Images Connect Us Together: Navigating Local Outbreaks Through Social Media Images in the Aftermath of a Public Health Crisis

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Social media images, curated or casual, have become a crucial component of communicating situational information and emotions during health crises. Despite its prevalence and significance in informational dissemination and emotional connection, there lacks a comprehensive understanding of visual crisis communication in the aftermath of a pandemic which is characterized by uncertain local situations and emotional fatigue. To fill this gap, this work collected 345,423 crisis-related posts and 65,376 original images during the Xi'an COVID-19 local outbreak in China, and adopted a mixed-methods approach to understanding themes, goals, and strategies of crisis imagery. Image clustering captured the diversity of visual themes during the outbreak, such as text images embedding authoritative guidelines and "visual diaries" recording and sharing the quarantine life. Through text classification of the post that visuals were situated in, we found that different visual themes highly correlated with the informational and emotional goals of the post text, such as adopting text images to convey the latest policies and sharing food images to express anxiety. We further unpacked nuanced strategies of crisis image use through inductive coding, such as signifying authority and triggering empathy. We discuss the opportunities and challenges of crisis imagery and provide design implications to facilitate effective visual crisis communication.

CCS Concepts: • **Human-centered computing → Human computer interaction (HCI)**.

Additional Key Words and Phrases: crisis imagery, information visualization, crisis communication, social computing, COVID-19

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1 INTRODUCTION

Social media has become a crucial information channel during crises. Characterized by de-centralized communication and crowdsourced information creation, social media affords a prominent place where people gather to cultivate situational awareness [20, 48, 50], route help-seeking requests [36, 97, 115] and provide mutual emotional support [37, 43, 117]. As the development of camera-embedded smartphones and high-speed internet eases the creation and sharing of images online, **social media imagery** is an increasingly substantial component in crisis communication. Millions of images are generated across different disasters [4] and transmit informative crisis-related messages [92].

Among different modalities in crisis communication, imagery has manifested a unique capability in delivering certain kinds of knowledge, sentiments, and experiences during crises [8, 9, 53, 75, 89, 94, 123]. For example, crisis images in COVID-19, whether formal visualizations [123] or non-formal

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memes [75], could effectively engage viewers with crisis information such as disease prevalence, and facilitate public decision making. Through specific visual elements, crisis imagery can also have an emotional impact on an audience [46, 75], with the power of persuasion [46] or raising collective emotion [9, 76]. A visual representation is also helpful for reaching and engaging audiences with relatively low literacy levels [35] and could facilitate their sensemaking under crises. Nonetheless, the majority of work in crisis communication has exclusively focused on textual content for analysis. The understanding of visual crisis communication through social media imagery, and the interplay between crisis text and images, are still limited.

The informational and emotional richness of crisis imagery has great potential in supporting crisis response during *local outbreaks in the aftermath of the pandemic* which are local situation-centered and emotionally fatigued [2, 14, 112]. In the aftermath of the pandemic, local outbreaks are common [68, 108], unpredictable, and affect local policies and residents' daily life [14], which poses new challenges for crisis response. People not only need to cultivate situational awareness of the rapidly shifting local policies [2, 113], but also have to retract to more constrained everyday behaviors and potentially suffer from crisis fatigue [112]. Further, local outbreaks are characterized by the information barrier, with segregated perceptions of crises between the affected local populations and the general public [102], which demands persuasive crisis communication to get attention from the outside world. Given the unique value of social media crisis imagery in information persuasion and emotional contagion, understanding the use of crisis imagery may shed light on how people utilize visual narratives to cope with these specific challenges of crisis communication in local outbreaks. In particular, unpacking which visual themes are presented in local outbreaks, and how people strategically adopt them to share situational information and vent emotions beyond textual narratives, may provide insight into efficient and effective multimodal crisis communication in the aftermath of the pandemic.

To fill this significant research gap, we propose the following research questions:

- **RQ1**: *What* themes of images do users share on social media during a health crisis local outbreak? (**Crisis Visual Themes**)
- **RQ2**: *For what* crisis communication goals do users share crisis images during the local outbreak? (**Crisis Visual Goals**)
- **RQ3**: *How* does the use of crisis images strategically facilitate crisis communication during the local outbreak? (**Crisis Visual Strategies**)

To answer the research questions, we adopted a mixed-methods approach to uncover themes, goals, and strategies of crisis imagery during the COVID-19 outbreak in Xi'an city in China. We collected 345,423 crisis-related posts and 65,376 original images from Weibo, a popular Chinese social media platform. We first used image clustering to distinguish diverse crisis visual themes such as text images and posters. By identifying information and emotions of crisis-related posts with images, we then revealed how the use of different visual themes significantly correlated with the informational and emotional goals in text, such as the proliferation of text images in disseminating the latest policies and the association between food image and anxiety in lockdown. Through the inductive coding of image-attached posts, we further identified four overarching strategic use of crisis images to facilitate crisis communication, including images as signs of authority, visual-based information enhancement, evidence to improve credibility, and triggers for empathy. We discuss opportunities (e.g., establishing emotional connections) and challenges (e.g., image-enhanced misinformation) of image-based crisis communication, reflect on the complementary roles of crisis images and language, and propose design implications to promote effective and accurate crisis communication through social media crisis images.

In summary, the contribution of this work to crisis communication literature in HCI and CSCW includes: (1) we propose an effective analytical structure to identify diverse crisis image themes, and capture a comprehensive taxonomy of visual representations in a COVID-19 local outbreak; (2) we uncover inter-modality correlations between text and images, demonstrating that crisis images of different types serve different informational and emotional goals; (3) we unveil nuanced and unique strategic use of social media crisis images to supplement or augment textual narratives, enhancing crisis communication as a whole; and (4) we provide design implications to facilitate accurate, efficient and effective visual crisis communication. This work sheds light on opportunities and challenges of visual-based crisis communication, and highlights the significance of understanding multimodal crisis communication as an organic whole.

2 RELATED WORK

2.1 Crisis Communication on Social Media and Challenges in Local Outbreaks

Crisis communication has been a crucial research topic that aims to understand and facilitate the communication of preparing for, responding to, and recovering from crises [17]. Traditional crisis communication on mass media largely highlights a one-way and top-down approach from authoritative agencies to the general public [104, 120]. The rapid development of social media has enabled two-way communication between the public and official agencies which emphasizes public participation and engagement in crisis response [26, 36, 123]. How users create, seek, and transmit crisis-related information on social media has attracted increasing research attention in the HCI and CSCW communities (e.g., [52, 69, 80, 97, 105]).

The two-way crisis communication on social media brings opportunities for crowdsourced information creation and dissemination [37, 118]. Based on that, nuanced crisis communication patterns have been discovered and investigated by HCI and CSCW researchers. One line of work looks at how people cultivate situational awareness of a crisis through collective sensemaking [20, 48–50, 95]. Under health crises like Zika and COVID-19 that are characterized by uncertainty, such a collective sensemaking process is substantial for risk assessment and decision making [34]. Another strand of work focuses on self-organized collaboration in response to help-seeking requests when crises happen [36, 51, 97, 98, 115, 124]. Online community members especially digital volunteers develop a set of strategies such as using specific hashtags [67, 116] and structuring posts with a specialized syntax [36, 97, 115] to facilitate the timely routing of help-seeking posts to the intended target(s). Owing to misinformation and conspiracy theories often becoming widely spread during crises [28, 96], researchers have also investigated the debunking efforts and procedures to cope [39, 114].

Local outbreaks in the aftermath of a pandemic, as a special type of public health crisis, pose unique challenges to citizens' crisis response. During local outbreaks, affected populations have to figure out and adapt to unpredictable local policies that influence their daily life [2, 14]. Also, local residents have to retract to constrain everyday behaviors, and may potentially suffer from fatigue with decreased motivation to comply with regulations [112]. Moreover, in such local outbreaks, there are segregated perceptions of crises between the affected local populations and the general public, which demands persuasive crisis communication to cross the information barrier [102]. Nonetheless, little work has looked at multimodal crisis communication during local outbreaks in the aftermath of public health crises. In this work, we aimed to particularly explore how people adopted visual narratives on social media to satisfy these specific communication needs, given images' unique capacity for attention attraction, informational persuasion, and emotional contagion.

