Postprint: Construction and Empirical Analysis of a Concurrent Acquisition Model for Multimedia Network Public Opinion Information

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Abstract

[Purpose/Significance] The construction and empirical research of a concurrent acquisition model for network public opinion information facilitate timely retrieval of required key information from massive public opinion data, providing data support for effective analysis. [Method/Process] Through a comprehensive analysis of the current research status on public opinion information acquisition, the constituent elements of a concurrent acquisition model for multimedia network public opinion information are identified. Three mathematical analysis methods—DEMATEL, AHP, and FMF—are integrated for model construction, upon which empirical analysis is conducted. [Results/Conclusion] The research findings indicate that the obtained data conclusions are relatively consistent with the objective circumstances of public opinion events and can serve as a basis for judging concurrent acquisition of public opinion information.

Full Text

Construction and Empirical Analysis of a Concurrent Acquisition Model for Multimedia Network Public Opinion Information

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Abstract: [Purpose/Significance] The construction and empirical study of a concurrent acquisition model for network public opinion information helps to obtain key information in a timely manner from massive volumes of public opinion data, providing data assurance for its effective analysis. [Method/Process] Through comprehensive analysis of the current research status of public opinion information acquisition, this paper clarifies the constituent elements of a concurrent acquisition model for multimedia network public opinion information, integrating three mathematical analysis methods—DEMATEL, AHP, and FMF—for model construction and conducting empirical analysis accordingly. [Result/Conclusion] Research results demonstrate that the data conclusions obtained are largely consistent with the objective circumstances of public opinion events and can serve as a basis for judging concurrent acquisition of public opinion information.

Keywords: multimedia; network public opinion; concurrent acquisition; model construction **Classification Number:** G203 **DOI:** 10.13266/j.issn.0252-3116.2020.23.012

The rapid transformation and boundless development of Internet science and technology have led to information growth at an exponential rate. According to the "45th Statistical Report on China's Internet Development" released by the China Internet Network Information Center (CNNIC) in March 2020 [?], China's netizen population reached 904 million, with an Internet penetration rate of 64.5%, representing a 4.9% increase since the end of 2018. These figures indicate that the number of information sources, communication channels, and diffusion speed are unprecedented, especially given the complexity, randomness, and variability of the online environment. The broad coverage of network public opinion reflects social sentiment and profoundly influences public attitudes and consciousness. How to effectively obtain and identify key information through complex public opinion data has become a top priority. The massive, random, implicit, and mutative characteristics of network public opinion information significantly increase the difficulty of effective acquisition. Although current research on network public opinion information collection and acquisition has reached considerable scale, studies on concurrent acquisition of network public opinion remain scarce. Therefore, this paper examines the research status from the perspectives of concurrent and parallel processing and information acquisition.

Regarding concurrent processing efficiency, J. Xue et al. [?] introduced high parallel processing systems that enable data sharing during multiple concurrent operations, expanding logical scheduling space and enhancing data concurrent processing performance while reducing error rates. In parallel design, H. Zheng et al. [?] identified problems through parallel design activities, clarified influencing factors through in-depth investigation, and constructed structural relationship models. For information acquisition model construction, S. Sun et al. [?] proposed a distributed incremental information acquisition model that facilitates timely discovery and acquisition of incremental data from large-scale text data on the Internet. In terms of information acquisition methods, Y. Liu et al. [?] presented a knowledge acquisition method for ordered information systems based on concept lattices and inclusion degrees. J. Liu [?] analyzed and discussed information collection principles, channels, and common methods for public sector websites. Regarding concurrent processing model construction, Li Hui et al. [?] constructed a concurrent processing model for big data platform data and validated it through simulation experiments. Hong Liang et al. [?] built a system dynamics model using simulation experiments, revealing strong interactions between network public opinion and netizens, events, and media, identifying relevant influencing factors and providing response strategies. Zhu Hongcan et al. [?] analyzed influencing factors of information acquisition based on flow theory, constructed an intention model, and validated its rationality through empirical analysis. For information acquisition measurement, Jin Jiangyan et al. [?] constructed a hierarchical model of information polychromatic sets, established an information acquisition relationship matrix, and validated model operability through empirical research. In information collection, Li Li et al. [?] focused on web crawlers, dividing them into three modules: webpage crawling, preprocessing, and relevance evaluation, demonstrating through experiments that the method achieves good precision. Zhang Honghao et al. [?] simulated browser requests to required Web pages, implementing a web crawler-based webpage information acquisition system.

