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Research article

Fine-grained detection on the public's multi-dimensional communication preferences in emergency events

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ABSTRACT

With the rapid development of Internet technologies, the public can participate in the information communication of emergency events more conveniently and quickly. Once an emergency occurs, the public will immediately express and disseminate massive information about the causes, processes and results of the emergency. In the process of information communication, the public often adopts diversified communication modes, and then shows differential communication preferences. The detection of the public's communication preferences can more accurately understand the information demands of the public in events, and then contribute to the rational allocation of resources and improve the processing efficiency. Therefore, this paper conducted finer-grained mining on the public's online expressions in multiple events, so as to detect the public's communication preferences. Specifically, we collected the public's expressions related to emergency events from the social media and then we analyzed the expressions from multiple dimensions to obtain the corresponding communication features. Finally, based on the comparative analysis of diversified communication features, static and dynamic communication preferences were obtained. The experimental results indicate that the public's communication preferences do exist, which is universal and consistent. Meanwhile, constructing a better social environment and improving people's livelihood are the fundamental strategies to guide public opinion.

1. Introduction

This is an era of borderless communication. With the development of Internet technologies (e.g. social media), the cost of public participation in information communication has decreased significantly, the communication speed has soared and the communication channels have proliferated [1,2]. The public can express their opinions or attitudes towards anything anytime, anywhere, including emergency events [3]. Emergency events here refer to events that occur suddenly, cause or may cause serious social harm and require emergency response measures. Once an emergency event occurs, a large number of discussions about the cause, process or relevant personnel of the event would be generated by the public. Meanwhile, the public disseminates information via diversified communication modes, and finally forms a complex public opinion. Previous studies have proved that there were differences in information communication modes among different groups, and the public may form diversified preferences in the process of information communication [4]. What is the communication preference? Are these communication preferences universal? Will preferences change dynamically?

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In order to answer above questions, this paper selected two marriage related emergency events as the research object to explore the public's communication preferences. Marriage is one of the important life experiences. Out of the yearning for a better emotional life, the public gets married and forms a family. However, the current divorce rate is rising, indicating that marriage related problems occur frequently and the public is tired of solving them. However, a stable emotional relationship and a good family atmosphere are extremely important for the growth of teenagers and the stability of society. Therefore, analyzing marriage related emergency events and then identifying the public's communication preference in the events can obtain the public's information demands and understand the public's marriage cognition. It can thus deal with marriage related emergencies more pertinently, guide public opinion and improve the proportion of positive marriage cognition. Specifically, we first collected the public's online discussions related to the emergency events, mainly the event related information released by the public on social media. Then, we conducted a fine-grained analysis on the corpus via various techniques (e.g. deep learning) to detect the public's communication preferences in multiple dimensions, including explicit communication and implicit communication, objective communication and subjective communication, normative communication and anomic communication, and communication topic preferences. Secondly, we explored whether the public's communication preference is affected by time. Finally, we got the multi-dimensional static and dynamic communication preferences of the public in marriage related emergency events. The experimental results show that the public's communication preference in emergencies does exist and is universal. Besides focusing on the public opinion constituted by explicit communication, we need to pay more attention to the large-scale implicit communication preferred by the public. In addition to the endogenous characteristics of the event (e.g. the nature and field of the event), the groups involved in the event play an important role in the communication of the event. Meanwhile, the public will not only talk about the facts, and public communication is divergent. In addition, a pleasant and relaxed atmosphere will enhance the public's desire for communication, and a good social environment and living conditions can improve the public's positive marriage cognition and even social cognition.

2. Related work

There are two types of research work related to our study: research on emergency events and research on information communication in emergency events.

2.1. Research on emergency events

The rapid growth and mobility of population and the quick development of economy and technology make the emergency events have an increasing impact on social development and public life. Hence, researchers from many domains have conducted studies on emergency event.

Emergency event prediction and detection are crucial topics as the emergency events could involve human injuries or even deaths [5]. Liu et al. [6] proposed a novel text classification method using the one-class Support Vector Machine for emergency event detection based on social media. Anbalagan and Valliyammai [7] investigated the streaming microblog tweets and incorporated significant metadata features (i.e. photographs and its geo-tag) to detect the disaster events for a specified time and location. Guo et al. [8] proposed a deep neural model for emergency event extraction. They used the bidirectional Long Short Term Memory and adopted Conditional Random Field to capture the interplay between triggers and arguments to automatically extract emergency events from online news reports. Zhang et al. [9] assumed that when an event occurred, affected semantic aspects would behave differently from its usual behavior and proposed an algorithm to detect events in time series in a general sense. Wang et al. [10] introduced an BERT-based text categorization method for classifying the emergency event reports.

In view of the possible human and financial losses caused by emergencies, it is necessary to analyze emergencies, especially the possible impact of emergencies. Wei et al. [11] proved that the reduction of the demands for industries closely related to 'face to face' communication had a clear impact on employment, residents' incomes, profit of enterprise etc. Li et al. [12] indicated that the proliferation of false public opinions in the network and the absence of public opinion warning and network guidance leaded to the problem of online public opinion increasingly serious.

Users with different properties have become increasingly important, especially in social knowledge creation and human intelligence utilization processes [13]. Therefore, many researchers focus on analyzing users from various groups in emergency events. Dreisiebner et al. [14] showed that emergency events often lead to an increase in users' demand for reliable information. Valsecchi and Durante [15] reported that provinces with a greater share of migrants in outbreak areas showed greater compliance with self-isolation measures. Many academic journal users have made great efforts to speed up the publication and dissemination of high-quality academic research, such as expediting editorial steps and providing open access [16].

2.2. Research on information communication

Information is crucial during an emergency event as it greatly shapes the public's opinion, behavior and even their psychological state [17]. Therefore, it is necessary to analyze the communication mode and preference of information related to emergencies [18].

Social media are important channels for disseminating information during emergencies [19]. Hence, many existing studies focus on analyzing information communication on social media about emergency events in various fields. Kalantari et al. [20] introduced a method for efficiently detecting event-specific and informative microblogs that were likely to be beneficial for emergency response. Zhang et al. [19] used the event of Hurricane Irma and combined it with the life cycle of online public opinion evolution to understand the effect of different types of emotional tweets on information dissemination. Yin et al. [21] analyzed the real data of COVID-19 information and proposed a comprehensive susceptible-reading-forwarding-immune model to understand the patterns of key information communication considering both public contact and participation. Sacco et al. [18] implied that public health policy strategies to counter the effects of the infodemic must not only focus on information content, but also on the social articulation of its diffusion mechanisms.

Analyzing the public involved in the communication of emergency information is the core step of emergency handling. Zhou et al. [13] identified users' roles based on their social connections and influential behaviors, so as to facilitate information sharing and propagation in social networking environments. Among them, the public' sentiment associated with information communication is also an important and hot research topic. Jiang and Liu [22] combined the traditional analysis method based on sentiment lexicon and two kinds of text sentiment based on semantic pattern to conduct sentiment analysis of online public online. Yue et al. [23] combined text analysis and image analysis technology to define the disaster scope of natural disasters, and conducted sentiment analysis and correlation analysis to mine the network public opinion in the disaster area. Luo et al. [24] proved the spatial spillover effect of online emotions, and the intensity of comments and public opinion had a promoting effect on it, while geographical distance had an obvious inhibitory effect on it.

