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Empirically Analyzing the Role of a Peak in Online Emergency Information Dissemination

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ABSTRACT When an emergency occurs, as a factor in online emergency information dissemination, the peak represents the maximum strength and turning point. However, the role of these peaks in emergencies is still unclear. In this article, we try to disentangle this problem and investigate the effect of these peaks on the lifecycle and influence of online emergency information dissemination. We first propose an Online Emergency Information Dissemination Process (OEIDP) model drawing from the ideas of system cybernetics and system identification to present the emergency lifecycle with a decay parameter, time constant, and delay parameter. Based on this model, we then analyze the effect of peaks using empirical data from the Weibo, WeChat, and 20000 media platforms of 169 emergencies. The results reveal the positive significant impacts of the peak time, peak volume, and spikes on emergency information dissemination. The results enable us to make accurate judgements when facing peaks and remind us of the need to balance the strongest manifestation and final influence. Our work complements the gaps on the peak effect in the existing communication literature and introduces the concept of system cybernetics to solve information dissemination which provides a new direction for future studies to solve related problems using system control techniques.

INDEX TERMS Online emergency, information dissemination, peak effect, system cybernetics.

I. INTRODUCTION

In recent years, online emergencies have become more frequent. As internet technology changes the way in which people seek information, online emergencies also become more impactful on individual enterprises and even the country [1]. Effectively studying information dissemination and the factors in these emergencies can help decision makers obtain important information and establish strategies to solve the related problems.

Researchers have investigated information dissemination problems and their internal mechanisms [2]–[4]. In these studies, scholars have addressed the characteristics of information dissemination and predicted the dissemination results. These studies describe the information dissemination process and help to understand the dynamics of information dissemination. However, we also find that an important problem was overlooked when we try to directly use these models to accurately solve an actual emergency management problem. What's the effects of a peak in information dissemination in enterprise emergencies?

Information dissemination in an online emergency is different from that in other situations, such as brand information dissemination and stock information dissemination. Information dissemination in an online emergency has a short lifecycle in which the peak of information dissemination means the biggest move. These peaks are likely to be of managerial importance because they capture the strongest manifestations of the focused awareness of, attention to, and interest in the enterprise, above and beyond random fluctuations.) [5]. Moreover, for public relations (PR) practitioners, when dealing with online emergency information dissemination, the peak has significance. The peak provides an early indication of the later development of the emergency, and it usually means the turn of the emergency. Understanding the effect of these turns often helps to make correct decisions based on the different stages of emergencies. Nevertheless, when facing the peak problem, the existing literatures focus

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on predicting and ignoring their effects. They propose different models to improve the volume prediction and time prediction accuracy. They try to identify the peak but ignore the effect of the peak on the emergency.

To fill this research gap, in this work, we investigate the role of peaks in online emergency information dissemination and study the effect of these peaks on the emergency lifecycle and influence. To achieve this goal, our work contains two major parts. First, to better present the emergency lifecycle, we propose an Online Emergency Information Dissemination Process (OEIDP) model based on the idea of system cybernetics. The two major kinds of existing models both have their shortages when applied in this study. The dissemination models focused on networks require relatively complete network structures. However, when an emergency occurs, online media information is generally abundant. News data do not have a network structure, and most are multiplatform data. The existing time series models focus on prediction. The parameters of these models help to predict the volume and overlook the lifecycle. To solve this problem and achieve the goal of studying the effect of peaks on the emergency lifecycle, we introduce the idea of cybernetics into information dissemination research area and propose this OEIDP model. Using the relevant inputs and transfer functions, includingdecay parameter T, time constant P, and delay parameters τ, we output the development process of an emergency to present the online emergency information dissemination lifecycle.

Next, using an empirical study, we demonstrate the effects of peaks on the emergency lifecycle and influence based on data taken from the Weibo, WeChat and 20,000 media platforms for 169 emergencies from2016 to 2018. We collected data from Zhiwei Data Company, a top Chinese intelligence service company. The results reveal that the peak time positively affects both the online emergency information dissemination volume and lifecycle. In addition, the peak volume only affects the online emergency information dissemination volume. Moreover, the number of spikes before a peak affects the lifecycle by decreasing people's participation intensity and it also positively affects the volume.

