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Promote citizen engagement with warnings —— an empirical examination of government social media accounts during public health crises

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Abstract

Background Effective warnings are important for preventing the spread of disease during the early stages of outbreaks. Social media serves as a valuable platform for disseminating warning messages. The success of warnings issued through government social media accounts (GSMAs) depends on citizen engagement. However, an incomplete understanding of the relationship between warning messages and audience responses has hindered the design of crisis communication strategies.

Methods We investigated the factors affecting citizen engagement with warnings on GSMAs during public health crises. Drawing on the Elaboration Likelihood Model (ELM) and the Crisis and Emergency Risk Communication (CERC) framework, model was developed to analyze the effects of central routes (content features) and peripheral routes (microstructural and source features) on citizen engagement, as well as the moderating effect of disease type. Data were collected from 38 Sina Weibo accounts of government agencies in China during two public health crises: COVID-19 and H1N1. Logit regression analysis was conducted to test the hypothesized relationships.

Results The results indicate that (1) positive emotional tendencies and more warning elements are associated with citizen engagement; (2) the relationship between message length and citizen engagement follows an inverted U-shape; (3) media richness and information style variety significantly enhance citizen engagement; and (4) disease type (emerging vs. reemerging infectious diseases) moderates the relationships between media richness, information style variety, source influence, and citizen engagement.

Conclusions Given that issuing warnings is critical to emergency management, our findings provide significant theoretical and practical insights, particularly for improving early government-public communication through social media platforms.

Trial registration Not applicable.

Keywords Government social media account, Public health crises, Warning messages, Citizen engagement, Risk communication

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Introduction

With population growth and climate change, humanity faces ongoing challenges from infectious diseases. Timely warning information before a large-scale outbreak is crucial for addressing ambiguous and slow-developing threats [1, 2]. In China, the centralized political structure enables the warnings dissemination managed by the government, ensuring a consistent and controlled flow of information nationwide [3, 4]. Governments play a critical role in timely, accurate information dissemination, helping to prevent the spread of misinformation and panic among the public [5–7]. Social media have become increasingly powerful tools due to wide reach and real-time connectivity. Government agencies establish social media accounts (GSMAs) to disseminate information [2]. GSMAs provide a platform for direct interaction between the public and authorities during crises, and messages from GSMAs can be amplified through user engagement [2]. Low public engagement with warnings may render the effectiveness of crisis communication efforts, potentially exacerbating the crisis, decreasing public morale, and reducing compliance with health interventions.

Studies suggest that disseminating warnings on social media is particularly challenging during the early stages of a crisis, when public awareness is limited, and the urgency of the situation is not yet widely recognized [8]. During later stages, extensive media coverage and public discourse increase the perceived significance of the crisis, leading to higher engagement. Warning posts also often compete with unrelated topics, trending events, and misinformation, which can divert user attention. Some individuals may remain unaware of warnings, while others may dismiss warnings as uninteresting or irrelevant [9]. Additionally, inconsistencies or a lack of detail in warnings can fuel skepticism or hesitation among the public. As the crisis progresses, clearer and consistent communication tends to build public trust, which, in turn, facilitates the dissemination of messages [2]. Consequently, it is imperative for government communicators to design effective warning strategies that actively engage the public.

Despite increasing scholarly attention to disseminating warnings through GSMAs during public health crises, significant gaps persist. First, existing research has predominantly relied on case studies and interviews to examine the institutional frameworks and implementation mechanisms for issuing warnings during infectious disease crises. Some studies have explored information design during the outbreak and recovery phases of a crisis [10]. However, limited attention has been paid to the relationship between the specific design of warnings and public engagement [7]. This gap weakens the effectiveness of warnings in facilitating timely prevention [11]. Our study addresses a critical but underexplored aspect of risk communication by analyzing how the design of warning messages influences public engagement.

Second, existing research on warning communication has largely focused on content elements, such as content type and emotional tone [4, 12–14]. However, far less attention has been given to surface-level processing pathways. In the early stages of public health crises, the public may lack the cognitive or affective capacity to engage with content-driven pathways, making peripheral cues particularly influential. This study draws on the Elaboration Likelihood Model (ELM) to investigate how warning strategies influence public engagement with social media through central and peripheral processing routes. It specifically evaluates the effectiveness of content-based, microfeature-based, and source-based strategies in driving engagement, offering governments actionable recommendations for designing messages.

Third, according to the CERC framework, citizens' engagement with messages is influenced by the context and circumstances of disasters [15–17]. In public health crises, variations in the scope, severity, and nature of diseases can significantly affect how warnings are perceived and acted upon. However, few studies have incorporated contextual variables to explain this impact. This study analyzed data from different public health crises to explore how information persuasion strategies affect public engagement across varying contexts. Specifically, emerging infectious diseases often evoke heightened uncertainty and fear, requiring distinct messaging strategies compared to re-emerging diseases, which are typically viewed as more familiar or manageable. Recognizing contextual differences is essential for refining warning strategies and tailoring them to the specific demands of diverse crises.

Above all, this study aims to investigate the design of warnings issued by GSMAs. Specifically, it evaluates the impact of central route variables (e.g., sentiment tendency and warning elements) and peripheral route variables (e.g., message length, dialogic loop, media richness, information style variety, source influence, and source activeness) on public engagement. The analysis considers two distinct types of public health crises: emerging and re-emerging infectious diseases. Data were collected from warning messages posted by thirty-eight verified microblog accounts managed by national and provincial government authorities. The findings offer valuable insights for improving digital dissemination of health crisis messages and enhancing the effectiveness of crisis communication.

The rest of this paper is organized as follows. Section 2 reviews the literature, while Section 3 introduces the research model and hypothesis. Section 4 describes the data collection and research methods, followed by the presentation of the results in Section 5. Section 6 discusses the key findings, implications, and limitations of the research. Section 7 concludes.

Literature review and theoretical background

Crisis and emergency risk communication(CERC) and warning information

The CERC framework combines established public health practices with principles of crisis communication. Described by Reynolds and Seeger as a hybrid approach, CERC provides a comprehensive strategy for delivering critical, lifesaving information during public health emergencies [18]. It emphasizes the importance of ongoing, two-way communication to engage the public, agencies, and other stakeholders. Incorporating public feedback and understanding behavioral responses can further improve communication quality. Previous research has used the CERC to evaluate the adequacy of news coverage and social media posts during public health crises, including bird flu, Ebola, depleted uranium exposure, and chemical spills [19]. However, while many studies have referenced and used CERC in case studies, few empirical tests of this framework have been conducted.

The complexity of crises demands carefully tailored communication strategies that align with each stage of the crisis lifecycle. According to CERC framework, the pandemic response consists of five stages: (1) pre-crisis, (2) initial event, (3) maintenance, (4) resolution, and (5) evaluation [20]. As risks evolve throughout these stages, the effectiveness and processes of communication change significantly. However, most research has focused on crisis communication during later stages, such as damage assessment, rescue efforts, and community recovery, while the pre-crisis and initial event stages remain underexplored [11]. This study focuses on the critical warning communications in the first two stages, which are typically one-way and informational, with limited community feedback in real-world scenarios. Furthermore, the CERC framework emphasizes that effective risk communication requires dynamic adjustments to address the nature of the disease, its transmission patterns, and audience needs. Because communication strategies depend on the specific type of crisis, it is essential to consider the unique characteristics of each threat when designing information strategies [15–17].

The International Strategy for Disaster Reduction (ISDR) defines warnings as the timely delivery of information issued by institutions, enabling individuals at risk to take measures to mitigate hazards and prepare for appropriate response [1, 8, 21]. Many warning communication policies highlight the importance of the integration of "multi-channel" information delivery systems [12]. Research underscores the role of social media in educating vulnerable populations and reaching broader audiences through key hashtags. However, Lindell et al. (2021) found that local news remained the most widely used information source [22]. Due to the potential for disasters to disrupt internet infrastructure, which could render social media ineffective, supplementary communication methods are essential.

Effective warnings should also minimize ambiguity, which often arises from unclear messaging, uncertainties regarding the nature or scale of the risk, and varying public perceptions of the crises [2, 3, 9]. Visual aids, especially detailed maps, are widely acknowledged for the ability to enhance public understanding [1–3]. Maps that delineate geographic impact areas, evacuation zones, and hazard-prone regions provide a clear representation of risks, enabling individuals to assess their proximity to danger and take appropriate actions. Additionally, warning communication requires audience-specific strategies tailored to the characteristics of the target population. Cuite et al. (2021) proposed a tiered warning notification system based on the severity of the emergency, complemented by diverse message formats designed to address community diversity [23]. While the aforementioned studies provide valuable insights into improving public warning communication, most research has primarily focused on natural disasters [9, 22]. This creates an opportunity to examine how effectively health authorities apply the CERC model during the pre-crisis or initial stages of warning communication in public health crises. Such an investigation could generate valuable evidence and insights to further strengthen the model.

