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How local outbreak of COVID-19 affect the risk of internet public opinion: A Chinese social media case study

Liyi Liu a, Yan Tu a,*, Xiaoyang Zhou b, c

a School of Safety Science and Emergency Management, Wuhan University of Technology, Wuhan, 430070, China
b The School of Management, Xi’an Jiaotong University, Xi’an, 710049, China
c Academy of Mathematics and Systems Science, Chinese Academy of Sciences, Beijing, 100190, China

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ABSTRACT

Motivated by the realistic demand of controlling the Internet public opinion risk caused by the local outbreak of COVID-19, this paper creatively proposes a COVID-19 local outbreak Internet public opinion risk grading research framework. The SMAA-FAHPSort II method combining Analytic Hierarchy Process Sort II (AHPSort II) method with Stochastic Multicriteria Acceptability Analysis (SMAA-2) method is introduced into this framework, to evaluate the Internet public opinion risk level of social media during the local outbreak of COVID-19. In addition, this framework is applied to a case of Internet public opinion risk evaluation on Microblog platform of China. According to the number of new cases per day in mainland China, this paper divides the period from May 7, 2020 to September 3, 2021 into seven stages. A total of more than 10,000 Microblog hot topics were collected, after screening and preprocessing, 5422 related topics are remained to help complete the Internet public opinion risk evaluation. The case study analysis results show that the number of days classified as moderate risk and above has reached more than 280. This proves that the local outbreak of COVID-19 will indeed increase the risk of Internet public opinion, and correlation analysis confirms that the level of public opinion risk is positively correlated with the severity of the epidemic in the real world. Furthermore, the effectiveness and advantages of the proposed method are verified by comparative analysis and sensitivity analysis. Finally, some effective public opinion management suggestions have been put forward. This paper can provide reference for the government to formulate or improve relevant strategies, and also has great significance for reducing the risk of Internet public opinion in social media.

1. Introduction

The COVID-19 has dramatically impacted the world. More than 200 countries and regions have been affected. As of August 19, 2021, confirmed cases in the world have exceeded 20 million, with more than 770 thousand deaths. The COVID-19 not only threatens human health in the real world, the Internet public opinion caused by COVID-19 but also has a negative impact on society [1]. Due to the isolation or work at home caused by COVID-19, social media has become the main channel for the public to know the event information and express their opinions [2]. Since 2020, there has been a lot of discussions about COVID-19 in major social media, such as Microblog, Twitter, Facebook, TikTok [3–6]. These discussions are accompanied by a large number of users’ emotions and accurate or false information [7]. When this information and users’ emotions collide with each other on the Internet, the risk of Internet public opinion will increase accordingly [8].

Internet public opinion on social media will show different characteristics with the development of events [9]. In the early stage of COVID-19 outbreak, rumors were the main factor affecting the development of Internet public opinion on social media. The main reason is that social media provides a platform for users to share information and exchange views, and the spread of false information will become more rapid [10]. When the spread of the virus was basically controlled, more discussions on different views will emerge in social media, such as supporting and opposing the isolation policy [11], or different views on vaccines [12]. Users’ different views and opinions on emergencies in social media are the key factors for the formation of Internet public opinion [13]. Uncontrolled Internet public opinion will affect the

* Corresponding author.
E-mail addresses: liulyi@whut.edu.cn (L. Liu), tuyan.belle@163.com (Y. Tu), x.y.zhou@foxmail.com (X. Zhou).

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regular operation of society [14]. Therefore, preventing and controlling internet public opinion have become one of the necessary means to reduce the harm of COVID-19 [15].

Events, Internet media, users and government are the main participants in Internet public opinion spread [16]. Many scholars have studied from the aspects of user emotion and government credibility and so on [17–19], but few scholars have paid attention to the Internet public opinion risk grading. Secondly, scholars have mostly conducted qualitative analysis on Internet public opinion risk during COVID-19 period [20], and few use quantitative Multi Criteria Decision Making/Aid (MCDM/A) analysis method to study Internet public opinion risk. Again, judging from the current situation, most countries in the world have passed the main outbreak period of the epidemic, and local small and medium-sized virus outbreaks will become the norm. However, most literatures focus on the early stage of COVID-19 outbreak (i.e., from late 2019 to early 2020). Therefore, it is urgent to study the latest epidemic situation.

In this paper, starting from the time period of the local outbreak of COVID-19, the research framework of social media Internet public opinion risk grading is constructed and applied to a practical case based on Microblog platform in China. The main contributions of this paper are as follows:

1. Construct the research framework and evaluation criterion system of social media Internet public opinion risk grading to evaluate the Internet public opinion risk level when COVID-19 breaks out locally.
2. Propose a new MCDM/A method (i.e., SMAA-FAHPSort II), which is based on Analytic Hierarchy Process Sort II (AHPSort II) method, Stochastic Multicriteria Acceptability Analysis (SMAA-2) method and fuzzy theory, to achieve quantitative evaluation of social media Internet public opinion risk level.
3. Take Microblog platform in China as a case study, the grading results of Internet public opinion risk caused by local outbreak of COVID-19 are obtained, and some effective management suggestions are put forward according to the research results.

The rest of the paper is organized as follows. Section 2 reviews the literature on Internet public opinion and MCDM/A methods. The risk evaluation research framework of Internet public opinion under COVID-19 local outbreak based on SMAA-FAHPSort II method is constructed in Section 3. In Section 4, the relevant knowledge used in this paper and the specific steps of SMAA-2 method and AHPSort II method is introduced. Section 5 presents the SMAA-FAHPSort II method and describes the relevant steps and key points. In Section 6, the evaluation method is applied to the case study of a Microblog platform, and some management suggestions are given. The final section sums up the conclusions.

2. Literature review

2.1. Social media internet public opinion

In the past decade, social media has gradually integrated into people’s lives [21], and the COVID-19 has accelerated this phenomenon [22,23]. Not only users, more and more news media and government organizations are also using social media to carry out their work [24]. Since the outbreak of COVID-19, many scholars have studied Social media Internet public opinion, which provides a way to reduce the harm of public opinion for stakeholders in the real world [25]. Yin et al. [26] proposed a multiple-information susceptible-discussing-immune (M-SDI) model, which predicts the trend of Internet public opinion based on the relevant data of the Microblog platform. Jelodar et al. [27] classified some COVID-19 comments on the Internet through natural language process (NPL) method, the research results of this article can help to formulate practical strategies. Xiang et al. [28] found through the survey that the opinions of the elderly are in a disadvantageous position in public opinion on the Internet. Calandra and Favareto [29] discussed how to use Artificial Intelligence (AI) technology to combat the negative impact of COVID-19 in real life and the Internet. Cervi et al. [30] analyzed the comments made by Donald Trump and Jair Bolsonaro on Twitter, and explained the guiding role of government image on Internet public opinion in COVID-19.

