The Journal of Supercomputing (2023) 79:6452–6470
https://doi.org/10.1007/s11227-022-04900-x

The predicting public sentiment evolution on public emergencies under deep learning and internet of things

Min Chen[1] · Wenhu Du[1]

Accepted: 16 October 2022 / Published online: 7 November 2022

Abstract

With the Internet's rapid development and the increasing amount of netizens, social contradictions frequently manifest over the Internet. Public emergencies develop and spread constantly online. Thus, it is of great significance to reasonably address the Online Public Sentiment (OPS) in the current critical stage of social transformation. The aim is to create a safe and credible network environment and realize the modern transformation of the dynamic evolution of OPS in public emergencies. Firstly, this paper expounds on the blocking process of the OPS evolution on public emergencies according to the Internet of Things-native big data. Then, it discusses the algorithm process of the Long Short-Term Memory (LSTM) Neural Network (NN) model. Further, it optimizes the LSTM NN model using the Adaptive Momentum Estimation (Adam). Finally, it simulates and predicts the OPS evolution using Artificial Intelligence technology and big data. The results show that the Adam-optimized LSTM NN model can predict the hotness of OPS in the dynamic evolution with high prediction accuracy. In predicting OPS evolution, the Mean Relative Errors (MRE) of the proposed Adam-LSTM, LSTM, and Backpropagation NN models are 0.06, 0.10, and 0.14, respectively. The proposed Adam-LSTM model presents the least MRE on the hotness of OPS. The relevant governments can refer to model-predicted OPS evolution to control public emergencies and OPS through the IoT. Therefore, the proposed Adam-LSTM model is feasible for predicting the OPS hotness. The finding has particular research significance for employing the LSTM model under the IoT in predicting the OPS evolution in public emergencies. Lastly, the OPS on public emergencies can be effectively guided thanks to the proposed Adam-LSTM prediction model and time nodes.

Keywords Internet of things · LSTM neural network · Artificial intelligence data · Adam method · Public emergency · Hotness of online public opinion

✉ Min Chen
xuancm@gmail.com

[1] Institute of Corporate Strategy and Corporate Culture, School of Business, Wenzhou University, Wenzhou, China

1 Introduction

In August 2021, news of a sex scandal went viral [1]. The protagonist Wu Yifan, a well-celebrated figure in China, has aroused formidable online bullying and public discussions. Such public emergencies-triggered Online Public Sentiment (OPS) is not alone. In the same year, other events followed, including celebrity corruption, the Henan flood, online fraud, food hygiene, and camera peeping. The mass involvement in public emergencies marks a more democratic social system. However, it might cause more devastating outcomes than the event itself, especially when public sentiments get fermented and out of control. Therefore, effective forecasting and control of OPS to prevent them from deteriorating is a matter of urgency. The prevailing Internet of Things (IoT) technologies might potentially create a favorable public sentiment environment. For example, combining IoT-native big data with Artificial Intelligence (AI) and Cloud Computing can contribute to the prediction, guidance, and intelligent control of OPS. It can promote scientific decision-making before major public emergencies [2, 3].

The present work starts from the development of OPS in emergencies in recent years and explores its dynamic evolution on the IoT platform. It models the hotness of OPS for predicting public emergencies and applies the LSTM NN model. Finally, the Adaptive Momentum Estimation (Adam) optimizer is employed to optimize the LSTM model. Great theoretical significance and practical value are provided to change the concept of traditional guidance ideas on OPS. The proposed model accurately grasps the interior features and potential laws of OPEs, guides OPS, and maintains online social security under the new situation. Figure 1 shows the technical framework of this paper.

Figure 1 is the research framework of this paper. Section 1 is the introduction, which describes the risks of public emergencies in the dynamic evolution of OPS. Also, the relevant guiding measures provide a background statement and introduce the research methods and framework. Section 2 is a literature review that summarizes and analyzes the current situation of the dynamic application of IoT in OPS. Then, Sect. 3 briefly explains the research materials and methods, and the harm of online public emergencies. Further, the IoT is used to discuss the OPS guidance process for public emergencies. Finally, the LSTM neural network algorithm is used to establish the prediction model of unexpected events. The Adaptive Momentum Estimation (Adam) method is chosen to optimize the LSTM model. Section 4 is the result analysis part, which mainly forecasts the popularity of public opinion on the IoT and LSTM neural network for public emergencies. Relevant suggestions are put forward for dealing with public emergencies. Finally, according to the research results, the performance of this model is analyzed. Section 5 is the conclusion, which summarizes the research and puts forward the research limitations.

2 Literature review

In recent years, open and interactive network media has developed rapidly, with which the Online Public Emergency (OPE) has a more rippling effect [4]. The IoT is playing an increasingly prominent role in presenting public emergencies and

