Understanding the effects of message cues on COVID-19 information sharing on Twitter

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Abstract

Analyzing and documenting human information behaviors in the context of global public health crises such as the COVID-19 pandemic are critical to informing crisis management. Drawing on the Elaboration Likelihood Model, this study investigates how three types of peripheral cues—content richness, emotional valence, and communication topic—are associated with COVID-19 information sharing on Twitter. We used computational methods, combining Latent Dirichlet Allocation topic modeling with psycholinguistic indicators obtained from the Linguistic Inquiry and Word Count dictionary to measure these concepts and built a research model to assess their effects on information sharing. Results showed that content richness was negatively associated with information sharing. Tweets with negative emotions received more user engagement, whereas tweets with positive emotions were less likely to be disseminated. Further, tweets mentioning advisories tended to receive more retweets than those mentioning support and news updates. More importantly, emotional valence moderated the relationship between communication topics and information sharing—tweets discussing news updates and support conveying positive sentiments led to more information sharing; tweets mentioning the impact of COVID-19 with negative emotions triggered more sharing. Finally, theoretical and practical implications of this study are discussed in the context of global public health communication.

1 | INTRODUCTION

In recent years, microblogging platforms, such as Twitter, have become an important communication channel for people to produce and share short messages containing information, feelings, and experiences. In public health crisis situations, Twitter is a powerful mechanism to facilitate quick communication and wide information dissemination (Hughes & Palen, 2009). Taking the recent COVID-19 pandemic as an example, news related to COVID-19 can be shared and retweeted on Twitter, reaching millions of users (Zheng et al., 2020a). In the early stages of COVID-19, by exchanging information on such microblogging platforms, individuals could create a shared understanding of the nature of the outbreak, particularly when most of them were quarantined at home. If such sharing were not successful, it might have impeded the progress of response to the pandemic (Nelson et al., 2021).

Analyzing and documenting human information behaviors on social media in the context of global public health crises are critical to informing crisis management (B. Xie et al., 2020). More specifically, considering the emerging, rapidly evolving COVID-19 situation, it is

important to understand factors that drive or inhibit information sharing on Twitter, with a focus on message features. This would inform scholars and practitioners on how to make use of these features to enhance the amplification of crisis messages, thereby achieving a higher level of information penetration across the globe (B. Xie et al., 2020).

While information sharing behavior during each crisis is inevitably unique, a significant body of research has suggested that Twitter features such as emotions and content types embedded in tweets can impact retransmission of messages (Bruns & Stieglitz, 2012; Son et al., 2019; Sutton et al., 2020; Xu & Zhang, 2018). In the context of the COVID-19 pandemic, numerous studies have examined the themes and sentiments related to COVID-19 using Twitter data (e.g., Abd-Alrazaq et al., 2020; Lwin et al., 2020; Xue et al., 2020; Zheng et al., 2020a). Although such findings enhance our understanding of public discussions and concerns about this global health crisis, there is a paucity of research exploring how different message features induce information sharing on Twitter. Compared to previous emerging health threats such as Ebola and Zika, COVID-19 is highly infectious and transmissible (Sutton et al., 2020). It has quickly become a morbid global pandemic, and its impact on our society is unprecedented and far-reaching. Characterizing the specific factors shaping information sharing in this emergent context is of importance for researchers and practitioners to propose evidence-based strategies to combat the invisible enemy.

This study therefore contributes to this research area by examining factors influencing information sharing behavior on Twitter in the early stage of the COVID-19 pandemic. In particular, we adopt the Elaboration likelihood Model (ELM) as a theoretical lens, which explains how individuals change their attitudes and behaviors through processing a variety of information cues in the messages (Petty & Cacioppo, 1986). We conceptualize information sharing behavior on social media as an outcome of information processing in the pandemic situation. Informed by ELM and prior research on crisis information sharing on Twitter (e.g., Bruns & Stieglitz, 2012; Son et al., 2019; Sutton et al., 2020; Xu & Zhang, 2018), we investigate the effects of three types of information cues—content richness, emotional valence, and communication topics, on virus-related information sharing. These are primary cues implicitly embedded in social media messages, which help people process voluminous information quickly in times of uncertainty (Xu & Zhang, 2018; Y. Zhang et al., 2020).

We used computational methods, combining topic modeling with several psycholinguistic indicators obtained from the Linguistic Inquiry and Word Count (LIWC) dictionary to measure these concepts and built a research model to assess their effects on information sharing. Theoretically, applying ELM to study COVID-19 information sharing on Twitter provides researchers with valuable insights about why certain types of crisis information go viral on social media under conditions of uncertainty. Practically, our results will better help government agencies and health professionals protect people's physical and mental health during a global public health crisis.

2 | LITERATURE REVIEW AND THEORETICAL FOUNDATIONS

2.1 | Information sharing during crises

Natural disasters, public health crises, and other extreme events create circumstances requiring prompt, efficient communication efforts. As seen in past research, when crises occurred (Son et al., 2019; Sutton, Gibson, et al., 2015), there was a dramatic increase in information seeking and sharing in the public. Rapid dissemination of crisis-related messages is vital for people to change behaviors and protect their safety and health (Sutton et al., 2020). For decades, crisis information has been diffused via mass media channels, such as television, radio, and broadcast. With the advent of digital technologies, such information has begun to be shared via social media platforms. Sharing risk-related information in the online setting enables a message to reach a wider range of audiences, potentially leading to lifesaving actions (Sutton, Ben Gibson, et al., 2015). Moreover, most social networking sites such as Twitter allow retransmission of the same message multiple times (Hawkins et al., 2001). People who are frequently exposed to the message may have greater confidence in message veracity, leading to further information sharing (Fragale & Heath, 2004). Evidence suggests that under conditions of imminent threat, repeated exposures to a portion of risk-related information are a prerequisite for information sharing and subsequent behavioral change (B. F. Liu et al., 2016).

As Twitter has evolved to become a widely used and legitimated source of news and information, its use during times of crises has received considerable attention from scholars and practitioners in recent years (Sutton et al., 2020). Previous studies have mainly examined three types of message-related factors influencing crisis information sharing on Twitter, namely, Twitter characteristics such as the inclusion of hashtags and/or hyperlinks (e.g., Son et al., 2020; Sutton et al., 2014, 2020; Sutton, Gibson, et al., 2015), tweet emotions (Wang & Lee, 2020; Xu & Zhang, 2018), and tweet content themes

(Chew & Eysenbach, 2010; Son et al., 2019; Sutton, Ben Gibson, et al., 2015). Collectively, these message features can be viewed as drivers or barriers of retransmission of crisis information, depending on the specific context.

