Tapping into Social Media in Crisis: A Survey

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Abstract

When a crisis hits, people often turn to social media to ask for help, offer help, find out how others are doing, and decide what they should do. The growth of social media use during crises has been helpful to aid providers as well, giving them a nearly immediate read of the on-the-ground situation that they might not otherwise have. The amount of crisis-related content posted to social media over the past two decades has been explosive, which, in turn, has been a boon to Language Technology (LT) researchers. In this study, we conducted a systematic survey of 356 papers published in the past five years to better understand the expanding growth of LT as it is applied to crisis content, specifically focusing on corpora built over crisis social media data as well as systems and applications that have been developed on this content. We highlight the challenges and possible future directions of research in this space. Our goal is to engender interest in the LT field writ large, in particular in an area of study that can have dramatic impacts on people's lives. Indeed, the use of LT in crisis response has already been shown to *save* people's lives.

1 Introduction: Language Technologies and Crises

The aftermath of the Haitian Earthquake of 2010 saw the development and deployment of language technologies at a large and national scale for the first-time ever in a crisis. Most notably, language technologies were developed for a language that most in the NLP field had never heard of, and likewise most aid providers did not speak, namely, Haitian Kreyòl. At its peak, in the hours and days after the earthquake, first-responders in Haiti were receiving over 5,000 SMS messages per hour asking for help, over 80% of which were in Kreyòl. In response to the desperate need, a diverse group of individuals, notably driven by the Haitians themselves, developed and deployed technologies that could process this load, with a heavy reliance on crowdsourcing, the latter of which tapped into Haiti's large world-wide diaspora. Although the language technologies developed at the time are archaic by today's standards, these technologies allowed for the rapid triaging of the SMS messages (Meier, 2015), geolocation (mostly through crowdsourcing) (Munro, 2013), and even machine translation (Lewis, 2010). The infrastructure and language technologies developed for this crisis were credited with saving thousands of lives (Munro, 2013).

The Haitian earthquake, and the crisis it caused, are not unique. In fact, natural or human-caused crises happen regularly around the globe. Populations tend to use social media (and SMS) to report on how they are being affected. The data posted to social media have proven essential for providing and directing aid. Further, in notable examples and ongoing research, language technologies have proven, or can be shown, to be essential tools in the crisis preparedness and response toolkit.

1.1 What is a crisis?

A crisis can be described as any *surprise* event that adversely affects public health or disrupts the routines of daily life, puts (large) groups of people in danger, may require aid for affected populations, is often unpredictable, and typically requires rapid response (Castillo, 2016). Even so, emergency service providers generally have plans or strategies for dealing with crisis events (Akerkar, 2020). Olteanu et al. (2015b) and Castillo (2016) describe the two principal super-types of disaster: natural and human-induced (anthropogenic), with meteorological, hydrological, geophysical, etc., all being natural, and shootings, bombings, wars, derailments, etc., all falling under human-induced. To see the full list of categories from Castillo (2016), see Table 1 in Appendix A.

The birth of the multidisciplinary field of Crisis Informatics (Hagar, 2010, 2014; Palen and Anderson, 2016) saw the first forays into the use of language technologies in crisis response, focused primarily on disaster warning, response and recovery. A notable (and likely first) example of social media use in crisis was on Twitter, where users reported localized information regarding the San Diego firestorm of 2007 (Sutton et al., 2008). However, it was not until Haiti in 2010 that the use of technologies for identifying and meeting local need demonstrated the potential for language technological solutions (albeit across SMS messages, not social media directly) (Munro, 2013). In the UK floods of 2012 it was noted that location information was discernible from tweets (Meier, 2015). This was followed by Typhoon Pablo in the Philippines in the same year where Tweets were systematically analyzed and categorized (Liu, 2014). However, the first Twitter classifier was developed after the Oklahoma tornadoes of 2013, *which was used and deployed during the crisis*, and used to classify the severity of need for directing aid appropriately (Meier, 2015).

Crucially, given the millions of users on social media platforms, information can be harvested to identify the need on the ground, summarize the extent of a disaster locally, and also direct need (as observed in Haiti in 2010 (Lewis et al., 2011)).

However, there are a host of issues that one must contend with when harvesting and processing data from social media platforms as relates to crises, all of which rely on language technologies: identifying the language and using language-specific tools for text or audio in a language (or relevant multilingual models); identifying named entities of various types within a text; identifying location information, including fine-grained mentions; extracting timeline information to provide a step-by-step view of a crisis as it unfolds; analyzing the sentiment or stance of affected populations from text; determining whether the messages are relevant to the crisis at hand, and if so, what urgency they represent (*i.e.*, *triage*); filtering out irrelevant content, such as misinformation or SPAM, or even disinformation; and, producing a summary of ongoing events for aid providers or government bodies (*i.e.*, a situation report, or *sitrep*). All of the above rely on, or would benefit significantly from, the use of language technologies.

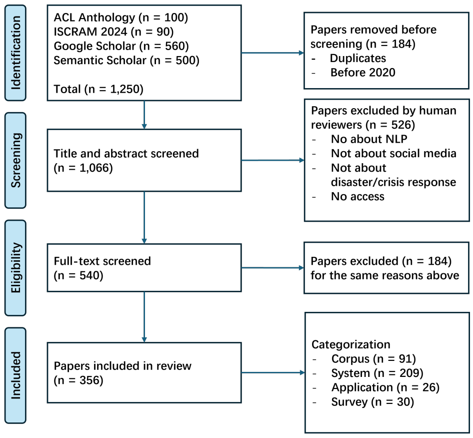

Figure 1: Flowchart of paper selection following PRISMA guidelines (Tricco et al., 2018).

1.2 What are the research questions?

In this paper, we conduct a systematic survey of the literature on language technologies as they are applied to crises. To our knowledge, this is the most extensive and thorough survey of its kind in this area: we reviewed over 350 papers published during the past five years on language technologies (LT) for crisis preparedness and response (CPR). The crucial research questions (RQ) we will address in this survey are as follows:

- RQ1: What kind of corpora are available for LT4CPR research? What are their properties?
- RQ2 What kind of approaches have been proposed to build LT systems for CPR?
- RQ3: What kinds of real-life crisis scenarios can LT systems potentially be applied to?
- RQ4: What are the main challenges and future directions for LT4CPR research?

This survey summarizes the current breadth and extent of language technologies in crisis preparedness and response (LT4CPR) and describes challenges and future directions for this interesting area of study.

2 Paper Selection

Our systematic review follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines (Tricco et al., 2018). We gathered a large number of relevant English articles published in the past five years, from January 2020 to December 2024. The process is illustrated in Figure 1, as explained below.

2.1 Inclusion criteria

For a study to be included in our survey, it must meet two criteria: First, it must directly pertain to a rapidly developing crisis such as natural disasters (*e.g.,* earthquake) or the onset of pandemics (*e.g.,* COVID-19) or human-induced crises (*e.g.,* break-out of a war); thus, studies on long-term crises such as drug wars and the opioid epidemic in the USA are excluded. Second, the study must either build a corpus consisting of social media data produced during a crisis or build NLP systems using social media data that aim to help crisis response.

2.2 The initial set of papers

Our search strategy employed three groups of keywords: (a) social media, (b) crisis OR disaster, (c) Natural Language Processing (NLP) OR Machine Learning (ML) OR Language Technology (LT) OR Artificial Intelligence (AI). These groups were combined to conduct searches across three sites: the ACL Anthology[1], Google Scholar[2], and Semantic Scholar[3]. Furthermore, we included relevant publications from CrisisNLP [4] and ISCRAM[5]. We found 1,250 papers from these five sources combined. After removing duplicates and papers published before 2020, there were 1,066 left, which formed our initial set of papers.

2.3 Two stages of screening

Although search queries were based on the inclusion criteria, many papers in the initial set failed to meet these criteria. We filtered out unqualified papers in two stages. First, four NLP graduate students manually checked the title and abstract of all papers in the initial set and removed any unqualified ones.

Second, we conducted a full-text screening of the 540 remaining papers and categorized them into four categories based on their foci: (1) corpus construction papers, which focus on building a dataset using social media messages during a crisis, (2) system development papers, which focus on building NLP systems that could be applied to some crisis situations, (3) application papers, which focus on building applications for a real crisis situation, and (4) survey papers. During the full-text screening, we recorded information (*e.g.,* the modality of a corpus), which would be needed for the various statistics reported in our study.

[1]https://aclanthology.org/
[2]https://scholar.google.com/
[3]https://www.semanticscholar.org/
[4]https://crisisnlp.qcri.org/
[5]https://iscram.org/publications/

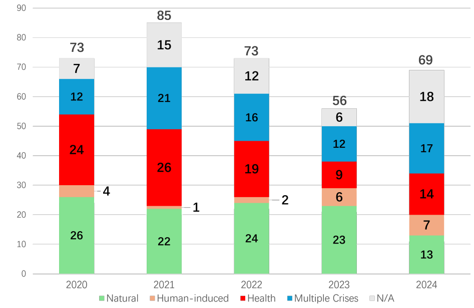

Figure 2: The papers included in this survey by year and crisis type. The grey bar, N/A, means the crisis type cannot be easily inferred from the writing of the papers.

Ultimately, 356 articles were kept for our survey, and their distribution by year of publication and crisis type are shown in Figure 2. For the next three sections, we will discuss the first three types of papers as the 30 survey papers in our final set either concentrated on some specific NLP task (*e.g.,* event detection (Edlim et al., 2024)) or were published a few years ago and thus could not capture most recent progress in this field (*e.g.,* (Baro and Palaoag, 2020)).

3 Corpus Construction

Out of the 356 papers in our final collection, 91 focus on corpus construction ("corpus papers"). In this section, we discuss the properties of the corpora with respect to modality, language, social media platform, and annotation type (see Figs 3-7). Each figure in this section has two pie charts: the left shows the numbers of corpora presented in the corpora papers, and the right shows the numbers of corpora used by the system papers.

The full list of corpus papers and the basic information on the corresponding corpora are in Tables 2– 6 in Appendix B. In addition, some well-known datasets released before 2020 are in Table 7 in the same appendix.

3.1 Modalities, languages, and platforms

Most of the corpora described in the corpus papers are text only (79), English only (47), and collected from Twitter alone (63).

Crisis type: Castillo (2016) defined two major categories of crises: natural vs. human-induced (see Table 1). As there was a surge of studies on COVID-19, we added a third category, *health-related crisis*, when reporting the number of cor-

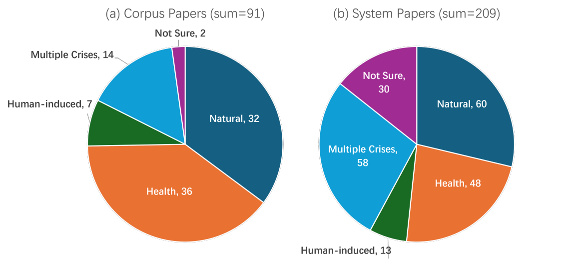

Figure 3: Number of corpora by crisis type as in (a) corpus papers or (b) system papers

pora by crisis type. Figure 3 shows the distribution of corpora over three crisis categories. Some corpora include data from multiple types of crises.