In addition, the design and development of communication system related to emergencies is also an important support to ensure smooth information communication. Lee et al. [25] presented an emergency communication system (ECS) which consisted of a wireless relay node, a disaster sensing and detection system, so as to provide reliability and improve information communication performance during emergency. Yun and Choi [26] proposed a robot-assisted management system capable of monitoring daily activities of students and promptly coping with abnormal events in the classroom environment. Sciullo et al. [27] proposed a novel phone-based ECS enabling long-range communication among survivors and rescue teams over critical environments, and improved scalability in large-scale environments. Li et al. [12] analyzed the current situation of college online public opinion, and designed three functional modules of early warning of college public opinion. Peng et al. [1] analyzed the features of development and the propagation characteristics, so as to construct a network public opinion early warning index system that included four first-level indicators and 13 s-level indicators.

The above analysis indicates that the existing research on emergency events has analyzed emergencies from many aspects, including the analysis on the public. In particular, analyzing the public's information communication can effectively support the governance decision of emergencies. However, the existing research on emergency information communication rarely conducted analysis on the public's communication preference, which may lead to the waste of relevant resources. This paper aims to conduct multi-dimensional analysis on the public's information communication during emergency events based on multiple technologies (e.g. sentiment analysis and topic extraction), and then identify the public's static and dynamic communication preferences, so as to provide more comprehensive support for the governance of emergencies.

3. Research questions

By mining the public's online communications about marriage-related events, this paper aims to answer the following questions to identify communication preferences of the public from multiple dimensions.

RQ1. Does the public have obvious communication preference in emergency events? If so, what are the communication preferences?

RQ2. Is the public's communication preference affected by time? For example, is there a clearly prefer communication period? Is there any difference in the communication mode or content in different periods?

4. Methodology

4.1. Data

The purpose of this paper is to explore the public's communication preferences via multiple granularity mining on marriage related emergency events. Two events were chosen, including: Event 1: A programmer committed suicide. On September 8, 2017, an online "suicide note" from WePhone developer Su was exposed and triggered a large number of forwarding. Su said he and his ex-wife Zhai met through a date website and he spent millions of RMB on his ex-wife before getting married. His ex-wife threatened himself with "he has tax evasion and WePhone has Internet phone function, which is grey operation" and asked for 10 million RMB and real estate. Event 2: A parturient jumped to death. On August 31, 2017, a parturient asked for cesarean section due to unbearable pain. After being rejected, she jumped out of the delivery center and died. On "who refused to perform caesarean section for the parturient", the hospital and family members insisted on their own words, causing heated discussion.

Based on the above brief introduction of the two events, we can see that both the two events involve human deaths. Death in event 1 was due to the breakdown of the marital relationship, and the man committed suicide due to the threat and blackmail from his ex-wife. Death in event 2 was due to the psychological collapse of the parturient in the process of giving birth. The two events involve two main aspects of marriage respectively. One is the emotional and relationship treatment of husband and wife in marriage, and the other one is the matters related to having children. It is the key that most of the public who have entered or are about to enter into marriage need to consider. It indicates that in addition to beautiful things (e.g. love), there are a lot of problems to be solved in marriage. The analysis of marriage related emergencies can explore the public's attitudes towards marriage and the opinions on problems about marriage, and then provide decision support for the handling of emergencies.

We collected public user generated content about the two events on social media as experimental data. As one of the most influential and active social media, the public is accustomed to expressing their opinions on events on Weibo, so we choose Weibo as the data acquisition platform. Specifically, firstly, two hot emergencies related to marriage were identified from the list of hot events on Weibo. Secondly, microblogs related to the selected events were collected. Finally, 253,707 microblogs were crawled and shown in Table 1. Users' names, microblog contents, launch dates, and the number of microblogs forwarded, commented, praised and read were included in the corpus. In addition, we conducted preliminary preprocessing on the corpus (including data filtering, Chinese word segmentation, etc.), and the basic statistical information is shown in Table 2.

4.2. Method

The primary purpose of this study is to mine users' communication preferences in marriage-related emergency events. The overall framework is shown in Fig. 1. Firstly, we collected microblog corpus of the emergency events. Secondly, we mined users' communication features in events, including detecting explicit communication and implicit communication, classifying objective communication and subjective communication, identifying normative communication and anomic communication, and extracting communication topics. Finally, we got multi-dimensional static communication preferences of the public, and analyze the effect of time to obtain dynamic communication preferences.

From Fig. 1, we can see the key step is mining users' communication features from multiple dimensions.

4.2.1. Explicit communication and implicit communication

Users may prefer different modes to disseminate information related to emergency events, including explicit mode and implicit mode. Information dissemination through forwarding, commenting or liking microblogs is often displayed on public pages, which can be regarded as explicit communication. Reading event-related microblogs can be regarded as implicit communication as the communication behavior is not displayed on public pages. Hence, we count the forwarding, commenting and liking numbers of relevant microblog corpus to measure users' explicit communication scores, and reading numbers of microblog corpus are used to measure users' implicit communication scores. The two scores can be calculated with Equations (1) and (2).

$$Sexplicit_i = \{\#forward_i, \#comment_i, \#like_i\} \tag{1}$$

$$Simplicit_i = \#read_i \tag{2}$$

Where $Sexplicit_i$ means the explicit communication scores of microblog i, $\#forward_i$, $\#comment_i$ and $\#like_i$ in the three-tuple are forwarding/commenting/liking numbers of microblogs i. $Simplicit_i$ means the implicit communication scores of microblog i, $\#read_i$ is the reading number of microblogs i.

4.2.2. Objective communication and subjective communication

The classification of objective communication and subjective communication aims to analyze the direct attitudes of users in the process of emergency information communication. We hold that information communication without subjective opinions but only objective facts can be regarded as objective communication, otherwise it should be regarded as subjective communication. This paper classifies the objective communication and subjective communication based on sentiment words in the microblog contents, and measures the sentiment polarities and sentiment intensities of subjective communication via the calculation of positive and negative sentiment words. As shown in Fig. 2, this paper uses sentiment lexicons to identify the sentiment words in the microblog corpus, then distinguishes the objective communication and subjective communication based on the number of sentiment words, and finally calculates the corresponding sentiment intensities. The calculation of sentiment polarity and intensity is shown in Equation (3)- (5).

$$Senti\_pol_i = \begin{cases} objective, \#\mathrm{senti\_words}_i = 0 \\ subjective, \#\mathrm{senti\_words}_i > 0 \end{cases} \tag{3}$$

$$Senti\_pol\_sub_i = \begin{cases} positive, \#\mathrm{pos}_i - \#\mathrm{neg}_i > 0 \\ Negative, \#\mathrm{pos}_i - \#\mathrm{neg}_i < 0 \end{cases} \tag{4}$$

$$Senti\_int\_sub_i = \frac{\#\mathrm{pos}_i + \#\mathrm{neg}_i}{\#\mathrm{words}_i} \tag{5}$$

Where $Senti\_pol_i$ means the sentiment polarity score of microblog i, $\#\mathrm{senti\_words}_i$ is number of sentiment words in microblog i. $Senti\_pol\_sub_i$ denotes sentiment polarity score of subjective microblog i, $\#\mathrm{pos}_i$ is number of positive words in microblog i, and $\#neg_i$ is

Table 1
Numbers of microblogs about the four emergency events.

