Social Media Usage During Disasters: Exploring the Impact of Location and Distance on Online Engagement

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ABSTRACT

Social media play an important role in emergency management. The location of citizens and distance from a disaster influence the social media usage patterns. Using the Tianjin Port Explosion, we apply the correlation analysis and regression analysis to explore the relationship between online engagement and location. Citizens' online engagement is estimated by social media. Three dimensions of the psychological distance – spatial, temporal, and social distances – are applied to measure the effects of location and distance. Online engagement is negatively correlated to such 3 kinds of the distance, which indicates that citizens may pay less attention to a disaster that happens at a far away location and at an area of less interaction or at a relatively long period of time. Furthermore, a linear model is proposed to measure the psychological distance. The quantification relationship between online engagement and psychological distance is discussed. The result enhances our understanding of social media usage patterns related to location and distance. The study gives a new insight on situation awareness, decision-making during disasters.

Key Words: emergency management, online engagement, psychological distance, social media usage

Social media facilitate the creation and sharing of information. They are recognized as the key communication channels during crisis, such as Twitter, Facebook, Sina Weibo, and WeChat. They can provide a large amount of volunteered information, such as observation, opinion, feeling, and psychological demand,[1-3] which helps decision makers to take action more quickly through providing collective intelligence.[4,5] A growing number of studies have explored the use of social media by emergency managers[6] and government officials,[7] as well as the general public.[8] It is unclear what drives and affects the use of social media, especially during emergency.[9] Understanding the reasoning behind social media usage will contribute to the optimal use of social media.[10]

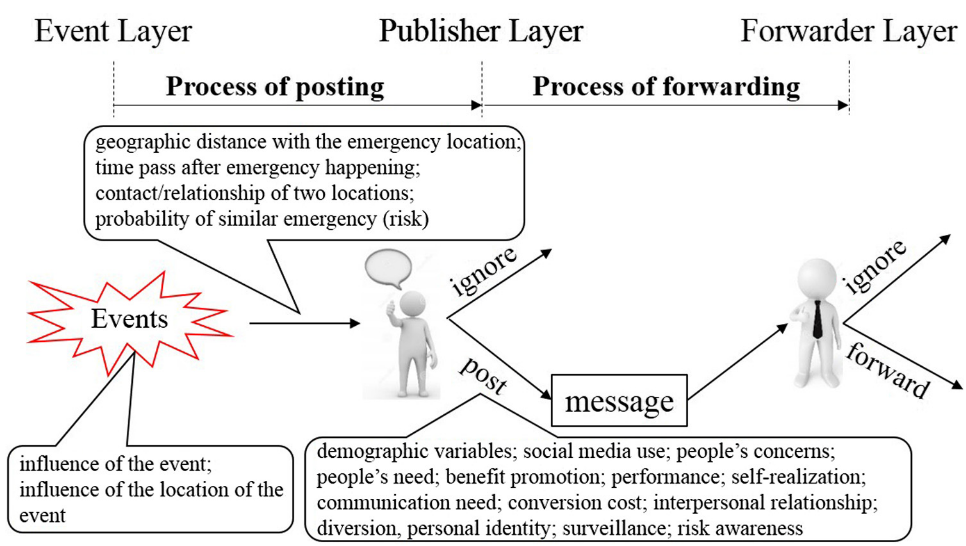
There are no time and space constraints in sharing and collaborating on social media.[11] But there is a significant difference in the social media usage pattern in terms of distance to the disaster site.[12,13] Citizens from affected areas turn to social media to share their experiences, seek help, and coordinate their response. Remote audiences participate in online interactions as spectators or volunteers who provide social support.[14] Not all users participate in online discussion during disasters. It is more likely that affected people will share information on social media compared with users from the relative, which indicates that location of citizens and distance from the disaster place play an important role on social media usage. Different from traditional distance, the distance during disasters is a subjective distance, which is more complex and may change given the situation. For example, when a disaster happens, 1 minute for affected people feels much longer than that for those who are farther away from the disaster.[15] In this paper, the psychological distance is introduced to measure this kind of subjective distance because it changes people's mental representation of an event.[16]

The concept of psychological distance, proposed by Beckerman in 1956,[17] measures the distance between distal object and our location based on an individual's direct experience and subjective judgment.[18] Relating to psychological distal objects helps manage humans' life effectively and has the ability to plan and coordinate with other individuals.[19] Psychological distance as a composite indicator is quantified by the integrated distance of geographic distance, time delay, relationship between events and people, and the probability of similar events occurring.

