Multi-criteria Evaluation of Social Media Platform's Rumor Refuting Capacity Based on Fuzzy Theory and TOPSIS Method

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Abstract. The significance of dealing with internet rumors or false information on social media is expanding, especially when an unexpected crisis erupts. The promotion of social media's rumor refuting capacity needs more attention. Based on this, in order to systematically evaluate the rumor refuting effect of social media platforms, so that platforms can find their own weaknesses and improve their operational capacity, this paper puts forward an evaluation system and evaluation methods for anti-rumor effect of social media platforms, and applies them to five mainstream social media platforms in China for evaluation and analysis. Suggestions are also given for social media platforms with relatively poor ratings to improve the effectiveness of rumor refutation. First, build the evaluation index system, use the analytic hierarchy process (AHP) method which combines triangular fuzzy number to determine the index weight, then divide the evaluation index into qualitative and quantitative indicators. For qualitative indicators, use intuitive fuzzy number set (IFNs) method to represent the information of the two comparisons of indicators. For quantitative indicators, collect real data and conduct standardized processing. Finally use TOPSIS method to evaluate the effectiveness of social media platform rumors, and get rankings. And, a sensitivity analysis will be performed to check the robustness of the final decision. Based on the results, relevant suggestions are given.

Keywords: Social media platform · rumor refuting · FAHP · intuitive fuzzy number · TOPSIS

1 Introduction

In the Internet era, massive volumes of information are flowing at a rapid rate in human society anytime and anywhere. At the same time, false news can be extensively distributed through numerous network channels [10]. Most Internet users, particularly on social media platforms, such as Weibo and Twitter, etc., have an access to a wider range of news at a lower cost, which simultaneously facilitates the spread of fake news or rumors [36]. According to the report issued by the Institute of Data Research of Nandu

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University, above 67 pieces of information per day are falsified by authoritative organizations on Weibo. Among them, in January, February and March 2020, the average daily verified rumors accounted for 15.6%, 54.7% and 29.7% of the amount of information release respectively (A report on the data of the pestilence 2020). The spread of incorrect information on social media has the potential to disrupt people's minds, mislead public opinion, even, more importantly, damage the government's legitimacy and instigate social unrest [37]. Thus, the detection and refutation of rumors on social networks has become a social security issue that cannot be ignored. Online social media platforms, as the most important medium for people to share, coordinate, and spread information [42], should take the lead to shoulder the responsibility for rumors. For one reason, online news on social networking platforms is released and shared by hundreds of millions of people spontaneously, unlike traditional media, where news is produced by recognized organizations [18]. If there isn't an accurate and systematic attempt for platforms to verify the fake news, the spread of online social media rumors may have large-scale negative impacts and can occasionally alter or even control crucial public events [3]. Therefore, the effectiveness of social media platforms in refuting rumors directly affects the spread and impact of rumors.

Existing research on rumor refuting platforms tended to focus on identifying rumors, influencing factors, and the rules of rumor propagation by constructing propagation models [20]. Most of the rumor propagation models are derived from epidemic models [19, 25], since it is similar to disease spreading. DK (Daley and Kenal) model and MT (Maki and Thomson) model was two classical rumor spreading models [11, 28]. Since then, numerous scholars have further developed rumor spread studies based on these two classic models. Thus, a series of modified rumor propagation model have been established. Some researchers studied the basic processes involved in rumor spread by introducing social reinforcement, hesitating mechanism, and other mechanisms [20, 39]. For the influencing factors of rumors, Jain, A. considered that time delay affects the crowds as well as expert intervention and government policy [2]. Furthermore, people's critical ability is another factor that can't be neglected. Individuals with critical ability can gather proof of inaccurate rumor information in effective methods and reduce rumor dissemination even more through effective feedback and rumor refutation information [20]. In addition, conscious behavior, educational level and population migration, which are as influencing factors on the spread of rumors, have been comprehensively analyzed though some works of literature [1, 13, 15]. In the field of multi-criteria decision-making, Xiaohui Yang, Hailong Ma and Miao Wang studied how to evaluate and enhance social media rumor refutation effectiveness with hesitant fuzzy judgments [9, 40]. There are also some scholars who specialize in researching rumor-busting platforms. Zongmin Li et al., establish an indicator system of rumor refuting capacity, evaluating the rumor refuting platform's refuting capacity with hesitant fuzzy judgments [24].

It has been seen that previous researchers contributed significantly to the advancement of technology and management for refuting rumors, which has encouraged us in terms of methodologies for evaluating the impact of rumor governance. However, there is currently lack of scientific systems for evaluating a rumor refuting platform's rumor refuting competence. And the elements that influence the outcomes of social media rumor refuting are mostly unexplored, especially for specific platforms, whose capacity of rumor refuting has been not analyzed yet, making it tough for the platform to comprehend essential variables while attempting to enhance the effect and capability of rumor regulation.

Practical ideas may be made to facilitate speeding up the rumor refuting process by acquiring research data on social media platforms and studying probable impacting elements of social media rumor refutation capacity. Figure 1 depicts this paper's overall framework. To measure the efficiency of a rumor refutation on social media platforms, rumor refutation effectiveness indexes are firstly established in this paper. Rumor refutation effectiveness indexes fall into two categories, which are qualitative and quantitative indexes. The index weight is an essential multi attribute parameter that has a direct impact on decision-making accuracy. Thus, the analytic hierarchy process (AHP) method which combines triangular fuzzy number is applied to determine the index weight, creating a more precise representation of the link between criterion and alternatives while calculating the weightage of each criteria (Li et al., 2021) [21]. Then, use intuitive fuzzy number method to represent the information of the two comparisons of qualitative indicators [5]. And for quantitative indicators, specific data is searched and conducted by standardized processing. After multiplying the data of qualitative and quantitative indicators and the weightage of each criteria, the TOPSIS method [17] is applied to some domestic mainstream social platforms to rank them and reveal of their imperfections. Finally, a sensibility analysis and compare analysis are used to analyses the validity of the proposed methodology. Relevant suggestions are therefore put forward to provides a reference for internet social platforms to formulate their rumor refuting strategies and improve the ability of rumor governance by establishing a scientific and reasonable multi-standard rumor refutation ability evaluation index system.

The rest of this study is organized as follows. Section 2 introduces different stages of rumors, which concerns influencing factors of rumor refutation. And then, constructs the evaluation indicator system. Section 3 develops evaluation methods to evaluate the rumor refuting effect of social media platforms, including FAHP method, intuitive fuzzy number set and TOPSIS method. Section 4 presents experimental analysis and discusses the results. This section also presents a sensitivity analysis and compare analysis to illustrate the merits of this evaluation model. Section 5 concludes and provides directions for future research.

2 Establishment of Evaluation Indicator System

2.1 Different Stages of Rumors

The last decade has had a lot of research into internet rumors. Various researchers provide various interpretations of rumor. The life cycle of rumors can be divided into different stages by researchers. Cao Jinsong believes that the development of network public opinion has to experience 4 stages: spread-gathering-discussion-popular and 3 crossings: outburst, sublimation and continuation [7]. Lan Yuexin and Deng Xinyuan divided network public opinion into occurrence stage, spreading stage and stabilizing stage [23]. J. IAO et al. divide the network public opinion reflected through a network event into 4 stages, including the incubation stage, growth stage, mature stage and declining stage [31].