Emergency events	#microblogs
Event 1: A programmer committed suicide	183,334
Event 2: A parturient jumped to death	70,373
In total	253,707

Table 2
Statistical information of microblogs about the four emergency events.

Events	#Total Words	Average words per microblog	Range of words per microblog	Most frequent words
Event 1	6,595,602	35.98	[1,3318]	Zhai (82,281)
Event 2	3,190,617	45.33	[1,3099]	Family members (37,749)

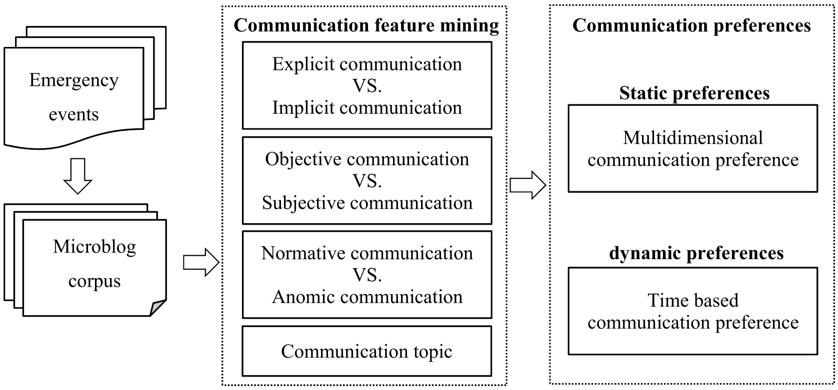


Fig. 1. Framework of user' communication preference analysis in multiple emergency events.

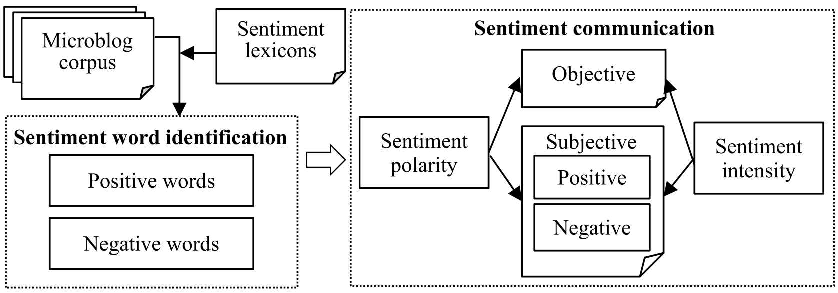


Fig. 2. Analysis on objective communication and subjective communication.

number of negative words in microblog *i*. $Senti\_int\_sub_i$ means sentiment intensity score of subjective microblog *i*, and $\#words_i$ is number of words in microblog *i*. Table 3 shows the examples of the objective and subjective microblogs.

4.2.3. Normative communication and anomic communication

Users adopt anomic mode to disseminate emergency related information will affect the development process of emergencies and then may pollute the Internet environment. Anomic communication refers to the use of anomic words for information communication, including foul language, slander or insult [28]. In cyberspace, the public is easily controlled by irrational and extreme emotions, causing a lack of calm analysis and wise judgment. Once the information related to emergency events is disseminated widely in an anomic mode, it may lead to bad consequences. Therefore, this paper identifies normative communication and anomic communication by mining event-related microblog contents. Specifically, we use a deep learning algorithm to represent the microblog corpus, and then use the supervised learning method to detect the communication category, as shown in Fig. 3. We annotated 10,000 microblogs as the training set (5000 microblogs per event), and got 6,000 normative microblogs and 4,000 anomic microblogs. The kappa coefficient [29] was used to evaluate the consistencies of annotation results by two annotators. The high kappa coefficients (0.8674 of event 1 and 0.8942 of event 2) reveal that our annotation results are reliable, and then a verifier checked and corrected the inconsistent annotation results to get the final annotation results. Secondly, we used the Doc2vec[1] algorithm to represent the microblog corpus as vector forms, and then trained a SVM classifier with the training corpus [30]. Finally, we identified the communication labels (normative or anomic) of all microblogs. The distribution of normative and anomic communication can be calculated by Equation (6).

$$Snor_i = \left\{ \frac{\#normative_i}{\#microblogs_i}, \frac{\#anomic_i}{\#microblogs_i} \right\} \tag{6}$$

[1] https://radimrehurek.com/gensim/models/doc2vec.html.

Table 3
Examples of objective and subjective communication.

Microblog contents	Communication category	
The death of WePhone founder Su has sparked public debate.	Objective communication	
The lawyer's diction is a true example of elegance	Positive	Subjective communication
Damn woman! [Anger]	Negative	

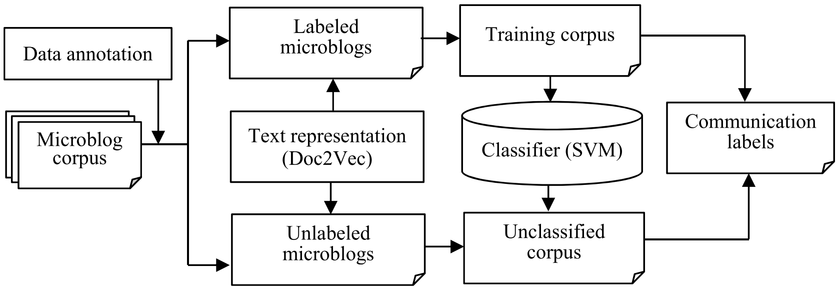


Fig. 3. Analysis on normative communication and anomic communication.

Where, $Snor_i$ denotes distribution of normative and anomic communication in event i. $\#normative_i$ means numbers of normative microblogs about event i, $\#anomic_i$ is numbers of anomic microblogs about event i. $\#microblogs_i$ means numbers of microblogs related to event i. The examples of the normative and anomic communication are shown in Table 4.

4.2.4. Communication topics

The communication topics related to emergency events can reflect users' concerns preferences about events. Identifying communication topics can reflect users' direct demands in emergencies, and then help to deal with emergencies. Hence, this paper extracted topics from event-related microblog contents based the LDA algorithm [31]. Meanwhile, as a microblog content may involve multiple topics, this paper selected the topic with the highest probability as the final topic category of the microblog. The distribution of communication topics can be calculated by Equation (7).

$$Stopic_i = \left\{ \frac{\#Topic_{i1}}{\#microblogs_i}, \frac{\#Topic_{i2}}{\#microblogs_i}, \ldots, \frac{\#Topic_{iN}}{\#microblogs_i} \right\} \tag{7}$$

Where, $Stopic_i$ denotes distribution of communication topics in event i. $\#Topic_{iN}$ means numbers of microblogs related to event i belongs to Topic N. Table 5 reports the examples of two communication topics in event 2.