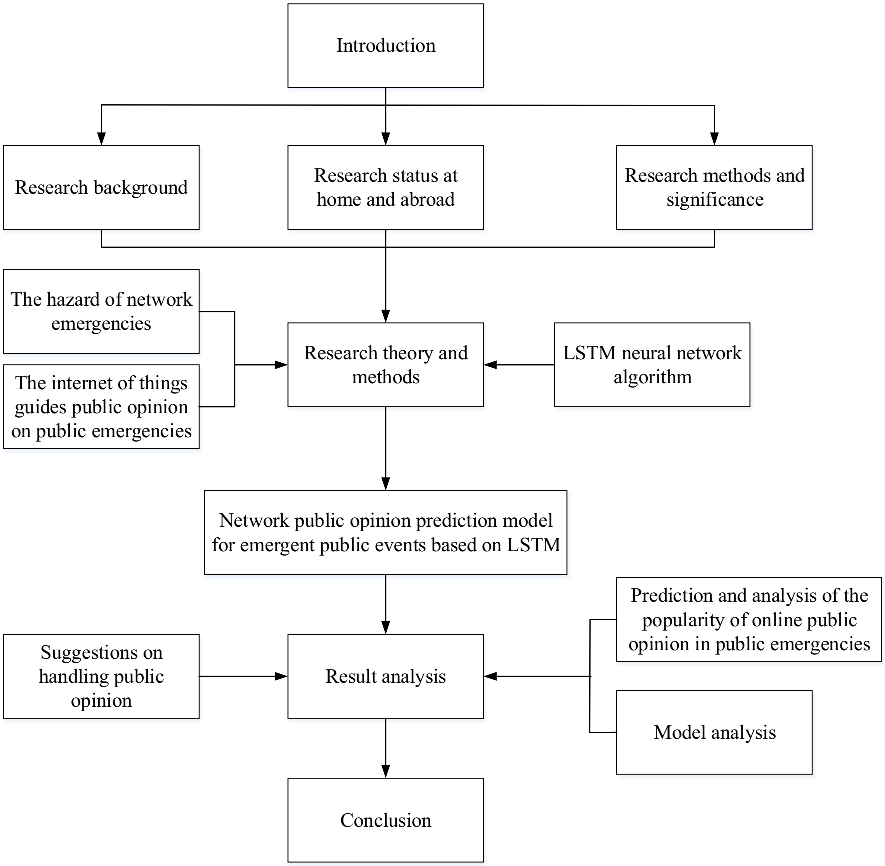

Fig. 1 Research technical framework

online communications [5]. It can well realize the realistic demands and opinions, especially the realistic response of government departments to OPS [6].

Regarding the factors affecting Internet users' emotional development in public emergencies, domestic scholars have researched the factors leading to public sentiment development in China [7]. The public emergencies-oriented risk evaluation and prediction systems are constructed using the fuzzy Analytic Hierarchy Process (AHP), grey statistics, and the information ecology theory. They put forward suggestions on public emergency management [8]. Foreign scholars use naive Bayes to predict the development of OPS in emergencies [9].

Regarding the research on the development of predicting OPS using Machine Learning, Shen et al. (2021) used the Support Vector Machine (SVM) algorithm to analyze the relevant data of Twitter and the emotional level of netizens during public emergencies [10]. Xiao et al. (2020) used Backpropagation Neural Network (BPNN) model to predict Microblog OPS, which effectively improved the prediction performance and shortened the model operation time [11]. Tavoschi et al. (2020) introduced machine learning methods and improvement methods to analyze network public opinions. The research proved the feasibility of machine learning in the prediction of network public opinions [12]. Yadav et al. (2020) introduced the popular Deep Learning (DL) models in emotion analysis and classification. The popular DL architecture's performance was discussed in the emotional analysis [13]. Jain et al. (2021) proposed a Cuckoo Search (CS)-optimized machine learning model to predict airline recommendations. The results showed that the CS-optimized extreme gradient lifting classifier outperformed other advanced technologies. The findings facilitated future customers to obtain relevant information before purchase [14].

Given the fact that OPEs are becoming more frequent and influential, effective governance methods must be used to explore and improve the public sense of laws and regulations and address both the symptoms and root causes. To begin with, the government should construct a rule-of-law network environment to promote legislation standardization and law enforcement. In particular, the construction should be strengthened on legal norms at the network technical level and many modules in the network community, based on the principle of law enforcement standardization. Besides, various resources should be utilized to improve the quality of law enforcement and the construction of network technical legal norms, enhance the flexibility of online law enforcement, and address both the symptoms and the root causes. The comparison of relevant literature is listed in Table 1.

The above studies have studied the public emergency-induced OPS from concept, basic theory, and government guidance perspectives. They continuously expanded and enriched the emergency OPS research system. In the network information society, many subjects gradually participate in developing relevant OPS. Given the emotional development of netizens in public emergencies and the prediction of the development of OPS by Machine Learning methods, and most of them are adopting qualitative and quantitative research methods. They emphasize the research on the dissemination and governance of OPS involving government, netizens, media, and other subjects. However, from the existing relevant literature, most public opinion studies focus on a specific type of public emergency. Some summarize the relevant propagation laws and governance strategies through the study of an event. For example, the dynamic development of OPS is not clear enough about the communication mechanism and influencing factors. The timely guidance and response to the

Table 1 Literature comparison

Document no	First author	Year of publication	Literature source
6	Merkley E	2020	Canadian Journal of Political Science/Revue canadienne de science politique
7	Boon-Itt S	2020	JMIR Public Health and Surveillance
8	Zhang W	2020	Journal of Risk and financial management
9	Wang B	2021	International Journal of Distributed Sensor Networks
10	Shen L	2021	JMIR medical informatics

development of OPS in public emergencies focus on specific measures for different participants. There is a lack of corresponding targeted governance measures at different stages of the development of online public opinion events. Moreover, the research results of a single case cannot meet the common needs of online public opinion coping strategies. Public emergencies are becoming more diversified in the social environment of information development. The development of different types of emergencies has different characteristics, and different governance measures should be taken. In addition, there is less research on the dynamic development of OPS for public emergencies. The research methods are single. Bayesian methods are mostly used, while other methods are less studied. Therefore, it is necessary to adopt new research methods to study the complex public emergency-induced OPS from the perspective of dynamic evolution. As such, it can enhance the persuasiveness of relevant research.

3 Methodology

3.1 Hazards of public emergencies-triggered OPS

OPE often features cross-regionality and amplified social contradictions and conflicts because of its diversified, anonymous, and large-scale netizen basis, and increases with the advancement of computer and networking technologies. Not surprisingly, network security concerns also hike [15]. As of June 2018, Chinese netizens are estimated to be over 802 million, which lays a solid basis for OPE expansion. In an OPE, real and false information is often mixed, and general public sentiments are mostly flushed by negative, malicious, and even politically manipulated verbal abusiveness. Coupled with virtualization, anonymity, and the absence of laws and regulations, people involved in online discussions cannot gain genuine information without a clear discrepancy ability. Meanwhile, the motivation and social identity of the information publishers are hard to discern, making network governance lame on OPEs. By and by, public sentiment will accumulate. Not finding an emotional outlet, the public might express dissatisfaction with government entities and the existing political and law systems online. In rare cases, it might cause estrangement and even opposition between the public and the government, seriously damaging the government's image.

In November 2017, the Ministry of Industry and Information Technology of the People's Republic of China formulated *The Emergency Plan for Online Public Emergencies* according to *The Network Security Law of the People's Republic of China* and *The National Emergency Plan for Network Security Events* and other laws and regulations. Government intervention reflects China's firm determination to ensure network security and clean network environments. With the advent of the era of big data, OPS features vast data volume, complexity, and generation speed [16]. The existing OPS guidance framework is no longer adequate to function normally [17], so a new scheme must be put forward according to ample OPS data.