Although these studies provide a deeper understanding of crisis communication on Twitter, comparatively limited research has employed theoretical perspectives, making it difficult for researchers and practitioners to explain and predict how various tweet features facilitate information sharing in a public crisis (Son et al., 2019). The use of data-driven approaches alone without any theoretical consideration to extract insights from big data platforms (e.g., Twitter) may lead to the faulty belief that having more data or employing more advanced computational approaches are panacea to mitigate health risks (E. W. J. Lee et al., 2021; E. W. J. Lee & Viswanath, 2020). In addition, how certain factors jointly influence information sharing during threat events remains understudied. It is important to explore these moderation effects as it reveals how a particular message feature may strengthen or diminish the relationship between other message features and information sharing (Chen, Min et al., 2020; Son et al., 2019). This provides implications in crafting more tailored crisis-related message to educate the public. With COVID-19 affecting the entire globe, it is especially pertinent to assess how virus-related information is disseminated on Twitter. In the next section, we introduce the ELM as a theoretical basis to understand information sharing.

2.2 | Elaboration likelihood model

When social media users deem that the information they read is important, they may share it with others (Li et al., 2014). Put differently, information sharing can be viewed as an outcome of information processing (Xu & Zhang, 2018). Existing research suggests that people use two different processing styles to process information (Bhattacherjee & Sanford, 2006; Mousavizadeh et al., 2020; Y. Zhang et al., 2020), leading scholars to adopt dual process theories, such as ELM, to examine information sharing behaviors on social media during crises (F. Liu et al., 2014; Xu & Zhang, 2018).

According to ELM, people process information in two ways (Petty & Cacioppo, 1986). The central mode, or systematic processing, describes an effortful and logical evaluation of a message. People using this mode tend to put more effort and motivation in scrutinizing messages, and they make decisions based on rules and logic. On the other hand, the peripheral mode, or heuristic processing, refers to an unconscious, automatic, and quick way of thinking. Here, people rely on heuristic cues (e.g., other

people's opinion) for decision-making. They are more inclined to use cognitive shortcuts in messages to form attitudes and behaviors.

Compared to other dual process theories such as the extended parallel process model (EPPM; Witte, 1992) and heuristic-systematic model (HSM; S. Chen & Chaiken, 1999), ELM is a more useful and suitable theoretical foundation to explain information sharing on social media in the context of public health crises. First, the antecedent variables in the EPPM (e.g., fear control, response efficacy, efficacy appraisal) mainly work for inducing health protective behaviors for some people who have low health knowledge or awareness. Such variables may not be directly relevant to information sharing regarding COVID-19, which is a salient issue about which most people are concerned. Second, while the HSM closely relates to ELM as it also describes two routes of information processing (systematic vs. heuristic), ELM focuses more on how people change their attitude and behavior (e.g., information sharing) through processing various information cues (Kitchen et al., 2014), whereas one limitation of HSM is its inability to define specific motivations of persuasion (Eagly & Chaiken, 1993).

ELM posits that when being confronted with information overload in a risky situation, most people are likely to process information in a peripheral route (Petty & Cacioppo, 1986). Amid the pandemic, large amounts of online messages such as tweets were being produced and viewed by many, which may be overwhelming for many (Lwin et al., 2020). This perceived information overload could induce most people to engage in peripheral route processing rather than central route processing because it would not be feasible to thoughtfully scrutinize every piece of information (Bhattacherjee & Sanford, 2006; Xu & Zhang, 2018). Moreover, it would be difficult to assess the validity of virus-related tweets using central cues (e.g., argument quality) as some social media users might not have a relatively high level of analytical skill for fact-checking (Islam et al., 2020). This is consistent with ELM, stating that when people's ability to process information decreases, peripheral cues become relatively more important determinants of attitude and behavior change (Kitchen et al., 2014; Petty et al., 1983). This argument has been validated in empirical research. For instance, F. Liu et al. (2014) found that people rely heavily on peripheral cues (e.g., content ambiguity, attractiveness) for online information processing because facts are hard to verify at the beginning of the natural disaster. Similarly, Xu and Zhang (2018) analyzed tweets discussing the missing Malaysian Airlines Flight 370 and found that people tended to use peripheral cues such as richness, sentiment, and relevance, to process information regarding this crisis event. For these reasons, this

study focused on peripheral cues as they are likely more prevalent in processing COVID-19 information on Twitter.

2.3 | Conceptual model and research hypotheses

Informed by the ELM as well as prior literature on crisis information sharing (e.g., F. Liu et al., 2014; Xu & Zhang, 2018; Y. Zhang et al., 2020), this study examines three main types of peripheral cues that may trigger information diffusion on Twitter at the early stages of the COVID-19 pandemic: Content richness, emotional valence, and communication topic. These cues are particularly evident in online conversations of global health crises. For example, the COVID-19 pandemic is characterized by ambiguity, uncertainty, and complexity, along with fatal consequences on various aspects of society (Tandoc & Lee, 2020). The public is highly sensitive to information relevant to the pandemic, especially when it contains source-related characteristics indicative of emotions and personal relevance (Xue et al., 2020). Under uncertain periods, people typically use information cues embedded in a message to make decisions on whether to fully read and share it. Figure 1 illustrates our conceptual model of how these message cues are associated with information sharing. First, we aim to test the effects of the three peripheral cues on COVID-19 information sharing. Additionally, we seek to explore the interaction effect between emotional valence and communication topics. The rest of this section elaborates on the theoretical bases for each relationship in the proposed model.

Content richness refers to information on social media being adequate, clear, and analytical for people to understand and process (Xu & Zhang, 2018). It can be assessed by message cues comprising the amount of information, presence of media elements and writing styles. First, the amount of information can be seen as a peripheral cue in that more information means more details, thereby increasing the quality of content (Petty & Cacioppo, 1986). Several studies have shown that during crisis situations, the more words a tweet contains, the more retweets it will receive (e.g., Son et al., 2020; Xu & Zhang, 2018). Second, the presence of multiple media elements (e.g., videos, pictures, URLs, hashtags) can be added as additional information to enhance content richness of text messages. Such cues create more direct sensory experiences through enhancing telepresence or vividness (J. Liu et al., 2017). Some studies suggest that in the context of public health crises or extreme events, the presence of media elements might discourage information sharing on social media. For example, J. Lee et al. (2015) found that tweets with hashtags received less retweets than tweets without hashtags. Likewise, Chen, Min et al. (2020) found that compared to the posts that include pictures and videos, plain text can trigger more user engagement (i.e., likes, reposts, and comments) on Weibo during the COVID-19 pandemic.

Third, recent research has suggested that writing style on social media (analytical vs. narrative) is another possible cue to reflect content richness (Pennebaker et al., 2015). Different writing styles may evoke different impressions, which in turn induce varying engagement behavior (Choi & Stvilia, 2015). In a risky situation, people tend to seek for information to reduce uncertainty and anxiety (Zheng et al., 2021). They prefer information written in an analytical style which is logical and consistent, avoiding chaotic and noisy information. F. Liu et al. (2014) studied rumor retransmission in disasters and showed that ambiguous information is lfess shared by online users. The above discussion leads to the following hypotheses:

> **H1a.** The amount of information in a tweet is positively associated with information sharing on Twitter during the COVID-19 pandemic.

