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Postprint: Emergency Severity Assessment and Early Warning Mechanisms in Social Media Environment

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Abstract

[Objective/Significance] The rapid spread and deterioration of emergency events necessitate that emergency management departments assess the severity of such events in real time and establish scientific early warning mechanisms. Social media platforms such as Weibo provide rich clues for real-time analysis and judgment of emergency events.

[Method/Process] This study constructs emergency event severity assessment indicators from dimensions including netizen influence, online media influence, situation diffusion, attitude tendency, and netizen sentiment, and proposes methods for influence tendency analysis and feature comparison of emergency event severity indicators. Using 1,107,308 Weibo posts from four social security incidents—namely, the “August 24 Yueqing Girl Killed in Ride-hailing Case” and “May 6 Zhengzhou Flight Attendant Killed in Ride-hailing Case” from 2018, the “August 27 Kunshan Knife Attack Case” from 2018, and the “Ctrip Parent-Child Center Child Abuse Incident” from 2017—as examples, the study classifies emergency event severity levels and establishes an emergency event early warning mechanism through influence tendency analysis of emergency event severity indicators.

[Results/Conclusions] The research results establish a quantitative grading standard for emergency events, providing methodological guidance and data support for the government to promptly adopt emergency management measures.

Full Text

Preamble

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Research on Emergency Severity Assessment and Early Warning Mechanisms in Social Media Environments

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Abstract: [Purpose/Significance] The rapid spread and deterioration of public emergencies necessitate that emergency management departments assess event severity in real time and establish scientific early warning mechanisms. Social media platforms such as Weibo provide rich clues for real-time emergency assessment. [Method/Process] This study constructs an emergency severity assessment index system from dimensions including netizen influence, internet media influence, event diffusion, attitude orientation, and netizen sentiment. It proposes methods for analyzing the influence tendency of severity indicators and comparing their features. Using 1,107,308 Weibo posts about four social security incidents—the “8·24 Yueqing Girl Ride-Hailing Murder Case” and “5·6 Zhengzhou Flight Attendant Ride-Hailing Murder Case” and “8·27 Kunshan Knife Attack Case” in 2018, and the “2017 Ctrip Kindergarten Abuse Incident”—the study divides emergency severity levels and establishes an early warning mechanism through influence tendency analysis. [Result/Conclusion] The results establish quantitative classification standards for public emergencies, providing methodological guidance and data support for government emergency management measures.

Keywords: severity assessment; early warning mechanism; public emergency; social media; influence tendency

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The Emergency Response Law of the People’s Republic of China defines public emergencies as “sudden occurrences that cause or may cause serious social harm and require emergency response measures, including natural disasters, accidents, public health incidents, and social security incidents” [1]. Such events are characterized by persistence, severe destructiveness, and suddenness. With the development of the internet, the penetration rate of social media represented by Weibo has risen rapidly, making these platforms crucial channels for public opinion dissemination, breeding grounds for opinion formation, and media for emergency propagation. Due to their sudden nature, emergencies tend to spread rapidly and extensively across networks, often causing public panic and even affecting trust in government, as seen in incidents like the “10·28 Chongqing Bus Crash” in 2018, the “August Shouguang Flood” in 2018, the “7·15 Changsheng Bio-Tech Vaccine Incident” in 2018, the “11·22 RYB Kindergarten Abuse Incident” in 2017, and the “6·22 Hangzhou Nanny Arson Case” in 2017.

In actual emergency management, classification and grading of emergencies are essential. China issued the National Overall Emergency Plan for Public Emergencies in 2006, followed by the Special Major and Major Public Emergency

Grading Standards. However, these standards contain vague terms such as “extremely large quantity” and “multiple,” and are primarily based on casualties and economic losses. Therefore, exploring the integration of social media indicators to reflect quantitative emergency grading is significant—it not only deepens research on the correlation of similar events based on social media features and improves existing classification standards, but also dynamically reflects emergency severity through indicator systems to enable rapid implementation of corresponding early warning measures.

Existing research on emergency severity assessment primarily focuses on technical improvements for accuracy, using methods such as cloud models [2], multi-class support vector machines [3], and K-Means clustering [4], with most studies targeting natural disasters. In constructing Weibo indicators for emergencies, scholars have proposed various frameworks, but these face quantification challenges, such as group pressure [5] and government information comprehensiveness [6]. For emergency early warning, research has proposed both theoretical frameworks [7] and indicator-based systems [8].

