Postprint: A Fuzzy Linguistic Evaluation of Network Information Pollution Status Based on the Scatter Degree Method

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Abstract

[Purpose/Significance] Online information pollution is widely abhorred by the general public. Conducting scientific evaluation of the status of online information pollution and placing this issue under public scrutiny helps enhance the efficiency of problem resolution. [Method/Process] This paper combines data from the 12321 Center and public questionnaire survey data, employs a fuzzy-linguistic improved "pulling apart" method to determine indicator weights, and uses the TOPSIS method to aggregate evaluation information. [Results/Conclusion] During the period from February 2014 to October 2016, the overall situation of online information pollution was relatively severe, with information pollution being most serious during the March-April 2015 period. The improved "pulling apart" method based on fuzzy language proposed in this paper demonstrates better discriminatory ability among evaluation units compared to the traditional "pulling apart" method.

Full Text

Preamble

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Research on the Evaluation Model for Network Information Pollution Status Based on Fuzzy Linguistic Assessments and the Scatter Degree Method

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Abstract

[**Purpose/Significance**] Network information pollution has become a source of intense public resentment. Conducting scientific evaluations of network information pollution status and placing this issue under public supervision can help enhance the efficiency of problem resolution. [**Method/Process**] This paper combines data from the 12321 Center with public questionnaire survey data, employs a fuzzy linguistic improved "scatter degree" method to determine indicator weights, and uses the TOPSIS method to aggregate evaluation information. [**Results/Conclusions**] During the period from February 2014 to October 2016, the overall network information pollution situation was severe, with the worst conditions occurring in March and April 2015. The improved scatter degree method developed in this paper demonstrates better discriminatory power among evaluation units compared to traditional approaches.

Keywords: network information pollution; scatter degree method; fuzzy linguistic evaluation; 12321 Center; social survey

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Introduction

The internet is a double-edged sword that brings convenience to people's lives while simultaneously creating network information pollution phenomena such as spam messages, harassing phone calls, and junk emails, which generate numerous negative impacts. Data from the 12321 Internet Illegal and Spam Information Reporting Center (hereinafter referred to as the "12321 Center") reveals that in the most recent year, Chinese netizens suffered economic losses of up to 91.5 billion RMB due to network information pollution—nearly equivalent to Tibet's total GDP for 2015 (102.6 billion RMB). The time lost by all netizens amounted to the equivalent of 3,822 human lifespans (based on the 2015 WHO report of average Chinese life expectancy: 74 years for males and 77 years for females, using an average of 75 years). What, then, is the current state of network information pollution? Does public perception align with the center's statistical data? How can we scientifically evaluate information pollution conditions in cyberspace? Addressing these questions and placing network information pollution under public scrutiny can help foster a "clear sky and healthy ecosystem" in our online spaces.

The term "information pollution" was first introduced by German scholar Rafael Capurro in his paper "Advances in Information Ecology" [1]. Information pollution primarily comprises two categories: first, harmful, toxic, deceptive, and misleading information mixed into media content; and second, information overload [2], which may lead to privacy breaches and losses in time, money, and psychological well-being. With the application of emerging information technologies such as big data, cloud computing, and mobile internet, information pollution has become a hot topic in network governance and public opinion guidance research [3]. Existing research mainly proceeds along two dimensions.

The first dimension examines information overload and its solutions. Information overload occurs when people receive excessive information that they cannot effectively integrate, organize, or internalize into useful knowledge, thereby affecting work, study, and interpersonal relationships [4]. M. J. Eppler et al. categorize the causes of information overload into five types: individual factors, information characteristics, task and process factors, organizational design, and information technology [5]. He Zhong et al. argue that information overload in online shopping environments creates choice difficulties for consumers, resulting in wasted time and psychological costs [6]. Wang Na and Zheng Qiaowei study information overload in WeChat subscription services, finding that current content suffers from duplication and low quality [7]. How, then, can information overload be resolved? Most scholars opt for technical solutions to reduce data dimensionality and help users obtain useful information, primarily through personalized recommendation algorithms and search engine technologies. Liang Laohui, from an information organizer's perspective, suggests that libraries should help users avoid information overload through information literacy education and consultation manuals [8]. Wang Na et al. conduct sampling surveys and analyses of information overload in ubiquitous networks, proposing the establishment of personalized recommendation mechanisms in mobile social networking sites [9, 10]. Wang Na and Tian Xiaomeng study how information organization design in Douban communities affects information overload and propose optimization strategies for folksonomy on the Douban platform [11]. Wang Youran, based on weighted small-world network theory, discovers that excessively short characteristic relationship lengths among members within single communities on social networking sites like Renren.com cause high repetition and homogenization [12]. Gao Xirong et al. establish an information value evaluation index system by searching keywords on CNKI [13]. Zhao Jingxian categorizes online reviews into four types: non-spam, deceptive, interfering, and low-value comments, establishes a spam review feature attribute table, and designs an online review text classification method based on neural networks and decision trees [14].