The main contributions of this paper are summarized as follows:

(1) Regarding the theoretical contributions, our paper has two main contributions. First, we investigate the problems with the peak effect, which is a supplement to the communication discipline. Second, we introduce the idea of system identification from system cybernetics into the perspective of information dissemination. System identification has been widely applied in many engineering and non-engineering fields. In addition, its application in information management focuses on Scientometrics [6], [7]. We bring this idea to the information dissemination perspective to propose a new direction of using information dissemination models for practical use.

(2) Regarding the practical contributions, our study provides theoretical and methodological support for PR people to intervene in emergencies. The results can give PR people guidance in peak times when they hold only limited information, and enable them to have a preliminary grasp of the development of the emergency. The results also guide PR people when they try to lead public opinion in an emergency.

The remainder of this paper is organized as follows. Section 2 provides the methodology used in the study. Section 3 presents the empirical results and analysis, and Section 4 provides the conclusion.

II. LITERATURE REVIEW

The pressing information dissemination process problem has led to a large number of researches in the field of computational communication. Scholars have proposed different dissemination models to identify the corresponding processes and mine the relevant internal mechanisms [8]–[13]. These studies can be summarized into two major perspectives: network dissemination [3] and time series information dissemination [2].

The literatures focused on networks dissemination strive to represent the dissemination process with micro networks. Through retracing the spreading path of information, the characteristics of information dissemination can be identified, and dissemination results can be predicted. The related models include cascade models [12], [14], [15], threshold models [8], [9], [16], and epidemic spreading models [4], [17]–[19]. The literatures of time series information dissemination focus on the macro dissemination of information. Using statistical methods, machining learning models, and other mathematical models, the features of dissemination can be reconstructed, and common patterns can be identified to predict results and trends. These models include SEISMIC models [4], the SIR and corresponding expanded models [18], [19], SH models [20], [21], and some other models that focus on specific tasks [2], [4].

These models describe the information dissemination process and help people understand the dynamic dissemination process and exogenous and endogenous factors. However, it is a considerable challenge to directly use these models during online emergencies.

First, the studies focused on the networks give their dissemination models based on a single platform, and they require relatively complete network structures. Thus, most previous studies used data from online social networks such as Twitter [3]. However, when an emergency occurs, online media information is generally abundant. News data do not have a network structure, and most are multiplatform data. Second, although time series models can use multiplatform data, most of previous studies focus on dissemination prediction [2], [4], [22]. They try to optimize the different models to give a better prediction of different characters in online emergency information dissemination. However, they overlook the information dissemination lifecycle in an online emergency. Moreover, ranges of parameters are commonly used to model dissemination with the goal of optimizing the accuracy of predictions. However, these parameters cannot always fully

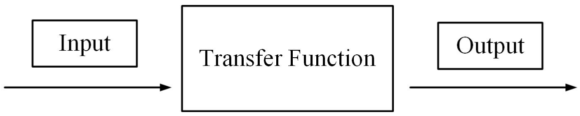

FIGURE 1. The online emergency information dissemination process described using system cybernetics.

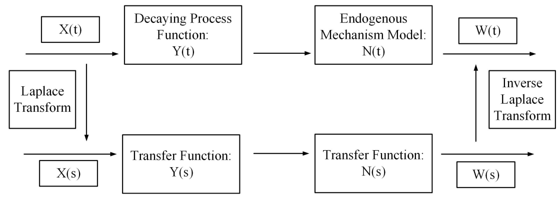

FIGURE 2. The overall process of the OEIDP model.

consider exogenous and endogenous factors. Although they provide high prediction accuracy, the underlying causes are often unclear. Especially, the impact of peaks is ignored. A peak always represents the turning point of the information dissemination in an online emergency, which is an important special point in this short lifecycle. In actual management, PR practitioners could make different decisions based on different stages of the emergency. The turning point represents the biggest change of the two stages. Moreover, since the peak can be affected by PR practitioners, it is significant to understand the impact of these peaks on online emergency information dissemination to give better suggestions to control the information dissemination.

Therefore, to fill these gaps, we conduct our study to investigate the effect of peaks based on an innovation information dissemination model that can describe the lifecycle of online emergency information dissemination.

