Public Opinion Crisis Management via Social Media Mining

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***Abstract*—Enterprises suffer tremendous economic and reputational losses in public opinion crises. However, providing specific guidance for enterprises to respond effectively to public opinion crises is challenging. This study proposes a netizen-centered approach to identify crisis response opportunities for enterprises by mining social media data. First, we identify the topics discussed by netizens with the Biterm Topic Model, thereby evaluating their importance levels. Then, the negativeness levels of crisis topics are quantified by sentiment analysis. Lastly, crisis response opportunities are quantitatively identified and prioritized by applying an opportunity algorithm that simultaneously considers each crisis topic's importance and negativeness levels. Experimental results demonstrate the validity and superiority of our approach. Moreover, we demonstrate that a very negative and less important topic in the growth stage will likely become very negative and important at the maturity of the crisis. This finding supports decision-making in response to critical topics at the early stage of a crisis, preventing the deterioration of the public opinion crisis.**

***Index Terms*—Crisis response opportunity, Topic modeling, Sentiment analysis, Opportunity algorithm.**

I. Introduction

IN 2017, United Airlines stock fell 4%, wiping out 800 million dollars in just three days, because of the negative public opinion triggered by forcibly dragging a passenger off an overbooked flight [1]. Investors are vulnerable to negative public opinions, which may result in irrational investments and abnormal stock price movements [2]–[4]. Listed companies suffered tremendous economic and reputational losses during the public opinion crises. It is critical for listed companies to take action, responding to crises quickly to reduce financial losses. The matching of information demands and supplies between the public and opinion crisis managers directly determines the effectiveness of crisis responses [5]–[7]. Therefore, understanding public concerns and attitudes from a netizen-centered perspective is essential for listed companies in developing effective response strategies.

This paper was supported by the National Natural Science Foundation of China (72274096, 72174087,72301136), Foreign Cultural and Educational Expert Program of the Ministry of Science and Technology of China (G2022182009L). (*Corresponding author: Peng Wu*)

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Social media data generated by netizens provides invaluable opportunities for understanding public concerns and attitudes in crises [8]–[10]. Researchers have attempted to mine public opinions from social media to improve crisis response strategies [11]–[13]. Most of these studies considered the important topics concerned by netizens as references to make emergency decisions [1], [11], [12], [14]. However, negative sentiments are the main driving force of the spreading of public opinions and the consequent stock price crash [15], [16]. Listed companies may preferentially deal with crisis topics with high significance and negativeness. We define these topics as crisis response opportunities because identifying those very important and negative topics helps the companies in the crisis vortex respond quickly to the issues that are most concerned by the public [12].

Therefore, in such a scenario, a quantitative and multi-disciplinary method for measuring crisis response opportunities is necessary [17]. Additionally, public attention changes over time. Crisis communication and response is time-sensitive [14]. These factors emphasize the importance of dynamically monitoring the changes in public opinion, so that opinion crisis managers can prevent the deterioration of the public opinion crisis. To extract knowledge from social media for listed companies' decision-making during public opinion crises, we pose the following research questions.

- RQ1: How to effectively capture public concerns and attitudes from social media data?
- RQ2: How to identify and rank crisis response opportunities to deliver decision support for companies?
- RQ3: What crisis response opportunities should be concerned in each phase of a public opinion crisis?

In this paper, we propose a quantitative approach to address the above questions. We identify the crisis response opportunities from the netizen-centered view for listed companies by combining topic mining, sentiment analysis and an opportunity algorithm [18], [19]. Firstly, crisis topics discussed by netizens on social media are firstly identified by a Biterm Topic Model (BTM) [20]. Their importance is measured by the ratio between the number of posts related to the crisis topic and the number of total posts about the crisis event. Secondly, the negativeness level of a crisis topic is quantified by using a BERT [21] classifier. Lastly, we measure the crisis response opportunities from the dimensions of importance and negativeness. The keywords of each crisis topic can be employed to develop specific and operable response strategies in real-world applications. We also analyze the crisis response opportunities in different phases based on a life-cycle theory [22].

The framework of identifying crisis response opportunities makes fourfold contributions. First, compared with previous works that simply considered important topics in their response mechanisms [1], [11], [23], we introduce both topic and sentiment measures to analyze public concerns and attitudes towards a crisis. Second, quantifying and ranking crisis response opportunities can indicate explicit crisis response directions and provide their priorities. Third, we identify the crisis response opportunities in each crisis phase and intuitively provide early warning signals. Fourth, experimental results of 20 crisis cases demonstrate that sensitive crisis topics with high negativeness despite low importance in the growth phase are significantly more critical in the next maturity phase and maintain high negativeness levels. Our approach can effectively capture them as crisis response opportunities in the growth phase and give them a higher priority. The framework is a practical tool for listed companies to respond to public opinion crises, thereby minimizing reputational and economic losses. This study responds to the work of Martinez-Rojas et al. [9] and Elbanna et al. [24], which require a method that can minimize netizen opinion from social media data and supply guidance in visualization for crisis response. Besides, it can be applied to various contexts since our method is domain-independent and methodologically reproducible.

The remainder of this paper is organized as follows: Section II reviews the related work; Section III explains our approach, which identifies crisis response opportunities from social media data by combining topic mining, sentiment analysis and the opportunity algorithm; Section IV demonstrates our experimental analysis results; Section V shows the validity and superiority of our approach; finally, Sections VI and VII present the discussion, and conclusions together with the future perspectives, respectively.

II. Related work

A. Crisis response opportunity detection

In recent years, public opinion crises about listed companies have frequently occurred. Many researchers have carried out in-depth discussions on the selection of crisis response strategies based on Image Repair Theory (IRT) [25] and Situational Crisis Communication Theory (SCCT) [26], [27]. Zhang et al. [28] indicated that an informational repair strategy, explaining and clarifying the focus issues of netizen concerns, is an effective response strategy. Providing authentic and reliable crisis information and interacting with stakeholders in time can reduce the negative impacts of a crisis event [29]. Crijns et al. [5] argued that personalized and accurate responses against negative public opinion are conducive to an organization's reputation. These qualitative studies provided valuable insights into different crisis response strategies and their effects. However, these qualitative studies failed to mine and conclude the concerns of netizens by quantitatively analyzing big data.

Social media data generated by netizens have been used for crisis response as a valuable resource for understanding public opinions [1], [9], [10]. Many researchers attempted to understand the concerns of netizens as references to make targeted crisis responses, such as extracting the information requirements of netizens in Tianjin Port Explosion Incident by an interactive topic modeling approach [11], analyzing the most discussed topics in a hurricane disaster by Latent Dirichlet Allocation (LDA) [12], [13], and extracting attribute preferences of public concern by text mining [23]. However, these studies only considered the important topics concerned by netizens as references to make emergency decisions. Negative sentiments are highly contagious in social networks [30], [31]. The seemingly unimportant topics with very negative sentiment polarities at the very beginning possibly trigger the spreading of public opinion crises [32]. It is necessary to consider the negative sentiment level of topics as references to gain a broad spectrum of the life-cycle of public crisis management.

Recently, a few studies attempted to combine topic detection and sentiment analysis for crisis response [33], [34]. Wang et al. [33] attempted to detect public opinion topics in multidimensional public opinion networks. By defining the psychological scores of paired keywords, they analyzed the sentiment tendency of each topic. However, they did not identify and rank crisis response directions to deliver specific decision support. Understanding the priorities of crisis response directions is beneficial to both optimize the resource distribution and design effective response strategies [12]. Despite the great contributions made by existing studies, some defects have been detected: (1) Most existing studies only focused on modeling topics in emergency decision-making, whereas the sentiments of netizens in those topics were ignored. (2) Lacking quantitative methods for analyzing the opportunity levels for crisis response and deriving their priorities. (3) Most research about emergency response mainly focused on natural disasters and public safety events [9], and little research mines social media data to provide guidance about how to respond to crises on behalf of the listed companies.

In this study, the crisis topics with high importance and low satisfaction (i.e., high negativeness) are highlighted as "crisis response opportunities" for the listed companies. We rank the opportunities with an opportunity algorithm to integrate the measures from the two dimensions. Thus, the ranking is more informative than previous decision-making methods based on a single dimension (either topic or sentiment). The comparison of our work with previous studies for crisis response is shown in Table I.

B. Topic modeling in crisis response

Targeted and personalized response to negative public opinion is beneficial to crisis communication and organizational reputation [5], [6]. Topic modeling is one of the most useful text-mining techniques used to analyze textual content and infer hidden topics in textual documents [36], [37]. It has been widely used to capture the concerns of netizens from social media data [11]–[13], [33], [38], [39]. LDA [40] is the most popular topic model in text analysis [36]. It works well on lengthy documents [36]. However, social media texts are typically short text data. Identifying topics from social media texts is a challenging task for LDA because a short text does not contain sufficient contexts to capture the word co-occurrence information [36].

TABLE I
COMPARISON OF OUR WORK WITH PREVIOUS STUDIES FOR CRISIS RESPONSE.