The second dimension focuses on network information security and personal privacy risk assessment. Xia Ri first proposed the concept of the Information Pollution Index (IPI) [15] and established an indicator system [16-17], but his classification of information pollution sources includes physical, documentary, electronic, and network types, containing excessive redundant information that no longer reflects realities in network society. Cheng Yanlin proposes seven dimensions for detecting network information pollution [18] but provides no specific quantification methods. Xie Youning and Niu Qin investigate life-type and production-type information pollution in rural settings [19], but their approach suffers from excessive subjectivity. Chen Guixiang surveys the status and attitudes of information pollution among university students [20], but limits analysis to statistical description of results. T. H. Hsu et al. apply the ANP method to evaluate tourism websites, finding that "security" is the primary concern [21]. Zhu Guang et al., based on information system security models [22], categorize privacy risk factors into platform vulnerability factors, user behavior vulnerability factors, and external threat factors, constructing a social network privacy risk assessment system and evaluating it using fuzzy evaluation methods [23].

A review of information pollution research reveals that current studies primarily focus on technical aspects. In reality, however, the source of information pollution is human beings themselves. With the popularization of mobile internet, the impact scope of information pollution has gradually expanded. Internet information pollution prevention and control constitute a social soft system problem characterized by fuzziness, complexity, and systematicity [24], making it impossible to fundamentally solve through technical approaches alone. Sociological research demonstrates that placing problems under public evaluation helps enhance problem-solving efficiency. Therefore, studying the negative impacts of information pollution from a public perspective holds significant importance for alerting humans to reflect on their own information behaviors, improving information literacy, and jointly maintaining a healthy cyberspace environment. In the domain of information pollution and its impact assessment, a few scholars have conducted exploratory research, but their indicator systems tend to be overly broad and inconsistent with current network society realities.

This paper combines information pollution and spam statistics provided by the 12321 Center with a public attitude survey questionnaire on information pollution experiences. It employs a fuzzy interval possibility degree algorithm to construct a symmetric matrix and obtains subjective weights based on this symmetric matrix, then applies the "scatter degree" method for secondary weighting to revise the purely objective weight results of the traditional scatter degree method. The results demonstrate that our proposed method can more comprehensively evaluate network information pollution status.

1. Construction of the Network Information Pollution Status Evaluation Index System

Information pollution comprises two major categories of pollution sources. However, considering that information overload is highly subjective—different people have different experiences—and currently lacks corresponding statistical support, this study focuses primarily on the first type of pollution information and temporarily excludes the second type.

Based on preliminary research findings [2], we adopt the 12321 Center's statistical categories as seven measurement indicators for network information pollution: spam emails, malicious websites, spam SMS, illegal SMS, spam MMS, harassing phone calls, and mobile application security issues (malicious APPs). This represents the most detailed and accurate statistics on network pollution information available to date.

Meanwhile, preliminary investigations revealed significant discrepancies between the 12321 Center's statistical data and public perception. For instance, malicious APPs appear frequently in statistical data, even exceeding the number of reports for spam SMS and harassing phone calls, yet public feedback shows the opposite pattern. To compensate for the one-sidedness of statistical data and drawing on the Failure Mode and Effects Analysis (FMEA) methodology used in fault detection [25-26], which employs occurrence, severity, and detection ratings to assess risk for failure modes, we designed the "Public Attitudes Toward Information Pollution Experiences" questionnaire. The survey investigates public cognitive attitudes from three perspectives: frequency of encountering information pollution (how often experienced), degree of harm already caused (psychological damage, time waste, or financial loss), and public aversion levels to various pollution information types. This approach integrates both statistical data and public cognitive attitudes to comprehensively evaluate network information pollution status.

2. Network Information Pollution Status Evaluation Model and Methods

Following the establishment of the evaluation index system, the next steps involve obtaining indicator weights and selecting information aggregation methods. The research framework is illustrated in [Figure 1: see original paper].

[Figure 1: see original paper] Research Framework for Network Information Pollution Status Evaluation

2.1. Weight Acquisition Method for Complementary Judgment Matrices Based on Fuzzy Interval Possibility Degree

Since people prefer using linguistic terms to evaluate things, such as "excellent," "good," "medium," or "poor," and human language possesses characteristics of fuzziness and complexity, scholars have developed corresponding weight acquisition methods based on fuzzy mathematics. Xu Zeshui proposed an interval possibility degree method for fuzzy linguistic scales [27] that can derive weights from raw data. This paper applies this method to evaluation matrices that use fuzzy linguistic assessments.

