Information Systems Frontiers
https://doi.org/10.1007/s10796-025-10626-x

The Sharing of Disaster-Related Information on Social Media

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Accepted: 18 June 2025

Abstract

This paper explores how two types of textual features—uncertainty-related features and self-regulation-related features—affect information diffusion amid disasters. We identify four textual expressions (i.e., insight, netspeak, work, and reward) of social media posts that generate negative impacts on the diffusion of information. Against the backdrop of the COVID-19 pandemic, we conducted an econometrical study of COVID-19-related posts collected from Weibo, followed by an experiment, to examine the proposed relationships between the reposting behavior and the four textual expressions. Theoretically, we examined the potential effects of information avoidance on the sharing of information on social media during disasters. This study can improve the predictive performance in future disaster-related studies of social media. Practically, government officers are advised that these features may generate negative impacts on the reposting behavior of those who read their posts and hinder the transfer of official information and policy announcements.

Keywords Social media · Information diffusion · Text mining · COVID-19 · Disaster management

1 Introduction

Disasters bring substantial challenges to humans. Disasters such as technological hazards, social crises, earthquakes, floods, and the recent COVID-19 pandemic all take a toll on the world, causing deaths, panic, environmental damage, and economic despair. Governments and corporations are searching for new strategies to mitigate these negative consequences of disasters (Chen et al., 2013; Park et al., 2015; Ngai & Lee, 2016). To achieve this goal, we first have to understand how human behaviors during disasters differ from those during normal periods. In particular, during disasters, people face much uncertainty, so acquisition of new information becomes a critical issue. User behavior on social media is highly relevant to information acquisition because social media plays a crucial role in information dissemination in the digital era (Susarla et al., 2012; Stieglitz & Dang-Xuan, 2013; Oh et al., 2013; Shi et al., 2014; Venkatesan et al., 2021). Specifically, during the recent COVID-19 pandemic, the usage of social media increased greatly, so it is even more important to understand behaviors on social media in order to formulate government strategy in dealing with disasters.

Previous researchers have studied the information-sharing mechanism on social media including influential factors that trigger reposting (Suh et al., 2010; Nesi et al., 2018; E et al., 2022). Two common approaches have been adopted by previous scholars to evaluate outcomes of reposting behavior on social media. The two approaches are measuring the number of reposts a post receives and verifying if a post has been reposted (e.g., Hong et al., 2011; Naveed et al., 2011; Nesi et al., 2018; Speily et al., 2018; Yan et al., 2012; Yang et al., 2022). For example, Yang et al. (2022) examined the relationship between whether a microblog was reposted, a binary variable, and the type of function to create requests for medical assistance on Weibo during

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Published online: 31 July 2025

COVID-19. Although scholars who were interested in learning why a post went viral tended to adopt the approach of measuring the reposting number of a post (Han et al., 2020; Hoang & Lim, 2012), adopting the other approach by examining the binary outcome of reposting enables researchers to understand better why a post remained inert. Thus, both approaches possess their own merits.

While it is important to know how to make social media information go viral and be seen by a majority of users, whether there is at least one other user who would like to share a post also matters. Although previous studies have examined predicting and factor discovering on whether social media messages were reposted (Suh et al., 2010; Nesi et al., 2018; E et al., 2022), the factors that trigger the social media posts to be shared (but not necessarily to become viral) still lack investigation, especially in the context of disasters like COVID-19.

Information diffusion has become a hot topic also in disaster-related research, such as that on natural disasters, technological hazards, social crises, and financial crashes (Lee et al., 2015; Chew & Eysenbach, 2010; Giannarakis & Theotokas, 2011; Oh et al., 2013; Wang et al., 2015; Josef & Helena, 2022; Chen et al., 2020). However, how certain types of posts spread on social media during disasters has been understudied. Previous studies have shown that people are unwilling to acquire information that brings about a feeling of uncertainty (Atkin, 1973). Furthermore, when threatened by potential health problems, people are more reluctant to process related information that makes them feel negative (Brashers et al., 2000; Babrow, 2001). The insufficient understanding and misinterpretation of information diffusion may lead to serious consequences, such as underestimating the importance of public health measures and overlooking the official guidance of emergency response personnel. Understanding why and how people avoid certain types of information tends to be an important issue that may benefit individuals by enabling the manipulation and filtering of information. Because disasters involve much uncertainty and many life-threatening risks, the impact of posts containing specific textual expressions related to these attributes of social-media spread is currently unknown but pending discovery.

Information avoidance on social media refers to the deliberate act of individuals avoiding or ignoring certain types of information presented on social media platforms. This behavior may be driven by various factors, including a desire to avoid unpleasant or distressing content. The motivation for exploring the effects of information avoidance on information diffusion lies in the urgency of addressing challenges posed by disasters, particularly the recent COVID-19 pandemic, and the recognition of the pivotal role social media plays in diffusion of information during such crises. Understanding information avoidance on social media during crises is vital for effective decision-making, public health communication, and emergency response. It influences the dissemination of crucial alerts, risk perception, and community resilience. Addressing avoidance is key to mitigating misinformation spread, preventing psychological distress, and tailoring crisis communication strategies. In this study, we drew on uncertainty-avoidance literature (Atkin, 1973) and terror-management theory (Greenberg et al., 1997) and proposed two types of textual features, namely, uncertainty-related features and self-regulation-related features, that may hinder information diffusion amid disasters. Against the backdrop of the recent COVID-19 pandemic, we collected COVID-19-related Weibo posts and their reposting behaviors by means of an automatic web crawler and examined the relationships between the proposed features and the reposting behaviors. The paper aims to contribute theoretical insights, offer practical suggestions, and fill a gap in understanding information-sharing behaviors in disaster contexts.

Our findings have several contributions. First, we contribute theoretically to the literature on textual analysis on social media by identifying four textual expressions (two in each of the two types of textual features discussed above) that are novel indicators of people's willingness to share information. In addition, we address and justify the importance of context-specific content analysis. Also, we provide evidence for social media information avoidance during disasters. Moreover, we offer practical suggestions for the information delivery of government and official news accounts on social media. Finally, the four textual expressions can also create business value by providing better advertisement proposals.

This rest of this paper is structured as follows. First, we review the literature related to information diffusion on social media, information-sharing behavior on social media during disasters, information avoidance for uncertain and life-threatening events, information-sharing behavior on social media during the COVID-19 pandemic, and the research gap. Next, we propose our hypotheses based on the literature. Then, we discuss how we tested our hypotheses by analyzing secondary data crawled from Weibo and conducting an online experiment as a supplementary analysis. Finally, we provide some general discussion on the results, implications, and limitations of the study and propose future research directions.

2 Literature Review

2.1 Information Diffusion on Social Media

According to diffusion theory (Rogers, 1962), *diffusion* is the process by which an innovation is shared by means of a certain medium in a network. Lee et al. (2015) adapted this diffusion theory to the psychology field to examine information diffusion on social media in the form of "tweet diffusion." In this way, the diffusion of information refers to the spread of an idea in the form of a post through online social-network activities. Further, reposting behavior on social media is regarded as information diffusion through the user network (Yang et al., 2012). Suh et al. (2010) identified and quantified the factors that influence the "repostability" of a post by transforming the repost count into a binary variable based on whether the post was reposted.

Many extant information systems (IS) studies have examined diffusion of social media posts and have identified various antecedents of the diffusion. According to Han et al. (2020), not only content-related factors (e.g., content features, content messages) but also creator-related factors (e.g., creator features, creator history) and their interactions influence the diffusion of information on social media.

Prior research has identified the effects of creator-related factors on the message diffusion. For instance, Susarla et al. (2012) found that the network position of the content creator had an impact on the success of YouTube videos. The position of a user in the network reflects the follower and following relationships, which, in turn, affect the probability of a video's being seen and shared with others. According to Goes et al. (2014), the more popular a creator is, the greater potential for his or her posts to be read by other users, and the more posts they are prone to produce on user-generated content platforms. In this way, the creator factors influence the information diffusion on social media. Dong et al. (2018), in the context of disasters, also drew similar conclusions. Thus, regardless of whether the contexts are life-threating events, features of users' networks, such as their followers and whom they follow, will likely affect the pattern of information diffusion. In addition, according to Shin and Ognyanova (2022), the reputation of the social media account may also have a major influence on the information-diffusion scale. All of these creator factors may influence whether a post is seen by others and may even affect the diffusion scale.