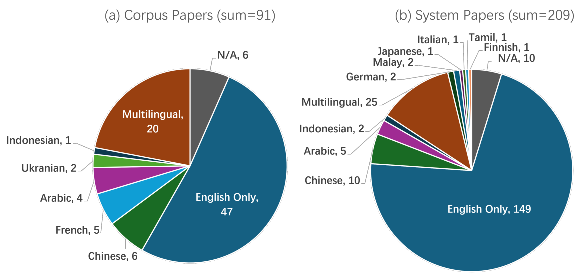

Figure 4: Number of corpora by language

Languages: Figure 4 shows languages of the corpora in our study. Of the 89 corpora that include text, 47 (52.8%) are English only. The next largest percentage is for multilingual corpora, with most of these including English in addition to other languages. Good examples of robustly multilingual corpora include Chowdhury et al. (2020), Imran et al. (2021a), and Abdul-Mageed et al. (2021). The latter two are particularly noteworthy with 67 and 100+ languages represented, respectively.

Modality: As shown in Figure 5(a), the large majority (81) of the 91 newly created corpora consist of text only; 2 corpora (Hassan et al., 2020; Alam et al., 2022), are images only; 6 include both text and images; 2 consist of more than two modalities (Yuan et al., 2021; Sosa and Sharoff, 2022).

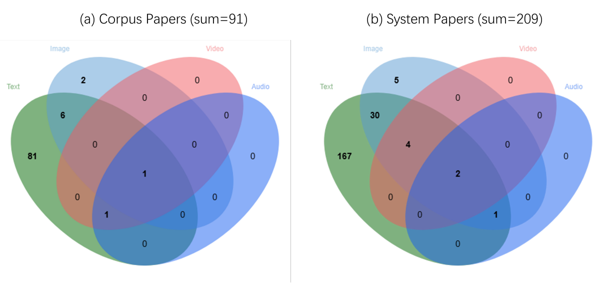

Figure 5: Corpora by modality.

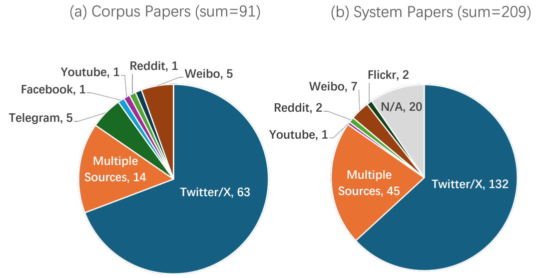

Figure 6: Number of corpora by social media platforms. N/A means the platform information is unspecified.

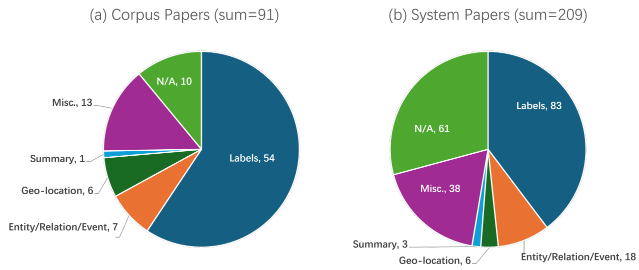

Figure 7: Number of corpora by annotation type. N/A means no additional annotation (A0).

Social Media Platforms: Fig 6 shows the sources of the data in the corpora. The large majority of corpora, 63 (69.2%), were built from social media messages on Twitter. This is because of the (historically) widespread use of the platform, especially for sharing the kind of microblog posts most useful for disaster situations. Additionally, Twitter is often used in research studies because its data are easy to obtain and distribute.

3.2 Types of annotation

The corpora papers vary with respect to the annotation types used over raw social media data. We group the annotation types into 6 broad categories, whose distributions are shown in Figure 7.

(A0) No annotation: 10 of 91 corpora are a collection of social media messages without additional annotation. For instance, Epic (Liu et al., 2020) is a large-scale epidemic corpus containing 20M tweets crawled from 2006 to 2020, including tweets related to three diseases (Ebola, Cholera and Swine Flu) and 6 global epidemic outbreaks. Such corpora are valuable resources for LT4CPR research even without additional annotations.

(A1) Labels: Out of 91 corpora, 54 include certain class labels. The labels can pertain to (a) Relevance and urgency of messages (*e.g.,* Enzo et al., 2022; Kayi et al., 2020), (b) Information source and reliability (*e.g.,* (Ahmed et al., 2020; Sosa and Sharoff, 2022)), (c) damage type and severity (*e.g.,* (Li et al., 2020; Alam et al., 2022)), and (d) sentiment, stance (*e.g.,* (Shestakov and Zaghouani, 2024; Vaid et al., 2022)), etc.

(A2) Entities, relations, and events: Seven out of 91 corpora annotated disaster-related entities, relations, or events; such annotations can be used to train emergent event detection systems (e.g., (Hamoui et al., 2020; Fakhouri et al., 2024)).

(A3) Geo-location: For applications such as assisting rescue efforts, geo-location needs to be fine-grained to the level of geo-coordinate or physical address (*e.g.,* (Chen et al., 2022; Faghihi et al., 2022)). In contrast, for applications such as monitoring public opinions during a pandemic, geo-location can be at the level of city, state, or even country (Arapostathis, 2021).

(A4) Summary and timelines: Informative reports that aggregate information from social media messages can be invaluable during crises. However, creating a corpus of such reports could require tremendous amount of human effort. Only two corpora in our survey do so: Vitiugin and Castillo (2022) collected crisis-related messages from Twitter and annotated all summaries for factual claims in the messages; CrisisLTSum (Faghihi et al., 2022) contains 1,000 crisis event timelines across four domains including wildfires, local fires, traffic and storms.

(A5) Miscellaneous: Nine corpora include annotations such as propagation networks (Haouari et al., 2021), situation frames and morphosyntactic annotations (Tracey and Strassel, 2020).

Notably, while parallel datasets in general domains (*e.g.,* news and law proceedings) are common and have been used to build MT systems in the past three decades, corpora consisting of translations of social media data are rare and none of the 20 multilingual corpora in Figure 4(a) include parallel social media data.

3.3 Annotation methods

For all corpora, social media messages are obtained by crawling the Internet, calling APIs offered by social media platforms, or leveraging existing datasets. The raw data is often preprocessed using filtering, removing noisy instances, etc.

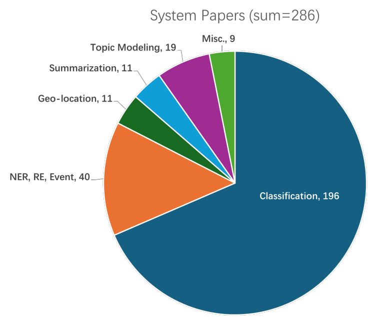

Figure 8: Number of systems by NLP tasks.

Among the annotated corpora in our survey, annotation was performed manually for roughly two thirds of corpora through crowd-sourcing platforms like Amazon Mechanical Turk (*e.g.,* (Sosea et al., 2022)) or by in-house annotators (*e.g.,* (Sarkar et al., 2020)). The remaining were annotated automatically through associated metadata such as Twitter's location features (*e.g.,* (Qazi et al., 2020)) or by running NLP systems such as language I.D. (*e.g.,* (Sosa and Sharoff, 2022)).

4 NLP System Development

Of 356 papers included in this survey, 209 (58.1%) focus on system development ("system papers").

4.1 NLP tasks

Despite the large number of system papers, they cover only a small number of NLP tasks, as shown in Figure 8.[6]

(T1) Classification: This group includes classification tasks such as emergency detection (*e.g.,* (Restrepo-Estrada et al., 2018; Gialampoukidis et al., 2021)), misinformation detection (*e.g.,* (Apostol et al., 2023; Naeem et al., 2024)), and disaster type classification (*e.g.,* (Lever and Arcucci, 2022; Zhang et al., 2024a)). 196 out of 286 systems (68.5%) fall into this category.

(T2) Entity, relation, and event: This group includes named entity recognition (*e.g.,* (Lai et al., 2022; Suleman et al., 2023)), relation extraction, and event extraction (*e.g.,* (Alam et al., 2019; Wang et al., 2024a)). 40 systems belong to this category.

(T3) Geo-location: This includes Geo-tagging and Location Mention Recognition (LMR) (*e.g.,*

[6]As a system paper may include systems for multiple NLP tasks, the total number of systems (286) in this pie chart is higher than the number (209) of system papers.

(Essam et al., 2021; Suwaileh et al., 2022)). 11 systems belong to this group.

(T4) Summarization: There are 11 systems on summarization, including timeline summarization (*e.g.,* (Khatoon et al., 2021)).

(T5) Topic modeling: 19 systems are on topic modeling (*e.g.,* (Bukar et al., 2022; Zhang et al., 2024b)), an important task during crisis situations.

(T6) Other tasks: There are 9 papers on various topics such as social network detection (*e.g.,* (Momin and Kays, 2023)) and visualization (*e.g.,* (Ma et al., 2022)).

4.2 Methodology

Among the six groups of tasks outlined above, T1, T2 and T5 have been well-studied in the NLP field; most system papers we surveyed simply applied the same methodology to the crisis domain. For T3, in order to identify Geo-locations, some studies (*e.g.,* (Apostol et al., 2023; Ferner et al., 2020)) used external knowledge to map location names to physical addresses while others (*e.g.,* (Belcastro et al., 2021)) took advantage of the geo-tags of content senders. For T4, summarization in the crisis domain can be very complex, as one would need to process on-going, noisy, often conflicting information from multiple information resources and/or modalities potentially in multiple languages. The summarization task often involves message classification and clustering, followed by crisis timeline extraction before a summary is generated (*e.g.,* (Faghihi et al., 2022)).

Due to space limits, we cannot explore the details of all system papers. We simply place them in four groups: rule-based, neural network (NN), non-NN statistical methods such as Random Forest and SVM, and others which include methods such as data augmentation. Figure 9 shows the number of the systems by year and approach.[7]

4.3 Evaluation

Tasks in T1-T4 correspond to annotation types A1-A4, as discussed in §3.2; therefore, they can be evaluated with the corresponding corpora. As shown in Figure 4(b)-6(b), the corpora used in the majority of system papers are English text from Twitter.

For T5-T6, because there are no labeled corpora serving as gold standards, the outputs (e.g., visualization of damaged regions) of those systems are often displayed but not evaluated quantitatively.

[7]The total number of systems in the figure (449) is much higher than the number of system papers (209) as it is common for a system paper to report results on multiple systems.

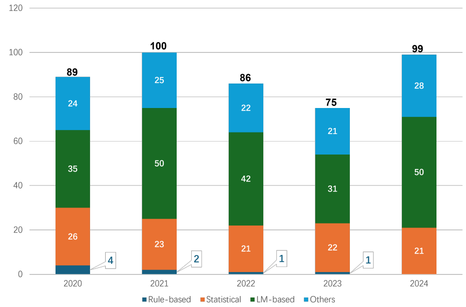

Figure 9: Number of systems by year and approach.