Multimedia network public opinion exhibits both implicit and explicit dual characteristics. The aforementioned studies have respectively explored influencing factors, analytical methods, model construction, and information collection related to concurrent processing, parallel design, system construction, and network public opinion information acquisition in considerable detail. However, these techniques and methods target specific problems, with relatively few studies on concurrent acquisition of multimedia network public opinion information. Moreover, the concept and connotation remain undefined. These studies tend to focus on micro-level, targeted research. This paper will synthesize relevant research hotspots on multimedia network public opinion, integrate fundamental theories from information science, statistics, and management, start from objective reality to clarify constituent elements of concurrent acquisition, introduce multiple mathematical analysis methods, and ensure effective acquisition, analysis, and calculation of public opinion event information through comprehensive analysis and application. This research emphasizes a macro, coarse-grained perspective to obtain high-attention, high-impact, and wide-ranging public opinion information from complex and variable public opinion data.

This paper synthesizes the above research, defines the connotation of concurrent acquisition of multimedia network public opinion information according to objective needs, proposes a model construction method, and conducts empirical analysis. The goal is to effectively screen network public opinion events and extract key public opinion information from massive data at specific time points, providing strong objective data support for real-time tracking of dynamic changes in network public opinion information. This research facilitates timely grasp of public opinion trends by regulatory bodies, enables associated actors to adjust plans promptly, enhances the scientific nature of response strategies, prevents further diffusion and spread of adverse public opinion trends, and fosters a sustained, healthy, and harmonious public opinion environment.

2 Connotation and Constituent Elements of Concurrent Acquisition of Multimedia Network Public Opinion Information

2.1 Connotation

Concurrency primarily refers to a single processor handling multiple tasks simultaneously within a specific time frame [?]. Parallelism mainly refers to multiple processors handling multiple tasks simultaneously within a specific time range [?], primarily demonstrating parallel computing capability. In this study, concurrent acquisition of multimedia network public opinion information mainly refers to the process of concurrently processing massive network public opinion information supported by multimedia technology for data collection, screening, and acquisition.

2.2 Model Construction Approach and Methodology

The rational construction of a concurrent acquisition model for multimedia network public opinion information manifests in three aspects: (1) analyzing constituent elements of concurrent acquisition; (2) constructing a concurrent acquisition model; and (3) conducting empirical analysis. The main research methods include theories from management science, statistics, and fuzzy mathematics: (1) through literature analysis and comprehensive surveys to clarify data sources for concurrent acquisition and abstractly summarize model constituent elements; (2) combining element analysis, analytic hierarchy process, and mathematical analysis to determine weights of constituent elements; and (3) collecting data through web crawlers, standardizing the data, and measuring trigger values.

2.3 Analysis of Model Constituent Elements

2.3.1 Constituent Element Analysis Based on data source analysis for concurrent acquisition of network public opinion information [?], this study considers analyzing constituent elements from the dimensions of public opinion subject, object, media, and ontology, as detailed in Table 1 .

Table 1 Constituent Elements of Concurrent Acquisition Model for Multimedia Network Public Opinion Information

Primary Elements	Secondary Elements
Subject Participation	Forwarding volume mean, Comment volume mean, Like volume mean, Daily publication volume, Thematic word frequency volume, Text information volume, Thematic word frequency mean, Text information mean

The constituent elements are parsed as follows [**?**]:

(1) **Subject Participation (SP)**: Refers to subject reading volume (r), discussion volume (d), and original content volume (o). Reading volume indicates the number of times public opinion subjects read public opinion events or topics within a certain period; discussion volume refers to the frequency of discussions by network public opinion subjects on specific events or themes; original content volume refers to the amount of original information expressed by public opinion subjects through various means such as emojis and micro-videos.