2.2 Visual Crisis Communication

Images inherently own distinguished power in delivering certain kinds of thoughts, experiences, emotions, and knowledge clearly and effectively, the role of which in communication could supplement written or oral language in many ways [30, 77, 88]. For instance, images have the potential of arousing emotional resonance crossing the language and cultural divide [87]. Recent technology development such as high-resolution mobile phone camera and low-cost digital image archives enables amateurs to curate and share images on social media conveniently [16, 76], which make social media imagery a rich research source [58]. A plethora of work has examined imagery on social media in various areas such as mental health [58], societal happiness [1], abusive behaviors [73] and politics [76].

Online *crisis imagery* has also attracted growing research attention in HCI and CSCW [8, 9, 11, 53, 63, 75, 89, 94, 123]. Some researchers have exploited the value of crisis imagery, as a special kind of data, to improve crisis-related decision-making, such as disaster type identification [6] and damage localization [53]. Many works also investigate how images with different visual characteristics are utilized for crisis communication. Among them, *crisis visualizations*, one category of images that aims to systematically represent crisis information and augment the quality of risk communication, have been widely explored [11, 78, 109, 123]. For example, Zhang et al. centered on COVID-19 crisis visualizations and looked at how they helped to convey information on disease prevalence, epidemiological simulations, and economic and social change [123]. *Crisis memes*, one kind of informal crisis images that involves participatory creation, also manifests unique roles in crisis communication such as being a visual analogy and visual pun [75].

Compared to crisis visualizations and memes as categories with special visual features, general crisis images that people post on social media tend to be more miscellaneous in visual topic and pattern, and are used for more diverse communication needs [9]. For instance, they might be either a random photo recording life under a crisis, or a screenshot of an article with the latest crisis-related policies. Such nature of heterogeneity of social media crisis images complicates the analysis that aims to figure out their roles in crisis communication. Focusing on a local outbreak in the aftermath of the COVID-19 pandemic, we developed an image-clustering approach to effectively group different crisis visual themes (RQ1) as a preliminary step. Based on it, this work further contributed to visual crisis communication by illustrating how social media crisis images satisfy different informational and emotional needs in crises (RQ2), and what unique strategies they provided to augment crisis communication beyond textual narratives (RQ3).

2.3 Social Media Imagery Analysis Techniques

The growth of image use in everyday communication on social media has fueled the development of social media imagery analysis [9, 58, 121]. Researchers have associated image data with other post- or user-relevant information for analysis based on specific tasks, such as text [1, 58, 73], geospatial data [9], social status of the user [99], and social engagement [7, 59]. For example, Bica et al. revealed the correlation between the severity of a disaster and the image tweet activity based on the geotag information [9].

Recent work has also begun to look specifically at the visual characteristics of social media imagery. For instance, Manikonda and Choudhury examined *visual features*, such as color palettes and visual saliency, that were manifested through mental health images on Instagram [58]. *Visual themes* were another significant topic of concern. Nonetheless, identifying meaningful and interpretable visual themes is a challenging task when images contain high-dimensional features [31]. Some existing works apply qualitative content analysis to establish theme categories (e.g., [5, 8, 12, 75]), but content analysis suffers from scalability and reproducibility concerns. The recent progress of

computer vision and deep learning enables more accurate quantitative thematic analysis at scale. Two representative approaches are supervised image classification [32, 111] and unsupervised image clustering [121]. Image clustering has exhibited its great performance in discovering meaningful patterns that are less subject to human annotation [42, 58, 74, 76, 121]. Nonetheless, *extracting low-dimensional representations* of images remains a bottleneck for image clustering tasks [121]. To present images as low-dimensional vectors, some prior work relied on human-assigned feature codes [76], and another line of scholarship leveraged visual feature descriptors like Scale-Invariant Feature Transform (SIFT) [21] and Speeded Up Robust Features (SURF) [58]. Transfer learning-based feature extraction, with the development of pretrained deep learning models, has recently shown tremendous potential in social media imagery analysis. For example, Zhang and Peng compared different visual feature extraction methods for political image clustering, and revealed that transfer learning significantly outperformed other methods [121].

This work customized image clustering with visual features extracted by transfer learning to unpack crisis image themes during a health crisis local outbreak. Considering the nature of heterogeneity in social media crisis images, we adopted a hierarchical image clustering approach to uncover the visual themes comprehensively and involved a human calibration procedure to enhance the interpretability of the clustering result. Such image clustering worked as a crucial step for a more in-depth analysis of the goals and strategies of social media crisis imagery.

3 METHOD

We adopted a mixed-methods approach to examine the characteristics of social media crisis imagery in a COVID-19 local outbreak. To systematically unpack crisis visual themes (RQ1, Section 3.3), we used image clustering to discern different visual elements in crisis imagery. To understand their crisis communication goals (RQ2, Section 3.4), we developed text classifiers to extract information and sentiments from original posts of crisis images, and made comparisons among different crisis visual themes. To further figure out the strategic use of images for these crisis communication goals (RQ3, Section 3.5), we conducted inductive coding of crisis image samples in the post context, unearthing its unique values in enhancing crisis communication. The overall analytic flow of this study is described in Figure 1.

3.1 Study Event: Xi'an COVID-19 Local Outbreak

The Xi'an COVID-19 local outbreak, caused mainly by SARS-CoV-2 Delta variant [65], is regarded as the most severe COVID-19 local outbreak in China after Wuhan outbreak as of January 2022 [110]. The first COVID-19 case of this event was reported on December 9, 2021 [110], at which time COVID-19 had infected more than 260 million people worldwide and caused more than 5 million deaths [70]. Following a dynamic zero-COVID strategy, the local government imposed a lockdown on December 23, 2021, which lasted for about one month till January 24, 2022 [110]. A total of 2053 cases were reported in Xi'an during this event [110]. The lockdown implemented a stay-at-home order, in which citizens needed permission to leave residential compounds or the city, affecting 13 million local residents [122]. We focus on visual crisis communication in this event as a typical example of a COVID-19 local outbreak with lockdown management, which might contribute to the understanding of civic response in similar health crisis events with highly contagious viruses, varied and strict management measures, and uncertain local situations.

3.2 Data Collection

We chose Weibo as the research site, which is the largest Chinese microblogging website and a significant social media platform for crisis communication in China [15, 80, 114]. To determine the data inclusion criteria, we first randomly browsed posts related to the Xi'an COVID-19 Local

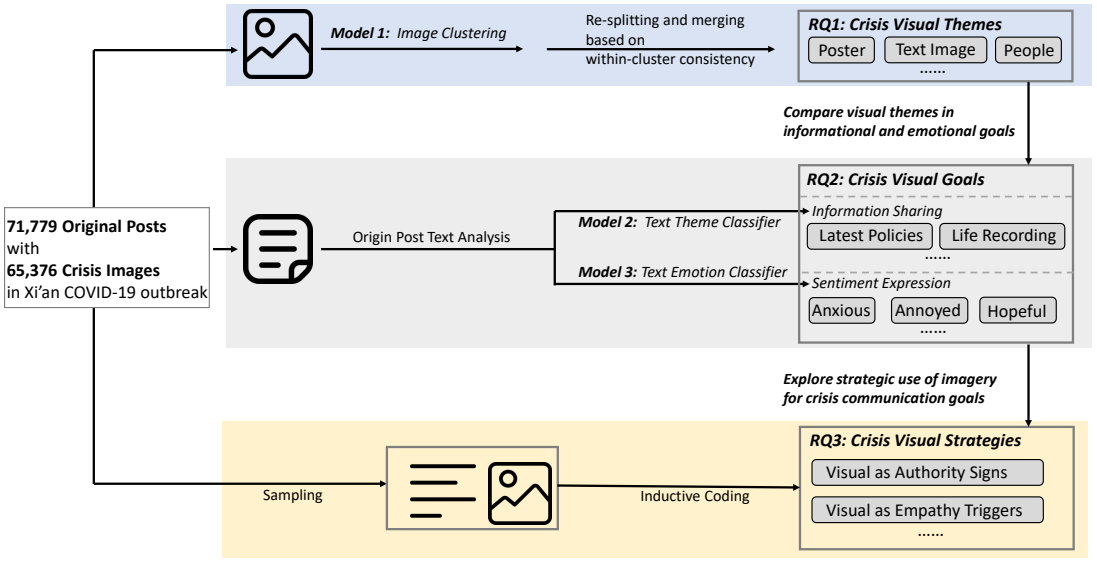

Fig. 1. The analytic flow to understand visual crisis communication during a COVID-19 local outbreak.