5. Experiment and result analysis

5.1. Analysis on multi-dimensional static communication preferences

5.1.1. Analysis on explicit communication and implicit communication

Fig. 4 shows the distribution of explicit (i.e. Fig. 4(a), (b) and 4(c)) and implicit (i.e. Fig. 4(d)) communication scores of emergency events, where abscissa is the explicit/implicit communication scores of emergencies, and ordinate represents the number of microblogs corresponding to the communication score. As can be seen from Fig. 4, information with higher explicit/implicit communication scores tend to get less numbers of microblogs, and the long tail phenomenon is existing in both explicit and implicit communication modes. It reveals that the proportion of microblogs that are widely disseminated is low, and most microblogs are disseminated in a low amount. In other words, whether explicit or implicit communication, only a small amount of event-related information is widely disseminated, and the dissemination degree of most information is low. Such phenomenon does not depend on the mode of information communication.

In order to further quantify the difference between explicit and implicit communication modes, we conducted descriptive statistics on explicit and implicit communication, as shown in Fig. 5. The abscissa refers to the mode in which the microblog is disseminated, and

Table 4
Examples of normative communication and anomic communication.

Microblog contents	Communication category
We don't know the whole truth of the matter!	Normative communication
Who are you Fu**ing threatening? This bit*h, we're done bullying! Just take it out on her!	Anomic communication

Table 5
Examples of communication topics.

Microblog contents	Communication topics
The man's family is really disgusting, and what about the woman's family when she gave birth??	Topic 1: Event related personnel
Won't refuse surgery for high costs.	Topic 2: Medical expenses

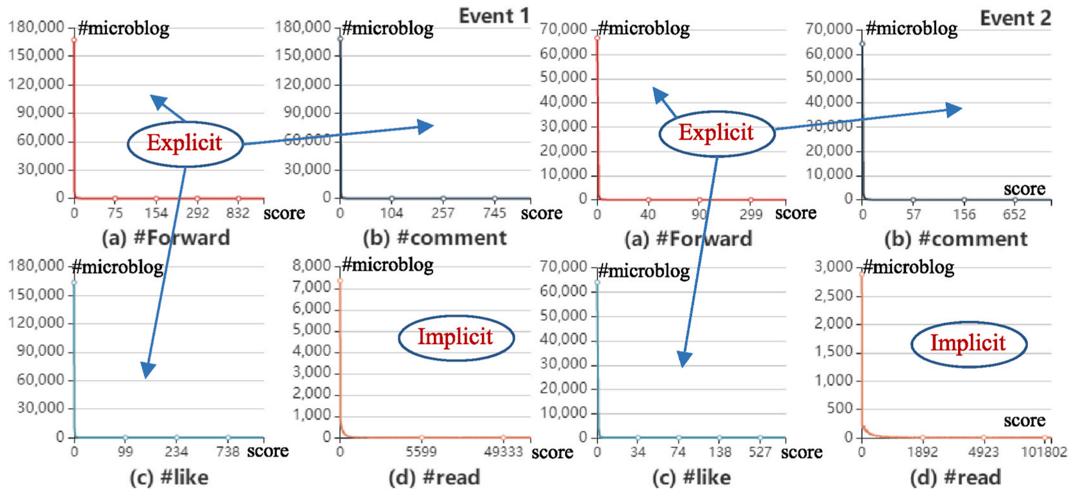


Fig. 4. Explicit communication and implicit communication.

the ordinate refers to the statistical indicators of the mode, including the maximum value, average value, median and total number. We can see from Fig. 5 that, the indicator scores of implicit communication mode are significantly higher than those of explicit communication mode.

Based on the analysis above, we can conclude that, regardless of the type or nature of emergencies, explicit communication and implicit communication always coexist. Meanwhile, the score of implicit communication is higher than that of explicit communication, which reveals that more users participate in event communication through implicit communication (i.e. reading) than explicit communication (i.e. forwarding, commenting or liking). Such participants can be called "silent majority". On the one hand, it may be related to the cost of communication. Generally, for users, the cost of reading is obviously lower than that of forwarding or other explicit communication behaviors, while such explicit communication behaviors are often the successor of reading. On the other hand, it may be due to the migration from online communication field to offline communication field. After receiving information online, users may generate a lot of discussion and communication offline, which also leads to their lack of explicit communication behaviors. Such phenomenon reminds us that the public opinion crisis may not only be caused by large-scale online explicit discussions, and the possible risks caused by implicit communication also need to be vigilant.

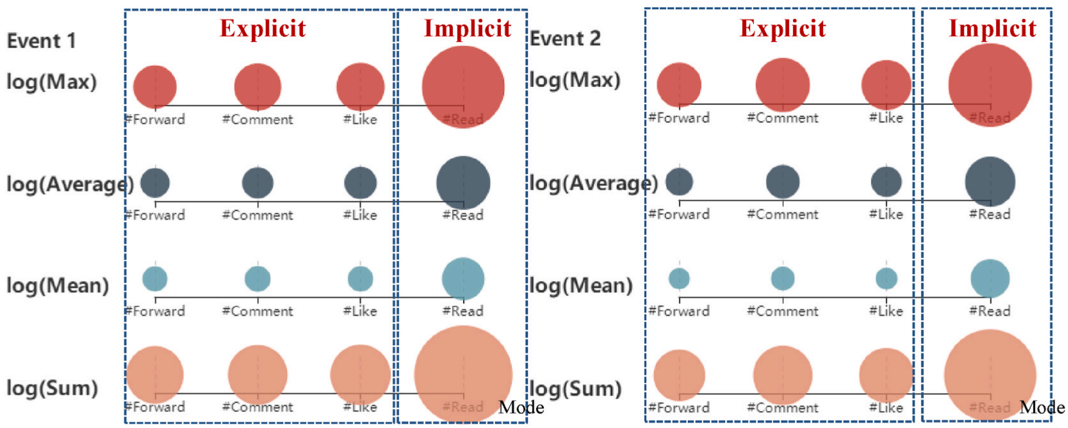


Fig. 5. Statistics of explicit communication and implicit communication.