Government use of social media in crisis management

Social media, with its capabilities for real-time information access, rapid updates, and interactive engagement, has become a critical tool for disseminating risk information across all stages of disasters [7]. Government agencies actively use GSMAs to release authoritative and verified information, aiming to bridge information gaps that often arise during crises, thereby reducing confusion and uncertainty. For example, situational updates on disease symptoms, transmission rates, and the number of confirmed cases help the public assess the severity of crises. Instructional guidance, such as advice on handwashing and mask-wearing, aids in disease prevention and equips individuals to respond effectively to crises [6]. More importantly, the networked nature of social media facilitates the rapid and widespread dissemination of information at relatively low cost [5, 7]. Official messages can reach a broad audience almost instantaneously, significantly enhancing both coverage and accessibility [5]. Rapid dissemination also strengthens public preparedness and combats misinformation.

In recent years, scholars have increasingly investigated how post-persuasion strategies are applied through GSMAs and the corresponding effects on engagement.

These strategies are generally categorized into message-specific and publisher-specific factors. Message-specific strategies focus on the design and content of posts: (1) Structure-focused factors: Elements such as pictures, hashtags, videos, headlines, mentions, and links can enhance the appeal and visibility of government posts [9, 24–26]. (2) Topic-focused factors: Existing research on GSMAs has explored how information content during the control and recovery phases of public health crises affects citizen engagement. For example, Chen et al. found that updates on the latest news and government measures positively affected online citizen engagement during the COVID-19 outbreak in China [5]. Landi et al. analyzed Facebook posts from Italy, the UK, and New Zealand during the pandemic, finding that appreciation posts for medical staff received more likes while government action posts generated more comments [13]. (3) Emotion-focused factors: Emotional cues, including emotional intensity and valence, significantly impact public engagement. Posts that resonate emotionally with audiences are more likely to foster interaction and promote trust [27]. In addition to message-specific strategies, publisher attributes, such as administration style, credibility, and authority, also lead to diverse outcomes on individual engagement [4, 28, 29]. Building on existing research, our study aims to develop a more comprehensive framework for warnings on GSMAs during public health crises to enhance public engagement.

Elaboration likelihood model

Originally proposed by Petty and Cacioppo, the Elaboration Likelihood Model (ELM) provides a theoretical framework for understanding how individuals process information to shape attitudes, make decisions, or modify behaviors [25, 30]. ELM posits that online information is processed through two distinct pathways: the central route and the peripheral route, determined by an individual's level of elaboration. The central route is associated with high elaboration, where individuals engage thoughtfully and critically with the content, while the peripheral route corresponds to low elaboration, relying on surface cues. Extensive research has highlighted the significant impact of both routes on recipients' cognition and confirmed the ELM's relevance in information adoption and participation. For example, Sussman and Siegal applied the ELM to online information dissemination, arguing that audiences' willingness to adopt information is influenced by the central route (information quality) and the peripheral route (source credibility) [31]. Similarly, Cheung et al. extended the ELM by identifying specific indicators of information quality and source credibility, which exert distinct influences on audiences' willingness to adopt information [32].

The central route involves the systematic and thoughtful evaluation of information, wherein individuals critically analyze arguments [33]. This route is activated when recipients are both motivated and capable of carefully examining the content. Attitude changes through the central route occur as individuals deeply assess issue-related arguments, with the process strongly influenced by the quality of the information, including its novelty, depth, and objectivity. Factors such as information completeness [34] and the sentiment expressed [35] are considered central route elements, shaping recipients' perceptions of information usefulness. For example, recipients of an SMS-based disaster alert who thoroughly examine the details to evaluate the validity of the warnings and the reliability of recommended actions are engaging in central route processing. The processing route is more likely to lead to enduring attitude changes and sustained behavior modification, as it allows individuals to internalize information and integrate it into existing belief systems [26, 28, 33].

In contrast, the peripheral route in ELM relies on heuristics and peripheral cues to form judgments, particularly when individuals lack the motivation, ability, or cognitive resources to thoroughly evaluate the message content. Rather than focusing on issue-relevant information, this route emphasizes easily accessible and superficial features of messages, such as information source, general impression, message length, or other surface-level characteristics that require minimal cognitive effort to process [30, 33]. Peripheral cues, which are external or surface-level attributes, influence perception and decision-making without requiring an in-depth understanding of the message substance [30]. For example, in the context of SMS-based disaster alert systems, recipients may rely on the sender's authority as a basis for assessing the relevance of message, rather than critically analyzing its content. While peripheral processing is efficient and often adequate for facilitating quick decision-making, it has notable limitations. Judgments formed through peripheral route tend to be less stable over time and are more vulnerable to external influences or contextual changes.

In summary, ELM illustrates how information recipients respond to and process given information based on various factors. User engagement in the context of disaster management begins with reading and processing of warning messages, manifesting as behavioral decisions following the assessment of such messages [26, 33]. Therefore, persuasive strategies for government agencies should enhance the quality of warnings through the central route, while simultaneously leveraging microstructural features of information and information sources via the peripheral route to maximize impact.

Research model and hypotheses

Research model

This study integrates the CERC and the ELM to develop a theoretical model linking the features of warning messages issued by GSMAs during public health crises to public engagement. The CERC framework highlights the importance of two-way communication that creates a feedback loop between information delivery and public response. It also emphasizes stage-specific communication strategies, as crisis priorities evolve, and underscores the role of contextual factors in shaping outcomes. Thus, our study focuses on the warning phase of a crisis and incorporates disease type as a moderating variable to identify optimal strategies across different crisis contexts.

Meanwhile, the ELM provides a complementary lens to examine how specific features of warnings drive public engagement. We conceptualize content features (e.g., sentiment tendency, warning elements) as central route variables, which involve systematic and deliberate processing. Microstructural features (e.g., message length, dialogic loop, media richness, information type variety) and source features (e.g., source influence, source activeness) are treated as peripheral route variables, relying on heuristic and surface-level processing. We hypothesize that warnings can stimulate public engagement through both central and peripheral routes, depending on individuals' motivation and ability to process the messages. This study proposes a cohesive conceptual model that explains the relationships among information features, contextual factors, and public engagement in crisis communication. It offers a robust theoretical foundation for developing more flexible and targeted communication strategies. The proposed theoretical model is illustrated in Fig. 1.

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Hypotheses regarding the central route

Content features and citizen engagement on GSMAs

GSMAs deliver posts with diverse emotional content, including happiness, fear, joy, anger, and anxiety. Positive and negative emotional expressions represent distinct categories of sentiment, and their influence on audience engagement varies depending on communication contexts [27]. During crises, GSMAs posts often benefit from adopting a positive emotional tone. This strategic use of positivity fosters trust and credibility, enhances public compliance, and encourages the dissemination of information. For instance, Feng et al. found that positive emotional messages elevated hope and addressed psychological needs under challenging circumstances [27]. Citizens have shown a preference for engaging with official Twitter accounts that share posts containing positive emotions. Liu et al. analyzed Facebook posts from 55 governments and organizations before and after Hurricane Harvey, and found that positive emotional expressions elicit empathy and help the public cope with the emotional distress caused by crises [36]. This, in turn, promotes community-supportive behaviors and fosters collective resilience. Beyond the affective responses of positive emotions, Barbara Fredrickson's broaden-and-build theory offers a cognitive framework that deepens our understanding of these findings [37]. This theory posits that positive emotions expand individuals' cognitive and attentional capacities, enabling them to think more