COVID-19 has affected most parts of the world. Some research on Internet public opinion has also been applied to different countries [31,32]. Ng and Loke [33] analyzed a Telegram group of more than 10,000 people in Singapore. The analysis results show that users’ participation in Internet information discussion is related to the disease alert level. Great minds think alike, by analyzing Facebook in Singapore, Shorey et al. [34] came to a similar conclusion. In Europe, Moreno et al. [35] conducted an online survey in Spain. The survey results show that the news media is the primary way for people to obtain information, and with the serious spread of COVID-19 in Spain, people’s trust in the authorities is also declining. Jarynowski et al. [36] suggested that the Polish government use social media to increase the influence of public health publicity on COVID-19. Eachempati et al. [37] adopted a multi-channel perspective to analyze the netizen sentiment in social media platforms in different countries (China, the United States, India, Italy and Iran) during the COVID-19 period. In China, analyzing the Internet public opinion risk of mainstream social media platforms has become a hot topic [9,37,38].

The spread of rumors is not only one of the components of the harm of Internet public opinion but also the difficulty of managing Internet public opinion [39]. Exposing rumors can effectively reduce the adverse harm brought by Internet public opinion [40]. Chen et al. [41] analyzed the rumors on the Microblog platform in the early COVID-19 period and found that Beijing City and Wuhan City were the leading centers for exposing false information. Zhao et al. [42] provides a variety of ways to combat rumors. Luo et al. [43] confirmed that fear is the main inducing factor for the spread of rumors among users in the COVID-19 period.

In summary, most Internet public opinion studies on COVID-19 focus on the initial stage of the most severe outbreak, although most countries have passed this stage. There are few literatures focus on the risk of Internet public opinion caused by local outbreak of COVID-19. The primary outbreak of COVID-19 has passed, scattered and irregular local outbreaks will be the norm faced by countries all over the world for a long time. Therefore, this paper creatively establishes a research framework for the risk of local outbreak of Internet public opinion to help reduce the risk of public opinion in a more extended period in the future.

2.2. Multi Criteria Decision Making/Aid

MCDM/A is often used to deal with complex problems in the real world [44]. The application scope of MCDM/A has covered many fields, such as medical [45], supplier [46,47], logistics [48]. In this paper, a new MCDM/A method SMAA-FAHPSort II is proposed by combining Analytic Hierarchy Process Sort II (AHPSort II) method with Stochastic Multicriteria Acceptability Analysis (SMAA-2) method and fuzzy theory. AHPSort II method has advantages in dealing with sorting problems [49]. It is developed from the AHPSort method by Miccoli and Ishizaka [50] to reduce the number of paired comparisons. Subsequently, the stability and effectiveness of AHPSort II method are verified [51,52]. SMAA-2 [53] is introduced into AHPSort II to deal with the missing data. SMAA-2 is an improved method of SMAA [54], which takes into account imprecision or missing data considering probability distributions on the space of criteria weights and the space of alternatives’ evaluations [55]. It allows the problem of missing data to be explained from the perspective of probability distribution [56]. SMAA-2 has been combined with MCDM/A methods such as Topsis [57], FlowSort [58] and VIKOR [59], and the integrated methods have been applied to different fields.
In summary, scholars of MCDM/A rarely explore the field of Internet public opinion. This paper proposes the SMAA-FAHPSort II method to evaluate the risk of social media Internet public opinion caused by COVID-19 local outbreak. The main reasons are:

1. AHPSort II and FAHPSort II has been a mature MCDM/A method, and its applicability in the field of Internet public opinion has also been confirmed [13,60].
2. SMAA-2 method can effectively solve the problem of missing data and uncertain weights in the evaluation process, which helps to reduce the decision making pressure of decision makers (DMs) and promote the process of evaluation.

Therefore, this paper creatively proposes SMAA-FAHPSort II method, which can be more suitable for the research background of Internet public opinion and improve the evaluation efficiency. Applying SMAA-FAHPSort II method to the field of Internet public opinion risk not only broadens the research scope of MCDM/A, but also provides a new solution for other scholars to explore the problems of Internet public opinion risk evaluation.

3. Research framework of Internet public opinion risk grading

In May 2020, after the efforts of the Chinese government and people, COVID-19 was basically eliminated [61]. However, with the passage of time, some sporadic local outbreaks will always set off a massive discussion on the Internet [62]. Therefore, when a local epidemic breaks out, the risk of public opinion on the Internet also increases. If the Internet public opinion is not reasonably managed and dredged, it may hurt the Internet and society [63].

3.1. Generation of Internet public opinion

Internet public opinion is a complex process of multi-party participation, and its main stakeholders include government, media, users and non-governmental organizations [13]. According to the Chinese epidemic prevention policy, during the COVID-19 period, the virus-related situation will be announced on the Internet every day. After the government publishes the case information, the responsibility of the media is to excavate relevant news and report some details. The media may advise you not to go to risky cities in the near future and call on you to wear masks. Users often choose to use “like”, “forward” and “comment” to express their emotions and attitudes towards the event, and convey the message to the people around them [64]. Not only that, the poster will often make efforts to maintain his own views, such as forwarding similar views and criticizing opposing views [65]. Social media has become a key place for users to protest and debate a certain event or opinion [66]. Unfortunately, some news media and individuals may spread false information or make false statements for their own interests [67]. At the same time, ordinary users may also accelerate the spread of rumors without knowing the real situation [68]. Therefore when a lot of events related information or views emerge in social media, false information and rumors will often be spread [64]. A large amount of real information and false information are filled in social media, which is the precursor of the formation of social media Internet public opinion.

In addition, people with different opinions and socioeconomic backgrounds will also express their views on the Internet [69]. The additional psychological pressure brought by the virus leads to many users’ negative comments on the Internet [63]. Most users with the same emotions will express their approval through likes, solidarity shares, and supportive comments [70]. Consequently, another important factor affecting the generation of Internet public opinion is that a large number of users express their views or refute opposing views in social media. If Internet public opinion is not managed and controlled in time, rumors and negative views will have a significant impact on society and reduce the credibility of the government. Therefore, it is imperative for the local outbreak of the epidemic to timely detect the risk of Internet public opinion and take management measures.

3.2. COVID-19 local outbreak Internet public opinion risk grading research framework

This paper proposes a COVID-19 local outbreak Internet public opinion risk grading research framework, as shown in Fig. 1. The framework is mainly divided into three parts: “preliminary work”, “operation”, “discussion and analysis”. Preparatory work refers to a series of work before the risk grading of social media Internet public opinion, such as determining a suitable social media platform, inviting experts in relevant fields, and formulating a plan. These processes need to be discussed and completed by DMs in real life. Operation means that the evaluation work at this time has entered the stage of SMAA-FAHPSort II method. According to the specific requirements and steps of SMAA-FAHPSort II method (introduced in Section 4 and Section 5), the data calculation work is completed by MATLAB and Python. The last part of this research framework is discussion and analysis, which is significant. After the operation part, some results will be obtained, which are indicative. Furthermore, the DMs need to analyze and discuss the results to finally determine the Internet public opinion risk level of social media platforms and corresponding management measures to control the Internet public opinion risk.

After the local outbreak of COVID-19, information such as “number of cases”, “scope of influence” and “epidemic prevention policy” and so on will spread to the Internet. This information will be discussed and forwarded by the media and users, which will form Internet public opinion. Therefore, after the local outbreak of COVID-19, in order to understand the public opinion risk on the Internet, we need to use SMAA-FAHPSort II method to evaluate the Internet public opinion risk level. Internet public opinion risk is a macro concept. Uncertain criteria weights and missing data will bring difficulties to this work during evaluation. Therefore, we innovatively combine SMAA-2 method with FAHPSort II method and propose SMAA-FAHPSort II method, which can effectively solve the problems of uncertain criteria weights and missing data.