Content-related factors have also been studied and demonstrated to significantly affect online information diffusion. For example, Son et al. (2013) studied the influence of content-message characteristics such as the inclusion of marketing campaigns, corporate social responsibility (CSR), and social issues by using the Twitter data of the telecom industry. Claussen et al. (2013) demonstrated that the quality of the content and description have more influence on information sharing on Facebook than does the network size (refers to the total number of connections or contacts that an individual has). Also, affective-related content (e.g., positive words, negative words, change of emotion, discrete emotions) has been demonstrated to affect the repost numbers in various contexts such as political communication (Stieglitz & Dang-Xuan, 2012; Lee et al., 2024).

Information on social media brings great value to online users because, besides providing material for random browsing, such information is used by large numbers of people to guide their behaviors (Kelly & Sharot, 2021). Various studies have examined people's information-seeking behavior on social media platforms for serious purposes. For example, Hooley et al. (2016) illustrated steps through which online users can take advantage of social media to get recruited for employment more easily online. Additionally, McCabe (2017) analysed LinkedIn and proposed social media marketing strategies for career advancement. These studies highlighted that social media is not only a platform for hedonic purposes but also a platform for the acquisition of serious information.

2.2 Information Diffusion During Disasters and the COVID-19 Pandemic

Several studies have examined information diffusion during various disastrous events, such as controversial events (Peslak, 2017), political events (Stieglitz & Dang-Xuan, 2012), and natural disasters (Chew & Eysenbach, 2010; Chen et al., 2020; Huggins et al., 2020). For example, research has shown that for tweets during the Boston bombing event in 2013, more followers, less reaction time, and exclusion of hashtags helped information diffusion (Lee et al., 2015). Furthermore, Neppalli et al. (2017) claimed that a tweet during the natural disaster of Hurricane Sandy was more likely to be shared when the emotional range was comparatively narrow. Moreover, by applying information-foraging theory, Wang et al. (2015) found that when people faced technological hazards, they used more terms in information-security-related search queries and had more pageviews for the related information, which indicates greater user attention. Besides the content features such as the number of terms, the content message has been highlighted in disaster-related content-analysis research, as well. For example, Giannarakis and Theotokas (2011) found that companies tended to increase performance on CSR before and during financial crashes in order to remedy the loss of reputation caused by financial disasters. Studies have also examined information sharing during social crises. For example, Ahmed et al. (2017) analysed 65,000 tweets during the Nirbhaya social movement and found that online emotional patterns were highly correlated with offline protest attitudes. In the context of public health events, according to a Twitter content-analysis case study during the 2009 H1N1 outbreak, users tended to avoid expressing humor and frustration in tweets about the outbreak, and they tended to favor content that contained links for official news from government sources as the outbreak developed (Chew & Eysenbach, 2010).

Beyond these studies, research that conducted content analysis of different development stages of disasters has provided further insights. In the context of natural disasters, by analyzing the tweets during Hurricane Harvey and dividing the whole event into four stages (disaster-before, disaster-during, disaster-short-after, and disaster long-after), Chen et al. (2020) found that positive tweets were more likely to go viral than were negative tweets. However, this effect decreased with the development of the disaster (Chen et al., 2020). Similarly, although anger and anxiety have been shown to appear more often in Twitter content at the beginning of a social movement, positive emotional expressions are widely used during the dominant period of a protest event (Ahmed et al., 2017). When a pandemic occurs, emotions and topics will change with the development of the pandemic and the occurrence of the corresponding major sub-events (events that are relevant to the pandemic). For example, when the World Health Organization (WHO) declared a disaster level of 6 on June 11, 2009, during the H1N1 flu pandemic, the number of tweets expressing concern increased (Chew & Eysenbach, 2010). Therefore, content messages may affect information diffusion at different disaster stages.

The recent COVID-19 pandemic not only tested global health systems but also provoked an information crisis, commonly known as an "infodemic." As such, the study of information-sharing behavior on social media during the pandemic has captivated researchers from various disciplines. Various methodologies have been proposed and implemented to study the information-sharing behavior on social media platforms during the pandemic.

Researchers have provided a comprehensive understanding of the nature and quality of shared information. A study conducted by Kouzy et al. (2020) pointed out how the emergence of the infodemic complicated the public's quest for reliable guidance. An essential aspect of content analysis is the categorization of shared information. Cinelli et al. (2020) classified COVID-19-related information into several categories, including health, politics, economy, society, and the environment, among others. They discovered that health-related information was most frequently shared, yet misinformation pervaded all categories. Beyond categorization, cultural and socio-demographic factors also play a role in shaping information-sharing behavior. Several studies have leveraged quantitative methods, including big data analytics and sentiment analysis, to discern patterns and trends of information sharing. For example, Abd-Alrazaq et al. (2020) undertook a large-scale analysis of COVID-19-related tweets to identify the dominant themes and sentiments. Similarly, Pei et al. (2022) found that the social influence according to repost counts and several creator characteristics drove people to repost social media messages. In the context of COVID-19, people often refused to trust uncertain information. Moreover, younger people, who generally comprise the majority of users on social media platforms, often experienced worse psychological conditions because of the uncertainty of their jobs and futures during the pandemic (Giorgi et al., 2020). In order to decrease these psychological consequences, they tended to avoid the relevant information. Researchers found unofficial news was also less likely to be reposted during a pandemic (Chew & Eysenbach, 2010). Instead, Hasson-Ohayon (2016) found heuristic thinking played an important role in COVID-19-related reposting decisions. Thus, insightful content with detailed appraisals of current affairs may attract social media users' attention.

2.3 Uncertainty Avoidance for Life-Threatening Events

People are motivated to seek or avoid information to reduce uncertainty. According to Atkin (1973), information need is "a function of extrinsic uncertainty produced by a perceived discrepancy between the individual's current level of certainty about important environmental objects and a criterion state that he seeks to achieve" (p. 206). People seek or avoid information and reduce their mental uncertainty to a level with which they are comfortable. For example, in the field of health communication, scholars found that patients (and people who believed that they were getting sick) tended to avoid information that made them feel uncomfortable or frustrated (Brashers et al., 2000; Babrow et al., 1999; Babrow, 2001). Exposure to this type of information results in an increase in mental uncertainty, which generally is already elevated among people who are ill or potentially ill.

To avoid mental uncertainty, people are more likely to agree upon and share information from reliable information sources (e.g., a tweet from a verified account) on Twitter during a disaster (Sutton et al., 2014). Certainty plays a pivotal role in the recovery of mental health after a disaster happens. To avoid long-term mental problems caused by a disaster, people will seek out information that meets their need for certainty (Boin et al., 2001).

Prior studies suggested that people's preference for information changes under the influence of life-threatening events. According to the terror-management theory (Greenberg et al., 1997), people adopt two types of strategies to overcome their existential anxiety in the face of death-related events. One strategy is upholding their cultural worldview to protect the symbolic self. When facing death anxiety, people will seek out whatever contributes to the stability of their inner beliefs and thus saves them from mental suffering to some extent (Fink, 2000). The other strategy is to bolster their self-esteem. Such deliberate adoption of bolstering self-esteem strategies requires limited self-regulatory resources (Arndt et al., 1997). Ferraro et al. (2005) proposed that these resources are driven to domains that are important sources of self-esteem from those domains that are less important. Specifically, they found that people tended to eat chocolate, which is an indulgent food, under the influence of mortality salience if physical appearance was not their source of self-esteem. The tendency for indulgence was also aligned with some empirical studies that indicated that mortality salience increased with the engagement of indulgent behavior such as speeding (Ben-Ari et al., 1999) and sex (Goldenberg et al., 2000). Jonas et al. (2003) and Pyszczynski et al. (1997) both suggested that such a tendency under the influence of life-threatening events may result in changes in information exposure for better cognitive consistency.

