



ORIGINAL PAPER

Open Access



Visual narratives of disaster on Instagram: a multimodal AI-assisted analysis

Manal Ginzarly^{1*}

Abstract

This paper explores Instagram as a platform for visual and emotional narratives of disaster across the response and recovery phases. Focusing on the extreme flooding that affected western Germany in July 2021, the study analyzes approximately 2,700 Instagram posts collected over a three-year period. It employs a mixed-methods approach combining generative artificial intelligence with qualitative and quantitative analyses. Images were interpreted by ChatGPT-4 under human supervision, and the resulting classifications were validated against manual coding, yielding an agreement rate of 80.73% and a Cohen's kappa of 0.74. Six visual themes were identified: flood damage, rescue operations, solidarity and resilience, media coverage, post-disaster recovery, and government involvement. The temporal distribution of these themes traces a movement from immediate impacts toward reconstruction and remembrance, while the emotional tone shifts from despair and anxiety toward more consistent expressions of hope. A statistically significant association was found between visual themes and emotional tones. A complementary thematic examination of hashtags shows how public discourse surrounding the disaster was framed, and indicates that images convey a more nuanced understanding of disaster impacts that hashtags alone cannot capture. The study demonstrates how AI-assisted visual analysis can facilitate the large-scale interpretation of social media image corpora and generate insights relevant to disaster response and recovery strategies.

Keywords Social media, Disaster response, Disaster recovery, Visual analysis, Sentiment analysis, AI-assisted analysis

1 Introduction

Extreme climate-related disasters, such as floods, storms, and hurricanes, have intensified worldwide in frequency, impact, and geographic distribution over recent decades (Bell et al., 2018). During such disasters, coordination gaps often emerge between professional responders and affected residents due to overwhelmed centralized systems, disrupted traditional communication infrastructures, limited interoperability, and weak pre-existing networks (Stolero et al., 2024). These conditions constrain

real-time information sharing related to needs, damages, and self-organization (Jaeger et al., 2007). In this context, social media use has emerged as a socio-technical innovation within disaster response and recovery, through which practices such as citizen reporting, community-oriented computing, distributed problem solving, and digital volunteering are enabled (Palen & Hughes 2018). The Sendai Framework for Disaster Risk Reduction highlights social media as a key tool for raising awareness, strengthening public education on disaster risks, and improving risk communication (UNISDR 2015). Social media provides real-time information during disasters, with affected individuals as primary content sources (Mavrodieva & Shaw 2021). This capability has proven vital in disaster response, as evidenced by numerous events globally (Mavrodieva & Shaw 2021).

*Correspondence:

Manal Ginzarly
Manal.Ginzarly@uliege.be

¹Department of Urban and Environmental Engineering, University of Liège, Allée de La Découverte 9, Liège 4000, Belgium

© The Author(s) 2026. **Open Access** This article is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 International License, which permits any non-commercial use, sharing, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if you modified the licensed material. You do not have permission under this licence to share adapted material derived from this article or parts of it. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by-nc-nd/4.0/>.

A growing body of research over the past decade has examined the use of social media in disaster contexts. These studies are predominantly quantitative, relying on Twitter (X) as the primary data source and focusing on textual content and the early phases of disaster events (Eriksson 2018; Rasmussen & Ihlen 2017). Natural Language Processing techniques, particularly content analysis, sentiment analysis, and topic modeling, have been most widely applied (Gopal et al., 2026; Rasmussen & Ihlen 2017; Reuter & Kaufhold 2018), while platforms such as Facebook and Instagram remain comparatively understudied and visual methods addressing photographs and videos are less frequently employed (Gopal et al., 2026). These studies have demonstrated the value of social media for situational awareness, emergency communication, volunteer coordination, and public sentiment monitoring during disasters. However, text-centered approaches are limited by short-text expression, low information quality and often overlook the nuanced dimensions of disaster communication (such as sarcasm, irony, ambiguity, slang, and context-dependent meanings) and the contextually embedded dimensions through which affect and lived experience are conveyed (Agarwal & Yiliyasi 2010; Ma et al., 2024). Moreover, the information mined from textual data may not reliably and adequately reflect actual damage conditions (Ma et al., 2024). The dominance of text mining methods is partly explained to the methodological challenges associated with studying visual social media data (Murthy et al., 2016).

Some studies have turned to visual social media data in disaster contexts, applying deep learning techniques, most notably convolutional neural networks (CNNs). This line of research has focused primarily on tasks such as damage assessment, incident detection, and image filtering for humanitarian response, often relying on transfer learning from pre-trained deep learning models (e.g., VGGNet, ResNet). Pre-training typically relies on large datasets such as ImageNet, after which the model is fine-tuned on annotated data for the target task. For example, Hassan et al. (2020) analyzed emotional responses evoked by disaster-related images from floods, hurricanes, landslides, droughts, wildfires, and earthquakes using a dataset of 4,003 Creative Commons–licensed images annotated by crowdsourced participants. Nguyen et al. (2017) processed social media imagery to assess damage severity and support emergency response prioritization, while Arif et al. (2020) examined the potential of deep learning models for disaster type and impact assessment using a curated dataset of 493 disaster images from South Asia. Despite their contributions, these approaches remain constrained by the limited availability of labeled training data and by their focus on predefined classification tasks (Alam et al., 2020).

Recent developments in Generative Artificial Intelligence (GenAI) offer new opportunities to address these limitations by enabling scalable and supervised analysis of visual content. Unlike conventional disaster-related image classification approaches that primarily focus on predefined tasks such as damage detection or scene categorization, GenAI can support more interpretive analysis that integrates visual description and affective assessment.

Against this backdrop, this study explores Instagram as a platform for visual narratives, leveraging both images and text to offer a more nuanced understanding of disaster events, extending the focus beyond immediate response to include recovery. The research question guiding this study is: What can social media posts reveal about the dynamics of disaster events, emotional responses, and recovery efforts in the short and long-term aftermath? To this end, a mixed-method that integrates GenAI-assisted visual analysis with qualitative thematic coding, emotional tone assessment, and hashtag analysis to examine how visual themes, emotional expressions, and discursive framings evolve over disaster phases. This approach is applied to a case study of the July 2021 extreme flood events in western Germany, which affected more than 107,000 people (Manandhar et al., 2023).

Empirically, this paper contributes to the growing literature on the use of social media during disasters by offering a longitudinal multimodal analysis of a major flood event. Methodologically, it demonstrates how AI-assisted image interpretation, combined with human supervision, can be used to analyze visual social media data at scale. The paper is structured into four sections. The first section outlines the theoretical framework, focusing on social media's role in disaster management, from response to recovery, and addressing disaster portrayal through citizen-informed perspectives via visual analysis. The second section describes the mixed-method approach used for the analysis of Instagram posts metadata. The third section presents findings, including identification of visual content and emotional tones in the photos, and their evolution over time in response to the disaster, as well as the thematic analysis of hashtags, offering insights into public discourse and the framing of the flood event. The final section discusses the results and highlights their implications for disaster management and recovery.

2 Role of social media in disaster response and recovery

Social media has emerged as a crucial tool in disaster management, playing an integral role in preparedness, response, and recovery efforts (R. I. Ogie et al., 2019). The crisis and post-crisis phases can be divided into

several stages: the acute phase (lasting from a few days to about two weeks), which involves immediate reactions, emergency response, and early recovery activities such as cleaning, provision of food and services, and restoration of basic functions; followed by short-term recovery (lasting from three months to about two years), which focuses on restoring critical systems and decision-making that guides subsequent actions; and finally, longer-term recovery and reconstruction, which lasts from two to approximately 10 years (NRC 2006; Oulahen et al., 2020).

During the response phase, social media has been used to disseminate disaster warnings, mobilize volunteers and organizations, address rumors, and coordinate response efforts (e.g., Banikalef et al., 2018; Subba 2016). Emergency managers increasingly rely on social media to communicate updates to the public, monitor how other emergency managers are using these platforms, and provide critical weather warnings (e.g., Lazreg et al., 2018; Olson et al., 2019). Research has particularly focused on the use of Twitter during the early phases of disaster response, with an emphasis on improving communication and situational awareness (Luna & Pennock 2018; Shibuya 2017). Hughes et al. (2014), for example, analyzed Twitter communications by police and fire departments during Hurricane Sandy in the north-eastern United States in 2012, demonstrating how official accounts were used to broadcast timely information and interact with the public. Subba (2016) examined the Nepal Police's Twitter project during the 2015 Nepal earthquake, identifying convergence behaviors like helpers and detectives through tweets on road conditions, missing persons, and rumor control. These findings underscore social media's role in fostering collaborative disaster responses between authorities and citizens. Banikalef et al. (2018) examined how, during the 2018 Dead Sea flash floods, Facebook was used by local communities for disaster warnings, volunteer mobilization, and coordination efforts. Other studies have combined georeferenced tweets with spatial data to link online activity to disaster proximity and severity, enhancing situational awareness for responders events (de Albuquerque et al., 2015). Research has also examined behavioral responses during disasters, such as changes in mobility patterns inferred from social media data (Hara 2015). Research has also applied machine learning techniques for the sentiment analysis on the various basic needs of the people affected by the disaster (Ragini et al., 2018), and conducted spatiotemporal analysis of tweets using natural language processing and statistical methods for hazards risk awareness (Karimiziarani et al., 2022). In parallel, efforts have been made to extract disaster impact information from social media using topic modeling techniques (Mihunov et al., 2022), although such approaches remain largely limited to textual content. In their review of the literature, Abdulhamid

et al. (2021) identified three main areas of focus in social media research during emergencies: information sharing, enhancing situational awareness for decision-making, and fostering collaboration among citizens, emergency management organizations, aid agencies, and digital volunteers. However, they also noted the absence of longitudinal studies that explore emergencies which cover both response as well as recovery (Abdulhamid et al., 2021).

To further extend this line of research, some studies have turned their attention to the role of social media in disaster recovery. This focus is captured in a recent review, which highlights social media's contributions to various recovery aspects, such as raising awareness, facilitating donations, fostering solidarity, supporting post-disaster reconstruction, disseminating information, and providing mental health support (R. I. Ogie et al., 2022a, 2022b). Social media platforms offer recovery managers key information on business reopening, cleanup efforts, re-entry after evacuation, infrastructure restoration, donations, fundraising, and volunteering activities during recovery (Huang & Xiao 2015). In line with these findings, research also shows that social media fosters discussions and storytelling around rebuilding efforts (Houston et al., 2015) and plays a key role in damage detection, mapping, and coordinating aid-seeking and aid-providing efforts (C. Zhang et al., 2019). Given the wide-ranging contributions of social media to disaster recovery, Shibuya (2017) proposed a framework for analyzing social media data for recovery phases, proposing the examination of topics discussed (content analysis), the tracking of people's mobility in affected areas (geo-tagged data analysis), and the analysis of mood and sentiment among the public (sentiment analysis).