2.1.1. Interval Possibility Degree for Fuzzy Linguistic Scales

Definition 1 Let matrix ( )ij n n be a fuzzy matrix if 0 ≤ a_{ij} ≤ 1.

Definition 2 Let fuzzy matrix ( )ij n n be a fuzzy complementary matrix if a_{ij} + a_{ji} = 1.

Definition 3 [28-30] Let interval numbers a = [a^-, a^+] and b = [b^-, b^+] define the operational rules: 1) Interval addition: a + b = [a^- + b^-, a^+ + b^+] 2) Scalar multiplication: λa = [λa^-, λa^+] where $\lambda \geq 0$

Definition 4 [27] Let interval numbers a = [a^-, a^+] and b = [b^-, b^+]. The possibility degree that a $\geq$ b is given by formula (1):

p(a $\geq$ b) = max{1 - max{(b^+ - a^-)/(a^+ - a^- + b^+ - b^-), 0}, 0}

This possibility degree has complementarity, meaning: p(a $\geq$ b) + p(b $\geq$ a) = 1.

2.1.2. Weight Acquisition Method for Complementary Judgment Matrices Based on Fuzzy Interval Scale Possibility Degree

Let surveyed object d_k D, where D = {d_1, d_2, …, d_t} evaluate pollution information type x_i on attributes G_j G = {frequency of encountering information pollution, degree of harm suffered, aversion to information pollution} using fuzzy linguistic assessments that form matrix ( )ij n m, where r_{ij} S and S = {very low, somewhat low, medium, somewhat high, very high} is the fuzzy linguistic scale. These are converted to corresponding interval numbers [27]:

very low = [0, 0.2], somewhat low = [0.2, 0.4], medium = [0.4, 0.6], somewhat high = [0.6, 0.8], very high = [0.8, 1]

The process for obtaining subjective weights based on fuzzy interval scale possibility degree is as follows:

Step 1: Aggregate all fuzzy interval matrices provided by survey respondents using formula (2), where r_{ij} is converted through fuzzy linguistic scales. For convenience, the aggregated fuzzy interval matrix is still denoted as ( )ij n m.

Step 2: For pollution information type x_i, calculate the sum of its attribute values: x_i = Σ_j r_{ij}.

Step 3: Perform pairwise comparisons of (x_i, x_j) for i, j = 1, 2, …, n using formula (1) to obtain the possibility degree matrix P = (p_{ij})_n×n. By definition, this possibility degree matrix is a complementary judgment matrix. Calculate the ranking weights using formula (3) [27, 31]:

ωi = (Σ_j p{ij} + n/2 - 1) / (n(n - 1)), for i = 1, 2, …, n

2.2. Secondary Weighting Using the "Scatter Degree" Method

In Guo Yajun's "scatter degree" method, evaluation indicator weights no longer reflect the relative importance among indicators but rather allow all indicators to participate in the evaluation process with equal "status." This method is "completely objective" [32]. However, in reality, the importance of various indicators relative to the evaluation objective is often unequal. Therefore, we first weight the raw data using the subjective weights obtained in Section 2.1, then apply the scatter degree method for secondary weighting. The calculation steps are as follows:

Step 1: Indicator consistency and dimensionless processing. We use standard deviation standardization as shown in formula (4):

y_{ij} = (x_{ij} - _j) / σ_j, for i = 1, 2, …, n; j = 1, 2, …, m

where _j and σ_j are the sample mean and standard deviation of the j-th indicator, respectively.

Step 2: Use the indicator weights ω = (ω_1, ω_2, …, ω*m) obtained from formula (3) to weight the dimensionless matrix A* = (y*{ij}*)n×m [33]. For convenience, the weighted data is still denoted as (y*{ij})_n×m.

Step 3: Apply the scatter degree method for secondary weighting. First, construct the real symmetric matrix H as shown in formula (5):

H = A^*T A*

Then, take ω* as the standardized eigenvector corresponding to the maximum eigenvalue of H. ω* is the final weight vector [34].