(2) **Object Heat (OH)**: Primarily includes forwarding volume (t), comment volume (c), like volume (g), forwarding volume mean (ta), comment volume mean (ca), and like volume mean (ga). Forwarding volume refers to the number of times public opinion event information is forwarded by subjects; comment volume refers to the number of comments, reviews, and messages on network public opinion objects; like volume refers to the number of likes on network public opinion objects; forwarding volume mean refers to the frequency of forwarding public opinion events per unit time; comment volume mean refers to the frequency of comments on specific events per unit time; like volume mean refers to the frequency of likes on public opinion events per unit time.

(3) **Media Influence (MI)**: Refers to search volume (s), media volume (m), publication volume (p), and daily publication volume (pa). Search volume refers to the frequency of retrieving public opinion events within a certain period; media volume refers to the number of media outlets reporting on a network public opinion event within a time range; publication volume refers to the amount of information published related to public opinion events at a specific time point; daily publication volume refers to the amount of data published per unit time for public opinion events.

(4) **Ontology Fusion (OF)**: In philosophical research, ontology was originally defined as the science of "being" [**?**]. With gradual research application, its connotation has become richer. In this study, ontology fusion refers to thematic word frequency volume (tf), text information volume (ti), thematic word frequency mean (tfa), and text information mean (tia).

Thematic word frequency volume refers to the number of public opinion thematic word frequencies centered on public opinion objects; text information volume refers to the content length embodied by public opinion objects themselves; thematic word frequency mean refers to the thematic word frequency in ontology information surrounding public opinion events within a certain period; text information mean refers to the amount of text in ontology information of public opinion events within a certain time range.

2.3.2 Measurement of Constituent Elements The ubiquitous nature of network public opinion information results from the joint action of various elements. Its effective acquisition requires computer science technologies such as big data processing, cloud computing, and cloud storage, combining intelligent processing with manual identification to collect and screen data and complete comprehensive measurement of each constituent element, which facilitates rapid identification and acquisition of public opinion information. By analyzing existing literature, this study employs DEMATEL, AHP, and FMF analysis methods for model construction.

3 Construction of Concurrent Acquisition Model for Multimedia Network Public Opinion Information

The model construction process generally consists of three stages: (1) identifying constituent elements in the concurrent acquisition process of network public opinion information; (2) assigning weights to each constituent element of the model; and (3) measuring constituent elements and calculating trigger values of the concurrent acquisition model. As shown in Figure 1 [Figure 1: see original paper].

Figure 1 Model Construction Process

3.1 Constituent Element Identification Model Based on DEMATEL

The DEMATEL analysis method was proposed by American scholars A. Gabus and E. Fontela to address complex social problems using expert knowledge and experience. It enables holistic analysis and identification of elements within a system and clarifies relationships and interactions among elements. The calculation steps are as follows [**?**]: (1) construct overall system elements, clarify primary constituent elements, and denote sub-elements as E_1, E_2, ..., E ; (2) assess the strength of relationships among elements, judging based on (none, weak, medium, strong) <=> (0, 1, 2, 3); (3) construct the direct influence matrix among system elements, denoted as E ; (4) analyze indirect influence relationships to obtain the normalized influence matrix E; (5) calculate the comprehensive influence matrix T using the formula $T = E(I - E)^{-1}$; (6) measure the influence degree, influenced degree, centrality, and causality of each element.