Aligned with these findings, research has demonstrated that social media plays a pivotal role in empowering communities during times of crisis. For instance, in an ethnographic study of Facebook use among individuals in a society experiencing conflict, Semaan and Mark (2012) found that Facebook enables people to recover from disruption, seek help, offer assistance, and rebuild their social networks. Similarly, in a study on the evolving functions of twitter during and after a disaster event, David et al (2016) demonstrate that social media serves as a platform for emotional expression, coordinating relief efforts, and soliciting help, including pledges from international aid agencies. In line with these observations, Glasgow et al. (2017) analyzed tweets from two major U.S. disasters, suggesting that social media can help monitor community resilience and provide valuable insights for disaster mental health support. Additionally, individuals engaging with disaster-related social media tend to show greater concern for victims, often leading to increased donations and volunteer efforts.

Social media's role extends beyond emotional and logistical support—it is also pivotal in documenting and disseminating information about environmental damage and the evolving needs of communities during and after disasters. Brandt et al. (2019) investigated the use of Twitter during South Carolina's flooding, finding that early tweets focused on environmental damage, health risks, and resource donations. Over time, the themes evolved to address the changing dynamics of the disaster response. Similarly, Fang et al. (2019) analyzed Weibo messages during the 2016 Wuhan flood, where discussions primarily revolved around traffic disruptions and daily life, with notable attention also given to emotional responses and the extent of damage caused. Both studies highlight the dynamic nature of social media discussions during disasters, which adapt to the changing circumstances on the ground. Hong et al. (2018) further demonstrate how social media data can track shifts in community sentiment during disaster recovery. In the aftermath of the 2014 Sewol ferry disaster in South Korea, social media initially expressed sympathy and hope, then shifted to demands for justice and accountability, and later became a platform for remembrance, reflecting long-term solidarity and social cohesion.

In terms of community mobilization during disaster recovery, Dahal et al. (2021) highlighted the significant contribution of Facebook in coordinating volunteer efforts and fundraising after the 2015 Gorkha earthquake in Nepal. However, they also point out challenges such as misinformation and the duplication of aid efforts, which can hinder recovery efforts despite the best intentions. Similarly, Willson et al. (2021) examined the use of Twitter during bushfire recovery in Australia. They found that positive messages around donations and support were common, but there were also significant discussions surrounding climate change and political inaction.

Despite the breadth of research on social media's contributions to disaster recovery and community resilience, current studies have a limitation: they primarily focus on unimodal, textual analyses of platforms like Twitter, Weibo, or Facebook. This approach overlooks the valuable role of images shared during crises, which can offer unique insights into emotional responses, lived experiences, and the unfolding situation on the ground. Instagram, in particular, has received little attention in crisis contexts. This article addresses this gap by investigating Instagram photos shared during the 2021 Bernd flood crisis in Germany. It applies a multimodal approach, integrating visual, textual, sentiment, and longitudinal analysis, to explore evolving narratives and emotions over time, providing a more comprehensive perspective on the role of social media in disaster recovery and resilience-building.

3 Visual analysis of disaster representation

Historically, journalists have controlled the representation of crises through images. However, the large volume of social media content has the potential to shift the politics of disaster representation, moving from top-down portrayals to bottom-up, citizen-informed perspectives (Murthy et al., 2016). Instagram is a highly popular medium that is able to visually and textually signify a disaster event through posts from a broad range of users (Filieri et al., 2021). The richness of Instagram as a research platform is due to its multimodal nature with photography and text occurring simultaneously in posts (Pearce et al., 2018). However, to develop a rigorous means of understanding how image dimensions, textual content, and affective feelings are deployed collectively to create meanings and interpretations of disaster, it is necessary to consider the roles and relationships between these modes (Blackwood et al., 2023). Moreover, studying visual social media data in the context of disaster remains methodologically challenging and the process is often labor-intensive, relying on human coding of images to identify themes and subjects (Murthy et al., 2016).

To overcome the challenge of big visual data analytics, Blackwood et al. (2023) analyzed a sample of 164 Instagram posts from the 2018–2019 Tasmanian wildfires to explore how locations were visually and textually represented. Their findings revealed that Instagram adds complexity to conventional mass media portrayals of disasters, which typically focus on trauma and suffering. In contrast, Instagram posts often frame these events in a more positive light. In their study on the role of Instagram in how victims experienced Hurricane Sandy in the US, Murthy et al. (2016) applied a manual coding framework. A team of six coders used this framework to categorize images based on disaster-related motifs, rather than attempting to interpret the nuances of the content (Murthy et al., 2016). Moreover, Bica et al. (2017) manually coded images shared on Twitter to categorize them based on their main focus and by distinguishing between local and global representations. To reduce the dataset, they coded the top 100 most retweeted image tweets from each category (local and global) over two time periods, creating a total of 400 image tweets Bica et al., 2017). While manual coding methods have been widely used in past studies, they often face limitations in terms of scalability and subjectivity in interpreting visual data. To address these challenges, this research incorporates GPT-4, the fourth generation of ChatGPT, as a tool to enhance the analysis of visual content. A recent study on GPT-4's capacity to handle and assess a spectrum of visual elements comparing its performance with human intuition, both inductive and deductive, has underscored GPT-4's impressive prowess in image analysis, including

identification, recognition, and contextual understanding of visual content (Johnson et al., 2023).

4 Methodological framework

Figure 1 illustrates an overview of the methodological workflow described in the following sub-sections.

4.1 Data acquisition and pre-processing

First, Instagram’s search function was used to identify the hashtags related to the 2021 flood event in Germany. Three hashtags were selected, #germanyflood, #germany-floods, and #hochwasser2021, because they were among the most widely used across different stages of the disaster. Their use enabled the identification of broader visual narratives related to destruction, solidarity, recovery, and public attention. The selected hashtags connected dispersed experiences of the floods within a shared space of visibility on Instagram. Finally, their extensive use enabled the collection of a large corpus of flood-related images, providing the scale necessary to experiment with GenAI-assisted visual analysis.

Photos and their embedded metadata, image URL, user name, date, and hashtags, were scraped in Python through the Instagram API for the period between July 2021 and July 2024. It is worth mentioning that the resulting corpus is bounded by the selection of hashtags and by the platform’s API functionality, algorithmic filtering, and datafication, which return a subset rather than the full data stream (Bossetta 2018; Samofalova 2024). Accordingly, approximately 5000 photos were collected. After removing duplicates, the final dataset comprised 2,690 photos. The images were saved in a folder with a specific reference code, and a CSV file was created with metadata for each photo. Each row in the CSV corresponds to one image, linked through the reference code to allow cross-analysis, ensuring that each photo can be accurately analyzed in relation to its context and attributes.

Ethical considerations related to the use of social media data were carefully considered throughout the research process. The study relied exclusively on publicly accessible Instagram posts related to the 2021 flood event in Germany. During data collection and preprocessing, usernames were anonymized to minimize risks of

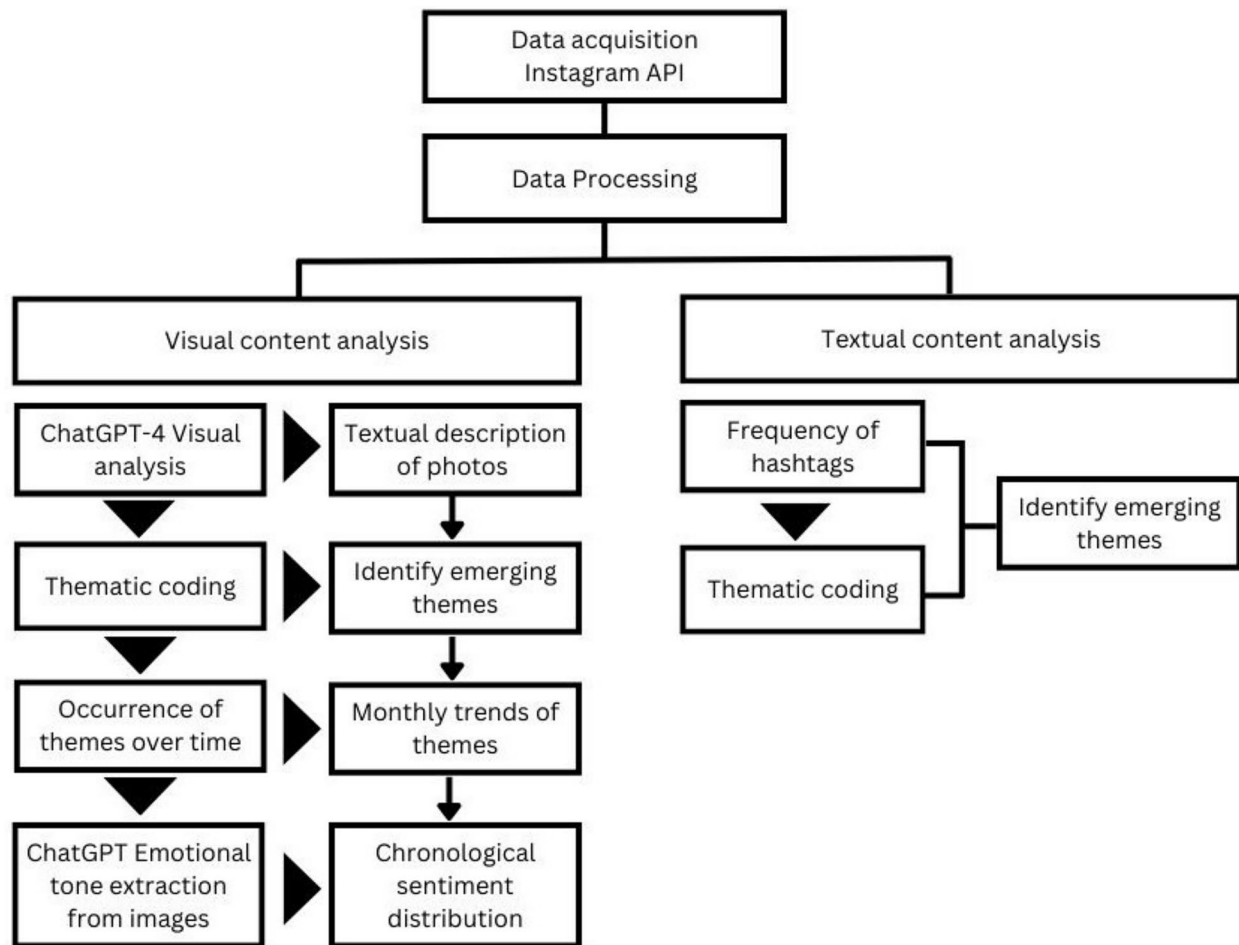


Fig. 1 Methodological workflow

traceability or individual identification. User profile information was consulted only temporarily to distinguish between different contributor types, such as individual users, NGOs, municipalities, and media organizations. Once the aggregated participation statistics were obtained, this information was deleted and not retained for further analysis or storage. The analysis focused on aggregated thematic and emotional patterns rather than individual users. Social media users themselves were not treated as the subject of analysis, and no attempt was made to identify or contact content creators. All data were securely stored and used exclusively for scholarly research purposes.