5 Real-life Applications and Deployment

NLP systems can potentially be used to assist crisis management in many ways, such as message triaging for humanitarian organizations (Kozlowski et al., 2020b; Amer et al., 2024), emergent event detection (Suwaileh et al., 2023c; Simon et al., 2021), geo-location for rescue efforts and situational assessment (Khanal et al., 2022; Suwaileh et al., 2022), generation of situation reports and crisis maps (Vitiugin and Castillo, 2022; Yang et al., 2022), monitoring and analyzing public emotions and responses (Wang et al., 2024b; Sosea et al., 2022), and helping the public acquire/process information (Hossain et al., 2020; Brunila et al., 2021a).

However, there are only 26 *application papers*, that is, papers that describe systems that attempt to address the "application" of LT to real-life situations (*e.g.,* to help aid providers). Of these, it is not clear how many have been adopted by the crisis community. This indicates a surprising gap given that one would *assume* that the system development work that is being done by LT researchers (described in §4) is intended to be used in actual crises.

6 Challenges and Future Directions

Our survey has shown that there has been a significant amount of work that has been done over just the past five years applying LT to crisis management. That said, there are still many challenges to be addressed. We highlight six primary challenges and possible future directions in the next sections.

6.1 Quality of social media corpora

There are many challenges in building large, high-quality corpora for LT4CPR research. First, it can be difficult to gather large amounts of social media data from real crises due to factors such as paywalls, identifying the channels being used for a crisis (*e.g.,* on Telegram, Reddit), the lack of public access to relevant content, etc. Second, social media data are noisy with misspellings, newly invented words, grammatical errors, etc., all of which complicate cleaning and annotation tasks (Derczynski et al., 2013). Third, social media data can contain inaccurate or misleading information, which is often reinforced (*e.g.,* Starbird et al., 2014), and thus mis- and disinformation detection can be an important step for using such data (Hossain et al., 2020). Finally, social media users can be quite different from the general population and any analysis based on social media messages must take this fact into account, *e.g.,* in order to understand the public's reaction to, for example, a hurricane evacuation order (Roy et al., 2021; Li et al., 2022c).

6.2 Lack of multilinguality

Chowdhury et al. (2020) points out that "there are a lot of disaster-prone non-English speaking countries." Nothing could be truer: from 1995 to 2022, there were 11,360 natural disasters around the globe, an average of about 398 disasters per year (Tin et al., 2024). Ranking these disasters by death toll or number of injuries (descending)—treating these figures as proxies for disaster severity—*none* of the approximately eighteen most severe disasters that occurred in these 17 years occurred in regions where English is an official language, and only *one* (Sri Lanka) even considers English semi-official.

Given that the bulk of injuries and lives lost occur where English is not spoken (per (Tin et al., 2024)), and that the bulk of corpora developed for LT4CPR are in English (see §3 and Appendix B), the value of resources created for non-English languages cannot be overstated, especially if intended for real-world use. Tools, thus, take a cue from available corpora, and §4 shows the same English-bias in the systems developed. There is value in working on English; yet we miss the boat by not working on other languages too.

A surprising gap in the LT research on social media in the crisis area is the general absence of Machine Translation research: in our search over the past five years only *one* paper focused on the use or development of MT (Amer et al., 2023). [8]

[8] Two recent papers, Lankford and Way, 2024 and Roussis, 2022 also address MT in crisis, specifically of COVID-19 related text, they do not cover social media, so were excluded from our survey.

If the preponderance of need is in non-English languages, and the bulk of the work in LT4CPR is in English, MT could be used as a "connective" technology (*e.g.,* translate data from affected languages into English for further processing).

That said, this deficiency might also be addressed by the growing use of LLMs (*e.g.,* GPT, LLaMa) and large multilingual models (*e.g.,* XLM-RoBERTa). We found 8 papers using such models for crisis matters, all from 2024. Although the bulk of these papers focus on classification and summarization tasks using LLMs (and one on inference (Giaccaglia et al., 2024)), two do explore multilingual uses (Wang et al., 2024a; Sathvik et al., 2024).

6.3 Lack of multimodality

A recurring theme in a number of the system papers is the need for multi-modal (image, text, audio, video) content. Applying LT techniques to multimodal content has garnered much interest in the field of late (Salesky et al., 2024; Haralampieva et al., 2022; Hu et al., 2024). Indeed, over 40 papers in our survey list the development of multimodal corpora or tools as relevant future directions for the field. One shows an interesting use case for text paired with images, Giaccaglia et al., 2024, whereby an LLM annotates images retrieved from Tweets, and combines annotations with the Tweet text to enhance (what they call *amplify*) classification into relevant humanitarian categories. Equally beneficial work could be done with video and/or audio to enhance various NLP tasks for triaging.

6.4 Lack of diversity in social media platforms

The data found in the corpora we surveyed is overwhelmingly from Twitter/X, and the bulk of the systems that were developed used Twitter data as well. Twitter has been the focus for so long because it was the go-to in the earliest days of Crisis Informatics (*e.g.,* (Sutton et al., 2008; Hughes and Palen, 2010; Vieweg et al., 2010)), and this tendency has clearly continued.

The hyper-focus on Twitter is an issue because it ignores the vast diversity of social media platforms being used, some much more heavily than Twitter, *e.g.,* Tiktok. Also, after Twitter's acquisition and shift to X, the resulting changes in policies and algorithms have driven users to flee the platform in favor of others. For these reasons and more, it will become increasingly important for researchers to acquire data from other platforms, both mainstream (*e.g.,* Youtube, Tiktok), and alternative (*e.g.,* Telegram, Bluesky).[9]

6.5 Lack of diversity in annotation types and NLP tasks

As shown in Figures 7-8, most of the existing corpora and NLP systems focus on producing three types of annotation or output: class labels, entity/relation/event, and geo-location. More studies are required on other types of annotation or output such as machine translation, situation reports, timeline extraction (*a la* Faghihi et al., 2022)[10], and visualization (*e.g.,* (Murakami et al., 2020)). These would vastly increase the utility of LT for aid providers and others in real-world settings.

6.6 Lack of engagement with the crisis community

Lewis et al. (2011) describes what they call a *Crisis MT Cookbook*, effectively a strategy for applying MT to future crisis events, using the Haitian crisis of 2010 as a guide. There are two crucial elements to this cookbook: (1) the *content* that would be most useful in crisis situations, and (2) the *infrastructure* to support relief workers.

As noted in §3 a large percentage of the papers we reviewed are corpus papers, and it could be argued that the data collected for these corpora are the *content* that would be useful for developing tools to battle future crises. They consist of real data collected from real users who were involved in real crises.

The next step is trickier: what do the consumers—relief workers, aid providers, etc.—of the tools that might be built over such corpora *need*? In other words, what does the *infrastructure* that they need look like? Do systems described in the papers we surveyed (see §4) fill the need of these consumers? It is clear that *some* of the authors have engaged directly with the crisis community (or work there themselves), as evidenced by the real applications described in §5. But, as a whole, how much of our infrastructural work thus far could be directly consumed in times of crisis?

7 Conclusion

In reviewing the hundreds of papers for this survey, it was obvious throughout almost all of them that the work was being done with good intent: most papers spoke directly to the need to provide aid in crisis situations, and many authors highlighted how their work could help. It was clear that the authors were doing their work with an eye on the greater good. This is laudable and utterly inspiring. In fact, it makes us proud to be LT researchers.

That said, good intentions cannot operate in a vacuum. An important question must be asked: is the work being done for any particular task being done based on *perceived* need, or being done based on *actual* need? If the former, then that disconnect might mean that the work we are doing, no matter how inspiring, may not be consumed by those we think might need it most. It does not diminish the work being done, but it does mean that our lofty aspirations might not be met.

The solution is simple: we should engage with the broader crisis community, *e.g.,* aid providers, NGOs, government bodies, affected communities (including language communities), crisis informatics researchers, crisis or disaster managers (including those operating in a local theater), and any others who engage in crisis response work. This is not necessarily something each individual member of our research community would need to or should take on, but rather the LT community writ large, specifically those who wish to take on the daunting tasks of creating LT4CPR.

The mere fact that there a few hundred papers written over the past five years in the LT4CPR space (per Appendix B and Figure 2) speaks volumes. LT4CPR is not just a passing fad nor some fancy new algorithm: those of us involved are genuinely interested, as a field, in improving the lives of others; indeed, as witnessed so many years ago in Haiti, in *saving* the lives of others.

We hope our survey will generate even more interest across the language technology disciplines in LT4CPR and that it will offer suggestions of differing research paths for those already involved. There is much that has already been done. But there is also so much more that we can do.

[9]It is also important to go where the users are. As an example, in June 2022 there were 1.7B regular users of Tiktok, yet Twitter/X had only 397M. Tiktok's user base is growing but Twitter/X's growth has been relatively flat. See this chart.

[10]It should be noted that Faghihi et al. (2022) is not a timeline extraction or summarization tool, but rather a benchmark designed to support the development of such tools. The benchmark consists of 1,000 crisis event timelines extracted from Twitter for several different crisis types. Resources such as this, which provide for benchmarking on difficult tasks—but tasks that are important to crisis managers—can be very useful for fostering and promoting LT work in such areas.

8 Limitations

This survey included only papers in English published in the five years of 2020-2024, and thus may have missed studies published in other languages or outside this time period.

Due to the large number of papers in the initial set, most papers were manually checked by only one annotator in each stage of screening; thus, annotation errors or inconsistencies are inevitable.

Finally, due to page limits for submission, while 356 papers are included in this survey from which we gathered our statistics, only a small subset of them are discussed individually in our paper.

9 Ethical Considerations

All the papers covered in our survey are publicly available. The two-stage screening process was done by researchers on our team. We are not aware of any ethical issues that arose while conducting our work.

References

Muhammad Abdul-Mageed, AbdelRahim Elmadany, El Moatez Billah Nagoudi, Dinesh Pabbi, Kunal Verma, and Rannie Lin. 2021. Mega-COV: A billion-scale dataset of 100+ languages for COVID-19. In *Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume*, pages 3402–3420, Online. Association for Computational Linguistics.

Naseem Ahmed, Tooba Shahbaz, Asma Shamim, Kiran Shafiq Khan, Samreen Hussain, and Asad Usman. 2020. The covid-19 infodemic: A quantitative analysis through facebook. *Cureus*, 12.

Rajendra Akerkar. 2020. *Big Data in Emergency Management: Exploitation Techniques for Social and Mobile Data*. Springer Nature, Cham, Switzerland.

Firoj Alam, Tausif Alam, Md Abul Hasan, et al. 2022. Medic: a multi-task learning dataset for disaster image classification. *Neural Computing and Applications*, 35:2609–2632.

Firoj Alam, Shafiq Joty, and Muhammad Imran. 2018a. Domain adaptation with adversarial training and graph embeddings. *Preprint*, arXiv:1805.05151.

Firoj Alam, Ferda Ofli, and Muhammad Imran. 2018b. CrisisMMD: Multimodal Twitter Datasets from Natural Disasters. In *Proceedings of the 12th International AAAI Conference on Web and Social Media (ICWSM)*.