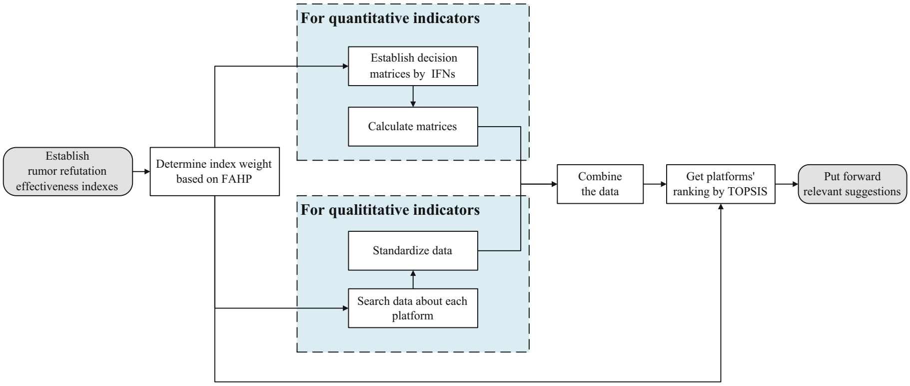

Fig. 1. The overall framework of this paper

Based on J. QIAO's classic four-stage model of emergency "life cycle", combined with the evolution characteristics of network public opinion, this paper divided its evolution stage into three stages of "incubation stage - growth stage - mature stage". The specific meanings are as follows:

(1) Incubation stage

In this stage, rumors arise because some people want to profit from them or have incomplete cognition, standing out once sufficient strength is accumulated.

(2) Growth stage

When breaks out in the incubation stage, the rumors will spread rapidly and cause an uproar in the network, attracting a widespread concern attached in the social media even the community.

(3) Mature stage

Most network users form the common opinion, such a mainstream opinion symbolizes that the event reaches the culminate in this stage.

Different stages of rumors require different platforms with different capabilities to cope with them. In the incubation stage of rumors, the capacity to **restrain** rumors is critical in determining whether there would someone to generate rumor. During growth stage, the **influence** of online social platforms on public opinion is critical since it decides whether rumors can be effectively transmitted. In mature stage, the dissemination of rumors is affected by the **guiding ability** of social platforms on the trend of rumors and rumor-mongers.

2.2 Selection and Determination of Indicators

Based on the statement above and previous research, this paper selected a new index system through three dimensions of "Restrain, Guidance and Influence" to evaluate the capacity of different platforms. The evaluation indicator system of the rumor governance and the explanation of indexes are shown in Table 1 and Table 2 respectively.

Table 1. The evaluation indicator system of the rumor governance

System	Targets	Indexes		types
Evaluation the effect of rumor refuting on social platforms	Guidance (B_1)	Rumor refuting information prominence	C_{11}	Qualitative
		The number of authoritative rumor refuting user	C_{12}	Positive
		Main rumor refuting disseminating form	C_{13}	Qualitative
	Influence (B_2)	UV	C_{21}	Positive
		Daily using time of users	C_{22}	Positive
		MAU	C_{23}	Positive
		DAU/MAU	C_{24}	Positive
	Restrain (B_3)	Punishment for rumor	C_{31}	Qualitative
		Rumor monitoring efficiency	C_{32}	Qualitative
		Rumor handling transparency	C_{33}	Qualitative
		Rumor processing timeliness	C_{34}	Qualitative

Table 2. The explanation of indexes

Indexes	Explanation
C_{11}	the timeliness and qualitative accuracy of the identification and capture of rumors
C_{12}	the degree of detail of the rumor event disclosed by the government or officially certified media with a strong mass base and credibility
C_{13}	including response speed, reaction speed, information release speed, and platform response speed to public opinion events
C_{21}	the implementation of punitive measures for rumor-mongers, including the intensity of the disposal of speech bans, account bans, and suspension of advertising revenues
C_{22}	the attracting nature of the functions of retrieval, inquiry and help, or the highlighting of data, information, news reports, texts, column recognition, etc.
C_{23}	the amount of platform organizers with a high organizational level or social status, including the number of accounts with "institutional certification" by professional institutions, official media or authoritative platforms
C_{24}	the narrative medium used in the process of dissemination of rumor dispelling information
C_{31}	the average number of unique visitors (UV) per day, refers to natural persons who access and browse this web page through the Internet
C_{32}	the average daily usage time of platform users
C_{33}	the number of non-repeat users who interact with the Company's products or services in a month
C_{34}	Ratio of Daily Active User and Monthly Active User, which represent the user stickness

2.2.1 Restrain

As a rumor carrier, the Internet platform is a key part of eliminating the adverse effects of rumors, and should perform its statutory obligations to bear the responsibility for governance of platform information, clarify the characterization of rumors, clarify the management mechanism for rumor makers, and build a reasonable set of rules and regulations for rumors, so as to have a certain binding force on online rumors and rumor makers. By establishing a new two-stage model of rumor dissemination and rumor debunking with a time effect, Zhang et al. found that the earlier the authoritative department published the rumor rebuttal, the greater the attraction of the rumor to readers and the smaller the influence of the rumor.[43].

The restrain is mainly evaluated by three indicators, including rumor monitoring efficiency, rumor handling transparency, and rumor processing timeliness.

2.2.2 Guidance

The guiding power of social platforms refers to the public opinion guide disseminating certain views and information in accordance with the expected guidance direction, and coordinating and balancing the public opinion operation process, thereby affecting the opinions, attitudes and tendencies of the public. In the public opinion response to major sudden public events, official authoritative information institutions grasp the initiative to guide public opinion, which can effectively eliminate the negative impact of rumors, playing an important role in maintaining stable social order. Debuking results can be disseminated more effectively when it's noticeable with using functions in the social platform such as pushing the results of the rumor rebuttal and the official information of the top debunking the rumors on the hot search list to guide the ideological trend, so as to guide the public to pay attention the important and correct information and make the information be known to more people so as to improve the rumor refutation efficiency and effects [26].

The guidance is mainly evaluated by three indicators, including rumor refuting information prominence, the number of authoritative rumor refuting user, and main rumor refuting disseminating form.

2.2.3 Influence

Influencing is the core of social media. With the innovative development of network technology and the deepening of media integration, people rely more on online social platforms to obtain information. Those platforms with larger user scale and stronger user stickiness are more able to gain public recognition and a higher frequency of use, and the information released in them is easy to be seen by more people, so the influence of rumor-busting information depends on the user base of social platforms, that is, the influence of the platform.

The influence is mainly evaluated from four indicators: average daily UV, average daily usage time of users, number of monthly active users, and DAU/MAU.