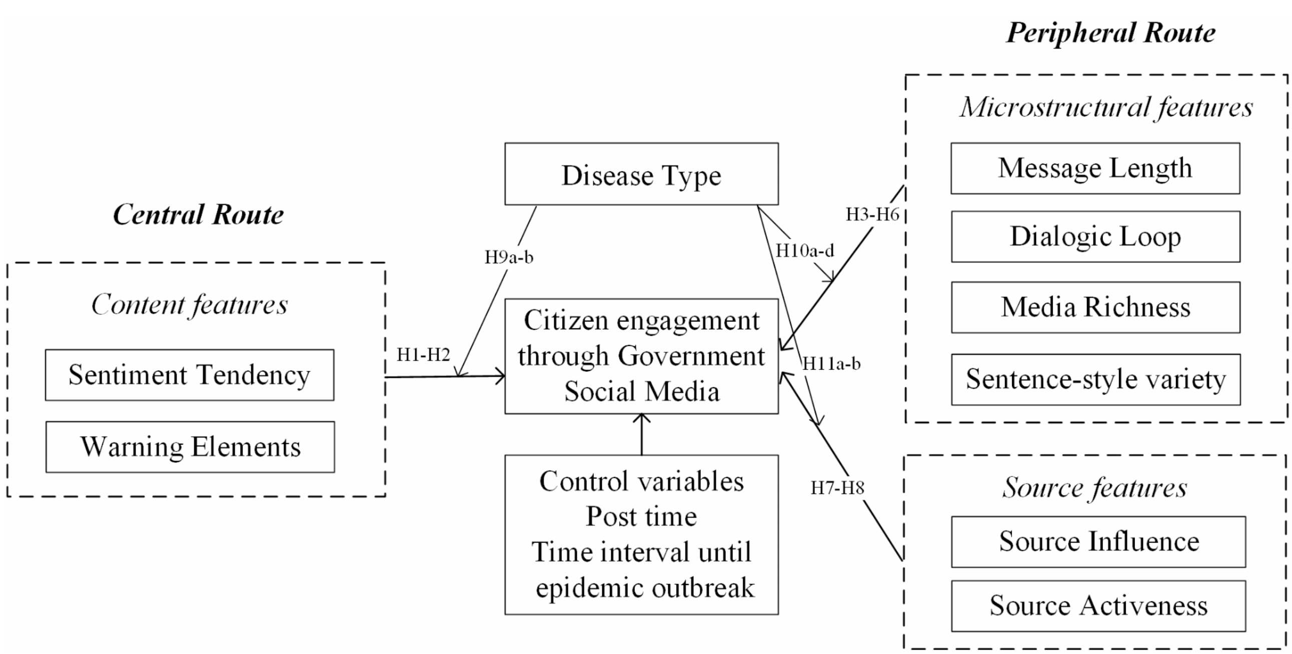

Fig. 1 Research model for warning information from GSMAs

flexibly, process information more critically, and engage more effectively with the environment [37]. In disaster communications, messages that stimulate positive emotions help individuals notice subtle informational details that may be overlooked in high-pressure situations [15, 17]. Moreover, positive emotions encourage thoughtful and deliberate participation in communication, aligning with the central route of ELM. In addition to broadening cognition and attention, such emotions play a pivotal role in building social connections [17]. Positive emotional expressions increase the likelihood that individuals will share and discuss information with others, thereby amplifying critical messages reach. Drawing on the above theoretical and empirical evidence, we propose the following hypothesis:

H1 Warnings with positive sentiments predict citizen engagement.

When crises occur, public engagement on social media often varies significantly across different topic categories. Studies have paid attention to topics during the disaster response and recovery stages. Sutton et al. found that tweets that detailed impacts and offered instructional information during a wildfire were more likely to be retweeted [38]. Similarly, messages focused on community recovery, disaster losses, and rescuers in the contexts of hurricanes and bombing incidents were found to positively influence retweet counts. Meanwhile, messages tailored to specific audiences (e.g., expressions of appreciation or closing announcements) tend to be shared less. Regarding media information during the COVID-19 epidemic, differences in content categories also produced differences in citizen engagement. Xie et al. found that information regarding government measures during crises had the most demand, reflecting public concern about potential risks and uncertainties [39]. Compared with information about frontline emergency services, the latest news about the epidemic effect and information about treatment were more attractive to users and affected citizen engagement [6].

Nevertheless, studies have yet to determine whether posts containing more warning elements are more likely to influence citizen engagement. Warning elements are specific and distinct during the initial stages of public health crisis. Mileti and Sorensen suggested that warning information design relies on elements such as hazard, guidance, location, time, and source [1]. These elements are foundational for constructing messages that not only inform but also motivate the public to take action. Wang et al. found that messages that comprehensively covered multiple warning elements were more likely to be shared among users during Hurricane Irma [4]. However, how (and to what extent) the use of one or more warning elements in a post affects citizen engagement in public health emergencies remains underexplored. Thus, we propose the following:

H2 Information containing more warning elements produces more citizen engagement than information with fewer elements.

Hypotheses regarding the peripheral route

Microstructural features and citizen engagement on GSMAs

Message length (i.e., the number of words in a post) plays a critical role in determining its informativeness. However, how message length influences citizen engagement in disaster contexts remains underexplored, with existing studies producing mixed results. For instance, Xu et al. found that the message length of tweets related to the Malaysia Airlines Flight 370 disaster had a monotonous positive relationship with sharing frequency [29]. They argued that longer messages tend to provide more comprehensive arguments, which enhances persuasiveness. Similarly, Li et al. found a positive correlation between message length and transmission during COVID-19, suggesting that longer messages are more widely shared [40]. These findings are rooted in the Need for Cognition Theory, which indicates that individuals are motivated to seek out and process more information to fulfill cognitive needs [41]. Longer messages provide greater detail and clarity, allowing audiences to analyze and evaluate information more effectively, ultimately enhancing engagement [42].

However, Cognitive Load Theory highlights the potential drawbacks of excessively long messages. When the length of a message exceeds an individual's cognitive processing capacity, cognitive overload may occur, causing resistance and reduced engagement with the content. Furthermore, linguistic studies indicate that overly lengthy messages can undermine clarity, persuasiveness, and argumentative focus, ultimately weakening audience responses. Son et al. analyzed 106,479 original tweets and 127,449 retweets related to the 2013 Colorado flood and found that message length negatively impacted both the average retweet time and frequency [14]. Their findings suggest that lengthy messages are particularly prone to inducing cognitive overload in high-stress situations, making them less likely to be shared by audiences.

Building on the theoretical details above, we hypothesize a nonlinear relationship between the length of warning messages and public engagement. The inverted U-shaped relationship between information length and online behavior has been well-documented in various research domains, such as financial crowdfunding [43], digital marketing [44], and online knowledge dissemination [45]. We propose that longer warnings are likely to positively influence public engagement with GSMAs, but only up to a certain threshold. Beyond this point, excessively long messages may hinder engagement. Consequently, we expect this relationship to follow an inverted U-shaped curve. Therefore, we propose the following hypothesis (H3):

H3 The relationship between warning length and citizen engagement has an inverted U-shape. The relationship is positive at lower levels of length; it dissipates at intermediate levels and becomes negative at higher levels.

Dialogic communication theory posits that for organizations to cultivate dynamic, lasting relationships with the public, they must incorporate dialogic loops into online communication. Many studies have focused on the potential of information technology to facilitate dialogue and build relationships between organizations and audiences, particularly through the use of social media [3, 5, 6, 9]. Technological tools (e.g., hyperlinks, hashtags, mentions) help transform one-way information transmission into more interactive conversations [5, 6]. Studies have connected commercial organizations' dialogic loops with citizens' use of technological features, reflecting citizen engagement. Men et al. found the dialogic loops of top social CEOs on Facebook could effectively encourage public engagement. Wang and Yang found that for-profit organizations' dialogic loops on Twitter influenced followers' retweets and likes [3]. Considering the COVID-19 context, Chen et al. analyzed Wuhan's official Weibo account to investigate how its use of dialogic loops influenced citizen engagement during the most critical phases of the pandemic [5]. Their findings revealed that citizens were more likely to like, repost, and comment on posts that incorporated multiple dialogic features. Similarly, Yang et al. studied the Wuhan government's Weibo account and found that the use of the @ sign in dialogic loops positively affected the number of comments and likes [46]. Aiming to validate the effect of dialogic loops in GSMA warning messages on citizen engagement, we propose the following hypothesis:

H4 Dialogic loops in warning messages positively predict citizen engagement.

Another important factor is media richness, which refers to the sensory experience provided by information in media environments [5, 14, 33]. Media richness is a summative term that includes diverse formats for content posting. Existing studies mostly focus on the relationship between images or videos and the single dimension of citizen engagement (likes, shares/retweets, comments) through social media, but the results are controversial. Most studies demonstrate that higher media richness elicits emotions more easily than text only, enhancing citizen participation [33]. These visual media formats can capture the audience's sensory perceptions, resulting in immersive and influential experiences. Others, meanwhile, have found that media richness doesn't influence citizen engagement. Chen et al. suggested that during epidemics, individuals care more about the textual content of information than the inclusion of visual media [5, 6]. Rahim et al. examined photos posted on the Malaysian Health Department's Facebook page and concluded that pictures had no significant effect on citizen engagement [47]. Yang et al. found that pictures increased the number of comments, whereas videos had the opposite effect [46].