> **H1b.** The presence of media elements is negatively associated with information sharing on Twitter during the COVID-19 pandemic.

> **H1c.** Analytic writing style is positively associated with information sharing on Twitter during the COVID-19 pandemic.

Social sharing of emotion theory posits that emotions can induce a person's desire to seek and share information (Rimé, 2009). In general, emotional valence involves two types of emotions (i.e., positive and negative) in a
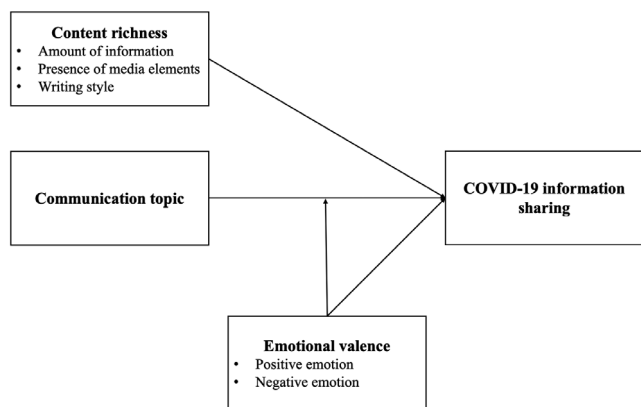

FIGURE 1 COVID-19 information sharing conceptual model

personal information experience. When people are exposed to posts with emotion on social media, they tend to share them as a way of regulating their own emotional status (Rimé et al., 2020). Sharing emotional posts also promotes other users' engagement behaviors, such as commenting, liking, and sharing (Ji et al., 2019). During a public crisis, negative sentiments such as anger, fear, and sadness are more persuasive, triggering wider information sharing (L. Zhang et al., 2017). On the other hand, positive sentiments (e.g., enjoyment, happiness) are also important because the public needs to seek reassurance and empathy in uncertain periods (Li et al., 2014). Sharing positive content on social media in this context may help boost others' mood and provide hope for coping with the crisis (Chen, Min et al., 2020). Lwin et al. (2020) found that negative sentiments such as fear, anger, and sadness were evolving in the early stages of COVID-19, driving information virality on Twitter. Further, tweets containing positive sentiments (e.g., joy) were prevalent as well (Lwin et al., 2020). Therefore, we hypothesize that:

> **H2a.** Tweets with positive emotions are positively associated with information sharing on Twitter during the COVID-19 pandemic.

> **H2b.** Tweets with negative emotions are positively associated with information sharing on Twitter during the COVID-19 pandemic.

Communication topics refer to the categories of discussions occurring on social media during an event. According to ELM, people are more likely to pay attention to the topics that are relevant to them personally (Petty & Cacioppo, 1986), resulting in information sharing behavior (Y. Xie et al., 2017). Previous studies have demonstrated the differentiated effects of communication topics on information sharing on Twitter. For example, by analyzing tweets about breast cancer awareness, Chung (2017) showed that those promoting organizational work had a negative effect on information diffusion. Chew and Eysenbach (2010) found that people are more likely to share news updates from credible sources, and personal experiences and opinions on Twitter during the N1H1 Swine Flu Pandemic in 2009. Similarly, disaster tweets discussing hazard impact received more retweets than those expressing gratitude (Sutton, Ben Gibson, et al., 2015). Therefore, we hypothesize that:

> **H3.** Communication topics will have differentiated effects on information sharing on Twitter during the COVID-19 pandemic.

Furthermore, tweet content and emotions might be inextricably linked, considering the inherently threatening nature of COVID-19. For example, whether intentionally or unintentionally, tweet discussions about the death toll or city lockdowns during the pandemic usually arouse negative emotions in the public (Abd-Alrazaq et al., 2020; Lwin et al., 2020). As such, it would be important to further explore the interaction effect between communication topics and emotional valence on triggering information sharing on Twitter based on findings from existing research. Research in other contexts has shown that tweets with some particular topics elicit higher emotional responses than tweets with other topics. The combination between topics and emotions may amplify subsequent behavioral responses. Here, E. W. J. Lee and Ho (2018) found that exposure to both text and visuals depicting risks significantly decreased public support for nuclear energy—a highly contentious topic that evokes strong emotions—as compared to less controversial sciences such as nanotechnology. Similarly, through a manual coding process of tweets about #BlackLivesMatter, Keib et al. (2018) showed that content about "Policy or Action" and "Group" conveying more emotional expressions received more retweets. Given the discussion above, we propose the following hypothesis:

> **H4.** Emotional valence will moderate the relationship between communication topics and information sharing on Twitter during the COVID-19 pandemic.

3 | METHOD

3.1 | Dataset

To test our proposed hypotheses, we used a publicly available dataset from an ongoing project that actively collected COVID-19 tweets from January 28, 2020 (Chen, Lerman et al., 2020). This project used a list of incrementally updated English keywords and accounts (e.g., coronavirus, corona, COVID-19, etc.) to crawl COVID-19-related conversations on Twitter. The dataset is available on GitHub and only Tweet IDs were released due to the Twitter's Terms and Conditions (https://github.com/echen102/COVID-19-TweetIDs). Hence, we used the tool *Hydrator* to retrieve tweets and Twitter users' profile information for analysis at the beginning of April 2020.

In our study, we examined the discussions after the declaration of COVID-19 as a pandemic by the World Health Organization on March 11, 2020. In particular, we focused on a 2-week snapshot of tweets between March
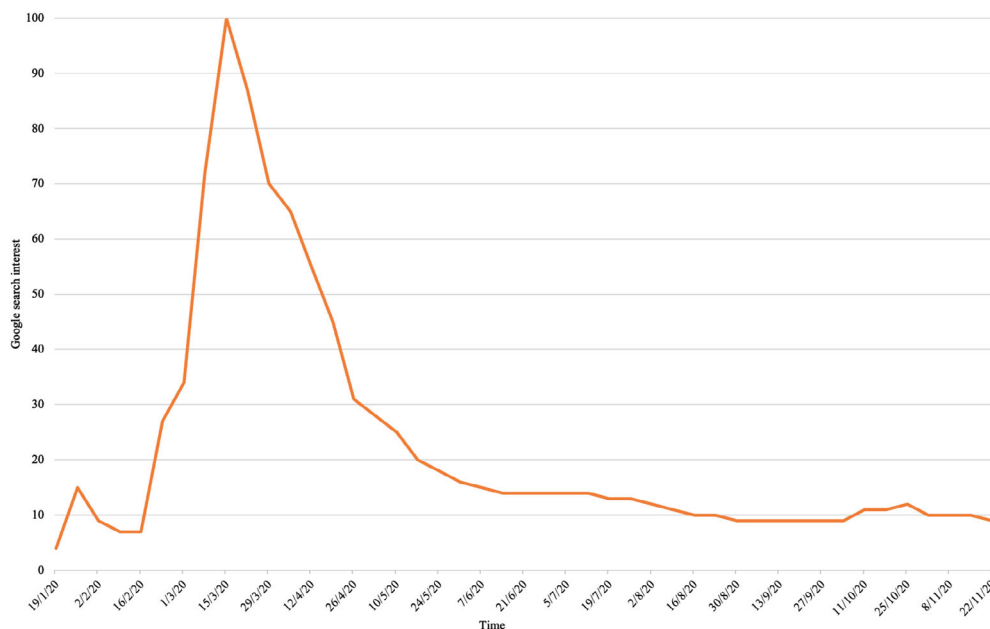
11, 2020 and March 25, 2020. This is because the declaration had a significant public influence and discussions related to COVID-19 dramatically increased on multiple social media platforms. To illustrate, the "interest over time" metric provided by Google Trends—an indication of the popularity of the search terms—showed that search interests for COVID-19 peaked in the two following weeks after the pandemic declaration. As shown in Figure 2, search interests rose significantly from March 11 to March 16 (search interests registered the highest score of 100 on Google Trends) after the pandemic was declared, and attention to COVID-19 remained high (above 50) till March 25. During these 2 weeks, a total of more than 15 million tweets were collected. Due to the sheer data size, we randomly selected 315,136 tweets (around 2% of the whole dataset) for analysis (Zheng et al., 2020b).