Information avoidance directly influences how information spreads or fails to spread within a population. For example, individuals selectively expose themselves to information that aligns with their beliefs, avoiding content that contradicts their notions (Frey, 1986). Psychological factors, including emotions and cognitive dissonance, play a role, as people may avoid information that induces discomfort (Frey, 1982; Sweeny et al., 2010). Understanding information avoidance provides insights into the barriers that individuals may face in receiving and sharing information. By understanding these dynamics, researchers and policymakers can develop more targeted communication strategies that address the specific challenges posed by information avoidance, ultimately enhancing the effectiveness of information diffusion efforts.

2.4 Research Gap

Our review revealed that the majority of existing research has concentrated predominantly on overarching factors that influence information-sharing behaviors, including typology, categorization, and socio-demographic factors. However, previous scholars apparently overlooked a rather unique difference of COVID-19 compared to other life-threatening events: COVID-19 was so widespread that it affected most, if not all, of the social media users whereas previous life-threatening events affected only a small subset of the users on social media platforms. Thus, during COVID-19, social media users were highly concerned with certainty and morality, both of which have not been examined by previous scholars in the context of widespread, life-threatening events. In light of this, we drew on previous literature on uncertainty avoidance (Atkin, 1973) and terror-management theory (Greenberg et al., 1997). Among common textual expressions defined by the LIWC (i.e., Linguistic Inquiry and Word Count dictionary) and commonly employed in social media posts (Pennebaker et al., 2015), we identified four influential textual expressions: insight, netspeak, work, and reward. We argue that these textual expressions have detrimental effects on information sharing amid life-threatening events although some of them may have positive influences on information sharing during normal periods. Our exploration of the impact of these expressions seeks to elucidate the mechanisms by which certain content types impede the propagation of information during life-threatening events versus during normal times.

3 Hypotheses Development

Reposting is one major behavioral mechanism that leads to information diffusion on social media such as Twitter and Weibo (Firdaus et al., 2018). Previous studies have drawn on theories of information diffusion to identify textual features of social media posts that facilitate information diffusion (Stieglitz & Dang-Xuan, 2012, 2013; Hoang & Lim, 2012; Son et al., 2013). Moreover, scholars have examined individuals' sentiments and successfully identified emotion-related words as antecedents of retweeting and reposting behavior (Berger & Milkman, 2012; Stieglitz & Dang-Xuan, 2013).

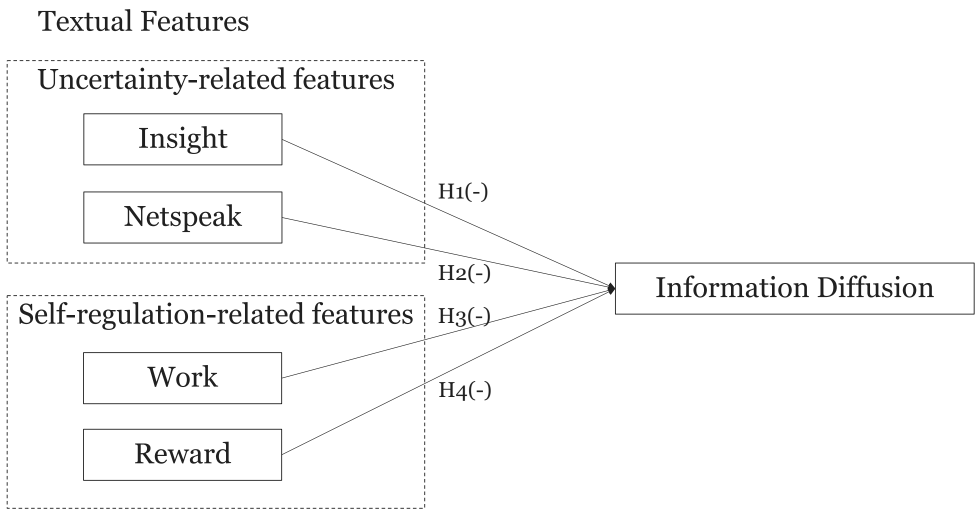
In the face of life-threatening events, social media users may perceive a strong sense of insecurity. Thus, findings on information diffusion during other, more normal times may no longer be applicable in the time of disasters. Drawing on the literature on uncertainty avoidance and the terror-management theory (e.g., Atkin, 1973; Brashers et al., 2000; Greenberg et al., 1997), we proposed four textual features, categorized into two groups, that render negative impacts on social media users' reposting behaviors. This theoretical framework is shown in Fig. 1.

3.1 Uncertainty-Related Textual Features

3.1.1 Insight-Related Words

Insight-related words pertain to appraisal and clarity seeking (Ritter et al., 2014; Hasson-Ohayon et al., 2016). According to LIWC, examples of such words are "think" and "know,"

Fig. 1 Theoretical Framework



which are categorized as *insights* in the LIWC dictionary. During usual times, these subjective appraisals of events tend to be more persuasive than factual-based contents (Heiphetz et al., 2014). People are eager to publicly present their opinions about controversial news on social media platforms to gain audiences (Kim & Ihm, 2020). The opinion serves as additional information to clarify the underlying logic of an event. From the perspective of uncertainty avoidance, it is possible that posts with these insight-related words leave readers with the impression that they have gained insights and new thoughts. Sometimes, so-called conspiracy theories that reveal information about "hidden agendas" of an action or an incident can further evoke readers' emotions and breed reposting behavior (Goreis & Kothgassner, 2020; Quinn et al., 2021). Consequently, it is common for important political and business news shared through official accounts to avoid personal insights and emotions.

However, during a global disaster like COVID-19, people are not only threatened with the possible infection by the disease and its consequences but also affected by a series of secondary disasters brought by people's responses to it, such as the tide of unemployment and financial crisis. The feelings of insecurity and fear heighten psychological uncertainty (Kruglanski & Orehek, 2012). A recent study on COVID-19 also indicated that tragic events, such as the death of a family member, were highly associated with a loss of certainty and mental-health issues (Dutheil et al., 2021). Thus, people tend to avoid information that would further increase their mental uncertainty (Brashers et al., 2000; Babrow et al., 1999; Babrow, 2001). From the perspective of uncertainty avoidance, insight-related words seem to leave an impression of skepticism instead of clarity during life-threatening events. In particular, most writers of social media posts are typical citizens without much authority and credibility in health-related topics. Thus, these insight-related words may have seemed rather subjective in the eyes of readers during the pandemic. We therefore hypothesized that these insight-related words in the social media posts would have a negative influence on reposting of the posts:

Hypothesis 1 (H1). Social media posts with insight expressions are less likely to be reposted during life-threatening disasters.

3.1.2 Netspeak-Related Words

Netspeak language refers to informal language that is used online (McCulloch et al., 1987). Some examples include "btw," which means "by the way," and "thx," which means "thanks" (Pennebaker et al., 2015). Such expressions are informal and often designed to be humorous or convenient. These words are often used for exaggeration and to attract people's attention. Usually, they appear on younger people's social media accounts. During normal times, netspeak language used in social media posts is likely to gain people's attention and enhance information diffusion. For example, Legocki et al. (2022) posited that informal languages, such as netspeak, can extend an online firestorm from one community to other communities. Likewise, in the context of crowdfunding, Jang and Chu (2022) found that the use of netspeak increased the number of donors.

Informal language used in social media posts, however, also implies a lower perceived authority and higher perception of uncertainty. Official accounts and other popular accounts are typically advised not to use this kind of informal language unless the audience is guaranteed to understand (Anurit et al., 2011). According to the Risk Information Seeking and Processing Model, in the context of health-related information such as COVID-19, individuals may be more inclined to seek and share information that is perceived as credible and reliable (Griffin et al., 1999).