III. METHOD

A. OEIDP MODEL

1) QUALITATIVE ANALYSIS OF OEIDP

Online emergency information dissemination is a complicated process that includes many factors. Recent studies have attempted to summarize these factors using exogenous and endogenous factors and proposed steady-state and nonstationary periods to analyze this complex process [2], [22], [23]. The exogenous factors include participative behaviors such as browse, reply, and speak. The endogenous factors encompass structure of the network, the people around users (such as fans), and the intrinsic attributes of the emergency. When an emergency occurs, online emergency information dissemination can be described as the effects of exogenous factors on endogenous factors. This approach aligns with the core concept of system cybernetics and system identification. In system cybernetics, the operating process of a system can be described as the effect of an input on a transfer function that causes an output. We can summarize this process as shown in Figure 1.

This approach to system identification treats the transfer function as an overarching black box. The input affects the transfer function, and the output is the result. Using this method, we can optimize the transfer function and the input to optimize the online emergency information dissemination process. Based on this idea, we first propose the overall process of our OEIDP model in Figure 2.

We first propose the online emergency endogenous development model. Using the method and idea of system identification, we deduce the endogenous mechanism model. This model reveals the endogenous development mechanism. Next, we compute the decay process of emergency information dissemination and combine it with the endogenous mechanism model using the transfer function method. At last, through quantifying the exogenous input function, we form the OEIDP model.

2) THE ENDOGENOUS DEVELOPMENT MODEL AND MECHANISM MODEL

We can perform a macro-analysis of the online emergency information dissemination endogenous development lifecycle. When an emergency occurs, the online emergency information will appear on the internet. In the early stage, the dissemination of information will be slow, and we call this period the incubation period [15], [24]. After a while, the dissemination speed will proliferate and will be sustained for a period of time. Then, as the number of people interested in the emergency decreases, the dissemination speed will gradually decrease to 0. The whole process increases with time and finally approaches 1. We consider the emergency process to be a continuous time series and propose the following model.

(a) The final emergency process consists of the cumulative process $W(t)$ and the residual process $w(t)$ as follows.

$$W(t) + w(t) = 1; \tag{1}$$

(b) The development speed of the emergency within a unit time $U(t)$ can be expressed as the derivative of the degree of emergency development $(W(t))$ at time t.

$$U(t) = \frac{\partial W(t)}{\partial t}; \tag{2}$$

(c) Following the qualitative analysis in the first paragraph of this section, we state the dissemination process speed develops with time and cumulative process $W(t)$. The larger the cumulative process $W(t)$ is, the slower the dissemination process speed. Based on this change in the development speed of an emergency, PR scholars divide the whole process into the incubation period, rising period, declining period and long-tail period [25]. Therefore, we can summarize that the development speed of an emergency within a unit time $(U(t))$ is relevant to -$W(t)$. Conversely, we assume that the development speed of an emergency within a unit time $(U(t))$ is relevant to $w(t)$. That is, the smaller $w(t)$ is, the slower $U(t)$; additionally, the larger $w(t)$ is, the faster $U(t)$. The corresponding ratio is P(t). For convenience in the following

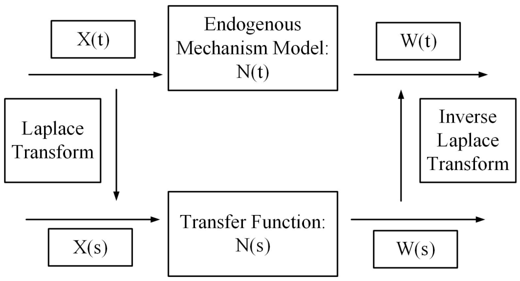

FIGURE 3. **The endogenous development process.**

computation, we use $\frac{1}{P(t)}$.

$$U(t) = \frac{w(t)}{P(t)}; \tag{3}$$

(d) In the initial stage of the emergency, i.e., within time τ, the emergency is relatively undeveloped. We assume that the development is 0 within this period.

$$W(\tau) = W(0) = 0; \tag{4}$$

As a result, we obtain the basic equation of the endogenous development process as follows.

$$\begin{cases} W(t) + w(t) = 1 \\ U(t) = \dfrac{\partial W(t)}{\partial t} \\ U(t) = \dfrac{w(t)}{P(t)}; \end{cases} \tag{5}$$

The corresponding boundary condition is as Equation 4.

$$W(\tau) = W(0) = 0$$

By solving the partial differential equation, we can obtain the following formula.

$$W(t) = 1 - e^{-\frac{(t-\tau)}{P(t)}}; \tag{6}$$

For convenience, we assume that $P(t)$ is time constant in time as P.

$$W(t) = 1 - e^{-\frac{(t-\tau)}{P}}; \tag{7}$$

This equation is the endogenous development model. Based on the analysis above, we can summarize this process in Figure 3.