Let the influence degree be set F, representing the comprehensive influence of elements in each row on other elements in the system. F is shown in formula (1):

$$F_i = \sum_{j=1}^{m} t_{ij}, \quad (i = 1, 2, 3, \dots, m)$$

Let the influenced degree be set D, representing the degree to which elements in each column are comprehensively influenced by other elements. D is shown in formula (2):

$$D_i = \sum_{j=1}^{m} t_{ji}, \quad (i = 1, 2, 3, \dots, m)$$

Let centrality be M , representing the position and role of element i in the entire system, as shown in formula (3):

$$M_i = F_i + D_i, \quad (i = 1, 2, 3, \dots, m)$$

Let causality be C , representing the causal relationship between element i and other elements, as shown in formula (4):

$$C_i = F_i - D_i, \quad (i = 1, 2, 3, \dots, m)$$

Finally, based on calculation results, analyze the comprehensive influence and interaction relationships among elements in the system.

3.2 Element Weight Model Based on AHP

AHP is primarily used for decision-making in complex problems with multiple levels and objectives. It is a comprehensive decision analysis method that quantifies subjective judgment results. The process generally involves constructing a hierarchical structure model, determining the judgment matrix, and conducting hierarchical single sorting and consistency testing. The testing criteria are shown in formulas (5) and (6) [?]:

When CR < 0.1, the calculation results are considered to satisfy consistency testing. Under this premise, element weight values are calculated.

3.3 Concurrent Acquisition Model Based on FMF

FMF belongs to the domain of fuzzy mathematics. In specific applications, the determination of its membership function is decisive for fuzzy sets. Through analysis and measurement of fuzzy elements, fuzzy membership degrees can achieve systematic measurement of constituent elements, satisfying both qualitative analysis and quantitative calculation. FMF has been widely studied and applied in numerous fields. Therefore, using fuzzy mathematical analysis to measure trigger values is feasible.

The steps are as follows [?]:

(1) **Set construction of constituent elements**. Constituent elements of concurrent acquisition of multimedia network public opinion information include 4 primary elements and 17 secondary elements. The trigger value is denoted as Z; the primary element set is denoted as U = {u_1, u_2, u_3, u_4}; secondary element sets are denoted as u_1 = {u_{11}, u_{12}, u_{13}}, u_2 = {u_{21}, u_{22}, u_{23}, u_{24}, u_{25}, u_{26}}, u_3 = {u_{31}, u_{32}, u_{33}, u_{34}}, u_4 = {u_{41}, u_{42}, u_{43}, u_{44}}.

(2) **Clarify membership grades of constituent elements**. Comprehensively measure each constituent element and construct the membership grade set V = {V_1, V_2, …, V }, where V represents the i-th membership grade with standard values G = {g_1, g_2, g_3, g_4, g_5} and median values Q = {q_1, q_2, q_3, q_4, q_5}. Based on objective actual conditions, this study defines five membership grades: "extreme, strong, medium, general, weak," corresponding to V = {a, b, c, d, e}, as shown in Table 3 .

Table 3 Quantification of Constituent Elements

Grade	Numerical Range (Median)
Extreme	(0.8, 1.0]
Strong	(0.6, 0.8]
Medium	(0.4, 0.6]
General	(0.2, 0.4]
Weak	(0, 0.2]

(3) **Calculate weights of elements at each level**.

(4) **Construct membership matrices**. Quantify elements in secondary elements, clarify membership levels of each element, and construct membership matrices, including comprehensive relationship, subject participation, object heat, media influence, and ontology fusion matrices R, R_u_1, R_u_2, R_u_3, R_u_4.

Based on the above analysis, construct r × matrices for each primary element, where r (0 ≤ i ≤ m, 0 ≤ j ≤ n) represents the membership degree of a certain element.

(5) **Calculate comprehensive measurement results**. This study introduces the fuzzy synthesis operator M(• , !), as shown in formula (8):

$$s_k = \min\left(1, \sum_{j=1}^{m} \mu_j r_{jk}\right), \quad (k = 1, 2, 3, \ldots, n)$$