Outbreak. We finally chose the most frequent keyword "Xi'an epidemic" (which sometimes appeared as a hashtag) for data collection. Applying the WeiboSuperSpider tool [44], we crawled posts whose text contained the "Xi'an epidemic" keywords and collected all the images within them. The data covered the period from December 9, 2021, when the first COVID-19 case was reported in this event, to January 24, 2022, the date when the Xi'an government lifted the lockdown. In total, we retrieved 345,423 relevant posts, and kept the 71,779 *original* posts contributed by 39,866 distinct users as the target dataset. Among them, 29,075 posts (40.5%) contained one or more images, and the total image number was 66,183. We collected 65,376 images after excluding some corrupted images.

3.3 RQ1: Uncovering Visual Content Themes with a Hierarchical Image Clustering Approach

To have a preliminary understanding of what users disclosed and shared through images in a COVID-19 local outbreak, we first aimed to unpack the themes of social media crisis images. We chose unsupervised image clustering [58, 74, 121] to categorize the data. Compared to the widely-adopted image content analysis of manually coding images and assigning theme labels [8, 75, 123], image clustering can scale image analysis to larger datasets and is less subject to reproducibility concerns. Also, in contrast to supervised image classification, image clustering is not restricted by the size and quality of the human-labeled training dataset. The recent development of transfer learning and deep neural networks further brought great potential for image clustering, especially in categorizing miscellaneous social media images [121]. Therefore, image clustering is well applicable for identifying visual themes of crisis imagery in the context of this work.

3.3.1 Transfer Learning for Low-Dimensional Feature Extraction. We adopted transfer learning [101] to extract low-dimensional features of high-dimensional pixel representations of images, which is

the bottleneck of unsupervised image clustering [121]. It outperforms visual-element-based extraction approaches such as bag-of-visual-words models [56, 91, 121], and achieves good performances in a variety of imagery analysis tasks [66, 121].

To find a suitable pretrained model, we performed a pilot experiment on 1000 image samples and tried various popular pretrained deep learning models, including VGG [90], ResNet [38], and MobileNet [41], for feature extraction. All models were pretrained on ImageNet [23], a large image database covering 1000 general categories, and thus had the generalizability to fit into our dataset. Specifically, for each candidate model, we iteratively (1) fed images into the model, (2) generated the last layer as the low-dimensional vector of images, (3) applied a basic clustering method (K-means, $N = 5$) to the extracted feature, (4) manually coded visual themes of 100 samples after clustering (5 clusters $\times$ 20 samples in each cluster), and (5) evaluated the clustering performance. As the models did not exhibit substantially different performance in the pilot study, we finally chose MobileNetV2 [86] with the highest feature extraction speed so as to facilitate further experiments when scaling up to the whole dataset. Assisted by MobileNetV2, we represented each image in the dataset ($224 \times 224 \times 3$) as a 1280-dimension vector, which was the last hidden layer (global average pooling layer [86]).

3.3.2 A Hierarchical Structure for Image Clustering. After converting images to low-dimensional representations, we adopted a hierarchical clustering structure to uncover visual content themes that were accurate and interpretable.

First, we tried different types of clustering methods, including centroid-based (i.e., K-means [55]), density-based (i.e., DBSCAN [47]) and distribution-based (i.e., Gaussian Mixture Model [82]) approaches. We manually compared results yielded from different methods and found that there was no substantial difference between them. Therefore, we chose K-means to categorize crisis images for simplicity. To determine an optimal K value, we defined the search space of K in a range of 5 to 20, and computed silhouette scores [84] for each candidate; $K = 6$ was finally adopted with a maximal silhouette score. We noticed that most generated clusters were surprisingly pure and clear (e.g., text images) but two clusters were a mixture of sub-themes (i.e., diverse types of photos). Therefore, we performed a re-splitting and merging step as detailed below.

As our ultimate goal was to generate clusters with content theme(s) that were pure and explainable to humans, we adopted *within-cluster consistency* [121] as a quantitative measure of whether our clusters were internally consistent, which could also guide further splitting or merging operations. With this in mind, we took the following steps:

(1) **Sampling:** Randomly sampling 50 images for each cluster to measure the within-cluster consistency. It yields 300 image samples (50 images $\times$ 6 clusters) in total.
(2) **Coding:** Two coders independently coded images and assigned theme labels l_j^i for image i in cluster j. When the goal of this round of coding was only to identify the visual content themes, the coders followed a descriptive coding process [75], focusing on visual types (e.g., text images and photos) and visual elements (e.g., medical staff and food), and did not take the context of image (e.g., post text and other images in the post) into consideration. They finally reached a consensus through several rounds of meetings, comparisons, and discussions.
(3) **Measuring Consistency:** For each theme t that appeared in Cluster C_j, we computed its prevalence $P_t = \frac{\sum_{i \in C_j} l_j^i = t}{|C_j|}$, i.e., the percentage of images belonging to this theme in the cluster. We defined a cluster as "*consistent*" when it had a dominant theme t whose prevalence was larger than a dominance threshold $thld_d$, i.e., $P_t > thld_d$. A larger dominance

threshold $thld_d$ denotes stricter consistency when the dominant theme is required to have a higher proportion in the cluster. In this work, we set $thld_d$ as 60%.

(4) **Splitting:** For each inconsistent cluster, we re-split it according to how many significant themes it contained. Specifically, we selected significant themes T_s whose prevalence P_t was greater than a significance threshold $thld_s$ (We set $thld_s$ as 20% in this work). Then, we set $K = |T_s|$ (number of significant themes) to separate the inconsistent cluster into K sub-clusters using K-means.

(5) **Merging:** After splitting the inconsistent clusters, we repeated sampling, coding, measuring consistency, and finding the dominant theme for each sub-cluster. No inconsistent sub-cluster was detected, indicating a two-level hierarchical structure was sufficient to distinguish visual themes in this work. We merged all clusters and sub-clusters with the same dominant theme.

In total, the image clustering yielded six clusters with distinct visual themes. Two coders independently annotated themes of 600 label-assigned samples (100 samples × 6 clusters) to evaluate the final performance. The average recall reached 79.5% with high inter-rater reliability (Cohen's Kappa = 0.86), indicating substantially good performance of hierarchical image clustering in uncovering visual themes.

3.4 RQ2: Investigating Visual Crisis Communication Goals with Text Analysis of Original Posts

RQ1 focused on visual features and generated a comprehensive taxonomy of crisis image themes during a COVID-19 local outbreak. It captured the substantial diversity of crisis imagery, ranging from text-embedded images with the latest policies to photos recording daily quarantine life. This led to a further question: *which goals do these diverse types of images serve for crisis communication*, and more importantly, *how different visual themes are adopted for different crisis communication goals*? To investigate this question, we (1) performed quantitative text analysis of original posts to unpack crisis communication goals; and (2) compared different visual themes in the informational and emotional objectives. The quantitative text analysis and inter-image comparison particularly focused on *information sharing* and *sentiment expression*, two significant communication objectives in crisis settings [37, 80, 81, 105, 118].

3.4.1 Text Analysis of Original Posts. We developed information and emotion classifiers for original post analysis as a preliminary step to figure out the visual goals, i.e., how different types of crisis images were used to fulfill different crisis communication needs.

Information Theme Classifier: To identify which types of information were disseminated in the local outbreak-related posts, we developed a codebook through inductive thematic analysis, and leveraged a text classifier to generalize the information themes to the whole corpus.

To establish the codebook of information themes, we used inductive thematic analysis to code a sample of posts [27], letting the codes naturally emerge. Specifically, two coders carefully read through 200 post samples independently, and generated codes of information themes (e.g., "*latest policies and measures*") that described the data. Through several rounds of discussions and comparisons, they reached a consensus on the theme codes, and returned to annotating every post in the 200 samples. The Cohen's Kappa ($\kappa = 0.91$) suggested substantial agreement between the two coders [61]. Finally, the two coders separately annotated another 400 posts each, generating 1,000 theme-assigned samples as the training dataset. An additional sample of 200 posts was further labeled as the test dataset. The codebook is shown in Table 1.

We applied Bidirectional Encoder Representations from Transformers (BERT) [24] to classify the local-outbreak-related posts for its good performance and generalizability in text classification tasks.

Table 1. The codebook of information themes of Weibo posts related to the Xi'an COVID-19 local outbreak.