Studies	Research problem	Topic	Sentiment	Ranking	Research field
[11]	Detecting information requirements	√			Public safety
[14]	Extracting hot topics	√			Public safety
[23]	Emergency risk decision	√		√	Public safety
[12]	Prioritizing victims' concerns	√		√	Disaster
[35]	Sentiment analysis of victims' demands		√		Disaster
[33]	Topic detection in public opinion network	√	√		Public safety
[1]	Identifying terms effecting stock prices	√			Finance
Ours	**Crisis response opportunity**	√	√	√	**Finance**

BTM models word co-occurrence patterns (i.e., biterms) on the corpus-level and can effectively identify topics in short texts. BTM achieved outstanding performance for identifying topics from social media texts, such as real-time Twitter [41], micro-blog short text data [42] and headline-based social news [43]. Existing studies show that BTM is an effective method to identify latent topics from short texts. Therefore, we adopt the BTM to identify crisis topics that netizens discuss on social media.

C. Sentiment analysis for crisis topics

Deep learning-based models have been powerful techniques for sentiment analysis tasks [44], [45]. Bidirectional Long Short-Term Memory (BiLSTM) [46] and LSTM [47] are popular models due to their advantages in processing sequence data [48]. Some scholars proposed several effective LSTM- and BiLSTM-based models for sentiment [49], [50]. Moreover, BERT has been shown as an effective tool for sentiment analysis with excellent accuracy [51]–[53]. BERT [21] can better understand words in a context, because it has learned substantial semantic and syntactic information during its pre-training procedure on large corpora. Although large language model (LLM) technologies have achieved remarkable results in natural language processing [54], [55], their performances were frequently exceeded by expert systems in specific domains [56], including sentiment analysis [57]. This is because expert systems were fine-tuned on domain-specific data, guided by task-oriented objectives. In this study, we use a BERT-based sequence classification model for sentiment analysis to measure the negative sentiment levels of the crisis topics. The BERT model is fine-tuned on our prepared dataset to learn domain-specific information about crisis events of listed companies and their associated sentiment polarities. LLMs are not adopted because of their large size and high computational demands.

D. Opportunity algorithm

Understanding the priorities of crisis response directions in crises is crucial to the success of crisis response [11], [12], [35]. The opportunity algorithm proposed with outcome-driven innovation (ODI) is useful for prioritizing unmet needs [18]. It quantifies opportunity significance by simultaneously considering the importance and satisfaction dimensions. The needs with high importance and low satisfaction are assigned higher scores, which are the identified improvement opportunities [18]. The need with the highest opportunity score has the best priority.

The opportunity algorithm has been employed in detecting product improvement opportunities [58], [59] and mining customer complaints and needs [60]. The opportunity algorithm is a simple yet effective method that integrates the measures of importance and sentiment into a matrix. Therefore, it is a suitable method to identify and prioritize crisis response opportunities in this study.

In summary, the main innovations of this study are as follows. (1) Compared with most previous works that simply focused on topic detection and tracking in their response mechanisms [1], [11], [23], we propose a framework to identify crisis response opportunities that can simultaneously consider public concerns and attitudes by topic modeling and sentiment analysis. Moreover, the proposed approach can effectively capture sensitive crisis topics with high negativeness despite low importance in the growth phase and give them a higher priority. (2) This study provides a quantifiable approach for identifying and prioritizing crisis response opportunities using an opportunity algorithm, simultaneously considering the importance and negativeness levels. Compared with previous qualitative studies [5], [28], [29], [61], this study can indicate explicit crisis response directions and provide their priorities. (3) This study mines social media data from the crisis management perspective to provide decision support for listed companies. Previous research about emergency response mainly focused on natural disasters and public safety events [9], [12], [23]. This study mines social media data to provide decision support about crisis response on behalf of the listed companies.

III. METHODOLOGY

This study proposes a framework that identifies crisis response opportunities and delivers decision support for listed companies to respond to crises effectively. The proposed framework consists of three steps in Fig. 1. First, crisis topics are identified with a topic model from social media data generated by netizens. Their importance levels are measured by the ratio between the number of posts related to the crisis topic and the number of total posts about the crisis event. Next, the negativeness levels of netizens for the crisis topics are quantified by a sentiment analysis classifier. Finally, the opportunity level of each crisis topic is quantitatively evaluated by an opportunity algorithm considering its importance and negativeness levels. As a result, the crisis response opportunities are deduced from the crisis topics with high opportunity scores. The specific response strategies can be made according to the identified keywords in future practices. Details of each step are presented in the following subsections.

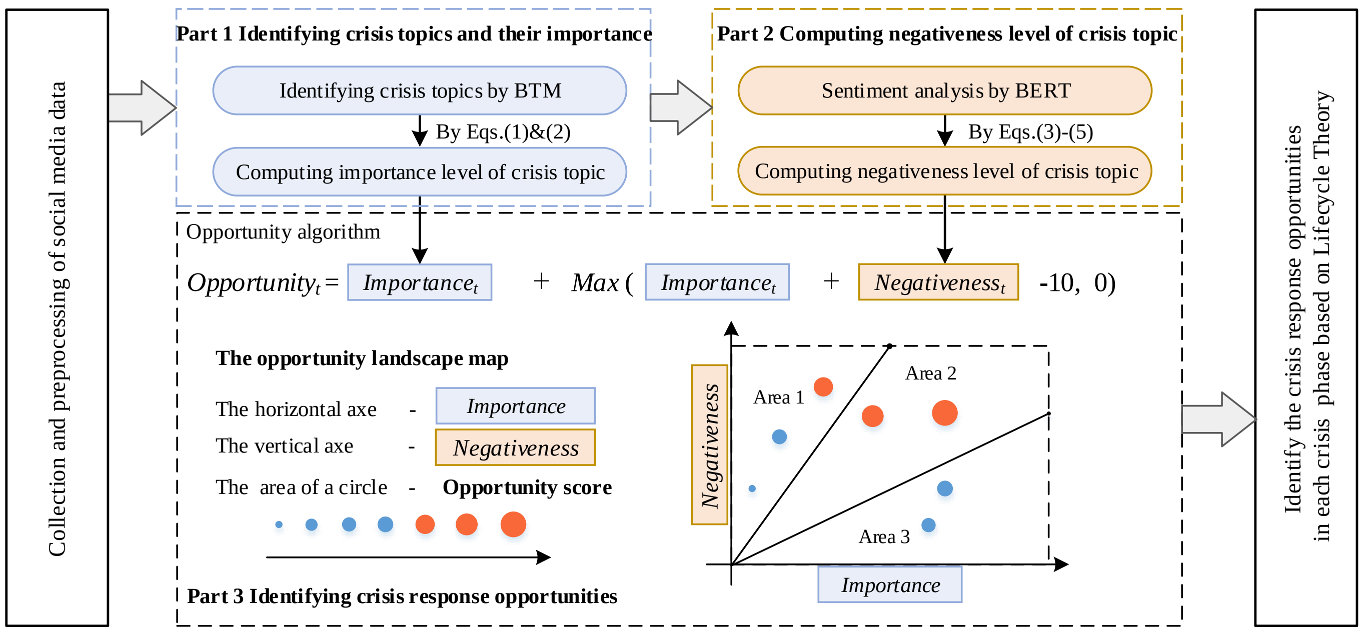

Fig. 1. Overview of the framework.

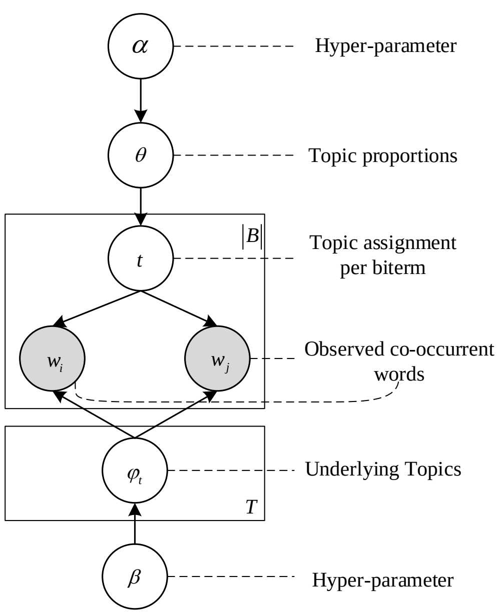

Fig. 2. Graphical model representation of BTM [20].

A. *Identifying crisis topics and their importance*

1) Identification of crisis topics: In this step, crisis topics are identified based on BTM. The BTM assumes that a biterm is a disordered word-pair co-occurring in a short text, where the two words in the biterm belong to the same topic [20]. The BTM models the topics from the whole biterm corpus instead of a single document. The modeling process of BTM is shown in Fig. 2. This method solves the problem of text sparsity in short text topic modeling and can effectively identify topics on short text data [36]. In this study, BTM is used to identify crisis topics from social media data generated by netizens.

Following previous research [11], the optimal topic number for BTM is determined by using coherence scores [62] in this study. Topic coherence is used to measure the semantic coherence of topics learned by topic models. The topic model with a higher coherence score is considered better in terms of its human interpretability [62]. Consequently, the posts published by netizens are input into the BTM, yielding n crisis topics $Topics = \{topic_1, topic_2, ..., topic_n\}$ for the posts.