This paper focuses on exploring the impact of location and distance on social media usage patterns. Online engagement means that Internet users go online to participate in discussion by posting messages, comments, and pictures on a political or social issue on a website or using their blogs to explore information, which is adopted to quantify the social media usage behavior

FIGURE 1

The Factors in Information Posting and Propagation Process.



of the public.[20] It is usually expressed as publishing, liking, commenting, or sharing messages.[21] It is measured as the total number of articles,[22] the number of tweets,[23] or the number of comments per user in response to events.[24] In this study, online engagement as the macro characteristics of users' social media usage behavior is measured by the number of original messages related to the event on social media. Further, we explore the relationship between online engagement and event location to improve our understanding on citizens' social media usage behavior.

RELATED WORK

Online Engagement and Psychological Distance

Social media usage behavior includes posting messages and forwarding them,[25] as shown in Figure 1. When disaster happens, social media users become aware of the situation, and some of them will post various messages online. Important information can then be propagated by their followers to a considerable extent.[26] Most current studies focus on the forwarding behavior. However, as the source of information, the behavior of information posting should be investigated. This study focuses on social media usage behavior from the information posting behavior.

A relationship exists between online behavior of the public and their psychological distance of an event.[17] Psychological distance has been used to test its effects on consumer online reviews[16] and on the linguistic concreteness of natural language use.[27] Psychological distance also helps enhance the understanding of users' online behavior during disasters. People may evaluate whether the disaster is physically close or distant, just occurring, or may happen for a while, pertains to themselves or others, and may happen again, to affect their behavior on how to respond to the disaster.[28] Lent et al.[23] observe that people might not fear being infected with the epidemic unless it became psychologically close. They examine that psychological distance increases when the Ebola outbreak becomes physically close. Similar to Lent et al.'s research, our study aims to explore the relationship between online engagement of the public and psychological distance during disaster.

Measurement of Psychological Distance

Psychologically distal objects are regarded as the things that do not happen to us right now, or may happen somewhere else or may happen to other people.[29] According to this definition, psychological distance is quantified by 4 dimensions: spatial distance, temporal distance, social distance, and likelihood (probability or hypotheticality), along with the dimensions of time, space, social network, and probability.[17,19] This study focuses on the first 3 dimensions. The fourth dimension, probability, is not considered here.

Spatial distance can be measured by the geographic distance to the reference point, which is an important factor in users' online behavior. People tend to make different decisions on the objects that are spatially near or far away.[30] Temporal distance is the distance to the reference point in the temporal dimension, which is found to influence the perceived hierarchy of incoming threats.[31] Social distance is defined as the degree of the personal closeness, personal involvement, or the willingness to engage in the relationship with the person.[32]

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TABLE 1

Some Examples of the Measurement of Each Dimension of Psychological Distance

Dimension	Measurement
Spatial distance	Geographic distance
	Nearby vs faraway place[19]
	Spatially distant (different rooms) vs spatially proximate (same room)[33]
Temporal distance	Future (eg, make decision within several days or several years) Past (eg, something belongs to the present or the past)[19]
	Present vs distant future or past
	Within specific time units (eg, 1 year ago vs 10 years ago); between units (eg, days from now vs centuries from now; last week vs next week)[27]
Social distance	Self vs other; familiar vs unfamiliar persons; a group you belong to vs a group you don't belong to[19]
	Socially distant (unacquainted) vs socially proximate (acquainted)[33]
	Interpersonal similarity [34]

The measurement of each dimension is a challenging problem. Some examples are provided in Table 1.

Based on the measurement of each dimension, the effects of psychological distance on humans' behavior will be considered quantitatively. However, 2 controversial questions should be answered first. How many dimensions should be considered? Are they considered simultaneously? Some researches (in Table 2) illustrate these answers. As shown in Table 2, 2 methods (questionnaire survey and regression analysis) are applied to test the effects of the psychological distance from various dimensions.