Firoj Alam, Ferda Ofli, and Muhammad Imran. 2019. Descriptive and visual summaries of disaster events using artificial intelligence techniques: case studies of hurricanes harvey, irma, and maria. *Behaviour & Information Technology*, 39:288 – 318.

Firoj Alam, Ferda Ofli, Muhammad Imran, Tanvirul Alam, and Umair Qazi. 2020. Deep learning benchmarks and datasets for social media image classification for disaster response. In *2020 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 151–158.

Firoj Alam, Ferda Ofli, Muhammad Imran, and Michael Aupetit. 2018c. A twitter tale of three hurricanes: Harvey, irma, and maria. *Preprint*, arXiv:1805.05144.

Firoj Alam, Umer Qazi, Muhammad Imran, and Ferda Ofli. 2021a. Humaid: Human-annotated disaster incidents data from twitter with deep learning benchmarks. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, pages 933–942.

Firoj Alam, Hassan Sajjad, Muhammad Imran, and Ferda Ofli. 2021b. Crisisbench: Benchmarking crisis-related social media datasets for humanitarian information processing. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 15, pages 923–932.

Humaid Abdulla Alhammadi. 2022. Rit using machine learning in disaster tweets classification using machine learning in disaster tweets classification.

Alaa Alharbi and Mark Lee. 2019. Crisis detection from arabic tweets.

Alaa Alharbi and Mark Lee. 2021. Kawarith: an Arabic Twitter corpus for crisis events. In *Proceedings of the Sixth Arabic Natural Language Processing Workshop*, pages 42–52, Kyiv, Ukraine (Virtual). Association for Computational Linguistics.

Shareefa Al Amer, Mark Lee, and Phillip Smith. 2023. Cross-lingual Classification of Crisis-related Tweets Using Machine Translation. In *Proceedings of Recent Advances in Natural Language Processing*, pages 22–31.

Shareefa Al Amer, Mark Lee, and Phillip Smith. 2024. Adopting ensemble learning for cross-lingual classification of crisis-related text on social media. In *Proceedings of the The Seventh Workshop on Technologies for Machine Translation of Low-Resource Languages (LoResMT 2024)*, pages 159–165.

Sanket Andhale, Pratik Mane, Mandar Vaingankar, Deepak Karia, and K. T. Talele. 2021. Twitter sentiment analysis for covid-19. In *2021 International Conference on Communication information and Computing Technology (ICCICT)*, pages 1–12.

Elena-Simona Apostol, Ciprian-Octavian Truică, and Adrian Paschke. 2023. Contcommrtd: A distributed content-based misinformation-aware community detection system for real-time disaster reporting. *Preprint*, arXiv:2301.12984.

S.G. Arapostathis. 2021. A methodology for automatic acquisition of flood-event management information from social media: the flood in messinia, south greece, 2016. *Information Systems Frontiers*, 23:1127–1144.

Hossein Azarpanah, Mohsen Farhadloo, and Rustam M. Vahidov. 2022. Crisis communications on social media: Insights from canadian officials twitter presence during covid-19 pandemic. In *Hawaii International Conference on System Sciences*.

Rufo Baro and Thelma Palaoag. 2020. Disaster sentiment analysis: Addressing the challenges of decision-makers in visualizing netizen tweets. *IOP Conference Series: Materials Science and Engineering*, 803:012039.

Jason Baumgartner, Savvas Zannettou, Megan Squire, and Jeremy Blackburn. 2020. The pushshift telegram dataset. *Preprint*, arXiv:2001.08438.

L. Belcastro, Fabrizio Marozzo, Domenico Talia, Paolo Trunfio, Francesco Branda, Themis Palpanas, and Muhammad Imran. 2021. Using social media for sub-event detection during disasters. *Journal of Big Data*, 8.

S. Boon-Itt and Y. Skunkan. 2020. Public perception of the covid-19 pandemic on twitter: Sentiment analysis and topic modeling study. *JMIR Public Health and Surveillance*, 6(4):e21978.

Ryan Boston, Naeem Seliya, and Mounika Vanamala. 2024. Analyzing tweets for disaster prediction. *2024 IEEE International Conference on Electro Information Technology (eIT)*, pages 439–443.

Mikael Brunila, Rosie Zhao, Andrei Mircea, Sam Lumley, and Renee Sieber. 2021a. Bridging the gap between supervised classification and unsupervised topic modelling for social-media assisted crisis management. In *Proceedings of the Second Workshop on Domain Adaptation for NLP*, Kyiv, Ukraine.

Mikael Brunila, Rosie Zhao, Andrei Mircea, Sam Lumley, and Renee Sieber. 2021b. Bridging the gap between supervised classification and unsupervised topic modelling for social-media assisted crisis management. In *Proceedings of the Second Workshop on Domain Adaptation for NLP*, pages 33–49, Kyiv, Ukraine. Association for Computational Linguistics.

Umar Ali Bukar, Fatimah Sidi, Marzanah A. Jabar, Rozi Nor Haizan Binti Nor, Salfarina Abdullah, and Iskandar Ishak. 2022. A multistage analysis of predicting public resilience of impactful social media crisis communication in flooding emergencies. *IEEE Access*, 10:57266–57282.

Carlos Castillo. 2016. *Big Crisis Data*. Cambridge University Press, New York.

Pei Chen, Haotian Xu, Cheng Zhang, and Ruihong Huang. 2022. Crossroads, buildings and neighborhoods: A dataset for fine-grained location recognition. In *Proceedings of the 2022 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies*, pages 3329–3339, Seattle, United States. Association for Computational Linguistics.

Shi Chen, Lina Zhou, Yunya Song, Qian Xu, Ping Wang, Kanlun Wang, Yaorong Ge, and Daniel Janies. 2021. A novel machine learning framework for comparison of viral covid-19-related sina weibo and twitter posts: Workflow development and content analysis. *J Med Internet Res*, 23.

Shi Chen, Lina Zhou, Yunya Song, Qian Xu, Ping Wang, Kanlun Wang, Yaorong Ge, and Daniel A. Janies. 2020. A novel machine learning framework for comparison of viral covid-19–related sina weibo and twitter posts: Workflow development and content analysis. *Journal of Medical Internet Research*, 23.

Jishnu Ray Chowdhury, Cornelia Caragea, and Doina Caragea. 2020. Cross-lingual disaster-related multi-label tweet classification with manifold mixup. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 292—298, Online. Association for Computational Linguistics.

Alfredo Cobo, Denis Parra, and Jaime Navón. 2015. Identifying relevant messages in a twitter-based citizen channel for natural disaster situations. In *Proceedings of the 24th International Conference on World Wide Web*, WWW '15 Companion, page 1189–1194, New York, NY, USA. Association for Computing Machinery.

Stefano Cresci, Maurizio Tesconi, Andrea Cimino, and Felice Dell'Orletta. 2015. A linguistically-driven approach to cross-event damage assessment of natural disasters from social media messages. In *Proceedings of the 24th International Conference on World Wide Web*, WWW '15 Companion, page 1195–1200, New York, NY, USA. Association for Computing Machinery.

Hassan Dashtian and Dhiraj Murthy. 2021. Cml-covid: A large-scale covid-19 twitter dataset with latent topics, sentiment and location information. *Preprint*, arXiv:2101.12202.

Leon Derczynski, Alan Ritter, Sam Clark, and Kalina Bontcheva. 2013. Twitter Part-of-Speech Tagging for All: Overcoming Sparse and Noisy Data. In *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP 2013)*, pages 198–206.

Shrey Desai, Cornelia Caragea, and Junyi Jessy Li. 2020. Detecting perceived emotions in hurricane disasters. In *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*, pages 5290–5305, Online. Association for Computational Linguistics.

Wahyu Dirgantara, Fairuz Iqbal Maulana, Subairi Subairi, and Rahman Arifuddin. 2024. The performance of machine learning model bernoulli naïve bayes, support vector machine, and logistic regression on covid-19 in indonesia using sentiment analysis. *Techné : Jurnal Ilmiah Elektroteknika*.

F W Edlim, Gregorius Edo, Rangga Kurnia Putra Wiratama, Riyan Mahmudin, Andi Solihin, Amelia Devi Putri Ariyanto, and Diana Purwitasari. 2024. Urgency detection of events through twitter post: A research overview. *2024 International Conference on Electrical Engineering and Computer Science (ICECOS)*, pages 1–6.

E Elakkiya, Rohit Bahadur Bista, and Chandan Shah. 2024. Deep learning approach for disaster tweet classification. *2024 15th International Conference on Computing Communication and Networking Technologies (ICCCNT)*, pages 1–5.

Laurenti Enzo, Bourgon Nils, Farah Benamara, Mari Alda, Véronique Moriceau, and Courgeon Camille. 2022. Speech acts and communicative intentions for urgency detection. In *Proceedings of the 11th Joint Conference on Lexical and Computational Semantics*, pages 289–298, Seattle, Washington. Association for Computational Linguistics.

Nader Essam, Abdullah Moussa, Khaled Elsayed, Sherif Abdou, Mohsen Rashwan, Shaheen Khatoon, Md Maruf Hasan, Amna Asif, and Majed Alshamari. 2021. Location analysis for arabic covid-19 twitter data using enhanced dialect identification models. *Applied Sciences*, 11.

Hossein Rajaby Faghihi, Bashar Alhafni, Ke Zhang, Shihao Ran, Joel Tetreault, and Alejandro Jaimes. 2022. CrisisLTLSum: A benchmark for local crisis event timeline extraction and summarization. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 5455–5477, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

M. R. Faisal, I. Budiman, F. Abadi, M. Haekal, M. K. Delimayanti, and D. T. Nugrahadi. 2022. Using social media data to monitor natural disaster: A multi dimension convolutional neural network approach with word embedding. *Jurnal RESTI (Rekayasa Sistem Dan Teknologi Informasi)*, 6(6):1037–1046.

Hussam N. Fakhouri, Basim Alhadidi, Khalil Omar, Sharif Naser Makhadmeh, Faten Hamad, and Niveen Z. Halalsheh. 2024. Ai-driven solutions for social engineering attacks: Detection, prevention, and response. *2024 2nd International Conference on Cyber Resilience (ICCR)*, pages 1–8.

Badreddine Farah, Omar El Bachyr, Guillaume Cleuziou, Anaïs Halftermeyer, Cécile Gracianne, Samuel Auclair, Adel Hafiane, and Raphaël Canals. 2024. M-CATNAT: A Multimodal dataset to analyze French tweets during natural disasters. In *Proceedings of the 21st ISCRAM Conference*, Münster, Germany.

Selim Fekih, Nicolo' Tamagnone, Benjamin Minixhofer, Ranjan Shrestha, Ximena Contla, Ewan Oglethorpe, and Navid Rekabsaz. 2022. HumSet: Dataset of multilingual information extraction and classification for humanitarian crises response. In *Findings of the Association for Computational Linguistics: EMNLP 2022*, pages 4379–4389, Abu Dhabi, United Arab Emirates. Association for Computational Linguistics.

Shihui Feng and Alec Kirkley. 2020. Online geolocalized emotion across us cities during the covid crisis: Universality, policy response, and connection with local mobility. *ArXiv*, abs/2009.10461.