4.2 Data processing

4.2.1 Visual analysis

The visual analysis was supported by a subscription-based GenAI model, ChatGPT-4, which was used to interpret the images and associated metadata through a pre-defined prompt. The prompt was designed to elicit a consistent, multi-step content analysis of each image, focusing on visible context, flood-related impacts, human presence and actions, and inferred emotional tone.

A prompt typically includes task instructions, optional input, and expected output examples, followed by the actual task (Mishra et al., 2025). For instance, one might prompt with the instruction: "Determine the sentiment of the following review." An example of such a review would be "The book was a fun read," with the expected sentiment being "positive" (Mishra et al., 2025). The analysis proceeded in two stages: (1) development and validation of the prompt on a pilot subsample, and (2) application of the refined prompt to the full dataset.

First, for each image, the model was first instructed to generate a general descriptive summary. The instruction was:

"You are assisting with the analysis of Instagram images related to the 2021 Germany flood disaster. For each image, please provide a brief and clear description of all visible elements in the image. Describe the setting (e.g., indoor/outdoor, urban/rural), the main objects or activities, and any notable visual elements. If there is any text visible in the image (e.g., signs, overlays), transcribe and include it as part of the description."

Next, the prompt was asked to identify two binary indicators (yes/no) and elaborate on them: (1) whether the image was related to flooding and (2) whether people were present in the image. The instruction specified:

"Determine whether the image is related to flooding. Answer 'yes' if the image clearly depicts flooding or

flood impacts. Answer 'no' if there is no visible evidence of flooding. If the image is flood-related, identify visible damages or impacts caused by the flood. Afterwards, indicate whether people are visible in the image. Answer 'yes' if any people are present, regardless of their role. Answer 'no' if no people are visible. If people are present, describe their actions and behaviors."

For each batch of images, the model returned its responses in a comma-separated values (CSV) table, with one row per image and separate columns for the image identifier, general description, flood relatedness (yes/no), damages and impacts (free text), presence of people (yes/no), behavior and actions (free text).

To ensure the accuracy and efficiency of ChatGPT's performance, we first tested the prompt results on 100 images, examining its ability to generate reliable descriptions and categorizations. During these tests, we discovered that processing more than 10 images at a time led to errors, likely due to the input limitations of ChatGPT. Therefore, it was decided that batches of no more than 10 images would be uploaded at once to avoid overloading the system and to maintain optimal performance. This method ensured that each batch's total input remained within a manageable length, preventing potential errors. Our testing aligns with previous studies that suggest that ChatGPT can experience problems when input exceeds certain limits (Lubiana et al., 2023).

4.2.2 AI-assisted thematic coding

Based on the AI-generated descriptions of 2,690 photos, a thematic analysis was conducted. A random sample comprising 30% of the dataset was manually coded by the researcher to categorize the images. Coding a random sample of 30% is a widely accepted method in qualitative research, providing sufficient representation while maintaining feasibility, especially when dealing with large datasets (e.g., Bryman 2016; Johannes & Ortiz 2024). Six main themes, each with several subthemes, emerged from this inductive coding. This manually sample was then used as input to ChatGPT-4, instructing the model to apply the same coding logic to the remaining 70% of the dataset.

The thematic instruction was: "attached is a CSV file with textual data describing images related to a flood event. Each cell describes one photo. Please assign for each image one primary thematic label that best captures the main focus of the image from the following set: (1) flood damage, (2) rescue operations and relief efforts, (3) solidarity and resilience, (4) media coverage and public awareness, (5) post-disaster recovery, and (6) government and official involvement. Process the attached file in batches of 30 rows. For each batch, save the result as

a new CSV file with two columns: photo description and assigned theme label. Keep the labels exactly as written. Use only one label per row. Do not invent or add extra labels. Do not skip any rows. After each batch of 30 rows, stop and return the results for only those 30 rows before continuing to the next batch.”

Human–AI comparison revealed 90% accuracy for binary coding (people, damage). Thematic alignment was initially lower, as nearly 70% of images were classified as “flood damage” by the AI. The automated classification tended to privilege the pervasive presence of flood damage over more latent themes, such as coordination, solidarity, or recovery, which were visually present but less salient. For example, an image described as “Residential buildings are partially submerged. A group of rescue workers in a boat navigating floodwaters” was initially classified by the AI under “flood damage”, illustrating how the pervasive presence of flood damage could dominate classification even when rescue activities were visible. To address this imbalance, additional decision rules were introduced. The refined instruction added: “If more than one thematic label could apply, choose the one that best represents the main focus of the image.” The refined AI-assisted thematic coding was validated by measuring its agreement with human annotations.

A subset of images was independently reviewed and manually coded using the same six thematic categories as in the main analysis. The human-coded labels were then compared with the AI-generated classifications to evaluate the consistency of the coding process. Inter-rater agreement was assessed using percentage agreement and Cohen’s Kappa coefficient. The analysis was conducted in Python using the pandas library for data processing and the scikit-learn package for calculating agreement metrics. The validation results showed substantial agreement between the AI-generated and human-coded classifications. The overall percentage agreement reached 80.73%, while Cohen’s Kappa coefficient was 0.74. Category-level performance further demonstrated strong classification consistency for themes such as solidarity and resilience ($F1 = 0.88$), rescue operations and relief efforts ($F1 = 0.84$), flood damage ($F1 = 0.83$). After conducting the thematic analysis, the distribution of the identified themes was examined over time to assess how the prominence of each theme evolved throughout the year. Specifically, the occurrence of each theme was tracked on a monthly basis to identify trends and shifts in the focus of posts from the immediate aftermath of the disaster to the longer-term recovery stages.

4.2.3 Emotional tone analysis

In social media analytics, sentiment analysis involves detecting hidden subjective expressions in text to mine people’s opinions on topics, events, individuals, or

services (Ragini et al., 2018). Sentiment analysis of social media posts during a crisis helps assess how affected people feel and respond to the help and information they receive (Kaur & Kumar 2015). This provides insights into areas to focus on, such as the type of help needed, and the information that should be publicized (Kaur & Kumar 2015).

Conventional methods for sentiment analysis of social media data primarily focus on text mining and do not account for the presence of multimodal data, such as images (Chen et al., 2023). Despite the development of various natural language processing techniques, sentiment analysis still faces challenges and progress (Chen et al., 2023). Sentiment classification is typically approached through machine learning models or lexicon-based methods. While machine learning models are trained using pre-labeled opinion data to predict the sentiment of new instances, lexicon-based methods rely on pre-defined dictionaries of sentiment words to classify emotions expressed in the data (Mao et al., 2024). However, existing sentiment classification frameworks are often limited in scope. For instance, tools like VADER, SentiWordNet, and AFINN are limited to positive, negative, and neutral ratings (Al-Shabi 2020), which can oversimplify the complex nature of emotional expression. Other dictionaries, such as EmosenticNet and the NRC lexicon, expand the range of emotional categories, identifying emotions like disgust, joy, fear, surprise, anger, and sadness. While these expanded dictionaries provide a deeper understanding of emotions, they still fall short in fully capturing the complexity of human sentiment (Chen et al., 2023).

In this paper, we used ChatGPT to extract sentiments, moving beyond reliance on a fixed set of predefined emotion taxonomy. This approach is supported by recent studies demonstrating ChatGPT’s efficacy in sentiment analysis (Belal et al., 2023). The emotional tone is inferred from the AI-generated textual descriptions of the images, including the general scene description and descriptions of visible human actions and behaviors. Similar to the visual analysis, the prompt was initially tested on a pilot sample of 100 images and refined to improve consistency and accuracy. Moreover, to maintain reliable performance, the analysis was conducted in batches of 30 image descriptions.

The initial exploratory pilot sample of 100 images produced open-ended interpretations with a high degree of semantic variability. For example, the first subset of 30 posts yielded 27 distinct emotional labels. Although these labels captured nuanced differences across posts, the extent of variation limited consistency and reduced their suitability for quantitative comparative analysis. To address, this issue, the pilot results were used as an initial input for the inductive identification of broader

emotional categories. Subsequent iterative prompting asked ChatGPT to group closely related emotional expressions into higher-level affective categories to reduce semantic fragmentation. The pilot sample size was considered sufficient once additional iterations no longer produced substantially new emotional groupings, indicating conceptual saturation. This iterative refinement process resulted in a final reduced taxonomy of seven broad emotional categories that were sufficiently distinct and consistently applicable across the dataset. Following the refinement stage, the final prompt constrained the model to assign only one dominant broad emotion per post. Because sentiment classification with large language models is highly sensitive to prompt design, careful consideration and continuous monitoring were maintained throughout the analysis process to ensure consistency and alignment with the intended coding framework.

After identifying the emotional tone, its chronological distribution across the different phases of the disaster event was further analyzed. Then, a quantitative association analysis was conducted to examine the relationship between the six visual themes and emotional tones. A chi-square test of independence was used to assess whether certain emotions were associated with specific themes. Standardized residuals were calculated to identify the strongest theme–emotion associations, while normalized Shannon entropy scores were used to compare emotionally concentrated themes with more emotionally heterogeneous ones. The analysis was conducted in Python using the *pandas*, *scipy*, and *numpy* libraries.

4.2.4 Thematic analysis of hashtags

To gain deeper insights into the online discourse surrounding the disaster event, an inductive thematic analysis was conducted on the hashtags, starting with the identification of their frequency, followed by the grouping of these hashtags into emerging themes based on their content and context.