After determining the evaluation method, a suitable Internet platform should be selected. Some experts in relevant fields should be selected to establish a criterion system, usually completed by reference and brainstorming. Then, choose the appropriate data for different criteria and parameters, and collect relevant data. The data that is not a deterministic number will be given after discussion by experts. The final Internet public opinion risk grading results will be obtained through simulation, iteration, discussion, and other steps.

The number of categories in Internet public opinion risk grading is an important issue. Mei et al. [60] and Liu et al. [13] divide Internet public opinion risk into four categories. However, the research period of this problem is longer, and the fluctuation of Internet public opinion caused by local outbreak of COVID-19 is larger due to more different severe conditions. Therefore, this paper sets up five categories in order to more accurately evaluate the risk of social media Internet public opinion. The highest risk level is described as “dangerous”, followed by “critical”, “moderate” and “bearable”, the lowest risk level is “secure”, and the description of the risk levels is shown in Table 1.

When the grading result is “dangerous” or “critical”, the representative needs to pay attention to the problem of Internet public opinion, and should immediately take coercive measures to control the risk of Internet public opinion. When the grading result is “moderate”, some measures to control the risk of Internet public opinion should be taken to avoid the deterioration of Internet public opinion risk. When the grading result is “bearable” or “secure”, intervention measures may not be taken, but it is necessary to continue to pay attention to the trend of public opinion in order to timely respond to possible changes in Internet public opinion risk in the future. At the same time, we suggest that after taking

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relevant public opinion control measures, the Internet public opinion risk can be re-evaluated after a certain time, such as 12 h or 24 h. This step can test the effect of public opinion governance. If the risk level is reduced, it indicates that the impact of public opinion intervention is significant. If the risk remains unchanged or increases, it proves that the effect of public opinion intervention is not substantial. We should consider the causes of this phenomenon, adjust intervention strategies, and learn from experience to eliminate the negative impact of public opinion as soon as possible.

It is worth mentioning that the Internet public opinion risk grading research framework proposed in this paper has been applied to Microblog as a case, which is one of the social media platforms with the largest number of users in the world. It should be emphasized that this research framework is fully applicable to other social media platforms (not just in China), such as Facebook, twitter. Different countries have different national conditions, and different social media platforms have different modes of operation. However, the formation and manifestation of Internet public opinion risk are unified. Therefore, it is suggested that the evaluation criterion system should be supplemented or adjusted when conducting Internet public opinion risk evaluation on other social media platforms to meet the actual situation of the social media platform.

4. The proposed methodology

In order to make the method proposed in this paper easy to understand, this chapter will explain some previous methods. The detailed quotation of symbols is shown in Table 2.

4.1. SMAA-2 method

Lahdelma et al. [54] creatively invented the SMAA method, which solved the problem that the decision makers (DMs) could not or was difficult to make an accurate decision when the criteria weights could not be obtained or the data of alternatives was incomplete. Subsequently, Lahdelma and Salminen [53] proposed the SMAA-2 method, an improvement of the previous one, it has a great practical significance when DMs deal with MCDM/A problems with uncertain values.

The SMAA-2 method can be divided into two cases: (1) The evaluation value of alternatives is determined; (2) The evaluation value of alternatives is stochastic. In order to save space, stochastic cases will be introduced as follows.

**Step 1.** The expected utility of $A_i$ on $C_j$ and the total expected utility is calculated.

$$ u_i = \int f(\xi) u_i(\xi) d\xi $$

(1)

Uncertain or imprecise evaluations of alternatives are represented by $\tilde{g}$ ($A_i$), under certain circumstances this value is denoted by $g$ ($A_i$).

$$ u_i(\xi, w) = \sum_j w_j u_j(\xi_j), w \in W $$

(2)
Table 2
Quotation.

| Symbol | Interpretation | Symbol | Interpretation |
|--------|----------------|--------|----------------|
| i      | Index of alternatives, i = 1, 2, ..., n | j      | Index of criteria, j = 1, 2, ..., m |
| y      | Index of classes, y = 1, 2, ..., l | r      | Ranking of alternatives, r = 1, 2, ..., d |
| o      | Index of reference points, o = 1, 2, ..., k | v      | Index of limiting profiles, v = 1, 2, ..., d |
| A_i    | ith alternative | C_j    | jth criterion |
| S_j    | yth class | w_j    | Weight of C_j |
| g(A_i) | Under certain circumstances, evaluation value of A_i in the C_j | f(w)   | Probability distribution |
| R(C)   | Function of evaluation value of alternatives | w       | Weight vector, w = (w_1, w_2, ..., w_m) |
| W_r     | Weight space of A_i got the rth place | W_r^k  | Weight space of A_i is divided into S_r |
| b_j    | Category acceptability index of A_i is divided into S_r | b_j^p  | Limiting profile regard to C_j |
| r_j^p  | Reference point regard to C_j | p_j^p  | Local priority of b_j^p |
| p_j    | Priority of r_j^p | P_j    | Global priority of r_j^p |
| N^α    | Number of iterations, N_0 = 10^0 | N^α(A_i) | Times of A_i is divided into S_r |

Step 2. In the case of missing weight information or DMs which cannot provide precise weight data, the weight space is defined as follows.

\[ W = \{ w \in R^m | w \geq 0 \text{ and } \sum_{j=1}^{m} w_j = 1 \} \]  

(3)

If the DMs can provide weight information, even if it is not a clear number, then the weight space W is limited by these preferences. For example, DMs provide information that the importance of different ranking positions. DMs can choose the d' value according to different needs, but the condition \( d' = \frac{a}{b} \geq 0 \) should be met.

Several common weights of \( d' \) are as follows: (1) \( d' = \frac{b-r}{m-r} \) (2) \( d' = \frac{(m-r)}{(m-1)} (3) d' = \frac{(m-1)}{(m-1)} \) \[ 53 \].

4.2. AHPSort II method

AHPSort method is a common Multi-Criteria Sorting method. Its purpose is to assign alternatives to predefined categories in order to help DMs. AHPSort II is an extension of AHPSort, trying to complete the established work with fewer comparisons than AHPSort.

Step 1. Define the goal and criteria.

Step 2. Define the classes. Usually, each class will use a semantics to describe it, such as “good”, “medium”, “bad”, etc. The order of each class is strict, alternatives in the higher level always have priority over the alternatives in the lower level.

Step 3. Determine limiting profiles of each class, denoted by b_j^p. This step is the core of the whole evaluation system. Different limiting profiles can have a great influence on drawing the judgment curve, but this problem was solved by SMAA-AHPSort II. b_j^p indicates the minimum performance needed on each C_j to belong to a class S_j. Whole classes require \( j \cdot (l - 1) \) limiting profiles to define.