Cornelia Ferner, Clemens Havas, Elisabeth Birnbacher, Stefan Wegenkittl, and Bernd Resch. 2020. Automated seeded latent dirichlet allocation for social media based event detection and mapping. *Information*, 11:376.

Akash Kumar Gautam, Luv Misra, Ajit Kumar, Kush Misra, Shashwat Aggarwal, and Rajiv Ratn Shah. 2019. Multimodal analysis of disaster tweets. *2019 IEEE Fifth International Conference on Multimedia Big Data (BigMM)*, pages 94–103.

Pablo Giaccaglia, Carlo A. Bono, and Barbara Pernici. 2024. Enhancing Emergency Post Classification through Image Information Amplification via Large Language Models. In *21st International Conference on Information Systems for Crisis Response and Management, ISCRAM 2024*, Münster, Germany.

Ilias Gialampoukidis, Stelios Andreadis, Stefanos Vrochidis, and Ioannis Kompatsiaris. 2021. Multimodal data fusion of social media and satellite images for emergency response and decision-making. In *2021 IEEE International Geoscience and Remote Sensing Symposium IGARSS*, pages 228–231.

Robert Grace. 2020. Crisis social media data labeled for storm-related information and toponym usage. *Data in Brief*, 30.

Christine Hagar. 2010. Crisis informatics: Introduction. *Bulletin of the American Society for Information Science and Technology*, 36(5):10–12.

Christine Hagar. 2014. Crisis informatics. *Journal of Geography and Natural Disasters*, 4(1).

Btool Hamoui, Mourad Mars, and Khaled Almotairi. 2020. FloDusTA: Saudi tweets dataset for flood, dust storm, and traffic accident events. In *Proceedings of the Twelfth Language Resources and Evaluation Conference*, pages 1391–1396, Marseille, France. European Language Resources Association.

Fatima Haouari, Maram Hasanain, Reem Suwaileh, and Tamer Elsayed. 2021. ArCOV-19: The first Arabic COVID-19 Twitter dataset with propagation networks. In *Proceedings of the Sixth Arabic Natural Language Processing Workshop*, pages 82–91, Kyiv, Ukraine (Virtual). Association for Computational Linguistics.

Veneta Haralampieva, Ozan Caglayan, and Lucia Specia. 2022. Supervised Visual Attention for Simultaneousmultimodal Machine Translation. *Journal of Artificial Intelligence Research*, 74.

Syed Zohaib Hassan, Kashif Ahmad, Steven Alexander Hicks, P. Halvorsen, Ala Al-Fuqaha, Nicola Conci, and M. Riegler. 2020. Visual sentiment analysis from disaster images in social media. *Sensors (Basel, Switzerland)*, 22.

Sanjana V Herur, Shalini M, Vanshika Jain, and Mamatha H R. 2023. Simple yet efficient model for disaster related data detection. *2023 IEEE 2nd International Conference on Data, Decision and Systems (ICDDS)*, pages 1–6.

Tamanna Hossain, Robert L Logan Iv, Arjuna Ugarte, Yoshitomo Matsubara, Sean Young, and Sameer Singh. 2020. COVIDLies: Detecting COVID-19 Misinformation on Social Media. In *Proceedings of the 1st Workshop on NLP for COVID-19 (Part 2) at EMNLP 2020*.

Wenbo Hu, Yifan Xu, Yi Li, Weiyue Li, Zeyuan Chen, and Zhuowen Tu. 2024. Bliva: A simple multimodal llm for better handling of text-rich visual questions. *Proceedings of the AAAI Conference on Artificial Intelligence*, 38(3):2256–2264.

Amanda Lee Hughes and Leysia Palen. 2010. Twitter adoption and use in mass convergence and emergency events. *International Journal of Emergency Management*, 6(3-4).

S. Höhn, S. Mauw, and N. Asher. 2022. Belelect: A new dataset for bias research from a “dark” platform. In *Proceedings of the International AAAI Conference on Web and Social Media*, volume 16, pages 1268–1274.

Muhammad Imran, Prasenjit Mitra, and Carlos Castillo. 2016. Twitter as a lifeline: Human-annotated Twitter corpora for NLP of crisis-related messages. In *Proceedings of the Tenth International Conference on Language Resources and Evaluation (LREC‘16)*, pages 1638–1643, Portorož, Slovenia. European Language Resources Association (ELRA).

Muhammad Imran, Umair Qazi, and Ferda Ofli. 2021a. Tbcov: Two billion multilingual covid-19 tweets with sentiment, entity, geo, and gender labels. arXiv:2110.03664.

Muhammad Imran, Umair Qazi, and Ferda Ofli. 2021b. TBCOV: two billion multilingual COVID-19 tweets with sentiment, entity, geo, and gender labels. *CoRR*, abs/2110.03664.

Shaunak Inamdar, Rishikesh Chapekar, Shilpa Gite, and Biswajeet Pradhan. 2023. Machine learning driven mental stress detection on reddit posts using natural language processing. *Human-Centric Intelligent Systems*, 3:80 – 91.

Becky Inkster. 2021. Early warning signs of a mental health tsunami: A coordinated response to gather initial data insights from multiple digital services providers. *Frontiers in Digital Health*, 2.

Gutti Gowri Jayasurya, Sanjay Kumar, Binod Kumar Singh, and Vinay Kumar. 2022. Analysis of public sentiment on covid-19 vaccination using twitter. *IEEE Transactions on Computational Social Systems*, 9:1101–1111.

Asinthara K, Meghna Jayan, and Lija Jacob. 2023. Categorizing disaster tweets using learning based models for emergency crisis management. In *2023 9th International Conference on Advanced Computing and Communication Systems (ICACCS)*, volume 1, pages 1133–1138.

Mahakprit Kaur, Taylor Cargill, Kevin Hui, Minh Vu, Nicola Luigi Bragazzi, and Jude Dzevela Kong. 2023. A novel approach for the early detection of medical resource demand surges during health care emergencies: Infodemiology study of tweets. *JMIR Formative Research*, 8.

Efsun Sarioglu Kayi, Linyong Nan, Bohan Qu, Mona T. Diab, and Kathleen McKeown. 2020. Detecting urgency status of crisis tweets: A transfer learning approach for low resource languages. In *International Conference on Computational Linguistics*.

Temitope Kekere, Vukosi Marivate, and Marie J. Hattingh. 2023. Exploring covid-19 public perceptions in south africa through sentiment analysis and topic modelling of twitter posts. *The African Journal of Information and Communication (AJIC)*.

Sarthak Khanal, Maria Traskowsky, and Doina Caragea. 2022. Identification of fine-grained location mentions in crisis tweets. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 7164–7173, Marseille, France. European Language Resources Association.

Shaheen Khatoon, Majed Alshamari, Amna Asif, Md Maruf Hasan, Sherif Abdou, Khaled Elsayed, and Mohsen Rashwan. 2021. Development of social media analytics system for emergency event detection and crisis management. *Computers, Materials & Continua*, 68:3079–3100.

Sandeep Khurana, Ruchir Chopra, and Bharti Khurana. 2021. Automated processing of social media content for radiologists: applied deep learning to radiological content on twitter during covid-19 pandemic. *Emergency Radiology*, 28:477–483.

Jannes Klaas. 2017. Disasters on social media.

Vrushali Koli, Jun Yuan, and Aritra Dasgupta. 2024. Sensemaking of socially-mediated crisis information. In *Proceedings of the Third Workshop on Bridging Human–Computer Interaction and Natural Language Processing*, pages 74–81, Mexico City, Mexico. Association for Computational Linguistics.

Diego Kozlowski, Elisa Lannelongue, Frédéric Saudemont, Farah Benamara, Alda Mari, Véronique Moriceau, and Abdelmoumene Boumadane. 2020a. A three-level classification of french tweets in ecological crises. *Inf. Process. Manag.*, 57:102284.

Diego Kozlowski, Elisa Lannelongue, Frédéric Saudemont, Farah Benamara, Alda Mari, Véronique Moriceau, and Abdelmoumene Boumadane. 2020b. A three-level classification of French tweets in ecological crises. *Information Processing and Management*, 57(5).

Sangeeta Kumawat, Gideon Sodipo, Deepak Palei, Safa Shubbar, and Kambiz Ghazinour. 2024. An evaluation of machine learning models for analyzing disaster-related tweets. *2024 7th International Conference on Information and Computer Technologies (ICICT)*, pages 105–110.

Kelvin Lai, Jeremy Porter, Mike Amodeo, David Miller, Michael Marston, and Saman Armal. 2022. A natural language processing approach to understanding context in the extraction and geocoding of historical floods, storms, and adaptation measures. *Information Processing & Management*, 59:102735.

Rabindra Lamsal, Maria Rodriguez Read, and Shanika Karunasekera. 2023. Billioncov: An enriched billion-scale collection of covid-19 tweets for efficient hydration. *Data in Brief*, 48:109229.

Séamus Lankford and Andy Way. 2024. Leveraging LLMs for MT in crisis scenarios: a blueprint for low-resource languages. arXiv:2410.23890.

Enzo Laurenti, Nils Bourgon, Farah Benamara, Alda Mari, Véronique Moriceau, and Camille Courgeon. 2022. Give me your intentions, I'll predict our actions: A two-level classification of speech acts for crisis management in social media. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 4333–4343, Marseille, France. European Language Resources Association.

Jake Lever and R. Arcucci. 2022. Sentimental wildfire: a social-physics machine learning model for wildfire nowcasting. *Journal of Computational Social Science*, 5.

William D. Lewis. 2010. Haitian Creole: How to Build and Ship an MT Engine from Scratch in 4 Days, 17 Hours, & 30 Minutes. In *Proceedings of the 14th EAMT*, Saint Raphaël, France.

William D. Lewis, Robert Munro, and Stephan Vogel. 2011. Crisis MT: Developing A Cookbook for MT in Crisis Situations. In *Proceedings of the Sixth Workshop on Statistical Machine Translation*, Edinburgh, Scotland.

Kai Li, Cheng Zhou, Xin (Robert) Luo, Jose Benitez, and Qinyu Liao. 2022a. Impact of information timeliness and richness on public engagement on social media during covid-19 pandemic: An empirical investigation based on nlp and machine learning. *Decision Support Systems*, 162:113752.

Lifang Li, Qingpeng Zhang, Xiao Wang, Jun Zhang, Tao Wang, Tian-Lu Gao, Wei Duan, Kelvin Kam-fai Tsoi, and Fei-Yue Wang. 2020. Characterizing the propagation of situational information in social media during covid-19 epidemic: A case study on weibo. *IEEE Transactions on Computational Social Systems*, 7(2):556–562.

Luanying Li, Lin Hua, and Fei Gao. 2022b. What we ask about when we ask about quarantine? content and sentiment analysis on online help-seeking posts during covid-19 on a q&a platform in china. *International Journal of Environmental Research and Public Health*, 20.

Tong Li, Xin Wang, Yong tian Yu, Guangyuan Yu, and Xue Tong. 2023. Exploring the dynamic characteristics of public risk perception and emotional expression during the covid-19 pandemic on sina weibo. *Syst.*, 11:45.