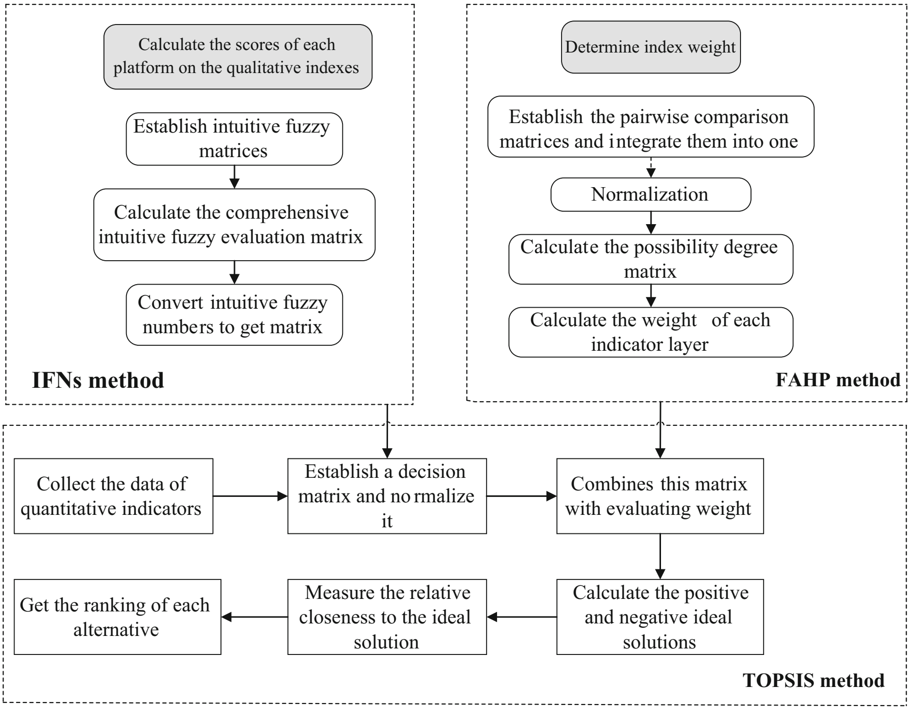

Fig. 2. The framework of this paper

3 Methodology

The evaluation of social media platform's rumor refuting capacity is designed by using of FAHP and TOPSIS method. The framework of this paper's method is shown as in Fig. 2.

3.1 Some Basic Definitions of IFS Theory

Proposed by Zedeh (1965) and generalized to intuitionistic fuzzy subsets by K. Atanassov, [6] fuzzy set theory has been widely used in several research fields. An Intuitionistic Fuzzy Set (IFS) is an extension of an ordinary fuzzy set, characterized by a membership function, a non-membership function, and a hesitancy function. In this section, we briefly review the basic concepts of IFS.

Definition 1
An intuitionistic fuzzy set A in X is a set of ordered triples, which was defined as an ordered pair of membership degrees given as [4]:

$$A = \{(x, \mu_A(x), v_A(x))|x \in X\}$$

where $\mu_A(x), v_A(x)$: $X \rightarrow [0, 1]$ are functions with the condition:

$$0 \leq \mu_A(x) + v_A(x) \leq 1$$

For each element $x \in X$, $\mu_A(x)$ and $v_A(x)$ represent the membership and non-membership degrees of the element x to A respectively. For each $x \in X$, we can compute the so-called, the intuitionistic fuzzy index of x in A defined as follows:

$$\pi_A(x) = 1 - \mu_A(x) - v_A(x)$$

where $\pi_A(x)$ is expressed as the lower bound of positive membership derived from evidence supporting that element x belongs to set A and the lower bound of negative membership derived from evidence opposing element x belongs to set A.

Definition 2
The membership degree and non-membership degree of element x in domain X belonging to A are denoted as an ordered pair $(\mu_A(x), v_A(x))$, called as Intuitive Fuzzy Number (IFN). For example: an ordered pair $(\mu_A(x), v_A(x)) = (0.7, 0.2)$ can be interpreted in the voting model as 70% voting for, 20% voting against, and 10% abstaining. Intuitive Fuzzy Number Set A can to be viewed as a set of intuitive fuzzy numbers, expressed as:

$$A = [(\mu_A(x_1), v_A(x_1)), (\mu_A(x_2), v_A(x_2)), \cdots, (\mu_A(x_n), v_A(x_n))]$$

Definition 3
A matrix $(Z = (x_{ij})_{m \times n})$ consisting of an IFN $\big(x_{ij}(i = 1, 2, \cdots, m; j = 1, 2, \cdots, n)\big)$ is called an intuitionistic fuzzy matrix.

Definition 4
Set $\check{a}_1, \check{a}_2$ are two intuitive fuzzy numbers on a given domain, which are expressed as follows:

$$\check{a}_1 = (\mu_1, v_1), \mu_1 \in [0, 1], v_1 \in [0, 1],$$

$$(\mu_1 + v_1) \in [0, 1]$$

$$\check{a}_2 = (\mu_2, v_2), \mu_2 \in [0, 1], v_2 \in [0, 1],$$

$$(\mu_2 + v_2) \in [0, 1]$$

Then the algorithm defining intuitionistic fuzziness is as follows:

$$\overset{\vee}{a}_1 + \overset{\vee}{a}_2 = (\mu_1 + \mu_2 - \mu_1\mu_2, v_1 v_2)$$

$$\overset{\vee}{a}_1 \overset{\vee}{a}_2 = (\mu_1\mu_2, v_1 + v_2 - v_1 v_2)$$

3.2 Determine Index Weight Based on FAHP

The index weight is an important parameter of multi attributes, which directly affects the accuracy of decision-making. The triangular fuzzy number is a valuable tool for solving decision-making difficulties in uncertain situations. The triangular fuzzy number, rather than a crisp number, is better suited to expert judgments that are uncertain [34]. The Fuzzy Analytic Hierarchy Process (FAHP) technique that combines fuzzy sets with AHP creates a more precise representation of the link between criterion and alternatives while calculating the weightage of each criteria (Islam, et al., 2020). Thus, this paper applies the FAHP approach to compute the weight of indexes.

Step 1: The problem is broken down into three layers, including object layer (O), rule layer (B), factor layer (F). Therefore, a hierarchical structure is established, which means the relationship between elements at one level and elements directly below that level.

Step 2: Qualitative comparison is made by comparing the two indexes - the data obtained from three decision experts represent a hierarchical structure [32], which is represented by three triangular fuzzy matrices expressed by:

$$L = (l_{ij})_{n\times n}, M = (m_{ij})_{n\times n}, N = (u_{ij})_{n\times n}$$

Among the three matrices, there are three fuzzy numbers for comparing a set of indictors in pairwise comparisons (such as the comparison between index C_1 and index C_2), shown respectively as:

$$(l_1, m_1, u_1), (l_2, m_2, u_2), (l_3, m_3, u_3)$$

Then, use the following formula to integrate the three fuzzy numbers into one:

$$\left(\frac{l_1 + l_2 + l_3}{3}, \frac{m_1 + m_2 + m_3}{3}, \frac{u_1 + u_2 + u_3}{3}\right) \tag{1}$$

Other fuzzy numbers are also combined in this way, finally resulting in a triangular fuzzy matrix called $C = (c_{ij})_{n\times n}$ that combines the ratings of three experts, where $c_{ij} = \left(c^l_{ij}, c^m_{ij}, c^u_{ij}\right)$ and it indicates the relative importance of indicator i to indicator j, and n indicates the number of weight indicators to be determined.