3.2 | Topic modeling

Data analysis was accomplished using Python 3.6 Jupyter Notebook. First, retweets (tweets containing "rt"), duplicate and non-English tweets were removed, resulting in 101,181 tweets for subsequent processing. To facilitate the content analysis of tweets, we further removed information such as hashtags, mentions, URLs, stopwords, and additional words that frequently appeared in the dataset (e.g., "coronavirus," "covid-19"). Further, relevant n-grams (sequences of words) in the tweets were extracted (e.g., "test_positive"). Finally, lemmatization was applied to reduce the inflection forms of words to their dictionary forms.

Latent Dirichlet Allocation (LDA) topic modeling was employed to identify popular COVID-19 topics discussed. This unsupervised machine learning technique automatically generates topics from documents and categorizes similar documents to one or more of these topics based on the distribution of words. In our analysis, we first produced topic models with the number of topics ranging from 2 to 20. This was done to ascertain the optimal number of topics that can best describe our corpus. Next, the quality of each model's fit was evaluated by computing the topic coherence score (Newman et al., 2010), which measures the semantic similarity between high scoring words in each topic. The coherence score value ranges from 0 to 1, and a higher value suggests better validity of the identified topics. Referring to Figure 3, the coherence score was the highest for the model with 17 topics (0.3798). Further, we verified that the 17-topic model was the most semantically meaningful and that each topic could be reasonably interpreted by manually assessing the words found in each topic.

Subsequently, we independently labeled the 17 topics based on the top 10 key terms for each topic. Table 1 presents the topic names with their associated terms. For example, the keywords for topic 2 were "advice," "hand," "face," suggesting that this topic might be related to advice on preventive measures. This was corroborated by examining tweets belonging to this topic. To illustrate, one tweet on March 24, 2020 wrote that "*Don't forget to wash your hands regularly with soap under running water or use alcohol-based hand rub to avoid coronavirus.*" Therefore, we labeled topic 2 as "advice to the public on COVID-19 prevention." In most cases, the labeling was consistent between researchers except for some minor

FIGURE 3 Topic coherence
score distribution
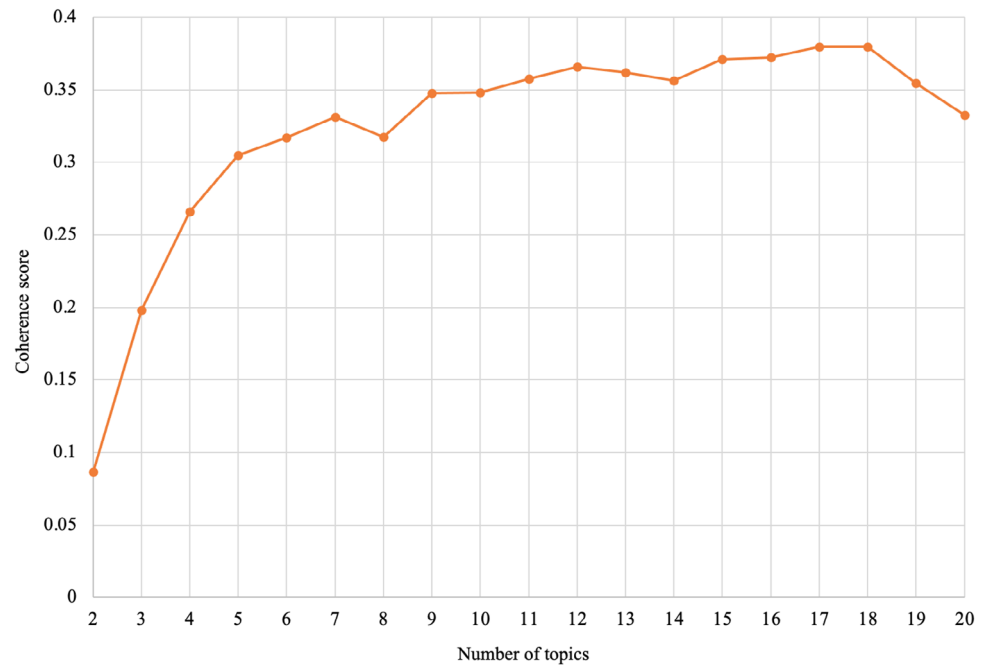
wording differences. Discussions among the researchers were done to resolve disagreements. In this way, we labeled all the 17 topics as shown in Table 1.

Finally, we used an inductive approach to further group the 17 topics generated by LDA topic modeling into broader concepts. The inductive coding process allows researchers to read and interpret textual data and identify the interrelations between textual codes, providing basis for developing theoretical concepts or themes (Glaser & Strauss, 1967). In particular, we independently grouped similar topics into one theme. As shown in Table 2, the four topics (topic 5, topic 8, topic 9, and topic 10) described the impact of COVID-19 on various aspects of society such as economy and international relations. These topics therefore were grouped and named as "impact." Next, we met to examine and compare our classification results. If there were any discrepancies in the grouping process, further discussions were done until all the researchers finally reached consensus. This inductive open coding process led to four themes: Impact, advisory, support, and news updates (see Table 2).

3.3 | Operationalization of variables

As part of our analysis, we used the most recent version of LIWC to extract measures of linguistic cues in our dataset of tweets (Pennebaker et al., 2015). LIWC is a text analysis program that extracts characteristics such as emotionality, attentional focus, and thinking styles in a given text document. The reliability and external validity of the measurement schemes in LIWC have been validated in previous studies (Munaro et al., 2020; Wang & Lee, 2020; Xu & Zhang, 2018).