2) Computation of the importance level: Additionally, the importance level of each crisis topic can be measured by computing the extent to which each crisis topic is mentioned by netizens. A high number of posts related to a crisis topic indicates that the crisis topic is frequently mentioned. Thus, this crisis topic can be defined as an important topic related to the event. Crisis topics reflect the primary concerns of netizens, which need to demand immediate attention for listed companies. Accordingly, all posts related to the same crisis topic are combined into a single document set and denoted as $Doc(Topics) = \{doc(topic_1), doc(topic_2), ..., doc(topic_n)\}$. The volume of discussion surrounding a specific topic is a critical indicator for crisis managers. Therefore, the importance score of a crisis topic i (IT_i) is defined as the ratio between the number of posts related to the crisis topic (PN_i) and the total number of posts about a crisis event. IT_i is given by

$$IT_i = \frac{PN_i}{\sum_{i=1}^{n} PN_i}, i = 1, 2, ..., n, \tag{1}$$

After computing IT_i, we normalize it in the range of 0-10 to generate the importance dimension value $(Importance)$ by

$$Importance_i = 10 \times \frac{IT_i - IT_{Min}}{IT_{Max} - IT_{Min}}, \tag{2}$$

where IT_{Min} denotes the minimum value of IT for all crisis topics; IT_{Max} denotes the maximum value of IT for all crisis topics.

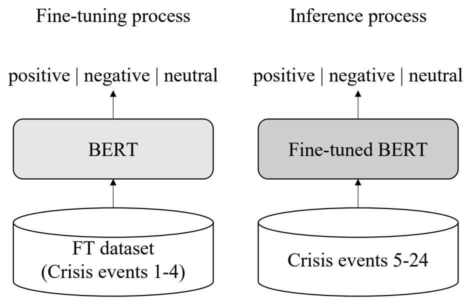

Fig. 3. Illustration of the sentiment classification based on fine-tuned BERT.

TABLE II
THE DETAILED STATISTICS OF FT DATASET.

Sentiment Polarity	Total	Train	Valid	Test
Positive	14047	11238	1405	1404
Negative	19412	15529	1942	1941
Neutral	16541	13232	1654	1655

B. Computing the negativeness level of crisis topic

1) Sentiment analysis using BERT: In this step, we aim to identify the sentiment polarities of posts by using a fine-tuned BERT model. The BERT model was pre-trained on large corpora to learn general semantic and syntactic information, then fine-tuning on our prepared dataset to learn domain-specific information that is about crisis events of listed companies and their associated sentiment polarities (positive, negative and neutral). Finally, we use the fine-tuned classifier to identify sentiment polarities. Fig. 3 illustrates the process of sentiment analysis based on fine-tuned BERT. In this work, the released BERT-base-chinese pre-trained model with 12-layer, 768-hidden, 12-heads leverage is employed [21]. Firstly, we collect 191,858 posts of 24 crisis cases about 20 listed companies from Guba[1]. These crisis cases occurred from June 1, 2015, to June 1, 2020. The overview of these crisis cases is shown in Appendix Table I. We randomly selected and manually labeled the sentiment polarities of 50,000 postings (19,412 negative posts, 16,541 neutral posts, and 14,047 positive posts) from crisis case 1 to crisis case 4 to build a domain-specific dataset. The labeled 50,000 posts are defined as the FT dataset that is used for fine-tuning the BERT to adapt the public opinion sentiment analysis task. 80% randomly selected posts are used for training the classifier; 10% posts are for validating; the rest of 10% posts are for testing. The detailed statistics of the FT dataset can be viewed in Table II. We employ the fine-tuned classifier and the associated training stop point and parameter setups that yield the highest accuracy on the validation set for downstream sentiment analysis of 20 crisis events (crisis case 5 to crisis case 24).

2) Computation of the negativeness level: Additionally, the satisfaction and negativeness levels of a crisis topic can be measured by analyzing the sentiment polarity (positive, negative, or neutral) of the posts belonging to each crisis topic. In this study, we use non-negative emotions to present satisfaction. Neutral posts also represent the non-negative emotions, indicating that the state has not triggered their intense negative emotions. The satisfaction level of the crisis topic i ($Satisfaction_i$) is given by

$$ST_i^{Sat} = \frac{PN_i^{Pos} + PN_i^{Neu}}{PN_i}, \tag{3}$$

$$Satisfaction_i = 10 \times \frac{ST_i^{Pos} - ST_{Min}^{Pos}}{ST_{Max}^{Pos} - ST_{Min}^{Pos}}, \tag{4}$$

where ST_i^{Sat} is the satisfying sentiment of the topic i, PN_i^{pos} and PN_i^{neu} are the numbers of positive posts and neutral posts, respectively. PN_i is the total number of posts related to the crisis topic i. However, in this study, we prefer to use the negativeness score to reflect the degree of negative sentiment of netizens, identifying crisis response opportunities, rather than using the satisfaction score. According to the calculation method of $Satisfaction_i$ (Eq 3 and Eq 4), the negativeness score is given by

$$Negativeness_i = 10 - Satisfaction_i. \tag{5}$$

C. Identifying crisis response opportunities

In this step, the opportunity algorithm is used to identify and prioritize the crisis response opportunities for listed companies. The opportunity algorithm is proposed for prioritizing unmet needs [18]. The most important but least satisfied needs receive the highest priority. The original algorithm is defined as [18]:

$$\begin{aligned} Opportunity_i =& Importance_i + \\ & Max(Importance_i - Satisfaction_i, 0) \end{aligned} \tag{6}$$

Lower satisfaction means a higher negativeness level. Given its application in crisis management, it is more appropriate to use netizens' negativeness level to reflect the emotional dimension while making the visualization effect of the crisis graph more intuitive. Therefore, according to Eq 5 and Eq 6, the original opportunity algorithm is modified as the following equation:

$$\begin{aligned} Opportunity_i =& Importance_i + \\ & Max(Importance_i + Negativeness_i - 10, 0) \end{aligned} \tag{7}$$

The crisis topics that are most important and most negative have the highest opportunity scores (priorities) for crisis response. The ranked opportunities can be visualized with a landscape map (Fig. 4). In the map, the horizontal and vertical axes and the area of a circle indicate the importance, negativeness and opportunity scores, respectively. The opportunity landscape map is divided into three areas, constrained by the average of the importance score and the average of the negativeness score. Crisis topics in Area 1 represent the topics that are less important but very negative. These crisis topics are potentially at risk of aggravating. Crisis topics in Area 2 represent crisis topics that are frequently discussed

[1]Guba (http://guba.eastmoney.com/) is a popular financial social media platform in China. It has a special discussion site for each stock allowing netizens to express their opinions.

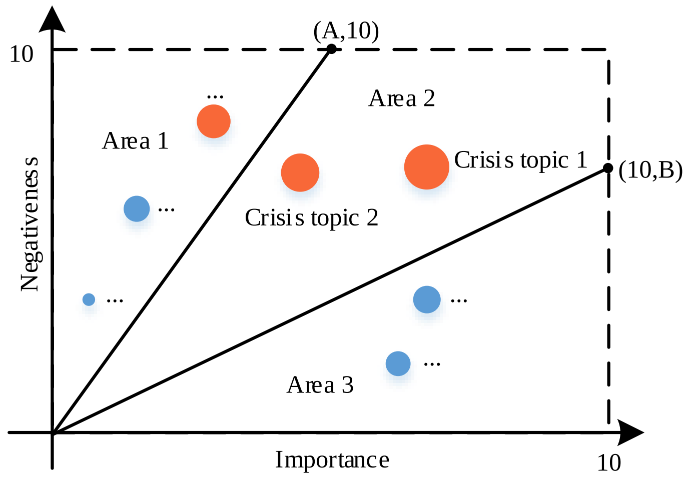

Fig. 4. The graphical representation of an opportunity landscape map. The horizontal and vertical axes indicate the importance and negativeness, respectively. The circles represent the crisis topics, and the size of the circle represents the opportunity score. The opportunity landscape map is divided into three areas, constrained by the average of the importance score (A) and the average of the negativeness score (B) of all crisis topics. These crisis topics with high opportunity scores indicate important crisis response opportunities. The crisis topics with the highest opportunity levels are highlighted in orange.

by netizens with very negative sentiments (high importance and negativeness scores). Crisis topics in Area 3 represent the topics that are important and less negative. Overall, those crisis topics with high opportunity scores indicate important crisis response opportunities.

IV. Experimental analysis

We first described the process of data collection and pre-processing in Section IV-A. Then, we present the process of identifying crisis response opportunities by the proposed approach based on a crisis case related to the listed company Tong Ren Tang Chinese Medicine (TRTCM) in Section IV-B. Finally, we conduct a statistical analysis of 20 crisis cases to prove the superiority of the proposed approach in Section IV-C.

A. Data collection and pre-processing

The 24 crisis cases selected in this study are subject to 22 listed companies. These crisis cases happened from June 1, 2015 to June 1, 2020. They were widely discussed on social media. Moreover, these crises resulted in abnormal stock price movements of the listed companies involved. The posts related to these crisis cases were collected from Guba. In total, we collect 191,858 posts, including the user ID, the title, the content, and the time of publication. The overview of these crisis cases is shown in Appendix Table I. Among them, the posts of crisis cases 1-4 are used to build a domain-specific dataset (FT dataset) to fine-tune the BERT model for sentiment analysis.

We cleaned the data by removing meaningless elements and performing Chinese word segmentation. The meaningless elements include hashtags, URLs, stop-words, special symbols and emoticons. Chinese word segmentation is performed to segment a sequence of Chinese characters in a sentence into a series of words. We also remove business advertisements and meaningless documents. Advertisements and meaningless documents are posts and comments with more than 150 words and do not contain keywords related to the involved companies.