Step 4. Determine the criteria weights. The criteria weights are obtained by pairwise comparing the importance of two criteria with the eigenvalue method of the AHP [71].

\[ A \cdot w = \lambda \cdot w \]  

(7)

where A is the comparison matrix; w is the priorities/weight vector; \( \lambda \) is the maximal eigenvalue.

Step 5. Determine reference points r_j^p, then calculate the priority of reference points and limiting profiles. The reference points can be determined by equal distance and this step needs to be repeated on each criterion. Unlike AHPSort, the local priority of limiting profiles will be calculated in this step together with the priority of the reference point. Compare in a pairwise comparison matrix the reference points and limiting profiles. The priority of reference points p_j^p and local priority of limiting profiles p_j^p can be obtained by Eq. (7).

In order to effectively reduce the number of pairwise comparisons in this step and simplify the calculation process of the method, the concept of “clusters” is proposed by Miccoli and Ishizaka [36]. Through the “joining point”, the limiting profiles and reference points are divided into different clusters to reduce the number of comparisons. Firstly, the priorities of elements in each cluster are calculated, and then the priority of all elements is calculated by the conversion rate of joining point between different clusters.

Step 6. Draw the priority curve of the reference point, with the abscissa as the reference point and ordinate as the priority. Through the triangular relationship between the alternative A_i and its adjacent two reference points r_j^p and r_j^p+1, it is easy to obtain the local priority of the alternative p_j. The formula for calculating p_j is

\[ p_j = p_j^p + \frac{p_j^{p+1} - p_j^p}{p_j^{p+1} - p_j^p} (q'(A_i) - r_j^p) \]  

(8)

where:

- r_j^p and r_j^{p+1} are two consecutive representative points regard to C_j.
Step 7. Derive the global priority, after obtaining the local priority for every criterion and the weight of each criterion.

\[ P_l = \sum_{j=1}^{n} P_l^{j}w_j \]

Step 8. Derive the class of alternatives, the comparison of \( P_l \) with \( P_l^j \) is used to assign the alternative \( A_i \) to a class \( S_r \). If limiting profiles have been defined, the alternatives are assigned to the class \( S_y \) which has an \( P_l^j \) just below the global priority \( P_l \).

\[ P_l \geq P_l^j \Rightarrow A_i \in S_r \]
\[ P_l^j < P_l \Rightarrow \omega_i \in S_y \]

Step 9. Repeat Step 6–8 for each alternative.

AHPSort II method reduces the number of comparisons and provides help for DMs in studying Multi-Criteria Sorting problems. Fig. 2 shows the general framework of the AHPSort II method.

4.3. Interval fuzzy number and linguistic fuzzy number

In many MCDM/A cases, DMs are often unable to give an accurate judgment on a certain attribute or cannot accurately quantify qualitative criteria, fuzzy set theory came into being [72]. Fuzzy theory has a judgment on a certain attribute or cannot accurately quantify qualitative criteria, which provides an auxiliary means for MCDM/A problems with uncertain information in the real world [73].

At present, there are many kinds of fuzzy set theories applied to MCDM/A problems, such as interval fuzzy, triangular fuzzy, intuitionistic fuzzy, linguistic fuzzy and so on. The method proposed in this paper is mainly designed to interval fuzzy and linguistic fuzzy. These two fuzzy sets are briefly introduced as follows.

(1) The connotation of interval number. Let \( R \) be the real number field, for any \( a^l, a^u \in R \) and \( 0 \leq a^l < a^u \), mark \( \tilde{a} = [a^l, a^u] \), call \( \tilde{a} \) the interval number, where \( a^l \) and \( a^u \) are the lower limit and upper limit of the interval number \( \tilde{a} \), respectively. Let \( m(\tilde{a}) \) and \( \omega(\tilde{a}) \) be the center and width of a respectively, where \( m(\tilde{a}) = (a^l + a^u)/2, \omega(\tilde{a}) = (a^u - a^l)/2 \). For interval numbers \( \tilde{a} \) and \( \tilde{b} \), if \( m(\tilde{a}) > m(\tilde{b}) \), then \( \tilde{a} > \tilde{b} \); if \( m(\tilde{a}) = m(\tilde{b}) \), then \( \tilde{a} = \tilde{b} \); if \( m(\tilde{a}) < m(\tilde{b}) \), then \( \tilde{a} < \tilde{b} \).

(2) The connotation of linguistic number. DMs often use linguistic fuzzy number to describe some qualitative criteria that cannot be quantified, such as comfort, reliability, cohesion and so on [74]. By suggesting a set of ordered natural languages, such as: very good, good, medium, poor, very poor, etc. By describing the performance of alternatives, linguistic fuzzy number can help DMs break through the constraints of digital form and reduce the decision-making pressure when facing the evaluation of qualitative criteria [75]. Linguistic fuzzy number are usually divided into 5–9 levels. According to the characteristics of criteria, this paper divides the performance of alternatives into 9 levels: very great (VG), great (GR), good (GO), medium good (MG), medium (ME), medium poor (MP), poor (PO), awful (AW), very awful (VA).

5. SMMA-FAHPSort II

In this section, we introduce the SMMA-FAHPSort II method. It allows the use of uncertainty and missing information to evaluate alternatives, determine criteria weights and some parameters. Firstly, we introduce the SMMA-FAHPSort II method, and give the required input data and the allowed data types, which shows that information defects are allowed. Then, we introduce the category acceptability index, elaborate on how it can be explained and applied according to the characteristics of the problem, and finally complete the decision.

5.1. Input of data

Step 1. Determine the form of input data. In SMMA-FAHPSort II, different data forms are allowed on different scales. The details are as follows:

- Evaluations the alternatives: can be defined by established real data or by DMs, deterministic number, interval number, linguistic fuzzy and stochastic data are allowed to be used;

- Evaluations the criteria: it includes the category acceptability index, which is divided into 5 levels: unacceptable, poor, medium, good, and excellent;'


- **Criteria weights:** by default, it is defined by the DMs. The DMs can give complete data or missing data, deterministic number, interval number, or ordinal to be used;

- **Limiting profiles:** should be defined by the DMs according to the performance of the alternatives with respect to criteria, deterministic number, interval number, linguistic fuzzy and stochastic data are allowed to be used;

- **Reference points:** defined by the DMs, deterministic number and linguistic fuzzy are allowed.

**Step 2.** Determine the evaluation value of alternatives, for values that can be measured or counted, deterministic number can be used to evaluate alternatives. If the DMs cannot give accurate values, interval number and stochastic data can be used. We represent the evaluation of alternatives using the random variables $\xi$ with a probability density function $f_\xi(\xi)$ in the space $X$ defined as:

$$X = \{ \xi \in \mathbb{R}^n \times \mathbb{R}^m : \xi_i, i = 1, 2, \ldots, m, j = 1, 2, \ldots, n \}$$

Specifically, we use the uniform distribution to evaluate alternatives defined by interval data. It is difficult to express and evaluate in digital form for some special criteria, such as comfort, reliability, and other qualitative criteria. DMs are allowed to use linguistic fuzzy number, such as “good”, “poor”, etc., to evaluate the performance of alternatives. This paper divides the performance of alternatives into 9 levels.