Xintian Li, Samiul Hasan, and Aron Culotta. 2022c. Identifying hurricane evacuation intent on twitter. In *In Proceedings of the 16th International AAAI Conference on Web and Social Media*.

Junhua Liu, Trisha Singhal, Lucienne Blessing, Kristin Wood, and Kwan Hui Lim. 2020. Epic: An epidemics corpus of over 20 million relevant tweets.

Sophia Liu. 2014. Crisis crowdsourcing framework: Designing strategic configurations of crowdsourcing for the emergency management domain. *Computer Supported Cooperative Work (CSCW)*, 23:389–443.

Yingdan Lu, Jennifer Pan, and Yiqing Xu. 2021. Public sentiment on chinese social media during the emergence of covid-19. Research Paper 2021-04, 21st Century China Center.

Mingjun Ma, Qiang Gao, Zishuang Xiao, Xingshuai Hou, Beibei Hu, Lifei Jia, and Wenfang Song. 2022. Analysis of public emotion on flood disasters in southern china in 2020 based on social media data.

Costanza Marini and Elisabetta Jezek. 2024. What to annotate: Retrieving lexical markers of conspiracy discourse from an Italian-English corpus of telegram data. In *Proceedings of the 20th Joint ACL - ISO Workshop on Interoperable Semantic Annotation @ LREC-COLING 2024*, pages 47–52, Torino, Italia. ELRA and ICCL.

E. Massaad and P. Cherfan. 2020. Social media data analytics on telehealth during the covid-19 pandemic. *Cureus*, 12(4):e7838.

R. McCreadie and C. Buntain. 2023. Crisisfacts: Building and evaluating crisis timelines. In *20th International Conference on Information Systems for Crisis Response and Management (ISCRAM 2023)*, pages 320–339, Omaha, NE, USA.

Patrick Meier. 2015. *Digital Humanitarians*. CRC Press, Boca Raton.

Khondhaker Momin and H M Imran Kays. 2023. Identifying crisis response communities in online social networks for compound disasters: The case of hurricane laura and covid-19. *Transportation Research Record Journal of the Transportation Research Board*, 0:0.

Hussein Mozannar, Yara Rizk, and Mariette Awad. 2018. Damage identification in social media posts using multimodal deep learning. In *International Conference on Information Systems for Crisis Response and Management*.

Robert Munro. 2013. Crowdsourcing and the crisis-affected community: lessons learned and looking forward from mission 4636. *Journal of Information Retrieval*, 16.

Akiko Murakami, Tetsuya Nasukawa, Kenta Watanabe, and Michinori Hatayama. 2020. Understanding requirements and issues in disaster area using geotemporal visualization of Twitter analysis. *IBM Journal of Research and Development*, 64(1/2):10:1–10:8.

Javaria Naeem, I Parlak, Kostas Karpouzis, Y Salman, Seifedine Kadry, and Omer Gul. 2024. Detection of misinformation related to pandemic diseases using machine learning techniques in social media platforms. *EAI Endorsed Transactions on Pervasive Health and Technology*.

Dat T. Nguyen, Ferda Ofli, Muhammad Imran, and Prasenjit Mitra. 2017. Damage assessment from social media imagery data during disasters. In *2017 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*, pages 569–576.

Demola Obembe, Oluwaseun Kolade, Funmi Obembe, Adebowale Owoseni, and Oluwasoye Mafimisebi. 2021. Covid-19 and the tourism industry: An early stage sentiment analysis of the impact of social media and stakeholder communication. *Journal of Information Management and Economics*, 2021:100040.

Alexandra Olteanu, Carlos Castillo, Nicholas A. Diakopoulos, and Karl Aberer. 2015a. Comparing events coverage in online news and social media: The case of climate change. In *International Conference on Web and Social Media*.

Alexandra Olteanu, Sarah Vieweg, and Carlos Castillo. 2015b. What to expect when the unexpected happens: Social media communications across crises. In *Proceedings of the Conference on Computer-Supported Cooperative Work (CSCW)*, Vancouver, British Columbia.

Alexandra Olteanu, Ingmar Weber, and Daniel Gatica-Perez. 2015c. Characterizing the demographics behind the blacklivesmatter movement. *Preprint*, arXiv:1512.05671.

Swati Padhee, Tanay Kumar Saha, Joel Tetreault, and Alejandro Jaimes. 2020. Clustering of social media messages for humanitarian aid response during crisis. *Preprint*, arXiv:2007.11756.

Leysia Palen and Kenneth M. Anderson. 2016. Crisis informatics—new data for extraordinary times. *Science*, 353:224–225.

Mohammad S. Parsa, Lukasz Golab, and S. Keshav. 2021. Climate action during covid-19 recovery and beyond: A twitter text mining study. *ArXiv*, abs/2105.12190.

Udit Paul, Alexander Ermakov, Michael Nekrasov, Vivek Adarsh, and Elizabeth Belding. 2020. outage: Detecting power and communication outages from social networks. In *Proceedings of The Web Conference 2020*, WWW '20, page 1819–1829, New York, NY, USA. Association for Computing Machinery.

Julia Proskurnia, Karl Aberer, and Philippe Cudré-Mauroux. 2016. Please sign to save... : How online environmental petitions succeed. In *EcoMo@ICWSM*.

Umair Qazi, Muhammad Imran, and Ferda Ofli. 2020. Geocov19: a dataset of hundreds of millions of multilingual covid-19 tweets with location information. *SIGSPATIAL Special*, 12(1):6–15.

Camilo Restrepo-Estrada, Sidgley Camargo de Andrade, Narumi Abe, Maria Clara Fava, Eduardo Mario Mendiondo, and João Porto de Albuquerque. 2018. Geo-social media as a proxy for hydrometeorological data for streamflow estimation and to improve flood monitoring. *Computers & Geosciences*, 111:148–158.

Dimitrios Roussis. 2022. Building End-to-End Neural Machine Translation Systems for Crisis Scenarios: The Case of COVID-19.

Kamol Chandra Roy, Samiul Hasan, Aron Culotta, and Naveen Eluru. 2021. Predicting traffic demand during hurricane evacuation using real-time data from transportation systems and social media. *Transportation Research Part C: Emerging Technologies*, 131.

Elizabeth Salesky, Philipp Koehn, and Matt Post. 2024. Benchmarking visually-situated translation of text in natural images. In *Proceedings of the Ninth Conference on Machine Translation*, pages 1167–1182, Miami, Florida, USA. Association for Computational Linguistics.

Rupak Sarkar, Hirak Sarkar, Sayantan Mahinder, and Ashiqur R. KhudaBukhsh. 2020. Social Media Attributions in the Context of Water Crisis. arXiv:2001.01697v1.

M. Janina Sarol, Ly Dinh, Rezvaneh Rezapour, Chieh-Li Chin, Pingjing Yang, and Jana Diesner. 2020. An empirical methodology for detecting and prioritizing needs during crisis events. In *Findings of the Association for Computational Linguistics: EMNLP 2020*, pages 4102–4107, Online. Association for Computational Linguistics.

MSVPJ Sathvik, Abhilash Dowpati, and Srreyansh Sethi. 2024. Ukrainian Resilience: A Dataset for Detection of Help-Seeking Signals Amidst the Chaos of War. In *Findings of the Association for Computational Linguistics: EMNLP 2024*, pages 294–300, Online. Association for Computational Linguistics.

Anatolii Shestakov and Wajdi Zaghouani. 2024. Analyzing conflict through data: A dataset on the digital framing of sheikh jarrah evictions. In *Proceedings of the Second Workshop on Natural Language Processing for Political Sciences @ LREC-COLING 2024*, pages 55–67, Torino, Italia. ELRA and ICCL.

Rainer Simon, Dražen Ignjatović, Georg Neubauer, Clemens Gutschi, Johannes Pan, and Siegfried Vössner. 2021. Applying data mining techniques in the context of social media to improve situational awareness at large-scale events. In *Proceedings of the International Conference on Electrical, Computer, Communications and Mechatronics Engineering (ICECCME)*, Mauritius.

Varvara Solopova, Tatjana Scheffler, and Mihaela Popa-Wyatt. 2021. A telegram corpus for hate speech, offensive language, and online harm. *Journal of Open Humanities Data*, 7(0):9.

Jose Sosa and Serge Sharoff. 2022. Multimodal Pipeline for Collection of Misinformation Data from Telegram. In *Proceedings of the 13th Conference on Language Resources and Evaluation (LREC 2022)*, pages 1480–1489, Marseille. European Language Resources Association (ELRA).

Tiberiu Sosea, Shrey Desai, Amitava Das, Anil Ramakrishna, Rudra Murthy, Mark Finlayson, and Eduardo Blanco. 2021. Using the image-text relationship to improve multimodal disaster tweet classification. In *Proceedings of the 18th ISCRAM Conference – Social Media for Disaster Response and Resilience*.

Tiberiu Sosea, Junyi Jessy Li, and Cornelia Caragea. 2024. Sarcasm detection in a disaster context. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 14313–14324, Torino, Italia. ELRA and ICCL.

Tiberiu Sosea, Chau Pham, Alexander Tekle, Cornelia Caragea, and Junyi Jessy Li. 2022. Emotion analysis and detection during COVID-19. In *Proceedings of the Thirteenth Language Resources and Evaluation Conference*, pages 6938–6947, Marseille, France. European Language Resources Association.

Kate Starbird, Jim Maddock, Mania Orand, Peg Achterman, and Robert M. Mason. 2014. Rumors, false flags, and digital vigilantes: Misinformation on twitter after the 2013 boston marathon bombing. In *Iconference 2014 Proceedings*.

Muhammad Suleman, Muhammad Asif, Tayyab Zamir, Ayaz Mehmood, Jebran Khan, Nasir Ahmad, and Kashif Ahmad. 2023. Floods relevancy and identification of location from twitter posts using nlp techniques. *Preprint*, arXiv:2301.00321.

Jeannette Sutton, Leysia Palen, and Irina Shklovski. 2008. Backchannels on the front lines: Emergent uses of social media in the 2007 southern california wildfires. In *Proceedings of the 5th International ISCRAM Conference*, Washington, DC.

Reem Suwaileh, Tamer Elsayed, and Muhammad Imran. 2023a. IDRISI-D: Arabic and English datasets and benchmarks for location mention disambiguation over disaster microblogs. In *Proceedings of ArabicNLP 2023*, pages 158–169, Singapore (Hybrid). Association for Computational Linguistics.

Reem Suwaileh, Tamer Elsayed, and Muhammad Imran. 2023b. Idrisi-re: A generalizable dataset with benchmarks for location mention recognition on disaster tweets. *Inf. Process. Manage.*, 60(3).

Reem Suwaileh, Tamer Elsayed, Muhammad Imran, and Hassan Sajjad. 2022. When a disaster happens, we are ready: Location mention recognition from crisis tweets. *International Journal of Disaster Risk Reduction*, 78:103107.

Reem Suwaileh, Muhammad Imran, and Tamer Elsayed. 2023c. IDRISI-RA: The first Arabic location mention recognition dataset of disaster tweets. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pages 16298–16317, Toronto, Canada. Association for Computational Linguistics.