$X(t)$ is an input and that physically represents the quantitative influence of the external environment. According to the analysis above, $X(t)$ can be treated as a step function. This research focuses on the trend. Therefore, the corresponding input is a dimensionless step function.

$$X(t) = \begin{cases} 0, & t < 0 \\ 1, & t \geq 0, \end{cases} \quad \text{where } t \text{ is time}; \tag{8}$$

This relation physically indicates that the external environment has a continuous and unvarying influence. $X(s)$ is the Laplace transform of this process.

$$X(s) = \frac{1}{s}; \tag{9}$$

In this case, $W(s)$ is the Laplace transform of $W(t)$, and the following equation can be obtained.

$$W(s) = \frac{e^{-\tau s}}{s(Ps+1)}; \tag{10}$$

$N(t)$ refers to the endogenous mechanism model, which reflects the effect of only the endogenous factors. $N(s)$ is the Laplace transform of $N(t)$. According to the transfer function algorithm, we can obtain the following formula.

$$W(s) = X(s) \times N(s); \tag{11}$$

Therefore, the following equation can be obtained.

$$N(s) = \frac{e^{-\tau s}}{(Ps+1)}; \tag{12}$$

This equation 12 is the Laplace transform of the endogenous mechanism model. In this equation, the time constant P determines the lifecycle of the endogenous emergency development. As we noted, P is related to the endogenous mechanism of the emergency, including the structure of the network, the users, and the intrinsic attributes of the emergency.

3) THE OEIDP MODEL WITH THE DECAY PROCESS FUNCTION

We consider the decay process of the participation intensity. In an online emergency, the "newness" of information decays over time. In addition to the participation of individuals, the process of seeking a certain thing or view varies from strong willed to weak willed, from peak to collapse, and from attraction to repulsion. Additionally, from the macro-perspective, when people are involved in an online emergency, their behavior varies from strong willed to weak willed and from peak to collapse. These behaviors at different scales are similar. We use the decay of radioactive substances in nature to model this decay process, which can be described as follows:

$$Y(t) = Ke^{-\alpha t}; \tag{13}$$

where K is constant but varies for different emergencies. As we focus on the dissemination process, for convenience, we use the dimensionless type form of this equation, in which K equals 1. For computational convenience, we use $T = \frac{1}{\alpha}$ to describe this process.

$$Y(t) = e^{-\frac{t}{T}}; \tag{14}$$

In this model, T represents the decaying effects, i.e., the decay of the participation intensity in the online emergency information dissemination lifecycle. The Laplace transform of the model is as follows.

$$Y(s) = \frac{1}{Ts+1}; \tag{15}$$

Based on the analysis above and the results in Figure 2, using the transfer function method, we use the convolution procedure of $N(t)$ and $Y(t)$ to compute the model as below:

$$W_1(s) = X(s) \times N(s) \times Y(s); \tag{16}$$

In this model, $W_1(s)$ refers to the Laplace transform of the output of process, which is the online emergency information dissemination process. Similar to the analysis above, $X(t)$ can be treated as a step function, therefore, $X(s) = \frac{1}{s}$. The result is as below:

$$W_1(s) = X(s) \times N(s) \times Y(s) = \frac{e^{-\tau s}}{(Ps+1)(Ts+1)s}; \tag{17}$$

Additionally, we have the OEIDP model as follows.

$$W_1(t) = 1 - \frac{Te^{-\frac{t-\tau}{T}}}{T-P} + \frac{Pe^{-\frac{t-\tau}{P}}}{T-P}; \tag{18}$$

In this equation, the time constant P determines the endogenous emergency development lifecycle. T represents the decay of the participation intensity, and τ represents the time that the emergency is relatively undeveloped. These three parameters determine the lifecycle of an online emergency information dissemination process.

B. EXPLANATORY ANALYSIS

In this section, we will investigate the effect of peaks on online emergency information dissemination. We will study how these peaks affect the emergency information dissemination process, and how these peaks affect the final emergency influence. We conduct this experiment at the sites of PR practitioners and try to give suggestions on what to do during emergencies.

1) CONTROL VARIABLES

In this study, in order to analyse the peak effect in different kind of online emergency information dissemination, we choose these three kinds of factors to be control variables.