2.3. Information Aggregation Using the TOPSIS Method

The TOPSIS method is a technique for aggregating evaluation information. Define the weighted Euclidean distance between evaluated unit i and the positive ideal unit x* as:

d_i^+ = √[Σ_j (ω*j^* (y*{ij} - y_j^*))^2], for i = 1, 2, …, n

Similarly, define the weighted Euclidean distance between evaluated unit i and the negative ideal unit x^0 as:

d_i^- = √[Σ_j (ω*j^* (y*{ij} - y_j$^{0))}$2], for i = 1, 2, …, n

Define the closeness coefficient as:

h_i = d_i^- / (d_i^+ + d_i^-)

Obviously, a larger closeness coefficient h_i is better, indicating the evaluated unit is farther from the negative ideal unit and closer to the positive ideal unit.

3. Empirical Analysis

3.1. Public Attitudes Toward Information Pollution Experiences Survey

Prior to questionnaire distribution, the survey content underwent repeated discussion and revision of item descriptions. Based on this, a pilot test with 30 participants was conducted to further refine questionnaire clarity. The questionnaire comprises three sections: (1) basic information including gender, age, occupation, weekly internet usage time, and mobile operating system type; (2)

main body with 21 items; and (3) one open-ended question: "What other types of information do you consider as information pollution? What harm have they caused you?" During November-December 2016, questionnaires were randomly distributed through the "Wenjuanxing" platform and at the Jiefangbei commercial district in Chongqing, where population density is highest.

Surveyors received necessary training before offline distribution. During distribution, one-on-one guidance was provided to ensure respondents completed the questionnaire according to their actual situations, guaranteeing result reliability. Under expert guidance, 438 questionnaires were distributed, with 417 valid questionnaires recovered (95.2% validity rate). The sample included 189 males (45.3%) and 228 females (54.7%). Respondent distributions by occupation, age, weekly internet usage, and mobile OS type are shown in [Figure 2: see original paper]-[Figure 5: see original paper].

[Figure 2: see original paper] Respondent Occupation Distribution
[Figure 3: see original paper] Respondent Age Distribution
[Figure 4: see original paper] Weekly Internet Usage Time
[Figure 5: see original paper] Mobile Operating System Type

Online questionnaire results were automatically tallied by Wenjuanxing with no missing data. Offline questionnaires were entered independently by two researchers using EpiData 3.1 to reduce entry errors. This portion had partial missing data (<5%), which was imputed using the Expectation Maximization (EM) method in SPSS.

3.2. Reliability and Validity Analysis

3.2.1. Reliability SPSS analysis revealed high reliability for the 417 questionnaires ($\alpha > 0.7$ indicates high reliability), meeting exploratory research requirements. Reliability coefficients for each item are shown in .

Questionnaire Reliability Coefficients

Measurement Items	Alpha if Item Deleted	Overall Alpha
Frequency of encountering information pollution	0.712	0.734
Harm from information pollution	0.708	
Aversion to information pollution	0.725	

3.2.2. Validity Common questionnaire validity types include content validity and construct validity. Content validity of this questionnaire was approved through discussion among five experts. Construct validity requires consistency of factors under each dimension, but since this questionnaire measures public cognitive attitudes toward different pollution information types, construct validity is not applicable to this research purpose and thus was not assessed.

3.3. Weight Calculation and Comparative Analysis

We obtained statistical data on various pollution information types from the 12321 Center for February 2014-October 2016 (shown in), then calculated three types of weights.

3.3.1. Objective Weight Calculation First, we standardized the data from the appendix using formula (4), then constructed real symmetric matrix H using formula (5) (shown in). Taking the eigenvector corresponding to the maximum eigenvalue of H yields objective weights, shown in column 2 of .

Among the seven pollution information types, "spam MMS" has the largest weight (0.174), while "harassing phone calls" has the smallest (0.109). This inversely correlates with public aversion levels—the more disliked the pollution type, the smaller its weight and thus lower its score. This aligns with intuitive experience: people typically give lower ratings to things they dislike, such as giving negative reviews for unsatisfactory online purchases.

Objective weights assign larger values to "spam MMS" and smaller values to "malicious APPs." This occurs because the reported quantities of these two pollution types differ by orders of magnitude from other types. To allow all indicators to participate equally in evaluation, the scatter degree method assigns smaller weights to "malicious APPs" with the highest report volume and larger weights to "spam MMS" with the lowest volume.

3.3.2. Public Subjective Weight Calculation The possibility degree matrix P calculated after aggregating questionnaire information is shown in . Public subjective weights ω are then calculated using formula (3), shown in column 4 of .

3.3.3. Comprehensive Weight Calculation After weighting the standardized matrix A with public subjective weights ω, we apply the scatter degree method for secondary weighting to obtain comprehensive weights, shown in column 6 of . Compared with the traditional scatter degree method, the objective weights derived from statistical data are revised, resulting in slightly increased weights for the most disliked pollution types (harassing phone calls and spam SMS) and slightly decreased weights for less criticized types. Except for "spam SMS" and "malicious APPs," which show large weight distribution differences, weights for other pollution types are relatively similar, indicating public perceptions align relatively well with 12321 Center statistics.