B. Results of identifying crisis response opportunities for TRTCM

1) Identifying crisis topics and their importance: We employed the Biterm 0.2.0 Python package to implement BTM to identify the crisis topics against TRTCM. To determine the optimal number of topics, the coherence scores of different models are calculated by varying the values of n from 2 to 30 in this study. The optimal number of topics is determined as 15 (n=15), where the model yields the maximal coherence score. The crisis topics and the top ten keywords of each topic are demonstrated in Table III. In order to express the crisis topics concisely, the real names of those crisis topics ("crisis topics" column in Table III) are manually named according to their keywords. According to the crisis topics, we combined the posts related to a crisis topic into a single document. As seen in Table III, the top three crisis topics are "expired honey", "responsibility" and "stock price crash", which netizens discuss most frequently. In addition, the average importance score is 2.3795, where 4 out of 15 crisis topics yield importance scores above the average.

2) Computing the negativeness levels of crisis topics: First, we fine-tuned a sentiment classifier with the FT dataset. The FT dataset excludes data related to the TRTCM crisis event. The classifier achieves 85.14% accuracy on the FT testing set (the benchmarking results will be shown in § V-B later). We use the classifier to predict sentiment polarities for the posts in the TRTCM dataset. Sentiment analysis results are shown in Table IV. A crisis topic with high negativeness indicates that netizens are generally unsatisfied with it. The three most negative crisis topics are "fraud & illegality", "stock price crash" and "close down". According to the keywords of those crisis topics, "fraud & illegality" represents the complaints that TRTCM should follow the delisted company Changsheng Bio-Technology Co., Ltd. (Changsheng) after falsifying the production records of their vaccines in 2018. "Stock price crash" is about the pessimistic prediction of TRTCM stock price. "Close down" shows the will of netizens that TRTCM should go bankrupt immediately. We also observe several metaphors, e.g., "stock crash", "expired honey", "cost of honey", and "brand power" among these very negative crisis topics, because metaphors were frequently used to express strong sentiments and opinions [63]. In summary, the average negativeness score is 4.2369. 6 out of 15 crisis topics have negativeness scores above the average.

3) Identifying the crisis response opportunities: The TRTCM opportunity results are presented in Table V. The crisis topics with high negativeness and importance scores yield high opportunity scores. It shows the most concerned topics in a crisis and possible response directions. Companies can look up the detailed keywords of each concerned topic

TABLE III
TRTCM CRISIS TOPICS AND THEIR IMPORTANCE LEVELS. #POSTS DENOTES THE NUMBER OF POSTS. IMPT. DENOTES THE IMPORTANCE LEVEL.

Crisis topics	Keywords	#Posts	Impt.
Expired honey	honey, TRTCM, expired, shelflife, fake, time, Jing Dong, sell, wilful, media	1600	10.00
Responsibility	TRTCM, honey, recall, responsibility, punishment, overrate, apologize, centennial, wilful, Chinese medicine	950	5.41
Stock price crash	limit down, drop, stock market, crash, TRTCM, today, gold price, last night, valuation, pharmaceutical stocks	574	2.76
Brand reputation	TRTCM, centennial, pity, market value, reputation, enterprise, profit, supervise, market	568	2.71
Pharmaceutical stocks crash	pharmaceutics, fall, drop, industry, index, stock, pharmaceutical stocks, keep away, Black Swans, escape	512	2.32
Government regulation	supervise, punish, food, pharmaceutics,gaol, government, penalty, inspection, industry, reduce	512	2.32
Fraud & illegality	Changsheng, delisting, forge, TRTCM, illegality, limit down, nature, expired, food, fake	482	2.10
Close down	close down, expired, company, product, forge, delisting, bankrupt, conscience, bad, society	474	2.05
Return	return, honey, continue, safety, just, buy, refund, worry, drink, supermarket	414	1.62
Food security	food, safety, ensure, endanger,public security, China, limit, company, delisting, forge	388	1.44
Brand Power	centennial, brand, signboard, believe, true, forefather, power, expired, state-owned enterprise, honey	344	1.13
Original equipment manufacturer (OEM)	OEM, factory, workshop, brand, produce, agency, responsible, company, business, market	294	0.78
Cost of honey	hundred, natural, cheap, expensive, honey, bee, sugar, pollen, process, water	288	0.73
Support	believe, support, honey, rectify, expired, deposit, opportunity, true, conscience, brand	230	0.32
Stock market crash	stock, fall, market, crash, market index, encumber, limit down, value, company, adjust	184	0.00

TABLE IV
NEGATIVENESS LEVEL OF THE CRISIS TOPICS FOR TRTCM. #POSTS IS THE TOTAL NUMBER OF POSTS. #NEG. IS THE NUMBER OF NEGATIVE POSTS. #NEU. IS THE NUMBER OF NEUTRAL POSTS. #POS. IS THE NUMBER OF POSITIVE POSTS. NGTNSS. DENOTES NEGATIVENESS. SATIS. DENOTES SATISFACTION.

Crisis topics	#Posts	#Neg.	#Neu.	#Pos.	Ngtnss.	Satis.
Fraud & illegality	482	352	122	8	**10.00**	0.00
Stock price crash	574	378	162	34	**8.44**	1.56
Close down	474	296	158	20	**7.70**	2.30
Pharmaceutical stocks crash	512	304	146	62	**7.04**	2.96
Stock market crash	184	96	68	20	**5.47**	4.53
Expired honey	1600	764	724	112	**4.51**	5.49
Brand reputation	568	254	294	20	**3.86**	6.14
Return	414	180	202	32	**3.59**	6.41
OEM	294	124	110	60	**3.30**	6.70
Responsibility	950	382	528	40	**2.88**	7.12
Cost of honey	288	110	158	20	**2.44**	7.56
Food security	388	142	220	26	**2.09**	7.91
Brand Power	344	116	146	82	**1.47**	8.53
Government regulation	512	156	346	10	**0.76**	9.24
Support	230	62	164	4	**0.00**	10.00

TABLE V
OPPORTUNITY SCORES OF CRISIS TOPICS FOR THE TRTCM CASE.

Crisis topics	Opp. Score	Crisis topics	Opp. Score
Expired honey	14.51	Return	1.62
Responsibility	5.41	Food security	1.44
Fraud & illegality	4.21	Brand Power	1.13
Stock price crash	3.95	OEM	0.78
Brand reputation	2.71	Cost of honey	0.73
Pharmaceutical stocks crash	2.32	Support	0.32
Government regulation	2.32	Stock market crash	0.00
Close down	2.05	–	–

to make their public response in an opinion crisis event in practice.

As shown in Table V, the top five crisis topics with the highest opportunity scores are “expired honey”, “responsibility”, “fraud & illegality”, “stock price crash” and “brand reputation”. These topics are also visualized in orange in the opportunity landscape map in Fig. 5.

The crisis topic “expired honey” has the highest opportunity level among all crisis topics because TRTCM sold expired honey. The crisis topic “responsibility” also shows a high

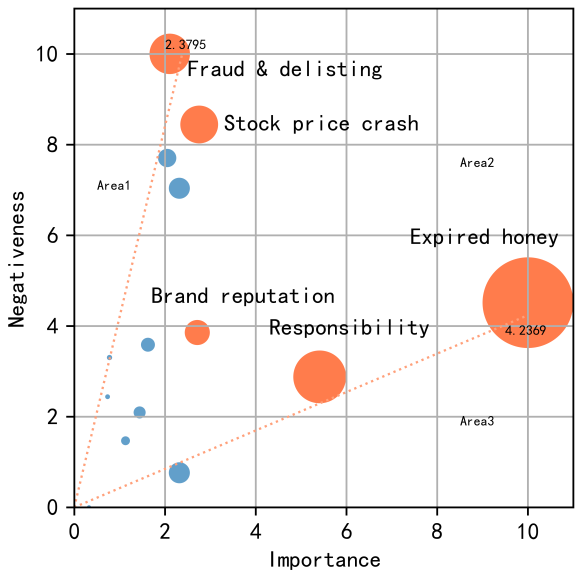

Fig. 5. Opportunity landscape map of TRTCM. The horizontal and vertical axes indicate the importance and negativeness scores, respectively. The circles represent the crisis topics, and the size of the circle represents the opportunity score. The average of importance and negativeness scores are 2.38 and 4.24, respectively. The top five crisis topics with the highest opportunity levels are highlighted in orange.

opportunity level. In particular, the keywords (see Table III) describe the expected actions that TRTCM should take from the perspective of netizens, such as “recall”, “punishment” and “apologize”. In light of this, TRTCM should immediately apologize to the public, recall the expired honey, compensate consumers, and consciously accept punishment to meet the demands of the public. The crisis topic “fraud & illegality” also presents a high opportunity level. According to the analysis of its keywords in Table III, TRTCM is influenced by the ripple effects of Changsheng. Thus, TRTCM should learn from the failure of Changsheng in public relationship (PR) management to avoid delisting. For the crisis topic “brand reputation”, most netizens are disappointed about TRTCM, which has a 300-year brand history. Thus, showing determination to correct mistakes and sticking to its brand spirit may be an appropriate crisis response.

Our crisis response opportunity identification method measures the response opportunities from both the importance and negativeness dimensions. Here, we conduct an ablation analysis to demonstrate the raking results based on different dimensions (importance, negativeness, and both). As shown in Table VI, “fraud & illegality” would not appear at the top if only importance levels are considered because its importance level is 7th among the 15 crisis topics. However, it has the highest negativeness level among the 15 crisis topics. As a result, its opportunity score is 3rd among the 15 crisis topics when negativeness and importance levels are considered together by the opportunity algorithm. As a consequence, “fraud & illegality” should be highlighted as a crucial crisis response opportunity and direction by listed companies. The results show that we can provide more precise decision support for listed companies.