Type	Definition	Example	Percentage in the Sample
Situational Information	Posts communicating situational COVID-19-related information, such as recent cases, social events, and scientific suggestions on new variants	*Up to now, a total of 1,451 cases have been diagnosed in Xi'an, including 2 critical illness cases and 11 serious illness cases. The critical illness rate was 0.14%, and the serious illness rate was 0.76%.*	34.9%
Attitude Disclosure	Expressing attitudes towards the COVID-19 local outbreak and relevant issues	*I'm not in the mood to eat meals and go to class. I want to go home... I beg COVID-19 to stop troubling Xi'an. Don't let Xi'an people be unable to go back hometown.*	29.8%
Life Recording under Lockdown	Recording personal life, status, and challenges under lockdown	*This is the first time I feel that the epidemic is so close to me... The community downstairs of my company has raised a cordon.*	23.4%
Latest Policies and Measures	Announcement or adjustment of the COVID-19 management policies and measures	*[IMPORTANT! Xi'an starts a new round of nucleic acid screening on December 27th] According to the news from the Xi'an Epidemic Prevention and Control Headquarters: From 12:00 on December 27th, Xi'an will start a new round of COVID-19 nucleic acid screening. Reminder: Keep social distance and protect yourself.*	11.9%

Specifically, we adopted BERT-wwm, a Chinese BERT model pretrained on Chinese Wikipedia [19], and fine-tuned it with our training dataset (N=1000) to adjust it to our specific tasks. The micro f1-score achieved 82.1% in the test dataset (N=200), indicating its substantially good performance. Finally, we leveraged the information theme classifier to assign theme labels to the whole dataset of original posts (N=71,779).

Emotional Type Classifier: To identify emotional types of text posts, we first tried some widely-adopted Chinese emotion prediction models (e.g., Jingdong Sentiment API [1] and SnowNLP [2]), yet we noticed that these models were not well-applicable to our context through manual evaluation. Therefore, we followed an emotion identification method similar to our information theme classification approach, including (1) codebook establishment through open coding [18] by two authors (N=100, Cohen's Kappa $\kappa = 0.91$), capturing emotions in this specific scenario; (2) annotation on training dataset (N=1000) and test dataset (N=200); and (3) BERT-based emotional type classification (micro f1-score = 78.6% on 5-class emotion classification). The open coding indicated that a single label could well represent each post, and five emotion classes were identified to effectively describe emotions in our samples:

- **Positive - Hopeful (19.9%[3]):** Mutual encouragement and wishes to overcome the difficulty;
- **Positive - Appreciative (4.3%):** Gratitude to medical staff, community workers, and other social connections in the local outbreak;
- **Neutral (52.2%):** Neutral posts such as news, latest policies, and unemotional life recording;

[1] https://neuhub.jd.com/ai/api/nlp/sentiment
[2] https://github.com/isnowfy/snownlp
[3] Percentage of each emotion denotes its proportion in the 1000 training dataset.

- **Negative - Annoyed (11.9%):** Feeling of annoyance when normal life was disturbed by the local outbreak and its relevant measures;
- **Negative - Anxious (11.7%):** The nervousness and worry due to the uncertainty during the local outbreak (e.g., uncertain lockdown time and food supply).

3.4.2 Comparison of Crisis Visual Goals. After identifying the information theme and emotion type of each post, we extracted the crisis image category of the post established in RQ1 (or the dominant category based on frequency if the post contained more than one image). We investigated how the transmitted information themes and emotions correlated with (1) whether crisis images was used or not, and (2) which types of crisis images were used. We also made inter-image-category comparisons and performed chi-square tests to evaluate whether there was a statistically significant difference in the conveyed information or emotions among different crisis image types.

3.5 RQ3: Understanding Strategies of Crisis Images with Inductive Coding

RQ1 and RQ2 leveraged computational approaches across visual and linguistic modalities to comprehensively unpack the rich *themes* and the nuanced informational and emotional *goals* of crisis imagery. The comparison of crisis communication goals among visual themes helped to statistically depict the *inter-modality correlation* between visual and text. Moving a further step, a more in-depth investigation of such inter-modality correlation, especially the strategic use of visuals to enhance crisis communication as a whole, could deepen the understanding of crisis image use. Therefore, we applied inductive coding to qualitatively look into the *visual strategies* in crisis communication, i.e., how crisis images *facilitated* information sharing and sentiment expression in the specific context.

Specifically, we sampled 1200 distinct images (200 images $\times$ 6 visual theme categories) identified in Section 3.3, and situated them within the original posts. We conducted inductive thematic analysis [27] and inductive emotion coding [75] on the data. Two authors (1) inductively coded the information themes and emotions expressed in both the image samples and corresponding post text; (2) compared visual-based and language-based information and emotions; (3) figured out *how they were related*; and finally (4) recorded how crisis visuals strategically *facilitated* the information and emotion sharing. Two coders took an iterative process of coding, comparing, and discussing to resolve the difference and finalize the codebook. The coding reached saturation given the sample size, so we did not code more data. This step of qualitative analysis helped to unpack how visual narratives manifested unique values and complemented text in crisis communication.

4 FINDINGS

This work provides a comprehensive description of the themes, goals, and strategies of crisis imagery during a COVID-19 local outbreak, promoting the understanding of *visual crisis communication* in general social media crisis images. In Section 4.1, we describe the taxonomy of crisis visual themes obtained from image clustering, showing distinct features of different visuals in this specific health crisis setting. We further demonstrate how these crisis image themes were substantially correlated with different informational and emotional objectives in Section 4.2, unearthing the specialized use of crisis images in crisis communication. In Section 4.3, we depict several unique strategies of visuals that contributed to effective crisis communication. Overall, these findings uncover not only the rich features of social media crisis imagery, but also its special values in promoting situational awareness and establishing emotional connections.

4.1 RQ1: Visual Themes

The image clustering yielded six representative visual themes as shown in Figure 2, including two text-embedded image categories [58]: *posters* and *text images*; and four "visual diary" image

categories that recorded life during the outbreak: *indoor objects*, *outdoor scenes*, *people*, and *food*. These crisis image themes communicated distinct visual elements in the local outbreak to enhance situational awareness and establish emotional connections. We detailed descriptive analysis of different visual themes, and started with two text-embedded image categories (all referenced figure examples are from Figure 2):

- **Posters** (22.7%, N=14,836): Images embedding some big-character text, especially with a solid-color background. Different from images with rich text about crisis information (text images), posters generally only had meta information (e.g., "latest news" in Figure *Posters, B*) of the post. Some poster-style photos, especially photos of COVID-19-related press conferences with the agency name embedded in a solid-color background (e.g., Figure *Posters, A and E*), also characterized this category. The simple and highlighted text information of posters helped to convey the core message and catch users' eyes at a glance. In a similar visual style, text-embedded visualizations and memes were also categorized into this visual theme though not in a great amount.
- **Text images** (16.0%, N=10,434): Images with plentiful embedded text. We noticed that plenty of authoritative regulations (e.g., the lockdown measures of the city) and community guidelines (e.g., communities' COVID-19 test notice) were shared by local residents in the form of images such as screenshots of government-posted articles, potentially due to the convenience of forwarding images in and outside the Weibo platform. Screenshots of chat messages (e.g., Figure *Text Images, J*) were another type of text image that provided situational information with original sources, such as the latest suggestions posted by community officers in a community group chat. Meanwhile, text images were also observed to convey some sensitive messages, such as conflicts with supply providers and rumors faked as chat logs with "political insiders", to circumvent moderation.

Below are the four "visual diary" image categories:

- **Indoor objects** (17.6%, N=11,480): Images capturing indoor objects that recorded everyday life during the lockdown. This category reflected people's resilience during this isolated lifestyle, such as making handicrafts (Figure *Indoor Objects, I*) and decorations (Figure *Indoor Objects, A*). Self-disclosure of mental status in quarantine such as anxiety or hopefulness was typical along with this type of visual diary, which is further demonstrated in Section 4.2.
- **Outdoor scenes** (17.2%, N=11,234): Outdoor photos such as streets, parks and attractions. Many images in this category demonstrated the emptiness of the city during the COVID-19 lockdown (e.g., Figure *Outdoor Scenes, C*), expressing the wish for a normal life. Also, some outdoor photos served as real-time proof of situations in the local community, such as the location of checkpoints of movement pass (Figure *Outdoor Scenes, D*) and the crowdedness of a specific COVID-19 test point that reminded community members to come later (Figure *Outdoor Scenes, J*).
- **People** (16.9%, N=11,040): Images of humans in the outbreak. Two important sub-theme of this category were (1) selfies and photos of families (e.g., Figure *People, A and I*), notable types of social media images to show their lives to others and connect with audiences [42, 58, 60], which might be valuable for social connections during lockdown; and (2) photos of medical staff and community workers in white, some recording and appreciating their contributions and sacrifices during the crisis (e.g., Figure *People, F*), and some showing conflicts between community workers and residents and criticizing specific workers on their abuse of power during the lockdown (e.g., Figure *People, H*).