D. Tin, L. Cheng, D. Le, R. Hata, and G.Ciottone. 2024. Natural disasters: a comprehensive study using EM-DAT database 1995–2022. *Public Health*, 226:255–260.

Jennifer Tracey and Stephanie Strassel. 2020. Basic language resources for 31 languages (plus English): The LORELEI representative and incident language packs. In *Proceedings of the 1st Joint Workshop on Spoken Language Technologies for Under-resourced languages (SLTU) and Collaboration and Computing for Under-Resourced Languages (CCURL)*, pages 277–284, Marseille, France. European Language Resources association.

A. C. Tricco, E. Lillie, W. Zarin, K. K. O'Brien, H. Colquhoun, D. Levac, D. Moher, M. D. J. Peters, T. Horsley, L. Weeks, S. Hempel, E. A. Akl, C. Chang, J. McGowan, L. Stewart, L. Hartling, A. Aldcroft, M. G. Wilson, C. Garritty, S. Lewin, C. M. Godfrey, M. T. Macdonald, E. V. Langlois, K. Soares-Weiser, J. Moriarty, T. Clifford, Tuncalp, and S. E. Straus. 2018. Prisma extension for scoping reviews (prisma-scr): Checklist and explanation. *Annual Intern. Medicine*, (7).

Roopal Vaid, Kartikey Pant, and Manish Shrivastava. 2022. Towards Fine-grained Classification of Climate Change related Social Media Text. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics: Student Research Workshop*, pages 434–443, Dublin. Association for Computational Linguistics.

Sarah Vieweg, Amanda Lee Hughes, Kate Starbird, and Leysia Palen. 2010. Microblogging during Two Natural Hazards Events: What Twitter May Contribute to Situational Awareness. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*.

C. Villavicencio, J. J. Macrohon, X. A. Inbaraj, J.-H. Jeng, and J.-G. Hsieh. 2021. Twitter sentiment analysis towards covid-19 vaccines in the philippines using naïve bayes. *Information*, 12(5):204.

Fedor Vitiugin and Carlos Castillo. 2022. Cross-lingual query-based summarization of crisis-related social media: An abstractive approach using transformers. In *In Proceedings of Proceedings of the 33rd ACM Conference on Hypertext and Social Media (HT-2022)*, pages 21–31.

Chenguang Wang, Davis Engler, Xuechun Li, James Hou, David J. Wald, Kishor Jaiswal, and Susu Xu. 2024a. Near-real-time earthquake-induced fatality estimation using crowdsourced data and large-language models. *International Journal of Disaster Risk Reduction*, 111.

Di Wang, Yuan Zhuang, Ellen Riloff, and Marina Kogan. 2024b. Recognizing social cues in crisis situations. In *Proceedings of the 2024 Joint International Conference on Computational Linguistics, Language Resources and Evaluation (LREC-COLING 2024)*, pages 13677–13687, Torino, Italia. ELRA and ICCL.

Haoyu Wang, Eduard Hovy, and Mark Dredze. 2015. The hurricane sandy twitter corpus. In *The World Wide Web and Public Health Intelligence - Papers Presented at the 29th AAAI Conference on Artificial Intelligence, Technical Report*, AAAI Workshop - Technical Report, pages 20–24. AI Access Foundation. Publisher Copyright: Copyright © 2015, Association for the Advancement of Artificial Intelligence (www.aaai.org). All rights reserved.; 29th AAAI Conference on Artificial Intelligence, AAAI 2015 ; Conference date: 25-01-2015 Through 30-01-2015.

J. Wang, Y. Zhou, W. Zhang, R. Evans, and C. Zhu. 2020. Concerns expressed by chinese social media users during the covid-19 pandemic: Content analysis of sina weibo microblogging data. *Journal of Medical Internet Research*, 22(11):e22152.

Y. Wang, E. Willis, V.K. Yeruva, et al. 2023. A case study of using natural language processing to extract consumer insights from tweets in american cities for public health crises. *BMC Public Health*, 23:935.

Zhuoli Xie, Ajay Jayanth, Kapil Yadav, Guanghui Ye, and Lingzi Hong. 2021. Multi-faceted classification for the identification of informative communications during crises: Case of covid-19. In *2021 IEEE 45th Annual Computers, Software, and Applications Conference (COMPSAC)*, pages 924–933.

Tengfei Yang, Jibo Xie, Guoqing Li, Lianchong Zhang, Naixia Mou, Huan Wang, Xiaohan Zhang, and Xiaodong Wang. 2022. Extracting disaster-related location information through social media to assist remote sensing for disaster analysis: The case of the flood disaster in the Yangtze River Basin in China in 2020. *Remote Sensing*, 14(5):1199.

Faxi Yuan, Yang Yang, Qingchun Li, and Ali Mostafavi. 2021. Unraveling the temporal importance of community-scale human activity features for rapid assessment of flood impacts. *IEEE Access*, 10:1138–1150.

Kiran Zahra, Muhammad Imran, and Frank O. Ostermann. 2020. Automatic identification of eyewitness messages on twitter during disasters. *Inf. Process. Manage.*, 57(1).

Jiale Zhang, Manyu Liao, Yanping Wang, Yifan Huang, Fuyu Chen, and Chiba Makiko. 2024a. Multi-modal deep learning framework for damage detection in social media posts. *PeerJ Computer Science*, 10.

Yuan Zhang, Lin Fu, Xingyu Guo, and Mengkun Li. 2024b. Dynamic insights: Unraveling public demand evolution in health emergencies through integrated language models and spatial-temporal analysis. *Risk Management and Healthcare Policy*, 17:2443 – 2455.

Shi Zong, Ashutosh Baheti, Wei Xu, and Alan Ritter. 2022. Extracting a knowledge base of COVID-19 events from social media. In *Proceedings of the 29th International Conference on Computational Linguistics*, pages 3810–3823, Gyeongju, Republic of Korea. International Committee on Computational Linguistics.

A Disaster Types

Table 1 shows Crisis categories and sub-categories from Olteanu et al., 2015b; Castillo, 2016.

B Corpus Papers Included in this Survey

Table 2-6 show the full list of 91 corpus papers included in this survey, with the basic information about the corpora presented in these studies:

- The columns show the corpus name, the year of the publication, social media platform, crisis type, modality, language, annotation type, and the link to the corpus or the publication.
- The crisis types are C1 (natural disaster), C2 (health-related crisis), C3 (human-induced crisis), and C4 (multiple types of crises).
- We use 3-letter language codes for Arabic (ara), Belarusian (bel), Catalan (cat), Chinese (zho), Croatian (hrv), English (eng), French (fra), German (deu), Indonesian (ind), Japanese (jpn), Portuguese (por), Russian (rus), Spanish (spa), Tagalog (tgl), and Ukrainian (ukr).
- Annotation types are A0-A6 as descibed in Section 3.2: A0 (no additional annotation), A1 (class labels), A2 (entities, relations, and events), A3 (geo-location), A4 (summary), and A5 (other types of annotaton).

While our corpus papers were published in 2020-2024, there are dozens of corpora that were released before 2020 and have been used in multiple studies since their release. We include those corpora in Table 7.

Category	Subcategory	Examples
Natural	• Meteorological • Hydrological • Geophysical • Climatological • Biological	• tornado, hurricane • flood, landslide • earthquake, volcano • wildfire, heat/cold wave • epidemic, infestation
Anthropogenic (Human-Induced)	• Sociological (intentional) • Technological (accidental)	• shooting, bombing • derailment, building collapse

Table 1: Crisis categories and sub-categories (from Olteanu et al., 2015b; Castillo, 2016)

Dataset	Year	Platform	Crisis Type	Language	Modality	Annotation	Link
ArCOV-19 (Haouari et al., 2021)	2020	twitter/x	C2	ara	text	A5	https://aclanthology.org/2021.wanlp-1.9/
COVIDLies (Hossain et al., 2020)	2020	twitter/x	C2	eng	text	A0	https://aclanthology.org/2020.nlpcovid19-2.11/
CrisisImage-Benchmarks (Alam et al., 2020)	2020	twitter/x, instagram	C1	N/A	image	A1	url
Crisis Tweets with Urgency Labels in English, Odia and Sinhala (Kayi et al., 2020)	2020	twitter/x	C1	multi	text	A1	https://github.com/niless/urgency
EPIC (Liu et al., 2020)	2020	twitter/x	C2	eng	text	A0	https://www.researchgate.net/publication/342197963_EPIC_An_Epidemics_Corpus_Of_Over_20_Million_Relevant_Tweets
EyewitnessTweets (Zahra et al., 2020)	2020	twitter/x	C1	eng	text	A1	https://crisisnlp.qcri.org
FloDusTA (Hamoui et al., 2020)	2020	twitter/x	C1	ara	text	A2	https://github.com/BatoolHamawi/FloDusTA
French Ecological Crisis (Kozlowski et al., 2020a)	2020	twitter/x	C1	fra	text	A1	https://github.com/DiegoKoz/french_ecological_crisis
GeoCoV19 (Qazi et al., 2020)	2020	twitter/x	C2	multi	text	A3	https://crisisnlp.qcri.org/covid19
HurricaneEmo (Desai et al., 2020)	2020	twitter/x	C1	eng	text	A1	https://github.com/shreydesai/hurricane
LORELEI Representative and Incident Language Packs (Tracey and Strassel, 2020)	2020	various	C1	multi	text	A1, A2, A5	https://aclanthology.org/2020.sltu-1.39/
Multilingual-BERT-Disaster (Chowdhury et al., 2020)	2020	twitter/x	C4	multi	text	A1	link
Pushshift Telegram (Baumgartner et al., 2020)	2020	telegram	C3	eng	text	A0	https://paperswithcode.com/dataset/pushshift-telegram
Social Media Attributions of Youtube Comments (Sarkar et al., 2020)	2020	youtube	C2	eng	text	A1	link
Storm-Related Social Media (SSM) (Grace, 2020)	2020	twitter/x	C1	eng	text	A1	https://data.mendeley.com/datasets/5c3cpnvgx3/1

Table 2: Corpus Papers in 2020-2024 and the corresponding datasets (Part 1)