3.2 The guiding process of IoT to OPS on OPEs

Given the volatile network environment, the static management philosophy is unsuitable for OPEs. To improve efficiency, the OPE governance must keep pace with the times by accurately and timely predicting the OPE occurrence and evolution. Accordingly, countermeasures must be offered in advance. In particular, applying IoT technologies to mine OPS big data can warn against OPEs and help governments get well-prepared before OPS gets wild over the Internet. Figure 2 illustrates the prediction of OPS under the IoT.

Figure 2 indicates that the model realizes the OPS monitoring by simulating the evolution process in public emergencies. Governments can use the model to monitor OPE by simulating early warning messages on emergencies over the IoT. Notably, OPEs contain miscellaneous information and are characterized by certain blindness and randomness. As an epoch-making technology, IoT encourages the mass to express their opinions freely. This, however, has facilitated some cynical groups with ulterior motives to hype particular events. It also provided platforms to vent anger, manipulate speech, distort social orders, and shake the social justice system. Unbridled OPS will destroy people's faith and value, disrupt the public discourse system, endanger social order, and affect harmony and stability. Technological advancement is no way turning back, so OPSs are destined to occur more frequently, transmit more quickly, and impact more broadly. For example, with the evolution of OPEs, Microblogs have become a technological basis for OPS on OPEs, especially on those incidents related to public figures. Now the pressure will be all on governance strategies; otherwise, there will be a severe negative impact on the public's trust in the government and social stability. The present paper claims that scientific methods must be the top priority in OPEs and OPS-oriented governance and control

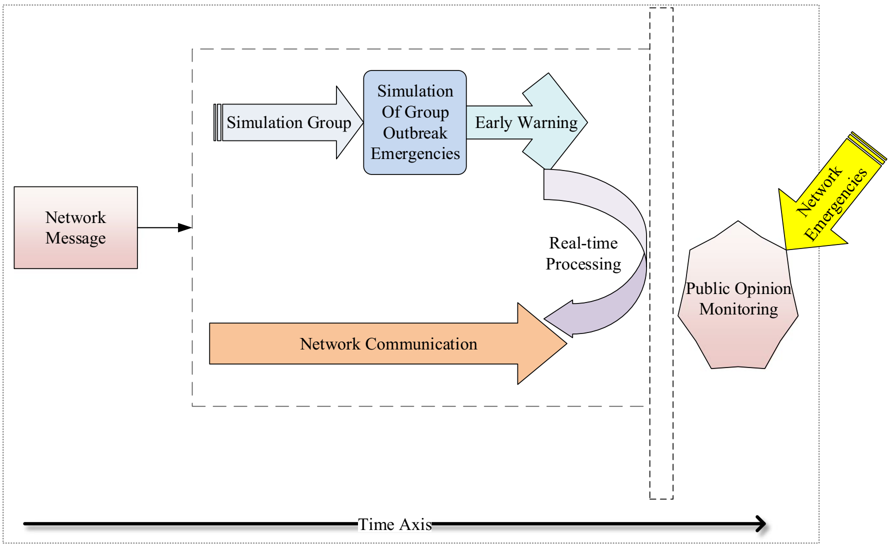

Fig. 2 Prediction of OPS on OPEs under the IoT

policies. As such, the objective law of Internet and Big Data Technology (BDT) can be fully utilized in government policies, including data mining, sentiment analysis, and psychological prediction based on massive online data.

3.3 The structure of the LSTM model

LSTM has an optimized memory mechanism over the Recurrent Neural Network (RNN) and thus can process long-term sequence data [18, 19] that RNN cannot. Meanwhile, LSTM utilizes a gate mechanism to store useful information and "forget" obsolete information. It can lend itself to gradient disappearance or explosion problems during long-sequence training. In short, LSTM outperforms ordinary RNNs on longer sequences. LSTM makes small modifications to the information through multiplication and addition. The information passes through a "cell state mechanism." In this way, LSTM can selectively remember or forget information. There are three different dependencies on information in a specific unit state. LSTM can be applied to Natural Language Processing (NL), Machine Translation (MT), image annotation, and automatic music generation. It plays an indispensable role in DL and big data. LSTM is a member of DL technology, with more structural and computational complexity, making it less feasible for deep-level learning. For example, Google Translation only applies the LSTM network structure with 7–8 layers. Additionally, overfitting may occur during training and learning deeper NN structures. Generally, dropout can be employed against deeper NN model overfitting. Figure 3 illustrates the structure of an LSTM NN model.

Figure 3 mainly comprises three large boxes representing three kinds of cells (consisting of multiple Memory Cells). However, it only represents the state of a cell at different timing. All data will only pass through one cell, and their weights will be updated continuously. Four small yellow boxes are in the middle cell, each representing a feedforward network layer and a classical NN structure. The activation function of 1, 2, and 4 is Sigmoid, and the activation function of the third is tanh. h_{t-1} represents historical information. X_t refers to the new information currently

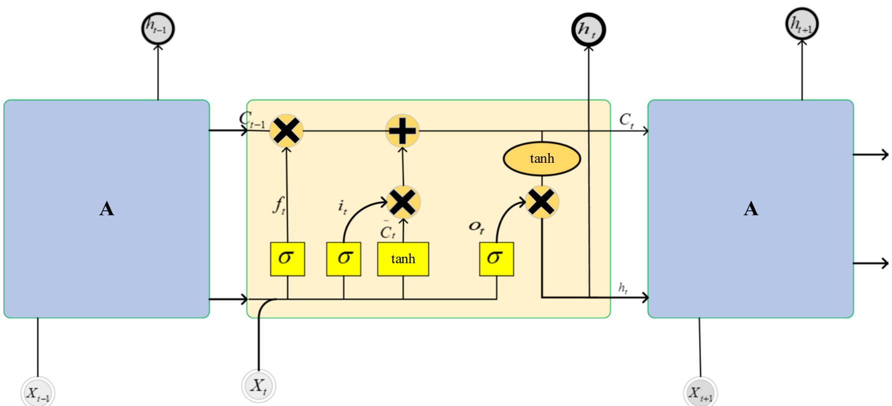

Fig. 3 LSTM structure

flowing into the cell. $C_{t-1} \rightarrow C_t$ means the cell state. The three $\sigma \rightarrow \otimes$ are called gates and are used to delete or add information to the cell state. σ stands for the Sigmoid function output, between (0,1), which is used as the gating state. The tanh function outputs between (-1,1), which is consistent with the characteristic distribution in most scenes, with 0 as the center. Additionally, the tanh function has a larger gradient near the input of 0 than the Sigmoid function.