Content richness was operationalized as three measures. The first was the word count (WC) of each tweet (Brysbaert et al., 2014). Second, the LIWC *Analytic* score, ranging from 0 to 100, was computed. A higher *Analytic* score refers to a higher degree of formal, logical, and analytical thinking in the text, whereas a lower score means a more narrative, intuitive writing style (Pennebaker et al., 2015). Third, content richness was also measured by ascertaining whether a tweet included a URL or hashtag (Bruns & Stieglitz, 2012).

Emotional valence was measured using LIWC categories of positive and negative emotion (Pennebaker et al., 2015; Wang & Lee, 2020; Xu & Zhang, 2018). Both positive emotion and negative emotion were constructed as continuous variables, ranging from 0 to 100 score. A larger value represents a higher volume of positive/negative emotions in the message.

Communication topic was measured using the four themes generated by the LDA topic modeling: Impact, advisory, support, and news updates. These topic categories reflected the main conversations related to the COVID-19 pandemic on Twitter.

The dependent variable, information sharing, was measured by the number of retweets (Son et al., 2020; Sutton, Ben Gibson, et al., 2015) obtained through Twitter's streaming API. The number of retweets captured information sharing on Twitter at the time of data collection.

Finally, previous studies (e.g., Son et al., 2019, 2020) have shown user profile factors including follower count,

TABLE 1 Topic labels with associated keywords

Topic no.	Topic name	Keywords	Rate (%)	Example
1	Responses by the US president	Trump, president, pandemic, response, team, american, america, administration, office, Donald	8.79	*"President trump held a tele-conference with governors to discuss coronavirus preparedness and response."* (March 16)
2	Advice to the public on COVID-19 prevention	Advice, good, thing, time, read, follow, hand, face, wait, hear	6.96	*"Do not forget to wash your hands regularly with soap under running water or use alcohol-based hand rub to avoid coronavirus."* (March 24)
3	Legislation related to COVID-19	Time, american, back, bill, real, house, democrat, vote, act, remember	6.49	*"House passes coronavirus response bill ensuring paid leave, unemployment insurance and free virus testing."* (March 14)
4	Showing support for stay-at-home measures	Home, stay, work, safe, order, quarantine, friend, love, family, issue	7.23	*"Stay at home to protect the people who literally cannot stay at home."* (March 22)
5	Impact on economy	Pandemic, global, economy, big, bad, tweet, deal, question, panic, fear	6.10	*"...There's a global recession/depression looming, unemployment is about to surge, while GDP collapses."* (March 25)
6	Public health emergency	Health, state, public, emergency, care, official, test_positive, person, govt, national	5.70	*"Newsletter on #coronavirus, a serious and urgent public health issue."* (March 12)
7	Reports on lockdown	Lockdown, day, country, close, school, shut, travel, open, city, announce	5.83	*"The Japanese government just announced a lockdown of Tokyo over this Saturday and Sunday..."* (March 25)
8	Impact on international relations	China, call, world, chinese, lie, medium, start, blame, Wuhan, control	6.61	*"Trump's national security adviser accuses China of a two-month cover-up which stopped the world getting to grips with corona..."* (March 12)
9	Shopping for groceries and essentials	Make, man, find, happen, run, guy, long, food, buy, feel	5.68	*"The grocery store has a line wrapped around the building & they only letting 5 people in at a time & most the shelves EMPTY..."* (March 17)
10	Impact on personal lives	Put, life, worker, give, pay, job, risk, sick, lose, money	4.98	*"I'm 62, high risk health, work NHS. Husband 70 with COPD. I have no pension, husband has approx 616/mth..."* (March 21)
11	Cancellation of activities and events	Week, due, year, cancel, outbreak, break, student, move, march, suspend	5.46	*"The Paris eternal have canceled their Overwatch League homestand event in France due to coronavirus..."* (March 11)
12	Mortality of COVID-19	People, die, India, kill, pm, lock, understand, dear, young, war	4.98	*"Hell, ya it is! People do not understand that this is the same virus that killed over 3,000 people in China."* (March 13)
13	News sharing about COVID-19	Today, news, show, watch, great, live, video, talk, end, full	4.79	*"A heartbreaking picture from Italy. Almost impossible to imagine their suffering."* (March 19)
14	Reports of confirmed cases/statistics	Case, death, Italy, report, update, number, confirm, break, day, total	5.65	*"#BREAKING France reports 112 more coronavirus deaths in 24 hours, up to 562: Government says..."* (March 21)
15	Government support to stop COVID-19 spread	Spread, government, stop, outbreak, plan, continue, place, part, measure, epidemic	4.22	*"The Venezuelan government has suspended rent payments and assumed the salaries of small and midsize companies..."* (March 24)

TABLE 1 (Continued)

Topic no.	Topic name	Keywords	Rate (%)	Example
16	Non-government support for fighting against COVID-19	Support, time, free, important, business, share, fight, give, check, provide	4.62	*"Kevin Love is really one of a kind, donating $100,000 to support staff with the Cavs and the arena to provide income..."* (March 12)
17	Medical resources for COVID-19	Symptom, medical, patient, test, hospital, doctor, testing, mask, positive, disease	5.92	*"The supply chain for critical medical supplies, including masks, ventilators and coronavirus tests, has broken down..."* (March 24)

TABLE 2 Themes of COVID-19 tweets

Theme	Definition	Topic
Impact	Impact of COVID-19 on various aspects (e.g., economy, personal life)	Topic 5: Impact on economy Topic 8: Impact on international relations Topic 9: Shopping for groceries and essentials Topic 10: Impact on personal lives
Advisory	Actions taken to combat the COVID-19 pandemic	Topic 1: Responses by the US president Topic 2: Advice to the public on COVID-19 prevention Topic 3: Legislation related to COVID-19 Topic 11: Cancellation of activities and events
News updates	Informational updates or sharing about the pandemic situation	Topic 6: Public health emergency Topic 7: Reports on lockdown Topic 12: Mortality of COVID-19 Topic 13: News sharing about COVID-19 Topic 14: Reports of confirmed cases/statistics Topic 17: Medical resources for COVID-19
Support	Responses/help/support from different parties in society	Topic 4: Showing support for stay-at-home measures Topic 15: Government support to stop COVID-19 spread Topic 16: Non-government support for fighting against COVID-19

friend count, and user status affect retweeting behavior. We therefore included these characteristics as control variables in our model by performing log transformation for better normality. Table 3 summarizes the concepts and measurements of this study.