This study focuses on social security incidents, collecting 1,107,308 Weibo posts about four recent social security incidents. Through literature review, we developed an emergency assessment indicator system, applied the entropy method for severity evaluation, and proposed an influence tendency analysis method for severity indicators. Combined with feature comparison and lifecycle theory, we designed a specific early warning mechanism. The findings offer valuable guidance for governments to adopt different early warning measures at various levels.

2 Related Research

2.1 Emergency Severity Assessment Research

Emergency severity assessment evaluates the seriousness of incidents based on their nature, controllability, and impact scope, considering factors such as socioeconomic losses, casualties, and social impact. This study attempts to reflect severity through social media manifestations and features. Severity assessment has evolved from theory-based to technology-based approaches, with early research focusing on system construction and later emphasizing grading accuracy.

Internationally, D. Mladan and V. Cvetkovic [9] analyzed emergency sources through causes, consequences, and intensity, proposing subjective severity assessment standards. To address subjectivity, B. Movahhedi et al. [10] developed a multi-dimensional severity grading system for power emergencies. With technological advances, scholars increasingly employ machine learning methods, such as S.L. Pang [11], who studied emergency algorithms for disaster event big data classification and sorting.

Domestically, Xue Lan and Zhong Kaibin [12] discussed China’s public emergency management framework, while Yang Jing et al. [13] linked emergencies

with resource availability and temporal factors. Subsequent researchers shifted toward machine learning, including grey clustering methods based on triangular fuzzy numbers [2], support vector machines for earthquake disasters [3], data field K-Means clustering to address subjectivity [4], and cloud model theory [14] to handle fuzziness and randomness.

However, existing research suffers from post-hoc assessment and single-dimensional standards, often focusing on natural disasters. This study constructs objective Weibo indicators with objective weighting to identify potential deterioration from social media data and proposes a severity influence tendency calculation formula for timely warnings.

2.2 Emergency Propagation and Indicator Construction Research

Research on online public opinion propagation is relatively mature. Studies have established Weibo posting patterns [15], identified propagation effects [16], and constructed non-linear dynamic diffusion models [17]. For propagation stages and key nodes, Chen Sijing, Li Gang et al. [18] proposed a dynamic identification method for key nodes considering user behavior and influence decay. Lan Yuexin [19] identified three stages of Weibo public opinion diffusion using calculus and MATLAB simulation. Zhao Jinlou et al. [20] analyzed network structures using SNA methods. An Lu and Wu Lin [21] introduced emotion sources and used word2vec to extract sentiment states across event lifecycles.

Current indicator systems provide valuable references. Dai Yuan et al. [22] proposed an early cybersecurity assessment system including diffusion, public attention, content sensitivity, and attitude orientation. Lan Yuexin [5] added content intuitiveness based on online public opinion evolution. Zhang Yiwen et al. [6] built an evaluation system for unconventional emergencies covering event explosiveness, media influence, netizen impact, and government guidance. For public health emergencies, 70 tertiary indicators were established [23]. Lifecycle-based frameworks include generation, diffusion, and decline risk indicators [24], later expanded with prevention risk indicators [25] and mobile social network early warning systems [26], with primary indicators covering intensity, attitude, growth rate, and subject [27].

Early research focused on theoretical frameworks, with limited quantification and empirical studies of terminal indicators. Subsequent scholars like Hong Zhiheng, Fu Changbo, and Liang Guanhua still relied heavily on subjective judgment for indicator construction and weighting. This study addresses these gaps through objective Weibo indicator construction and weighting.

2.3 Emergency Early Warning Mechanism Research

Early warning mechanism research comprises two aspects: severity assessment-linked warnings and theoretical system construction. Zeng Runxi and Xu Xiaolin [28] divided early warning indicators into sources, signs, and situations,

while Liu Xuan et al. [8] constructed unconventional emergency warning indicators from netizen, government, media, and event perspectives. D. Cui [29] proposed water pollution emergency warning indicators, using methods including interval evaluation [30], Delphi and fuzzy comprehensive evaluation [31], and web user logs [32].

Theoretically, X. Yuan et al. [33] established a Wuhan water pollution prediction system. Early frameworks divided warnings into prevention, planning, and preparation [7]. With IT development, integrating human and machine intelligence became essential [34], leading to data warehouse-centered information management frameworks [35], multi-system collaboration [36], and comprehensive management systems covering collection, decision-making, and execution [37], with emergency mining and prevention becoming research priorities [38].

These studies provide valuable references but share limitations of event-centric, post-hoc, and single-dimensional approaches that may not suit social media environments.