5 Results

In 2021, the total number of unique Instagram posts reached 1,869, but this figure decreased substantially in subsequent years: 487 in 2022, 229 in 2023, and 105 in 2024. The week with the highest number of posts occurred between Monday, July 12, 2021, and Sunday, July 25, 2021, with 898 unique posts. The lifespan of disaster-related hashtags has been addressed in a growing body of work, which attributes variation in social media activity between the acute phase and the aftermath of a disaster to various factors. Some concern the properties of the event itself, namely its damaging effects, the duration of the crisis, and its visibility in news coverage (Valdez et al., 2020). Others concern the properties

of the online public, namely the diversity and number of participating actors and the interactivity of their network practices, such as mentioning others (Glasgow & Fink 2013). Previous research also shows that participation is unevenly distributed across the disaster cycle: emergency agencies, journalists, NGOs, volunteers, and community organizations perform distinct communicative functions that concentrate in the response phase and often declines as the emergency response transitions into longer-term recovery (R. Ogie et al., 2022a, 2022b). Studies further suggest that this decline in event-related hashtag activity may be accompanied by shifts in communication practices, including greater reliance on private messaging and closed groups (e.g., WhatsApp groups) (Ginzarly et al., 2025). A further factor shaping the lifespan of event-related hashtags concerns the marking of local content itself. Posts produced within crisis-affected areas frequently lack the event keywords through which such content is retrieved, since residents of a shared geographic area tend to presuppose a common frame of reference and rely instead on hyperlocal tags (Vieweg et al., 2010; Kogan et al., 2015; Bui 2019). A decline in tagged posts may therefore reflect reduced visibility rather than reduced activity. Taken together, these findings suggest that the decline observed in the present dataset reflects activity associated with the event-related hashtags used for data retrieval, rather than providing a direct measure of overall community engagement and online mobilisation. As communication practices evolve during the recovery phase and users adopt hyperlocal or alternative channels, a growing proportion of relevant content may therefore remain uncaptured.

A large portion of the Instagram content was generated by unique users, with 958 individual users posting only once, 162 posting exactly twice, and 61 users posting three times. The majority of contributors shared only one or two posts, indicating a distributed pattern of engagement. The majority of contributors shared only one or two posts, indicating a highly distributed pattern of engagement. A smaller group of users, 70 in total, posted between four and ten times. However, one account had a particularly large number of posts: a nonprofit flood relief organization, namely *DZN Hilfsorganisation*, with 341 posts. This was followed by a regional news outlet (*SWR Aktuell*) with 140 posts, a camping and outdoor community (*Dachzeltnomaden*) with 58 posts, the municipality of Stolberg with 49 posts, a popular German radio station (*SWR3*) with 37 posts, the mayor of Stolberg with 23 posts, and another nonprofit organization (*Help – Hilfe zur Selbsthilfe*) with 19 posts.

5.1 Visual representation of the disaster

The visual analysis of the photos identified six main themes, each encompassing several subthemes. The

most prominent theme was "solidarity and resilience," with 968 occurrences (36%), followed by "flood damage" with 633 occurrences (23.5%), and "rescue operations and relief efforts" with 496 occurrences (18.4%). Other key themes include "post-disaster recovery" (335 occurrences), "media coverage and public awareness" (223 occurrences), and "government and official involvement" (35 occurrences). This thematic distribution differs from existing studies that focus on automated classification and mainly emphasize physical damage. For example, Nguyen et al. (2017) focused on three levels of damage severity in disaster imagery (severe, mild, little-to-no damage) while J. Zhang et al. (2024) developed a six-way classification scheme based on categories such as floods, fires, infrastructure damage, human-related content, and non-damage images. Dar et al. (2024) proposed a social context-aware multimodal framework integrating textual, visual, and contextual social media data to improve disaster-content classification. While these approaches significantly enhance automated disaster-content categorization, they remain centered on predictive optimization and predefined categories. Moreover, they face challenges related to feature extraction, multimodal interpretation, and model generalizability (J. Zhang et al., 2024). Solidarity and resilience emerged as the dominant visual narrative, highlighting representations of collective action and volunteerism that are often overlooked in conventional disaster image classification frameworks.

The temporal distribution of themes shows how the visual narratives represented within the retrieved corpus evolved from immediate impact to longer-term community response. Figure 2 illustrates the distribution of photo themes from July to December 2021, with the

highest counts in July, the response and immediate aftermath of the disaster, primarily attributed to "flood damage," "solidarity and resilience," and "rescue operations and relief efforts." In August, representations of solidarity and relief operations became more prominent than those of flood damage, suggesting an early turn from documenting destruction toward highlighting mutual aid and volunteer mobilisation.

In 2022, "solidarity and resilience" remained relatively stable from January to July with a pronounced peak in July. This increase coincides with the anniversary of the flood and may reflect heightened attention to remembrance and the symbolic role of July as a time for the community to express resilience and reflect on progress made since the disaster. Moreover, the theme of "post-disaster recovery" experienced gradual growth in the second half of 2022, with peaks in July, August, and September (Fig. 3). Within the retrieved corpus, these patterns point to a transition from immediate disaster documentation toward representations of recovery efforts.

This temporal evolution highlights the added value of longitudinal multimodal analysis. Previous studies have primarily focused on real-time event detection, sentiment classification, and information extraction from social media data during disaster events (Ma et al., 2024). While these approaches are highly effective for rapid crisis monitoring, they often provide limited insight into how narratives and emotional tones evolve throughout the recovery process. The present analysis captures how visual narratives associated with the flood-related hashtags under study evolved from immediate disaster response toward remembrance, resilience, and longer-term recovery over time.

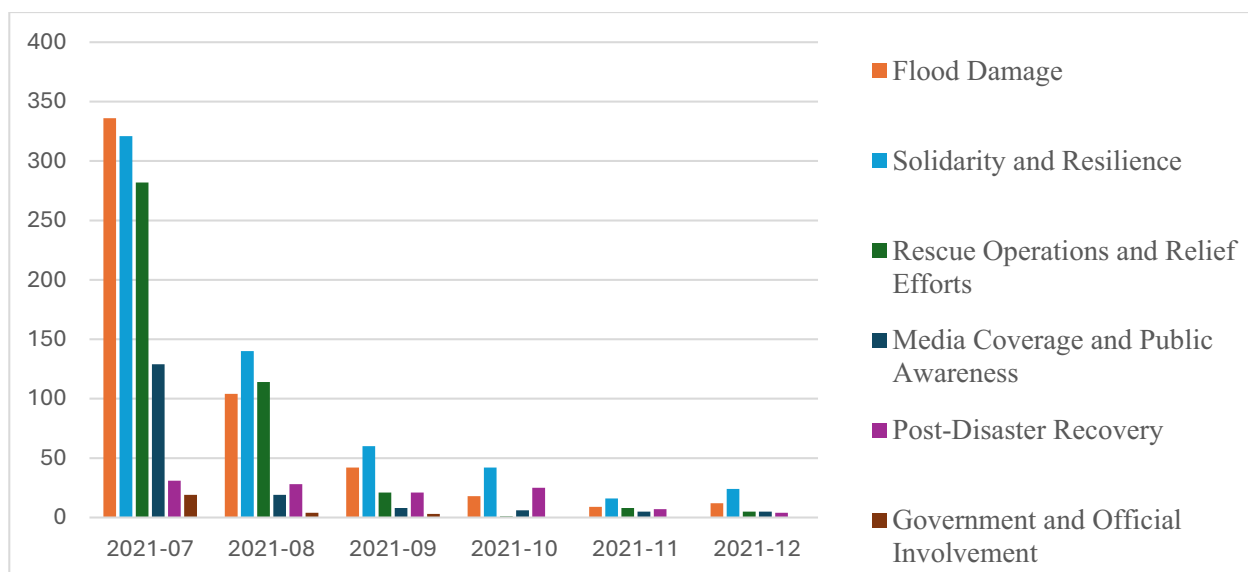


Fig. 2 Varying distribution of photos themes per month in 2021

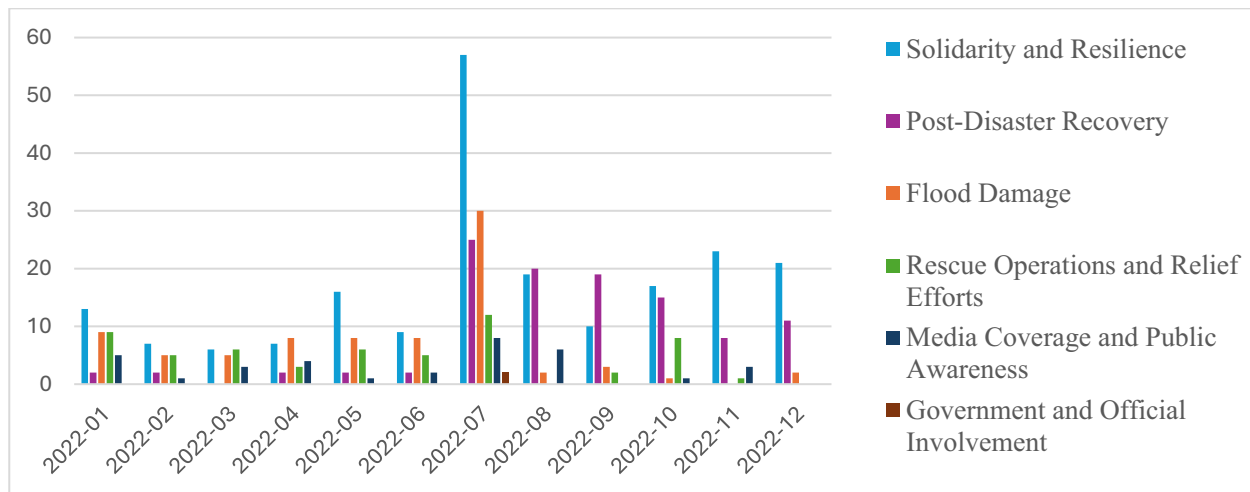


Fig. 3 Varying distribution of photos themes per month in 2022



Fig. 4 ChatGPT Description of the photo: an aerial view of a flood-affected area. The flooded streets submerge cars, buildings, and rail tracks. A red train is visible, partially submerged in the water. The flood appears to be widespread, with several buildings surrounded by water



Fig. 5 ChatGPT Description of the photo: a severely damaged urban street with broken roads, debris, and muddy water flowing

The following section provides an in-depth exploration of the six key themes identified in the visual analysis, each capturing a distinct aspect of the flood event and its aftermath. Within these themes, various subthemes further illustrate how each theme materializes visually in the corpus and the complexity and multifaceted nature of the community's response, recovery efforts, and the ongoing impact of the disaster.

Theme 1: flood damage—the images under this theme visualize the scale of destruction to homes, roads, and urban environments (Figs. 4 & 5). The most occurrent subthemes include:

Floodwaters submerging areas: Descriptions of whole neighborhoods submerged by floodwaters, streets, parks, public spaces.

Destruction of infrastructure: Descriptions of collapsed or damaged bridges, roads, train



Fig. 6 ChatGPT Description of the photo: Rescue workers in wetsuits and helmets, pushing a rescue boat through floodwaters in a residential street



Fig. 7 ChatGPT Description of the photo: A group of military personnel and volunteers work together to clear large piles of flood debris, including damaged furniture and household items, in an urban area

stations, highways, and power lines, due to flooding.

Damage to buildings: Descriptions of homes partially or completely submerged, with damaged walls, roofs, and foundations.