Synthesize the weight values w (i = 1, 2, 3, 4) of secondary elements u_1, u_2, u_3, u_4 with corresponding membership matrices to obtain comprehensive membership values F_1, F_2, F_3, F_4:

$$F_1 = w_1 \cdot (r_{u1_1}, r_{u1_2}, r_{u1_3}) \quad (9)$$
$$F_2 = w_2 \cdot (r_{u2_1}, r_{u2_2}, r_{u2_3}, r_{u2_4}, r_{u2_5}, r_{u2_6}) \quad (10)$$
$$F_3 = w_3 \cdot (r_{u3_1}, r_{u3_2}, r_{u3_3}, r_{u3_4}) \quad (11)$$
$$F_4 = w_4 \cdot (r_{u4_1}, r_{u4_2}, r_{u4_3}, r_{u4_4}) \quad (12)$$

Based on the above formulas, integrate calculations to obtain the single-element fuzzy comprehensive measurement matrix F_u.

According to formula (14), comprehensively operate W with F_u to obtain the comprehensive measurement membership result F:

$$F = W \cdot F_u \quad (14)$$

(6) **Trigger value calculation**. Comprehensively measure fuzzy measurement values and fuzzy membership grades to obtain the trigger value for concurrent acquisition of public opinion, as shown in formula (15):

$$Z = F \cdot G^T \quad (15)$$

Where Z represents the membership function, F represents the fuzzy measurement membership value of certain public opinion information, and G represents the public opinion membership weight value.

4 Empirical Analysis

4.1 Acquisition of Network Public Opinion Data Sources

This study takes Sina Weibo as the research object for information acquisition, primarily using automatic collection via Jisouke to crawl network public opinion events from 2018-2019. The events include: "Russia World Cup," "Xiaomi Hong Kong Listing," "Changchun Changsheng Vaccine," "Shaanxi Mercedes-Benz Female Owner Rights Protection," "Chongqing Porsche Female Owner Assault," and "Typhoon Lekima Landing," abbreviated as "Event1"-"Event6" respectively. The data sources involve blogger ID, blog posts, comment volume, publication time, forwarding volume, discussion volume, like volume, reading volume, search volume, publication volume, original volume, text information volume, media volume, thematic word frequency volume, etc. Due to different social impacts, the data collection volume varies across events. Partial data collection results are shown in Figure 2 [Figure 2: see original paper].

During data acquisition, due to various subjective and objective factors and limitations, the data shown above represents only partial collected data. This paper focuses on measuring the crawled data sources.

4.2 Constituent Element Identification

4.2.1 Calculation of Constituent Element Data Sources Based on the above constituent elements, this study invited several experts and scholars in the research field to score the degree of mutual influence among constituent elements. Integrating the scoring results according to research needs, a direct influence matrix E was established. The normalized matrix E and comprehensive influence matrix T were calculated, with results shown in Table 4 .

Figure 2 Screenshot of Russia World Cup Data Sources

Table 4 Comprehensive Influence Matrix T

[Table content preserved with elements E_1-E_{17} showing influence values]

Using formulas (1)-(4), the influence degree, influenced degree, centrality, and causality of constituent elements were calculated, with results shown in Table 5 .

Table 5 Comprehensive Influence Index of Constituent Elements

[Table content showing influence degree, influenced degree, centrality, and causality values for elements E_1-E_{17}]

4.2.2 Analysis of Constituent Element Data Source Calculation Results Table 5 reveals close relationships among constituent elements. Centrality and causality are generally more recognized perspectives. Therefore, this study's identification of constituent elements and analysis of interaction degrees primarily explore these two dimensions.

(1) Centrality Analysis: Larger centrality values indicate greater element function and influence. According to Table 5, elements E_4, E_{12}, E_{13}, and E_{14} show larger centrality values and stronger comprehensive influence compared to other elements. Elements E_1, E_2, E_5, E_6, E_7, E_8, E_{10}, E_{11}, E_{15}, E_{16}, and E_{17} show moderate centrality values, indicating they still exert influence on other elements. Elements E_3 and E_9 show relatively smaller centrality values but remain within the system without significant deviation. Based on centrality results, all constituent elements are closely interconnected with strong interaction intensity.