2.4 Theoretical Foundations

This study is based on correlation theory, similarity theory, and crisis management theory. Correlation theory posits that nothing exists independently—physical, social, and information spaces exhibit anomalies during emergencies that can be mined through social media features. Similarity theory suggests analogous patterns among similar events, enabling generalizable indicator systems and early warning frameworks.

Regarding crisis definitions, P.T. Hopmann views crises as threats to decision-makers' fundamental goals requiring rapid response in abnormal social contexts [39]. Xue Lan defines crises as threats to social system values requiring timely critical decisions in non-normal situations [40]. Crisis classification is diverse, including natural/human-induced and political/economic/social crises, necessitating comprehensive management. Robert Heath's crisis management theory emphasizes pre-, during-, and post-event management to mitigate impacts, providing a framework for monitoring, prevention, and handling. This study applies these principles to assess severity through Weibo features and implement stage-based warnings.

3 Research Methods

3.1 Emergency Severity Assessment Indicator Design

Indicator selection follows scientific, objective, operational, and comprehensive principles. Based on social media propagation characteristics, we identify five essential elements: netizens, internet media, event status, attitudes, and emotions. Netizens, as primary stakeholders, directly affect severity through posting, forwarding, commenting, and liking (collecting is rare [26,41-42] and thus

excluded). Internet media amplifies attention through reporting behavior, measured by media institutions and news quantity [6]. Event status reflects propagation extent and severity, captured through duration and spatial diffusion rate [5,22,24]. Attitudes reveal overall public stance (positive, negative, neutral) [5-6], while emotions quantify sentiment distribution. Both reflect public evaluation of severity and influence event trajectories.

We designed the indicator system shown in Table 1, converting some indicators to rate forms for dynamic severity reflection. The base indicator layer includes:

- (1) **Netizen Influence (A11)**: Posting rate (A111), forwarding rate (A112), commenting rate (A113), and liking rate (A114). Due to large data volumes, we randomly sampled original posts with >1 forward/comment per time period.
- (2) **Internet Media Influence (A12)**: New media institutions (A121) and news reporting rate (A122), based on certified media bloggers.
- (3) **Event Diffusion (A13)**: Event duration (A131) and city diffusion rate (A132), using forwarders' geolocation data.
- (4) **Attitude Orientation (A14)**: Original content orientation (A141), forward comment orientation (A142), and comment orientation (A143). We used Baidu AI sentiment analysis (range [0-1], lower values indicating more negative attitudes), averaging results. For comments, we randomly sampled 20% following the Pareto principle.
- (5) **Netizen Sentiment (A15)**: Negative (A151), neutral (A152), and positive (A153) sentiment counts, summing original posts, forward comments, and sampled comments.

All indicators are positive except attitude orientation, which we converted by subtracting from 1 before standardization using formula (1).

3.2 Entropy Method for Emergency Severity Assessment

We grouped Weibo entries by hour, extracted indicators, and created a Weibo-indicator matrix where v_{ij} represents the j -th indicator value for the i -th group. The entropy method, proposed by C.E. Shannon, evaluates indicator discreteness. The calculation process:

- (1) **Data Standardization:**

$$X_{ij} = \frac{v_{ij} - \min_{0 \leq i \leq n}(v_{ij})}{\max_{0 \leq i \leq n}(v_{ij}) - \min_{0 \leq i \leq n}(v_{ij})} \quad (1)$$

where $i = 1 \dots n$ (samples) and $j = 1 \dots m$ (indicators).

- (2) **Proportion Calculation:**

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^n x_{ij}} \quad (2)$$

(3) **Entropy Value:**

$$f_j = -k \sum_{i=1}^n p_{ij} \ln(p_{ij}) \quad (3)$$

where $k = 1/\ln(n)$.

(4) **Redundancy:**

$$d_j = 1 - f_j \quad (4)$$

(5) **Weight:**

$$W_j = \frac{d_j}{\sum_{j=1}^m d_j} \quad (5)$$

(6) **Severity Score:**

$$F = \sum_{j=1}^m W_j \cdot X_{ij} \quad (6)$$

3.3 Influence Tendency Analysis of Severity Indicators

To determine how indicator value ranges affect severity levels, we calculated the proportion of Weibo groups at each severity level within each indicator range. The formula is:

$$\text{Influence Tendency} = \frac{\text{Groups at severity level } i \text{ in range}}{\sum_{i=1}^4 \text{Groups at severity level } i \text{ in range}} \quad (7)$$

where severity levels correspond to: “/” = 1, “I” = 2, “II” = 3, “III” = 4. Preliminary experiments determined range boundaries, which were then merged based on influence patterns.