Submerged vehicles and debris, including furniture, vehicles, and other household items or public transportation like trains submerged in floodwaters.

Before and after comparisons: aerial views and Comparative images showing the extent of water damage before and after floods.

Damage to cultural heritage: sites affected by floods, such as museums, churches, monuments, or artworks.

Theme 2: rescue operations and relief efforts—This theme emphasizes the collective effort to provide immediate aid. It shows the role of global and local



Fig. 8 ChatGPT Description of the photo: Debris removal and cleanup efforts after disaster and significant damage in urban area. With text saying helping hands after heavy flood in Germany

humanitarian organizations in providing aid (Figs. 6 & 7). The most occurrent subthemes include:

Rescue operations: Depictions of emergency responders, including fire departments, police, military personnel engaged in rescue missions. This includes the use of boats or helicopters for evacuations.

Aid and relief distribution: Descriptions of efforts to provide food, water, clothing, medical assistance and supplies, temporary shelters, and other essentials to flood victims.

Fundraising and support: organizations, both governmental and non-governmental, and fundraising campaigns GoFundMe campaigns coordinating efforts for relief fund distribution, food banks, donation drives, and charity events aimed at helping flood victims.

Volunteer activities, community's efforts for relief, such as people unloading relief supplies, assisting with cleanup, and offering aid in flood-affected areas.

Theme 3: solidarity and resilience—this theme highlights community engagement and collective action (Figs. 8 & 9). The most occurrent subthemes include:

Community support and collective action: scenes of people working together such as helping each other clean up.



Fig. 9 ChatGPT Description of the photo: A large group of volunteers standing in a muddy area near a historic stone structure. They are smiling and appear to have been involved in flood cleanup efforts



Fig. 10 ChatGPT Description of the photo: a promotional event poster featuring a community cleanup after the flood. The poster mentions "Helpers for Helpers" and lists the event details

Appeals for help: Text overlays and media posts encouraging donations or showing support for flood victims. Messages such as "disaster relief available", "volunteer today", or "help rebuild".

Empathy and support: Texts showing messages of empathy for flood victims, as well as fundraising efforts to help those affected.

Emotional responses expressions of hope during recovery efforts. (e.g., wedding ring found.

Religious ceremonies and monks in prayer, showing the spiritual side of the community during the crisis.



Fig. 11 ChatGPT Description of the photo: a flood disaster in Western Europe, with a flooded street and a sign indicating the severity of the event. The caption describes the flood as the worst in a century, highlighting the impact of climate change

Cultural symbols of solidarity, such as graffiti murals with uplifting messages, and *memorial candles* representing remembrance.

Theme 4: media coverage and public awareness—this theme highlights different communications and information dissemination by the media through social media. Most of these posts are accompanied with written messages in the images, providing essential context regarding the flood event, recovery efforts, and safety measure among others (Figs. 10 & 11). The most occurrent subthemes include:

Climate change awareness and increased flood risk, including references to climate change's role in exacerbating weather events, with some captions urging for climate action and prevent future disasters, posts emphasizing the link between climate change and the increased frequency and severity of floods.

News coverage, including televised reports and news articles reporting on the scale of flooding, the location of affected areas and efforts to address the crisis.

Crisis aftermath, including reports and posters summarizing the aftermath, including death tolls, evacuation efforts, and recovery operations.

Political accountability, with the focus on preventing future flood disasters.

Theme 5- post-disaster recovery – this theme highlights the efforts of the community and



Fig. 12 ChatGPT Description of the photo: a group of individuals posing together, smiling and enjoying a break after working on recovery efforts. They are surrounded by tools and materials and the setting looks like a worksite

government in flood recovery (Figs. 12 & 13). The most occurrent subtheme includes:

Reconstruction and repair efforts to restore and rebuild affected areas, business reopening, and temporary infrastructure. Photos showing equipment, workers, machinery, materials, and construction sites. Housing projects, rebuilding schools, public infrastructure repair, local business restoration.

Theme 6: government and official involvement (Figs. 14 & 15)– the most occurrent subtheme includes:

Government officials and figures visiting flood-affected areas.

Inspection and assessment of damage by authorities.

Political involvement in the flood aftermath, including statements and recovery plans.

Post-flood evaluations and emergency response efforts by governmental bodies.

5.2 Emotional tone

Overall 59% of the images feature people, while the remaining 41% do not, consisting mainly of posts related to flood damage and media coverage. The emotional tone was primarily derived from the facial expressions of individuals in the images and the textual descriptions produced in the visual analysis. The analysis of emotional



Fig. 13 ChatGPT Description of the photo: a woman is using a power tool (jackhammer) to break apart the floor inside a building. The background shows a construction or repair setting with exposed beams and walls

tones in the images reveals nine distinct themes: joy, empathy, hope, seriousness, anxiety, sadness, despair, and neutral. From July 2021 to November 2021, three months after the disaster event, the most prevalent emotional tone was hope (431 occurrences), followed by neutral (317), despair (277), sadness (231), and anxiety (214). Other emotional tones included seriousness (136), empathy (118), and joy (41). The following figure (Fig. 16) illustrates the distribution of these emotional tones during this period. Results indicate a peak in “despair” during July 2021, which gradually declined in the following weeks. This decline reflects the community’s gradual adaptation and coping process. As the emotional tone of despair declined, hope remained the most dominant with a consistent presence throughout the period. The emotional tone became more neutral as the event progressed, suggesting a transition from crisis to resilience.



Fig. 14 ChatGPT Description of the photo: A group of people, including officials, gathered in front of damaged houses after floodwaters caused destruction. There are visible flood impacts in the background, such as debris and a construction vehicle in the area



Fig. 15 ChatGPT Description of the photo: Officials and a former Chancellor visiting a flood-damaged site

The quantitative analysis revealed a statistically significant association between visual themes and emotional tones ($\chi^2(70)=460.82$, $p<.001$), indicating that emotional expressions varied across thematic categories. The quantitative analysis revealed a statistically significant association between visual themes and emotional tones ($\chi^2(70)=460.82$, $p<.001$), indicating that emotional expressions varied across thematic categories. Examination of standardized residuals showed that certain themes displayed distinctive emotional profiles. “Flood damage” was primarily associated with despair (28.85%; residual=11.51). “Rescue operations and relief efforts” were strongly associated with anxiety (17.52%; residual=4.82), while hope remained the most frequent emotional tone (26.68%). “Solidarity and resilience”

combined hope (29.96%; residual=2.18), neutrality (22.15%; residual=2.33), and joy (8.46%; residual=3.96), indicating a more emotionally diverse narrative. “Post-disaster recovery” was dominated by hope (32.14%; residual=2.07) and joy (14.63%; residual=7.15), suggesting a shift toward rebuilding and optimism. “Media coverage and public awareness” was primarily associated with sadness (21.32%; residual=3.04) and seriousness (11.68%; residual=2.59).

The findings demonstrate how the proposed GenAI-assisted approach extends existing methods of sentiment analysis in disaster-related social media research. In their systematic review of social media posts sentiment analysis for disaster risk management, Ilyas and Sharifi (2025) note that most studies rely on lexicon-based tools using dictionaries of positive and negative words, machine learning techniques such as Decision Tree and Random Forest algorithms, deep learning models including Convolutional Neural Networks, or hybrid approaches, integrating lexicon-based and machine learning-based tools. They conclude that a main limitation of existing approaches is that they remain highly language-dependent, with most studies relying heavily on English-language datasets, limited lexicon availability, and the complexities associated with translation (Ilyas & Sharifi 2025). The use of GenAI-assisted analysis helps address some of these limitations by enabling multilingual interpretation and by inferring emotional meanings not only from textual content, but also from visual elements and contextual information embedded in images.

5.3 Hashtags analysis

Table 1 presents the frequency of individual hashtags in the posts. Results revealed that the most frequently used hashtags, after those related to the actual disaster event (e.g., #flood, #flooding, #germanyflood), were those associated with community resilience and solidarity. These hashtags emphasize unity, perseverance, and collective efforts, highlighting the importance of shared experiences and mutual support in overcoming challenges (e.g., #strongertogether, #theStoryWeTell, #wekeepgoing, #weAHRfamily, #oneteam). This was followed by location-specific hashtags tied to particular places or regions (e.g., #ahrta), then hashtags related to relief efforts and organizations (e.g., #relieforganization, #floodrelief, #firedepartment), climate-related hashtags (e.g., #climatechange, #climatecrisis), and, lastly, those associated with media coverage.

Since a single post can contain multiple hashtags related to the same or different themes, the frequency of hashtags does not necessarily reflect the frequency of themes within posts. In total, 603 posts include hashtags related to solidarity and resilience, while 980 posts fall under rescue and relief efforts. There is an overlap of 582

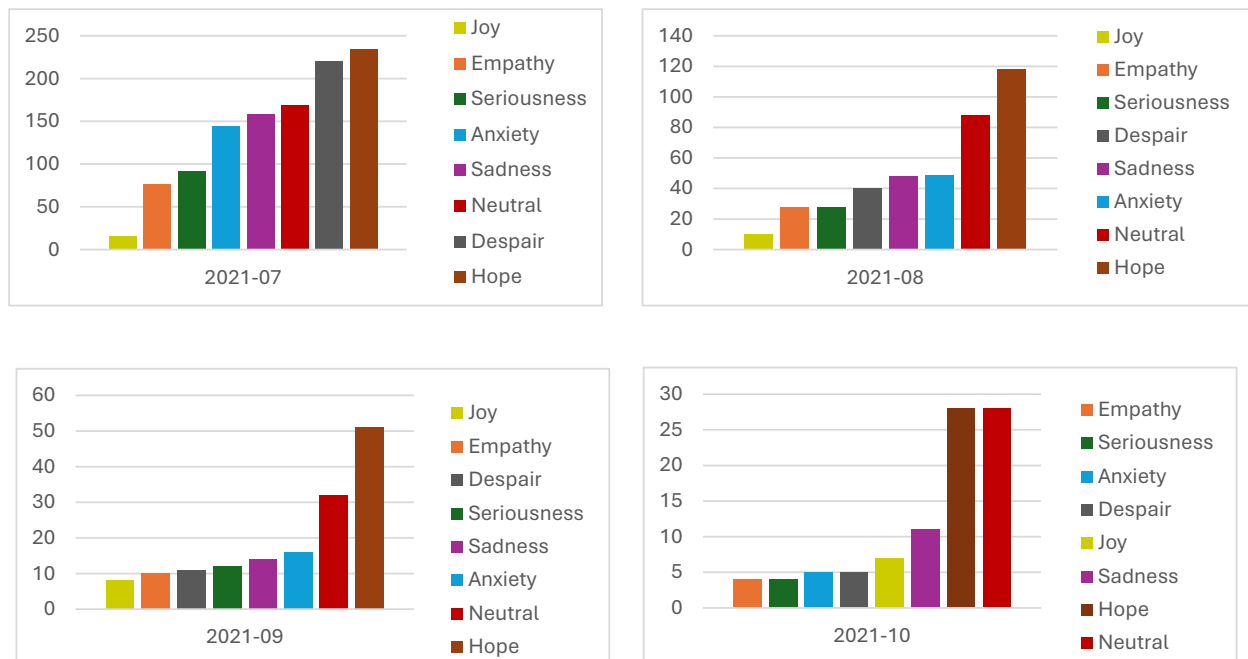


Fig. 16 Frequency of emotions per month from July till Oct 2021

posts (21.6%) that showcase both themes simultaneously, Leaving 187 posts (7%) uniquely classified under solidarity and resilience, and 398 posts (14.8%) under rescue and relief efforts. Only 197 posts (7.3%) are classified under the climate-related theme, of which 147 overlap with location-related posts.