3.4 | Data analysis

As noted above, the dependent variable was operationalized as retweet count. It was a type of count data and the distribution was over-dispersed as the variance was much higher than the conditional mean. Thus, the assumption of normal distribution was violated, indicating that the standard ordinary least squares regression was not a good fit. We instead used negative binomial regression in our analysis because it can correct the problem of over-dispersion, and does not assume equal means and variances (Son et al., 2020; Sutton, Ben Gibson,

et al., 2015). Also, we built hierarchical regression models to examine the influence of content richness, emotions, communication topics, and interaction effects (topics and emotions) on retweet count.

4 | RESULTS

Table 4 shows the results of our analyses. As is evident from Model 3, WC ($\beta = -0.073$, IRR = 0.93, $p < .001$), analytic writing style ($\beta = -0.003$, IRR = 1.00, $p < .001$), inclusion of a URL ($\beta = -1.947$, IRR = 0.14, $p < .001$), and inclusion of a hashtag ($\beta = -1.037$, IRR = 0.35, $p < .001$) were all negatively, significantly associated with retweet count. Thus, H1b was supported while H1a and H1c were not supported. The incidence rate ratios (IRR) or exponentiated values were calculated to interpret the regression coefficients of indicator variables. For example, while holding all other predictors constant in the model, a one-

Concept	Measures	Definition	Mean (SD) or %
Control variables	Ln(followers)	Log-transformed number of followers of tweet *i*'s author at time *t*	6.30 (2.00)
	Ln(friends)	Log-transformed number of friends of tweet *i*'s author at time *t*	6.49 (1.59)
	Ln(status)	Log-transformed total number of past tweets of tweet *i*'s author at time *t*	9.51 (1.99)
Content richness	WC	Number of words in tweet *i*	18.71 (9.37)
	Analytic	Degree of analytic writing in tweet *i*	72.67 (30.90)
	Incl. URL	If tweet *i* contains a URL	24.21%
	Incl. Hashtag	If tweet *i* contains a hashtag	21.81%
Emotional valence	Positive emotion	Amount of positive emotion in tweet *i*	3.10 (6.62)
	Negative emotion	Amount of negative emotion in tweet *i*	2.55 (5.71)
Communication topic	Impact	Tweet *i* discusses the impact of COVID-19	23.36%
	Advisory	Tweet *i* discusses preventive measures	27.71%
	Support	Tweet *i* discusses support from entities	16.07%
	News updates	Tweet *i* discusses latest virus-related news	32.86%
Information sharing	Retweet count	Number of retweets of tweet *i* at time *t*	1,585.83 (8,392.45)

unit change in a tweet's WC decreases the rate of obtaining a retweet by a factor of 0.93.

H2 stated that two types of emotional valence were positively associated with information sharing. We found that positive emotion was negatively related to retweet count ($\beta = -0.031$, IRR $= 0.97$, $p < .001$) while negative emotion was positively related to retweet count ($\beta = 0.009$, IRR $= 1.01$, $p < .001$). As such, H2 was partially supported.

H3 stated that communication topics could have differentiated effects on information sharing. Compared with the reference group of "Advisory" and holding all other predictors constant, the topics "Support" and "News updates" were negatively associated with retweet count ($\beta = -0.150$, IRR $= 0.86$, $p < .001$; $\beta = -0.109$, IRR $= 0.90$, $p < .001$). However, the association between "Impact" and retweet count was nonsignificant. A boxplot that visualizes the distribution of retweet count for the four different topics is shown in Figure 4. Consistent with the model testing results, the figure shows that compared to the theme "Advisory," the themes "News updates" and "Support" received a bit less retweets. Thus, H3 was supported.

Finally, H4 proposed that there were interaction effects between emotional valence and communication topics on information sharing. First, for the interactions between positive emotion (PE) and communication topics, as shown in Figure 5, although the overall effect of positive emotion on retweet count was negative,

compared to the reference group "PE × Advisory", the interactions "PE × Support" ($\beta = 0.009$, IRR $= 1.01$, $p = .004$) and "PE × News updates" ($\beta = 0.026$, IRR $= 1.03$, $p < .001$) were positively associated with retweet count. However, the interaction effect "PE × Impact" on retweet count was not statistically significant. This suggests that the topics "Support" and "News updates" could weaken the negative impact of PE on retweet count. Second, for the moderating effect of negative emotion (NE) on communication topics, compared to the reference group "NE × Advisory", the interaction "NE × Impact" was positively associated with retweet count ($\beta = 0.015$, IRR $= 1.01$, $p < .001$). In contrast, the interaction "NE × News updates" was negatively associated with retweet count ($\beta = -0.010$, IRR $= 0.99$, $p = .01$). The association between the interaction "NE × Support" and retweet count was nonsignificant. Therefore, H4 was supported.

5 | DISCUSSION

Drawing on ELM, this study examined how three types of peripheral cues (content richness, emotional valence, and communication topics) were associated with information sharing on Twitter in the early stage of the COVID-19 pandemic. More importantly, we extended extant research by investigating the moderating effect of emotional valence on the relationship

TABLE 4 Negative binomial regression predicting retweet count of COVID-19-related tweets

Variables	Model 1 Estimate (SE)	IRR	Model 2 Estimate (SE)	IRR	Model 3 Estimate (SE)	IRR
Control variables						
Ln(followers)	0.098*** (0.007)	0.81	0.095*** (0.007)	0.91	0.095*** (0.007)	0.91
Ln(friends)	−0.049*** (0.007)	0.96	−0.051*** (0.007)	0.95	−0.054*** (0.007)	0.95
Ln(status)	0.143*** (0.006)	1.23	0.144*** (0.006)	1.15	0.144*** (0.006)	1.15
Content richness						
Word count			−0.073*** (0.001)	0.93	−0.073*** (0.009)	0.93
Analytic			−0.003*** (0.002)	0.99	−0.003*** (0.002)	1.00
Incl. URL			−1.938*** (0.020)	0.14	−1.947*** (0.020)	0.14
Incl. Hashtag			−1.036*** (0.021)	0.36	−1.037*** (0.020)	0.35
Emotional valence						
Positive emotion			−0.021*** (0.001)	0.98	−0.031*** (0.002)	0.97
Negative emotion			0.011*** (0.001)	1.01	0.009*** (0.002)	1.01
Communication topic						
Advisory (reference)			—	—	—	—
Impact			0.082*** (0.023)	1.09	0.010 (0.028)	1.01
Support			−0.135*** (0.26)	0.87	−0.150*** (0.032)	0.86
News updates			−0.050* (0.021)	0.95	−0.109*** (0.025)	0.90
Interaction						
PE × advisory (reference)					—	—
PE × impact					0.005 (0.004)	1.00
PE × support					0.009** (0.003)	1.01
PE × news updates					0.026*** (0.003)	1.03
NE × advisory (reference)					—	—
NE × impact					0.015*** (0.003)	1.01
NE × support					−0.101 (0.006)	0.99
NE × news updates					−0.010* (0.004)	0.99
Model fit						
Null deviance (DF)	126,232 (101,180)		135,022 (101,180)		135,104 (101,180)	
Residual deviance (DF)	124,833 (101,177)		124,054 (101,168)		124,047 (101,162)	
AIC	1,201,411		1,192,297		1,192,228	

Note: Standard errors in parentheses.