5.1.2. Analysis on objective communication and subjective communication

Fig. 6 reports the objective and subjective communication results of the two emergency events (Fig. 6(a) shows event 1 and Fig. 6 (b) shows event 2). The pie charts in Fig. 6 show the proportions of subjective communication and objective communication. It can be seen from the pie charts that for the information communication of emergency events, users often generate more subjective contents (the green parts in the pie charts, including positive communication and negative communication, about 75% in event 1 and 70% in event 2) to express their attitudes than disseminate objective information (the red parts of the pie charts, i.e. objective communication, about 25% in event 1 and 30% in event 2). It reveals that social networks are flooded with subjective information, the communication analysis of which can help shape the development of public sentiment [32]. Meanwhile, the proportions of negative communication (about 54% in event 1 and 41% in event 2) are significantly higher than that of positive communication (about 21% in event 1 and 29% in event 2). Therefore, we can conclude that in emergency events, especially in the malignant events, although the government or relevant functional institutions will call on the public to treat the events calmly and rationally, the public often still form massive subjective expressions from their own perspectives based on own cognition. The subjective communication, especially mass negative expressions, may hinder the effective handling of events [19,33], but on the other hand, these massive negative expressions are also the driving force for relevant departments to deal with events more quickly and efficiently.

The bar charts in Fig. 6 show the sentiment intensity of each microblog, in which the abscissa represents the microblog about the event, and the ordinate represents the sentiment intensity score of the corresponding microblog. We can see that the average intensity scores of event 1 and event 2 are 0.23 and 0.18 respectively. It indicates that the users' sentiments in event 1 is more excited, which may be related to the group involved in the events. In event 1, users mainly debated whether there was intentional marriage fraud. The investigation results of the debate directly affected the vital interests of massive marriageable public, including men and women. Event 2 is about pregnant women, which has attracted more attention from female groups, especially young women. In other words, event 2 is more likely to arouse empathy among young women. The population of this group is significantly less than the former (i.e., the sympathetic group in event 1), and the sentiment is relatively mild. In addition to the differences in the public's communication of the two events, we need to pay more attention to the common problems reflected in the process of event communication. About 28% of microblogs in event 1 and about 21% of microblogs in event 2 got sentiment intensity scores higher than 0.5. This reveals that in the two events, more than 20% of the information was disseminated with strong sentiment intensity. Since the public is often easily influenced by extreme sentiments, more attention should be paid to expressions with strong sentiments in the handling of emergencies, so as to curb large-scale sentiment infection.

Therefore, it can be concluded that the subjective communication, especially negative subjective communication, is the main feature of emergency communication, which is easy to cause the expansion of malignant public opinion. Meanwhile, the public is vulnerable to extreme emotions. Hence, it is very necessary to identify and measure the communication sentiments, and then carry out corresponding communication guidance.

5.1.3. Analysis on normative communication and anomic communication

Fig. 7 shows the distributions of normative communication and anomic communication of emergencies. We can see from Fig. 7 that normative communication is the main communication mode. In other words, most users participate in the information communication

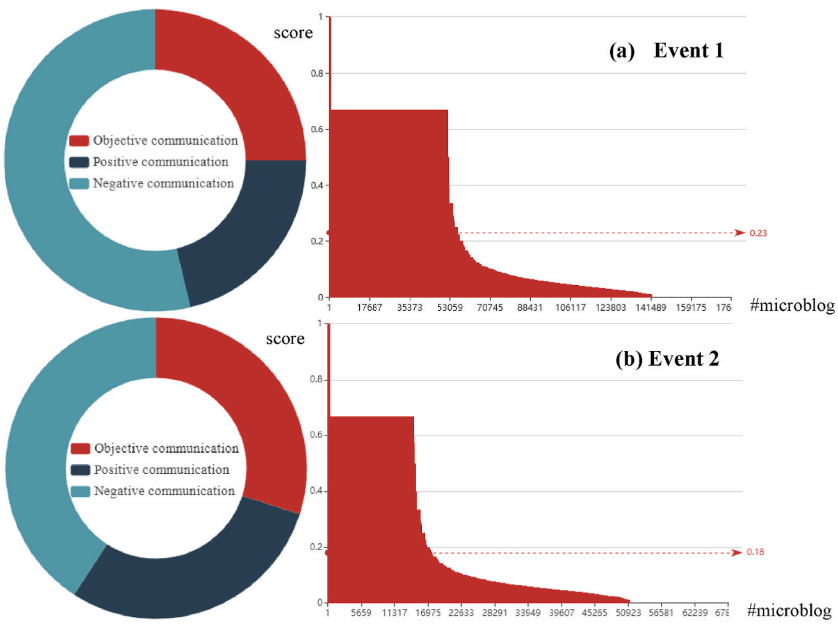


Fig. 6. Objective communication and subjective communication.

of emergencies normatively. However, nearly 20% of information communication is based on anomic expressions.

The anonymity of the network makes some users express arbitrarily. Hate speech, offensive language and bad words can be seen everywhere in the network. These anomic expressions are not conducive to the handling of emergencies. Moreover, once anomic expressions are spread on a large scale, they may cause public imitation, especially the imitation by youth groups, which is extremely unfavorable to the governance of cyberspace. In addition, the impact of the network environment on real life is also obvious. Currently, teenagers' interpersonal communication is often accompanied by a large number of anomic expressions (Li et al., 2020). Cyberspace is not an extrajudicial space. The normative guidance of online information communication should become the routine task of information communication research.

5.1.4. Analysis on communication topics

Five topics of each emergency event were extracted, as shown in Table 6. The discussion of relevant personnel has always been the most important topic (Topic 1 of event 1 and event 2). Once an emergency occurs, the public will quickly spread relevant information about the event, and the personnel related to the event is often the most concerned by the public. Who is the victim? Who is the perpetrator? The public's discussion of the personnel often reflects the public's demand for the basic truth of the event. Meanwhile, the topics generated by the public's rational thinking about events are also important topics for the public to participate in the dissemination of emergency information, such as the discussion of law (Topic 2) in event 1 and the discussion of medical expenses (Topic 2) and medical means (Topic 5) in event 2. In addition, the detailed and the extended discussion on the events reveal that the public not only pays attention to the in-depth communication of the event, but also conducts the in-breadth communication in the process of event-related information communication. Hence, we can conclude that communication topics in emergencies are diverse, the coexistence of rational thinking and emotional expression and the co-occurrence of communication depth and breadth form complex communication features.

5.2. Analysis on time based dynamic communication preferences

5.2.1. Analysis on time based explicit communication and implicit communication

Fig. 8 shows the explicit and implicit communication preferences of users in different time periods. It can be seen from Fig. 8 that, users' implicit communication preferences are much higher than explicit communication, while fluctuation states of the two modes are similar. We divide the 24 h of a day into three time periods, as shown in Table 7.

Based on Table 7 and Fig. 8, we can see that in time period 1, most users are in sleep and less information is disseminated. In time period 2, users gradually participate in the information communication of emergency events, and users' participation reaches the highest at 9 a.m. Due to the rapid development of mobile communication devices, the public has more convenient access to information and stronger demand for information, so that the first thing after waking up is usually to surf the Web and obtain the latest information. In addition, most enterprises start working at 8–9 a.m. It indicates that the work efficiency of users in the first working hour is relatively low, and users often pay attention to various current news. Then, the public will gradually enter the working state and continue until 4 p.m., they reduce the explicit and implicit communication of events. With the approach of off-duty time, the public begins to browse and spread event information again. The communication heat reaches the highest at 6 p.m. as most users are used to browsing and spreading network information after finishing their day's work. In time period 3, most users reduce the communication of information at dinner time (7 p.m.), and then disseminate event related information on a large scale again.