Both the visual analysis and hashtag analysis address common themes such as solidarity and resilience, rescue and relief efforts, and flood damage, but they represent them in distinct ways that offer different insights. In the visual analysis, themes like solidarity and resilience are conveyed through concrete, real-world actions, such as images of people helping each other or attending memorials. These images provide emotional and contextual insights, showing how communities engage in specific actions to support each other, from organizing relief efforts to cleaning and rebuilding. Additionally, the visual analysis captures the diversity of responses within the community, illustrating various forms of collective action. This contrasts with the hashtag analysis, where hashtags like *#strongertogether* or *#wekeepgoing* are used more abstractly to represent the concept of resilience.

Similarly, the theme of rescue and relief efforts in the visual analysis is illustrated through real-time actions, such as rescue teams in action and community-driven relief operations. This offers a more dynamic view of the immediacy of these efforts, with detailed depictions of individuals and groups physically involved in aid distribution, often highlighting the cooperation and shared responsibility between locals, volunteers, and officials. In contrast, the hashtag analysis identifies relief-related

terms like *#floodrelief* or *#rescueservice*. It captures the categorical nature of the theme but falls short of capturing involvement and coordination of various efforts that are visible in the images.

When it comes to flood damage, the visual analysis offers a powerful portrayal of the physical scale of destruction. Photos of submerged buildings, collapsed infrastructure, and before-and-after comparisons provide a tangible sense of the disaster's impact on the landscape. These images offer a spatial understanding of the damage, helping to grasp the magnitude of the destruction in a way that hashtags like *#flooding* or *#germanyfloods* cannot.

The use of multimodal analysis reflects broader developments in disaster research, where combining social media metadata is increasingly recognized as valuable for understanding crisis events. Previous studies have shown that integrating visual and textual information can improve the classification and mapping of disaster-related content (Hao & Wang 2020; Ofli et al., 2020) and enhance situational awareness and supporting humanitarian response (Khanmohammadi et al., 2023). However, these studies remain focused on optimizing machine learning performance rather than unpacking the narrative of events. For instance, Hao and Wang (2020) combined textual messages and image content from Twitter and Flickr to develop hierarchical classifiers for disaster damage assessment. Textual data were processed through a keyword-based method to identify damage-related information. Images were analysed using a pre-trained

Table 1 Frequency of hashtags and thematic entries. Note: A single post can include hashtags from multiple themes, leading to overlaps between themes

Hashtag theme	Most frequent hashtags	Percentage of theme-related posts (multiple themes possible per post)
Flood-related	#flood2021 (2182), #floodingdisaster (1193), #flood (1018), #germany-floods (273), #eifel-flood (209)	100
Rescue and relief efforts	#dznrelieforganization (335), #nonprofit (333), #NGO (328), #relieforganization (309), #floodrelief (206), #firedepartment (204), #disasterrelief (166), #deployment (119), #rescueservice (45)	36.4
Solidarity and resilience	#solidarity (584), #strongertogether (554), #theStoryWeTell (412), #rooftoptentnomads (405), #wekeepgoing (384), #humanity (376), #weAHRfamily (364), #solidarityAHR (337), #unstoppabletogether (312), #oneteam (301), #wefortheeifel (296), #bearersofhope (274), #helpinghands (263), #wecanhandlethis (257), #volunteering (180)	22.4
Location-related	#ahrtal (500), #ahrweiler (371), #Rhineland (281), #ahr (184), #germany (164), #dernau (128), #eifel (121)	11.3
Climate-related	#climatechange (140), #climatecrisis (89), #climate (45), #climateaction (33), #climatechangeisreal (23), #stopclimatechange (7)	7.3
Media coverage	#swr (151), #swraktuell (138)	5.7

ResNet18 CNN that extracted scene-level features and classified on-topic disaster images.

6 Discussion and conclusion

This study employed a multidimensional analytical framework, combining visual, thematic, and emotional analysis of Instagram posts related to the 2021 flood disaster in Germany. Using AI alongside qualitative coding, the approach provided valuable insights into the dynamics of the disaster. The visual analysis offered a nuanced understanding of the disaster's impact and how

communities engaged with the crisis, insights that would not be captured through hashtag analysis alone.

A significant trend emerging from the results is the temporal evolution of activity and visual narratives associated with the hashtags under study. The highest number of Instagram posts occurred in July 2021, during the immediate aftermath of the disaster, with dominant themes such as *flood damage*, *solidarity and resilience*, and *rescue operations and relief efforts*. These themes captured the raw immediacy of the disaster, the urgent response of actors, and community mobilization. However, there was a noticeable decline in posts throughout 2022 and 2023, with a noticeable drop to 105 posts in 2024. While this pattern is consistent with previous studies documenting declines in event-related hashtag activity as disasters transition from the acute response phase to longer-term recovery (R. I. Ogie et al., 2022a, 2022b), it should also be understood in relation to the mutual agencies of human and non-human actors and the affordances of digital infrastructures (Brown et al., 2021). Researchers' choices shape which forms of online activity become visible in the resulting dataset, while users' evolving hashtag practices influence how disaster-related content is encountered and retrieved. In the present case, the three hashtags under study provided a broad entry point into flood-related posts, while more hyperlocal hashtags were not included within the scope of this study. Accordingly, the observed themes and their temporal variation capture patterns of visual representations associated with the hashtags under study, rather than the full range of disaster-related content shared on Instagram. Within this temporal pattern, the distribution of themes reveals important changes in the content of the posts over the study period. In particular, the increase in posts related to *post-disaster recovery* during the second half of 2022 suggests a growing emphasis on rebuilding. The *solidarity and resilience* theme was not only the most prominent in the immediate post-disaster months but also remained consistently relevant throughout 2022, particularly in July, which marks the anniversary of the disaster. This sustained presence highlights the continued prominence of collective action and solidarity in the visual narratives and the symbolic importance of this period for reflecting on recovery. Social media played a crucial role in facilitating community building and organization during this time, providing a platform for individuals and groups to coordinate efforts, share resources, and mobilize support for recovery activities. Social media provided a platform for both individual and collective expressions of support, as evidenced by the widespread use of hashtags such as #strongertogether, #wekeepgoing, and #unstoppabletogether.

The media coverage theme in this study underscores the essential role of social media in raising awareness

and disseminating information about the disaster and its aftermath. Posts within this theme highlighted not only the immediate impacts of the floods but also extended into broader discussions on climate change and its exacerbating effect on extreme weather events. Hashtags such as #climatechange and #climateaction were used, suggesting a connection between the disaster and climate change awareness. However, despite the presence of these hashtags, the frequency of their occurrence was relatively low in comparison to other themes, with #climatechange appearing only 140 times out of 2,690 posts (approximately 5.2%). This finding contrasts with studies that have relied on Twitter data, where climate change-related information has been identified as one of the most frequent topics. For instance, Moghadas et al., (2023), in their study of Twitter data during the 2021 floods in Germany, used Latent Dirichlet Allocation (LDA) for topic modeling and found that climate change-related discussions were among the most prevalent. However, this difference in the prevalence of climate change-related content across platforms can be attributed to the fundamental differences in how each platform is used. Twitter, which is text-based and encourages brief, concise communication, is more conducive to discussions that revolve around hashtags and key messages. Tweets are short and limited to a few characters, typically conveying a quick, impactful message to a broad audience. Instagram is primarily photo-oriented allowing visual storytelling. This highlights the variability in how different social media platforms engage with disaster narratives and their role in shaping public discourse.

The emotional tone analysis provides a nuanced understanding of the community's psychological response over time. Notably, the emotional tone of the images evolved from initial despair and anxiety following the floods to more consistent expressions of hope over time, suggesting that the community adapted to the challenges posed by the disaster and signaling a transition from crisis to resilience. This emotional evolution aligns with the visual representation, where themes of resilience and solidarity were central, reinforcing the idea that emotional resilience is as crucial as physical rebuilding in disaster recovery.

The performance of GenAI in generating accurate descriptions of image content opens a further line of inquiry. Future research could move beyond representational analysis to systematically contrast online narratives with real-world indicators of recovery. For example, GenAI outputs could be used to extract structured information about damage, infrastructure status, or recovery activities from large image corpora, which could then be triangulated with official statistics, field assessments, or remote-sensing data. Such an approach would allow researchers to examine not only how disasters are visually

narrated, but also how closely these narratives align with, diverge from, or obscure material conditions on the ground. This raises critical issues for the epistemic status of AI-mediated visual analysis, in particular concerning how far AI-generated descriptions can be treated as reliable proxies for “what is in the image” and under what conditions they can support robust inferences about real-world disaster recovery status. Addressing these issues will require methodological frameworks that explicitly account for the affordances and blind spots of GenAI, as well as the socio-technical dynamics of platformed visibility that shape which aspects of recovery become visible, and accessible in the first place.

In conclusion, this study underscores the importance of visual storytelling, offering a new dimension to existing research that typically focuses on text-based platforms like Twitter. This approach provides a more nuanced representation of the disaster by capturing its scale and contextualizing solidarity, mobilization, and recovery efforts. This insight supports both the response phase, by delivering real-time disaster information, and the recovery phase, by highlighting rehabilitation and restoration efforts. By doing so, it provides practical evidence for policymakers to integrate social media monitoring and engagement into their crisis management strategies.

Authors' contributions

Manal Ginzarly: Conception and design of the research, collection of data, data analysis and interpretation.

Funding

This work was supported by the MSCA Postdoctoral Fellowship (HORIZON-MSCA-2022-PF 01) under Grant number 101106194.

Data availability

Data will be available upon publication. Mendeley Data, V1, <https://doi.org/10.17632/4p37mr28x2.1>.

Declarations

Competing interests

The authors declare no competing interests.