3.4 Emergency Early Warning Research

We classify severity into three levels: General, Medium, and Severe, corresponding to four warning levels: No Warning (Gray), General Warning (Yellow), Medium Warning (Orange), and Severe Warning (Red). Gray indicates no severity; Yellow indicates general social/property impact; Orange indicates significant impact; Red indicates major or greater impact.

According to national emergency response requirements, general emergencies are handled at county level, larger ones at municipal level, major ones at provincial level, and particularly major ones nationally. Given limited cases, we merged major and particularly major into “Severe,” creating three grades: General (Level I), Medium (Level II), and Severe (Level III). Warning thresholds are determined through feature comparison and influence tendency analysis, examining both within-event indicators and across-event indicators.

4 Experiments and Results Analysis

4.1 Data Collection and Preprocessing

The National Overall Emergency Plan doesn't explicitly define incident mechanisms. For social security incidents, the *Introduction to Social Security Emergency Management* defines them as events in the social security domain caused by human factors that threaten or cause serious harm, requiring urgent government measures [43]. According to Article 50 of the Emergency Response Law, public security organs are primary responders, and criminal cases belong to this category [44].

We selected four recent influential criminal cases: the “8·24 Yueqing Girl Ride-Hailing Murder Case,” “5·6 Zhengzhou Flight Attendant Ride-Hailing Murder Case,” “8·27 Kunshan Knife Attack Case” (2018), and “Ctrip Kindergarten Abuse Incident” (2017). Data collection yielded 1,107,308 Weibo posts (Table 2), stored in MongoDB. After cleaning and hourly grouping, we extracted indicators for 783 data rows.

Table 2 Data Statistics for Four Incidents (Unit: posts) | Incident | Original Posts | Media Posts | Forwards | Comments | Likes | Total | |———|

Incident	Original Posts	Media Posts	Forwards	Comments	Likes	Total
Yueqing Girl Murder	36,896	1,278	85,963	195,849	66,073	386,059
Zhengzhou Flight Attendant Murder	24,725	1,149	55,788	119,128	40,408	241,198
Kunshan Knife Attack	23,898	931	73,477	157,107	49,078	304,491
Ctrip Kindergarten Abuse	15,636	550	40,241	84,732	34,401	175,560

Severity levels were determined based on official response mechanisms (Table 3): - **Severe (Level III)**: Yueqing case (major case mechanism, intermediate court involvement) and Ctrip case (Shanghai Women's Federation identified as severe child harm) - **Medium (Level II)**: Zhengzhou case (municipal handling) and Kunshan case (municipal handling)

4.2 Correlation Analysis of Severity Assessment Indicators

Spearman correlation analysis validated the indicator system. With significance level $p < 0.05$ and $|\text{coefficient}| > 0.8$ indicating high correlation, results showed: - Netizen influence indicators (A111-A114): highly correlated - Internet media indicators (A121-A122): highly correlated - Event diffusion indicators (A131-A132): significantly negatively correlated - Netizen sentiment indicators (A151-A153): highly correlated - Attitude orientation indicators (A141-A143): no significant correlation

Netizen influence and sentiment indicators showed high inter-correlation. Forwarding rate correlated with city diffusion rate, which also correlated with sentiment indicators.

4.3 Emergency Severity Assessment

After converting attitude indicators, we calculated weights: - Netizen influence: $A_{11} = \{0.68599, 0.093633, 0.102482, 0.173177\}$ - Internet media: $A_{12} = \{0.130937, 0.096399\}$ - Event diffusion: $A_{13} = \{0.019637, 0.068625\}$ - Attitude orientation: $A_{14} = \{0.00156, 0.003096, 0.003555\}$ - Netizen sentiment: $A_{15} = \{0.07831, 0.085564, 0.074423\}$

Substituting into formula (6) and scaling by 100, we established severity levels (Table 4). The highest score during each event determined its final grade: - Yueqing: 100 (Level III, Severe) - Zhengzhou: 56 (Level II, Medium) - Kunshan: 55 (Level II, Medium) - Ctrip: 65 (Level III, Severe)

These align with official classifications from Section 3.1.