We use $t\_time\_zone_i$ to represent the i_{th} period of the emergencies' first time period. According to people's rest habits, we divide the time periods into the 4 periods of 1 - 8 am, 8 am - 1 pm, 1-7 pm, and 7 pm – 1 am. We treat the time period from 1 - 8 am as the baseline.

Next, we use e_type_j to represents the j_{th} type of the emergency. We use Zhiwei Data Company's emergency classification standard to classify emergencies. The types of emergencies are Nation Level, Internet, Enterprise, Social issue, Sports and Entertainment (S&E), and Rumor. We treat the Nation Level type as the baseline.

At last, we use $e\_sentiment_k$ to represent the k_{th} sentiment of this emergency. We use Zhiwei Data Company's emergency sentiment classification method to classify the different sentiments of these emergencies into positive, neutral, and negative. We treat negative as the baseline.

2) FOCAL INDEPENDENT VARIABLES

To study the effect of peaks on online emergency information dissemination, we first use two intuitive parameters to represent the peak.

We use *peak_volume* to represent the volume of a peak. It also represents the strongest manifestations of focused awareness of, attention to, and the biggest influence of the emergency.

We use *peak_time* to represent the time of a peak. This parameter represents the speed at which emergency becomes most influential. It also represents the time of the inflection point and means the change of different PR decisions.

The temporal dynamics of online emergency information dissemination does not evolve smoothly. The peak is not directly reached. Before the peak, there are many spikes existed. These spikes are caused by a wide range of behaviors [24] and they reflect people's attention model of the emergency before the peak. In other words, these spikes reflect the types that emergency comes to the peak, that is, the type of the peak. Therefore, in this study, we use *n_spkie_before* to represent the number of spikes before the peak or the type of peak.

3) DEPENDENT VARIABLES

In this study, we attempt to investigate the effect of spikes on online emergency information dissemination. We use two kinds of parameters to represent the dependent variables.

The first kind of parameters represents the lifecycle of the online emergency information dissemination. We use the parameters in the OEIDP model:

The time constant P determines the lifecycle of the endogenous emergency development and also represents the development speed of the online emergency.

The decay parameter T represents the decay of the participation intensity and also represents the decay speed of people continuing to pay attention.

The delay parameter τ represents the time that the emergency is relatively undeveloped and also represents most of the incubation period.

The other kind of parameter represents the final influence of the online emergency information dissemination. We use the final volume, *volume*, to represent it.

4) EXPLANATORY MODEL

We use four separate regression models to test the peak effects and measure (1) the effects on emergencies' lifecycles and (2) the effects on emergencies' final influence.

We first analyze the effects of the parameters of the OEIDP models, T, τ and P, to investigate the effects on the lifecycle. The models are as follows:

$$\begin{aligned} ln\ \tau = \ & \beta_0 + \beta_1 \cdot\ ln\ peak\_volume + \beta_2 \cdot ln\ peak\_time + \beta_3 \\ & \cdot n\_spkie\_before + \sum \beta_{ai} \cdot t\_time\_zone_i + \sum \beta_{bj} \\ & \cdot e\_type_j + \sum \beta_{ck} \cdot e\_sentiment_k + \varepsilon; \end{aligned} \tag{19}$$

$$\begin{aligned} ln\ P = \ & \beta_0 + \beta_1 \cdot\ ln\ peak\_volume + \beta_2 \cdot ln\ peak\_time + \beta_3 \\ & \cdot n\_spkie\_before + \sum \beta_{ai} \cdot t\_time\_zone_i + \sum \beta_{bj} \\ & \cdot e\_type_j + \sum \beta_{ck} \cdot e\_sentiment_k + \varepsilon; \end{aligned} \tag{20}$$

$$\begin{aligned} ln\ T = \ & \beta_0 + \beta_1 \cdot ln\ peak\_volume + \beta_2 \cdot lnpeak\_time + \beta_3 \\ & \cdot n\_spkie\_before + \sum \beta_{ai} \cdot t\_time\_zone_i + \sum \beta_{bj} \\ & \cdot e\_type_j + \sum \beta_{ck} \cdot e\_sentiment_k + \varepsilon; \end{aligned} \tag{21}$$

TABLE 1. The detailed description of the data.

Name	Description
Weibo	Enterprise-related information published with Weibo account, including: 1. Posts that contain related keywords (define keywords through communication with enterprises), 2. Comments on the posts, 3. Shares of the posts, 4. Likes of the posts.
WeChat platform	Gather all data of associated articles in real time according to keywords
Web media	Over 20000 media are included, such as central media (like the CCTV and People's Daily), new media (like The Paper) and technology-related media (like Huxiu).