3.4 The algorithm of LSTM

The LSTM structure is divided into the "forgetting stage", "selecting stage" and "outputting stage". Figure 4 demonstrates the processes of different stages of LSTM.

In Fig. 4, the forgetting stage determines what information will be discarded from the cell state. This decision is made through the layer called forget gate. The forget gate will read h_{t-1} and X_t, decide which historical information to forget according to the new input. Through the forget gate, f_t can be obtained. The proposed OPS management model can predict OPS based on the available information; the cell state contains the critical OPE information [20, 21]. The correctly predicted OPS information will override the previous information. The two vectors representing new and old information will be spliced to output a value between 0 and 1. This fraction indicates how much information to forget. For example, in the cell state C_{t-1}, 1 means "completely retained", and 0 means "completely discarded". (W_f stands for the weight matrix, and b_f represents the deviation).

$$f_1 = \sigma(W_f[h_{t-1}, x_t] + b_f) \tag{1}$$

Selecting stage determines what new information will be stored in the cell state, where there are two parts. Initially, the Sigmoid layer: the "input gate layer" determines what value will be updated. Then, the tanh layer creates a new candidate vector $\underset{t}{\tilde{C}}$, which will be added to the state. Next, the cell state is updated using the Sigmoid and tanh functions. With the output of the last time (h_{t-1}) and the current data input (x_t), i_t is obtained through the input gate. Now the old cell state is updated from C_{t-1} to C_t. The old state is multiplied with f_t to discard some information and added with $i_t * \underset{t}{\tilde{C}}$ to obtain the new candidate value. The candidate value changes according to the updated degree of each state. Finally, the temporary state C_t at the current time is obtained through the united state.

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\overline{C}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t \times C_{t-1} + i_t \times C_t \tag{4}$$

Output stage. Finally, the output needs to be determined. The Sigmoid layer determines which part of the cell state will be output. The tanh function calculates the cell state. Then, the tanh and Sigmoid functions' output will be multiplied to

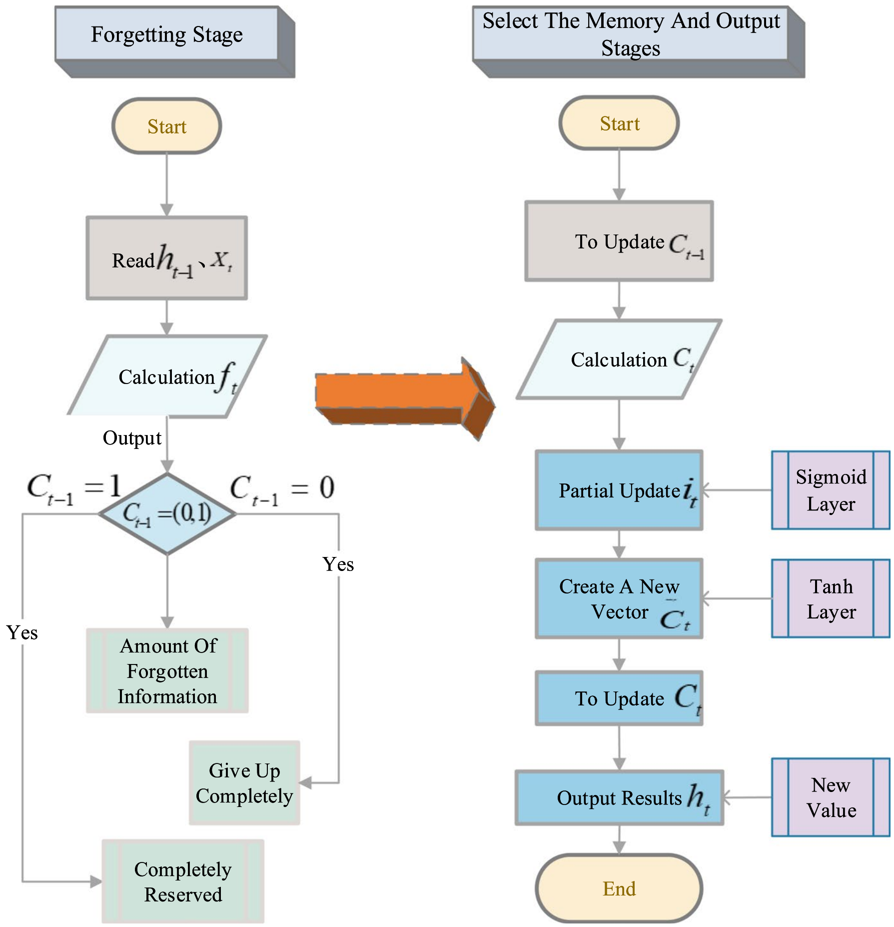

Fig. 4 Flow of LSTM algorithm at different stages

generate a numerical value $\in(-, 1)$ and re-imported into the model as the input signal. Lastly, the final output is determined. Equation (5) counts o_t based on the previous output and the current input using the output gate. Equation (6) calculates the final output h_t combined with the current cell states C_t and o_t[22, 23].

$$o_t = \sigma(W_0 \cdot [h_{t-1}, x_t] + b_0) \tag{5}$$

$$h_t = o_t \times \tanh(C_t) \tag{6}$$

Equation (7) calculates the parameters of one LSTM layer.

$$4[d_h(d_h + d_x) + d_h] \tag{7}$$

In Eq. (7), d_x represents the input, and d_h stands for the output.

Equation (8) calculates the parameters of one bidirectional LSTM layer.

$$2 \times 4[d_h(d_h + d_x) + d_h] \tag{8}$$

3.5 LSTM-based OPS prediction model on OPEs

The LSTM function is visualized by simulating the dynamic evolution of OPS on OPE using facts, evidence, and public statements. Suppose an OPE happens, and then the OPS on OPE ferments over the IoT and comes to a turning point when the public attention shifts from the real "victim" to their private sentiments. Then, anyone involved in this OPE might become the center of attention for an emotional outlet, and new information will be added. LSTM can simulate such sequential events to yield a reliable OPS prediction based on the state of OPE and OPS evolution. Figure 5 manifests the simulation prediction diagram.