During the pandemic when many people lacked clarity in their health-related knowledge, people likely tended not to expose themselves to informal social media posts that generated uncertainty. Instead, people probably opted to read posts that were composed of formal, authoritative language. The use of such netspeak language could leave an impression that the source of the information was not credible or trustworthy. Thus, netspeak on social media platforms could have a detrimental effect on users' certainty. From the perspective of uncertainty avoidance, we thus argue that the lack of formality of the netspeak language adversely affects social media users' sense of certainty during disasters when people lack mental certainty.

Moreover, the informality of netspeak language may hinder effective communication and comprehension of important information. When individuals are already experiencing a sense of uncertainty, the use of casual language can further complicate their understanding of critical details and instructions, leading to potential confusion and misunderstanding. Specifically, when people are seeking information or reassurance during uncertain and distressing times, the use of informal language in social media posts may lead to a decreased level of engagement and trust. Thus, people are likely less engaged in social media posts composed of such language:

Hypothesis 2 (H2). Social media posts with netspeak language are less likely to be reposted during life-threatening disasters.

3.2 Self-Regulation-Related Textual Features

3.2.1 Work-Related Words

During normal times, people often use social media platforms to seek job information, and such use is becoming more common (Karaoglu et al., 2022; McCabe, 2017). As a result, people may also share their job-related experiences and emotions online (Kajanová et al., 2017). However, their behaviors may change during a pandemic.

The terror-management theory suggests that people tend to spend self-regulatory resources on bolstering their self-esteem to cope with existential anxiety, which is attributed to death-related events such as natural disasters (Greenberg et al., 1997; Ferraro et al., 2005). They will shift their attention to concepts that pertain to literal and symbolic immortality. These religious and cultural concepts contrast with work that is highly attached to the materialistic world. Thus, during the pandemic, work-related words such as "work" and "task" in social media posts drove people away from reading and sharing them with others.

In addition, work typically consumes self-regulatory resources (Vohs & Heatherton, 2000). People have to restrain themselves from leisure and enjoyment in order to focus on work. Thus, it is arguable that work-related posts are cognitively attached to the use of self-regulatory resources. Thus, during disasters, people lack self-regulatory resources to spend on activities other than bolstering self-esteem. They invest their self-regulatory recourses into concepts related to mortality instead of issues involving serious, everyday work. Given that social media users tend not to engage in work-related posts during disasters when they have inadequate self-regulatory resources to spend on activities other than enhancing self-esteem, we posited that:

Hypothesis 3 (H3). Social media posts with work-related words are less likely to be reposted during life-threatening disasters.

3.2.2 Reward-Related Words

Reward-related words such as "bonus" and "award" commonly indicate extrinsic outcomes of contribution of resources. The association between reward-related words and job hunting on social media is strong because remuneration is a kind of reward. Online sharing and discussion of rewards from financial investments is also common on social media today (Chen et al., 2019). Previous scholars, such as Sprenger et al. (2014) and Li et al. (2018), examined the information diffusion of posts on social media related to stock returns. Other non-social-media studies, such as that by Clewett and Murty (2019), also indicated that in normal circumstance, people will be motivated to seek and share reward-related information and avoid information that brings negative feelings at the same time.

We thus proposed that reward-related words are implicitly associated with the concept of work because rewards are payoffs or favors received in daily life after serious contributions to tasks. According to the terror-management theory (Greenberg et al., 1997), people are more likely to commit their self-regulatory resources to bolster their self-esteem against life-threatening events. The materialistic reward-related words, similar to work-related words, contrast with religious and cultural ideas of immortality. Thus, reward-related words may lose popularity during a pandemic when people's lives are threated. Thus, we proposed the following hypothesis:

Hypothesis 4 (H4). Social media posts with reward-related words are less likely to be reposted during life-threatening disasters.

4 Methodology

We tested our hypotheses using secondary data crawled from Weibo.com and analysed the texts in the posts. The analysis results showed that all four features proposed impacted users' sharing behavior of social media posts in the context of COVID-19. The details are discussed in the following subsections.

4.1 Data

Chinese Weibo data were collected with a web crawler. Our dataset included 39,362 COVID-19-related Weibo posts contributed by 24,778 different users as well as their numbers of reposts, comments, and likes from January 20, 2020, to March 29, 2020. Following previous research on COVID-19-related social media content analysis, we selected the posts by keyword using Chinese words representing COVID-19 (Kaur et al., 2021). We selected the time period according to the major development period of COVID-19 in mainland China as shown in Fig. 2. As seen in that figure, which is based on the data provided by the National Health Commission of China[1], the period of COVID-19 started from the outbreak to the plateau, which indicates a complete cycle for the pandemic. We argue that the social media opinions from the currently discovered first-wave large-scale spread of COVID-19 is representative in demonstrating the association between wording and sharing behavior.

In addition to the Weibo post information, we crawled the corresponding creator information, which included the verified status, number of follows, number of followers, and number of posts for each creator.

4.2 Hypothesis Testing

Data preprocessing was necessary for Chinese text analysis, and our data preprocessing steps are shown in Fig. 3. Contrary to English texts, there is no space between words in Chinese texts. Thus, tokenization was the first step for Chinese Weibo texts. In this experiment, we used Jieba[2] for tokenization and applied the Simplified Chinese LIWC (C-LIWC) lexicon in the construction of some of the control variables and the independent measures. Following previous research on information diffusion that transformed the repost count into a binary variable (whether a post was ever reposted) (Suh et al., 2010; Hong et al., 2011; Nesi et al., 2018), we used a binary variable on reposting as the dependent variable to measure the diffusion of information on social media. Therefore, in our study, the measure was set to 1 if a post were reposted at least once and 0 if not. We focused on the presence or absence of reposts rather than

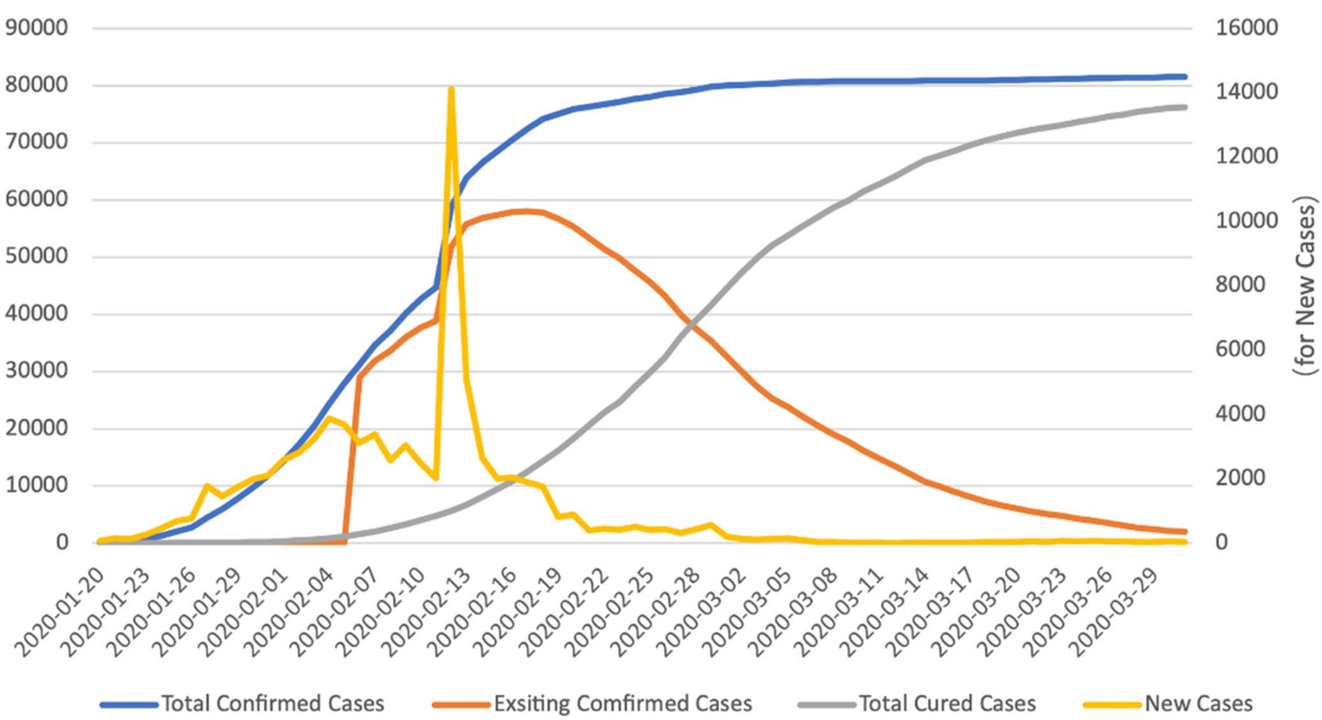


Fig. 2 The Trend of COVID-19 Cases in Mainland China

[1] Data source: National Health Commission of the People's Republic of China. http://www.nhc.gov.cn.