METHODOLOGY

Regression analysis is conducted to explore the relationship between online engagement of the public and psychological distance during disaster. Three dimensions of psychological distance (spatial, temporal, and social distances) are selected to test the relationship. A linear regression model is applied to explore the relationship between online engagement and psychological distance. To remove the distributional skewness, online engagement is log-transformed. We assume that there is a linear relationship between the log-transformed online engagement and 3 dimensions, as shown in Formula 1.

$$\log(\mathit{Online\ Engagement}) = a_0 + a_1 \cdot \mathit{Spatial\ Distance} + a_2 \cdot \mathit{Temporal\ Distance} + a_3 \cdot \mathit{Social\ Distance} \tag{1}$$

where a_0 is the constant, a_1 is the coefficient of spatial distance, a_2 is the coefficient of temporal distance, and a_3 is the coefficient of social distance. We also propose the relationship between psychological distance and various dimensions can be measured by a linear model as Formula 2.

$$\mathit{Psychological\ Distance} = b_1 \cdot \mathit{Spatial\ Distance} + b_2 \cdot \mathit{Temporal\ Distance} + b_3 \cdot \mathit{Social\ Distance} \tag{2}$$

where b_1 is the coefficient of spatial distance, b_2 is the coefficient of temporal distance, and b_3 is the coefficient of social distance. At last, the relationship between the log-transformed online engagement and psychological distance may be defined by a linear model as Formula 3.

$$\log(\mathit{Online\ Engagement}) = c_0 + c_1 \cdot \mathit{Psychological\ Distance} \tag{3}$$

where c_0 is the constant, and c_1 is the coefficient of psychological distance.

The regression analysis is used to determine these coefficients.

CASE STUDY

The Tianjin Port explosion is used as an example to analyze the impact of the location and distance on citizens' online engagement from the perspective of psychological distance.

TIANJIN PORT EXPLOSION INCIDENT

The Tianjin Port explosion, a serious safety crisis, happened in China in 2015. A hazardous material warehouse, located in the Tianjin Binhai District, exploded on August 12, 2015. There were 2 large blasts, as shown in Figure 2. The first blast occurred at 11:34 PM on August 12, 2015. After 30 seconds, the second one occurred.[37,38] The explosions caused a great damage to the local community; 165 people were killed, 798 were injured, and a large number of buildings were damaged. Cumulative loss was up to US$9.923 billion by December 10, 2015. The explosions resulted in fierce discussion on social media. Many users expressed their opinion, experience, needs, and concerns on Sina Weibo and WeChat to provide a large amount of information.

Measurement of Online Engagement

Online engagement is measured by the number of original messages related to the event on Sina Weibo (one of the most popular microblogs in China). The keyword-based method is used to search and collect the disaster-related social media data based on the Sina Weibo API (the open application programming interface). The disaster-related data were collected through 2 sets of key words in Chinese, including "Tianjin" and "explosion" or "Tianjin explosion." The data were collected from August 12 to August 27, 2015 (16 days). Only Chinese microblogs were collected and there was no location constraint in the process of data searching. The messages posted in China or overseas matching the key words were added to the dataset. The volume of the dataset was

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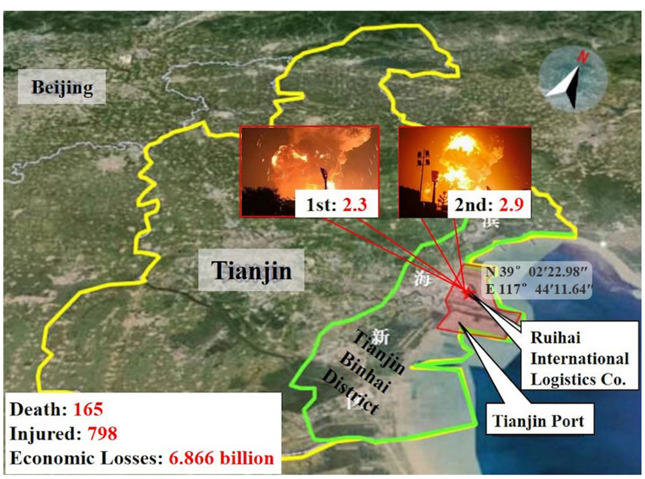
TABLE 2