Figure 5 shows the simulation and prediction of the LSTM-based OPS prediction model. This model simulates the evolution of OPS. Firstly, it uses web crawler technology to obtain the text quantity of the public emergency-induced OPS. OPS is generated on a specific OPE. Then, the data are standardized using the deviation standardization method. The initial OPE will be forgotten, and the model selectively inputs and stores information according to the evolution of OPS. Then, the LSTM model is used to train the model. The input data format of the neural network is in matrix form. During the training process, LSTM_1 and LSTM_2 network structures obtain the number of hidden layer training layers through multiple training. The

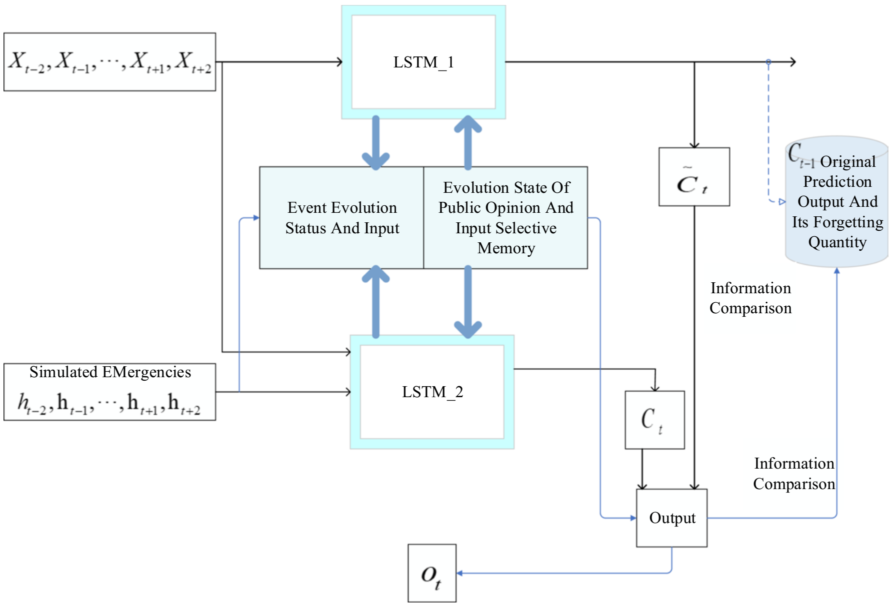

Fig. 5 LSTM-based OPS prediction model

memory unit C_t is refined through continuous training, which improves the training accuracy of the LSTM model. Finally, the original output results are obtained according to the information comparison. The purpose is to predict the new round of OPS information and then select the event results to tell the evolution in the dynamic deduction process of OPS.

4 Experimental design and performance evaluation

4.1 Datasets collection

LSTM is a time-cycle NN suitable for processing and predicting events with relatively long intervals and delays in time series. Here, eight hotspot cases of public emergencies in August 2021 are screened and analyzed by Yifang software. They are the sexual assault of Alibaba employees, the Wu Yifan incident, the death of a 22-year-old Henan woman in Tibet on foot, celebrity corruption rectification, Henan floods, fraud on online-dating websites, food-hygiene concerns, and micro camera peeping events. Then, the experimental data are collected to predict the OPS within the time node of 1 ~ 4 days from the beginning of a public emergency. Table 2 gives the experimental case data.

4.2 Experimental environment

Here, the centos6.8 environment is used on a personal computer with a Windows or Linux operating system. TensorFlow and Python3.6 are deployed together with the Pychart Linux Python development tool and Tensorflow running environment. At the same time, the hardware environment chooses the Intel Xeon Platinum 8163

Table 2 Data about experimental cases

Public emergency	Hotness	Continued time on the list
Sexual assault of Alibaba employees	1,236,367	2 h 55 min
WuYifan incident	1,828,568	1 h 28 min
A 22-year-old Henan woman died on foot in Tibet	1,870,775	5 h 25 min
Celebrity corruption rectification	1,177,187	2 h 3 min
Henan flood	5,505,862	7 h 40 min
Fraud on online dating websites	807,045	4 h 7 min
Food hygiene concern	1,111,067	4 h 36 min
Micro camera peeping	383,733	31 min

Data source: microblog history search; website: http://weibo.zhaoyizhe.com

2.5 GHz Central Processing Unit (CPU), with a 250G hard disk and an 8 GB Random Access Memory (RAM).

4.3 Hyperparameters setting

IN LSTM NN training, the data are scaled to solve the sequence prediction problem. When the network is suitable for scale-free data with a series of values, the input with large values may slow down the learning and convergence speed of the network. In some cases, it will prevent the network from learning objectively. Before fitting the LSTM model to the dataset, the data must be converted. Before fitting the model and making predictions, data are preprocessed by the following steps.

First, sequence data are converted into static ones. Specifically, the difference with a lag of 1 is used to eliminate the growth trend in the data.

Second, the time series problem is transformed into a supervised learning problem. Specifically, the data group follows the input–output mode. It can take the observation value of the previous time step as input to predict the observation value of the current time state.

Third, the observed value is converted into a specific interval. Specifically, the data are scaled to [-1, 1] to meet the default hyperbolic tangent activation function of LSTM. Before the calculated value and error value are derived, these transformations are reversed on the predicted value to return to the original interval.

Hyperparameter settings are shown in Table 3.

4.4 Performance evaluation

This section analyzes eight OPEs and the hottest OPS in August 2021 using Apache Ant software. Then, OPS information within four days is predicted from the beginning of the public emergency using the LSTM-based OPS prediction model. Figure 6 compares the predicted and the real amount of OPS information.

Figure 6 implies that, over time, the amount of OPS information is relatively stable within 1–2 days of the event. By the third day, OPS information have gradually decreased until it disappears. It is speculated that the event may end temporarily. In the third and fourth days, the OPS information reappears with an increasing trend. Possibly, the event has a new starting point and has started to attract attention. Then, the LSTM mode-predicted OPS information is fitted with the curve of real OPS

Table 3 Hyperparameter setting

Parameter	Numerical value
Learning rate	0.002
Training rounds (epoch)	500
Batch_size	1
Activate function	sigmoid
Feature learning function	LSTM

information. As a result, the LSTM-based OPS prediction model is feasible to mine the OPS evolution on OPEs. However, there is still some irrelevance.

Next, the LSTM model is optimized based on the first-order Adam optimizer to replace the traditional Stochastic Gradient Descent (SGD) process. Adam optimizer can iteratively update the NN weight based on the training data.