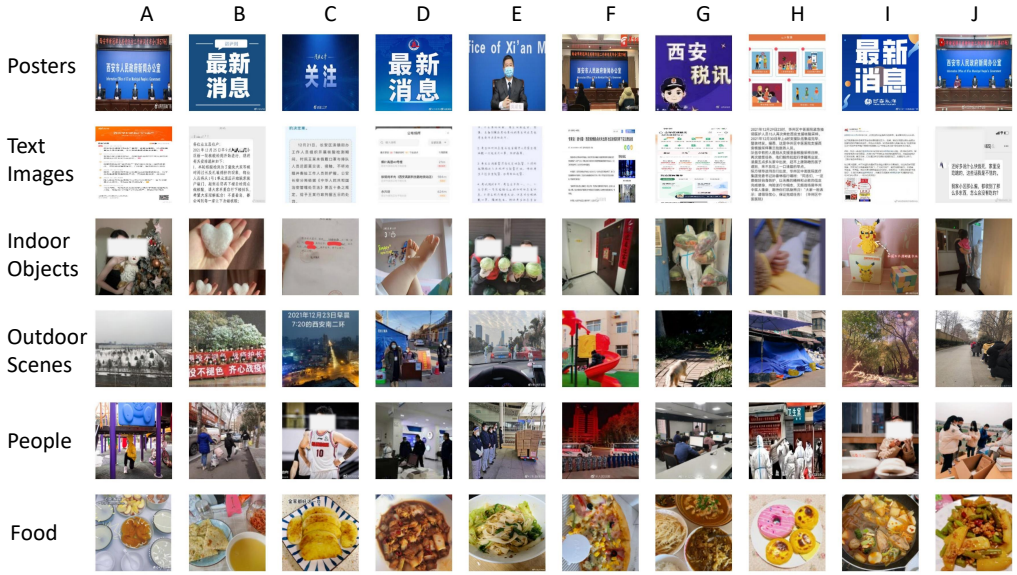

Fig. 2. Image content themes during the Xi'an COVID-19 local outbreak based on image clustering (each row represents one image cluster). The image examples of each cluster (N=10) were picked from random samples (N=20), instead of crisis images nearest to cluster centers, to demonstrate the in-cluster diversity.

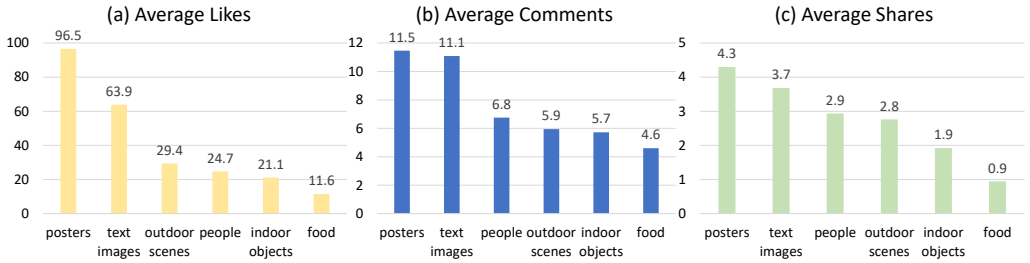

Fig. 3. Comparison of different visual themes in public engagement indexes: (a) likes, (b) comments, and (c) shares.

- **Food** (9.7%, N=6,532): plated food and drinks. In addition to recording everyday dishes, these food images also communicated information about the food supply of the local community during the lockdown to other affected citizens in the city.

Different visual themes exhibited substantial differences in public engagement indexes (i.e., likes, comments, and shares) as shown in Figure 3. The differences in average comments and shares between visual themes were statistically significant under the one-way ANOVA test ($p < 0.05$). Generally, users were most engaged in posts with *posters* images which received the most likes, comments, and shares, followed by *text images*. In comparison, users were less engaged in the other four "visual diary" categories. One potential reason might be that visual messages passed through posters and text images (e.g., screenshots of government-posted articles) were more likely to be generalized to different settings and useful to other citizens, while photos recording daily life might be more personal and related to specific scenarios.

RQ1 Summary: Through image clustering, we captured a comprehensive taxonomy of crisis visual themes during a local health crisis outbreak, including *posters* and *text images* as two text-embedded categories, and four "visual diary" types presenting life in lockdown. These visual themes attracted different levels of user engagement (e.g., *posters* and *text images* received more likes, comments, and shares). It demonstrated **the diversity of visual communication** during a local outbreak in Chinese social media, and implicitly reflected some specialized use of crisis images, such as the prevalence of *posters* relating to the latest and authoritative information. In the next section, we explicitly described how these diverse visual themes were adopted for different informational and emotional goals, providing a quantitative view of visual-text correlation.

4.2 RQ2: Visual Goals

Through text analysis of the posts that contained crisis images, we unveiled how different themes of crisis images were adopted for different objectives in information sharing and emotional expression during the COVID-19 outbreak. These provided a comprehensive picture of the crisis communication *goals* of crisis images.

4.2.1 Descriptive Statistics. Using the information theme classifier described in Section 3.4.1, we captured the proportion of four information themes in crisis-related posts during the local outbreak. Specifically, *situational information* (N=26,963, 37.6%) and *attitude disclosure* (N=25,291, 35.2%) were the two most popular information categories. The prevalence of these two categories echoes prior works on crisis response [36, 80, 81]. *Life recording under lockdown* accounted for 20.0% crisis-related posts (N=14,389), and information about the *latest policies and measures* had the smallest proportion (N=7.2%, N=5,136).

The text emotion analysis revealed that in addition to the *neutral* category, two negative emotions (i.e., *annoyed* and *anxious*) and two positive emotions (i.e., *hopeful* and *appreciative*) characterized emotions that users disclosed during the local outbreak. In the whole dataset, the total proportion of negative emotions (22.5%, with $P_{anxious} = 12.4\%$ and $P_{annoyed} = 10.1\%$) was close to the total proportion of positive emotions (23.4%, $P_{hopeful} = 20.0\%$ and $P_{appreciative} = 3.4\%$). Therefore, there was an upsurge in negative emotions in the aftermath of the pandemic compared to the initial COVID-19 outbreak in Wuhan in Chinese social media [106]. It highlighted the prevalence of anxiety and annoyance, serving as a warning of unhealthy mental well-being that might be due to COVID-19 fatigue [112] under repetitive and uncertain outbreaks.

These descriptive statistics helped to contextualize the crisis imagery regarding information sharing and sentiment expression in the corpus. Next, we focused on how different types of crisis images were adopted for different informational and emotional goals.

4.2.2 Information Sharing. Figure 4 demonstrates the proportions of crisis information themes in different types of crisis images. Through a chi-square test, we revealed that there was **a statistically significant difference in shared information among different crisis image types** ($p < 0.001$). It suggests that the types of images used in a post largely correlated with the messages the post aimed to target. We underscore the following critical findings: (1) Compared to crisis-related posts without images, image-attached posts were far more widely adopted to share the *latest policies and measures*. It indicates that images were widely leveraged to signify or demonstrate formal and official information, which will be further illustrated in Section 4.3; (2)*posters* contained the highest proportion of *situational information* (41.05%) and the *latest policies and measures* (21.99%), followed by *text images*. In comparison, all remaining categories had less than 25% *situational information* and less than 5% *latest policies and measures*. This finding indicates that *posters* and *text images* had been broadly used to transmit policies and other situational information that were crucial in crisis response; (3) *People*, *outdoor scenes*, *indoor objects* and *food* all had a high proportion (greater