Some Examples of the Quantitative Researches of Psychological Distance

Authors	Field	Method	Dimensions	Simultaneously or in Isolation
Carmi & Bartal, 2014[31]	Perception of environmental threat	Questionnaire survey	Temporal distance	
Boothby et al., 2016[33]	Amplification of shared experience	Survey study	Social distance, spatial distance	In isolation
Darke et al., 2016[35]	Decision-making on unfamiliar online retailers	Survey study	Physical distance, social distance	In isolation
Snefjella & Kuperman, 2015[27]	Concreteness of language on social media	Regression analysis	Spatial distance, temporal distance, social distance	In isolation
Huang et al., 2016[16]	Consumer online reviews	Regression analysis	Spatial distance, temporal distance	Simultaneously
Lim et al., 2012[36]	Co-experience on social media	Regression analysis	Spatial distance, temporal distance, social distance	Simultaneously

FIGURE 2

Location and Local Map of the Tianjin Port Explosion.



27 635. Searching results give the detailed information of the data, which are divided into 3 categories: (1) the user's information, including the nickname, ID, region, birthday, short introduction, and labels; (2) the information on the message's text, including content, hashtag, post time, visual information (eg, pictures or videos), and URL; and (3) posting media (eg, mobile phone, computer).

The noisy data should be filtered from the dataset, because they can easily prevent crisis managers from acquiring the meaningful information. Some data collected through the machine key word-matching may not be related to the disaster. The manual classification is performed to filter unrelated data.[39] Twenty graduate students participated in labeling the collected data into the disaster-related or unrelated categories. Each student read and labeled the message manually because each microblog message was a short text. The message label unrelated for the first time is double-checked by the second student in case of a wrong classification. If both students make the same conclusion, the message is removed. But when the second student label is related, the message is added to the dataset. The region of the author, message content, and post time were critical in this study. The data with incomplete information therefore were removed from the dataset. Finally, 5171 pieces of the messages were labeled unrelated in all 27 635 messages; 22 464 pieces of messages remained. All valid data were with the geographic location of the author (user's region) and post time.

In order to measure the online engagement of different areas, we used the spatial aggregation analysis on disaster-related data based on the geographic location. The messages posted by the citizens in the same province were classified into 1 category. The data from overseas were removed from the dataset. Online engagement was non-dimensional.

Measurement of Psychological Distance

In this study, we used spatial distance, temporal distance, and social distance to analyze the relationship between online engagement and psychological distance. Psychological distance is considered at the provincial level. In the Tianjin Port explosion, the reference points of spatial distance, temporal distance, and social distance are Tianjin, the time of the explosion, and the citizens in Tianjin, respectively.

Spatial Distance

Spatial distance measures the geographic distance from the reference point (Tianjin city) to a study location. In order to test the effects of psychological distance on the restaurant review online, the geographic distance is defined as the distance from the reviewer's place to the reviewed restaurant.[16] Similar to this study, it is assumed that the region in the user's profile is the location of the posting messages. However, the region may be

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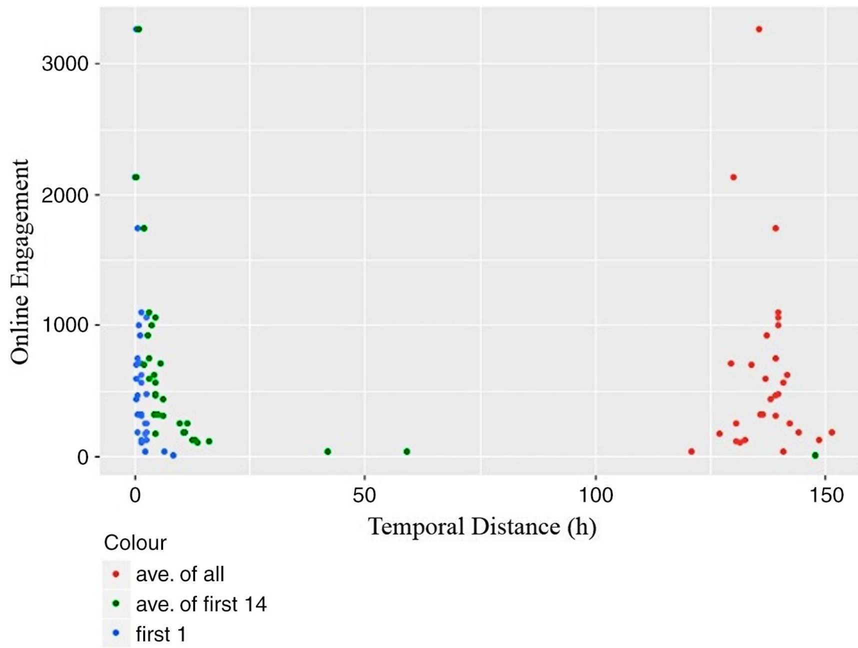
FIGURE 3