Further, Backpropagation Neural Network (BPNN) is used to learn the hotness of OPS on OPE. Figure 7 presents the hotness of OPS on OPE under different models.

As in Fig. 7, the average hotness of OPS under the BPNN model is $1.55 * 10^5$ times, which is far greater than the actual value. Under the Adam-LSTM model, the OPS hotness is $1.40 * 10^5$ times, compared with $1.43 * 10^5$ of the average hotness of the real OPS, with a tiny deviation. The Adam optimizer has optimized the LSTM model with higher prediction accuracy. Meanwhile, it requires less memory and has a gradient diagonal in scaling invariance. Hence, the Adam optimizer is suitable for optimization problems with large-scale data and parameters. Figure 8 compares the prediction errors of different models.

According to Fig. 8, the relative error is Adam-LSTM model < LSTM model < BP model. The Mean Relative Error (MRE) of the Adam-LSTM, LSTM, and BPNN models in predicting OPS is 0.06, 0.10, and 0.14, respectively. Therefore, the proposed Adam-LSTM model can reduce the relative prediction error on the hotness of OPS on OPE. The Adam algorithm is suitable for non-stationary targets and problems with high noise or sparse gradients, and it can explicitly explain hyperparameters using a few parameters.

In case of a public emergency, instantaneous, comprehensive, and authentic news coverage is essential. The news-releasing agency must be authoritative and claim full social responsibilities. Otherwise, OPS might evolve towards resentment and outrage. Remarkably, cyberspace has shown an increasingly important discourse power in ideological reconstruction. The conflict of interests and discourse power

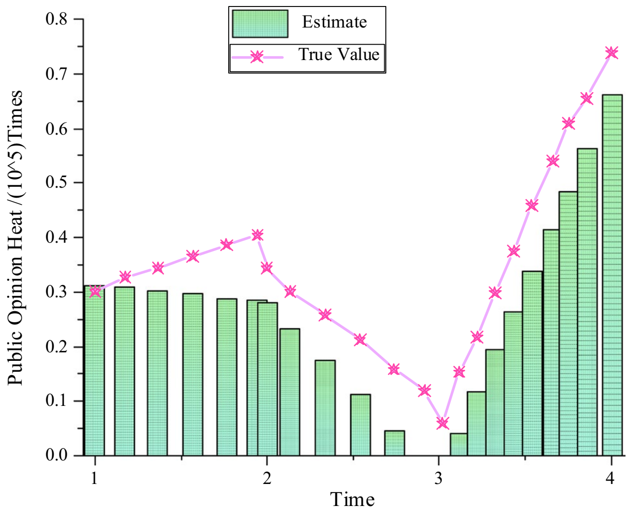

Fig. 6 Comparison between the LSTM-predicted and real amount of OPS information

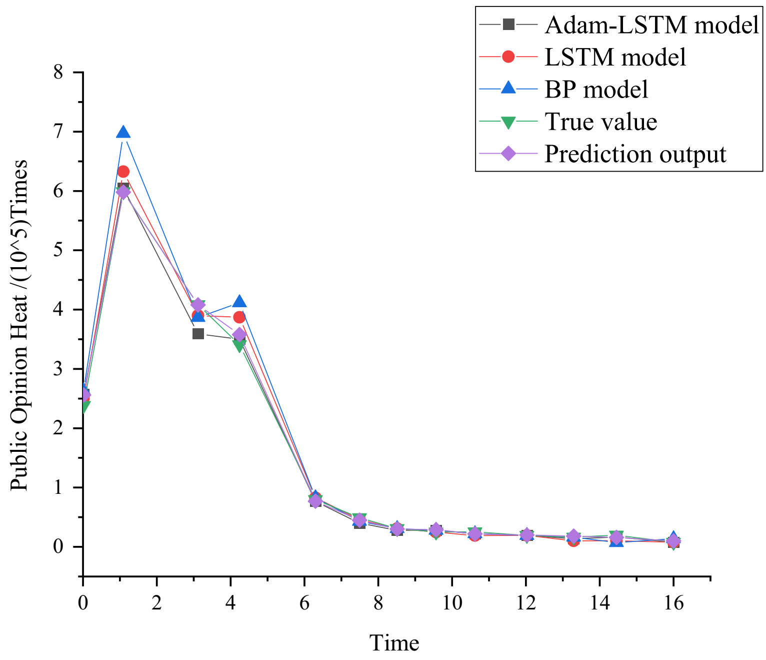

Fig. 7 Hotness of OPS on OPE under different models

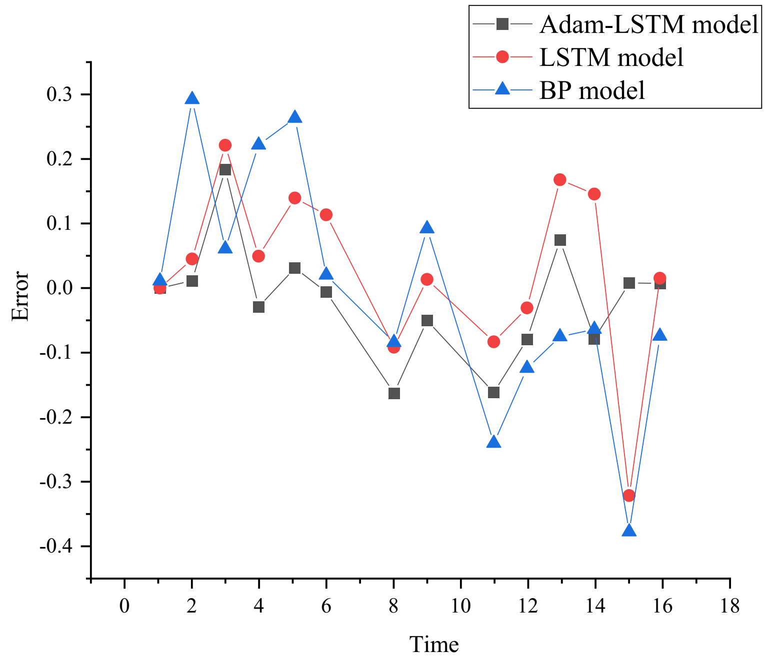

Fig. 8 Relative errors of different models on OPS prediction

competition behind OPEs is becoming increasingly intense. As more people prefer online space to real life, a harmonious online ecological environment can contribute to OPE governance and rumor prevention. The superficial, rigid, and monotonous management will never work. The government should adhere to people-orientation and emotion-tending principles to maintain and purify the network environment. In other words, administrators should actively carry out monitoring and early warning on social mentality and group emotions and enhance interaction with Internet users. Furthermore, they should actively guide Internet users and intervene appropriately based on root cause analysis of social emotions and mentality changes affecting OPS. The online ecological environment must be given full consideration from a universal and systematic perspective in this process. Eventually, analyzing the dynamic evolution of OPS on OPEs can provide experience and reference for future public sentiment guidance. The suggestions are detailed in several steps below.