Step 3: The row sum of the triangular fuzzy number complementary judgment matrix was calculated by Eq. (1) and normalized to yield a triangular fuzzy number weight vector $w^c = \left(w^c_1, w^c_2, \cdots, w^c_n\right)$

$$w^c_i = \frac{\sum_{j=1}^n c_{ij}}{\sum_{i=1}^n \sum_{j=1}^n c_{ij}} = \frac{\sum_{j=1}^n \left(c^l_{ij}, c^m_{ij}, c^u_{ij}\right)}{\sum_{i=1}^n \sum_{j=1}^n \left(c^l_{ij}, c^m_{ij}, c^u_{ij}\right)}$$

$$= \left(\frac{\sum_{j=1}^n c^l_{ij}}{\sum_{i=1}^n \sum_{j=1}^n c^u_{ij}}, \frac{\sum_{j=1}^n c^m_{ij}}{\sum_{i=1}^n \sum_{j=1}^n c^m_{ij}}, \frac{\sum_{j=1}^n c^u_{ij}}{\sum_{i=1}^n \sum_{j=1}^n c^l_{ij}}\right) \tag{2}$$

Step 4: Make pairwise comparisons of the triangular fuzzy numbers in weight vector w^c, and obtain the corresponding possibility degree expressed as $p_{ij}\left(w_i^c \geq w_i^c\right)$ by the possibility degree formula. Supposing that $a = (a_l, a_m, a_u)$, $b = (b_l, b_m, b_u)$, the calculation of the possibility degree is as follows:

$$\begin{aligned} \mathrm{p(a \geq b)} &= \lambda \max\{1 - \max(\frac{b_m - a_l}{a_m - a_l + b_m - b_l}, 0), 0\} \\ &+ (1-\lambda)\max\{1 - \max(\frac{b_u - a_m}{a_u - a_m + b_u - b_m}, 0), 0\} \end{aligned} \tag{3}$$

Hence, the corresponding possibility degree matrix is established as $P = (p_{ij})_{n\times n}$, and then the weight of the index of the criterion layer is obtained by using the following formula:

$$\overline{w}_i^c = \frac{1}{n}\left(\sum_{j=1}^{n} p_{ij} + 1 - \frac{n}{2}\right) \tag{4}$$

Step 5: Based on the method of determining the index weight of the criterion layer, the index weight of the index layer under the C_i-type index is calculated as:

$$a_i = a_{ij}(j = 1, 2, \cdots, n_i), i = 1, 2, \ldots, n$$

where n denotes the number of the index at the criterion layer, n_i denotes the number of the index layer under the i-type index.

Step 6: Calculate the weight of each indicator layer relative to O (objective layer):

$$w_r = \overline{w}_i a_{ij}, i = 1, 2, \cdots, n, j = 1, 2, \ldots, n_i \tag{5}$$

where $r = 1, 2, \ldots, h$, r is the r^{th} of h index.

Thus, we got the weight of h indexes denoted as:$w^C = (w_1, w_2, \ldots, w_h)$ and it consist of the weight of l non-quantitative indicators' and ℓ quantitative indicators', which can be expressed as: $h = l + \ell$.

3.3 Calculate the Scores of Each Platform on the Qualitative Indexes

Step 1: Expert viewpoints are represented. Based on the research literature of language variable evaluation information, this paper adopts 7-granularity language variable $S = S_{-3}, S_{-2}, S_0, S_1, S_2, S_3$, which means {extremely high, very high, high, general, low, very low, extremely low}. The language variables the corresponding intuitionistic fuzzy sets are shown in Table 3: To decide whether category i or j is preferred, each expert chooses an element based on the semantic relationship presented in Table 3 [38]. As a result, a decision-making group composed of K experts evaluated the scores of m platforms to be evaluated on l non-quantitative indicators. The opinion of the k^{th} expert is represented by $\overline{d}_{ij}^k = \left(\overline{\mu}_{ij}^k, \overline{v}_{ij}^k\right)$ and it represents the k^{th} expert's preference for category i above category j. Thus, the fuzzy positive reciprocal matrix can be defined as:

$$\overline{D}_{ij}^k = (\overline{d}_{ij}^k)_{m\times l}, k = 1, 2, \ldots, K$$

Table 3. Intuitionistic preference matrix for categories

Language variable	Scale	Linguistic scales
S_{-3}	(0.9,0.1)	extremely high
S_{-2}	(0.8,0.15)	very high
S_{-1}	(0.7,0.2)	high
S_0	(0.5,0.3)	general
S_1	(0.3,0.6)	low
S_2	(0.2,0.75)	very low
S_3	(0.1,0.9)	extremely low

Step 2: Based on the Intuitive Fuzzy Weighted Average (IFWA_w) operator, K intuitive fuzzy matrices can be aggregated into an intuitive fuzzy matrix, and a comprehensive intuitive fuzzy set decision matrix can be obtained. The specific process is expressed as follows [14]:

$$IFWA_w\left(\overline{d}_{ij}^1, \overline{d}_{ij}^2, \ldots, \overline{d}_{ij}^K\right) = \left(1 - \prod_{k=1}^{K}\left(1 - \overline{\mu}_{ij}^k\right)^{w_s}, \prod_{k=1}^{K}\left(\overline{v}_{ij}^k\right)^{w_s}\right) \tag{6}$$

Methods for aggregating interval-valued intuitionistic fuzzy information and application to decision making,

where $w = (w_1, w_2, \ldots, w_K)^T$ is the weight vector of $\overline{d}_{ij}^k (k = 1, 2, \ldots, K)$, and $w_s \in [0, 1], \sum_{s=1}^{K} w_s = 1$

According to Definition 4, $\overline{d}_{ij}^k (k = 1, 2, \ldots, K)$ is still an intuitive fuzzy number after aggregation by IFWA. From the original K fuzzy matrices, a comprehensive intuitive fuzzy evaluation matrix is obtained, which is:

$$D_{ij} = (d_{ij})_{m\times l}$$

where $d_{ij} = \left(\mu_{ij}, v_{ij}\right), i = 1, 2, \ldots, m, j = 1, 2, \ldots, l$

Step 3: In order to unify TOPSIS with other quantitative index data, an intuitive fuzzy number is now converted to a real number according to the following formula:

$$\lambda_{ij} = \frac{\mu_{ij} + \pi_{ij}\left(\frac{\mu_{ij}}{\mu_{ij}+v_{ij}}\right)}{\sum_{i=1}^{m}\left(\left(\mu_{ij} + \pi_{ij}\left(\frac{\mu_{ij}}{\mu_{ij}+v_{ij}}\right)\right)\right)}, (j = 1, 2, \ldots, l) \tag{7}$$

where $\pi_{ij} = 1 - \mu_{ij} - v_{ij}, \lambda_{ij} \in [0, 1], \sum_{i=1}^{m} \lambda_{ij} = 1$

After conversion, we get a matrix composed of real numbers, which is denoted as $\overline{C}_1 = \left(\lambda_{ij}\right)_{m\times l}$.

3.4 Rank Platforms Based on TOPSIS Aggregation Method

Set c_{iq} denotes the data of the $i^{th}(i = 1, 2, \ldots, m)$ platform on the $r^{th}(q = 1, 2, \ldots, h)$ attribute.

Step 1: Normalize the index data

Due to the complexity of decision-making and the uncertainty of events, the index data must be standardized and oriented to achieve a unified measurement system [27]. Thus, normalize the index data of various platforms. Firstly, indicators are divided into two categories according to the characteristics of the indicators: Positive and Negative Indicators. The formulas (8) and (9) are used to deal with these indicators separately.