(2) Causality Analysis: Calculations show that E_{11}, E_{12}, E_{13}, E_{14}, E_{15}, E_{16}, and E_{17} have positive values as causal elements with greater influence. Conversely, E_1, E_2, E_3, E_4, E_5, E_6, E_7, E_8, E_9, and E_{10} have negative values as result elements with relatively weaker influence. This clarifies that all elements exert certain degrees of influence and function.

Overall, the data measurement results are relatively concentrated. Although local influence relationships show slight weakness, they still exist within the system and interact with other constituent elements. Therefore, this study includes all these elements in the research scope, collectively forming indispensable important elements for concurrent acquisition of multimedia network public opinion information.

4.3 Determination of Constituent Element Weights

According to formulas (5) and (6), the consistency ratio for primary elements CR_W = 0.073358; for secondary elements, CR_{WP} = 0.033199, CR_{WH} = 0.089587, CR_{WI} = 0.043327, CR_{WF} = 0.073358. All CR values are less than 0.1, passing consistency testing.

The calculated weights of primary and secondary constituent elements are:

$$W = (0.15118 \quad 0.50829 \quad 0.26534 \quad 0.0752)\,, \quad W_p = (0.63699 \quad 0.25828 \quad 0.10473)$$

$$W_h = (0.1175 \quad 0.055285 \quad 0.56501 \quad 0.2622)\,, \quad W_i = (0.41546 \quad 0.22944 \quad 0.14317 \quad 0.063232)$$

$$W_f = (0.035406 \quad 0.1133 \quad 0.50829 \quad 0.26534 \quad 0.15118 \quad 0.0752)$$

The determination of these weight values plays a crucial role in calculating trigger values.

4.4 Trigger Value Calculation

(1) Element assembly: Primary elements U = {SP, OH, MI, OF}; secondary elements u_1 = {r, d, o}, u_2 = {t, c, g, ta, ca, ga}, u_3 = {s, m, p, pa}, u_4 = {tf, ti, tfa, tia}.

(2) Clarify membership grades and data standardization: According to Table 3, V = {weak, general, medium, strong, extreme}, with standard values G = (0.2, 0.4, 0.6, 0.8, 1). Based on data source acquisition conditions, data were standardized [**?**] to provide normalized values for constructing membership relationship matrices.

(3) Quantify membership matrices: Quantify membership grades of each element and construct standardized membership matrices [**?**]. The method is as follows:

For each normalized element value n , membership functions are defined across intervals [e,d), [d,c), [c,b), [b,a) with linear interpolation.

(4) Comprehensive measurement of constituent elements: Using formulas (8)-(12), standardized data were measured to obtain single-element fuzzy membership values for each event.

(5) Trigger value calculation: Using formula (15), trigger values for each event were calculated:

- Event1 (Russia World Cup): Z = 0.861
- Event2 (Xiaomi Hong Kong Listing): Z = 0.313
- Event3 (Changchun Changsheng Vaccine): Z = 0.662

- Event4 (Shaanxi Mercedes-Benz Female Owner): Z = 0.430
- Event5 (Chongqing Porsche Female Owner): Z = 0.408
- Event6 (Typhoon Lekima): Z = 0.568

The concurrent acquisition trigger values for "Event1"-"Event6" are shown in Figure 3 [Figure 3: see original paper].

Figure 3 Trigger Values for Concurrent Acquisition of Network Public Opinion Events

Based on Figure 3, the events are sorted by trigger value magnitude: "Event1" > "Event3" > "Event6" > "Event4" > "Event5" > "Event2".

4.5 Analysis of Experimental Results

Based on the constructed concurrent acquisition model for multimedia network public opinion information, this study collected and processed data from various events and conducted in-depth analysis from the perspectives of event membership grade classification and concurrent acquisition trigger values.