**Step 3.** Determine the limiting profiles, limiting profiles is a key factor in determining whether alternatives are assigned to different classes. In the original AHPSort II method, a slight deviation in the value of the limiting profiles may cause an alternative to be assigned to completely different classes. DMs often feel tremendous pressure when defining limiting profiles. Therefore, SMAA-FAHPSort II provides interval number, stochastic data and linguistic fuzzy to help DM make better decisions. The limiting profiles expressed in interval numbers or stochastic data are represented by random variable $\psi$ with a probability density function $f_\psi(\psi)$ in the space $Y$. The space $Y$ is defined by:

$$Y = \{ \psi \subseteq \mathbb{R}^{(k+1)} \times \mathbb{R}^m : \psi_{ij} - \psi_{ik} \leq 0, \forall h, h = 1, 2, \ldots, k, j = 1, 2, \ldots, n \}$$

For the criteria defined in Step 2 as expressed by linguistic fuzzy number, the limiting profiles of the criteria should also be expressed by linguistic fuzzy number. For example, the reliability of a system needs to be divided into “reliable ($K_1$)”, “general ($K_2$)” and “unreliable ($K_3$)”. The DMs will use linguistic fuzzy numbers to evaluate alternatives’ performance, and the evaluation value may be “good”, “very poor” or other. If we take “good” as the limiting profile between “reliable ($K_1$)” and “general ($K_2$)”, in addition, take “poor” as the limiting profile between “general ($K_2$)” and “unreliable ($K_3$)”. If only the reliability criterion is considered, an alternative wants to be classified as “reliable ($K_1$)”, its evaluation should not be lower than “good”, if DM thinks that evaluation an alternative is “very poor”, it will be classified as “unreliable ($K_2$)”.

**Step 4.** Determine the criteria weights, deterministic number is the most acceptable form of weight data, but in real world MCDM/A problems, DMs may only provide the ordinal information of weights or missing information for some reasons. In the case of completely missing information, criteria weights can assume any value in the set of feasible weights, which is defined in Eq. (2), following a uniform distribution.

Another possibility of criteria weight information provided by DMs is interval number. For instance, in a case with three criteria ($C_1$, $C_2$, $C_3$), DMs think that the most important criterion is $C_1$, the least important criterion is $C_2$, and the importance of $C_3$ is in the middle (i.e., $w_1 > w_3 > w_2$). At this time, the weight space is composed of Eq. (3) and the constraint condition “$w_1 > w_3 > w_2$.”

When DMs use interval number to define criteria weights, the weight space will be reduced compared with completely missing information. For instance, the information given by the DMs is that the importance of $C_1$ is between 0.4 and 0.7, the importance of $C_2$ is between 0.1 and 0.3, and the importance of $C_3$ is between 0.2 and 0.5. In that case, the weight space is composed of Eq. (3) and the constraint condition “$0.4 < w_1 < 0.7, 0.1 < w_2 < 0.3, 0.2 < w_3 < 0.5$”. It should be noted that in order to avoid conflict with Eq. (3), the sum of the lower limits of the criteria weight interval should be less than or equal to 1, and the sum of the upper limits should be greater than or equal to 1.

**Step 5.** Determine the reference points and obtain the reference point priority curve. This step is the same as Step 5 and Step 6 of the AHPSort II method. It is worth mentioning that the criteria evaluated by linguistic fuzzy number do not need to establish a reference point. The local priority of the limiting profiles and alternatives corresponding to the criteria are directly obtained by pairwise comparison of the limiting profiles with alternatives by Eq. (7), just like the same step in the AHPSort method [76].

### 5.2. Simulation and iteration

**Step 6.** Take values of stochastic variables to complete a simulation. For the deterministic number, we directly use the number for the classification operation of AHPSort II. For variables with interval numbers and stochastic data, first, we need to determine the distribution function of the variable, then generate stochastic values by using probability distribution, apply for the determined numbers and generate random values to AHPSort II. Finally, the calculation method of the local priority of the alternatives evaluated by linguistic fuzzy number has been given in Step 6 of AHPSort II method. After all $p_i$ are obtained, each alternative is assigned to a predefined class through Step 7-8 of AHPSort II method.

**Step 7.** Repeat the stochastic value in the previous step. The number of iterations in the whole process should be $10^4$ (ten thousand) [77].

**Step 8.** When the last iteration is completed, the category acceptability index $b^i_S$ is calculated for all alternatives through the following formula.

$$b^i_S = \frac{N^i(A)}{N^i} \leq 1 \quad (13)$$

where $b^i_S$ represents the frequency that $A_i$ is assigned to $S_j$ throughout the iterative process.

### 5.3. Extension and discussion

**Step 9.** When the category acceptability index is obtained, the DMs need to discuss according to the obtained results.

In a simple case, if $b^i_S = 0$, it is obvious that the alternative $A_i$ will not be assigned to $S_j$. If $b^i_S = 1$, the alternative $A_i$ will undoubtedly be assigned to $S_j$ regardless of other parameters.

In complex situations, for an alternative $A_k$, $b^i_S > 0$ ($S_j, S_j \in S_j$). The DMs to discuss the final result according to the actual needs, some discussion schemes are as follows.

- More deterministic information can effectively reduce the situation that an alternative is divided into multiple different classes. In this case, DMs can choose to collect more deterministic information about criteria weights, evaluation information, limiting profiles and so on. Subsequently, repeat the step of SMAA-FAHPSort II.
During COVID-19, millions of netizens used social media every day to disseminate information, dispel rumors and provide psychological assistance, with unexplained pneumonia. Subsequently, the coronavirus causing pneumonia was named COVID-19. For a long time, there was no effective treatment for COVID-19 breaks out locally, we collectively refer to the time when the number of new cases is concentrated as a stage, and ignore the days when there are no new cases. Therefore, we, according to the number of new cases, divided the research scope (2020/5/7–2020/9/3) into seven stages, namely: 2020/5/7–2020/5/23 (stage 1), 2020/6/11–2020/7/5 (stage 2), 2020/7/16–2020/8/15 (stage 3), 2020/10/27–2021/2/6 (stage 4), 2021/3/26–2021/4/20 (stage 5), 2021/5/13–2021/6/21 (stage 6), 2021/7/14–2021/9/3 (stage 7). The advantage of dividing the research scope into different stages is that this paper can focus on understanding the objective Internet public opinion when there is a local outbreak of COVID-19. Comparing the research results of different stages can also draw some new conclusions, which will help us better understand the Internet public opinion brought by COVID-19.

Next, the Microblog platform Internet public opinion risk analysis under the local outbreak of COVID-19, for stage 1, will be displayed. For simplicity, the 17 days of stage 1 will be referred to as D1–D17 (i.e., 2020/5/7 is D1, 2020/5/8 is D2, and so on).

In order to focus on the risk of Internet public opinion when COVID-19 breaks out locally, we collectively refer to the time when the number of new cases is concentrated as a stage, and ignore the days when there are no new cases. Therefore, we, according to the number of new cases, divided the research scope (2020/5/7–2021/9/3) into seven stages, namely: 2020/5/7–2020/5/23 (stage 1), 2020/6/11–2020/7/5 (stage 2), 2020/7/16–2020/8/15 (stage 3), 2020/10/27–2021/2/6 (stage 4), 2021/3/26–2021/4/20 (stage 5), 2021/5/13–2021/6/21 (stage 6), 2021/7/14–2021/9/3 (stage 7). The advantage of dividing the research scope into different stages is that this paper can focus on understanding the objective Internet public opinion when there is a local outbreak of COVID-19. Comparing the research results of different stages can also draw some new conclusions, which will help us better understand the Internet public opinion brought by COVID-19.