For the positive indicators:

$$\overset{\sim}{\mathrm{C}}_{ir} = \frac{c_{ir} - \underset{1 \le i \le m}{min}\ c_{ir}}{\underset{1 \le i \le m}{max}\ c_{ir} - \underset{1 \le i \le m}{min}\ c_{ir}} \tag{8}$$

For the negative indicators:

$$\overset{\sim}{\mathrm{C}}_{ir} = \frac{\underset{1 \le i \le m}{max}\ c_{ir} - c_{ir}}{\underset{1 \le i \le m}{max}\ c_{ir} - \underset{1 \le i \le m}{min}\ c_{ir}} \tag{9}$$

where $i = 1, 2, \ldots, m$ and $r = 1, 2, \ldots, h$

Then, the following formula (10) is used for normalization to obtain the value between [0,1]. Thus, we can get a standardized evaluation matrix denoted as $D = \left(\overset{\sim}{\mathrm{C}}_{ir}\right)_{m \times h}$.

$$\overline{C}_{ir} = \frac{\overset{\sim}{\mathrm{C}}_{ir}}{\sum_{i=1}^{m} \overset{\sim}{\mathrm{C}}_{ir}} \tag{10}$$

where $i = 1, 2, \ldots, m$ and $r = 1, 2, \ldots, h$

Step 2: Calculate the positive and negative ideal solutions.

The weighted normalized decision matrix expressed as $Z = (z_{ir})_{m \times h}$ is determined by weighting the standardized decision matrix, which is shown as:

$$\mathrm{Z} = diag(w^{C}) \times \mathrm{D} = \mathrm{diag}(w_1, w_2, \ldots, w_h) \begin{bmatrix} C_{11} & C_{12} & \cdots & C_{1h} \\ C_{21} & C_{22} & \cdots & C_{2h} \\ \vdots & \vdots & \ddots & \vdots \\ C_{m1} & C_{m2} & \cdots & C_{mh} \end{bmatrix}$$

$$= \begin{bmatrix} w_1 C_{11} & w_1 C_{12} & \cdots & w_1 C_{m1} \\ w_2 C_{21} & w_2 C_{22} & \cdots & w_2 C_{m2} \\ \vdots & \vdots & \ddots & \vdots \\ w_h C_{1h} & w_h C_{2h} & \cdots & w_h C_{mh} \end{bmatrix} \tag{11}$$

Then determination of the positive-ideal and negative-ideal solutions is derived as:

$$Z^{+} = \left[z_1^{+}, z_2^{+}, \ldots, z_n^{+}\right] = [max\{z_{11}, z_{21}, \ldots, z_{m1}\}, \\ max\{z_{12}, z_{22}, \ldots, z_{m2}\}, \cdots, max\{z_{1h}, z_{2h}, \ldots, z_{mh}\}] \tag{12}$$

$$Z^{-} = \left[z_1^{-}, z_2^{-}, \ldots, z_h^{-}\right] = [min\{z_{11}, z_{21}, \ldots, z_{m1}\}, \\ min\{z_{12}, z_{22}, \ldots, z_{m2}\}, \cdots, min\{z_{1h}, z_{2h}, \ldots, z_{mh}\}] \tag{13}$$

Step 3: Evaluate the separation (positive and negative) measures for each alternative.

$$d_i^{+} = \sqrt{\sum_{r=1}^{h} (z_r^{+} - z_{ir})^2}, i = 1, 2, \ldots, m. \tag{14}$$

$$d_i^{-} = \sqrt{\sum_{r=1}^{h} (z_r^{-} - z_{ir})^2}, i = 1, 2, \ldots, m. \tag{15}$$

Step 4: Measure the relative closeness to the ideal solution.

According to the equation proposed by Chen (2000) [8], a relative closeness to the positive ideal solution was defined to get the ranking order of decision elements. The relative closeness S_i of the alternatives to the positive ideal solution is defined as follows:

$$S_i^{+} = \frac{d_i^{-}}{d_i^{+} + d_i^{-}}, 0 < S_i < 1, i = 1, 2, \ldots, m \tag{16}$$

The larger S_i^{+} is, that is, the smaller the distance between the scheme and the optimal solution is. The smaller $S_i^{+} is$, the smaller the distance between the scheme and the worst solution is.

We rank the alternatives according to their relative closeness. The best alternatives are those with higher S_i^{+} values because they are closer to the positive ideal solution.

4 Experimental Analysis

4.1 Case Description

With the rapid development of social networks, the propagation of rumors has increased faster, and their impact has been more extensive than before due to the convenience of the Internet. Rumors have been discovered to influence public opinions, aggravate economic losses, and even have political ramifications [22]. Especially since the outbreak of COVID-19, a lot of epidemic rumors have come up, some of which have had a critical impact on people's lives and societal stability [16]. Rumors about the epidemic online are growing rapidly. According to a report released by Weibo's official account, the platform properly managed 77,742 false information in 2019 (Weibo, 2019). Thus, it is a matter of great urgency to control the spread of rumors effectively and reduce the negative impact of rumors on society globally.

Recently, news aggregation platforms have become the primary way for users to obtain information. According to the Global Digital Report 2019, there are 911 million

Table 4. The basic overview of five major Chinese streaming platforms

Platforms	Introduce
Micro-blog	Sina Weibo is the Chinese counterpart of Twitter, with a larger, more open dissemination than Wechat, which only enables users to post to verified friends [41].
Zhihu	Zhihu, the largest online knowledge community in China, is a comprehensive knowledge exchange community that combines knowledge questions and answers and high-quality reading clubs in China [12].
TikTok	TikTok is a rising video-sharing platform that is popular among adolescents [35]. Its core function is to encourage users to express themselves and share 15 s of short music videos by setting up topic challenges, enriching music scenes, setting movie and audio templates, etc.
Toutiao	Toutiao is one of the news aggregation platforms with more than 600 million active monthly users, and the penetration rate of the entire network is close to 80% [33].
Kuaishou	Kuaishou is one of the most frequently used micro-vlogging apps or short video social apps [29], which is similar to TikTok.

active users of social media in China, accounting for 65% of the total population. The average time spent on social media per person per day is 88.6 min. Social media has become an indispensable part of people's lives. At the same time, the rapid spread of rumors relying on social media platforms has attracted people's attention with their rapidity and breadth of impact [30]. Thus, in this paper, five major Chinese streaming platforms are selected, including Micro-blog, Zhihu, TikTok, Toutiao and Kuaishou. Their basic overview is shown in the following Table 4.

4.2 Calculation

Based on the evaluation model of rumor refutation effect of rumor refutation platform established above, this paper conducts a comprehensive fuzzy evaluation on 11 specific evaluation indicators od factor layer from the three aspects of guidance (B_1), restrain (B_2) and influence (B_3), so as to evaluate the rumor refutation effect of social media platform.

Step 1
In this study, three decision experts were invited as decision makers to evaluate the importance of indicators at each level based on their practical experience. For ruler layer including guidance (B_1), restrain (B_2) and influence (B_3), the scores of the pair-wise comparisons were represented by positive triangle fuzzy numbers as listed in Table 5.