It can be concluded that the development of social media technology makes the public keen to express their emotions and opinions on the Internet [34]. Even late at night, a large number of users still search and disseminate information. However, the public is more inclined to participate in the communication of emergency information during non-working hours. Meanwhile, the initial working hours and near off-duty hours are also hot periods for information communication.

5.2.2. Analysis on time based objective communication and subjective communication

Fig. 9 shows the sentiment intensities of the events in different time periods. We can see from Fig. 9 that the sentiment intensities of the public in period 1 (wee hours) are significantly higher than that in other periods, and the fluctuation is obvious. It indicates that the public is more likely to be emotional in the state of fatigue, and then may make extreme expressions. Therefore, public opinion supervision in the early morning needs more investment to avoid large-scale infection of strong sentiments.

5.2.3. Analysis on time based normative communication and anomic communication

Fig. 10 shows the ratios of anomic communication about two events in different time periods. Fluctuation curves of the anomic communication in different events are similar. Meanwhile, it can be seen from Fig. 10 that the ratios of anomic communication are high at 4:00, 8:00, 12:00 and 20:00. It indicates that the public is more likely to express anomic information when they are sleepy,

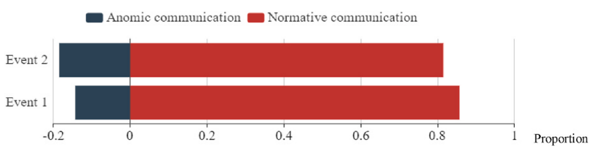
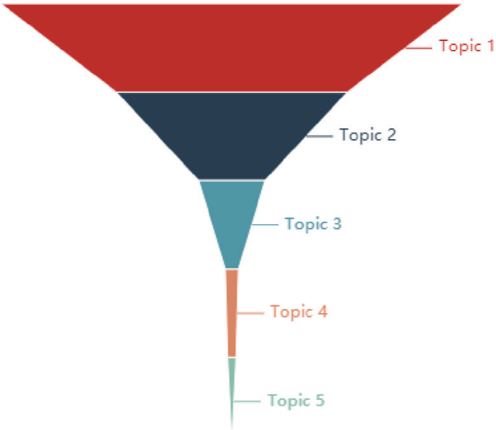
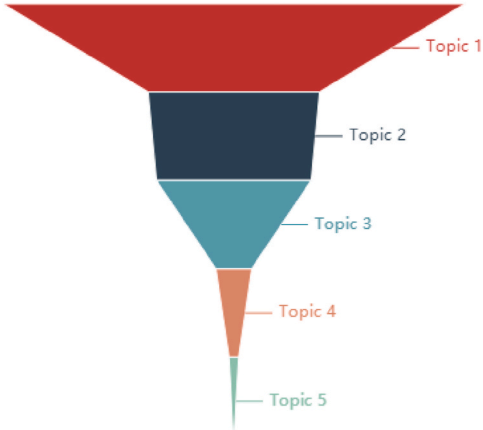


Fig. 7. Normative communication and anomic communication.

Table 6
Topics and topic distributions of the emergency events.

Events	Event 1	Event 2
Topics	Topic 1: Event related personnel Topic 2: Resort to law Topic 3: Details of the event Topic 4: Other similar events Topic 5: Extended content of the event	Topic 1: Event related personnel Topic 2: Medical expenses Topic 3: Extended content of the event Topic 4: The public's attitudes Topic 5: Medical means
Topic distributions		

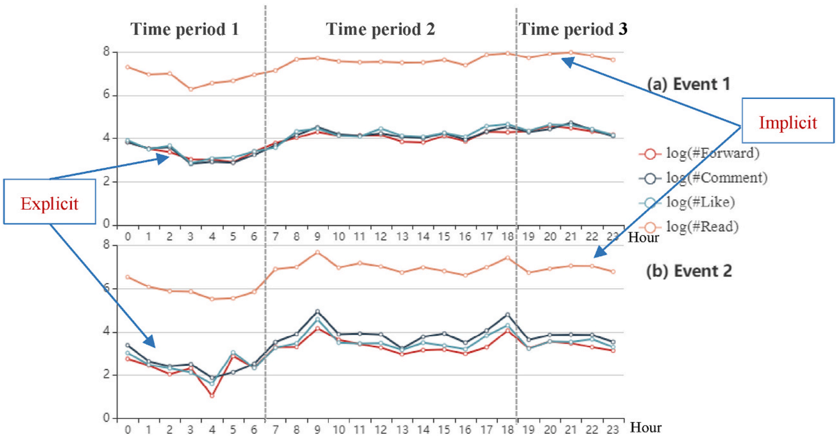


Fig. 8. Time based explicit communication and implicit communication.

Table 7
Time periods in the 24 h.

Time period	Hours
Time period 1	0:00–6:00 (Wee hours)
Time period 2	7:00–18:00 (Working hours)
Time period 3	19:00–23:00 (Evening)

hungry or tired. In other words, when the user is in a poor physical or mental state, it is more likely to cause anomic communication. It reveals that the treatment of emergencies cannot be accomplished in one move. Only the long-term improvement of public living standards (including economy, education, etc.) can cultivate the public's more stable and good physical and mental state. Then, in the face of emergencies, the public can disseminate emergency related information in a normative manner, so as to fundamentally and effectively promote the prevention, monitoring and processing of emergency events.

5.2.4. Analysis on time based communication topics

Fig. 11 shows the topic distribution of events in different time periods. It can be seen from Fig. 11 (a), the public prefers to

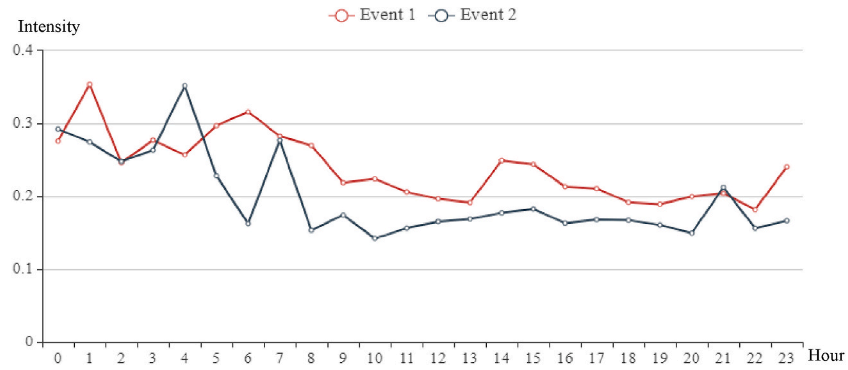


Fig. 9. Time based sentiment intensities.