Media richness theory suggests that the effectiveness of media depends on its alignment with specific contexts and tasks [36]. When media with high richness is inappropriately applied to certain tasks, it can yield suboptimal results. In the case of warnings issued during public health crises, such messages may initially be met with skepticism or resistance from the public. This reaction often arises from the unexpected and alarming nature of the warnings, combined with factors such as distrust or information overload, which can desensitize audiences. Furthermore, not all individuals can directly process or fully comprehend textual warnings. By utilizing visually impactful media, organizations can address barriers of disbelief, prompting the public to take action. Thus, we propose H5:

H5 The media richness of warnings positively influences citizen engagement.

Posts can use various sentence styles, including declarative, interrogative, and exclamatory forms. The choice of sentence style reflects "how something is being said", which can influence how messages are perceived and processed by audiences [38]. While many studies have focused on the effectiveness of individual sentence styles, they often neglect how combining different styles might synergistically enhance citizen engagement. According to Wang et al., tweets containing declarative, exclamatory, and interrogative statements had significant positive effects on retweet counts during Hurricane Irma [4]. Lee and Yu found that the use of interrogative sentences promoted reposts during the 2013 flood in Colorado [48]. Sutton et al. found that interrogative sentences increased retweets during blizzards and floods [38]. Research in communication and psychology indicates that combining these styles can enhance message memorability and resonance, particularly in high-pressure disaster scenarios where audiences may be overwhelmed by information [25]. We can present warnings in a layered approach by combining different sentence styles: questioning to engage, declaring to inform, and exclaiming to alert. This method can ensure that messages are not only heard but also adopted by audiences, regardless of initial perceptions or knowledge of the crisis. Thus, we propose the following:

H6 Information style variety in warnings positively influence citizen engagement.

Source features and citizen engagement on GSMAs

Previous research on ELM highlights the importance of source influence as a critical factor in the peripheral route of information processing [49]. Source influence, defined as "the ability to affect how others might act and to effectively spread information," is particularly vital in disaster contexts, where timely dissemination of critical information can significantly impact public decision-making [49, 50]. Information originating from influential sources tends to elicit greater citizen engagement, as these sources are often perceived as more credible and authoritative. A common metric for quantifying source influence is the number of followers an account has. From a network perspective, highly influential accounts are typically characterized by large audiences and central positions within communication networks, which enhance the ability to effectively disseminate information [8]. For instance, Burnap et al. found that during a terrorist incident, the number of followers had a positive effect on the spread of crisis-related tweets [51]. Similarly, Roy et al. observed that tweets related to Hurricane Sandy received more attention when posted by accounts with a large follower base [52]. In addition to followers, the number of accounts an information source follows is another key indicator of influence. Specifically, sources that follow fewer accounts are often perceived as more autonomous, as they demonstrate the ability to independently generate and curate information without excessive reliance on external inputs [53]. Thus, we propose that the number of followers is positively correlated with source influence, whereas the number of accounts followed is negatively correlated with source influence. Both factors ultimately shape public engagement. Accordingly, we propose the following:

H7 For warnings, source influence positively influences citizen engagement.

Source activeness represents the frequency with which a source posts content on social media platforms. This includes the regularity of updates, which reflects the source's commitment to maintaining an ongoing presence and dialogue with audience. Such activity provides valuable insights into the long-term dynamics of accounts. For instance, active updates by government agencies can attract and retain public attention, stimulate audience engagement, and enhance the credibility of the information shared [54, 55]. Source activeness of GSMAs is increasingly recognized as a metric for evaluating government performance and public satisfaction during crises. Xu et al. found a positive correlation between WeChat users' activeness and information dissemination [55], emphasizing the importance of maintaining an active presence to enhance information spread. Similarly, Hu et al. demonstrated that maintaining activeness is essential for warning publishers to establish a strong connection with recipients [54]. Individuals are more likely to focus on active publishers who can provide immediate updates and engagement in disaster warnings. However, evidence also suggests that overactive accounts on microblogging sites (i.e., those who post too many messages) might be perceived as spammers [56, 57]. As the frequency of updates increases, the marginal effect on citizen engagement decreases. Given our focus on GSMAs during public health crises, the potential for information overload or spamming resulting from source activeness is not considered. Thus, we propose the following:

H8 For warnings, source activeness positively influences citizen engagement.

Moderating role of disease type

In addition to warning information obtained from GSMAs, the type of disease also influences citizen engagement during public health crises. Previous studies have suggested that people hold varying risk perceptions and exhibit different behavioral responses when faced with distinct types of crises [15, 54, 58]. Specifically, the relationship between warning messages and public online engagement is significantly moderated by the type of infectious disease, which can be categorized as either emerging or reemerging. The impact of central and peripheral routes on citizen engagement with warning information also varies depending on the disease type.

Warning messages about emerging infectious diseases are particularly critical, as they not only inform the public but also educate them about unfamiliar risks [59, 60]. In such cases, individuals heavily rely on official communications for guidance [5, 6]. Reemerging infectious diseases involve known diseases that resurface after a significant decline in incidence. Although potentially dangerous, the public often perceives reemerging diseases as less threatening due to previous exposure or historical knowledge. Consequently, warning messages in reemerging contexts may struggle to capture public attention and stimulate engagement, as familiarity fatigue or underestimated risk perceptions can attenuate impact [54].

While most studies focus on warning messages designed for a single crisis context, some research has explored the effects of varying disaster types on public responses. For example, Hong et al. analyzed tweets during 18 snowstorms in Maryland, USA, and found that the theme of citizen and local government responses became more significant as the snowstorms intensified [61]. Similarly, Chen et al. observed that the diffusion depth of health-related help-seeking information during COVID-19 was significantly greater compared to nonepidemic or minor outbreak contexts [17]. We propose that the type of infectious diseases (emerging vs. reemerging) interacts with warning features, including content, microstructure, and source attributes, significantly influence citizen engagement. Hence, we suggest the following:

H9a-b Diseases type moderates the relationship between content features (sentiment tendency, warning content elements) and citizen engagement.

H10a-d Diseases type moderates the relationship between microstructural features (message length, dialogic loop, media richness, information style variety) and citizen engagement.

H11a-b Diseases type moderates the relationship between source features (source influence, source activeness) and citizen engagement.

Data and methods

Data collection

Sina Weibo, one of leading social media platforms in China, facilitates information exchange and dissemination through online social networks. As of the second quarter of 2023, the platform reported over 570 million daily active users. By December 31, 2021, the number of certified government social media accounts (GSMAs) on Weibo had reached 177,437 [62]. Due to its high efficiency in information diffusion, Weibo has become the preferred platform for authorities to issue warnings during crises. Consequently, Weibo was selected as the data source for this study. We targeted 38 government microblog accounts at the national and provincial levels as warning data sources. These accounts were chosen based on strong operational performance, consistent focus on emergency response, and high levels of user engagement, evidenced by significant numbers of likes, retweets, and comments. National-level accounts typically release warnings directed at specific provinces or cities, while provincial-level accounts issue warnings relevant to administrative regions, including both provincial areas and subordinate districts.

To examine how the central route, peripheral route, and disease type influence citizen engagement with warnings, we collected data from two public health crises: COVID-19 and H1N1. COVID-19 represents an emerging disease, while H1N1 is a re-emerging one. This distinction allows us to identify variations in citizen engagement following the release of warnings for different diseases. Data collection was conducted in two rounds, each corresponding to a period when warnings were actively disseminated by GSMAs. The first round spanned from December 24, 2019, to January 24, 2020, during the early stages of COVID-19 as a novel infectious disease. During this period, the Chinese government issued a series of warnings to raise public awareness and encourage precautionary behaviors, such as avoiding crowded places, wearing masks, and maintaining proper hygiene. After January 24, 2020, strict lockdown measures were imposed, signaling a transition from the warning phase to a mandatory control phase. Messages during this later no longer emphasized voluntary actions but instead focused on enforcing compliance with government restrictions.

The second round of data collection occurred from February 1 to February 15, 2023, during the re-emergence of H1N1 influenza. A significant increase in seasonal flu cases was reported across multiple cities in China, prompting governments to issue warnings via social media to prevent the spread of the disease. However, after February 16, 2023, the rapid surge in cases overwhelmed hospitals in several regions, necessitating the implementation of emergency response measures. This marked a shift from the warning phase to the control phase, where efforts focused on managing the outbreak and preventing the collapse of the healthcare system. In summary, the two data collection periods were carefully aligned with the warning phases of both crises.

We used a combination of automated text mining and manual review to systematically collect and filter the data, ensuring its relevance and reliability. Python scraped post content and account information within the specified periods. In the first phase, keywords such as "pneumonia of unknown cause," "Wuhan pneumonia," "novel coronavirus," and "COVID-19" were used to identify relevant posts. In the second phase, "H1N1" and "seasonal flu" were applied. Following the automated data collection, a manual review was conducted to validate the precision of the filtering process and exclude irrelevant posts. During data preprocessing, we removed posts with missing values for retweets, likes, or comments, as well as nonoriginal content such as retweets or reposts, as these didn't represent original messages produced by government accounts. After a rigorous filtering process, a final dataset of 2,125 samples was obtained. To ensure comprehensive data coverage, we also updated daily metrics throughout the observation period, including each account's followers and the number of comments, likes, and retweets received by each post.