[2] https://github.com/fxsjy/jieba.

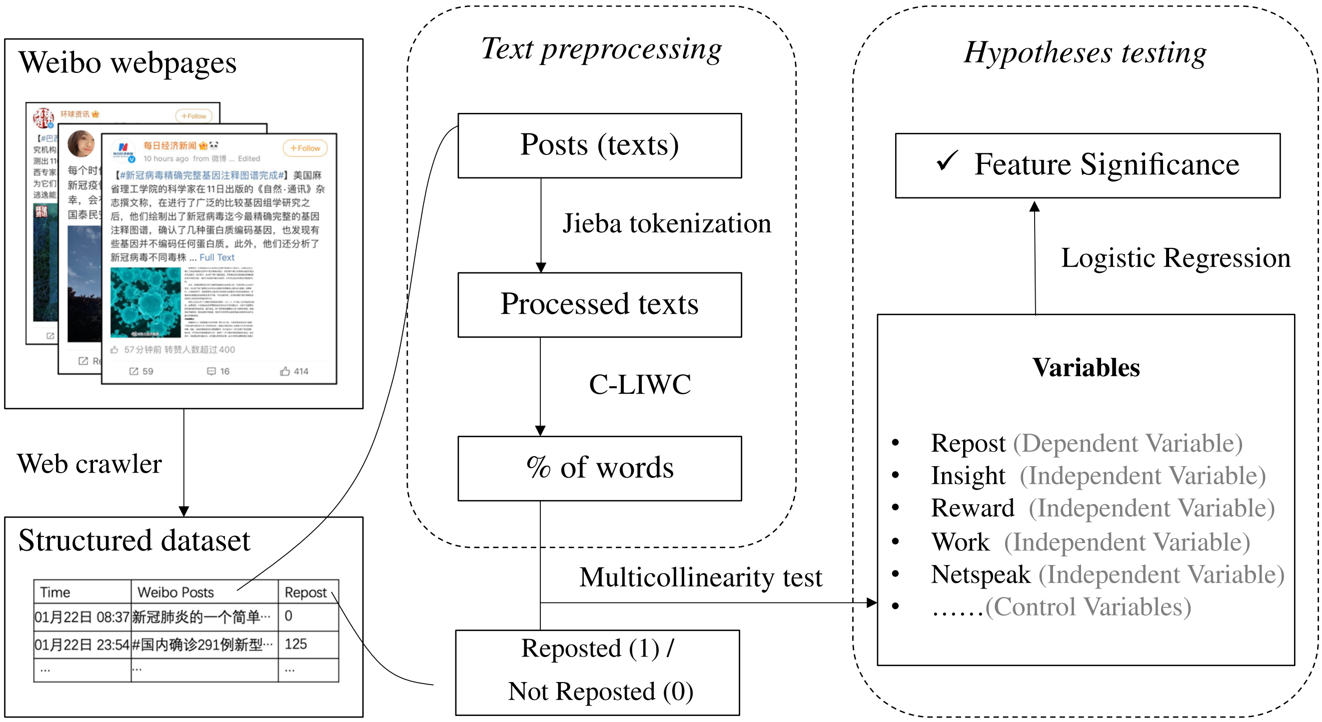


Fig. 3 Data Pre-processing, Variable Extraction and Experimental Set-up

Table 1 Example of words in C-LIWC 2015

Category	Example (C-LIWC 2015)	No. of Words
Insight	决心 (decided), 假定 (presume), 反思 (introspection), 始料未及 (unexpected), 怀疑 (doubt)	259
Netspeak	亦可赛艇 (exciting), 886 (goodbye), 友尽 (end of friendship), 弃坑 (not into something anymore), 鬼畜 (reasonless)	209
Work	上司 (boss), 下岗 (laid-off), 亏待 (unfairly), 任务 (task), 倒闭 (go out of business)	444
Reward	奖金 (bonus), 促销 (promotion), 夺取 (despoil), 挑战 (challenge), 窃取 (steal)	120

Note. “No. of words” is the number of words identified in each category in C-LIWC.

dealing with the specific counts. By considering whether a post had been reposted at least once, the binary measure focused on capturing the presence or absence of a significant behavior. This can help researchers understand the factors that drive engagement and sharing, which are often important in social media contexts. Thus, we adopted binary logistic regression (Menard, 2004) in this study.

4.3 Measures

During the experiment, the four independent variables are insight, reward, work and netspeak expressions. Content characteristics (emotions, function words, and topic-related words) and creator characteristics (user-verified status, follower number, following user number, and historical posts count) were included as control variables to avoid other textual and user-identity effects.

LIWC has evolved from a lexicographical-linguistic tool to a modern textual-analysis tool in the fields of linguistics, psychology, and information systems in the form of a combination of dictionaries and application software (Pennebaker et al., 2015). The psychology constructs were strong fits for the independent variables in our research. The four proposed features insight, netspeak, work, and reward are reflected by the percentage of words in those corresponding subcategories of C-LIWC. Examples of such words are shown in Table 1.

The word count, the fraction of function words, and emotions were also measured by C-LIWC by the percentage of their appearances in the content. Table 2 provides descriptions of the variables.

4.4 Regression Results

After processing the crawled Weibo posts' data with the creator information and the conversion of text information to quantified measures, we generated the data in the logistic model. Table 3 presents the descriptive statistics. Table 4 shows the results of the logistic regression. The test result showed a non-significant effect (p=.349), which means there was no effect between the sharing of COVID-19-related content on social media and the degree of insight

Table 2 Variable descriptions

Variables	Description
Dependent Variable	
Repost	A binary variable indicating the post had been reposted (coded as 1) or not (coded as 0).
Independent Variables	
Insight	Percentage of words indicating insight expression in the post.
Netspeak	Percentage of words indicating netspeak language in the post.
Work	Percentage of work-related words in the post.
Reward	Percentage of reward-related words in the post.
Control Variables	
Verified	A binary variable indicating the creator of the post was a verified user (coded as 1) or not (coded as 0).
Follow	Number of users the creator of the post follows.
Follower	Number of the users following the creator of the post.
Post_num	Number of total posts of the creator of the post.
Word_count	Post length in terms of number of words in the post.
Pronoun	Percentage of pronouns in the post.
Ppron	Percentage of personal pronouns in the post.
Prep	Percentage of prepositions in the post.
Auxverb	Percentage of auxiliary verbs in the post.
Adverb	Percentage of common adverbs in the post.
Pos_emo	Percentage of words indicating positive emotions in the post.
Anx	Percentage of words indicating anxiety in the post.
Anger	Percentage of words indicating anger in the post.
Sad	Percentage of words indicating sadness in the post.
Health	Percentage of health-related words in the post.

expression. Thus, Hypothesis 1 was not supported by the results.

Hypothesis 2 postulated the relationship between an informal language type, netspeak, and the sharing of Weibo posts. The logistic regression test exhibited a significant negative relationship (b = −0.09, p<.001). Thus, social media content with netspeak was less likely to be reposted in the context of COVID-19. This result supported Hypothesis 2.

As explained in the hypothesis-development section of this paper, when a post had work-related words, we hypothesized that it should have been less likely to have been reposted. For Hypothesis, the independent variable was the percentage of work-related words in every Weibo text. The significance level was p<.001 with a negative coefficient of b = −0.021, supporting Hypothesis 3.