First, mastering laws about OPS is a prerequisite for the practical guidance of the OPS evolution. For example, webcasts, short videos, and other platforms have become a new path of information dissemination. Young netizens are among the most active online public. On the other hand, online information dissemination features high diversification, mobility, fragmentation, and socialization. Thus, it makes OPE management and cripples the old management concept of hierarchical authentication more complex. The real-time government response has risen to top priority. Accordingly, China has issued laws for major institutions to release authoritative information on public opinions within 5 h and hold a press conference within 24 h. This has put forward clear requirements for the release of public emergency information.

Second, the timely announcement and interventions are the basic guarantee for effective OPE guidance. Relative authorities should report the OPE uninterruptedly, upholding a responsible, serious, and sincere attitude instead of sealing, blocking, deleting, or intentionally postponing the information. In specific operations, the official microblog, WeChat, and official websites can form an authoritative information release matrix to track OPS dynamic evolution and refute false information in time. Meanwhile, the government should pay attention to the timely disclosure of relevant information at all stages of event disposal and highlight the importance and responsibility consciousness of related departments.

Third, clear announcements should be made with the help of mainstream media and third parties. As the "gatekeeper" and the "ballast" of OPS in the information age, the mainstream media is responsible for guiding OPS and stabilizing society after OPEs. They play an essential role in eliminating false and preserving the truth of network information, correcting and restraining netizens' emotions, responding to concerns, and dispelling doubts. It is the bridge and link between the departments involved and the public. Mainstream media also help OPE governance and OPS guidance. Additionally, with the help of authoritative third parties, such as relevant experts, scholars, and popular science accounts, it is conducive to condensing people's hearts and supporting the disposal work.

Fourthly, offline disposal is fundamental for effective OPS governance. The focus should be cast on calming OPS, fundamentally solving problems, and resolving contradictions as far as possible. Experience shows that the public is primarily concerned with solving offline problems, such as rescue progress, cause investigation, hidden danger, system repair, and casualty arrangement.

4.5 Discussion

This paper mainly analyzes applying LSTM to predict public emergencies-triggered OPS dynamic evolution under the IoT environment. Han et al. (2021) put forward corresponding strategies for OPS evolution using information communication, cluster analysis, and synergy theories to study the development of OPS in public emergencies [24]. Their result echoes the research findings of the present work: rapid interpretation and control of OPS on public emergencies through the IoT dramatically reduces the occurrence of irreversible events after the OPE outbreak. Li et al. (2020) studied the classification and prediction of OPS in public emergencies through case analysis, literature research, and system clustering methods. They established the OPS prediction model for different public emergencies [25]. However, the factors of the OPS evolution are complex under different public emergencies. The literature method cannot comprehensively predict and control the OPS during public emergencies and might cause a single and one-sided dynamic deduction. Therefore, this paper uses IoT-native big data to pinpoint specific OPS hotness and effectively solve one-sided deduction problems. Jia et al. (2020) studied the OPS data on public emergencies using data mining to timely excavate users' emotional development and reply in time [26]. Their research findings suggest that the OPS hotness prediction is highly significant in OPS control. Based on this, the present work simulates and predicts the specific OPS hotness on OPE using AI, big data, and LSTM NN technologies based on IoT. The LSTM model is optimized by the Adam optimizer. As a result, the proposed Adam-LSTM model can minimize the relative error between the real and the predicted hotness of OPS. As such, the government can control the OPS on public emergencies according to the time node and reduce the negative impact of OPS evolution.

5 Conclusion

A study is conducted on the dynamic evolution of OPS in public emergencies and to predict the hotness of OPS through AI technologies under IoT and big data. The proposed Adam-LSTM model is mainly implemented based on LSTM (used for OPS hotness prediction) and optimized by the Adam optimizer. The numerical results corroborate that the LSTM-predicted OPS information fits well with the curve of real OPS information. It proves that it is feasible to use LSTM to mine the OPS evolution in public emergencies. Besides, the average hotness of OPS under the BPNN model is $1.55 * 10^5$ times, which is much greater than the real value. By comparison, under the proposed Adam-LSTM model, the predicted hotness is $1.40 * 10^5$ times, very close to real OPSS hotness ($1.43 * 10^5$ times). The MRE of the proposed Adam-LSTM, LSTM, and BPNN in predicting OPS is 0.06, 0.10, and 0.14, respectively. Therefore, the predicted OPS hotness under the proposed Adam-LSTM model is the closest to the real value. Finally, the errors of the three models are compared. The Adam-LSTM model can minimize the relative error between the real and the precited OPS hotness in public emergencies.

Some deficiencies in this work need further exploration. Factors affecting the dynamic evolution of OPS on OPEs are extremely complex and much trivial. First, the factors that affect the dynamic evolution of public opinion in public emergencies are the subject of public opinion and the objective reasons for the evolution of public opinion. There are too many influencing factors. In addition, due to the limited data selected from the model training dataset, the model prediction results may be affected. Therefore, the research on the dynamics of OPS for public emergencies needs to be further deepened. In the future, factors affecting the dynamic evolution of OPS on OPEs will be screened before model implementation to improve the LSTM-based OPS prediction model. Thereby, the proposed model will help effectively guide OPS and control OPEs in the future. Additionally, because OPEs sometimes cause great changes and fluctuations in IoT-native data, the research might present a relative error. Follow-up research can collect more extensive research data and investigation, expanding the practical application ability of the research model.

Acknowledgements The authors acknowledge the help from the university colleagues.

Fundings This research was supported by the project "Research on the dynamic evolution mechanism of network public opinion of public emergencies and the ability of local governments to cope with them" (Grant No. 21wsk169) (Wenzhou Philosophy and Social Science Planning in 2021).

Data availability statement The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Declarations

Conflict of interest All Authors declare that they have no conflict of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent Informed consent was obtained from all individual participants included in the study.