Received: 3 February 2026 / Revised: 16 August 2026 / Accepted: 18 September 2026

Published online: 28 September 2026

References

- Abdulhamid, N. G., Ayoung, D. A., Kashefi, A., & Sigweni, B. (2021). A survey of social media use in emergency situations: A literature review. *Information Development*, 37(2), 274–291. <https://doi.org/10.1177/0266666920913894>
- Agarwal, N., & Yiliyasi, Y. (2010). *Information quality challenges in social media*. Proceedings of the 2010 International Conference on Information Quality (ICIQ). 12–14 November 2010 Little Rock, Arkansas, SA
- Alam, F., Ofli, F., Imran, M., Alam, T., & Qazi, U. (2020). Deep Learning Benchmarks and Datasets for Social Media Image Classification for Disaster Response. 2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM), 151–158. <https://doi.org/10.1109/ASONAM49781.2020.9381294>

- Al-Shabi, M. (2020). *Evaluating the performance of the most important Lexicons used to Sentiment analysis and opinions Mining*.
- Arif, Amin, M. A., Ali, A. A., & Rahman, A. K. M. (2020). Visual attention-based comparative study on disaster detection from social media images. *Innovations in Systems and Software Engineering*, 16(3–4), 309–319. <https://doi.org/10.1007/s11334-020-00368-1>
- Banikalef, A., Al Bataineh, K., & Atoum, M. (2018). Exploring facebook affordances in natural disaster: a case study of the 2018 dead sea flash floods in Jordan. *International Journal of Engineering and Technology*, 4, 5001–5006. <https://doi.org/10.14419/ijet.v7i4.25862>
- Belal, M., She, J., & Wong, S. (2023). *Leveraging ChatGPT As Text Annotation Tool For Sentiment Analysis* (arXiv:2306.17177). arXiv. <https://doi.org/10.48550/arXiv.2306.17177>
- Bell, J. E., Brown, C. L., Conlon, K., Herring, S., Kunkel, K. E., Lawrimore, J., Lubert, G., Schreck, C., Smith, A., & Uejio, C. (2018). Changes in extreme events and the potential impacts on human health. *Journal of the Air & Waste Management Association*, 68(4), 265–287. <https://doi.org/10.1080/10962247.2017.1401017>
- Bica, M., Palen, L., & Bopp, C. (2017). Visual Representations of Disaster. *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing*. https://www.academia.edu/97930921/Visual_Representations_of_Disaster
- Blackwood, G., Hardy, A., Dodd, B., Ooi, C. S., & Williams, K. (2023). Natural disaster on Instagram: Examining representations of the 2018–2019 Tasmanian fires. *Annals of Tourism Research Empirical Insights*, 4(1). Scopus. <https://doi.org/10.1016/j.jannale.2022.100082>
- Bossetta, M. (2018). The digital architectures of social media: Comparing political campaigning on Facebook, Twitter, Instagram, and Snapchat in the 2016 U.S. election. *Journalism & Mass Communication Quarterly*, 95(2), 471–496. <https://doi.org/10.1177/1077699018763307>
- Brandt, H. M., Turner-McGrievy, G., Friedman, D. B., Gentile, D., Schrock, C., Thomas, T., & West, D. (2019). Examining the role of Twitter in response and recovery during and after historic flooding in South Carolina. *Journal of Public Health Management and Practice*, 25(5), E6–E12. <https://doi.org/10.1097/PHH.0000000000000841>
- Brown, S., Davidovic, J., & Hasan, A. (2021). The algorithm audit: Scoring the algorithms that score us. *Big Data & Society*, 8(1), 2053951720983865. <https://doi.org/10.1177/2053951720983865>
- Bryman, A. (2016). *Social research methods*. Oxford University Press.
- Bui, T. X. (Ed.). (2019). *Proceedings of the 52nd Annual Hawaii International Conference on System Sciences: January 8–11, 2019, Maui, Hawaii*. University of Hawaii at Manoa, Hamilton Library, ScholarSpace. Hawaii International Conference on System Sciences.
- Chen, Q., Ragusa, E., Chaturvedi, I., Cambria, E., & Zunino, R. (2023). Text-image sentiment analysis. In A. Gelbukh (Ed.), *Computational linguistics and intelligent text processing* (pp. 169–180). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-23804-8_14
- Dahal, L., Idris, M. S., & Bravo, V. (2021). It helped us, and it hurt us: The role of social media in shaping agency and action among youth in post-disaster Nepal. *Journal of Contingencies and Crisis Management*, 29(2), 217–225. <https://doi.org/10.1111/1468-5973.12329>
- Dar, S. S., Rehman, M. Z. U., Bais, K., Haseeb, M. A., & Kumar, N. (2024). A social context-aware graph-based multimodal attentive learning framework for disaster content classification during emergencies. *Expert Systems with Applications*, 259, 125337. <https://doi.org/10.1016/j.eswa.2024.125337>
- David, C. C., Ong, J. C., & Legara, E. F. T. (2016). Tweeting Supertyphoon Haiyan: Evolving functions of Twitter during and after a disaster event. *PLoS ONE*, 11(3), e0150190. <https://doi.org/10.1371/journal.pone.0150190>
- de Albuquerque, J. P., Herfort, B., Brenning, A., & Zipf, A. (2015). A geographic approach for combining social media and authoritative data towards identifying useful information for disaster management. *International Journal of Geographical Information Science*, 29(4), 667–689. <https://doi.org/10.1080/13658816.2014.996567>
- Eriksson, M. (2018). Lessons for crisis communication on social media: A systematic review of what research tells the practice. *International Journal of Strategic Communication*, 12(5), 526–551. <https://doi.org/10.1080/1553118X.2018.1510405>
- Fang, J., Hu, J., Shi, X., & Zhao, L. (2019). Assessing disaster impacts and response using social media data in China: A case study of 2016 Wuhan rainstorm. *International Journal of Disaster Risk Reduction*, 34, 275–282. Scopus. <https://doi.org/10.1016/j.ijdrr.2018.11.027>
- Filieri, R., Yen, D. A., & Yu, Q. (2021). #ILoveLondon: An exploration of the declaration of love towards a destination on Instagram. *Tourism Management*, 85, 104291. <https://doi.org/10.1016/j.tourman.2021.104291>
- Ginzarly, M., Teller, J., & Dujardin, S. (2025). Social media use in disaster response: Empowering community resilience. *International Journal of Digital Earth*. <https://doi.org/10.1080/17538947.2025.2521791>
- Glasgow, K., & Fink, C. (2013). Hashtag lifespan and social networks during the London riots. In A. M. Greenberg, W. G. Kennedy, & N. D. Bos (Eds.), *Social computing, behavioral-cultural modeling and prediction* (Vol. Vol. 7812, pp. 311–320). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-642-37210-0_34
- Glasgow, K., Fink, C., Vitak, J., & Tausczik, Y. (2017). "Our hearts go out": Social support and gratitude after disaster. 463–469. Scopus. <https://doi.org/10.1109/CIC.2016.069>
- Gopal, L. S., Prabha, R., Thirugnanam, H., Ramesh, M. V., & Malamud, B. D. (2026). Review article: Social media for managing disasters triggered by natural hazards: A critical review of data collection strategies and actionable insights. *Natural Hazards and Earth System Sciences*, 26(1), 215–250. <https://doi.org/10.5194/nhess-26-215-2026>
- Hao, H., & Wang, Y. (2020). Leveraging multimodal social media data for rapid disaster damage assessment. *International Journal of Disaster Risk Reduction*, 51, 101760. <https://doi.org/10.1016/j.ijdrr.2020.101760>
- Hara, Y. (2015). Behaviour analysis using tweet data and geo-tag data in a natural disaster. *Transportation Research Procedia, Transport Survey Methods: Embracing Behavioural and Technological Changes Selected Contributions from the 10th International Conference on Transport Survey Methods 16–21 November 2014, Leura, Australia*, 11, 399–412. <https://doi.org/10.1016/j.trpro.2015.12.033>
- Hassan, S. Z., Ahmad, K., Hicks, S., Halvorsen, P., Al-Fuqaha, A., Conci, N., & Riegler, M. (2020). *Visual Sentiment Analysis from Disaster Images in Social Media* (arXiv:2009.03051). arXiv. <https://doi.org/10.48550/arXiv.2009.03051>
- Hong, J. Y. J., Kim, N., Lee, S., & Kim, J. H. (2018). Community Disaster Resilience and Social Solidarity on Social Media: A Semantic Network Analysis of the Sewol Ferry Disaster. *Information Research: An International Electronic Journal*, 23(3). <https://eric.ed.gov/?id=EJ1196300>
- Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Goldstein Hode, M., Halliwell, M. R., Turner McGowen, S. E., Davis, R., Vaid, S., McElderry, J. A., & Griffith, S. A. (2015). Social media and disasters: A functional framework for social media use in disaster planning, response, and research. *Disasters*, 39(1), 1–22. <https://doi.org/10.1111/disa.12092>
- Huang, Q., & Xiao, Y. (2015). Geographic situational awareness: Mining tweets for disaster preparedness, emergency response, impact, and recovery. *ISPRS International Journal of Geo-Information*. <https://doi.org/10.3390/ijgi4031549>
- Hughes, A. L., St. Denis, L. A. A., Palen, L., & Anderson, K. M. (2014). Online public communications by police & fire services during the 2012 Hurricane Sandy. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, 1505–1514. <https://doi.org/10.1145/2556288.2557227>
- Ilyas, B., & Sharifi, A. (2025). A systematic review of social media-based sentiment analysis in disaster risk management. *International Journal of Disaster Risk Reduction*, 123, 105487. <https://doi.org/10.1016/j.ijdrr.2025.105487>
- Jaeger, P. T., Shneiderman, B., Fleischmann, K. R., Preece, J., Qu, Y., & Wu, P. F. (2007). Community response grids: E-government, social networks, and effective emergency management. *Telecommunications Policy*, 31(10), 592–604. <https://doi.org/10.1016/j.telpol.2007.07.008>
- Johannes, B. L., & Ortiz, S. E. (2024). How Facebook is used to promote ENDS products near four Big 10 universities: A qualitative analysis. *Journal of American College Health*, 72(1), 210–218. <https://doi.org/10.1080/07448481.2022.2027425>
- Johnson, O. V., Alysari, O. M., Akhtom, D., & Johnson, O. E. (2023). Image Analysis through the lens of ChatGPT-4. *Journal of Applied Artificial Intelligence*, 4(2), Article 2. <https://doi.org/10.48185/jaai.v4i2.870>
- Karimiziarani, M., Jafarzadegan, K., Abbaszadeh, P., Shao, W., & Moradkhani, H. (2022). Hazard risk awareness and disaster management: Extracting the information content of Twitter data. *Sustainable Cities and Society*, 77, 103577. <https://doi.org/10.1016/j.scs.2021.103577>
- Kaur, H. J., & Kumar, R. (2015). Sentiment analysis from social media in crisis situations. *Communication & Automation International Conference on Computing*, 251–256. <https://doi.org/10.1109/CAAI.2015.7148383>
- Khanmohammadi, S., Golafshani, E., Bai, Y., Li, H., Bazli, M., & Arashpour, M. (2023). Multi-modal mining of crowd-sourced data: Efficient provision of humanitarian aid to remote regions affected by natural disasters. *International Journal of Disaster Risk Reduction*, 96, 103972. <https://doi.org/10.1016/j.ijdrr.2023.103972>
- Kogan, M., Palen, L., & Anderson, K. M. (2015). Think Local, Retweet Global: Retweeting by the Geographically-Vulnerable during Hurricane Sandy. *Proceedings*