Table 4 Severity Levels and Warning Thresholds | Severity Score | Severity Level | Warning Level | |-----|-----|-----| | [0-10] | / | Gray (No Warning) | | [10-30] | I | Yellow (General) | | [30-60] | II | Orange (Medium) | | [60-100] | III | Red (Severe) |

4.4 Influence Tendency Analysis of Severity Indicators

We conducted pre-experiments with small intervals, then merged ranges based on influence patterns. Final intervals were determined by indicator characteristics and multiple trials. For netizen influence (Table 5): - **No influence** (“/”): Posting rate <100, forwarding rate <500, commenting rate <1000, liking rate <2000 - **General influence** (“I”): Posting rate [100-300), forwarding [500-1000), commenting [1000-2000), liking [2000-6000) - **Medium influence** (“II”): Posting rate \$ \$300, forwarding [1000-3000), commenting [3000-6000), liking [8000-80000) - **Severe influence** (“III”): Posting rate \$ \$500, forwarding \$ \$3000, commenting \$ \$6000, liking \$ \$80000

Critical transition zones require attention: commenting rate [2000-3000) and liking rate [6000-8000) may escalate to medium severity.

4.5 Feature-Based Emergency Early Warning Research

Within-event comparison (Yueqing case, Figure 1 [Figure 1: see original paper]) shows: - From onset to outbreak (2-3 hours), rates grow exponentially - During outbreak, netizen influence and sentiment peak - In spread period, rates remain high but stable - In decline, all rates gradually approach zero - Negative sentiment far exceeds neutral/positive during outbreak/spread, converging over time

Across-event comparison (posting rates, Figure 2 [Figure 2: see original paper]) reveals: - Severe events (Yueqing, Ctrip) show consistent linear growth in onset - Medium events (Zhengzhou, Kunshan) have prolonged onset before outbreak - Kunshan shows multi-peak outbreak with exponential growth - Severe events maintain higher rates longer during spread - Decline rates fall below 100

4.6 Early Warning Analysis

Based on influence tendency and feature comparison, we propose the early warning mechanism in Table 6 :

- (1) **Gray Warning (No Warning):** When all indicators are at low levels (e.g., posting <100/hour, forwarding <500/hour), events are in onset/decline or during 1-5 AM. However, exponential growth during onset or after 5 AM signals potential escalation.
- (2) **Yellow Warning (General):** Medium indicator ranges indicate outbreak/spread periods. Authorities should activate yellow warning to prevent deterioration.
- (3) **Orange Warning (Medium):** Higher ranges (posting \$ \$300/hour, forwarding [1000-3000]/hour) indicate significant impact. Orange warning is required.
- (4) **Red Warning (Severe):** Very high ranges (posting \$ \$500/hour, forwarding \$ \$3000/hour) indicate major impact requiring immediate red warning.

Special considerations: - Prolonged low-level activity requires monitoring - Attitude orientation indicators (original content, forward comments, comments) stable at [0.6-0.8) during onset/outbreak/spread need attention; large fluctuations during decline require no warning - Transition zones (e.g., commenting [2000-3000), liking [6000-8000)) need careful monitoring to prevent escalation

5 Conclusion and Discussion

This study on social security incidents developed an emergency severity assessment indicator system, validated correlations, conducted severity evaluation, analyzed indicator influence tendencies, and established an early warning mechanism through lifecycle-based visualization. Innovations include:

1. **Social media-based severity assessment:** Unlike traditional economic/casualty-based studies of natural disasters, this research explores severity assessment from a social media perspective, establishing associations between event severity and social media features using objective entropy weighting. Results align with national standards, providing quantitative methods for emergency management.
2. **Influence tendency analysis:** Based on statistical principles, we calculated indicator ranges' influence on severity levels by computing proportions of Weibo groups, enabling dynamic early warning mechanisms with practical value for managers.

Findings: - The indicator system shows expected correlations: event duration negatively correlates with city diffusion; netizen influence correlates with sentiment; attitude indicators are independent - Entropy method provides dynamic

severity assessment consistent with official classifications - Feature comparison reveals lifecycle patterns: exponential growth during onset, peak rates during outbreak, stability in spread, and gradual decline - Dynamic warnings vary by time (e.g., gray warnings during 1-5 AM) but maintain previous levels if already activated

Limitations: The social media-based indicators primarily apply to publicly disclosed social security incidents classified by casualties. Future research should expand to other emergency types and extract common/key factors to improve generalizability.

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Author Contributions

An Lu: Conceived research ideas, designed methodology, revised manuscript.

Chen Miaomiao: Collected and analyzed data, created figures, drafted manuscript.

Li Gang: Conceived research ideas, revised manuscript.

Note: Figure translations are in progress. See original paper for figures.

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