References

1. Cui H, Kertész J (2022) Born in Rome or Sleeping Beauty: Emergence of hashtag popularity on a microblogging site. arXiv preprint arXiv, 2203(1):14802. https://doi.org/10.48550/arXiv.2203.14802
2. Miravet-Verde S, Burgos R, Delgado J et al (2020) FASTQINS and ANUBIS: two bioinformatic tools to explore facts and artifacts in transposon sequencing and essentiality studies. Nucleic Acids Res 48(17):e102–e102. https://doi.org/10.1093/nar/gkaa679
3. Song S, Guo Z, Wang X et al (2021) RETRACTED ARTICLE: The correlation between social transformation economic risk and Internet public opinion. Behav Inf Technol 40(7):723–733. https://doi.org/10.1080/0144929X.2020.1722750
4. Larrouquere L, Gabin M, Poingt E et al (2020) Genesis of an emergency public drug information website by the French Society of Pharmacology and Therapeutics during the COVID-19 pandemic. Fundam Clin Pharmacol 34(3):389–396. https://doi.org/10.1111/fcp.12564

5. Muniz-Rodriguez K, Ofori SK, Bayliss LC et al (2020) Social media use in emergency response to natural disasters: a systematic review with a public health perspective. Disaster Med Public Health Prep 14(1):139–149. https://doi.org/10.1017/dmp.2020.3
6. Merkley E, Bridgman A, Loewen PJ et al (2020) A rare moment of cross-partisan consensus: Elite and public response to the COVID-19 pandemic in Canada. Can J Polit Sci/Revue Canadienne de science politique 53(2):311–318. https://doi.org/10.1017/S0008423920000311
7. Boon-Itt S, Skunkan Y (2020) Public perception of the COVID-19 pandemic on Twitter: sentiment analysis and topic modeling study. JMIR Public Health Surveillance, 6(4):e21978. https://doi.org/10.2196/21978
8. Zhang W, Wang Y, Yang L et al. (2020) Suspending classes without stopping learning: China's education emergency management policy in the COVID-19 outbreak. J Risk Financ Manage 13(3):55. https://doi.org/10.3390/jrfm13030055
9. Wang B, Wang E, Zhu Z et al. (2021) An explainable sentiment prediction model based on the portraits of users sharing representative opinions in social sensors. Int J Distrib Sens Netw 17(10):15501477211033765. https://doi.org/10.1177/15501477211033765
10. Shen L, Yao R, Zhang W et al (2021) Emotional attitudes of Chinese citizens on social distancing during the COVID-19 outbreak: analysis of social media data. JMIR Med Inf 9(3):e27079. https://doi.org/10.2196/27079
11. Xiao Y, Li J, Zhu Y et al (2020) User Behavior prediction of social hotspots based on multimessage interaction and neural network. IEEE Trans Comput Soc Syst 7(2):536–545. https://doi.org/10.1109/TCSS.2020.2969484
12. Tavoschi L, Quattrone F, D'Andrea E et al (2020) Twitter as a sentinel tool to monitor public opinion on vaccination: an opinion mining analysis from September 2016 to August 2017 in Italy. Hum Vaccin Immunother 16(5):1062–1069. https://doi.org/10.1080/21645515.2020.1714311
13. Yadav A, Vishwakarma DK (2020) Sentiment analysis using deep learning architectures: a review. Artif Intell Rev 53(6):4335–4385. https://doi.org/10.1007/s13042-018-0799-4
14. Jain PK, Yekun EA, Pamula R et al (2021) Consumer recommendation prediction in online reviews using Cuckoo optimized machine learning models. Comput Electr Eng 95(1):107397. https://doi.org/10.1016/j.compeleceng.2021.107397
15. Munawar H S, Qayyum S, Ullah F et al. (2020) Big data and its applications in smart real estate and the disaster management life cycle: a systematic analysis. Big Data Cognit Comput 4(2:4. https://doi.org/10.3390/bdcc4020004
16. Murphy J, Link MW, Childs JH et al (2014) Social media in public opinion research: Executive summary of the AAPOR task force on emerging technologies in public opinion research. Public Opin Q 78(4):788–794. https://doi.org/10.1093/poq/nfu053
17. Han X, Wang J, Zhang M et al (2020) Using social media to mine and analyze public opinion related to COVID-19 in China. Int J Environ Res Public Health 17(8):2788. https://doi.org/10.3390/ijerph17082788
18. Ding G, Qin L (2020) Study on the prediction of stock price based on the associated network model of LSTM. Int J Mach Learn Cybern 11(6):1307–1317. https://doi.org/10.1007/s13042-019-01041-1
19. Zheng H, Lin F, Feng X et al (2020) A hybrid deep learning model with attention-based conv-LSTM networks for short-term traffic flow prediction. IEEE Trans Intell Transp Syst 22(11):6910–6920. https://doi.org/10.1109/TITS.2020.2997352
20. Lu W, Rui H, Liang C et al (2020) A method based on ga-cnn-lstm for daily tourist flow prediction at scenic spots. Entropy 22(3):261. https://doi.org/10.3390/e22030261
21. Ma D, Song X, Li P (2020) Daily traffic flow forecasting through a contextual convolutional recurrent neural network modeling inter-and intra-day traffic patterns. IEEE Trans Intell Transp Syst 22(5):2627–2636. https://doi.org/10.1109/TITS.2020.2973279
22. Kumar A, Islam T, Sekimoto Y et al. (2020) Convcast: An embedded convolutional LSTM based architecture for precipitation nowcasting using satellite data. Plos One 15(3):e0230114. https://doi.org/10.1371/journal.pone.0230114
23. Poth CN, Bulut O, Aquilina AM et al (2021) Using data mining for rapid complex case study descriptions: Example of public health briefings during the onset of the COVID-19 pandemic. J Mixed Methods Res 15(3):348–373. https://doi.org/10.1177/15586898211013925
24. Li L, Zhang Q, Wang X et al (2020) Characterizing the propagation of situational information in social media during covid-19 epidemic: A case study on weibo. IEEE Trans Comput Soc Syst 7(2):556–562. https://doi.org/10.1109/TCSS.2020.2980007

25. Jia Q, Guo Y, Wang G et al. (2020) Big data analytics in the fight against major public health incidents (Including COVID-19): a conceptual framework. Int J Environ Res Public Health 17(17):6161. https://doi.org/10.3390/ijerph17176161