traffic management department. It uses online public opinion to integrate decision-making and establish a feedback mechanism. Only by winning every battle in response to online public opinion can we seize the commanding heights of public opinion, firmly grasp the right to speak and initiative, change the passive situation of public opinion response, and create a better public opinion atmosphere for the smooth development of traffic management.

6. Conclusion

Internet public opinion is a double-edged sword. Governmental departments must establish a suitable and effective public opinion management mechanism and build a good public opinion environment to help make decisions and maintain social harmony. This article discusses the multidimensional dynamic and predictive model of network public opinion based on the integration of smart transportation and big data. First, this article analyzes the big data technology in smart transportation. Then, we introduced the relevant theory of network public opinion and designed a prediction model of smart transportation network public opinion. Finally, this article optimized the model through experiments and calculated a variety of index data before and after optimization. It is found that the optimization not only simplifies the analysis process of network public opinion by removing some indicators with minimal influence, but also is similar to the comprehensive data result before optimization without significant difference, which proves the feasibility of the experimental optimization process. The future work is to further optimize the prediction model of online public opinion, make the analysis process of the model simpler and more efficient, and promote the prediction model of online public opinion.

Data Availability

No data were used to support this study.

Conflicts of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgments

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