In these equations, $ln\tau$, lnP, and lnT are the logarithmic form of the three parameters in the OEIDP model. The coefficients measure the impacts of the factors on the parameters. ε is the error. Next, we analyze the effect on the online emergency information dissemination volume, *volumn*, to investigate the effect on emergencies' final influence. We use the logarithmic form $\ln volumn$ to represent *volumn*. The model is as follows:

$$\begin{aligned} ln\ volumn &= \beta_0 + \beta_1 \cdot ln\ peak\_volume + \beta_2 \cdot lnpeak\_time \\ &\quad + \beta_3 \cdot n\_spkie\_before + \sum \beta_{ai} \cdot t\_time\_zone_i \\ &\quad + \sum \beta_{bj} \cdot e\_type_j + \sum \beta_{ck} \cdot e\_sentiment_k + \varepsilon; \end{aligned} \tag{22}$$

IV. EMPIRICAL RESULTS

A. DATA SET

We collected data from online emergencies in cooperation with Zhiwei Data. Zhiwei is a leading company for mining and providing public opinion information. This information encompasses different types of events for enterprises, public security, entertainment, and so on. And the data sources include Weibo, Wei Xin, and more than 20000 online media platforms. We focus on the total volume of information at 10-minute intervals. A detailed description of the data is given in Table 1.

The complete period starts from the date when the emergency occurs and ends on the date of entry into the long-tail period. Through cooperation with Zhiwei, we found that an emergency starts at the time when the related keywords first appear online. Finally, we compiled a data set of 169 online emergencies in 2018. The emergency type number is shown in Table 2.

B. MODEL FITTING RESULTS

We fitted the 169 emergencies and used the determination coefficient R^2 to evaluate the result. R^2 is calculated as follows.

$$R^2 = 1 - \frac{\sum_{i=1}^{m} \left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{m} \left(y_i - \bar{y}_i\right)^2}; \tag{23}$$

TABLE 2. The descriptive analysis of THE Emergency type data.

Emergency type	N	volume	
		Min	Max
National	11	77	50397
Internet	12	69	15743
Enterprise	41	54	67431
Social issue	64	57	110000
Sports and entertainment (S&E)	29	195	41868
Rumor	12	47	2154
total	169		

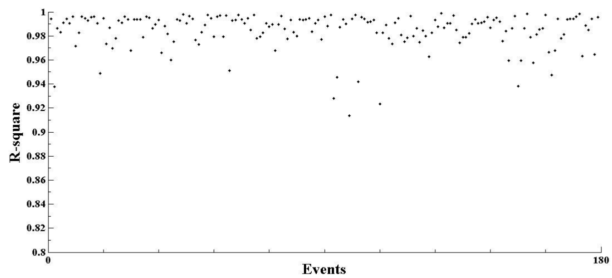

FIGURE 4. R-squared results.

We use MATLAB to fit the model. The results of the OEIDP model are shown in Fig. 4.

In Fig. 4, we show that the model has a good fit to the online emergency information dissemination. The average R_square is 0.9754.

To further illustrate the effectiveness and accuracy of the model, we use the simulation analysis to show the fitting ability of this model in the complete information dissemination process. We use example emergencies for each category and perform simulation results. These are six typical emergencies including National level, Internet, Enterprise, Social issue, Sports and entertainment, and Rumor. These respective emergencies are as follows: (a) Three Chinese killed in Nigeria, Nation level; (b) the "Ten Most Influential AI Leader in the world" article came out and Yanhong Li was the only Chinese representative, Internet; (c) the article "The death of Baidu searching engine" Explodes on the Internet, Enterprise; (d) Railway Officials Forcibly Occupy a Seat, Social issue; (e) "Running Men" Officially Announce Lineup Change, Sports and entertainment; and (f) 62 viruses Existed in "Individual Income Tax" app, Rumor. The results are in Fig. 5.

The X-axis represents the time, and Y-axis represents the process. We can observe that although the emergency types are different, the results are similar. In Fig. 5, the black lines are the original data, and the blue lines are the fitting results. According to Fig. 5, a good fitting result for the OEIPD is obtained, which fits the results of Fig. 4. Therefore, the model is proven to be effective and feasible.