To test Hypothesis 4, we used the same regression method on the percentage of reward words as the independent variable and the corresponding binary repost status as the dependent variable. According to the regression result, the negative influence was significant (b = −0.043, p=.001), which means reward-related expressions in content had a negative impact on the audience's repost behavior. Thus, Hypothesis 4 was supported.

Overall, the analysis results supported all hypotheses except Hypothesis 1. By extending the linguistic and topic-content features, we identified features as negative indicators of the sharing of pandemic-related posts on social media during the outbreak of COVID-19 in China. Netspeak, work, and reward expressions had a negative impact while insight-related expressions did not show significance in this study. Therefore, to investigate the effect of insight expressions in the texts in the context of COVID-19, we needed to know how these four variables worked in general cases outside the context of COVID-19.

4.5 Comparison with General Posts

To explore the significance of the results, particularly the distinctive effects within the context of COVID-19, we gathered an additional set of data. This dataset represents a broader spectrum of Weibo posts, not exclusively tied to COVID-19, allowing us to assess whether the identified four types of expressions also influence information diffusion in a general context. Unlike COVID-19-related posts, which can be found by searching for keywords containing "COVID-19," collecting general Weibo posts requires a broader approach due to the restrictions on unlimited data retrieval, which may cause performance issues or downtime. To compile the general Weibo dataset, we adopted a previously used method of searching for comprehensive keywords across social media. García-Perdomo et al. (2018) organized social media posts into 10 categories: international affairs, government/politics and defense, sports, economy/banking/finance, civil rights, entertainment, odd news, life/society, crime, and science. Thus, we crawled 43,419 posts related to these categories in the same period (January 20–March 29, 2020) to construct the general Weibo dataset, and those posts were the input of the econometric model for robustness tests. Table 3 includes the statistical description of the dataset used for that robustness check.

Similar to the processing procedure of the COVID-19 dataset, we quantified the text-related control measures and the four independent variables using LIWC. Then, we applied logistic regression. In order to confirm that the explored significant features applied only to pandemic-related social media content, we expected the impact of these features on the general Weibo dataset during the same period to be non-existent for the three variables that showed a negative effect in Sect. 4.3. We controlled the sources and period; in other words, the two datasets were from the same social media platform and from the same time period. Also, data were crawled by the same web crawler, so they were

Table 3 Descriptive statistics

	COVID-19-related posts (N=39,362)				General posts (N=43,419)			
Variables	Min	Max	Mean	SD	Min	Max	Mean	SD
Insight	0.00	100	2.68	3.38	0.00	100	3.43	3.96
Netspeak	0.00	100	0.73	2.02	0.00	33.33	0.52	1.61
Work	0.00	100	4.11	4.52	0.00	100	5.34	5.89
Reward	0.00	100	0.57	1.85	0.00	100	0.75	1.77
Repost	0.00	1	0.22	0.41	0.00	1	0.18	0.38
Verified	0.00	1	0.46	0.5	0.00	1	0.34	0.47
Follow	0.00	20,006	917.46	1,784.21	0.00	20,432	781.39	1,742.86
Follower	0.00	140.06 m	0.24 m	2.29 m	0.00	140.06 m	0.22 m	2.12 m
Post_num	0.00	4.29 m	26,519.61	70,066.34	0.00	4.29 m	34,871.53	0.18 m
Word_count	0.00	132	48.79	24.15	0.00	109	48.96	23.16
Pronoun	0.00	100	2.26	3.46	0.00	60	3.42	4.39
Ppron	0.00	100	1.32	2.67	0.00	50	2.01	3.33
Prep	0.00	100	4.31	3.66	0.00	37.5	4.53	3.73
Auxverb	0.00	100	1.19	2.34	0.00	50	1.58	2.64
Adverb	0.00	100	5.13	5.14	0.00	100	6.05	5.75
Pos_emo	0.00	100	2.32	3.88	0.00	100	3.65	4.6
Anx	0.00	100	0.32	1.19	0.00	50	0.27	1.05
Anger	0.00	100	0.23	1.17	0.00	83.33	0.53	1.77
Sad	0.00	100	0.16	1.05	0.00	50	0.22	0.95
Health	0.00	100	1.71	3.01	0.00	50	1.2	2.55

Note. m = million

Table 4 Logistic regression result for COVID-19-related posts

Variables	b	SE	Wald	df	Sig.	Exp(b)
Independent Variables						
Insight	0.005	0.005	0.876	1	0.349	0.005
Netspeak	−0.09	0.013	46.728	1	0.000	0.914
Work	−0.021	0.004	37.218	1	0.000	0.979
Reward	−0.043	0.013	11.212	1	0.001	0.958
Control Variables						
Verified(binary)	1.641	0.037	1,989.593	1	0.000	5.161
Follow	0.000	0.000	0.004	1	0.951	1
Follower	0.000	0.000	960.021	1	0.000	1
Post_num	0.000	0.000	43.473	1	0.000	1
Word_count	0.012	0.001	218.004	1	0.000	1.012
Pronoun	0.006	0.008	0.524	1	0.469	1.006
Ppron	−0.01	0.011	0.779	1	0.378	0.99
Prep	0.012	0.004	6.932	1	0.008	1.012
Auxverb	0.007	0.008	0.952	1	0.329	1.007
Adverb	−0.001	0.004	0.162	1	0.688	0.999
Pos_emo	0.000	0.005	0.000	1	0.989	1
Anx	−0.024	0.015	2.336	1	0.126	0.977
Anger	0.021	0.012	2.975	1	0.085	1.021
Sad	−0.016	0.022	0.493	1	0.482	0.985
Health	0.013	0.005	7.651	1	0.006	0.013
Constant	−3.179	0.055	3,350.621	1	0.000	0.042

selected and collected by the same rules and procedures and with the same data structure.

According to Table 5, the effects proposed in Hypotheses 2 and 4 were not applicable to the general cases, as shown by the insignificance in the regression results. It is interesting to note, however, that insight expressions in Hypothesis 1 showed a positive effect (b=0.011, p=.006) in this general dataset, which indicated a negative change in the effect of insight expressions from the general social media posts to the posts in the context of COVID-19. Moreover, there

Table 5 Logistic regression result for general posts

Variables	b	SE	Wald	df	Sig.	Exp(b)
Independent Variables						
Insight	0.011	0.004	7.482	1	0.006	1.011
Netspeak	−0.011	0.01	1.098	1	0.295	0.989
Work	−0.017	0.003	39.285	1	0.000	0.983
Reward	−0.008	0.01	0.653	1	0.419	0.992
Control Variables						
Verified(binary)	1.243	0.031	1,614.988	1	0.000	3.467
Follow	0.000	0.000	42.585	1	0.000	1
Follower	0.000	0.000	772.196	1	0.000	1
Post_num	0.000	0.000	1.058	1	0.304	1
Word_count	0.01	0.001	199.575	1	0.000	1.01
Pronoun	−0.005	0.006	0.532	1	0.466	0.995
Ppron	0.003	0.008	0.152	1	0.696	1.003
Prep	−0.008	0.004	3.338	1	0.068	0.992
Auxverb	0.000	0.006	0.004	1	0.95	1
Adverb	−0.006	0.003	3.807	1	0.051	0.994
Pos_emo	−0.013	0.004	12.462	1	0.000	0.987
Anx	−0.009	0.013	0.464	1	0.496	0.991
Anger	0.064	0.008	72.021	1	0.000	1.066
Sad	0.064	0.014	22.189	1	0.000	1.066
Health	−0.039	0.007	31.452	1	0.000	0.962
Constant	−2.631	0.051	2,676.522	1	0.000	0.072

was a negative effect ($b = -0.017$, $p < .001$) shown in work-related expressions in this general dataset.