Variable measurement

Sentiment tendency.

To estimate the sentiment tendency of each post, we employed a Python-based approach that uses a sentiment lexicon and integrates the SnowNLP library [5, 6, 11]. Initially, each post was segmented word by word using the Jieba database. The segmentation of extended texts was facilitated by the hidden Markov model and Viterbi algorithms. Subsequently, we used the sentiment word list service from SnowNLP, a Python library designed for Chinese text processing. A naive Bayes classifier was trained to assign sentiment values to words through its machine-learning mechanism. The sentiment score of a sentence was calculated using a weighted method based on assigned values. Posts with a sentiment score exceeding 0.5 were characterized as having a positive sentiment and assigned a value of 1, while posts with a sentiment score below 0.5 were classified as negative and assigned a value of -1.

Warning elements Following Sutton et al. [2], Wang et al. [4], and Yang et al. [28], we manually coded the data to facilitate the generation of new codes derived directly from the data, which are often absent in automated methods. During the analysis of warning information, researchers could refine codebooks when encountering new themes or concepts, enabling more accurate categorization. To conduct this analysis, we invited three postgraduate students to manually code the data. A codebook was constructed based on the warning framework proposed by Mileti and Sorensen, supplemented with public health emergency elements suggested by other researchers [1, 56]. Through an iterative refinement process, the codebook generates new categories and merges them with existing categories. Table 1 presents the main contents of the codebook, including the definitions of coding categories and descriptive examples.

To capture the diversity of warnings disseminated to the public, each post was coded into one or more categories, generating an index variable that represents the number of warning elements (ranging from 1 to 5) in each message. First, the coders participated in a two-hour training session to establish coding norms. They were blinded to the research hypothesis as well as the number of retweets, likes, and comments, ensuring unbiased identification of content codes. Second, to test reliability, the coders randomly and independently coded 20% of the sample data using the predefined codebook. Intercoder reliability was assessed using Cohen's kappa, which yielded a value of 0.92. This high level of agreement between coders confirms the reliability of the coding process.

Message length The length function in Python 3.7 quantifies message length by counting the number of words, ensuring precise evaluation. This method eliminates the subjectivity and inconsistency associated with human estimation [26].

Dialogic loop Following the indicators proposed by Ji et al. [33], Wang and Yang [3], and Zhang et al. [11], we measured three items "the use of hashtags," "the use of mentions," and "the provision of external links." Dialogic loops were dummy-coded into four categories: noninteractive posts were coded as 0, while posts incorporating one, two, or all three interactive elements were coded as 1, 2, and 3, respectively.

Media richness Drawing on Ji et al. [33], Wang et al. [26], and Chen et al. [5], media richness was categorized into three levels. Low vividness was assigned to purely textual information; medium vividness included photos and

Table 1 Warning element coding definitions and example posts

Categories	Definition and example posts
Guidance for adopt protective behavior	*Detailed behavior guidance, explaining how the public can act to maximize the protection of health and safety;* [#What Can We Do Besides Wearing Masks?#]: At home: Change shoes when returning from outside, wash hands frequently with soap and water, clean regularly after having guests; Outside: Avoid multiple transfers, try not to go to the hospital, do not touch stray cats and dogs or wild animals.
Lastest news about the epidemic	*Current progress of the epidemic, informing about the number of cases, affected areas, timeline, etc.;* [National Health Commission: #440 Cases of Novel Pneumonia Confirmed, 9 Deaths#] As of 24:00 on January 21, the National Health Commission has received reports from 13 provinces (regions, cities) across the country, with a cumulative total of 889 confirmed cases of novel coronavirus pneumonia, and 20 deaths.
Characteristics of epidemic description	*Descriptive information about the epidemic, including symptoms, routes of transmission, the cause of disease, assident, etc.;* # Health Science Popularization # What is the COVID-19? How is it related to SARS (Severe Acute Respiratory Syndrome) and MERS (Middle East Respiratory Syndrome)? Why has the COVID-19 been classified as a Class B infectious disease, and why is the government implementing prevention policies for Class A infectious diseases? Click on the image for authoritative answers!
Closures and openings	*The opening or closing of facilities, activities, roads, etc.;* Starting from 24:00 on January 23, 2020, passenger transportation in Huanggang city area has been temporarily suspended. Without special reasons, the passage for leaving the Huanggang city area at the train station is temporarily closed. Resumption time will be announced later.
Government crisis response measures	*Measures taken by the government in response to the epidemic.* #Health release# Health departments at all levels should maintain surveillance systems to monitor epidemic trends, and carry out typing and identification of influenza viruses and epidemiological investigations. At the same time, they should carry out epidemic prevention and control work in a timely manner and take effective measures to control the spread of the epidemic.

images presenting static pictorial content; and high vividness was defined by videos, which offer maximum media richness due to dynamic imagery and sound. These levels were coded as 1, 2, and 3, respectively.

Information style variety This variable was measured in two steps. First, following the methods of McAndrew and De Jonge [21] and Wang et al. [26], sentences were categorized based on punctuation and phrasing. Sentences were classified as exclamatory if they included an exclamation mark ("!") or an interjection, interrogative if they contained a question mark ("?") or interrogative words, and declarative if they ended with a period and lacked both exclamatory and interrogative features. Second, the stylistic diversity of information was assessed based on the types of sentences within each post. Posts containing only declarative sentences were coded as having low stylistic diversity (code 1). Posts combining two types of sentences were coded as having medium diversity (code 2), and posts incorporating all three sentence types were coded as having high diversity (code 3).

Source influence Drawing on Shao et al. [49] and Wu and Shen [50], source influence was measured as being positively associated with the number of followers and negatively associated with the number of accounts followed. Sources with a high follower-to-following ratio can reach a broader audience without relying heavily on others. In social media networks, such accounts are often viewed as having greater social capital, reflecting a central position and the ability to attract others. Therefore, the follower-to-following ratio was used to measure the influence of GSMAs.

Source activeness Following Zhang et al. [56] and Zhang et al. [57], the total number of posts made by an account during the specified observation periods was calculated to determine publishers' activity levels.

Citizen engagement Governments have transitioned from disseminating propaganda to using social media as a means of transparent communication. Our study evaluated citizen engagement by considering the number of retweets, likes, and comments as quantitative indicators of social media interaction [5, 6, 10].

To ensure model stability, several control variables were included. Previous studies have shown that post time and proximity to an epidemic outbreak (measured as the time interval until the outbreak) can influence the diffusion of government microblogs [28]. Therefore, these two variables were incorporated as control variables.

Model estimation

To assess the hypotheses, multivariate moderation regression is used to analyze the data. The regression model was proposed as follows:

$$\text{Model 1}: lnCitizen\,Engagement = \alpha_0 + \alpha_1 Con + \sigma_1 \quad (1)$$

$$\text{Model 2}: lnCitizenEngagement = \alpha_0 + \alpha_1 Con + \alpha_1 X_i + \sigma_2 \quad (2)$$

X_i =[*Sen_Ten*, *War_Ele*, *Mes_Leng* Mes_Leng^2, *Dia_Loop*, *Med_Ric*, *Sen_Var*, *Sour_Inf*, *Sour_Activ*].

$$\begin{aligned}&\text{Model3}: lnCitizenEngagement = \alpha_0 + \alpha_1 Con + \alpha_i X_i \\ &+\gamma_1 (Typ) * (Sen\_Ten) + \gamma_2 (Typ) * (War\_Ele) \\ &+\gamma_3 (Typ) * (Mes\_Leng) + \gamma_4 (Typ) * (Mes\_Leng^2) \\ &+\gamma_5 (Typ) (Dia\_Loop) + \gamma_6 (Typ) * (Med\_Ric) \\ &+\gamma_7 (Typ) * (Sen\_Var) + \gamma_8 (Typ) * (Sour\_Inf) \\ &+\gamma_9 (Typ) * (Sour\_Activ) + \sigma_3\end{aligned} \quad (3)$$

α_0 represents the intercept term, while α_i and γ_i are vectors of coefficients for the corresponding variable and interaction terms, respectively. X_i is a vector of regressors. $\sigma_1, \sigma_2, \sigma_3$ represent the random error terms. Model 1 is the baseline model, including only control variables and citizen engagement. Model 2 expands upon Model 1 by incorporating variables related to content features (i.e., sentiment tendency, warning content elements), microstructural features (i.e., message length, dialogic loop, media richness, information style variety), and source-specific features (i.e., source influence, source activeness). Model 3 builds on Model 2 by adding interaction terms between warning features and disease type. Given the positive skewness, the dependent variable is log-transformed. To test the hypothesized inverted U-shaped relationship between message length and citizen engagement, the model includes a squared term for message length. This relationship is confirmed if the linear term for word count is positive, the squared term is negative, and both coefficients are statistically significant, controlling for all other factors. For hypotheses involving higher-order terms, variables are mean-centered to reduce multicollinearity and facilitate interpretation. To address error variance dependence [14], a robust regression procedure is used to estimate the model. All analyses are performed using Stata version 15.0.