Next, the Microblog platform Internet public opinion risk analysis under the local outbreak of COVID-19, for stage 1, will be displayed. For simplicity, the 17 days of stage 1 will be referred to as D1–D17 (i.e., 2020/5/7 is D1, 2020/5/8 is D2, and so on).
Step 1. Determine the goal and evaluation object. For stage 1, the goal is to get the Internet public opinion risk level of the Microblog platform, and the evaluation object is the complete time interval of stage 1.

Step 2. Determine the evaluation criteria of Internet public opinion risk of Microblog platform and the data forms of criteria. Through experts discussion and literature review, the risk classification criteria of Internet public opinion under local outbreak of COVID-19 are shown in Table 3.

Step 3. Determine the weights of criteria. The SMAA-2 method supports a variety of criteria weights processing methods. In this case, experts did not give specific criteria weights data, but gave ordering information of \( W_2 > W_3 > W_1 > W_4 > W_5 > W_6 \). This means that experts believe that criterion \( C_2 \) should have the largest weight, followed by criterion \( C_3 \), and criterion \( C_6 \) should have the smallest weight. In the calculation process, the criteria weights will be random follow the order information, but their sum is guaranteed to be 1.

Step 4. Determine the evaluation value of the criteria. For the criteria with deterministic number, the criteria data is usually obtained by searching data or consulting literature. For linguistic criteria, the criteria data is determined by expert evaluation. For interval and random criteria, the required interval range or probability density function is given by experts after discussion, and then iteration is carried out. The detailed data of stage 1 can be seen in Table 4.

Step 5. Define limit profiles and reference points. In the original AHPSort II method, this is the core step of evaluation, which directly determines the level to which the alternative will be classified. Therefore, in order to get accurate evaluation results, experts often bear great decision-making pressure in this department. When experts cannot accurately give some parameters, or have low confidence in them, it is likely to affect the final evaluation results. In this step, experts defined the specific values of reference points and limit files. Detailed can be found in Table 5.

Step 6. Obtain the local priority of reference point. Reference points are divided into three clusters and linked with “joining point”. The priority of reference points in each cluster is obtained by the characteristic root method of AHP method. Then the standardized priority is obtained by the proportion between “joining point”. \( C_1 \) will be shown as a case, as shown in Table 6 and Table 7. For all criteria, the value of the 0th reference point is 0, so their priority will be given 0 directly without participating in the comparison.

Step 7. According to the previously specified data form, 10,000 random values conforming to the corresponding probability density function are produced for each stochastic parameter. In this step, we

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Table 3

| Direction | Criteria                  | Interpretation                                      | Data form |
|-----------|---------------------------|----------------------------------------------------|-----------|
| Microblog | Reading volume of hot topics (\(C_1\)) | Average reading volume of hot topics on the day | Deterministic |
|           | Discussion volume of hot topics (\(C_2\)) | Average discussion volume of hot topics on the day | Deterministic |
|           | Number of hot topics (\(C_3\)) | The number of topics related to the epidemic situation on the hot search list that day | Deterministic |
|           | Media influence (\(C_4\)) | The impact of the media on public opinion | Linguistic |
|           | Negative emotions of users (\(C_5\)) | Proportion of negative emotions when users discuss on Microblog | Interval |
|           | Time of browse information (\(C_6\)) | Average time for users to browse epidemic information through Microblog | Normal |

1 Hot search list is published by Microblog according to the heat of the topics, topics in hot search list are called hot topics.
need to operate the performance of criteria $C_5$ and $C_6$ and criteria weights.

**Step 8.** Derive the local priority of limiting profiles and every single day in stage 1. The priority of reference points can help us complete this task through Eq. (8). Since 10,000 sets of stochastic parameters were generated in the previous step, this step will produce 10,000 sets of results.

**Step 9.** Derive the global priority of limiting profiles every day in stage 1. With the help of Eq. (9), we can complete this task, but we still need to obtain 10,000 sets of results.

**Step 10.** Complete the Internet public opinion risk classification according to the global priority of alternatives and limiting profiles, and count all iterative results. According to Eq. (13), the category acceptability index of every single day in stage 1 is shown in Table 8.

**Step 11.** Explanation and discussion of category acceptability index. In order to better analyze the classification results, the average results of 10,000 iterations will be shown. The results of Internet public opinion risk analysis in stage 1 are shown in Fig. 6.

Repeat the above steps for stage 2 — stage 7. The results and details of stage 1 to stage 7 are shown in Fig. 8.
6.2. Results analysis and discussion

6.2.1. Analysis of internet public opinion risk grading results

Fig. 6 shows the average global priority for stage 1, except May 8, 2020 and May 22, 2020 (i.e., D2 and D16), Internet public opinion risk in the other 15 days is moderate (i.e., $S_5$). This means that during the local outbreak of COVID-19 in stage 1, there is a certain degree of Internet public opinion risk, which needs to be paid attention to. Fig. 7 shows the contribution rate of different criteria to the public opinion risk of the day in stage 1. The cooperation proportion of criteria $C_1$ and $C_2$ exceeds 40% in 90% of the days in stage 1, and criteria $C_2$ has the largest risk contribution rate in more than 80% of the days. This means that the most important factor affecting the local outbreak of COVID-19 Internet public opinion is the users’ participation in relevant topics, and a hot topic is likely to affect the risk of Internet public opinion.

In order to explore the Internet public opinion risk caused by the local outbreak of COVID-19 during the period of normalized epidemic prevention and control, we divided the period from May 7, 2020 to September 3, 2021 into seven different stages, and the sum of the days of these seven stages are 304. From the overall perspective of the seven stages, the Internet public opinion of COVID-19 is generally stable but potentially dangerous. In a total of 304 days of research, the number of days finally classified into different categories is 1, 21, 201, 76, 5 (from left to right corresponds to $S_1$-$S_5$), it can be seen in Fig. 9. The number of days classified as moderate risk and above has reached more than 280 days, proving that the local outbreak of COVID-19 still brings public opinion risk to the Internet.

Fig. 10 shows the new confirmed cases number curve and the Internet public opinion risk curve from stage 1 to stage 7. There is a similar trend between the Internet public opinion risk curve and the new confirmed cases number curve. Therefore, the correlation analysis between Internet public opinion risk and epidemic situation will be introduced in the next section to explore the impact between Internet public opinion risk and actual epidemic situation.

6.2.2. Correlation analysis between internet public opinion risk and epidemic situation

Internet public opinion risk curve is related to the development status of the epidemic for each stage. In other words, the more serious the epidemic is, the higher the Internet public opinion risk is, and the Internet public opinion risk will be reduced when the epidemic is controlled.