4.6 Discussion

Drawing on information avoidance against uncertainty and life-threatening events on social media, our findings suggest online users are less likely to share posts with textual expressions that are related to uncertainty and self-regulation. Specifically, our results indicate that two of the proposed features, netspeak (Hypothesis 2) and reward (Hypothesis 4), were only significant for pandemic-related posts, which further supports our hypotheses by suggesting that COVID-19 was a unique disaster context. Also, Hypothesis 1 was partially supported by showing a negative shift. Although we cannot conclude that insight expressions in social media posts have a negative effect on the extent of sharing, it is obvious that the positive effect of insight expressions in general cases was lost in the context of COVID-19. Lastly, Hypothesis 3 was supported in the main study, and the effect was applicable for general posts.

In general, social media works as a public platform that allows users to share their thoughts and opinions. Some of the opinion-based, insight-related posts are well accepted and attract people to share them. However, this was not the case during COVID-19. According to our study, the effect of insight expressions that showed opinion-based information had a negative shift from the general context to the context of COVID-19. This shift may be due to the idea that people were not interested in or were unwilling to share opinion-based information under the influence of uncertain information (such as changes in the number of infected people, community vaccination policies, and new vaccines) about COVID-19. Thus, people's behavior regarding insight expressions on social media during COVID-19 remains understudied. From the results of the main study shown in Tables 4 and 5, Hypothesis 1 was partially supported by the positive effects in general posts, as discussed. To further explore people's sharing behavior towards posts with insight expressions on social media during COVID-19, we conducted an online experiment. By manipulating the presence of these words in social media posts, we aimed to observe their effects on sharing behavior. This supplementary study was conducted through MTurk. In the experiment with 249 participants, we found that participants were less likely to repost information containing insight-related words compared to posts without them. The results of the supplementary study provide further support for Hypothesis 1, indicating that insight-related words negatively affected users' intention to repost in the context of COVID-19. Details of the experiment are provided in Appendix A.

Besides opinion-based, insight-related expressions, netspeak brings people the feeling of uncertainty by conveying information using informal language, which is less likely to be used in official reports or news. Our result illustrates that people avoided sharing content using netspeak in the context of COVID-19, which accords with the finding that people will avoid sharing uncertain information during disasters (Sutton et al., 2014).

According to our results, work- and reward-related topics had a negative effect on the sharing of content on social media, indicating less self-regulatory resource consumption on work and reward during disasters. People likely avoid acquiring and sharing information that conflicts with their intention to build self-esteem during a life-threatening disaster like COVID-19. Notably, work-related words also showed a negative effect on sharing in the general dataset. That result accords with the function of social media as a release for most users, so they are also unlikely to invest self-regulatory resources into work-related content in general cases.

5 General Discussion

Our study provides evidence for factors that hinder information diffusion on social media during a disaster. By testing our hypotheses using text analysis followed by a supplementary experiment, we filled the research gap and contributed to the understanding of the effect of uncertainty and self-regulation on the sharing of social media content. Following the available content and creator categories summarized by Han et al. (2020), we found that four textual expressions were negatively related to sharing behavior or showed a negative shift from the general dataset to the context of COVID-19. Specifically, insight expressions and netspeak expressions undermine the content's authority, and work-related and reward-related content affect self-regulation. Furthermore, we found a significant decline in people's willingness to share when an original post used an insight expression in the context of COVID-19.

5.1 Theoretical Contribution

Our research has three theoretical contributions. First, we contribute to the literature on textual analysis of social media by identifying two types of textual features that are novel as indicators of information sharing. Our work plays a role in the exploration of textual features when predicting users' willingness to repost social media content. Most text analyses in previous research focused on sentiment and emotion (Pennebaker & Francis, 1996; Berger & Milkman, 2012; Stieglitz & Dang-Xuan, 2013; Ahmed et al., 2017). Although further studies took into account other content characteristics such as function words (Chung & Pennebaker, 2007) and other textual features (Chew & Eysenbach, 2010; Han et al., 2020), there has still been a lack of investigation of other psychology-based expressions such as expressions about uncertainty and self-regulation. Thus, our work provides new evidence that many valuable textual expressions could be explored by considering deeper insights into psychological factors. Furthermore, although past research has summarized the features that affect the sharing of social media information by including other content or creator-related features and even the interactions among those features (Han et al., 2020), our research is the first to suggest four novel features from two insightful aspects, uncertainty and self-regulation, which influenced the sharing of social media posts during COVID-19. By extending the information type that could be used in future text-mining research, we provide new thoughts on factors that affected users' information behavior during COVID-19. This contribution is helpful in gaining a better understanding of pandemic-related public preferences.

Second, we address and justify the importance of context-specific content analysis (e.g., during disasters). We hold that the effects of features should rely on the context. A majority of literature has provided a general conclusion on the effects of specific textual features (Ferrara & Yang, 2015; Han et al., 2020; Berger & Katherine, 2012). In our study, the effective feature showed different significances when applied in the general context and the context of COVID-19. For example, insight was positively related to the repost number of a post, which meant a post with insight-related expressions was likely to be shared on social media in general, but the effect was different in the context of a disaster such as COVID-19. According to our supplementary study, insight expressions were negatively related to repost intention. People were reluctant to share posts with insight expressions when they were related to COVID-19. Therefore, the effect of one textual feature may work differently in different contexts. This finding matches those in previous research in which emotions or other textual features showed different effects on people's sharing intentions (Goes et al., 2014; Chen et al., 2020). Therefore, going beyond a general conclusion on the effect of the four features proposed in our research on social media content, we conclude our findings by providing a context of COVID-19, which was a major disaster that happened recently and had a great influence people's lives around the world.

Finally, we provide evidence for social-media information avoidance during disasters. Our findings deepen the understanding of information avoidance involving uncertainty and self-regulation during COVID-19 by testing the four relevant features' effects on information sharing. Based on previous research on uncertainty and self-regulation expression (Atkin, 1973; Sutton et al., 2014), we contribute by bringing more specific and representational features to these expression types. Past research suggested that insight and netspeak expressions make people feel uncertain during disasters while work and reward are referred to as self-regulatory resource consumption. However, they all had a negative effect on sharing in the context of COVID-19. To our knowledge, there is no previous work confirming that information avoidance appears on social media in the form of diminishing intention to share. The negative effects concluded from our main study and supplementary study suggest that people tend to be less likely to share uncertain information and expend fewer self-regulatory resources on activities that are relevant to materialism during life-threatening events. Therefore, our research adds to information avoidance and terror-management theory under disasters.

5.2 Practical Implications

Our study also sheds light on the practice of information sharing and information diffusion on social media. By extending effective content features during COVID-19, government officials can better evaluate the words they express on official accounts, thus ensuring important information is conveyed and spread effectively to ensure the safety of people and property in the event of a pandemic. Although most research has provided suggestions on how to make viral social media content by using specific words (Hoang & Lim, 2012; Han et al., 2020), we strongly recommend that official accounts use words that are effective in a specific context when posting information to promote sharing. For example, when an official news account posts information on an entertainment show, people may be attracted by the netspeak, making them willing to share the news. On the contrary, people may not trust the content with netspeak when the news is about mortality-related events such as COVID-19. In such situations, people tend to share information with formal language that makes them feel more certain. More importantly, if government officials want to post important information on social media about a disaster like COVID-19 and expect the content to be spread widely and quickly, insight expressions and informal netspeak language should be avoided. Also, they should avoid content that may drain the audiences' self-regulation resources, such as work- and reward-related information.

In addition to providing guidance to government and official news accounts' information delivery on social media, our identification of the four features can create business value by providing better advertisement proposals for commercial information about COVID-19, such as vaccination and the promotion of new protective tools and antiviral drug sales. For instance, when online retailers post advertisements about a new anti-virus face mask, they should avoid uncertainty-inducing expressions and expressions that may consume people's self-regulation resources, in order to get their advertisements spread more virally and sell more products. Thus, our findings provide more cues other than simple emotional expressions that will affect the spread of information, especially in the context of COVID-19.

6 Conclusion

As discussed, previous literature has shown that a large number of textual features are influential in social media content sharing. Our research, however, examined novel features that are influential in the context of disaster. Theoretically, we contribute to the literature about textual analysis on social media by identifying four features that are novel as indicators of information sharing under the context of life-threatening events such as COVID-19. Also, we provide evidence for social media information avoidance during disasters. Practically, our study helps in guiding the publication of governmental and business information on social media in order to increase the sharing of content among users.