4) Crisis response opportunities in different phases: The evolution of online public opinion about a specific event usually has a life cycle [64]. The crisis topics that are the primary interest of netizens change over time. To discover the crisis response opportunities in different phases, in line with Du et al. [14], we divide the life-cycle of crisis events into three stages: (1) Growth (LC1) - The number of reviews about an event suddenly increases during a certain period, meaning that more and more netizens are paying attention to it. The impact of an event increases. (2) Maturity (LC2) - The impact of the event reaches a peak. The number of reviews starts to decrease gradually, although it still remains at a high level. (3) Recession (LC3)- The number of reviews tends to stabilize at a low level. Next, we identify the crisis response opportunities in each phase. The opportunity landscape maps in the life-cycle of the event are shown in Fig. 6.

As shown in Fig. 6 (1), in the growth phase (LC1), the attention of netizens is relatively focused on discussing the news regarding TRTCM selling expired honey. Customers also claimed their compensation online. Other crisis topics are mainly distributed in Area 1 with high negativeness and low importance levels. These topics have the potential risk of aggravating the crisis.

As shown in the Fig. 6 (2), in the maturity phase (LC2), the attention of netizens is divided, e.g., “fraud & illegality”, “compensation”, “apology” and “brand reputation”. These topics are mainly distributed in Area 2. These are the key concerns that PR managers should actively respond to during the peak of the event.

As shown in the Fig. 6 (3), in the recession phase (LC3), the attention of netizens is relatively concentrated again. Netizens mainly discuss the responsibility of TRTCM, although the negativeness level of this topic is low. The crisis gradually subsides. However, some netizens still insist that TRTCM should be delisted, as Changsheng did.

Fig. 6 highlights two points that must be taken into account in public opinion crisis management. First, the crisis topics with high negativeness levels but low importance (Area 1) in the growth phase (LC1) are likely to provoke more discussions and exacerbate the crises (Area 2) in the maturity phase (LC2). For example, “fraud & illegality” moves from LC 1 Area 1 to LC2 Area 2 in Fig. 6. Second, the crisis topics with high negativeness levels in the recession phase still need to be noticed because they may potentially reignite the crisis.

C. Statistical analysis of different crisis cases

We identified crisis response opportunities in each life cycle stage for 19 other crisis events (Crisis Cases 6-24). The crisis topics with high negativeness levels despite the low importance in the growth phase (LC1), e.g., “fraud & illegality” in LC1 in TRTCM (Crisis Cases 5), are called sensitive crisis topics. The sensitive crisis topics of these crisis events are presented in Appendix Table II.

We attempted to statistically analyze the evolution characteristics of these sensitive crisis topics in the life-cycle of the crisis event. Firstly, to analyze the change of importance level of these sensitive crisis topics between LC1 and LC2

TABLE VI
THE RAKING RESULTS BASED ON IMPORTANCE (IMPT.), NEGATIVENESS (NGTNSS.), AND OPPORTUNITY (OPP.) LEVEL (THE NUMBERS IN PARENTHESES).

Crisis topics	Impt.	Crisis topics	Ngtnss.	Crisis topics	Opp.
Expired honey	1 (10.00)	**Fraud & illegality**	**1 (10.00)**	Expired honey	1 (14.51)
Responsibility	2 (5.41)	Stock price crash	2 (8.44)	Responsibility	2 (5.41)
Stock price crash	3 (2.75)	Close down	3 (7.70)	**Fraud & illegality**	**3 (4.21)**
Brand reputation	4 (2.71)	Pharmaceutical stocks crash	4 (7.04)	Stock price crash	4 (3.95)
Pharmaceutical stocks crash	5 (2.32)	Stock market crash	5 (5.47)	Brand reputation	5 (2.71)
Government regulation	6 (2.32)	Expired honey	6 (4.51)	Pharmaceutical stocks crash	6 (2.32)
Fraud & illegality	**7 (2.10)**	Brand reputation	7 (3.86)	Government regulation	7 (2.32)
Close down	8 (2.05)	Return	8 (3.59)	Close down	8 (2.05)
Return	9 (1.62)	OEM	9 (3.30)	Return	9 (1.62)
Food security	10 (1.44)	Responsibility	10 (2.88)	Food security	10 (1.44)
Brand Power	11 (1.13)	Cost of honey	11 (2.44)	Brand Power	11 (1.13)
OEM	12 (0.78)	Food security	12 (2.09)	OEM	12 (0.78)
Cost of honey	13 (0.73)	Brand Power	13 (1.47)	Cost of honey	13 (0.73)
Support	14 (0.32)	Government regulation	14 (0.76)	Support	14 (0.32)
Stock market crash	15 (0.00)	Support	15 (0.00)	Stock market crash	15 (0.00)

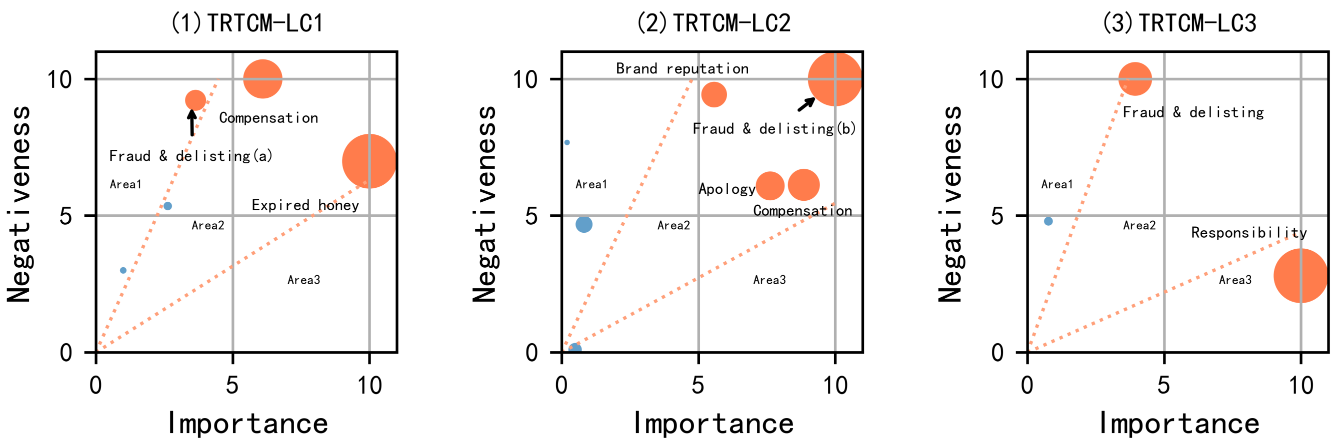

Fig. 6. Opportunity landscape map for each phase in life-cycle of TRTCM. (1) TRTCM-LC1,(2) TRTCM-LC2 and (3) TRTCM-LC3 show the opportunity landscape map in the growth stage, maturity stage and recession stage, respectively.

(Hypothesis 1 in Table VII), our null hypothesis is: "There is no significant difference in the importance level of sensitive crisis topics between LC1 and LC2". The paired sample T-test is conducted to examine the null hypothesis. Table VII shows the results of the T-test. As a premise, the normality tests (0.19>0.05 in LC1, 0.30>0.05 in LC2) indicate that the importance scores of considered sensitive crisis topics in LC1 and LC2 follow the normal distribution and meet the basic assumption of the T-test. The result of the T-test of Hypothesis 1 demonstrates that there are significant differences ($p<0.05$) in the importance levels of sensitive crisis topics between LC1 and LC2. Moreover, the mean of importance levels in LC2 is greater than it in LC1 (6.45>3.39). This indicates that the importance level of these sensitive crisis topics has increased significantly from LC1 to LC2.

Secondly, the paired sample T-test is also conducted to statistically analyze the change in the negativeness level of these sensitive crisis topics between LC1 and LC2. Our null hypothesis (Hypothesis 2 in Table VII) is: There is no significant difference in the negativeness level of sensitive crisis topics between LC1 and LC2. The result of the T-test of Hypothesis 2 demonstrates that there are no significant differences ($p>0.05$) in the negativeness levels of sensitive crisis topics between LC1 and LC2. Besides, the means of negativeness level of these sensitive crisis topics are 8.38 and 8.81 in LC1 and LC2. This indicates that the negativeness levels of sensitive crisis topics continue to be high from LC1 to LC2.

The above analysis of Hypothesis 1 and Hypothesis 2 shows that sensitive crisis topics with high negativeness levels, despite the low importance in LC1 are significantly more important in LC2, and the negativeness levels are still high. Consequently, it is necessary to consider both the importance and negativeness levels for identifying crisis response opportunities. It is of great significance for effective crisis response to identify these sensitive crisis topics as crisis response opportunities in LC1.

TABLE VII
RESULT OF T-TEST.

Hypothesis 1	H0: There is no significant difference in the importance level of sensitive crisis topics between LC1 and LC2.			
Crisis stage	Importance mean	Normality test (p-value)	T Value	P Value
LC1	3.39	0.19	-9.17	< 0.05
LC2	6.45	0.30		
Result	There is significant difference in the importance level of sensitive crisis topics between LC1 and LC2.			
Hypothesis 2	H0: There is no significant difference in the negativeness level of sensitive crisis topics between LC1 and LC2.			
Crisis stage	Negativeness mean	Normality test (p-value)	T Value	P Value
LC1	8.38	0.08	-1.54	> 0.05
LC2	8.81	0.07		
Result	There is no significant difference in the negativeness level of sensitive crisis topics between LC1 and LC2.			