Abbreviations: IRR, incidence rate ratio; NE, negative emotion; PE, positive emotion.

*p < .05. **p < .01. ***p < .001.

between communication topic and information sharing.

First, for the content richness peripheral cue, its four constituent measures (WC, analytical writing style, inclusion of URLs, and inclusion of hashtags) were negatively related to information sharing. The conclusions regarding the impact of content richness of tweets on information sharing is inconsistent in the existing work and this effect might be dependent on the research context. In particular, some studies found that content richness has a strong effect on information sharing under quotidian conditions (Chung, 2017; J. Liu et al., 2017; Suh et al., 2010); however, other researchers argued that this effect may not work during crisis settings (Chen, Min et al., 2020; J. Lee & Xu, 2018). Our study further demonstrates that in the context of global health crises like COVID-19, plain and short text can trigger more information sharing. After the pandemic declaration, people were anxious about the coronavirus and were overloaded with online information. In this situation, social media users tended to read
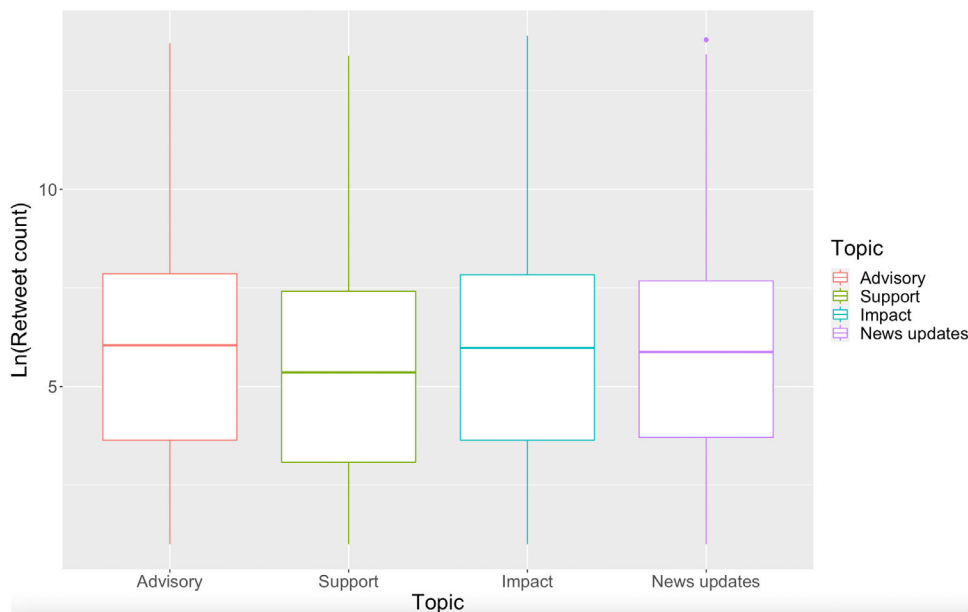
FIGURE 4 Distribution of retweet count for the four communication topics
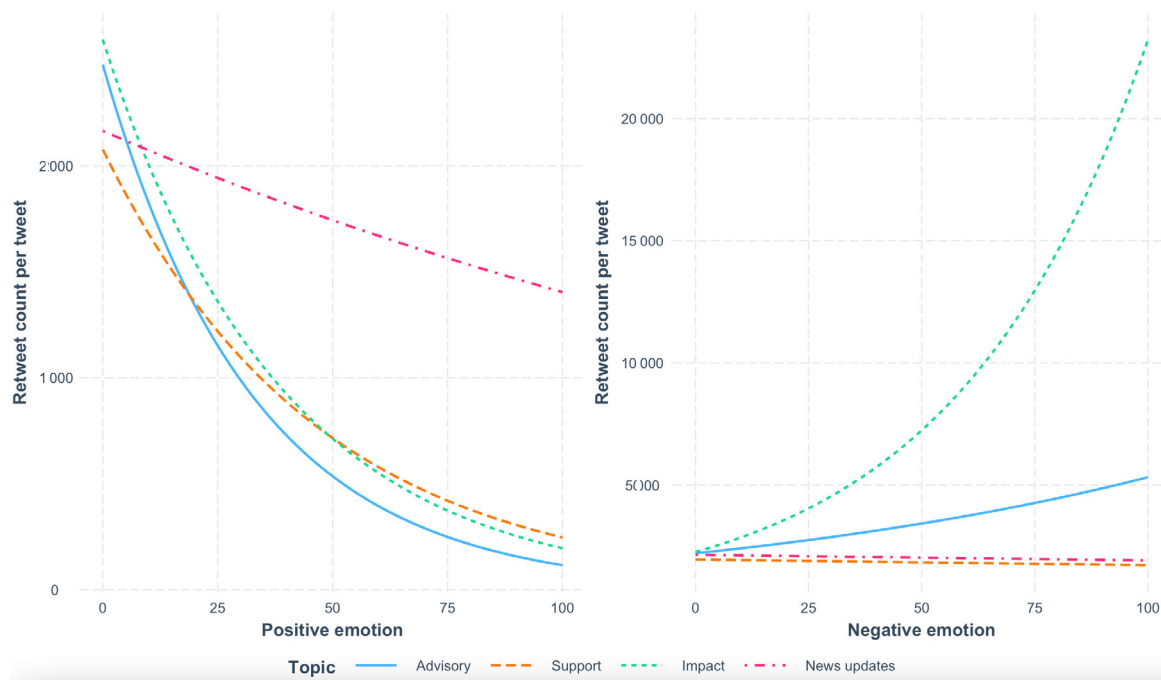

FIGURE 5 Interaction effects between emotions and topics predicting information sharing

short and concise messages without any links to external resources or hashtags. This helped them save information processing cognitive effort (Islam et al., 2020). Furthermore, in times of public health crises, an analytic writing style might not be appealing. Instead, people may prefer to read content written in a more speculative and stimulating manner (Xu & Zhang, 2018; Ziegele et al., 2014). Perhaps people were tired of reading excessive but similar COVID-19 information on various social media sites, and

were more likely to share something interesting or unique, such as personal stories (Meraz & Papacharissi, 2016; Papacharissi, 2015; Papacharissi & de Fatima Oliveira, 2012).

Second, this study identified the impact of emotional valence on information sharing during public health crises. As suggested by ELM, audiences pay attention to emotional cues in a message (Petty & Cacioppo, 1986), especially for online discussions (Falavarjani et al., 2021).