Although we have highlighted the theoretical contributions and practical implications, this study still has several limitations. First, we only focused on a short time period after the outbreak of COVID-19 in China. The duration of COVID-19 was relatively long in comparison to many previous disasters' durations. However, we focused on the major development period of COVID-19 in Mainland China from its occurrence to the time when the number of confirmed cases diminished to a comparatively small number. Future studies can explore the influence on information sharing during different periods of COVID-19. Because the development of a pandemic has different stages and the attitudes of social media users at different stages may vary with the development of the disaster (Chen et al., 2020), the features in previous literature and those proposed in this study may have different effects at different stages. Analyzing the social media disaster data in stages, such as the initial stage of development, the outbreak stage, and the extinction stage, is an important future research direction.

Second, because the COVID-19 pandemic was uncertain and life threatening, it was strongly associated with existential anxiety and mortality. However, the influence of work- and reward-related content during other non-life-threatening disasters may be softened. Therefore, although our findings had validity in the COVID-19 context, how they work during other disasters needs further investigation, especially in different types of disasters such as financial crises. On one hand, features proposed in previous studies (Pennebaker & Francis, 1996; Peslak, 2017; Berger & Milkman, 2012; Han et al., 2020) and discovered in this study can influence the virality of social media content. These features can be further used as indicators to determine whether a disaster-related text is likely to be shared. On the other hand, future studies can further explore typical features of other disasters, such as natural and human-caused disasters, and identify corresponding textual expressions that may affect virality on social media during these disasters. Lastly, it should be noted that words can be used with different meanings in different contexts. For example, the word "promotion" can mean being moved up to a higher rank (related to "work" and "reward"), but it can also be used to discuss the promotion of vaccination for COVID-19. Thus, caution is needed when interpreting the results of this study, and more advanced text-analysis methods may be used to address this issue in future studies.

Appendix A: Online Experiment

Experiment Design

Pretest

In order to gain a deeper understanding of the underlying mechanisms that drove information sharing on the topic of COVID-19, our study aimed to establish a controlled environment in which we could manipulate variables and observe their effects on participants' behavior. A critical aspect of our research involved manipulating a linguistic feature, insight-related words, within the context of information sharing. We hypothesized that the presence or absence of this linguistic feature would significantly impact participants' intentions to share COVID-19-related information. By systematically varying the presence of these words in the information presented to participants, we aimed to better evaluate the causal relationship between linguistic features and participants' sharing intentions. It is important to note that although intention to share and actual behavior may not always perfectly align, measuring intention in our experiment served as a pragmatic and effective proxy for assessing actual sharing behavior within the experimental context. By examining participants' intentions to share information, we sought to capture their inclination and willingness to engage in information sharing, which closely aligns with the primary focus of our study. Specifically, we directly manipulated the linguistic feature (i.e., insight-related words) in a COVID-19 social media post and examined each participant's intention to share the post. The stimuli of the posts mimicked the real social media posts regardless of formatting and post length. To further improve the generalizability of the finding, the participants of this study were recruited from Amazon Mechanical Turk (MTurk), a widely used crowdsourcing platform in research that offers task-release and data-gathering services.

To prepare the post stimuli in the main study, we conducted a pretest to confirm that the post stimuli in the insight (vs. not) condition were perceived to contain (vs. not contain) insight-related words. Fifty-six participants were recruited from MTurk for a small monetary compensation for this pretest. They were randomly assigned to the treatment or the control group. In the treatment group, the linguistic style of the post used words such as "believe" and "infer," which are insight words that express personal feelings. In the control group, the post with the same meaning did not use such insight-related words. For instance, "I know getting a COVID-19 vaccine can make some kids nervous" is a post with insight expression via the clause "I know." On the contrary, "News stations report that getting a COVID-19 vaccine can make some kids nervous" is a good fit for the control group because the topic is the same, but the insight expression word is removed. Meanwhile, the length and other features were kept the same for the treatment and control groups. Each participant read three pieces of news (randomly ordered). For each post, we asked participants, "Insight words are words that express opinion-based feelings such as 'know,' 'believe,' and 'infer.' To what extent do you think the post you just read includes insights words?" Participants then responded via a 7-point Likert scale (1 = *not at all* to 7 = *definitely*). We selected one post for the main study. The results showed that participants perceived the post in the treatment (vs. control) group to be more likely to contain insight-related words (M_{insight} = 5.929, SD = 1.245 vs. $M_{\text{non-insight}}$ = 3.250, SD = 2.119, t = 5.857, p < .001), indicating our manipulation of the post we used in the main study was successful.

Procedure

We recruited We recruited 257 participants from MTurk for a small monetary compensation. According to the suggestions of Lowry et al. (2016), we used screening questions to rule out eight participants who stated that their data should not be used in our analysis. Finally, we used the responses of 249 participants (50.35% female, M_{age} = 40.61) in the analysis. In the experiment, we asked participants to join an online reading task. Each participant was randomly assigned to one of two conditions (insight vs. not) and viewed a social media post. The post display simulated a regular Facebook post, with the poster's information hidden (see Fig. 4) to prevent any confounding effects (Moravec et al., 2020). After participants read the post, we examined their intention to repost as a measure of our dependent variable. We also asked questions related to our control variables such as questions about

Fig. 4 Example of a Post (Insight vs. Not) in the Experiment

participants' social media usage, the percentage of reposting behavior, and demographics (e.g., gender, age, education, and income).

Results

To make sure differences in participants' intentions to repost were caused by the inclusion of the target expressions (i.e., insight-related words), we first performed a manipulation check. As expected, the results showed that the likelihood of observing the insight-related words was significantly higher in the treatment group than in the control group ($t=10.676$, $p<.001$). Our analysis of variance (ANOVA) results showed that in the context of COVID-19, people were less likely to repost social media information with insight-related words than without such words ($M_{\text{insight}} = 2.09$ vs. $M_{\text{control}} = 2.63$, $F[1, 248]=5.289$, $p=.022$). The findings still held after taking all the covariates into consideration ($F[1, 248]=4.837$, $p=.029$).

Discussion

The results in this supplementary study provide further support for Hypothesis 1 that insight-related words negatively affected users' intention to repost in the context of COVID-19. Not only did a negative shift exist in the effect of insight expressions in social media content on the number of reposts from the general context to the COVID-19 context, but also the insight expressions diminished people's willingness to share in the context of COVID-19, which aligned with Hypothesis 1. This finding indicates people may prefer to repost factual information rather than opinion-based information during disasters (e.g., COVID-19).

Acknowledgements We thank the universities and funding agencies for supporting the project and the participants who joined the online experiment.

Authors' Contributions E and Chau conceived of this study. E was responsible for data collection and analysis. The online experiment was conducted by E and Deng. The manuscript was written by all the authors. Revisions were made by E and Lee. Yang and Chau supervised the project.

Funding The research was supported in part by the National Natural Science Foundation of China (No. 72301216; Bingjie Deng), the Educational Commission of Guangdong Province (No. 2021ZDZX1069; Lili Yang), the Key Laboratory of TechFin in SUSTech (Lili Yang), and the University of Hong Kong Seed Funding for Basic Research (No. 104006696; Michael Chau).

Data Availability The data used in this study includes both survey data and web-crawled data. The survey data, which was collected through MTurk, is available upon reasonable request. However, due to ethical and legal constraints, the web-crawled data used in this research cannot be disclosed.
Competing Interests.
The authors have no competing interests to declare that are relevant to the content of this article.

Declarations

Ethics Approval and Consent to Participate All procedures performed in this study were in accordance with the ethical standards. For the online experiment, participants were assured of the confidentiality and anonymity of their responses, and they were informed that they could withdraw from the study at any time without penalty. No personally identifiable information was collected during the survey, and data were stored securely to ensure privacy.

Consent for Publication All authors have given their consent for the publication of this manuscript.

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