C. EXPLANATORY ANALYSIS

In this section, we investigate the role of peaks in the online emergency information dissemination lifecycle based on the explanatory model. The results are given in Table 3. Model 1

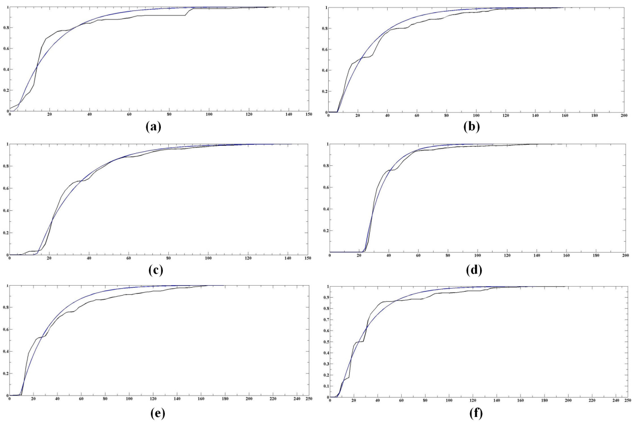

FIGURE 5. Six events OEIDP fitting results.

TABLE 3. Explanatory results.

	Model 1	Model 2	Model 3	Model 4
	Decay	Time constant	Delay	Volume
Peak_volume	-0.197	0.058	0.067	1.144***
Peak_time	0.564***	0.126**	0.431***	0.219***
n_spikes_before	0.096***	0.017	-0.013	0.029**
$t\_time\_zone_2$ (8 am - 1 pm)	-0.066	0.185	0.477*	0.152
$t\_time\_zone_3$ (1-7 pm)	0.740	0.034	0.735***	0.001
$t\_time\_zone_4$ (7 pm – 1 am)	0.401	0.106	0.144	0.124
e_type_2 (Internet)	-1.379*	0.699**	-0.173	0.106
e_type_3 (Enterprise)	-0.676	0.054	-0.295	-0.079
e_type_4 (Social issue)	-0.098	0.345	-0.371	0.148
e_type_5 (S&E)	-0.698	0.306	-0.425	-0.048
e_type_6 (Rumor)	-0.413	-0.206	0.422	-0.103
$e\_sentiment_2$ (Positive)	-0.248	0.194	0.330	0.019
$e\_sentiment_3$ (Neutral)	-0.022	-0.198	-0.496***	-0.077
_cons	0.698	3.745***	2.400***	2.025***
N	169	169	169	169
R^2	0.342	0.243	0.311	0.853
Adjusted R^2	0.287	0.180	0.253	0.841

* p<0.1, ** p<0.05, *** p<0.01

(column 1), Model 2 (column 2), and Model 3 (column 3) present the effects of peaks on the emergency information dissemination lifecycle. Model 4 (column 4) presents the effect of peaks on the emergency information dissemination influence.

Model 1 (Eq. 21) presents the effect of peaks on the decay parameter T. We find that the peak time and the number of spikes before a peak have statistically positive significant impacts on the decay. The peak time produces a coefficient of 0.564 ($p<0.01$) and the number of spikes produces a coefficient of 0.096 ($p<0.01$). However, the peak volume does not have a statistically significant impact.

Model 2 (Eq. 20) and Model 3 (Eq. 19) reveal similar results for the effect of peaks on the emergency information dissemination lifecycle. Only the peak time has a statistically significant impact, and both its impacts are positive. The peak time has a coefficient for the 0.126 ($p<0.5$) on time constant P and has a coefficient of 0.431 ($p<0.01$) for the delay.

These results prove the effect of peaks on the online emergency information dissemination lifecycle. First, the most influential aspect is the peak time. Since the decay parameter T represents the decay of the participation intensity (Eq. 13, Eq. 14), the time constant P determines the lifecycle of the endogenous emergency development, and the delay parameter τ represents the time of the incubation period, we found that the longer the time length before the peak, the lower the participation intensity of people($T = 1/\alpha$), the longer the development of the endogenous emergency, and the longer the incubation period. In other words, the peak time has a positive impact on the emergency information dissemination lifecycle. Next, the peak volume has no statistically significant impact on the lifecycle. Moreover, the spikes affect people's participation intensity.