The Scatter Plots of Different Measurements of Temporal Distance.



the place of residence, and some people may not be in this place when disaster happens. For example, the users may be on a business trip to Tianjin. The users will perceive greater risk and have a higher probability to post messages about the explosion. Because the real-time geographic data are difficult to obtain, it is assumed that all users are in the registration place on Sina Weibo when the explosion occurs.[12]

The circle distance, the shortest distance between 2 points on a circle, is widely used to calculate the spatial distance.[16] The reachability between 2 locations is not represented in this method. In order to describe the reachability between other locations and Tianjin, the distance is measured based on the transportation route between 2 locations. In this paper, the spatial distance is calculated by the shortest highway distance between 2 locations that are the province of the user's region and Tianjin. Spatial distance between 2 locations is quantified based on the route data from Google Maps. The distance between different provinces ranges from 1 km to 3671 km ($M = 1393.23$, $SD = 880.99$). To remove the distributional skewness, spatial distance is defined as the log-transformed form of the distance. The dimension of the spatial distance is log(km). If the user's region is in Tianjin, the spatial distance is assigned as zero.

Temporal Distance

The temporal distance is quantified by the time when users post their event-related messages in reference to the explosion. For users, the temporal distance is quantified by the time difference between disaster time and their first messages. For a province, the data are the messages posted by all citizens in the province, and temporal distance of the province is the average time for all data.

There is a question on how to choose the number of messages used in the calculation for each province. In this study, we have compared 3 widely used methods, which are the average of all data, the value of the first data, and the average of a fixed number of the data. The comparative analyses are shown in Figure 3. When all data are used, the values range between 120.7 and 148.6. There is no significant difference for the provinces. The reason is that there are different numbers of microblogs on the explosion in different provinces, and the different number of microblogs reduces their difference of temporal distance. For the messages in the same province, temporal distance of each user fits the normal distribution. Though the users in different provinces have a quick response on social media, the average value becomes very large because there is a large number of the messages produced, and some users post messages after a long delay. For the Qinghai province, the users have a relatively slow response, and the average value becomes small because the total number of messages is small. The range of temporal distance of different provinces is from 0 to 6.48 hours if the first message is used. Uncertainty is obvious by using this method. Therefore, the same number of the data in different provinces is selected to quantify temporal distance.

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Becaues there are only 14 messages in the Qinghai province, temporal distance is quantified as the average of the first 14 data in all provinces, which gives a better explanation for temporal distance than the previous methods. The dimension of the temporal distance is hours.

Social Distance

The social distance between a province and Tianjin is measured based on the interaction activity between 2 places. A simple kind of interaction is transportation. Planes, trains, and cars are the 3 most popular ways of transportation between 2 cities in China. When the distance is long, people tend to choose planes or trains, but driving a car or taking a train may be their preference in the short distance. The threshold in this study is the distance that requires 4 hours to drive a car on the highway, and planes and trains will be used beyond 4 hours. We first discuss the measurement of social distance in long-distance. The flight information is obtained from the Ctrip website (http://www.ctrip.com/), the official website for air ticket booking. The train information is obtained from the website of *12306* (http://www.12306.cn/mormhweb/), the official website for train ticket booking. For each province, we only count the number of flights and trains between the provincial capital and Tianjin. The number of trains is easy to measure from the website of *12306*. However, the flight information needs further processing. Searching flight information on the Ctrip, we can obtain the number of direct flights and transit flights. However, not all transit flights are taken into consideration. The transit flights that need to transfer 2 or more times are ignored. The transit flights that stop over 5 hours are also ignored. To measure the weights of flights and trains, we normalize the number of flights and trains separately. Social distance is defined as the reciprocal of the result. The equation is shown in Formula 4 in long-distance.

$$sd_i = \frac{1}{\frac{nf_i}{sf} + \frac{nt_i}{st}} \tag{4}$$

where sd_i is the social distance from the province i to Tianjin; nf_i is the number of flights from the province i to Tianjin; sf is the sum of flights from all provinces to Tianjin; nt_i is the number of trains from the province i to Tianjin; st is the sum of trains from all provinces to Tianjin. The social distance of Tianjin is set to be 1. The social distance is non-dimensional.