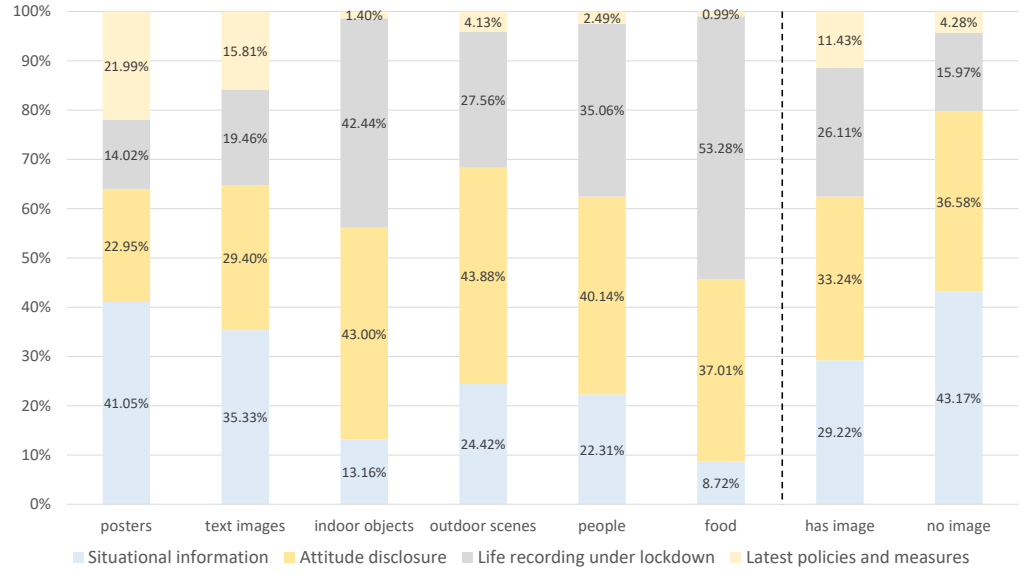

Fig. 4. Proportion of crisis-related information themes in different types of crisis images. The chi-square test indicates a statistically significant difference in shared information among different crisis image types ($p < 0.001$).

than 70%) of posts for *life recording under lockdown* and *attitude disclosure*. Therefore, these four crisis image categories largely captured and embodied the public livelihood and mentality, which is crucial when strict lockdown measures are enforced [3, 85].

4.2.3 Sentiment Expression. Figure 5 demonstrates the proportions of crisis-related emotions in different types of crisis images. The chi-square test denoted that there was **a statistically significant difference in expressed emotions among different crisis image types** ($p < 0.001$). We note the following important findings: (1) crisis-related posts containing images were generally more positive than posts without images; (2) *posters* was the most emotionally-neutral category, followed by *text images*, which might be related to their nature for illustrating or signifying crisis-related information. Nevertheless, *text images* contained a notable proportion of negative emotions. After manually reviewing a set of samples, we realized that users frequently posted screenshots (as *text images*) to disclose their anxiety when the COVID-19 situation got worse (e.g., screenshots of an authoritative article on newly confirmed cases), or annoyance at the negligence of some staff (e.g., screenshots of chat revealing some staff's abuse of power); (3) *outdoor scenes* and *people* were strongly correlated with positive emotions, e.g., using outdoor scenery to express the wish for a normal life. In particular, the *people* category had the highest proportion of *appreciative* emotion, when some users posted photos of medical staff to express their gratitude; (4) *food* was surprisingly the most negative category, especially with the highest *anxiety* percentage. We observed that some users posted *food* images to express their worry about food shortages or dissatisfaction with the food supply under lockdown; (5) *indoor objects*, recording the isolated quarantine life, was the most emotional category with high volumes of both positive and negative emotions.

RQ2 Summary: Through text classification, we unveiled four dominant information types (i.e., *Situational Information, Attitude Disclosure, Life Recording under Lockdown,* and *Latest Policies and Measures*) and five emotion categories (*Hopeful, Appreciative, Neutral, Annoyed*, and *Anxious*) in the

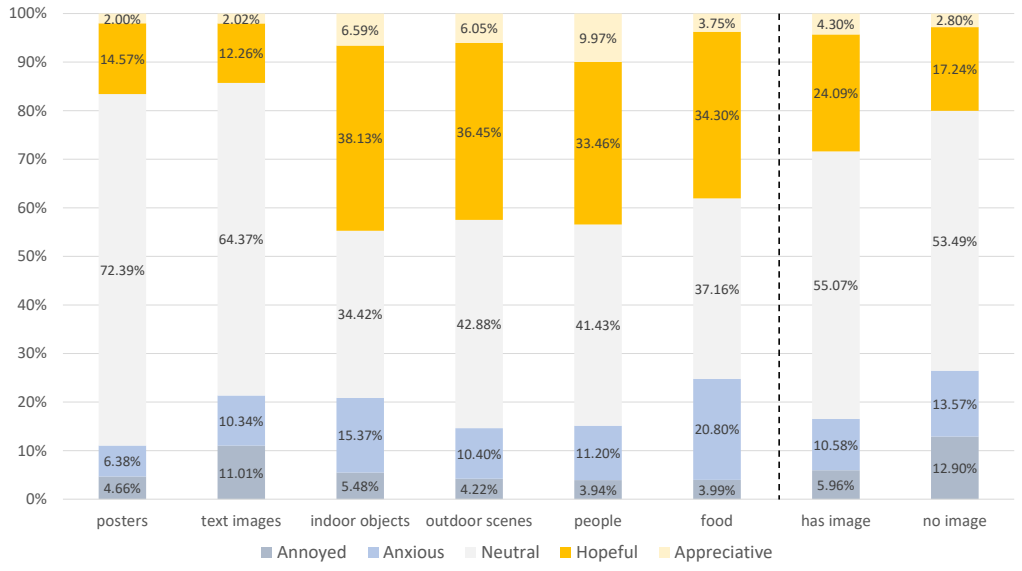

Fig. 5. Proportion of crisis-related emotion categories in different types of crisis images. The chi-square test indicates a statistically significant difference in vented emotions among different crisis image types ($p < 0.001$).

corpus, and quantified their correlations with crisis visual themes. Results indicated statistically significant differences in shared information and expressed emotions among different crisis image types, e.g., the wide use of *posters* in disseminating the *latest policies and measures*, and the prevalence of *anxious* emotions regarding *food* images. These findings demonstrate **inter-modality correlations** in crisis communication. In the next section, we provide more nuances on such inter-modality correlation, revealing how the strategic use of visuals complemented text narratives and contributed to effective crisis communication.

4.3 RQ3: Visual Strategies

In this section, we demonstrate the representative strategies of social media images to facilitate crisis communication, including *images as signs of authority*, *images as visual-based information enhancement*, *images as evidence to improve credibility*, and *images as triggers for empathy*.

4.3.1 Images as Signs of Authority. Adopting crisis images to signify authority surprisingly characterized visual crisis communication during the local outbreak in China as shown in Figure 6. These images might not contain rich authoritative information in themselves, yet helped to capture public attention, and attract users to read the post text with authoritative situation updates or guidelines. Typical examples of this strategy are posters with some big-character text (e.g., *"authoritative statement"* in Figure 6a, and *"pandemic latest updates"* in Figure 6b) embedded in a solid-color background, a clear indicator of official information in Chinese social media. Photos of officials in the epidemic prevention press conference (Figure 6c) were another kind of sign that implied an authoritative message in the text. Some users also forwarded images of government documents in COVID-19 management (Figure 6d) to signify the authority of the transmitted text. Original posts along with this crisis image type mostly communicated the *latest policies and measures* and *situational information*. These images shed light on how official, organizational, and some individual

Fig. 6. Crisis visual strategy 1: images signifying authority. Images with this strategy can be (1) big-character text embedded in a solid-color background, e.g., *"authoritative statement"* in A and *"pandemic latest updates"* in B; (2) photos of officials such as C, or (3) government documents such as D. They might not contain rich authoritative information within visual representations, but attract attention to and signify the authority of the post.

users leveraged visuals to denote and strengthen the authority of posts, and thus promote the transmission and acceptance of the communicated crisis information during the local outbreak.

4.3.2 Images as Visual-based Information Enhancement. How experts and citizens use data visualization language (e.g., chart-based temporal visualization and map-based geospatial visualization) to better present crisis information has been a focus in crisis informatics literature [8, 75, 123]. This work revealed that users leveraged diverse visual representations, as "visualizations" in a broad sense, to convey what was difficult or obscure to express through plain language. Such crisis images well supplemented and enhanced situational crisis information in the post text. For example, Figure 7a applied a diagram to elucidate the relationship and location of the infected population through epidemiological investigation, and Figure 7b used a table to clearly summarize helplines in different districts during the local outbreak. QR codes, a special pattern to condense and route useful crisis information, were also frequently observed to achieve information augmentation, such as in Figure 7c (public transport update during lockdown) and Figure 7d (helplines during lockdown). These examples point to ways in which multimodal communication with crisis images could enrich the presented situational knowledge in local outbreaks, going beyond what plain language could capture.