Dataset	Year	Platform	Crisis Type	Language	Modality	Annotation	Link
#Outage (Paul et al., 2020)	2020	twitter/x	C1	eng	text	A1	https://dl.acm.org/doi/abs/10.1145/3366423.3380251
(Ahmed et al., 2020)	2020	facebook	C2	eng	text	A1	link
(Boon-Itt and Skunkan, 2020)	2020	twitter/x	C2	eng	text	A1	https://publichealth.jmir.org/2020/4/e21978
(Chen et al., 2020)	2020	twitter/x, weibo	C2	multi	text	A1, A2	link
(Feng and Kirkley, 2020)	2020	twitter/x	C2	eng	text	A3	link
(Hassan et al., 2020)	2020	twitter/x, flickr, google	C1	N/A	image	A1	link
(Li et al., 2020)	2020	weibo	C2	zho	text	A1	https://ieeexplore.ieee.org/abstract/document/9043580
(Massaad and Cherfan, 2020)	2020	twitter/x	C2	eng	text	A2, A3	https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7250522/
(Padhee et al., 2020)	2020	twitter/x	C1	eng	text	A1	https://arxiv.org/abs/2007.11756
(Sarol et al., 2020)	2020	twitter/x	C2	eng	text	A2	https://aclanthology.org/2020.findings-emnlp.366/
(Wang et al., 2020)	2020	weibo	C2	zho	text	A1	https://www.jmir.org/2020/11/e22152/
CML-COVID (Dashtian and Murthy, 2021)	2021	twitter/x	C2	multi	text	A0	https://dataverse.tdl.org/dataset.xhtml?persistentId=doi:10.18738/T8/W1CHVU
CrisisBench (Alam et al., 2021b)	2021	twitter/x	C4	multi	text	A1	https://crisisnlp.qcri.org/crisis_datasets_benchmarks
DisRel (Sosea et al., 2021)	2021	twitter/x	C1	eng	text, image	A1	https://github.com/tsosea2/DisRel
HumAID (Alam et al., 2021a)	2021	twitter/x	C4	eng	text	A1	https://crisisnlp.qcri.org/humaid_dataset#
Kawarith (Alharbi and Lee, 2021)	2021	twitter/x	C4	ara	text	A1	https://github.com/alaa-a-a/kawarith
Mega-COV (Abdul-Mageed et al., 2021)	2021	twitter/x	C2	multi	text	A1	https://aclanthology.org/2021.eacl-main.298/
Telegram Chat Corpus (Solopova et al., 2021)	2021	telegram	C3	eng	text	A1	https://osf.io/ck3gd/

Table 3: Corpus Papers in 2020-2024 and the corresponding datasets (Part 2)

Dataset	Year	Platform	Crisis Type	Language	Modality	Annotation	Link
TBCOV (Imran et al., 2021b)	2021	twitter/x	C2	multi	text	A1, A2, A3	https://crisisnlp.qcri.org/tbcov
(Andhale et al., 2021)	2021	twitter/x	C2	eng	text	A1	https://ieeexplore.ieee.org/abstract/document/9509933
(Arapostathis, 2021)	2021	twitter/x	C1	eng, spa, tam	text	A1, A3	link
(Brunila et al., 2021b)	2021	twitter/x	C1	eng	text	A1	https://aclanthology.org/2021.adaptnlp-1.5.pdf
(Chen et al., 2021)	2021	twitter/x, weibo	C2	eng, zho	text	A1	link
(Inkster, 2021)	2021	digital service providers	C2	eng	text	A1	link
(Khurana et al., 2021)	2021	twitter/x	C2	eng	text, image	A1	https://rdcu.be/d9XBI
(Lu et al., 2021)	2021	weibo	C2	zho	text	A3	https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3757135
(Obembe et al., 2021)	2021	twitter/x	C2	eng	text	A1	link
(Parsa et al., 2021)	2021	twitter/x	C4	eng	text	A1	link
(Villavicencio et al., 2021)	2021	twitter/x	C2	eng, tgl	text	A1	https://www.mdpi.com/2078-2489/12/5/204
(Xie et al., 2021)	2021	twitter/x	C2	eng	text	A1	https://ieeexplore.ieee.org/abstract/document/9529603
(Yuan et al., 2021)	2021	twitter/x	C1	eng	text, image, video, audio	A1, A2	link
BelElect (Höhn et al., 2022)	2022	telegram	C3	rus, bel	text	A1	https://ojs.aaai.org/index.php/ICWSM/article/view/19378
ClimateStance + ClimateEng (Vaid et al., 2022)	2022	twitter/x, reddit	C1	eng	text	A1	link
CovidEmo (Sosea et al., 2022)	2022	twitter/x	C2	eng	text	A1	https://github.com/tsosea2/CovidEmo
CrisisLTLSum (Faghihi et al., 2022)	2022	twitter/x	C1	eng	text	A2, A3	link
Finegrained Location Tweets (Khanal et al., 2022)	2022	twitter/x	C4	eng	text	A3	link
HarveyNER (Chen et al., 2022)	2022	twitter/x	C1	eng	text	A3	https://github.com/brickee/HarveyNER
HumSet (Fekih et al., 2022)	2022	various	C4	eng, fra, spa	text	A2	https://github.com/the-deep/humset
MEDIC (Alam et al., 2022)	2022	twitter/x, instagram, flickr, bing, google	C1	N/A	image	A1	https://rdcu.be/d9Yjt

Table 4: Corpus Papers in 2020-2024 and the corresponding datasets (Part 3)

Dataset	Year	Platform	Crisis Type	Language	Modality	Annotation	Link
(Alhammadi, 2022)	2022	twitter/x	C4	eng	text	A1	link
(Azarpanah et al., 2022)	2022	twitter/x	C2	multi	text	A1	link
(Faisal et al., 2022)	2022	twitter/x	C2	eng	text	A1	https://jurnal.iaii.or.id/index.php/RESTI/article/view/4525
(Jayasurya et al., 2022)	2022	twitter/x	C2	eng	text	A1	https://ieeexplore.ieee.org/document/9606194
(Laurenti et al., 2022), (Enzo et al., 2022)	2022	twitter/x	C2	fra	text	A1	https://aclanthology.org/2022.lrec-1.462/
(Li et al., 2022a)	2022	weibo	C2	zho	text	A2	link
(Li et al., 2022b)	2022	various	C2	zho	text	A1	link
(Li et al., 2022c)	2022	twitter/x	C1	eng	text	A1	https://ojs.aaai.org/index.php/ICWSM/article/view/19320
(Shestakov and Zaghouani, 2024)	2022	twitter/x	C3	eng	text	A1	link
(Sosa and Sharoff, 2022)	2022	telegram	C2	eng, zho, spa, rus, deu	text, video, audio	A1	link
(Vitiugin and Castillo, 2022)	2022	twitter/x	C1	eng, spa, fra, cat, tgl, hrv, deu, jpn, por	text	A1, A2, A4	https://dl.acm.org/doi/10.1145/3511095.3531279
(Zong et al., 2022)	2022	twitter/x	C2	eng	text	A2	https://aclanthology.org/2022.coling-1.335/
BillionCOV (Lamsal et al., 2023)	2023	twitter/x	C2	multi	text	A0	link
CrisisFACTS (McCreadie and Buntain, 2023)	2023	twitter/x, facebook, reddit	C1	eng	text, image	A4	https://eprints.gla.ac.uk/295806/
IDRISI (Suwaileh et al., 2023c), (Suwaileh et al., 2023b), (Suwaileh et al., 2023a)	2023	twitter/x	C1	ara, eng	text	A2, A3	https://github.com/rsuwaileh/IDRISI/
(Herur et al., 2023)	2023	twitter/x	C1	eng	text	A1	link
(Inamdar et al., 2023)	2023	reddit	C2	eng	text	A6	link
(K et al., 2023)	2023	twitter/x	C1	eng	text	A1	https://ieeexplore.ieee.org/abstract/document/10113105
(Kaur et al., 2023)	2023	twitter/x	C2	eng	text	A1	link
(Kekere et al., 2023)	2023	twitter/x	C2	eng	text	A2	link
(Li et al., 2023)	2023	weibo	C2	zho	text	A1	link
(Wang et al., 2023)	2023	twitter/x	C1	eng	text	A1	link
(Wang et al., 2023)	2023	twitter/x	C2	eng	text	A1, A5	https://rdcu.be/d91vB

Table 5: Corpus Papers in 2020-2024 and the corresponding datasets (Part 4)

Dataset	Year	Platform	Crisis Type	Lang/Modality	Annotation	Application	Link
Complotto (Marini and Jezek, 2024)	2024	telegram	C3	eng, ita	text	A1	https://aclanthology.org/2024.isa-1.6/
Crisis Social Cues (Wang et al., 2024b)	2024	twitter/x	C1	eng	text	A1	link
HurricaneSarc (Sosea et al., 2024)	2024	twitter/x	C1	eng	text	A1	https://github.com/tsosea2/HurricaneSarc
M-CATNAT (Farah et al., 2024)	2024	twitter/x	C1	fra	text	A1	link
Ukrainian Resilience (Sathvik et al., 2024)	2024	twitter/x, reddit	C3	ukr	text	A1	link
(Boston et al., 2024)	2024	twitter/x	C1	eng	text	A1	link
(Dirgantara et al., 2024)	2024	twitter/x	C2	ind	text	A1	link
(Elakkiya et al., 2024)	2024	twitter/x	C4	eng	text	A1	link
(Fakhouri et al., 2024)	2024	twitter/x	C4	eng	text	A2	link
(Koli et al., 2024)	2024	twitter/x	C2	eng	text	A1	https://aclanthology.org/2024.hcinlp-1.7/
(Kumawat et al., 2024)	2024	twitter/x	C4	eng	text	A1	link

Table 6: Corpus Papers in 2020-2024 and the corresponding datasets (Part 5)

Dataset	Year	Platform	Crisis Type	Lang/Modality	Annotation	Application	Link
ClimateCovE350 (Olteanu et al., 2015a)	2015	twitter/x	C4	eng	text	A1	link
CrisisLexT26 (Olteanu et al., 2015b)	2015	twitter/x	C4	eng	text	A1	link
ChileEarthquakeT1 (Cobo et al., 2015)	2015	twitter/x	C1	spa	text	A1	link
SoSItalyT4 (Cresci et al., 2015)	2015	twitter/x	C1	ita	text	A1	link
SandyHurricane-GeoT1 (Wang et al., 2015)	2015	twitter/x	C1	eng	text	A3	link
CrisisNLP (Imran et al., 2016)	2016	twitter/x	C4	eng, spa, fra	text	A1	`https://crisisnlp.qcri.org/lrec2016/lrec2016.html`
BlackLivesMatter-U/T1 (Olteanu et al., 2015c)	2016	twitter/x	C3	eng	text	A1	link
Environmental-PetitionTweets (Proskurnia et al., 2016)	2016	twitter/x	C3	eng	text	A1	link
Damage Assessment Dataset (DAD) (Nguyen et al., 2017)	2017	twitter/x	C1	N/A	image	A1	`https://crisisnlp.qcri.org`
Disasters on Social Media (DSM) (Klaas, 2017)	2017	twitter/x	C4	eng	text	A1, A3	link
CrisisMMD (Alam et al., 2018b)	2018	twitter/x	C1	eng	text, image	A1	`https://crisisnlp.qcri.org/crisismmd`
Hurricane Tweets (ISCRAM2018) (Alam et al., 2018c)	2018	twitter/x	C1	eng	text, image	A1	`https://crisisnlp.qcri.org`
NEQ + QFL (ACL2018) (Alam et al., 2018a)	2018	twitter/x	C1	eng	text	A1	`https://crisisnlp.qcri.org`
Damage Multimodal Dataset (DMD) (Mozannar et al., 2018)	2018	twitter/x, instagram	C1	eng	text, image	A1	link
ArabicFloods (Alharbi and Lee, 2019)	2019	twitter/x	C1	ara	text	A1	link
CleanCrisisMMD (Gautam et al., 2019)	2019	twitter/x	C4	eng	text, image	A1, A2, A3	link

Table 7: Social media crisis datasets published before 2020