V. MODEL PERFORMANCE BENCHMARKING

We have embedded a topic model and a sentiment analysis classifier in our framework. We benchmark our methods with different baselines to show their utilities based on the TRTCM crisis case and FT dataset. The TRTCM crisis case is used to evaluate topic modeling. The FT data is used for training, validation, and testing the sentiment analysis task.

A. Evaluation analysis of topic modeling methods

LDA [40], as the most popular topic model [36], is included as a baseline for extracting crisis topics. To evaluate the quality of crisis topics, we used a perplexity measure [40] and expert evaluation. Perplexity is a popular metric and a standard method to measure topic models [14], [65], [66]. It is equivalent to the inverse of the geometric mean per-word likelihood [40]. It measures the uncertainty of a post belonging to a particular topic. Generally, a lower perplexity score reveals a higher prediction power of the model. Following previous studies [67], [68], we also adopt a coherence measure (CM) [69], a reasonable method by human judgment, to evaluate the inferred crisis topics. The CM value is defined as the ratio between the number of relevant words and the total number of candidates. Three Chinese doctoral students who are familiar with the TRTCM case and related posts were invited to evaluate whether each word is relevant to the crisis topic.

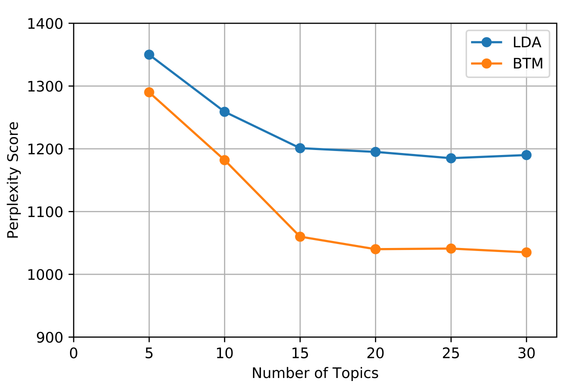

Fig. 7. Perplexity scores of LDA and BTM (the lower the better).

Fig. 7 shows that BTM outperforms the LDA model in identifying crisis topics because a lower perplexity corresponds to a better effect of the model on its prediction power. Moreover, we show three crisis topics with the highest opportunity scores and their top 10 keywords in Table VIII. The last row in the table shows the CM values in different topics and methods. As seen in Table VIII, the CM values of BTM are higher than that of the LDA model in the three crisis topics. An effective keyword set with less irrelevant keywords helps us understand the specific response directions. The evaluation results show a better performance of the BTM over the LDA model. Therefore, BTM was selected to extract crisis topics from our approach.

B. Evaluation analysis of sentiment analysis methods

Two recent baseline models for sentiment classification are introduced to select the most appropriate method for sentiment analysis, computing the negativeness levels of crisis topics. BiLSTM and Attention-BiLSTM are chosen due to their effectiveness in capturing contextual dependencies in sequential data and their widespread use in sentiment analysis tasks.

- BiLSTM [46]: This model employs Bidirectional Long Short-Term Memory (LSTM) layers to encode both forward and backward contextual information in an input sequence. Unlike standard LSTM, which only captures past dependencies, BiLSTM enhances sentiment classification by considering both preceding and succeeding words, making it well-suited for sentiment analysis [48]. Its ability to learn long-range dependencies has led to its widespread adoption in various natural language processing (NLP) tasks [70], [71].
- Attention-BiLSTM [72]: This model extends BiLSTM by incorporating an attention mechanism, which dynamically assigns higher importance to words that contribute most to sentiment classification. This mechanism allows the model to focus on sentiment-bearing words while filtering out less relevant content, improving interpretability and performance in sentiment classification tasks. Due to its ability to highlight key sentiment indicators, it has been widely applied in sentiment analysis and crisis-related NLP research [73]–[75] .

TABLE VIII
CM VALUES OF LDA AND BTM. ITALICS ARE IRRELEVANT TO THE TOPICS.

Expired honey		Responsibility		Fraud & illegality	
BTM	LDA	BTM	LDA	BTM	LDA
honey	TRTCM	TRTCM	TRTCM	Changsheng	Changsheng
TRTCM	honey	honey	honey	delisting	delisting
expired	forge	recall	punishment	forge	limit down
Shelflife	***market***	responsibility	recall	TRTCM	***enterprise***
fake	***enterprise***	punishment	***body***	illegality	forge
time	consumer	***overrate***	responsibility	limit down	market index
Jing Dong	Changsheng	apologize	***maotai***	***nature***	pharmaceutics
sell	***cost***	centennial	centennial	expired	fake
wilful	expired	wilful	***yunnan baiyao***	***food***	***adjust***
media	shelflife	***Chinese medicine***	***history***	fake	***industry***
80%	70%	80%	60%	80%	70%

TABLE IX
PARAMETER SETTING OF DIFFERENT MODELS FOR SENTIMENT ANALYSIS.

Parameter	BERT	BiLSTM	Attention-BiLSTM
Dropout probability	0.1	0.5	0.5
Batch size	16	32	32
Learning rate	0.00005	0.001	0.001
Hidden state	768	128	128

TABLE X
RESULTS OF SENTIMENT CLASSIFICATION BY USING DIFFERENT MODELS.

Model	ACC
BiLSTM	70.47%
Attention-BiLSTM	71.65%
BERT	**85.14%**

The parameters of the examined models were randomly initialized. We used Adam optimizer [76] to update the parameters. The batch size for training BERT is 16. We employed dropout on the dense layer. The dropout rate is 0.1. The learning rate is 0.00005. The detailed setups of our model and the baselines are shown in Table IX. We trained the model with 3 epochs. The stop point and hyper-parameters were given by the model that yields the best performance on the validation set. We employed accuracy as the measure.

The benchmarking results of sentiment classification are shown in Table X. The BERT model achieves the best performance with an accuracy of 85.14%, which outperforms the BiLSTM and Attention-BiLSTM by 14.67% and 13.49%, respectively. The results indicate the utility of the BERT model in our sentiment analysis task. Therefore, it is embedded in our framework.

VI. DISCUSSION

A. Theoretical contribution

This study offers a new approach to the decision support systems of crisis management. It makes several theoretical contributions to the field of crisis management:

(1) This study proposes a framework for mining social media data to capture netizen concerns. Most previous studies mining social media data to improve crisis response focused on topic detection and tracking [11], [14]. In contrast, we incorporate topic modeling and sentiment analysis techniques for public opinion crisis decision-making.

(2) This study provides an efficient approach for identifying and prioritizing crisis response opportunities using an opportunity algorithm, simultaneously considering the importance and negativeness levels. Moreover, the opportunity landscape map based on a life-cycle theory demonstrates the crisis response opportunities in each crisis phase and intuitively provides early warning signals. This study responds to the works of [24] and [9], which require a method that could mine netizen opinions from big data, supplying visualized guidance for crisis response. The approach can be used in various contexts because it is domain-independent.

(3) This study finds that the sensitive crisis topics with high negativeness despite low importance in the growth phase are significantly more important and still very negative in the next maturity phase. Our approach can effectively capture them as crisis response opportunities in the growth phase and give them a higher priority. Compared to previous studies which have used the importance of topics as references to make decisions in crises [1], [11], [23], our framework also includes negativeness, which can provide more precise decision supports.

(4) This study mines social media data from the crisis management perspective to provide decision support for listed companies. Previous research on crisis management mainly focused on public safety and disasters [9], [12], [23]. Besides, previous research on the financial domain by social media data mining techniques focused on predicting stock price movements and optimizing investment portfolios [77], [78]. This study fulfills the gap in crisis management.

B. Practical implications

This study provides important practical significance for listed companies. Although listed companies try to communicate to regulate the negative sentiments of netizens effectively, the reality is that they do not know what netizens are mostly concerned about. The proposed approach identifies the crisis response opportunities using netizens-generated social media data, which provides explicit directions for crisis responses. The opportunity landscape map shows the focused topics of crisis managers at each crisis phase. Furthermore, our approach can also suggest specific response strategies according to the keywords of crisis topics. By using our approach, the listed companies could design a soft system as an efficient aid to guide the investors in minimizing the crisis reputational threats and stabilizing their stock prices.

VII. Conclusion

This paper proposes a social media mining approach to quantitatively identify the crisis response opportunities for listed companies. Firstly, the crisis topics discussed by netizens on social media are identified by the BTM. The importance of a topic is measured by the ratio between the number of posts related to the crisis topic and the number of total posts about the crisis event. Secondly, the sentiment polarity of each post is classified by a fine-tuned BERT model. The negativeness level of each crisis topic is measured by the ratio between the number of negative posts and the total number of posts in a crisis topic. Finally, crisis response opportunities are identified by an opportunity ranking algorithm based on the importance and negativeness of factors in decision-making. Moreover, we visualize and analyze the changes in crisis response opportunities based on a life-cycle theory. The statistical analysis of 20 different crisis cases demonstrates that the sensitive crisis topics with high negativeness despite low importance in the growth phase become significantly more important and still very negative in the next maturity phase. Our approach can effectively capture them as crisis response opportunities in the growth phase and give them a higher priority. Consequently, our framework can provide more precise decision support. In addition, The evaluation results indicate our approach is effective, outperforming the baseline methods with higher accuracy in topic modeling and sentiment analysis tasks.