Correlation analysis will be conducted between the evaluation results of Internet public opinion risk and the actual epidemic data to explore the impact of the epidemic situation on Internet public opinion risk. The data analysis of Spearman correlation is conducted on Statistical Package for the Social Sciences (SPSS24.0), which is shown in Table 9. It can be seen from Table 9 that both Internet public opinion risk and the number of microblog topics have significant positive correlations with the new confirmed cases number and the number of provinces with new cases ($p < 0.01$).

6.3. Comparative analysis

In this section, the data from the case study will be applied to the FAHPSort II method to compare with the SMAA-FAHPSort II method. Two different results illustrate the advantages of SMAA-FAHPSort II method. For FAHPSort II method, the weight of criteria is determined by experts through pairwise comparison matrix, while for SMAA-FAHPSort II method, completely uncertain weight information and ordinal weight information are displayed respectively. In the case analysis of this paper, the data of $C_5$ and $C_6$ are obtained randomly. In the traditional FAHPSort II method, the data of these two criteria will be evaluated as triangular fuzzy numbers by experts like Krejčí and Ishizaka [78]. The comparison results of the two different methods are shown in Table 10.

In the FAHPSort II method, all alternatives are classified into a single category. In the 17 days of stage 1, 1 days were classified as critical risk (i.e., $S_4$), 12 days were classified as moderate risk (i.e., $S_3$) and the remaining 4 days were classified as bearable risk (i.e., $S_2$).

In the analysis of missing criteria weights of SMAA-FAHPSort II method, almost all alternatives are classified into three different classes, except D9, D12, D13, D14, these are classified into two different classes. Although each alternative is divided into several different categories, the proportion of alternatives divided into a class with a probability of more than 70% is 16/17, which means they can still be easily divided into a separate class.

In the analysis of ordinal criteria weights of SMAA-FAHPSort II
method, due to the weight information becomes accurate to a certain extent, each alternative obtains the category acceptance index, and the weight is more contracted and concentrated than the missing criteria weights. In the 17 days of stage 1, 13 days were classified into only one classes. Furthermore, in the days classified into two different categories, there are also great differences among different categories. This means that in SMAA-FAHPSort II method, the more information the DMs knows, the more centralized the category acceptability index of alternatives will be.

For the missing criteria weights and ordinal criteria weights in SMAA-2 method, the resulting class acceptability indicator can be discussed in different ways, as described in Section 4. Suppose we take “alternatives will be classified into the category with the highest category acceptable index” as the principle to determine that alternatives are classified into a category in the SMAA-FAHPSort II method. Then, when the criteria weights is missing, more than 2/3 of the alternatives produce the same classification results. In the case of ordinal criteria weights, the classification results are more similar to the FAHPSort II method. This shows the consistency of results between SMAA-FAHPSort II and FAHPSort II methods. Obviously, some advantages of SMAA-FAHPSort II can be found. Firstly, SMAA-FAHPSort II can deal with the missing data of some alternatives. Secondly, SMAA-FAHPSort II does not need to define criteria weights. The missing or ordinal criteria weights and other possible situations can be accepted. In addition, DMs can discuss the category acceptance index according to the actual situation of specific classification problems in terms of results. Thus, the
Comparison between FAHPSort II method and SMAA-FAHPSort II method for stage 1.

Table 10

|            | FAHPSort II | SMAA-FAHPSort II |
|------------|-------------|------------------|
|            |     |       |       |       |       |       |       |       |       |       |       |       |       |
| Date       |   | Classes |     |     |     |     |     |     |     |     |     |     |     |       |
|            |   |        | S1  | S2  | S3  | S4  | S5  | S6  | S7  | S1  | S2  | S3  | S4  | S5  |       |
| D1         |   | S1     | 0   | 49  | 9949| 2   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D2         |   | S4     | 0   | 5   | 4932| 5067| 0   | 0   | 0   | 521 | 9479| 0 |
| D3         |   | S1     | 0   | 55  | 9941| 4   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D4         |   | S5     | 0   | 25  | 9954| 21  | 0   | 0   | 0   | 10,000| 0 | 0 |
| D5         |   | S6     | 0   | 6   | 9050| 944 | 0   | 0   | 0   | 9882 | 118| 0 |
| D6         |   | S2     | 0   | 143 | 9840| 17  | 0   | 0   | 0   | 10,000| 0 | 0 |
| D7         |   | S3     | 0   | 87  | 9909| 4   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D8         |   | S4     | 0   | 701 | 9298| 1   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D9         |   | S5     | 0   | 510 | 9490| 0   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D10        |   | S6     | 0   | 189 | 9810| 1   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D11        |   | S2     | 0   | 24  | 9941| 35  | 0   | 0   | 0   | 10,000| 0 | 0 |
| D12        |   | S1     | 0   | 623 | 9377| 0   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D13        |   | S2     | 0   | 763 | 9237| 0   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D14        |   | S3     | 0   | 2099| 7901| 0   | 0   | 0   | 0   | 10,000| 0 | 0 |
| D15        |   | S4     | 0   | 55  | 9921| 24  | 0   | 0   | 0   | 9986 | 0 | 0 |
| D16        |   | S1     | 0   | 13  | 7015| 2972| 0   | 0   | 0   | 49  | 9951| 0 |
| D17        |   | S2     | 0   | 673 | 9323| 4   | 0   | 0   | 0   | 10,000| 0 | 0 |

1. Note: ***p < 0.01.

6.4. Sensitivity analysis

Fig. 10. New confirmed cases number curve and the Internet public opinion risk curve.

Table 10

Comparison between FAHPSort II method and SMAA-FAHPSort II method for stage 1.

Table 11

| Variable                     | Correlation coefficient | p value |
|------------------------------|-------------------------|---------|
| Internet public opinion risk | 0.381***                |         |
| New confirmed cases number   |                         |         |
| Number of provinces with new cases | 0.458***        |         |
| Number of microblog topics  | 0.661***                |         |
| New confirmed cases number   |                         |         |
| Number of provinces with new cases | 0.708***        |         |

The original ordinal information given by experts in case analysis is: (W2 > W3 > W1 > W4 > W5 > W6). This ordinal information will be changed in sensitivity analysis. The way to change ordinal information is to set any one criterion to be the first ranking in the ordinal information, and the ordinal information of the other criteria remains unchanged. Based on this, a total of 6 kinds of ordinal information are generated, including ST1 (W1 > W2 > W3 > W4 > W5 > W6), ST2 (W2 > W3 > W1 > W4 > W5 > W6), ST3 (W3 > W2 > W1 > W4 > W5 > W6), ST4 (W4 > W2 > W3 > W1 > W4 > W5 > W6), ST5 (W5 > W2 > W3 > W4 > W1 > W6), ST6 (W6 > W2 > W3 > W4 > W1 > W5). The results of stage 1 under the 6 kinds of ordinal information are shown in Fig. 11. When the ordinal information is changed, the average global priority of the alternatives is varied. However, the results of different ordinal information still maintain similarity. For example, the highest average priority always appears in D2 or D16, and all the lowest average priorities are D14. The results of sensitivity analysis are consistent with the actual situation and are similar to the results of case analysis. Therefore, the proposed method is insensitive to the change of ordinal information, which proves the effectiveness and stability of the method.