Results and analysis

Hypothesis test

Table 2 presents the descriptive statistics and correlations of the main variables. For each model, we examined the VIF values of all variables in Table 3. The highest VIF observed across the models was 2.045, well below the threshold of 5.0, indicating that multicollinearity was not a significant concern in regression analyses.

Table 3 presents the results of the multiple linear regression model predicting citizen engagement. The

Table 2 Correlations and descriptive statistics

Variables	Mean	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *Dialogic loop*	0.74	1									
(2) *Media richness*	1.65	0.18**	1								
(3) *Information style variety*	1.21	0.32*	0.17**	1							
(4) *Message length*	627.98	0.04**	-0.21**	-0.13**	1						
(5) *Sentiment tendency*	0.17	0.12**	0.09*	0.15**	-0.04	1					
(6) *Warning elements*	2.18	0.07*	-0.14**	0.06	0.21**	0.08	1				
(7) *Source influence*	7632.42	0.21**	0.13**	0.18**	-0.06	0.11**	-0.02	1			
(8) *Source activeness*	68128.32	0.15**	0.16**	0.11**	-0.04	0.06	-0.06**	0.29**	1		
(9) *Time of post*	4.91	0.07**	0.23**	0.17**	-0.15**	0.05*	0.03	0.16**	0.14**	1	
(10) *Time interval*	9.28	0.17*	-0.12**	0.21**	0.21**	-0.06**	0.12**	0.08**	-0.07*	0.06**	1

**Significantly correlated at the $P<0.01$ significance level; *significantly correlated at the $P<0.05$ significance level

Table 3 Research model multiple regression analysis results

Variables	Model		
	M1	M2	M3
Time of post	-0.132**(-2.414)	-0.174***(-4.017)	-0.183**(-6.028)
Time interval	0.251***(6.425)	0.282***(4.916)	0.304*** (7.903)
Sentiment tendency (ST)		0.138***(4.832)	0.201***(7.143)
Warning elements (WE)		0.264***(5.034)	0.319***(8.125)
Message length (ML)		0.254**(2.671)	0.267**(2.865)
Message length^2(ML^2)		-0.199**(-2.177)	-0.203**(-2.261)
Dialogic loop (DL)		-0.074(-0.907)	-0.082(-1.362)
Media richness (MR)		0.296***(9.733)	0.319***(9.697)
Information style variety (SV)		0.376***(11.247)	0.410***(12.101)
Source influence (SI)		0.347***(9.024)	0.365***(10.223)
Source activeness (SA)		0.249***(4.812)	0.234***(4.946)
*Disease type * ST*			0.093(1.143)
*Disease type * WE*			0.087(1.121)
*Disease type * ML*			0.058(0.892)
*Disease type * ML^2*			-0.042(-0.757)
*Disease type * DL*			-0.076(-1.147)
*Disease type * MR*			0.283***(5.522)
*Disease type * SV*			0.381***(10.436)
*Disease type * SI*			0.175**(3.572)
*Disease type * SA*			0.072(0.906)
VIF	2.045	3.088	2.761
F	25.147	30.324	34.921
R^2	0.104	0.261	0.326
Adj R^2	0.098	0.274	0.313

t statistics in parentheses. *$P<0.10$, **$P<0.05$, ***$P<0.01$

adjusted R-squared and F-statistic values indicate that the model demonstrates a reasonable fit. The regression results provide several key insights. For the central route of content features, positive emotional tendency is significantly associated with citizen engagement in warnings from GSMAs (α_2=0.138, t = 4.832, $P<0.01$), supporting H1. This finding suggests that incorporating positive emotional expression into warning content is likely to increase the public's willingness to share information. The coefficient for warning elements is significantly positive at $P<0.01$ (α_3=0.264, t = 5.034), indicating that a greater number of warning elements embedded in tweets is associated with higher levels of citizen engagement on social media. This result provides support for H2.

Regarding the peripheral route of microstructural features, the operationalization of message informativeness, as measured by post length, reveals a complex relationship with citizen engagement. Specifically, post length is significantly positively associated with citizen engagement within a certain range; however, this relationship becomes negative when post length exceeds that range. The regression coefficient for post length (α_4 = 0.254, t = 2.671, $P<0.05$) and its squared term (α_5 =−0.199, t =-2.177, $P<0.05$) are both significant, confirming an inverted U-shaped relationship and providing support for H3. H4, which posits that warning posts with high levels of dialogic loops are less likely to attract citizen engagement, is *not* supported. Dialogic loops are negatively associated with citizen engagement during public health crises but are not statistically significant (α_6 = –0.074, t = –0.907, $P > 0.1$). Thus, H4 is *not* supported. We find support for the media richness hypothesis (H5), as the coefficient for retweet counts (α_7 = 0.296, t = 9.733, $P <$ 0.01) is positive and statistically significant. Similarly, the regression results show that the coefficient for information style variety is positive and significant (α_8 = 0.376, t = 11.247, $P < 0.01$), indicating that warning messages incorporating more varied sentence styles are associated with higher levels of public engagement. This finding provides strong empirical support for H6.

Regarding the peripheral route of source features, both source influence and source activeness are positively and significantly associated with citizen engagement. H7 posits that warnings issued by influential accounts are more likely to generate higher levels of citizen engagement (α_9 = 0.347, t = 9.024, $P < 0.01$). Specifically, the influence of a publisher reflects its reliability in providing timely and accurate warning information during crises. Similarly, the results for H8 indicate that source activeness is a significant predictor of citizen engagement (α_{10} = 0.249, t = 4.812, $P < 0.01$). This finding suggests that more active publishers are better able to attract public engagement.

To examine the effect of moderator variables, we incorporate disease type and interaction terms into a multiple regression model. For sentiment tendency (γ_1 = 0.093, t = 1.143, $P > 0.1$, H9a) and warning elements (γ_2 = 0.087, t = 1.121, $P > 0.1$, H9b), disease type does not significantly affect citizen engagement with GSMAs. Consequently, H9 is not supported. H10a–d posit that disease type moderates the effect of microstructural factors on retweeting. Among the four interactions, two emerge as significant: H10c (disease type * media richness) and H10d (disease type * sentence-type variety). The interaction between media richness and disease type (γ_6= 0.283, t = 5.522, $P < 0.01$) is a significant predictor of citizen engagement. Posts with high levels of media richness are more likely to attract engagement during emerging infectious disease crises. Disease type also moderates the relationship between information style variety and citizen engagement (γ_7= 0.381, t = 10.436, $P < 0.01$). H11a-b state that disease type moderates the effect of source features on citizen engagement. The effect of source influence on citizen engagement is significantly moderated by disease type (γ_8 = 0.175, t = 3.572, $P < 0.05$). However, the moderating effect of disease type on source activeness (H11b) is not significant (γ_9 = 0.072, t = 0.906, $P > 0.1$). Overall, disease type significantly moderates the relationships between media richness, information style variety, source influence, and citizen engagement.

Robustness check

We conduct two tests to assess the robustness of our findings. First, we use the number of likes and comments as proxies for retweets to measure the dependent variable —— citizen engagement. These variables capture individuals' information behaviors after receiving warning messages, reflecting public preferences. The results are presented in Table 4. Second, we divide the dataset into two subsamples and re-run the model. The analysis is conducted separately for each disease type (emerging and reemerging infectious diseases), with disease type excluded as a moderating variable. This approach allows us to examine the robustness of both the central and peripheral routes without the moderating effect of disease type. The results are reported in Table 5. In summary, the outcomes of all robustness tests are consistent with our initial findings, reinforcing the validity and reliability of our proposed model.

Discussion and implications

Summary of findings

This study offers a novel analysis of strategies adopted by the Chinese government in using social media for early warnings during public health crises. Drawing on ELM and CERC, we examine two key aspects of warnings. The central route focuses on content features, while the peripheral route is assessed through microstructural and source-specific features. Furthermore, we introduce disease type as a moderating variable to explore the underlying mechanism influencing engagement.