Trains and cars are used in the short distance. The social distance is measured similarly to the situation in long-distance. We can obtain the cars' information from the website of China Highway (http://www.china-highway.com/).

Regression and Analysis Results

The relationship between social media usage behavior of the public and several kinds of distance is shown in Table 3.

Correlation Analysis

For the regression analysis, we analyze the correlation between the dependent variables and independent variables using SPSS 20.0 (IBM Corp, Armonk, NY). The results are presented in Table 4. All correlations between the log-transformed online engagement and psychological distance are significant at the 0.01 level (2-tailed). It proves that there is a significant relationship between social media usage and psychological distance.

Regression Analysis

The relationship between online engagement and psychological distance is regressed by SPSS 20.0 (IBM Corp, Armonk, NY). The regression model fits the relationship relatively well (R^2 = 0.718, adjusted R^2 = 0.687), and the coefficients of all variables are significant at the 0.05 level, as shown in Table 5.

The model is shown in Formula 5.

$$\begin{aligned}\log(\mathit{Online\ Engagement}) = 3.515 \\ -(0.233 \times \mathit{Spatial\ Distance} \\ +0.007 \times \mathit{Temporal\ Distance} \\ +0.005 \times \mathit{Social\ Distance})\end{aligned} \tag{5}$$

Based on the regression analysis, there is a multivariate linear relationship between log-transformed online engagement and psychological distance. Social media usage is negatively correlated with spatial distance. It means that people will be aware of low risk if they are far from the place. People who live close to the event location tend to pay more attention to the disaster. Social media usage is negatively correlated with temporal distance, which indicates people may pay less attention when the disaster has taken place for a long time. Social media usage is also negatively correlated to social distance, which indicates that citizens in an area that interacts rarely with Tianjin may pay less attention to the disaster.

We are aware that the value of R^2 is not very high in the regression analysis. The reason may be that some provinces have similar psychological distance, but their online engagement is quite different. For example, the spatial distances from Shanghai and Shaanxi to Tianjin are close, but online engagement data of 2 provinces are 1003 and 467, respectively.

Based on the characteristics of Formula 5, psychological distance is measured by a linear model, as shown in Formula 6. Psychological distance is positively correlated with 3 dimensions. Then the relationship between online engagement and psychological distance is described by Formula 7. The model indicates that there is a linear relationship between log-transformed online engagement and psychological distance. Social media usage of the public is negatively correlated

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TABLE 3

Values of All Variables and Their Descriptive Statistics

	Province	Spatial Distance (log[km])	Temporal Distance (h)	Social Distance	Online Engagement
Values	**Anhui**	2.97	4.61	39.92	483
	Beijing	2.14	0.80	4.26	3272
	Chongqing	3.25	4.94	30.75	322
	Fujian	3.25	4.54	26.04	568
	Gansu	3.18	12.41	27.04	128
	Guangdong	3.32	1.93	13.27	1744
	Guangxi	3.37	11.39	39.78	256
	Guizhou	3.33	12.97	48.34	132
	Hainan	3.43	16.17	48.34	118
	Hebei	2.51	2.05	10.46	707
	Heilongjiang	3.08	6.35	13.59	313
	Henan	2.84	5.56	12.81	709
	Hubei	3.06	3.16	18.84	593
	Hunan	3.16	5.98	45.22	436
	Inner Mongolia	2.79	10.46	61.58	185
	Jiangsu	2.96	3.12	12.37	1106
	Jiangxi	3.13	9.85	35.68	258
	Jilin	2.99	10.87	10.46	184
	Liaoning	2.84	4.1	6.66	626
	Ningxia	3.08	41.78	39.78	36
	Qinghai	3.24	147.65	135.4	14
	Shaanxi	3.04	4.62	28.27	467
	Shandong	2.52	4.60	6.29	1062
	Shanghai	3.03	3.52	9.04	1003
	Shanxi	2.71	4.07	21.86	325
	Sichuan	3.26	3.02	21.82	749
	Tibet	3.56	59.04	169	35
	Tianjin	0	0.24	1	2140
	Xinjiang	3.50	13.57	75.17	110
	Yunnan	3.42	4.67	22.54	172
	Zhejiang	3.06	2.56	16.15	928
Descriptive Statistics	**N**	31	31	31	31
	Minimum	0	0.24	1	14
	Maximum	3.56	147.65	169	3272
	Mean	2.97	13.57	33.93	618.74
	SD	0.63	27.61	36.39	696.37