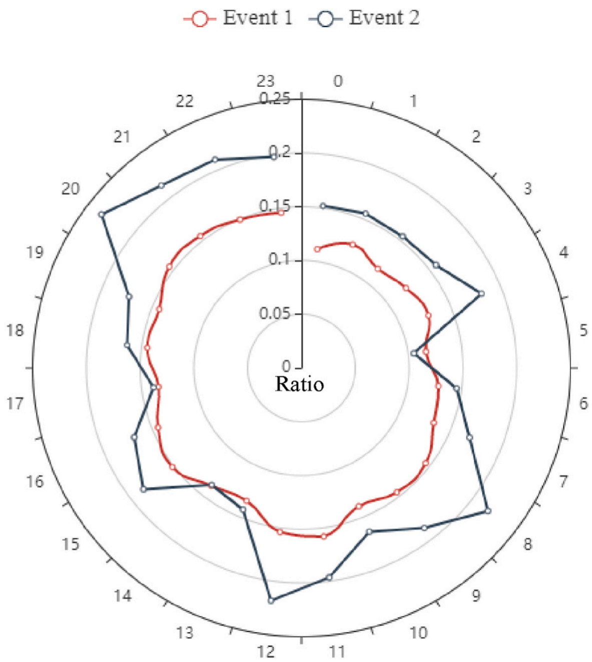


Fig. 10. Time based normative communication and anomic communication.

participate in the discussion of Topic 1 (*Event related personnel*) during working hours, while discussing Topic 2 (*Resort to law*) during non-working hours, especially in the early morning. The distributions of the other three topics have no clear time difference. For Fig. 11 (b), most of the information communication about Topic 1 (*Event related personnel*) occurs in working hours, while discussion about Topic 2 (*Medical expenses*) and Topic 3 (*Extended content of the event*) are mainly published in non-working hours. Meanwhile, Topic 2 is mostly communicated in the early morning and Topic 3 is in the evening. In addition, Topic 4 (*The public's attitudes*) has an obvious communication peak at 10 a.m., and this topic involves the public's vote on the attitude towards the event. Therefore, 10 a.m. may be the prime time for interactive topics. In other words, if the government and the media want to interact with the public about emergencies, this period of time may be a better choice. In conclusion, the public usually participates in the discussion of hot topics during working hours. Meanwhile, the public often discusses relatively relaxed topics during entertainment time, while serious topics (e.g. law, medical treatment, etc.) are released in the dead of night. It reflects that there are clear differences in the topic preference of the public in different time periods. It is easy to spread relaxed topics in a noisy atmosphere, and the public prefers to think about serious topics in a quiet atmosphere.

6. Discussion

6.1. Correlation analysis on the multi-dimensional communication preferences

Based on the analysis above, we can conclude that the public has diverse communication preferences in different dimensions. Is

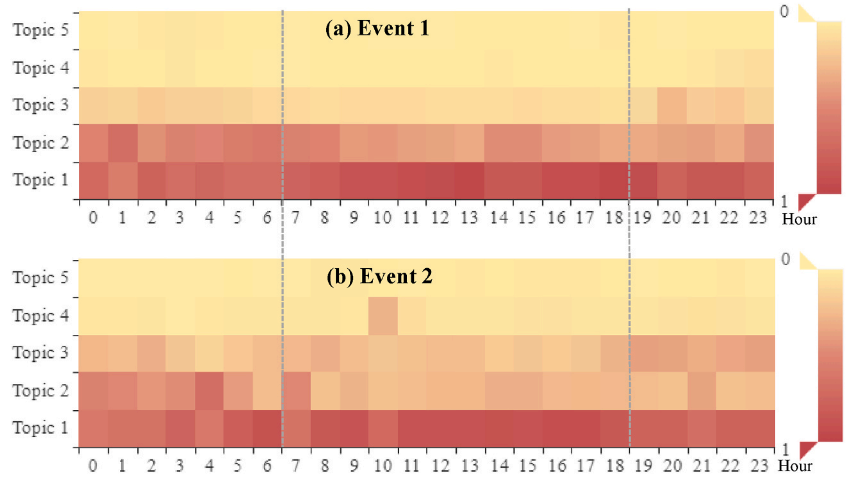


Fig. 11. Time based communication topics.

there a correlation between these preferences? Does the communication preference of one dimension affect the preferences of other dimensions? In order to detect the correlation between communication preferences from different dimensions, we divided the preferences, as shown in Table 8. This paper mainly analyzed the communication preferences of the public's wordings, sentiments and topics. The public's wording preferences can be divided into two categories: normative wordings and anomic wordings. Sentiments include sentiment polarity and sentiment intensity. For sentiment polarity, it mainly includes three categories: positive, negative and neutral (i.e. objective). For sentiment intensity, we divide it into five categories according to the intensity score. The communication topics can be divided into five categories according to the topics about the events.

For quantifying the correlation between communication preferences, we conduct a contingency correlation analysis on the multi-dimensional communication preferences. The results are shown in Table 9. It can be seen from Table 9 that, there are significant correlations between the public's communication preferences in different dimensions, especially communication topic preferences and sentiment preferences.

Fig. 12 shows the distributions of correlations between communication preferences from different dimensions, and the larger nodes indicate stronger correlations. We can see from Fig. 12 that, for anomic communication, negative communication is more than positive communication, while in normative communication, negative communication is less than positive communication. It indicates that the public with negative sentiment is more likely to conduct anomic communication. In emergencies, whether it is anomic or normative communication, the proportion of sentiment intensity C1 is the highest. It indicates that when expressing stronger sentiments, users do not necessarily use anomic words, and normative expression can also express their strong sentiments. From another point of view, most users can express with normative words even under the strong sentiments, which reflects the current better network quality of the public and the enrichment of governance means [35].

For communication topics, Topic 1 has the highest amount of anomic expressions, that is, anomic expressions are most likely to occur in the discussion of the relevant personnel. In the process of information communication, the public will condemn the wrongdoer or potential wrongdoer of the event, which is easy to form anomic communications. The sentiment intensity levels and proportions of positive sentiment of Topic 2 in event 1 and event 2 are significantly higher than other topics. Topic 2 is about law in event 1 and about medical expenses in event 2. The public has expressed strong positive sentiments in the two aspects. It reveals that the public is relatively satisfied with the government's current policies and measures in the rule of law and medical security. After the occurrence of malignant events, the public tends to seek legal support and believes that they can obtain better medical security. This reflects the Chinese government's investment and achievements in improving people's livelihood over the years.

Table 8
Multi-dimensional communication preferences.

Wording class	Sentiment		Topic
	Sentiment polarity	Sentiment intensity	
C1 Normative		C1 [0, 0.2)	Topic 1
C2 Anomic	C1 (positive)	C2 [0.2, 0.4)	Topic 2
	C0 (Neutral)	C3 [0.4, 0.6)	Topic 3
	C-1 (Negative)	C4 [0.6, 0.8)	Topic 4
		C5 [0.8, 1]	Topic 5

Table 9
Contingency correlation coefficients.