4.3.3 Images as Evidence to Improve Credibility. Information credibility on social media has been a concern during health crises when rumors, conspiracy, and misinformation abound [48, 93, 119]. We found that social media users widely took images as evidence to improve the credibility of the shared information during the local break. Such visual evidence can either be physical photos (e.g., Figure 8a proving the crowdedness of COVID-19 test in a local community), digital pictures (e.g., Figure 8b proving poster's donation), or screenshots of mobile applications (e.g., Figure 8c and Figure 8d). Such visual evidence was a powerful way to demonstrate one's difficulties and challenges, especially when social media users in non-affected areas had no concrete idea of the local outbreak situation. For example, Figure 8c used a chat screenshot to reveal the price gouging during the local outbreak, and Figure 8d used a screenshot of an online shopping and ordering platform to give evidence of the supply shortage, both of which were persuasive ways to deliver particular challenges in the crisis. These images provide empirical evidence of how users take advantage of crisis images to convince others on social media. Nevertheless, we warn that visual-enhanced persuasion might potentially be more detrimental when containing unverified information, which is detailed in Section 5.1.

4.3.4 Images as Triggers for Empathy. Through inductive coding, we identified that images were widely used as triggers to gain empathy and build emotional connections during the outbreak.

Fig. 7. Crisis visual strategy 2: images as visual-based information enhancement. Images with this strategy can be (a) a diagram demonstrating epidemiological investigation, (b) a table summarizing helplines, (c) a colored table updating public transport information with a QR code, or (d) a QR code linking to helplines. These images, as "visualization" in a broad sense, efficiently convey situational information extending beyond textual narratives.

Fig. 8. Crisis visual strategy 3: images as evidence to improve credibility. Images with this strategy can be (a) a physical photo proving the crowdedness of the COVID-19 test venues, (b) a digital picture proving donation, (c) a chat screenshot proving price gouging (*"high price is normal during hard times"*), and (d) a screenshot of an online ordering platform (every item "*sold out*") proving supply challenges. With visuals as evidence, these images manage to improve credibility and convince others when communicating situational information.

Such images typically contained cultural, societal, or situational visual constructs that captured the sharing experience of the affected local population. For instance, Figure 9a and Figure 9b represent Terracotta Warriors and ancient buildings respectively, which were cultural symbols of the Xi'an city. The cultural symbols were integrated into the local challenge of the COVID-19 crisis, serving a role to call for unity and courage to overcome the difficulty. Figure 9c and Figure 9d used field photos of an empty street and a COVID-19 test at night to raise empathy among local residents under quarantine, expressing the wish for normal life and admiration of medical staff. These examples shed light on how users exploit the power of the emotional contagion of visual symbols for collective emoting during a crisis.

Fig. 9. Crisis visual strategy 4: images as triggers for empathy. Images with this strategy can be local cultural symbols (Terracotta Warriors in A and ancient buildings in B) and local field photos (an empty street in C and a COVID-19 test at night in D). These visual elements could raise empathy among affected citizens with a common ground and transmit specific emotions such as encouragement.

RQ3 Summary: In this section, we described rich and nuanced strategies of crisis image use in contributing to effective crisis communication, including *images as signs of authority*, *images as visual-based information enhancement*, *images as evidence to improve credibility*, and *images as triggers for empathy*. These findings not only revealed the unique values of visual narratives in engaging, persuasion, and emoting, but also reflected how the strategic use of crisis images supplemented and enhanced text narratives to fulfill informational and emotional needs.

5 DISCUSSION

By investigating themes, goals, and strategies of crisis images in a COVID-19 local outbreak, this work enriches the understanding of the unique patterns and values of social media crisis imagery. In this section, we discuss the opportunities and challenges along with the proliferation of crisis imagery, rethink the complementary roles of crisis images and language in crisis communication, and look into the particularity of visual communication in the aftermath of the COVID-19 pandemic. We finally provide design implications for image-based searching and image-combined moderation to facilitate accurate and effective visual crisis communication.

5.1 Unpacking Visual Crisis Communication on Social Media: Opportunities and Challenges

Existing work largely focuses on public textual communication to comprehend how people collaboratively cultivate situational awareness, adjust risk perceptions, and exchange informational and emotional support on social media under health crises(e.g., [33, 48, 102]). This work contributes to the literature on crisis communication by comprehensively unpacking visual communication on social media during a local health crisis. We reveal how crisis image use could be rich and nuanced in themes, goals, and strategies, and plays a significant role to fulfill diverse communication needs in crises. In this section, we situate our findings within the existing literature, uncovering opportunities and challenges of visual communication in health crises.

The hierarchical image clustering effectively captured different crisis visual themes based on visual elements, which sheds light on how users developed diverse crisis image use to adapt to specific needs. For example, *text images* embedded rich situational information in a single image, providing a convenient way for cross-platform sharing; in comparison, *posters* strengthened the

timeliness and credibility with highlighted meta information, managing to capture the audience's attention to the post text. Even different visual symbols of "visual diary" such as selfies and food, common in general social media for self-disclosure and social connection [42, 58], could convey crisis-specific information that visually enhances mutual understanding, cultivates situational awareness, and facilitates decision making (e.g., photos of long queues waiting for COVID-19 tests implying the crowdedness, and food images indicating community supply). These findings reflect the *diversity and malleability of crisis imagery in conveying situational information with public wisdom*. It provides new evidence of self-organized civic participation and collective intelligence for crisis response [20, 72] through social media images, and adds nuances to the understanding of strategic communication in collectively cultivating risk perceptions and assessments [22, 34]. In addition, these findings demonstrate that images could be a rich resource for public health researchers to *uncover public understanding and attitudes towards health crises and crisis-related policies*, which resonates with prior work [29, 40]. When images carry significant crisis communication roles, excluding image-based information could potentially lead to biases in understanding public opinions.

This work also revealed simple yet powerful emotional narratives [75, 107] in crisis images that could raise empathy among those sharing similar experiences and identities as described in Section 4.3.4. A photo of an empty fridge might express more anxiety than a large paragraph describing the food shortage, and a motivational poster integrating local cultural symbols might evoke more unity and courage than one thousand words. To this end, visual cues would not only serve as *a vehicle for emotional disclosure* [58], but also *establish emotional connections and stimulate solidarity* among the affected populations in the crisis. This provides a new perspective on how visual narratives manage to build collective memory [76] through cultural, societal, and situational constructs to transmit specific emotions during crises. We also discovered the strong correlation between visual cues and the expressed emotions given the specific context in Section 4.2 (e.g., the prevalence of anxiety in *food* images). These findings provided empirical evidence on how different visual symbols might be given different emotional values in the crisis setting, shedding light on the potential of *affective visualization for crisis response* [75].

On the other hand, given that crisis response and politics are tightly intertwined [45], we warn that such emotion-embedded crisis images might be exploited to *weaponize emotion for political purposes* [10, 89] *or conspiracy theories* [48]. When particular emotions like fear or anger may influence people's crisis assessment and response [22, 54], weaponized emotion may lead to biased perceptions and even exacerbate rumors and conflicts during crises. Such a hidden danger was particularly notable when prioritizing information valence over veracity characterizes crisis communication in Chinese social media [57]. As such, it is significant for future work to situate crisis images in the sociopolitical context and examine the dynamics of affective visual narratives surrounding political objectives, persuasive communication, and information credibility.

This work also enriches the understanding of how *visual-based misinformation* [13] may go viral during local outbreaks. The information gap between local and non-local populations (or even different local communities during lockdown) naturally characterizes local outbreaks [102], in which crisis images shared by local stakeholders can be particularly persuasive. Section 4.3.3 indicates that images, whether field photos or digital screenshots, were frequently used as evidence to improve credibility when "pictures don't lie". It vastly increases the misinformation risk when pictures do lie - for example, rumors expressed in faked screenshots of chat history [64], or appropriated photos from other scenarios [9]. The emotions embedded in visual narratives may further promote the spread of visual-based misinformation. Therefore, we suggest future researchers look into the dynamic of how image-based misinformation affects local/non-local user perceptions and

online/offline crisis response [13, 25, 100], pay attention to the debunking effort of individuals and communities, and develop AI-supported or crowdsourcing-based countermeasures to cope.

5.2 Multimodal Crisis Communication: Rethinking the Complementary Roles of Crisis Images and Language

Images and language, two common modalities in social media, have been considered as two supplementary vehicles for communication and jointly provide affecting and persuasive narratives [58]. Nonetheless, how visual and linguistic elements complement each other to fulfill informational and emotional needs in crisis communication has been less investigated. This work reveals the nuances of the complementary roles of the two modalities in crisis communication.