Regarding the central cue of ELM, we confirm the effectiveness of positive emotional appeals in driving citizen engagement (*H1*). A positive tone in communication by GSMAs, not only reinforces their authority but also builds greater public trust [36]. This trust motivates individuals to engage with the message, thereby amplifying the impact of the information. The effects, however, differ significantly between government posts and public posts during public health crises. While positive emotions in government communications foster a sense of security and trust, negative emotions in public posts mobilize higher levels of interaction by drawing on concern and urgency. Additionally, the findings indicate that posts containing more warning elements are more likely to drive citizen engagement (*H2*), consistent with the conclusions of Wang et al. [3, 4] and Sutton et al. [2]. Including more warning elements enhances information comprehensiveness, addressing multiple aspects of the crisis and equipping the public with the necessary knowledge to understand the threat and respond appropriately. Moreover, the inclusion of additional warning elements

Table 4 Robustness test of alternative dependent variable likes and comments

DV	Retweets					
Alternative DV	**Likes**			**Comments**		
	M1	**M2**	**M3**	**M1**	**M2**	**M3**
Time of post	-0.191**(-2.237)	-0.186***(-3.924)	-0.196***(-6.862)	-0.187**(-2.179)	-0.179***(-3.865)	-0.103***(-7.141)
Time interval	0.267**(5.338)	0.276***(5.054)	0.321***(6.831)	0.253**(4.396)	0.264***(4.947)	0.307***(6.435)
Sentiment tendency (ST)		0.158**(2.182)	0.253***(7.973)		0.166***(4.042)	0.242***(7.664)
Warning elements (WE)		0.289***(5.753)	0.306***(7.854)		0.291***(5.869)	0.312***(7.743)
Message length (ML)		0.235**(2.471)	0.242***(3.125)		0.246**(2.908)	0.231***(3.067)
Message length^2(ML^2)		-0.205**(-2.612)	-0.198**(-2.137)		-0.212**(-2.638)	-0.187**(-2.054)
Dialogic loop (DL)		-0.059(-0.872)	-0.069(-0.935)		-0.054(-0.863)	-0.073(-1.026)
Media richness (MR)		0.271**(2.333)	0.304***(8.426)		0.267**(2.288)	0.321***(8.692)
Style variety (SV)		0.394***(12.616)	0.375***(9.672)		0.383**(2.17)	0.383***(9.729)
Source influence (SI)		0.319***(7.624)	0.346***(9.142)		0.301***(7.523)	0.352***(8.841)
Source activeness (SA)		0.232**(2.365)	0.227***(2.815)		0.228***(3.710)	0.218***(4.632)
*Disease type * ST*			0.086(1.095)			0.074(0.943)
*Disease type * WE*			0.063(1.210)			0.047(0.542)
*Disease type * ML*			0.052(0.783)			0.064(0.727)
*Disease type * ML^2*			-0.053(-0.846)			-0.061(-0.963)
*Disease type * DL*			-0.066 (-0.935)			-0.072(-0.818)
*Disease type * MR*			0.276***(5.313)			0.263***(6.024)
*Disease type * SV*			0.364***(9.318)			0.341***(8.045)
*Disease type * SI*			0.171**(3.493)			0.188**(4.327)
*Disease type * SA*			0.066(0.871)			0.062(0.803)
F	23.268	31.245	35.272	24.153	33.436	36.716
R^2	0.104	0.273	0.310	0.142	0.287	0.324
Adj R^2	0.093	0.261	0.307	0.121	0.271	0.318

t statistics in parentheses. *$P<0.10$, **$P<0.05$, ***$P<0.01$

Table 5 Robustness test of the divided samples

Variables	**Emerging infectious diseases**		**Reemerging infectious diseases**	
	M1	**M2**	**M1**	**M2**
Time of post	-0.203***(-4.372)	-0.193***(-4.167)	-0.198***(-4.158)	-0.184***(-3.986)
Time interval	0.281**(5.629)	0.254***(4.954)	0.264**(5.084)	0.213***(4.732)
Sentiment tendency (ST)		0.179**(2.387)		0.162**(2.105)
Warning elements (WE)		0.312***(6.570)		0.348***(7.458)
Message length (ML)		0.243**(2.411)		0.263***(4.523)
Message length^2(ML^2)		-0.198**(-2.432)		-0.204***(-2.976)
Dialogic loop (DL)		-0.047(-0.768)		-0.052(-0.856)
Media richness (MR)		0.272**(3.443)		0.258**(2.294)
Style variety (SV)		0.395***(11.254)		0.372***(10.123)
Source influence (SC)		0.345***(9.127)		0.324***(8.042)
Source activeness (SA)		0.247***(4.926)		0.253***(5.012)
F	24.155	30.467	25.342	33.619
R^2	0.102	0.265	0.137	0.274
AdjR^2	0.091	0.243	0.121	0.258
N	670	670	1455	1455

t statistics in parentheses. *$P<0.10$, **$P<0.05$, ***$P<0.01$

improves clarity and reduces uncertainty [2, 3]. When individuals receive specific and comprehensive warnings, they are more likely to feel empowered to take action.

Regarding the peripheral cue of ELM, we find that warning length exhibits an inverse U-shaped relationship with citizen engagement (*H3*). Initially, longer warnings provide more details, which is essential for understanding epidemic risks and encouraging engagement, as individuals seek specific instructions on how to protect themselves. However, as message length increases, its benefits diminish, eventually leading to cognitive overload and heightened anxiety. Excessive information overwhelms the audience, ultimately reducing citizen engagement [14]. Thus, it is critical to identify a balance in message length to maximize engagement.

We find no correlation between dialogic loops in GSMA warning information and citizen engagement (*H4*). This finding is *not* in line with previous research on information strategies during the control phase of the Queensland floods and the outbreak phase of Ebola [63, 64], which emphasized the effectiveness of dialogic loops in fostering public engagement and trust. It also diverges from the principles of dialogic communication theory. The discrepancy likely arises from the unique characteristics of warning communication, which differ significantly from the contexts where dialogic loops are typically applied. Warnings are designed to operate under distinct conditions, prioritizing the delivery of urgent, actionable information to mitigate risks. In time-sensitive scenarios, such as the early stages of outbreaks, audiences often prioritize concise, decisive, and actionable guidance over interactivity [33]. Dialogic loops in such situations may delay the transmission of critical information, increase cognitive load, and compromise the immediacy required to prompt swift action. Additionally, heightened anxiety and uncertainty make audiences less receptive to extended dialogic exchanges. Once the initial shock subsides, however, dialogic communication may become more effective by addressing lingering concerns and clarifying uncertainties. The approach aligns more closely with the communication needs of the control and recovery phases of a crisis. These findings highlight the importance of tailoring communication strategies to the demands of each phase.

This study finds that the media richness of warning information is positively associated with citizen engagement (*H5*), consistent with the findings of Bonsón et al. [24], Zhang et al. [56], and Xie et al. [39], who found that pictures and videos can enhance citizen engagement under conditions of uncertainty. Rich media simplify complex details in warnings, such as pathogenesis or preventative measures for infectious diseases, which are often challenging to convey through plain text. Additionally, information style variety has a statistically significant effect on citizen engagement (*H6*). A diverse range of information styles captures attention more effectively by breaking the monotony of communication [9]. The combination of varied sentence forms ensures that information not only reach a broader audience but also resonate on a deeper emotional level, thereby fostering greater citizen engagement.

Source influence (*H7*) and source activeness (*H8*) are positively associated with citizen engagement, which aligns with the findings of Cai et al. [8]. Accounts with more followers and fewer followings are perceived asmore influential. During public health emergencies, warnings disseminated by such influential accounts leverage their authoritative and credible reputations, thereby enhancing public engagement. The results for H8 indicate that more active publishers attract greater public attention. Increased source activeness reflects an account's commitment to organizing warnings and its expertise in information dissemination. Consequently, our findings suggest that both source influence and source activeness are strong predictors of public engagement with warnings during public health crises.

The results support *H10c*, *H10d*, *and H11a*, indicating that disease type significantly moderates the relationship between media richness, information style variety, source influence, and citizen engagement. These findings emphasize the need to tailor risk communication strategies to the specific characteristics of emerging and reemerging infectious diseases [16]. During outbreaks of emerging infectious diseases, the public faces high levels of uncertainty and ambiguity, which often trigger heightened anxiety and an increased sense of urgency. In such contexts, individuals are more likely to rely on peripheral cues– such as rich media formats, action-oriented and concise messaging, and credible sources– to reduce uncertainty and comprehend unfamiliar information. These cues simplify novel content and establish confidence in the information, thereby encouraging greater public engagement [15]. In contrast, reemerging infectious diseases, which the public is already familiar with, tend to evoke less urgency due to perceived lack of novelty. In such cases, individuals rely more on pre-existing knowledge to guide decision-making, reducing dependence on media richness or information style variety. Consequently, the effectiveness of these features in promoting public engagement diminishes in the context of reemerging diseases [28, 65].