4.5.1 Event Membership Grade Classification This study classifies membership grades of public opinion events into four levels: (1) If the membership grade is extreme or strong, the event has extensively covered numerous regions, with public opinion subjects demonstrating extremely high active participation across different time-space contexts, causing significant impact and rapid diffusion. In this case, the trigger state is directly activated to initiate evolutionary tracking. If the public opinion event has positive feedback, it should be promoted and encouraged; otherwise, monitoring and tracking should be implemented, with reasonable response decisions formulated based on tracking trends to guide, clarify, and alleviate concerns while real-time understanding of the event's evolutionary changes. (2) If the membership grade is medium, consider whether to further conduct topic evolutionary tracking from two perspectives: first, if the trigger value exceeds the interval median, initiate evolutionary tracking; second, if below the interval median, stop acquiring public opinion information while referencing the event's essential attributes to decide whether to continue. (3) If the membership grade is general, trigger mode is generally unnecessary, but regulatory bodies may decide based on the event's nature and actual needs. (4) If the membership grade is weak, it can generally be ignored without trigger mode, requiring only periodic monitoring.

The membership grade classifications for events "Event1"-"Event6" are shown in Table 6 .

Table 6 Numerical Results of Concurrent Acquisition for Network Public Opinion Events

Network Public Opinion Event	Trigger Value	Membership Grade
Russia World Cup (Event1)	0.861	Extreme
Xiaomi Hong Kong Listing (Event2)	0.313	General
Changchun Changsheng Vaccine (Event3)	0.662	Strong
Shaanxi Mercedes-Benz Female Owner (Event4)	0.430	Medium
Chongqing Porsche Female Owner (Event5)	0.408	Medium
Typhoon Lekima (Event6)	0.568	Medium

Event1 shows the highest trigger value at the extreme membership interval. Event3 ranks second with a strong membership grade, relatively close to the extreme interval. Event6 has a medium membership grade, approaching the strong interval. Events4 and 5 also fall within the medium interval, while Event2 belongs to the general level.

4.5.2 Trigger Result Analysis The analysis reveals that events with extreme or strong membership grades include Event1 and Event3. Events with medium grades include Event6, Event4, and Event5. Event2 belongs to the general level. Specifically, Event1 is an international sports event promoting sportsmanship and should be supported with trigger mode activated for real-time dynamic tracking and positive energy dissemination. Event3 is a high-profile healthcare topic that generated widespread attention and negative impacts from its inception, requiring regulatory attention. Trigger mode should be activated for multi-perspective evolutionary tracking, with reasonable response strategies formulated in real-time based on tracking trends, including accountability, investigation, and legal pursuit of responsible parties, while monitoring netizens' views, attitudes, and emotions for timely guidance and resolution to prevent escalation of negative sentiment. Event6 concerns natural disasters with sudden and random characteristics. Its result value falls in the medium interval but exceeds the median, reaching trigger status and enabling evolutionary tracking. Regulatory bodies should monitor and track in real-time, take targeted measures based on statistical results, enhance public awareness and security, and maintain positive trends. Events4 and 5 are social topics within the medium interval but with trigger values below the median, requiring no evolutionary tracking. Both share common factors related to automobiles with similar topics and close trigger values, though regulatory bodies may make decisions based on actual conditions. Event2 concerns electronics technology with relatively low results, reflecting people's livelihoods, and regulatory bodies may respond accordingly.

The analysis shows that Event1, Event3, and Event6 all meet trigger conditions and can undergo evolutionary tracking. Events4, Event5, and Event2 do not require trigger mode activation in this study, though regulatory bodies may flexibly decide whether to track based on objective circumstances.

Comparison reveals that the experimental case analysis closely approximates real-world network public opinion information evolution, objectively reflecting acquisition conditions to a certain extent. The constructed model facilitates rapid and effective acquisition of major network public opinion events, helps regulatory bodies assess trend changes, enables timely response strategies, and prevents potential crises. It also supports evolutionary tracking, real-time monitoring, and timely adjustment of corresponding plans to foster a healthy network public opinion environment. This process effectively identifies influential network public opinion events and provides objective data support for real-time analysis.

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Author Contributions

XU Yejing: Overall writing and revision of the paper; **HUANG Wei:** Formulation of research proposition and ideas, paper guidance and final version approval; **ZHAO Jiangyuan:** Data collection and organization.

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