- of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing, CSCW '15, 981–993. <https://doi.org/10.1145/2675133.2675218>
- Lazreg, M. B., Chakraborty, N. R., Stieglitz, S., Potthoff, T., Ross, B., & Majchrzak, T. A. (2018, August 24). Social Media Analysis in Crisis Situations: Can Social Media be a Reliable Information Source for Emergency Management Services? *Designing Digitalization (ISD2018 Proceedings)*. 27th International Conference on Information Systems Development. <https://www.research.ed.ac.uk/en/publications/social-media-analysis-in-crisis-situations-can-social-media-be-a>
- Lubiana, T., Lopes, R., Medeiros, P., Silva, J. C., Goncalves, A. N. A., Maracaja-Coutinho, V., & Nakaya, H. I. (2023). Ten quick tips for harnessing the power of ChatGPT in computational biology. *PLoS Computational Biology*, 19(8), e1011319. <https://doi.org/10.1371/journal.pcbi.1011319>
- Luna, S., & Pennock, M. J. (2018). Social media applications and emergency management: A literature review and research agenda. *International Journal of Disaster Risk Reduction*, 28, 565–577. <https://doi.org/10.1016/j.ijdr.2018.01.006>
- Ma, Z., Li, L., Mao, Y., Wang, Y., Patsy, O. G., Bensi, M. T., Hemphill, L., & Baecher, G. B. (2024). Surveying the use of social media data and natural language processing techniques to investigate natural disasters. *Natural Hazards Review*, 25(4), 03124003. <https://doi.org/10.1061/NHREFO.NHENG-2047>
- Manandhar, B., Cui, S., Wang, L., & Shrestha, S. (2023). Post-flood resilience assessment of July 2021 flood in Western Germany and Henan, China. *Land*, 12(3), Article 3. <https://doi.org/10.3390/land12030625>
- Mao, Y., Liu, Q., & Zhang, Y. (2024). Sentiment analysis methods, applications, and challenges: A systematic literature review. *Journal of King Saud University - Computer and Information Sciences*, 36(4), 102048. <https://doi.org/10.1016/j.jksci.2024.102048>
- Mavrodieva, A. V., & Shaw, R. (2021). Social media in disaster management. In R. Shaw, S. Kakuchi, & M. Yamaji (Eds.), *Media and disaster risk reduction: Advances, challenges and potentials* (pp. 55–73). Springer. https://doi.org/10.1007/978-981-16-0285-6_4
- Mihunov, V. V., Jafari, N. H., Wang, K., Lam, N. S. N., & Govender, D. (2022). Disaster impacts surveillance from social media with topic modeling and feature extraction: Case of hurricane harvey. *International Journal of Disaster Risk Science*, 13(5), 729–742. <https://doi.org/10.1007/s13753-022-00442-1>
- Mishra, A., Danzy, B., Soni, U., Arunkumar, A., Huang, J., Kwon, B. C., & Bryan, C. (2025). PromptAid: Visual prompt exploration, perturbation, testing and iteration for large language models. *IEEE Transactions on Visualization and Computer Graphics*. <https://doi.org/10.1109/TVCG.2025.3535332>
- Moghadas, M., Fekete, A., Rajabifard, A., & Kötter, T. (2023). The wisdom of crowds for improved disaster resilience: A near-real-time analysis of crowdsourced social media data on the 2021 flood in Germany. *GeoJournal*, 88(4), 4215–4241. <https://doi.org/10.1007/s10708-023-10858-x>
- Murthy, D., Gross, A., & McGarry, M. (2016). Visual social media and big data. Interpreting Instagram images posted on Twitter. *Digital Culture & Society*, 2(2), 113–134. <https://doi.org/10.14361/dcs-2016-0208>
- Nguyen, D. T., Ofli, F., Imran, M., & Mitra, P. (2017). Damage Assessment from Social Media Imagery Data During Disasters. *Proceedings of the 2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining 2017*, 569–576. <https://doi.org/10.1145/3110025.3110109>
- NRC. (2006). *Facing hazards and disasters: Understanding human dimensions*. National Academies Press.
- Ofli, F., Alam, F., & Imran, M. (2020). Analysis of Social Media Data using Multimodal Deep Learning for Disaster Response. In A. L. Hughes, F. McNeill, & C. Zobel, (Eds.), *Social Media for Disaster Response and Resilience*.
- Ogie, R. I., Clarke, R. J., Forehead, H., & Perez, P. (2019). Crowdsourced social media data for disaster management: Lessons from the PetaJakarta.org project. *Computers, Environment and Urban Systems*, 73, 108–117. Scopus. <https://doi.org/10.1016/j.compenvurbysys.2018.09.002>
- Ogie, R. I., James, S., Moore, A., Dilworth, T., Amirghasemi, M., & Whittaker, J. (2022a). Social media use in disaster recovery: A systematic literature review. *International Journal of Disaster Risk Reduction*, 70, 102783. <https://doi.org/10.1016/j.ijdr.2022.102783>
- Ogie, R., Moore, A., Wickramasuriya, R., Amirghasemi, M., James, S., & Dilworth, T. (2022b). Twitter data from the 2019–20 Australian bushfires reveals participatory and temporal variations in social media use for disaster recovery. *Scientific Reports*, 12(1), 16914. <https://doi.org/10.1038/s41598-022-21265-6>
- Olson, M. K., Sutton, J., Vos, S. C., Prestley, R., Renshaw, S. L., & Butts, C. T. (2019). Build community before the storm: The National Weather Service's social media engagement. *Journal of Contingencies and Crisis Management*, 27(4), 359–373. <https://doi.org/10.1111/1468-5973.12267>
- Oulalen, G., Vogel, B., & Gouett-Hanna, C. (2020). Quick response disaster research: Opportunities and challenges for a new funding program. *International Journal of Disaster Risk Science*, 11(5), 568–577. <https://doi.org/10.1007/s13753-020-00299-2>
- Palen, L., & Hughes, A. L. (2018). Social media in disaster communication. In H. Rodríguez, W. Donner, & J. E. Trainor (Eds.), *Handbook of disaster research* (pp. 497–518). Springer International Publishing. https://doi.org/10.1007/978-3-319-63254-4_24
- Pearce, W., Özkuş, S. M., Greene, A. K., Teeling, L., Bansard, J. S., Omena, J. J., & Rabello, E. T. (2018). Visual cross-platform analysis: Digital methods to research social media images. *Inf Commun Soc*, 1–20. Scopus.
- Ragini, J. R., Anand, P. M. R., & Bhaskar, V. (2018). Big data analytics for disaster response and recovery through sentiment analysis. *International Journal of Information Management*, 42, 13–24. <https://doi.org/10.1016/j.ijinfomgt.2018.05.004>
- Rasmussen, J., & Ihlen, Ø. (2017). Risk, crisis, and social media: A systematic review of seven years' research. *Nordicom Review*, 38(2), 1–17. <https://doi.org/10.1515/nor-2017-0393>
- Reuter, C., & Kaufhold, M. (2018). Fifteen years of social media in emergencies: A retrospective review and future directions for crisis informatics. *Journal of Contingencies and Crisis Management*, 26(1), 41–57. <https://doi.org/10.1111/1468-5973.12196>
- Samofalova, Y. (2024). Strategies and challenges for constructing and collecting visual corpora from image-based social media platforms. *Studies in Communication Sciences*, 1–16. <https://doi.org/10.24434/j.scoms.2024.01.3881>
- Semaan, B., & Mark, G. (2012). "Facebooking" towards crisis recovery and beyond: Disruption as an opportunity. 27–36. Scopus. <https://doi.org/10.1145/2145204.2145214>
- Shibuya, Y. (2017). Mining social media for disaster management: Leveraging social media data for community recovery. 2018-January, 3111–3118. Scopus. <https://doi.org/10.1109/BigData.2017.8258286>
- Stolero, N., Elkady, S., Labaka, L., Verlin, J., Branlat, M., & Adini, B. (2024). Using social media in disaster management: The perceptions of emergency responders versus the public. *Risk, Hazards & Crisis in Public Policy*, 15(2), 128–161. <https://doi.org/10.1002/rhc3.12301>
- Subba, R. (2016). Online Convergence Behavior, Social Media Communications and Crisis Response: An Empirical Study of the 2015 Nepal Earthquake Police Twitter Project. <https://doi.org/10.24251/HICSS.2017.034>
- UNISDR. (2015). *Sendai Framework for Disaster Risk Reduction 2015–2030—English*. <https://climate-adapt.eea.europa.eu/en/metadata/publications/sendai-framework-for-disaster-risk-reduction-2015-2030>
- Valdez, D., ten Thij, M., Bathina, K., Rutter, L. A., & Bollen, J. (2020). Social media insights into US mental health during the COVID-19 pandemic: Longitudinal analysis of Twitter data. *Journal of Medical Internet Research*, 22(12), e21418. <https://doi.org/10.2196/21418>
- Vieweg, S., Hughes, A. L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: What twitter may contribute to situational awareness. *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, CHI '10*, 1079–1088. <https://doi.org/10.1145/1753326.1753486>
- Willson, G., Wilk, V., Sibson, R., & Morgan, A. (2021). Twitter content analysis of the Australian bushfire disaster 2019–2020: Futures implications. *Journal of Tourism Futures*, 7(3), 350–355. (world). <https://doi.org/10.1108/JTF-10-2020-0183>
- Zhang, C., Fan, C., Yao, W., Hu, X., & Mostafavi, A. (2019). Social media for intelligent public information and warning in disasters: An interdisciplinary review. *International Journal of Information Management*, 49, 190–207. <https://doi.org/10.1016/j.ijinfomgt.2019.04.004>
- Zhang, J., Liao, M., Wang, Y., Huang, Y., Chen, F., & Makiko, C. (2024). Multi-modal deep learning framework for damage detection in social media posts. *PeerJ Computer Science*, 10, e22622. <https://doi.org/10.7717/peerj-cs.2262>

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.