Model 4 (Eq. 22) presents the effect of peaks on the volume of emergency information dissemination. From the results, we find that the three parameters of the peak all have statistically positive significant impacts on the volume. The peak volume produces a coefficient of 1.144 ($p<0.01$). The peak time produces a coefficient of 0.219 ($p<0.01$). Finally, the number of spikes produces a coefficient of 0.029 ($p<0.05$). These results prove the effect of peaks on online emergency information dissemination influence. The peak volume has the most significant role among the three aspects. Moreover, through the R^2 (0.853) and Adjusted R^2 (0.841), we can also reveal the significant impact of peaks on online emergency information dissemination influence.

The results in Table 3 disentangle the role of peaks in online emergency information dissemination. The peaks have significant impacts on both the online emergency information dissemination lifecycle and influence. The peak time can increase the lifecycle of an emergency by increasing the endogenous development and decreasing people's participation intensity. The peak volume can increase total emergency information dissemination volume together with the peak time. The spikes represent a special type that can improve the effect of peak.

These results can guide the actual management of online emergency information dissemination. For PR practitioners, they can form preliminary judgements about the trend and influence of an emergency based on when the emergency peaks and make decisions about what to do next. Additionally, they can optimize the PR method based on this conclusion.

First, if we want to expand the influence of an emergency, we should not only increase the peak, but we should also increase the peak time. For example, we can analyze some actual behaviors, such as using an online "water army" to post massive articles. "Water army" behavior will soon increase the volume. However, if this behavior lasts a short time, it would make the peak time short. Although it would accumulate a bigger "highest influence", the total influence of this behavior would not be enough. If we want to expand the influence of an emergency, the water army should proceed relatively slow and make the emergency reach its peak later. Additionally, we can produce some spikes to progressively reach the peak.

Second, if we want to decrease the influence of an emergency, just deleting information (e.g., Internet deletion) is not necessarily appropriate. Although deleting information would decrease the volume of information within a certain time, it would also slow down the emergency come to peak. Therefore, it would increase people's participation intensity and increase the influence of the emergency in a way. Consequently, if we want to decrease the influence of an emergency, we should not only decrease the volume within a certain time but also increase the short-term information accumulation speed.

V. CONCLUSION

When facing online emergency information dissemination, the peak represents the strongest manifestation of an emergency, and it usually represents the inflection point of the development of the emergency. Understanding the role of these peaks can help to disentangle the relationship between the strongest manifestation and final result of the emergency information dissemination and help PR practitioners make proper decisions. However, current studies focus on predicting and identifying these peaks and ignore their effects.

To solve this problem, we conduct an empirical study to investigate the effect of peaks on the online emergency information dissemination lifecycle and influence. Based on the proposed OEIDP model combining the ideas and methods of system identification, which has an average determination coefficient R^2 of 0.9754 using empirical data from 169 emergencies, we study the effect of peaks on the online emergency information dissemination lifecycle. The peak time positively affects all three parameters, including the decay parameter T, time constant P, and delay parameter τ, in the OEIDP model, which represents the lifecycle. The spikes before peaks also affect the lifecycle by decreasing the people's participation intensity. Moreover, the peak time, the peak volume, and the spikes all affect the final volume of the emergency, which represents the influence of the emergency. The R^2 (0.853) and Adjusted R^2 (0.841) of this model reveal the relative significant impact of peaks on an emergency's influence. These results can guide PR practitioners when facing emergencies by showing that if we want to improve the final influence of an emergency, we should slowly increase the amount of information and create some spikes. Conversely, if we want to decrease the final influence of an emergency, we should not only delete information but also increase the short-term information accumulation speed.

Our study makes both theoretical contributions and practical contributions. Theoretically, in this article, we introduce the idea of system cybernetics to conduct a modelling analysis of information accumulation, which brings a new direction to solve information dissemination-related problems by drawing from the ideas and methods from system cybernetics including feedback, PID, etc. Moreover, we investigate the problems with the peak effect, which complements the gaps in the existing communication literature. Practically, our study provides new insights into solving PR problems. The results enable these PR practitioners to give more accurate suggestions when facing peaks and guide these PR practitioners on how to balance these strongest manifestations and their final influence.

This article steps into the study of peaks. Subsequent studies will follow this direction and conduct more detailed explorations into the mechanism, attributes, and different kinds of effects of the peaks in information dissemination problem. Moreover, this article marks the starting point for the application of the idea of system cybernetics to solve information dissemination problems. Subsequent studies will also focus on how to use system cybernetics technology to detect and control the peaks in these information dissemination problems. Additionally, regarding the actual applications, we will explore more effective and concentrated methods to handle online emergency information dissemination from the PR perspective.

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