Implications for research

Theoretical implications

The current research provides significant theoretical contributions. First, this study contributes to the crisis communication literature by offering new insights into how GSMAs design warnings to enhance public engagement. It highlights the importance of the warning phase, which has traditionally been overlooked in favor of greater emphasis on the crisis control and recovery stages [5, 7]. The warning phase, however, plays a pivotal role in shaping public preparedness by facilitating risk recognition and action. We consider this valuable disaster communication processes and address citizens' distinct information needs. Our research advances understanding of warning strategies and proposes a nuanced framework for early crisis communication.

Second, our study integrates the Elaboration Likelihood Model (ELM) and the Crisis and Emergency Risk

Communication (CERC) framework to investigate online engagement during public health crises. Unlike previous studies that primarily focused on central cues while overlooking peripheral cues, our research develops a more comprehensive and multidimensional model. The proposed model incorporates content features, microstructural features, and source attributes to analyze the relationship between information features and public engagement. Moreover, this study extends ELM by applying it to the context of crises, particularly emerging infectious diseases. During such crises, individuals are more likely to rely on peripheral cues rather than engage in extensive cognitive processing. This study enhances our understanding of ELM's applicability in non-traditional contexts.

Third, we explore the moderating effect of disease type (emerging vs. reemerging infectious diseases) on the relationship between warnings and citizen engagement. Few studies have incorporated environmental variables into crisis communication research, most have focused on single disaster events, limiting the generalizability of findings. This study highlights how variations in infectious diseases impact public engagement by integrating disease type into the model. Due to the public's lack of familiarity with emerging infectious diseases, such as COVID-19, the dissemination of information and public responses differ categorically from reemerging infectious diseases. Emerging diseases are associated with an unparalleled sense of urgency, significant uncertainty, and considerable politicization, all of which pose unique challenges to warnings. Our findings provide evidence that disease type interacts with media richness, information style variety, and source influence to shape citizen engagement. These results indicates the need for flexible, context-specific warning strategies tailored to the unique challenges posed by different types of infectious diseases.

Practical implications

Our findings have significant implications for government practices on social media during outbreaks. First, GSMAs should incorporate more visuals, such as pictures and videos, into warning messages. For instance, an animated post showing a rising graph of infection rates with a flashing "Stay Home" alert can emphasize urgency. Multimedia elements enhance the accessibility of complex information, especially for diverse audiences with varying levels of health literacy. Governments should also explore emerging technologies like augmented reality (AR) to create immersive experiences, such as visualizing infection hotspots, to prompt action. To avoid the monotony of straightforward statements, governments should adopt more dynamic and varied sentence structures to capture attention. Combining rhetorical questions with exclamations can create a compelling rhythm that underscores urgency. For example, "What can you do to stop the virus? Everything! Wear a mask, avoid crowds, and get vaccinated!". The expression not only breaks the monotony of declarative statements but also inspires a sense of personal responsibility and immediate action. When editing messages, it is crucial to maintain an appropriate text length, as overly long or excessively short messages can reduce citizen engagement. On platforms like Weibo, messages should ideally range from 140 to 280 characters to ensure readability, engagement, and adherence to platform-specific restrictions.

Second, while incorporating more warning elements into a single message is recommended, a layered structure can help prevent public confusion and address the diverse needs of different audiences. A layered approach consists of three components: core information, which conveys the main points concisely for quick dissemination of critical content; supplementary information, which provides additional context and scientific evidence for those seeking further details; and detailed explanations, which offer in-depth medical insights and policy specifics, accessible via external links or resources. Moreover, governments should design warning messages that incorporate positive emotions while maintaining scientific accuracy and credibility. Such messages should emphasize hope, a sense of control, and collective responsibility to enhance public confidence. To avoid overly optimistic or misleading content, a review process should be established. This approach balances emotional resonance and factual accuracy, improving the overall effectiveness of warning messages.

Third, the number of followers is a key determinant of public engagement, as GSMAs with larger audiences are more effective at amplifying warning messages. To increase visibility, governments should promote official accounts across various platforms, including traditional media (e.g., TV, radio, and newspapers) and government social media. Collaborations with influencers, experts, and public figures can further extend reach by encouraging their followers to engage with official content. Moreover, active GSMAs significantly enhance public engagement. Governments should leverage algorithmic recommendations to prioritize official content in news feeds, especially during the early stages of public health crises. Coordinated schedules for releasing alerts are essential to ensure timely updates, while analytical tools (e.g., Twitter Analytics, Weibo Insights) can identify peak user activity periods to maximize reach and engagement.

Limitations and suggestions for future research

First, this study examines the effects of warning information strategies on online engagement, measured through metrics such as retweets, likes, and shares. While this study offers valuable insights into how citizens interact with warnings on social media, it does not address whether such engagement translates into offline behaviors — the ultimate goal of warnings during disasters. The relationship between governments' use of social media for issuing warnings and citizens' offline compliance remains underexplored. Future research should investigate the connection by investigating how online engagement influences concrete actions, such as evacuation, seeking shelter, or adopting protective measures. Such exploration would provide a more holistic understanding of the real-world effectiveness of warning systems.

Second, the effectiveness of warnings disseminated through GSMAs may vary depending on cultural factors, societal norms, individualism, and platform-specific features. It would be risky to generalize the findings without appropriate caution. For example, platforms popular in other regions, such as Twitter, Facebook, or TikTok, may exhibit different communication and engagement patterns due to unique functionalities. Cultural factors, such as trust in authority and the values of collectivism versus individualism, also play a crucial role in shaping public responses to warnings. In collectivist cultures like China, individuals may prioritize community well-being and show greater willingness to follow government instructions. In contrast, individualist cultures may emphasize personal autonomy and skepticism toward authority, potentially leading to different response patterns. Future research should conduct cross-cultural and cross-platform analyses to identify both universal patterns and cultural differences in responses to warnings. Additionally, individual characteristics — such as demographics (e.g., age, gender, education), digital literacy, and prior experience with social media — could be examined by integrating survey data or other datasets.

Third, this study has limitations in measuring warning features due to the simplification of complex constructs. For instance, reducing sentiment tendency to a simple positive or negative classification ignores important dimensions like emotional intensity (the strength of emotional expression) and emotional presence (explicit vs. implicit communication). These dimensions likely interact and play a role in shaping public engagement. Similarly, classifying sentence styles based solely on interrogative or exclamatory punctuation and words provides a narrow perspective, neglecting other important factors like rhetorical strategies, syntactic complexity, and lexical diversity. To address these limitations, future research could adopt natural language processing (NLP), computational linguistics, and machine learning techniques to improve the measurement of variables. Tools such as emotion-specific lexicons, like the NRC Emotion Lexicon, can capture a broader range of emotional categories. Incorporating multimodal data, including images and audio, could further enhance the analysis of emotional valence. Additionally, online experiments could systematically manipulate rhetorical strategies and lexical diversity to better understand how these factors influence audience engagement.

Conclusion

This study investigated how Chinese government agencies use social media to promote citizen engagement during the initial stages of public health crises. Drawing on the Elaboration Likelihood Model (ELM) and the Crisis and Emergency Risk Communication (CERC) framework, we examined the content, microstructural, and source features of warnings, as well as the moderating effects of disease type, to predict citizen engagement. The results show that positive affective tendencies in warning messages and the number of warning elements influence public participation. Media richness and information style variety are significant predictors of citizen engagement through government social media accounts (GSMAs). The relationship between message length and citizen engagement follows an inverted U-shape. Additionally, source influence and activeness positively affect user behaviors, including shares, likes, and comments. The findings also reveal that disease type (emerging vs. reemerging infectious diseases) moderates the relationships between media richness, information style variety, source influence, and citizen engagement. Specifically, during outbreaks of emerging diseases, using multimedia, diverse information styles, and more influential information sources to convey warning messages is particularly effective in promoting citizen engagement. This study contributes to the field of public health risk communication both theoretically and practically. Future research should investigate additional factors influencing citizen engagement with warning messages during crises to provide further evidence and insights.

Abbreviations

GSMAs	Government social media accounts
ELM	Elaboration likelihood model
CERC	Crisis and emergency risk communication

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
This research does not require ethical assessment and does not involve clinical trials, animals or other data that require approval for use.

Consent for publication
The manuscript does not contain any details or images relating to individual persons. Consent for publication has been sought from participants in study.

Competing interests
The authors declare no competing interests.

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