Through qualitative analysis of crisis images within the context of a post, we revealed the distinct strategies of images to spotlight, enhance, and enrich situational information in the text. Images could either serve as simple yet powerful signs of authority (Section 4.3.1), catching public attention on the text-based authoritative guidelines; work as an auxiliary component to support and verify the linguistic argument (Section 4.3.3), visually improving the information credibility; or embody rich situational information within images themselves through various visualization approaches (Section 4.3.2), thus breaking the limit that text can express. These findings enrich the understanding of multimodal information sharing [71] by **unpacking dynamics of visual-language correlations in crises**. Crisis images are more than a standalone component with visualized information, but connect with text and enhance the entire information through attention attraction, credibility indication [71] and information embodiment [75]. These visual-language correlations exhibit the potential to correspondingly alleviate the critical challenges in *heterogeneity*, *credibility*, and *quality* of crisis information on social media [72]. Moreover, the inter-modality correlations also afford user empowerment with evolving user-developed strategies for effective crisis communication, which resonates with prior work [37, 79]. To this end, we call for more fine-grained investigations of public strategies in establishing visual-language correlations to cope with specific challenges in crisis communication (e.g., attracting attention to critical posts among heterogeneous crisis information [36]), and how they influence risk perceptions and emergency responses.

Social media images also play an irreplaceable role that complements language in communicating emotions during crises. On the one hand, visual elements afford particular values in emotion expression through emotion embodiment [75] and emotion contagion through constructing collective memory [9, 76], which extend beyond linguistic narratives. On the other hand, when image-based emotion venting might suffer from ambiguity and subjectivity in interpretation [9], language is critical for contextualizing the visual constructs and facilitating emotion comprehension, achieving complementarity in emotional communication. On this note, it is warranted for future work to examine the strategic use and misuse of inter-modality emotional connections in crisis settings. For example, it is significant in understanding how conspiracy theorists may build malicious inter-modality connections [62], e.g., situating unrelated but emotional crisis images within misinformation, to promote the spread of crisis-related rumors.

Generally, this work enriches the understanding of inter-modality correlation that empowers users for strategic crisis communication. Unpacking such inter-modality correlation would be as important as understanding information in each modality. Therefore, we suggest *a holistic view* that takes the text and visual as an organic whole for further researchers to get a comprehensive understanding of multimodal crisis communication [103], focusing on not only the uniqueness of one modality, but also the correlation and complementarity between modalities.

5.3 Fatigued and Situation-centered: Visual Crisis Communication in the Aftermath of Pandemic

Besides offering implications for crisis imagery, this work also provides plenty of empirical evidence on the unique dynamics and challenges of a local COVID-19 outbreak in the aftermath of the pandemic. In this section, we uncover how specific needs are raised in this context, and discuss how crisis images could support effective and efficient communication for local crisis response.

First, we notice that mental and behavioral fatigue became a new threat of outbreaks in the aftermath of the COVID-19 pandemic. As indicated in Section 4.2.3, the proportion of negative emotions reached 22.5%, indicating even more negative emotions on social media than public attitudes during the initial outbreak in 2020 [106]. Also, being annoyed by how COVID-19 and relevant measures repeatedly affected people's lives became a dominant negative emotion category. These findings echo the mental status of "lockdown" fatigue [83] or variant fatigue [83], with gradually decreased motivations to comply with COVID-19 regulations and guidance. On this note, with rich emotions embedded in visual representations, crisis imagery could be a useful channel for public health agencies to actively track public mental health and propose measures to mitigate public anxiety and annoyance among local residents. Besides, as many citizens on Chinese social media take communicating "positive energy" as a crisis response approach [57], crisis images could serve as a possible medium to establish public confidence among local populations with its unique power in building emotional connections as shown in Section 4.3.4.

Meanwhile, Section 4.2.2 suggests that in the aftermath of the pandemic, understanding the mechanisms of disease transmission and prevention measures was a less prevalent topic, which differs from the beginning of a health crisis [37]. Instead, cultivating awareness of the latest and local situations and regulations became one of the most critical goals. In this sense, crisis images could facilitate information dissemination and comprehension among local populations in many ways: they could provide a realistic portrait of the local or personal situation (e.g., a photo of food supply from the local community), a vivid and explicit description of local crisis situations and policies (e.g., a map-based visualization on risky areas), or an integrated and easy-to-share information medium (e.g., an all-in-one text image of policy summary). How to facilitate the creation, sharing, and searching of crisis images to facilitate the routing of valuable situational information is thus a crucial topic during local outbreaks.

5.4 Design Implications

5.4.1 Image-based Crisis Information Searching. This work posits that crisis imagery is a significant source of situational crisis information, from authoritative guidelines in text images to realistic situation descriptions in public-generated photos. Nevertheless, many posts with information-rich images lacked detailed text "transcription", which might lead to the absence of some relevant visual data when users search for crisis-related information. To cope, we propose three design implications to enhance crisis information searching: (1) AI-based image information extraction. This work reveals that different visual themes naturally develop in a health crisis, and these themes are algorithmically distinguishable. Therefore, it indicates the feasibility of taking image clustering to group different visual themes and applying specialized computer vision approaches to extract important crisis information (e.g., Optical Character Recognition for text images to extract the crisis-related labels). Nevertheless, automatically labeling and explaining more complex crisis visuals (e.g., diagram-based visualization) is still a challenge; (2) crowdsourced image labeling. Leveraging public wisdom might be a promising approach to assess and label crisis images, e.g., inviting social media users to evaluate whether an image is crisis-related, to which extent it helps to cultivate situational awareness, and what categories it belongs to; (3) Enhancing image tagging

by creators. Before users share crisis images on social media, it might be beneficial to suggest and guide image creators to add explicit crisis-related hashtags for the image, or provide an image description that is invisible to users but helps the search interface interpret it.

5.4.2 Image-combined Crisis Information Moderation. The findings on crisis visual strategies in Section 4.3 indicate that crisis images are frequently used as original evidence to improve credibility and special symbols to signify authority. When these crisis images work to "convince" users of the transmitted crisis information, it could be particularly detrimental when mistakes happen in the visual evidence itself. Therefore, we suggest an image-combined crisis information moderation mechanism to establish a more healthy and robust crisis information environment. Considering that forwarding crisis images could be at a very low cost, an interface that reminds users to double-check their credibility would be significant when they tend to share images without reliable sources during crises. Besides, we also suggest an AI-supported tool that prioritizes images with higher potential risks (e.g., images signifying authority) to help moderators in credibility checking and filtering out misinformation.

5.5 Limitations

This work investigated the themes, goals, and strategies of social media crisis images during a COVID-19 local outbreak, deepening the understanding of visual crisis communication in HCI and CSCW. Nonetheless, this work has the following limitations: (1) this work focuses on a COVID-19 local outbreak in China which happened in the aftermath of the pandemic. Therefore, some of the findings may not be generalized to other health crisis settings; (2) under factors such as self-deleting outdated crisis-related posts [36], moderation and censorship, a small proportion of posts were missed in data collection, which might affect our findings slightly; (3) the image clustering method managed to capture visual elements such as people and objects in crisis images, but was still limited in discerning detailed visual themes, such as topics of text image; (4) as a secondary analysis, we did not investigate how the affected population perceived crisis images, and understanding users' perceptions on crisis images might provide more in-depth findings of the crisis visual strategies. When multimodal crisis communication has been an increasingly prevalent practice, we call for broad investigations into different crisis communication settings to reveal the full potential of crisis imagery. As a further step, it is also of great significance for future work to propose and evaluate proof-of-concept interfaces to facilitate and enhance visual crisis communication as well as maximally reduce visual-based misinformation.

6 CONCLUSION

This work makes the first investigation into how crisis communication is characterized and facilitated by social media crisis images during COVID-19 local outbreaks. Focusing on the Xi'an local outbreak in China, we collected 345,423 crisis-related posts and 65,376 original images on a popular Chinese social media platform Weibo, and conducted a mixed-methods study to understand visual themes, goals, and strategies in crisis communication. Through an image clustering approach, we unpacked the diversity of crisis imagery with two text-embedded visual categories (i.e., posters and text images) and four "visual diary" types that recorded life during the health crisis (e.g., outdoor scenes during quarantine). We demonstrated how different visual types were leveraged to fulfill various informational and emotional communication goals, e.g., using text-highlighted posters to signify the latest policies and embedding anxiety into visual diaries of quarantine life. Users developed strategic use of crisis images as signs of authority, visual-based information enhancement, evidence to improve credibility, and triggers for empathy. We discuss opportunities and challenges

of visual crisis communication, reflect on the inter-modality correlation and complementarity, and propose design implications to facilitate effective and accurate visual crisis communication.

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