According to Eq. (1), the fuzzy judgment matrix is obtained:

$$C = \begin{bmatrix} (1, 1, 1) & (1.189, 2.056, 3.333) & (0.540, 0.811, 1.333) \\ (0.302, 0.744, 1.467) & (1, 1, 1) & (0.567, 1.133, 2.200) \\ (0.833, 1.778, 2.500) & (0.778, 1.438, 2.667) & (1, 1, 1) \end{bmatrix}$$

Table 5. The pair-wise comparisons of ruler layer

		B_1	B_2	B_3
Expert 1	B_1	(1,1,1)	(2/3,5/2,7/2)	(1/3,3/5,1)
	B_2	(2/7,2/5,3/2)	(1,1,1)	(1/5,1/3,3/5)
	B_3	(1,5/3,3)	(5/3,3,5)	(1,1,1)
Expert 2	B_1	(1,1,1)	(2/5,2/3,3)	(2/7,1/3,1)
	B_2	(1/3,3/2,5/2)	(1,1,1)	(1,5/3,3)
	B_3	(1,3,7/2)	(1/3,3/5,1)	(1,1,1)
Expert 3	B_1	(1,1,1)	(5/2,3,7/2)	(1,3/2,2)
	B_2	(2/7,1/3,2/5)	(1,1,1)	(1/2,7/5,3)
	B_3	(1/2,2/3,1)	(1/3,5/7,2)	(1,1,1)

From Eq. (2), an assembled triangular fuzzy number weight vector of rule layer(B) is obtained:

$$w^b = \left(w_1^b, w_2^b, w_3^b\right) = ((0.165, 0.352, 0.786), (0.113, 0.262, 0.647), (0.158, 0.385, 0.856))$$

For the triangular fuzzy number pairwise comparison, given the decision maker's risk attitude λ= 0.5. Then, calculate the corresponding possibility degree matrix from Eq. (3) established as:

$$\mathrm{P} = \begin{bmatrix} 0.5 & 0.676 & 0.457 \\ 0.324 & 0.5 & 0.292 \\ 0.543 & 0.708 & 0.5 \end{bmatrix}$$

The weight vector of the criterion layer (B_1, B_2, B_3) is derived from Eq. (4):

$$\mathrm{w_i^c} = (w_1^c, w_2^c, w_3^c) = (0.378, 0.206, 0.417)$$

Similarly, the weights of each index layer are as follow:

$$\left(w_{11}^c, w_{12}^c, w_{13}^c\right) = (0.483, 0.261, 0.256)$$

$$\left(w_{22}^c, w_{22}^c, w_{23}^c, w_{14}^c\right) = (0.293, 0.278, 0.293, 0.135)$$

$$\left(w_{33}^c, w_{33}^c, w_{33}^c, w_{34}^c\right) = (0.479, 0.202, 0.167, 0.152)$$

From the Eq. (5), the weight vector of each index layer compared with O (objective layer) can be calculate as presented as Table 6.

Table 6. The weight of each indicators

Rule layer (B)	Weight	Factor layer (F)	Weight
$B1$	0.378	$C11$	0.183
		$C12$	0.099
		$C13$	0.097
$B2$	0.206	$C21$	0.060
		$C22$	0.057
		$C23$	0.060
		$C24$	0.028
$B3$	0.417	$C31$	0.200
		$C32$	0.084
		$C33$	0.070
		$C34$	0.063

Step 2

For qualitative indicators ($c_{11}, c_{13}, c_{31}, c_{32}, c_{33}, c_{34}$), use the intuitive fuzzy method to evaluate, and here the intuitive fuzzy numbers of the three experts on five social media are given in Table 7.

Through the aggregation operator given by Eq. (6), when each expert is given the same weight, i.e. w_s takes 1/3, then, aggregate the above three intuition. After that, using the equation Eq. (7), the scores of each platform under the qualitative indexes can be calculated, denoted as matrix $\overline{C}_1$, which is presented in fuzzy matrices into an intuition fuzzy matrix D_{ij}, denoted in Table 8 and Table 9.

Step 3

Collect the data of quantitative indicators required under the remaining five indicators, including $C_{12}, C_{21}, C_{22}, C_{23}, C_{24}$. According to China Mobile Internet Database December 2021 and Mobile Internet Industry-wide Report -- "Enlightenment on the Development of Mobile Internet in China", original data (which is the value of factor layer index) in the thesis is collected, which is shown in Table 10 in detail.

After getting the data of the rumor refutation effect of social media platforms: Microblog, Zhihu, TikTok, Toutiao and Kuaishou, combine the data with the scores of qualitative indicators of each platform. Normalize the data by using Eq. (8), Eq. (9) and Eq. (10). All of the indicators in this paper are defined as positive indicators. After the above calculation process, multiply the weight of each assessment and the value of normalized matrix to construct a weighted normalizing matrix given in Table 11, the bold portion indicates the largest item.

Table 7. The intuitive fuzzy numbers of the three experts

Platform	$C11$	$C13$	$C31$	$C32$	$C33$	$C34$
Micro-blog	(0.80,0.15)	(0.8,0.1)	(0.7,0.2)	(0.8,0.1)	(0.5,0.4)	(0.81,0.15)
	(0.7,0.1)	(0.8,0.1)	(0.84,0.1)	(0.75,0.2)	(0.6,0.3)	(0.9,0.1)
	(0.75,0.20)	(0.90,0.10)	(0.70,0.20)	(0.80,0.15)	(0.75,0.20)	(0.87,0.13)
Zhihu	(0.30,0.60)	(0.5,0.4)	(0.4,0.5)	(0.8,0.1)	(0.62,0.3)	(0.63,0.3)
	(0.4,0.3)	(0.6,0.35)	(0.5,0.25)	(0.6,0.3)	(0.7,0.2)	(0.7,0.2)
	(0.35,0.50)	(0.55,0.35)	(0.55,0.35)	(0.40,0.60)	(0.40,0.50)	(0.66,0.27)
TikTok	(0.7,0.2)	(0.7,0.2)	(0.9,0.1)	(0.6,0.3)	(0.6,0.2)	(0.27,0.7)
	(0.75,0.2)	(0.75,0.1)	(0.7,0.15)	(0.8,0.2)	(0.6,0.2)	(0.4,0.6)
	(0.60,0.25)	(0.72,0.20)	(0.45,0.50)	(0.50,0.40)	(0.50,0.40)	(0.35,0.60)
Toutiao	(0.5,0.3)	(0.6,0.3)	(0.4,0.5)	(0.7,0.21)	(0.4,0.5)	(0.35,0.5)
	(0.5,0.3)	(0.6,0.2)	(0.45,0.4)	(0.7,0.15)	(0.3,0.6)	(0.5,0.5)
	(0.25,0.60)	(0.60,0.30)	(0.40,0.45)	(0.40,0.40)	(0.40,0.50)	(0.30,0.70)
Kuaishou	(0.6,0.25)	(0.7,0.2)	(0.7,0.2)	(0.6,0.3)	(0.63,0.2)	(0.256,0.6)
	(0.7,0.2)	(0.82,0.1)	(0.65,0.3)	(0.5,0.4)	(0.4,0.3)	(0.4,0.55)
	(0.60,0.25)	(0.72,0.20)	(0.50,0.40)	(0.48,0.40)	(0.45,0.50)	(0.38,0.60)