In future work, the following studies may be interesting for the community. Firstly, crisis management varies significantly across company types and industries. The crisis response opportunities for different types of companies should be discussed. Future research should explore a comparative industry-based framework for crisis response. A more granular, data-driven approach to sector-specific crisis management would enable listed companies to refine response strategies and enhance resilience in an increasingly volatile public discourse landscape. Secondly, a coupled analysis could be conducted to analyze the effects of official responses on the evolution of crisis response opportunities. Finally, to enhance public communication effectiveness, it is possible to employ cognition modeling tools [79] to examine the cognitive patterns of the general public [80]. This analytical approach enables a comprehensive understanding of which types of language are most impactful in communicating with the public.

CRediT authorship contribution statement

Yu Ma: Conceptualization, Methodology, Writing-original draft. **Rui Mao**: Conceptualization, Methodology, Writing - review & editing. **Peng Wu**: Project administration, Supervision, Funding acquisition. **Erik Cambria**: Writing - review & editing, Supervision.

Declaration of competing interest

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

References

[1] S. Lim and C. S. Tucker, "Mining Twitter data for causal links between tweets and real-world outcomes," *Expert Systems with Applications: X*, vol. 3, p. 100007, 2019.

[2] D. C. Broadstock and D. Zhang, "Social-media and intraday stock returns: The pricing power of sentiment," *Finance Research Letters*, vol. 30, pp. 116–123, 2019.

[3] H. Hong, Q. Ye, Q. Du, G. A. Wang, and W. Fan, "Crowd characteristics and crowd wisdom: Evidence from an online investment community," *Journal of the Association for Information Science and Technology*, vol. 71, no. 4, pp. 423–435, 2020.

[4] K. Du, F. Xing, R. Mao, and E. Cambria, "Financial sentiment analysis: Techniques and applications," vol. 56, no. 9. Association for Computing Machinery, 2024, pp. 1–42.

[5] H. Crijns, V. Cauberghe, L. Hudders, and A.-S. Claeys, "How to deal with online consumer comments during a crisis? the impact of personalized organizational responses on organizational reputation," *Computers in Human Behavior*, vol. 75, pp. 619–631, 2017.

[6] L. Hong, C. Fu, J. Wu, and V. Frias-Martinez, "Information needs and communication gaps between citizens and local governments online during natural disasters," *Information Systems Frontiers*, vol. 20, no. 5, pp. 1027–1039, 2018.

[7] X. Lin, P. R. Spence, T. L. Sellnow, and K. A. Lachlan, "Crisis communication, learning and responding: Best practices in social media," *Computers in human behavior*, vol. 65, pp. 601–605, 2016.

[8] J. Kim and M. Hastak, "Social network analysis: Characteristics of online social networks after a disaster," *International Journal of Information Management*, vol. 38, no. 1, pp. 86–96, 2018.

[9] M. Martinez-Rojas, M. del Carmen Pardo-Ferreira, and J. C. Rubio-Romero, "Twitter as a tool for the management and analysis of emergency situations: A systematic literature review," *International Journal of Information Management*, vol. 43, pp. 196–208, 2018.

[10] A. Saroj and S. Pal, "Use of social media in crisis management: A survey," *International Journal of Disaster Risk Reduction*, vol. 48, p. 101584, 2020.

[11] Q. Deng, Y. Gao, C. Wang, and H. Zhang, "Detecting information requirements for crisis communication from social media data: An interactive topic modeling approach," *International Journal of Disaster Risk Reduction*, vol. 50, p. 101692, 2020.

[12] M. Jamali, A. Nejat, S. Ghosh, F. Jin, and G. Cao, "Social media data and post-disaster recovery," *International Journal of Information Management*, vol. 44, pp. 25–37, 2019.

[13] J. Kim and H. Park, "A framework for understanding online group behaviors during a catastrophic event," *International Journal of Information Management*, vol. 51, p. 102051, 2020.

[14] Y. Du, Y. Yi, X. Li, X. Chen, Y. Fan, and F. Su, "Extracting and tracking hot topics of micro-blogs based on improved Latent Dirichlet Allocation," *Engineering Applications of Artificial Intelligence*, vol. 87, p. 103279, 2020.

[15] S. I. Seok, H. Cho, and D. Ryu, "Firm-specific investor sentiment and the stock market response to earnings news," *The North American Journal of Economics and Finance*, vol. 48, pp. 221–240, 2019.

[16] L. Malandri, F. Xing, C. Orsenigo, C. Vercellis, and E. Cambria, "Public mood–driven asset allocation: the importance of financial sentiment in portfolio management," *Cognitive Computation*, vol. 10, no. 6, pp. 1167–1176, 2018.

[17] E. Cambria, R. Mao, M. Chen, Z. Wang, and S.-B. Ho, "Seven pillars for the future of artificial intelligence," *IEEE Intelligent Systems*, vol. 38, no. 6, pp. 62–69, 2023.

[18] J. S. Pinegar, "What customers want: Using outcome-driven innovation to create breakthrough products and services," *Journal of Product Innovation Management*, vol. 23, no. 5, pp. 464–466, 2006.

[19] E. Cambria, X. Zhang, R. Mao, M. Chen, and K. Kwok, "SenticNet 8: Fusing emotion AI and commonsense AI for interpretable, trustworthy, and explainable affective computing," in *Proceedings of International Conference on Human-Computer Interaction (HCII)*, Washington DC, USA, 2024, pp. 197–216.

[20] X. Cheng, X. Yan, Y. Lan, and J. Guo, "BTM: Topic modeling over short texts," *IEEE Transactions on Knowledge and Data Engineering*, vol. 26, no. 12, pp. 2928–2941, 2014.

[21] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, 2019, pp. 4171–4186.

[22] S. Fink, "Crisis management: Planning for the invisible [M]. American," *Management Association, New York*, 1986.

[23] X. Xu, X. Yin, and X. Chen, "A large-group emergency risk decision method based on data mining of public attribute preferences," *Knowledge-Based Systems*, vol. 163, pp. 495–509, 2019.

[24] A. Elbanna, D. Bunker, L. Levine, and A. Sleigh, "Emergency management in the changing world of social media: Framing the research agenda with the stakeholders through engaged scholarship," *International Journal of Information Management*, vol. 47, pp. 112–120, 2019.

[25] W. L. Benoit, "Image repair discourse and crisis communication," *Public Relations Review*, vol. 23, no. 2, pp. 177–186, 1997.

[26] W. T. Coombs and S. J. Holladay, "Helping Crisis Managers Protect Reputational Assets: Initial Tests of the Situational Crisis Communication Theory," *Management Communication Quarterly*, vol. 16, no. 2, pp. 165–186, 2002.

[27] L. Wang, C. G. Schuetz, and D. Cai, "Choosing Response Strategies in Social Media Crisis Communication: An Evolutionary Game Theory Perspective," *Information & Management*, vol. 58, no. 6, p. 103371, 2021.

[28] N. Zhang, X. Guo, L. Zhang, and L. He, "How to repair public trust effectively: Research on enterprise online public opinion crisis response," *Electronic Commerce Research and Applications*, vol. 49, p. 101077, 2021.

[29] S. Y. Lee, "Stealing thunder as a crisis communication strategy in the digital age," *Business Horizons*, vol. 63, no. 6, pp. 801–810, 2020.

[30] J. Berger, "Arousal Increases Social Transmission of Information," *Psychological science*, vol. 22, no. 7, pp. 891–893, 2011.

[31] D. Camacho, A. Panizo-LLedot, G. Bello-Orgaz, A. Gonzalez-Pardo, and E. Cambria, "The four dimensions of social network analysis: An overview of research methods, applications, and software tools," *Information Fusion*, vol. 63, pp. 88–120, 2020.

[32] R. Fan, K. Xu, and J. Zhao, "An agent-based model for emotion contagion and competition in online social media," *Physica a: statistical mechanics and its applications*, vol. 495, pp. 245–259, 2018.

[33] G. Wang, Y. Chi, Y. Liu, and Y. Wang, "Studies on a multidimensional public opinion network model and its topic detection algorithm," *Information Processing & Management*, vol. 56, no. 3, pp. 584–608, 2019.

[34] K. Garcia and L. Berton, "Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA," *Applied Soft Computing*, vol. 101, p. 107057, 2021.

[35] J. R. Ragini, P. R. Anand, and V. Bhaskar, "Big data analytics for disaster response and recovery through sentiment analysis," *International Journal of Information Management*, vol. 42, pp. 13–24, 2018.

[36] I. Vayansky and S. A. Kumar, "A review of topic modeling methods," *Information Systems*, vol. 94, p. 101582, 2020.

[37] X. Wu, T. Nguyen, and A. T. Luu, "A survey on neural topic models: Methods, applications, and challenges," *Artificial Intelligence Review*, 2024.

[38] C. Duong, Q. Liu, R. Mao, and E. Cambria, "Saving earth one tweet at a time through the lens of artificial intelligence," in *2022 International Joint Conference on Neural Networks (IJCNN)*, Padua, Italy, 2022, pp. 1–9.

[39] C. Duong, V. C. Raghuram, A. Lee, R. Mao, G. Mengaldo, and E. Cambria, "Neurosymbolic AI for mining public opinions about wildfires," *Cognitive Computation*, vol. 16, pp. 1531–1553, 2024.

[40] D. M. Blei, A. Y. Ng, and M. I. Jordan, "Latent dirichlet allocation," *Journal of machine Learning research*, vol. 3, pp. 993–1022, 2003.

[41] H. U. Khan, S. Nasir, K. Nasim, D. Shabbir, and A. Mahmood, "Twitter trends: a ranking algorithm analysis on real time data," *Expert Systems with Applications*, vol. 164, p. 113990, 2021.