Contingency correlation coefficient		Sentiment polarity	Sentiment intensity	Topic
Event 1	Wording class	0.194, sig = 0.000	0.248, sig = 0.000	0.272, sig = 0.000
	Sentiment polarity		0.546, sig = 0.000	0.530, sig = 0.000
	Sentiment intensity			0.700, sig = 0.000
Event 2	Wording class	0.203, sig = 0.000	0.234, sig = 0.000	0.274, sig = 0.000
	Sentiment polarity		0.559, sig = 0.000	0.571, sig = 0.000
	Sentiment intensity			0.704, sig = 0.000

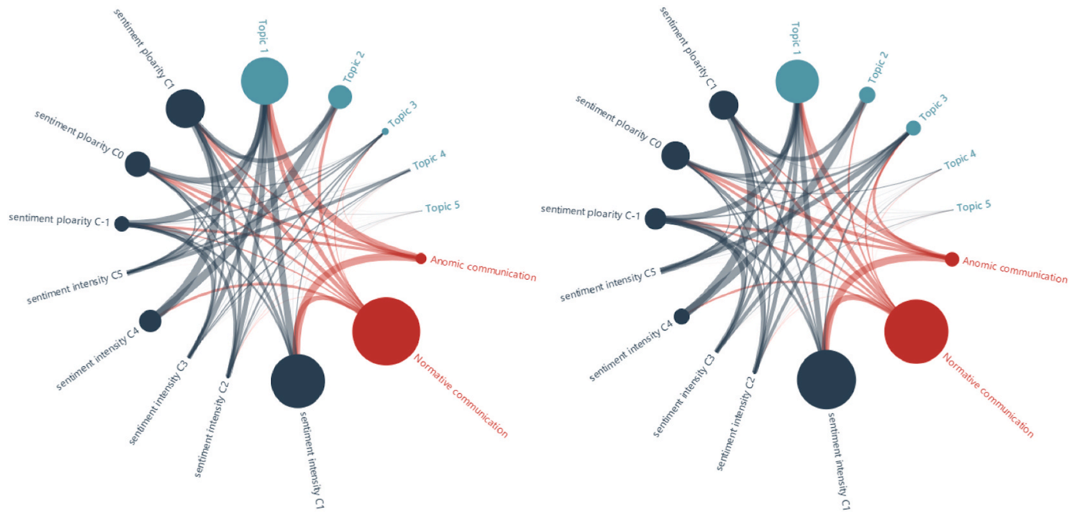


Fig. 12. Correlations of the public's multi-dimensional communication preferences.

6.2. *Finer-grained analysis of explicit communication*

We conducted finer-grained analysis on the explicit communication. Fig. 13 shows the subdivision results of explicit communication modes in emergency events (Fig. 13(a) shows event 1 and Fig. 13(b) shows event 2). There are two main ways for users to publish event related information, namely, generating original information (the red parts in the pie charts) and forwarding existing information (the green parts in the pie charts). The forwarding information can be further divided into *only forwarding the existing information* (the dark green parts in the pie charts) and *creating the original information while forwarding* (the light greens parts in the pie charts).

From Fig. 13, we can see that most users participate in the communications of emergency events by forwarding information. Meanwhile, users prefer to express their opinions when forwarding information, rather than just forwarding information. Therefore, we can hold that social media users in most cases disseminate original information of emergency event by quoting the others' expressions. With the information forwarding behavior, users prefer to express their own views, which is a common form of cascade communication. It can be concluded that the management of emergencies needs to clarify the content, source and attitude tendency of original information with high forwarding. The effective guidance of such original information is helpful to deal with events efficiently and with lower consumption, and then avoid possible malignant effects.

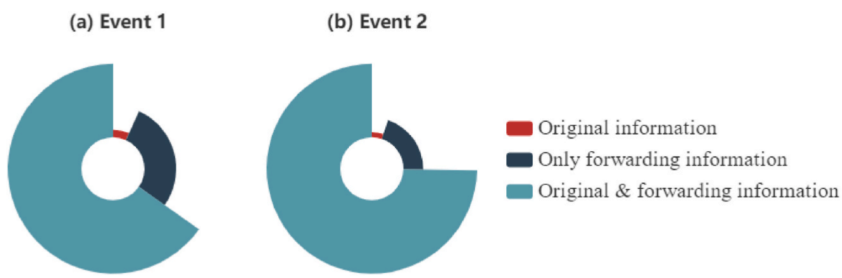


Fig. 13. Subdivision of explicit communication behaviors of the public in emergencies.

7. Conclusion

This paper explored static and dynamic communication preferences of the public in marriage-related emergency events by conducting finer-grained mining on users' online expressions.

In answer to the first research question, the communication preferences are obvious. Compared with the explicit communication, the implicit communication may cause worse harm because of its concealment. The sentiment preference of emergencies is related to the groups involved in events. The identification of group characteristics is an important link in emergency management. Benefit from long-term governance through multiple channels and strategies, normative communication is the mainstream communication mode, but the influence of anomic communication on the network environment cannot be ignored. The public's topic preference for emergencies is similar, and the "person" in the event is always the focus of public attention, whether it is the fault or the victim. Meanwhile, the public's information needs are both perceptual and rational. While expressing their opinions, they will widely discuss the practical problems in the events and the current protection of people's livelihood.

Regarding the second research questions, time period is one of the key factors affecting the public's communication preference. Non-working hours are the main information dissemination time. Meanwhile, due to the development of social media and other network technologies, the public can participate in the information communication of emergencies at any time (even late at night). In addition, the public's physical and mental state and living environment will significantly affect the public's dynamic communication preferences. A peaceful physical and mental state and good social life security can avoid the occurrence of large-scale negative public opinion and facilitate the handling of emergencies.

In conclusion, the methodology of this paper offers some suggestions for identifying communication preferences of the public in emergency events. It indicates that it is important and necessary to explore multiple dimensions of communication features and depict the public's communication preferences from multiple perspectives, including static and dynamic communications. The existing communication preferences reflect that relevant departments need to consider the preferences in the process of emergency management, so as to construct more appropriate governance strategies, avoid resource waste and improve governance efficiency. In addition, in terms of academic implication, this paper proposes more research paths and expands the research object, which can provide reference for the research about emergency event and public opinion.

Our study is subject to a few limitations. Firstly, this paper mainly explores the public's four dimensions of communication preference in emergencies. In fact, the public's communication preferences are complex and diverse [18]. In addition to sentiment and topics, there are many other dimensions, such as geographical affinity preference, age [36] and gender [37,38] etc. Therefore, it is necessary to integrate more dimensions of communication preferences. In future work, we can optimize algorithms to improve the analysis results of existing communication preference dimensions, while adding more technologies to expand the communication mining dimension, thereby improving the comprehensiveness and reliability of communication preference conclusions. Secondly, this paper only detected the public's communication preferences, but did not analyze the possible causes of these preferences. In the follow-up research, we will expand the data source (including event types, numbers etc.), so as to identify more preference dimensions, and explore the causes of preference simultaneously, thus to extend the existing research results and supplement more details.

Author contribution statement

Qingqing Zhou: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Data availability statement

The data that has been used is confidential.

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.

The authors have no interests to declare.

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