Table 8. Intuition fuzzy matrix $\boldsymbol{D_{ij}}$

Platform	$C11$	$C13$	$C31$	$C32$	$C33$	$C34$
Miro-blog	(0.75,0.14)	(0.84,0.10)	(0.76,0.16)	(0.78,0.14)	(0.63,0.29)	(0.86,0.12)
Zhihu	(0.35,0.45)	(0.55,0.37)	(0.49,0.35)	(0.64,0.26)	(0.59,0.31)	(0.66,0.25)
TikTok	(0.69,0.22)	(0.72,0.16)	(0.75,0.20)	(0.66,0.29)	(0.57,0.25)	(0.34,0.63)
Toutiao	(0.43,0.38)	(0.60,0.26)	(0.42,0.45)	(0.62,0.23)	(0.37,0.53)	(0.39,0.56)
Kuaishou	(0.64,0.23)	(0.75,0.16)	(0.63,0.29)	(0.53,0.36)	(0.50,0.31)	(0.35,0.58)

Then, determined the positive-ideal and negative-ideal solutions by using formula given in Eq. (12) and Eq. (13):

$$Z^{+} = \{0.066, 0.068, 0.034, 0.031, 0.020, 0.020, \\ 0.014, 0.072, 0.035, 0.019, 0.034\}$$

$$Z^{-} = \{0.000, 0.000, 0.000, 0.000, 0.000, 0.000, \\ 0.000, 0.000, 0.000, 0.000, 0.000\}$$

Table 9. The scores of each platform

Platform	$C11$	$C13$	$C31$	$C32$	$C33$	$C34$
Miro-blog	0.254	0.233	0.246	0.237	0.224	0.320
Zhihu	0.133	0.157	0.172	0.198	0.214	0.265
TikTok	0.231	0.214	0.235	0.195	0.226	0.129
Toutiao	0.161	0.181	0.143	0.204	0.134	0.150
Kuaishou	0.222	0.215	0.203	0.166	0.202	0.137

Table 10. Original data of quantitative index

Platform	$C12$(\one)	$C21$(\Billions)	$C22$(\min)	$C23$(\Billions)	$C24$(\Billions)
Micro-blog	21	11648	43.8	5.73	2.49
Zhihu	1	13184	70	0.8376	0.45
TikTok	14	230.08	101.7	6.72	6.4
Toutiao	78	720	110	4.1	1.2
Kuaishou	3	182.4	87.3	4.811	3.22

Table 11. Weighted normalizing matrix

Criterion		Micro-blog	Zhihu	TikTok	Toutiao	Kuaishou
B1	C11	**0.066**	0.000	0.053	0.015	0.048
	C12	0.018	0.000	0.011	**0.068**	0.002
	C13	**0.034**	0.000	0.026	0.011	0.026
B2	C21	0.028	**0.031**	0.000	0.001	0.000
	C22	0.000	0.008	0.017	**0.020**	0.013
	C23	0.016	0.000	**0.020**	0.011	0.013
	C24	0.005	0.000	**0.014**	0.002	0.007
B3	$C31$	**0.072**	0.021	0.065	0.000	0.042
	$C32$	**0.035**	0.016	0.014	0.019	0.000
	$C33$	0.019	0.017	**0.019**	0.000	0.014
	$C34$	**0.034**	0.024	0.000	0.004	0.001

After that, we can get d_i^+, d_i^- and S_i^+ by using the Eq. (14), Eq. (15) and Eq. (16) about our five platforms. Finally, based on the values of S_i^+, the rank of these five platforms can be got shown in Table 12. As can be observed from the data, the ranking

Table 12. The rank of these five platforms

Platforms	*di−*	*di+*	*Si+*	Ranking
Micro-blog	0.122	0.055	0.689	**1**
Zhihu	0.051	0.118	0.301	**5**
TikTok	0.096	0.078	0.554	**2**
Toutiao	0.076	0.105	0.421	**4**
Kuaishou	0.074	0.095	0.436	**3**

of the platforms in descending order is Toutiao, Micro-blog, TikTok, Kuaishou, Zhihu. And Toutiao's rumor-disputing capacity is pretty high overall.

4.3 Result Analysis

Figure 3 shows that Micro-blog, which is ranked first, is particularly prominent in the five aspects of rumor rebuttal information, the main rumor rebuttal dissemination form, rumor punishment, rumor monitoring efficiency, and rumor processing timeliness, making it stand out among the five evaluation objects. We can also see that Weibo performs badly in daily using time of users, but has a stronger overall performance in other indicators. TikTok is close to Weibo in terms of MAU, DAU/MAU, and rumor processing transparency, however it performs badly in terms of rumor processing time. Kuaishou, who comes in third, does badly in UV and Rumor monitoring efficiency, but has a better balancing strength across the table. Toutiao receives good marks for the number of authoritative rumor refuting user, as well as daily using time of users, but there are still some flaws in terms of rumor publicity and rumor handling transparency. Zhihu ranked the fifth performed better in UV, but performed common in other areas, even gain lots of the lowest scoring metrics, which also led to its worst performance in this assessment. It is suggested to make full use of the communication form of Q&A, and encourage official rumor-busting media and leaders to settle on the platform, in order to enhance its own guidance.

4.4 Sensitivity Analysis

Since subjective weight has such a significant impact on assessment outcomes, and the weight coefficients of the 11 indicators in this study are acquired by subjective empowerment, it is necessary to analyze the influence of changes in index weight sensitivity on evaluation results. For scheme a_i, a_k belongs to A, if the weight of the current h^{th} indicator ω_h changes $\varphi_{h,i,k}(1 \leq \text{i}, k \leq m, l \leq h \leq n)$, the scheme sort point of a_i and a_k is called $\varphi_{h,i,k}$ as the minimum absolute change, then $\varphi^{'}_{h,i,k}$=$\varphi_{h,i,k} \times 100/\omega_h$ is the relative minimum change.

Set $D_h = \min\left|\varphi'_{h,i,k}\right|(1 \leq i, k \leq m), S_h = 1/D_h$, then call S_h the sensitivity coefficient of the h^{th} index. The larger the sensitivity coefficient is, the easier it is to change the

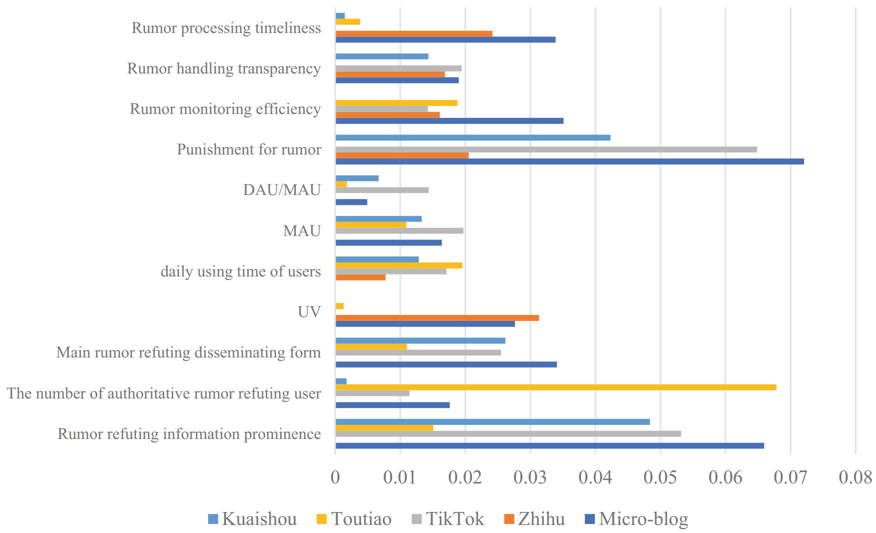

Fig. 3. Indicator score result

ranking of the evaluation results, namely the scheme sorting is less sensitive to the running value with the smaller the critical value and the larger the sensitivity coefficient.