The large weight differences for spam SMS and malicious APPs stem from discrepancies between public perception and statistical data. For spam SMS, despite strong public aversion, some instances go unreported. Interviews revealed that over 50% of the public directly delete spam messages without reporting them. Some respondents have mobile security software with blocking capabilities but still check intercepted messages for fear of misoperation before deletion.

For malicious APPs, the weight difference arises because major app stores collaborate with the 12321 Center to filter out numerous malicious APPs before users download them, resulting in lower public awareness despite high statistical reporting.

3.4. Evaluation Information Aggregation

Since all evaluation indicators are negative (smaller values indicate better performance, meaning less pollution, also called cost-type indicators), we set the positive ideal system as the minimum values after standardization and the negative ideal system as the maximum values. Finally, we use the TOPSIS method from Section 2.3 to aggregate evaluation information, scaling results by 100 to produce scores in the [0,100] interval for better intuitive understanding. Higher scores indicate less network information pollution, while lower scores indicate more severe pollution. The comparison between results from the improved scatter degree method and the traditional method is shown in .

Comparison of Evaluation Results: Improved vs. Traditional Scatter Degree Method

The left side of shows results from the improved method. During the evaluation period, overall network information pollution status scores clustered around 80, indicating less-than-ideal conditions. Scores were higher in January 2016 and August 2016, reflecting relatively less pollution and better network environments. The lowest score (14.84) occurred in March-April 2015, likely due to concentrated pollution incidents during this period rather than the time span itself, as other two-month periods like May-June 2016 and June-July 2015 showed scores closer to average levels.

The right side of shows final rankings using the traditional scatter degree method on statistical data alone. Comparing both methods reveals that the improved approach expands the score range from [19, 96] to [15, 99]. Overall rankings show little difference, though February and March 2014 exchange positions. The improved method polarizes evaluated units—making good performers better and poor performers worse—thereby more clearly revealing information pollution conditions across time periods. This demonstrates that the improved algorithm provides better discriminatory power among evaluated units.

4. Conclusions and Outlook

This paper designed a public attitude survey on information pollution experiences, calculated public subjective weights based on fuzzy interval possibility degree symmetric matrices, and applied the scatter degree method for secondary weighting to revise objective weights calculated from statistical data. Using the improved scatter degree method, we evaluated information pollution status from February 2014 to October 2016. Compared with traditional methods, the improved approach expands the scoring interval and exchanges the rankings for February and March 2014. This confirms that the improved method offers better discriminatory power among evaluation units and better embodies the "scatter degree" characteristic.

Compared with previous research, this study combines public attitude surveys with statistical data to more comprehensively measure current information pollution status. Overall, the information pollution situation remains severe. Using the improved scatter degree method, most time periods scored around 80, with March-April 2015 showing the most serious pollution. Survey results also revealed significant discrepancies between public perception and center statistics for seven pollution types. For instance, while the 12321 Center reports substantially higher numbers of malicious APPs than other pollution types, our social survey found that the public is most averse to spam SMS and harassing phone calls, with lower reported frequency and harm from malicious APPs. This phenomenon arises from differences between public perception and statistical data. For malicious APPs, mobile security software and app store review measures may be effective; for spam SMS, nearly half of the public directly deletes messages without reporting, causing underreporting; for harassing phone calls, high public aversion may stem from telephony being a rich communication medium that leaves strong subjective impressions reflected in questionnaire responses. Additionally, spam MMS shows low levels in both center statistics and public reports. With the development of instant messaging tools like QQ and WeChat, MMS is becoming obsolete, suggesting that MMS and SMS pollution statistics could be merged.

This study has limitations. First, it focuses primarily on the first category of network information pollution, though surveys revealed serious information overload problems in social tools like WeChat. Second, to enhance reliability, we used both online and offline channels, with the offline sample concentrated in Chongqing, showing obvious regional characteristics. Future research could employ stratified sampling nationwide for broader, more representative coverage. Finally, this study only surveyed public attitudes during November-December 2016. Although psychology suggests negative information leaves deeper, longer-lasting impressions, subsequent research should conduct annual surveys to reflect dynamic changes in public cognition and enhance result timeliness.

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Author Contributions:
Wan Xiaoyu: Conceived the research framework and revised the paper;
Wang Zaiyu: Wrote the paper, performed data modeling and analysis;
Jiang Ting: Distributed questionnaires and collected data.

Note: Figure translations are in progress. See original paper for figures.