[42] W. Li, Y. Feng, D. Li, and Z. Yu, "Micro-blog topic detection method based on BTM topic model and K-means clustering algorithm," *Automatic Control and Computer Sciences*, vol. 50, no. 4, pp. 271–277, 2016.

[43] Y. Xia, N. Tang, A. Hussain, and E. Cambria, "Discriminative Bi-Term Topic Model for Headline-Based Social News Clustering," in *The Twenty-Eighth International Florida Artificial Intelligence Research Society Conference on Artificial Intelligence for Big Social Data Analysis*, 2015, pp. 311–316.

[44] P. Wu, X. Li, S. Shen, and D. He, "Social media opinion summarization using emotion cognition and convolutional neural networks," *International Journal of Information Management*, vol. 51, p. 101978, 2020.

[45] C. Fan, J. Lin, R. Mao, and E. Cambria, "Fusing pairwise modalities for emotion recognition in conversations," *Information Fusion*, vol. 106, p. 102306, 2024.

[46] A. Graves and J. Schmidhuber, "Framewise phoneme classification with bidirectional LSTM and other neural network architectures," *Neural networks*, vol. 18, no. 5-6, pp. 602–610, 2005.

[47] S. Hochreiter and J. Schmidhuber, "Long Short-Term Memory," *Neural computation*, vol. 9, no. 8, pp. 1735–1780, 1997.

[48] S. Minaee, N. Kalchbrenner, E. Cambria, N. Nikzad, M. Chenaghlu, and J. Gao, "Deep learning based text classification: A comprehensive review," *ACM Computing Surveys*, vol. 54, no. 3, p. Article 62, 2021.

[49] W. Li, L. Zhu, Y. Shi, K. Guo, and E. Cambria, "User reviews: Sentiment analysis using lexicon integrated two-channel CNN–LSTM family models," *Applied Soft Computing*, vol. 94, p. 106435, 2020.

[50] P. Wu, X. Li, C. Ling, S. Ding, and S. Shen, "Sentiment classification using attention mechanism and bidirectional long short-term memory network," *Applied Soft Computing*, vol. 112, p. 107792, 2021.

[51] F. Ren, L. Feng, D. Xiao, M. Cai, and S. Cheng, "DNet: a lightweight and efficient model for aspect based sentiment analysis," *Expert Systems with Applications*, vol. 151, p. 113393, 2020.

[52] F. Chen, Z. Yuan, and Y. Huang, "Multi-source data fusion for aspect-level sentiment classification," *Knowledge-Based Systems*, vol. 187, p. 104831, 2020.

[53] R. Mao and X. Li, "Bridging towers of multi-task learning with a gating mechanism for aspect-based sentiment analysis and sequential metaphor identification," in *Proceedings of the AAAI Conference on Artificial Intelligence*, vol. 35, 2021, pp. 13 534–13 542.

[54] M. M. Amin, E. Cambria, and B. W. Schuller, "Will affective computing emerge from foundation models and general artificial intelligence? a first evaluation of chatgpt," *IEEE Intelligent Systems*, vol. 38, no. 2, pp. 15–23, 2023.

[55] F. Xu, Q. Lin, J. Han, T. Zhao, J. Liu, and E. Cambria, "Are large language models really good logical reasoners? a comprehensive evaluation and beyond," *IEEE Transactions on Knowledge and Data Engineering*, vol. 37, no. 4, pp. 1620–1634, 2025.

[56] R. Mao, G. Chen, X. Zhang, F. Guerin, and E. Cambria, "GPTEval: A survey on assessments of ChatGPT and GPT-4," in *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*. Torino, Italia: ELRA and ICCL, 2024, pp. 7844–7866. [Online]. Available: https://aclanthology.org/2024.lrec-main.693

[57] M. M. Amin, R. Mao, E. Cambria, and B. W. Schuller, "A wide evaluation of ChatGPT on affective computing tasks," *IEEE Transactions on Affective Computing*, vol. 15, no. 4, pp. 2204–2212, 2024.

[58] J. Choi, S. Oh, J. Yoon, J.-M. Lee, and B.-Y. Coh, "Identification of time-evolving product opportunities via social media mining," *Technological Forecasting and Social Change*, vol. 156, p. 120045, 2020.

[59] B. Jeong, J. Yoon, and J.-M. Lee, "Social media mining for product planning: A product opportunity mining approach based on topic modeling and sentiment analysis," *International Journal of Information Management*, vol. 48, pp. 280–290, 2019.

[60] J. Joung, K. Jung, S. Ko, and K. Kim, "Customer complaints analysis using text mining and outcome-driven innovation method for market-oriented product development," *Sustainability*, vol. 11, no. 1, p. 40, 2019.

[61] N. Zhang, X. Wang, X. Guo, X. Cheng, and Z. Pang, "How organization response influences public sentiment and behavior in online crises: The role of response strategies, tenor of discourse and executives," *Public Relations Review*, vol. 50, no. 1, p. 102395, 2024.

[62] D. Mimno, H. Wallach, E. Talley, M. Leenders, and A. McCallum, "Optimizing semantic coherence in topic models," in *The 2011 conference on empirical methods in natural language processing, Association for Computational Linguistics*, 2011, pp. 262–272.

[63] R. Mao, K. He, C. B. Ong, Q. Liu, and E. Cambria, "MetaPro 2.0: Computational metaphor processing on the effectiveness of anomalous language modeling," in *Findings of the Association for Computational Linguistics: ACL*. Bangkok, Thailand: Association for Computational Linguistics, 2024, pp. 9891–9908.

[64] L. An, W. Zhou, M. Ou, G. Li, C. Yu, and X. Wang, "Measuring and profiling the topical influence and sentiment contagion of public event stakeholders," *International Journal of Information Management*, vol. 58, p. 102327, 2021.

[65] W. Wang, Y. Feng, and W. Dai, "Topic analysis of online reviews for two competitive products using latent Dirichlet allocation," *Electronic Commerce Research and Applications*, vol. 29, pp. 142–156, 2018.

[66] L. Hagen, "Content analysis of e-petitions with topic modeling: How to train and evaluate LDA models?" *Information Processing & Management*, vol. 54, no. 6, pp. 1292–1307, 2018.

[67] Y. Chen, H. Zhang, R. Liu, Z. Ye, and J. Lin, "Experimental explorations on short text topic mining between LDA and NMF based schemes," *Knowledge-Based Systems*, vol. 163, pp. 1–13, 2019.

[68] S. Xiong, K. Wang, D. Ji, and B. Wang, "A short text sentiment-topic model for product reviews," *Neurocomputing*, vol. 297, pp. 94–102, 2018.

[69] P. Xie and E. P. Xing, "Integrating document clustering and topic modeling," *The Twenty-Ninth Conference on Uncertainty in Artificial Intelligence*, pp. 694–703, 2013.

[70] S. Aslan, "A deep learning-based sentiment analysis approach (mf-cnn-bilstm) and topic modeling of tweets related to the ukraine–russia conflict," *Applied Soft Computing*, vol. 143, p. 110404, 2023.

[71] N. Ramshankar and J. P. P.M., "Automated sentimental analysis using heuristic-based cnn-bilstm for e-commerce dataset," *Data & Knowledge Engineering*, vol. 146, p. 102194, 2023.

[72] P. Zhou, W. Shi, J. Tian, Z. Qi, B. Li, H. Hao, and B. Xu, "Attention-based bidirectional long short-term memory networks for relation classification," in *Proceedings of the 54th annual meeting of the association for computational linguistics*, vol. 2, 2016, pp. 207–212.

[73] G. Xu, Z. Zhang, T. Zhang, S. Yu, Y. Meng, and S. Chen, "Aspect-level sentiment classification based on attention-bilstm model and transfer learning," *Knowledge-Based Systems*, vol. 245, p. 108586, 2022.

[74] Y. Huang, Q. Liu, H. Peng, J. Wang, Q. Yang, and D. Orellana-Martín, "Sentiment classification using bidirectional lstm-snp model and attention mechanism," *Expert Systems with Applications*, vol. 221, p. 119730, 2023.

[75] A. Upadhyay, Y. K. Meena, and G. S. Chauhan, "Satcobilstm: Self-attention based hybrid deep learning framework for crisis event detection in social media," *Expert Systems with Applications*, vol. 249, p. 123604, 2024.

[76] D. P. Kingma and J. Ba, "Adam: A method for stochastic optimization," *The 3rd International Conference on Learning Representations*, pp. 7–9, 2014.

[77] Y. Ma, R. Mao, Q. Lin, P. Wu, and E. Cambria, "Multi-source aggregated classification for stock price movement prediction," *Information Fusion*, vol. 91, pp. 515–528, 2023.

[78] ——, "Quantitative stock portfolio optimization by multi-task learning risk and return," *Information Fusion*, vol. 104, p. 102165, 2024.

[79] R. Mao, X. Li, K. He, M. Ge, and E. Cambria, "MetaPro Online: A computational metaphor processing online system," in *Proceedings of the 61th Annual Meeting of the Association for Computational Linguistics (System Demonstration)*, 2023, pp. 127–135.

[80] R. Mao, K. Du, Y. Ma, L. Zhu, and E. Cambria, "Discovering the cognition behind language: Financial metaphor analysis with MetaPro," in *2023 IEEE International Conference on Data Mining (ICDM)*. Shanghai, China: IEEE, 2023, pp. 1211–1216.

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