Our results show that different emotions may exert varying effects on social media information sharing. Although prior literature has suggested that positive content can be shared more on social media (Li et al., 2014; Pang & Ng, 2016; Xu & Zhang, 2018), we surprisingly found that positive sentiments discouraged information sharing. This might be because in the initial stage of the pandemic, uncertainty was pervasive as COVID-19 was a newly identified and poorly understood disease. In this situation, the public might be more drawn to sharing and consuming negative content on social media to collectively cope with the situation (Ji et al., 2019; Lwin et al., 2020). Put differently, Twitter helped people mitigate negative emotions caused by the uncertain situation.

Third, this study showed the impact of different communication topics on information sharing. Our 17 topics reflected the diversity of the narratives surrounding the pandemic, and social media such as Twitter play a crucial role in meeting individuals' information needs (Zheng et al., 2020b). Furthermore, ELM suggests that people pay attention to messages that are relevant to them (Petty & Cacioppo, 1986). Our study supported this argument by showing that the public perceived some topics as more important than others, especially those related to physical and mental well-being. Compared with tweets related to support and news updates, tweets about advisories led to more retweeting. That is, in the early stage of pandemic, people were concerned more about the actions they could take to protect themselves. Therefore, we suggest that during crises, while audiences discuss different types of topics on social media, they tend to diffuse information that is more personally relevant in order to meet others' perceived information needs.

Lastly and importantly, this study revealed interaction effects between emotional valence and communication topics on information sharing. While previous studies on ELM showed that different peripheral cues embedded in social media content might have varying effects on persuasion and behavior change (Mousavizadeh et al., 2020; Xu & Zhang, 2018; Y. Zhang et al., 2020), our findings provide novel insights on how message cues can interact with each other to exert a synergistic impact on information diffusion. Interestingly, we found that while the main effect of PE on information sharing is negative, tweets conveying positive sentiments discussing news updates and support led to more sharing, compared to tweets mentioning other topics. This suggests that although people generally ignored well-meaning positive messages that aimed to encourage others in the initial stage of the pandemic, positive tweets associated with certain topics uncharacteristically received more retweets than others. In contrast, news updates with negative emotions received less retweets,

despite the fact that negative emotions in general increased retweeting behavior. Put differently, when reading news updates about the pandemic, people sought a sense of hope and reassurance while avoiding negativity. Additionally, tweets discussing impact in a negative tone were more likely to be retweeted. Here, users may intend to share the negative consequences of COVID-19 hoping to obtain emotional support from others. In summary, our results suggested that peripheral cues such as emotions and topics embedded in a message should not be examined in isolation due to interaction effects that may impact information sharing.

6 | CONCLUSION

6.1 | Theoretical implications

This study makes the following theoretical contributions. First and foremost, we extend the ELM literature by examining the interaction between message cues on social media. While many studies have been conducted to examine information diffusion on Twitter during crises (Son et al., 2020; Sutton, Ben Gibson, et al., 2015; Xu & Zhang, 2018), these studies did not consider the confluence of information needs and emotions that collectively induce sharing behavior. Our study empirically tests the fit between communication topics and emotional valence, while also leveraging ELM as a theoretical foundation. Our results demonstrate that in a public health crisis, how people process and share information is dependent on the synergistic effects between content and emotions. Our results add new knowledge to the ELM literature by revealing the interaction effects between peripheral cues when people process information in times of uncertainty.

Second, compared with prior ELM work studying information processing on social media (Hamshaw et al., 2018; Xu & Zhang, 2018; Y. Zhang et al., 2020), we used an innovative attempt to operationalize and measure the three tweet message cues through combining computational linguistics with human inductive coding. Such an approach provides a more comprehensive picture of ongoing discussions of the pandemic on Twitter. Also, it contributes to the ELM literature by offering novel ways of operationalizing concepts in the peripheral route.

Third, we extend current research on crisis information sharing into the context of the COVID-19 pandemic. Global health crises are unique since their impacts can spread fast and far (B. Xie et al., 2020). Therefore, studying and analyzing information sharing behavior in such an urgent and unique context are timely and important for scholars to make sense of how the public responds to

such crises. Based on the existing literature on crisis information sharing and ELM, we proposed a research model to examine the relationships between various peripheral cues embedded in tweets and COVID-19 information sharing. Findings of this study shed light on the differentiated effects of tweet message cues on information sharing during the current pandemic.

6.2 | Practical implications

This study also has practical implications. First, in the context of a pandemic, constructing public health tweets and messages laden with too much information (i.e., content richness) may be counterproductive (Chen, Min et al., 2020). When disseminating messages, government and emergency agencies should keep content short and informative to help recipients efficiently comprehend the latest news with lower cognitive load. While a tweet containing more information may build situational awareness, a short message can help the audience to quickly grasp the main topic in this urgent situation, which in turn leads to message amplification among the public. Second, it is important for health educators to understand public information needs during crisis situations. The communication topics discussed on Twitter are a reflection of such needs, which can be automatically tracked by software in different stages of a crisis. Studying these needs allow health educators to target different groups and promote specific messages to reduce uncertainty and anxiety (Zheng et al., 2020b). Third, this study illuminates the synergistic effect between communication topics and emotional valence on information dissemination. Health organizations reaching out to the public should imbue their tweets with positivity for content relating to "news updates" or "support" to promote sharing. Meanwhile, highlighting various impacts of the pandemic with negativity can also attract public attention. In summary, our findings may inform public agencies about how to effectively reach different populations when the next global health crisis arises.

6.3 | Limitations and future directions

This study has several limitations that open opportunities for future research. First, we only examined a small sample of tweets after the pandemic declaration. The topics identified in our study may therefore not cover all discussions on Twitter. Future studies should consider a larger sample of tweets in other time periods to ascertain the stability of these topics. Second, we only focused on English tweets. Twitter discussions about the pandemic

in other languages may yield different insights, which is worthwhile to examine in future work. Third, Twitter data are noisy and unstructured, and the LIWC dictionary may not comprehensively capture sentiment and other nuances of the English language. Thus, manual coding process for these variables can be used in future research if data sizes are manageable. Fourth, we only focused on a single case (i.e., the COVID-19 pandemic), which may limit the generalizability of the findings.

Future studies in this area could extend our work by examining the effects of other peripheral cues in online messages (e.g., source credibility, information complexity) on information diffusion. Also, it is interesting to investigate if these message cues support different information needs among the public during different phases of a global health crisis (Son et al., 2019). Finally, a variety of social media platforms apart from Twitter, such as Facebook and WeChat play a vital role in crisis information sharing. It is instructive to study different information management behaviors on these platforms and their role in global health crises (B. Xie et al., 2020).

To conclude, social media such as Twitter are crucial information conduits during public health crises, as we have witnessed in the COVID-19 pandemic. Identifying the underlying mechanisms (e.g., content richness, emotional valence, communication topics) and their synergistic effects related to peripheral route processing would empower government agencies/health organizations to strategically craft effective and lifesaving messages that cut through information noise. Our findings not only extend current knowledge but also serve as a stepping-stone in enabling social media to become a public health megaphone that sounds alarms—with the right information—that would save lives.

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