According to Table 11, the values of $\varphi_{h,i,k}$ and $\varphi'_{h,i,k}$ can be calculated, and the results are shown in the Table 13. $\varphi_{h,i,k}$ or $\varphi'_{h,i,k}$ value of negative indicates a change in scheme ordering caused by an increase in weight, while a positive value of $\varphi_{h,i,k}$ or $\varphi'_{h,i,k}$ indicates a change in scheme ordering caused by a decrease in weight. Table 14 shows the critical weight change value D_j and sensitivity coefficient S_j for each attribute.

The sensitivity coefficient with the greatest value is c_{12}, with a critical value of 22.463 and a sensitivity coefficient of 0.044518, respectively. That is, changes in the number of authoritative rumor refuting user indicator weight are more likely to affect the evaluation scheme's ranking.

4.5 Compare Analysis

In this section, FAHP method is made comparison with AHP method to show its superiority. Based on the expert, each indicator is compared in pairwise. Then rank platforms based on TOPSIS aggregation method, the comparison results between AHP and FAHP in the calculation of weights are shown in the Table 15.

As a result, we can see that the optimal solution remains the same, while the ranking of several solutions that with similar performance changed. It can be inferred that intuitionistic ambiguity influences decision-making to some extent, allowing decision-makers to convey their thoughts more clearly, which can reduce uncertainty and randomness in the determination process of the indicator weight.

Table 13. All possible changes in the minimum absolute/minimum relative variation

Ranking Pairs	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}
(1,2)	–/–	–/–	–/–	–/–	−0.453/−790.835
(1,3)	–/–	–/–	–/–	–/–	–/–
(1,4)	–/–	−0.526/−533.307	–/–	–/–	−0.784/−1368.834
(1,5)	–/–	–/–	–/–	–/–	–/–
(2,3)	–/–	–/–	–/–	–/–	–/–
(2,4)	–/–	−0.232/−234.967	–/–	–/–	–/–
(2,5)	–/–	–/–	–/–	−0.489/−809.518	–/–
(3,4)	0.081/44.550	−0.022/−22.463	0.095/97.869	−0.692/−1145.749	−0.127/−221.233
(3,5)	–/–	–/–	–/–	−0.26/−431.042	–/–
(4,5)	–/–	–/–	–/–	−0.242/−400.216	–/–
C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}
–/–	−0.398/−1432.256	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	–/–
–/–	–/–	–/–	–/–	–/–	−0.662/−1050.902
–/–	–/–	0.07/35.019	−0.067−79.203	–/–	−0.398/−631.364
–/–	–/–	–/–	−0.707/−841.801	–/–	−0.377/−598.047
–/–	–/–	–/–	–/–	−0.496/−709.003	−0.374/−594.175

Table 14. D_j and S_j of each index

	C_{11}	C_{12}	C_{13}	C_{21}	C_{22}	C_{23}	C_{24}	C_{31}	C_{32}	C_{33}	C_{34}
D_j	44.550	22.463	97.869	400.216	221.230	–	1432.260	35.019	79.203	709.000	594.170
S_j	0.022	0.045	0.010	0.002	0.005	–	0.001	0.029	0.013	0.001	0.002

Table 15. The comparison results between AHP and FAHP

	S_i^+-FAHP	S_i^+-AHP	Rank-FAHP	Rank-AHP
Micro-blog	0.689	0.800	1	1
Zhihu	0.301	0.395	5	4
TikTok	0.554	0.467	2	2
Toutiao	0.421	0.432	4	3
Kuaishou	0.436	0.292	3	5

4.6 Management Suggestions

According to the above study, some suggestions for online social platform to improve their rumor refuting capacity are as follows.

(1) Increase the number of authoritative rumor refuting users

As we seen above, the sensitivity of the number of authoritative rumor refuting users (C_{12}) is the highest, indicating that it has significant impact on ranking of the social platform. The platform with low score in this index can cooperate with multi-level government network information office to establish information cooperation. Give full play to the authoritative advantages and channel advantages of mainstream media, transmitting authoritative rumor-busting information, the public information judgment ability and literacy will be improved subtly.

(2) Improve rumor refuting information prominence

According to above analysis, Zhihu and Toutiao are relatively backward in the score of rumor refutation information prominence (C_{11}), and this indicator also has a great impact on the ranking. Since users are more reliant on search engines in the age of new media, thus highlighting the information of refuting rumors, and setting up sections in categories can be beneficial to improve rumor refuting information prominence. The platform may use the search engine to guide users, place rumor dispelling information at the top of the page, and actively push rumor dispelling information to effectively manage network rumors. A special section of rumor dispelling information is set up to label the rumor dispelling information, aiming to accurately guide the public to receive rumor dispelling information.

(3) Improve the Rumor handling transparency and timeliness

It is recommended for Kuaishou and Toutiao to further improve the rumor monitoring mechanism, transparent the processing process and results of rumors, for they perform relatively poorly both on timeliness and transparency. The efficiency of rumor monitoring can be greatly improved with intelligent algorithm prediction, so as to identity and block the spread of rumors in time. Thus, they may apply a rumor refutation mechanism attach to intelligent algorithm to increase the transparency and timeliness of rumor handling.

5 Conclusion and Future Researches

With the rapid development of social networks, the propagation of rumors has increased faster in recent years. Social media platforms have become the major sources of rumors, particularly during the COVID-19 outbreak in China. To deal with this situation, Social media platforms have launched different rumor refutation mechanisms. A scientific, systematic, universal and measurable evaluation index system is constructed in this paper. Based on this evaluation index system, we propose a group decision-making method, fuzzy theory and TOPSIS method, to evaluate the capacity of rumor refuting platform including Microblog, TikTok, Kuaishou, Toutiao and Zhihu. Our innovation is that we combined qualitative and quantitative methods to improve the reliability of evaluation results and makes up for the deficiency of previous qualitative research. The ranking of social media platforms was gained in this paper and the results indicate that Zhihu, Kuaishou and Toutiao had relatively lower scores to deal with rumors than Microblog and TikTok. Some suggestions for online social platform were proposed, which may improve their rumor refuting capacity. The evaluation index system this paper constructed can be applied to assist users in selecting the right platform for rumor detection and promoting the platform to optimize operation, and ultimately achieving an effective response to rumor information generated in public emergencies. What's more, since the results obtained closely reflect the reality of domestic social platforms, the proposed method can be considered as an effective approach to assessing the capacity of rumor refuting platform, and it is further illustrated by comparative analysis and sensitivity analysis. Thus, this method proposed in this paper can be used as a tool to evaluate rumor refuting capacity in other platforms, which may provide a strong basis for platforms to improve their rumor management ability.

This study can be further extended. The evaluation indicators in this paper are summarized base on previous literature and related evaluation indicators systems of rumor refuting capacity. Since the factors influencing the rumor refuting capacity of social platforms varies with the environment of the internet, it is recommended that big data can be applied to discover the potential factors. Besides, the method of machine learning, such as the Support Vector regression (SVR) and Natural Language Processing (NLP), can also be combined into this problem to further improve the affective of fuzzy evaluation method. In future research, we will consider using machine learning to identify potential impact indicators, refine and optimize the indicator system, and further improve the scientificity and accuracy of the evaluation system.

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