6.5. Managerial suggestions

By analyzing the Internet public opinion risk of COVID-19 local outbreak since Chinese epidemic prevention and control entered the normalization stage, this paper explores the development law of Internet public opinion and the factors of Internet public opinion risk in detail from the research results. Some management suggestions will be summarized to provide stakeholders of Internet public opinion to reduce the Internet public opinion risk caused by the local outbreak of COVID-19.

![Fig. 11. Sensitivity analysis results.](image-url)
(1) Adjust the public opinion management strategy according to the epidemic situation

Internet public opinion is a complex process involving multiple parties [80]. The correlation analysis in this paper shows that the severity of epidemic spread is positively correlated with the risk of Internet public opinion. When more new confirmed cases appear in reality, the number of related topics on the Internet will increase, and the risk of Internet public opinion will also rise. Not only that, this paper also found that Internet public opinion risk was positively correlated with the number of provinces with new cases. This means that when COVID-19 spreads to more regions, it will significantly increase the Internet public opinion risk. Therefore, the government should timely adjust the management strategy of Internet public opinion according to the situation of the epidemic. For example, when the number of newly confirmed cases suddenly increases, the government and media can explain the reasons for the increase in the number of newly confirmed cases to the public in order to calm the emotions of users.

(2) Strengthen psychological counseling for users to relieve pressure

In the risk assessment of Internet public opinion, the “proportion of negative emotions” (i.e., C5) provides a non-negligible contribution to the final results, especially when the impact scope of the virus is expanded. By analyzing the research data of this paper, Fig. 12 shows the top 20 toponyms concerned by netizens in the 304 day hot search. Among them, the toponyms with the highest frequency are local outbreak cities (or provinces) of COVID-19. Due to the policy of regional closure or isolation, people in the COVID-19 outbreak areas often have greater psychological pressure. The social media platform can set up a psychological counseling channel to provide services for users in the epidemic area, and push the official psychological counseling contact information to the top. Alleviating and eliminating the negative emotions of users are of great significance to maintain the stability of the Internet.

(3) Actively push useful information to users

In social media, users prefer to read and search for relevant information rather than make original posts [81]. Fig. 13 shows some of the most frequently searched keywords, including confirmed, new, case. Enterprises can push the relevant posts of these keywords to users to reduce the search time of users. Another advantage of actively pushing relevant information is that it can prevent users from being misled by false information when obtaining information. Pushing more real information to users is one of the ways to reduce the spread of false information in social media. Similarly, Internet platforms can improve the Internet environment by promoting heroic deeds and moving stories. For example, police and doctors are the two most frequently mentioned occupations. We found that posts praising the police and doctors tended to have more positive comments. Enterprises can actively push touching stories and news to users. Publicizing the moving stories in the process of anti-epidemic can improve people’s belief in overcoming the epidemic.

7. Conclusions

7.1. Main findings

Affected by COVID-19, social media platforms have gradually become an integral part of people’s lives since 2020. A large number of discussions on COVID-19 may cause public opinion risks on the Internet. Therefore, it is significant to evaluate the Internet public opinion risk according to the current situation of the epidemic. In this paper, we propose SMAA-FAHPSort II method to evaluate the risk of Internet public opinion in the local outbreak of COVID-19. The main contributions and innovations of this paper can be summarized as follows: (1) Most of the research objects in the existing literature focus on the early stage of the epidemic, and this paper considers the local outbreak period after the peak epidemic. Obviously, the latter is more in line with the current situation of most countries. (2) This paper proposes SMAA-FAHPSort II method, which can deal with the problem of uncertain or missing data in the process of public opinion evaluation, which lays a foundation for obtaining accurate evaluation results. In the comparative analysis with the FAHPSort II method, some advantages of SMAA-FAHPSort II method are described. (3) Based on SMAA-FAHPSort II method, this paper constructs an Internet public opinion risk evaluation framework for COVID-19 local outbreak. This method can quickly and effectively evaluate the risk level of Internet public opinion in the local outbreak of COVID-19. (4) The proposed framework is applied to the public opinion risk research of Microblog platform from May 7, 2020 to September 3, 2021. The study found that the Internet public opinion risk of Microblog will increase with the severity of the actual epidemic situation. (5) This paper analyzes the influencing factors of Internet public opinion from the research results, and provides some management suggestions for authorities, enterprises and users.

7.2. Theoretical and practical implications

Based on the current situation of COVID-19, this study uses AHPSort II method and SMAA-2 method with the help of interval fuzzy number
and linguistic fuzzy number to creatively propose SMAA-FAHPSort II method, and thus constructs a research framework for social media Internet public opinion risk grading. The main power and practical enlightenment of this paper are as follows:

In theory, this research creatively proposes a new MCDM/A method (i.e., SMAA-FAHPSort II), which enriches the research content in the field of MCDM/A. Secondly, in the field of MCDM/A, few scholars apply the MCDM/A method to Internet public opinion risk evaluation problem. Based on the SMAA-FAHPSort II method, this study builds a research framework of social media Internet public opinion risk grading, and expands the research scope of the MCDM/A field. In addition, the SMAA-FAHPSort II method provides a new scheme for other scholars to study issues related to MCDM/A. Subsequently, the research background of this paper is the local outbreak of COVID-19, where there are few relevant literatures. Therefore, the social media Internet public opinion risk grading framework constructed in this paper has important theoretical contributions to exploring the Internet public opinion risk under the local outbreak of COVID-19. Then, the case analysis and management suggestions based on Microblog provide a theoretical reference for the government and enterprises to understand the degree of Internet public opinion risk and formulate Internet public opinion risk control policies and measures. Finally, this paper also provides theoretical enlightenment for social media platforms in other countries to reduce the harm of Internet public opinion risk.

In practice, this research provides important enlightenment for the government to control the risk of Internet public opinion and eliminate the negative impact of Internet public opinion against the background of local outbreak of COVID-19. As far as the government is concerned, when there is a local outbreak of COVID-19 in the country, it should not only take measures to prevent the spread of the epidemic, but also pay attention to the Internet public opinion risk caused by the discussion of COVID-19 on social media. The case study results of this paper provide a learning sample for countries to control the risk of Internet public opinion, when local outbreak of COVID-19 occurs. According to the results of the case study, this paper provides some management suggestions for the stakeholders. These suggestions can play a positive role in controlling the risk of Internet public opinion in the local outbreak of COVID-19 and reducing the harm of negative Internet public opinion.

7.3. Limitations and future research

Internet public opinion is a macro concept with multi-stakeholder participation. There are some limitations of this research work: (1) Due to China’s Internet policy, it is difficult to obtain data from non-Chinese social media platforms. Therefore, this paper lacks comparative analysis of social media platforms in different countries. (2) The analysis of the obtained data in this paper is not comprehensive enough, lacking the analysis of text and emotion.

In the future, there remain several interesting and valuable study directions. Firstly, text mining and machine learning methods may help in the face of colossal Internet text data. Secondly, research on more Internet platforms will be an attractive direction.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Credit author statement

Liyi Liu: Data curation, Formal analysis, Methodology, Writing – original draft. Yan Tu: Supervision, Formal analysis, Methodology, Writing – review & editing. Xiaoyang Zhou: Conceptualization.

Data availability

Data will be made available on request.

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