Online engagement ranges from 14 to 3272 (M = 618.74, SD = 696.37), which is the log-transformed for further analysis.

TABLE 4

Results of Correlation Analysis

		Spatial Distance	Temporal Distance	Social Distance	log(Online Engagement)
Spatial Distance	Pearson correlation	1	.207	.380*	−.500**
	Sig. (2-tailed)		.264	.035	.004
Temporal Distance	Pearson correlation	.207	1	.771**	−.736**
	Sig. (2-tailed)	.264		.000	.000
Social Distance	Pearson correlation	.380*	.771**	1	−.781**
	Sig. (2-tailed)	.035	.000		.000
log(Online Engagement)	Pearson correlation	−.500**	−.736**	−.781**	1
	Sig. (2-tailed)	.004	.000	.000	

*Correlation is significant at the 0.05 level (2-tailed).
** Correlation is significant at the 0.01 level (2-tailed).

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TABLE 5

Regression Results

Independent Variables	Model Coefficient (SE)
Intercept	3.515*** (0.266)
Spatial distance	–0.233** (0.094)
Temporal distance	–0.007** (0.003)
Social distance	–0.005** (0.002)

*$P \leq 0.1$.
** $P \leq 0.05$.
*** $P \leq 0.001$.

with psychological distance, which is consistent with that in Liberman.[29]

$$Psychological\ Distance = 0.233 \times Spatial\ Distance + 0.007 \times Temporal\ Distance + 0.005 \times Social\ Distance \quad (6)$$

$$\log(Online\ Engagement) = 3.515 - Psychological\ Distance \quad (7)$$

We proved that there is a linear relationship between social media usage of the public and psychological distance during a major disaster like Tianjin Port explosion, which happened suddenly and caused severe damage to the city areas. The relationship model in this study can be applied to the similar disasters. Physical and social distances between 2 locations can be calculated in advance. Once a similar disaster happens, the location of the disaster can be determined, and physical and social distances can be obtained directly. Online engagement is then the function of temporal distance. The social media usage of the public can be assessed quickly after a disaster. In other events, such as a hurricane, we should consider the probability of the event to measure psychological distance. This study helps increase our understanding of social media usage to support decision-making.

CONCLUSION

This study helps improve the understanding of the impact of location and distance on social media usage. We uses the Tianjin Port explosion as an example to collect multi-source data. Citizens' online engagement is estimated by the disaster-related social media data collected from Sina Weibo. The impact of location and distance is measured using 3 dimensions of psychological distance. Based on the correlation analysis and regression analysis, the following conclusions can be made.

First, location and distance have a great impact on online engagement of the public during disasters. Three dimensions (spatial, temporal, and social distances) of psychological distance are used to evaluate the location and distance. Citizens who live close or have more interaction with the location of the disaster tend to pay much more attention to the disaster. Second, there is a linear relationship between social media usage behavior and psychological distance. Online engagement is negatively correlated with psychological distance. Third, psychological distance can be measured by a linear model using 3 dimensions. Psychological distance is positively correlated with spatial, temporal, and social distances. Fourth, a linear relationship exists between social media usage behavior and psychological distance, and the intensity of social media usage decreases as psychological distance increases.

This study gives a new insight into emergency management. On one hand, it helps for social media users to participate in the response process. On the other hand, it helps emergency managers improve the understanding of online engagement influenced by location and distance.

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