Social Media Sentiment Analysis and Opinion Mining in Public Security: Taxonomy, Trend Analysis, Issues and Future Directions

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Abstract

The interest in social media sentiment analysis and opinion mining for public security events has increased over the years. The availability of social media platforms for communication provides a valuable source of information for sentiment analysis and opinion mining research. The content shared across the media gives potential input to the physical environment and social phenomena related to public security threats. The input has been used to: monitor public security threats or emergency events, analyzing sentiment and opinionated data for threat management and the detection of public security threat events using geographic location-based sentiment analysis. However, a systematic survey that describes the trends and latest developments in this domain is unavailable. This paper presents a survey of social media sentiment analysis and opinion mining for public security. This paper aims to: understand the progress of the current state-of-the-art, identify the research gaps, and propose potential future directions. In total, 200 articles published from 2016 to 2023 were considered in this survey. The taxonomy shows the key attributes and limitations of the work presented in the surveyed articles. Subsequently, the potential future direction of work on sentiment analysis in the public security domain is suggested for interested researchers.

Keywords: Sentiment analysis; Opinion mining; Public security; Public threat; Taxonomy

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Abstract

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Keywords: Sentiment analysis; Opinion mining; Public security; Public threat, Taxonomy

1. Introduction

Ensuring public security has long been a core factor of a stable country. Over time, the definition of security has broadened to encompass a range of sectors and domains, including environmental, societal, economic, and political. Additionally, the concept of security has deepened to include individual safety and well-being, not just national or state-level security (Stevens & Vaughan-Williams, 2016). According to the Oxford dictionary, security encompasses the activities involved in protecting a country, building, or person against attack and danger, as well as the state of feeling happy and safe from danger or worry (Hornby & Cowie, 1995). In general, public security consists of: maintaining social privacy, eliminating risks, and the optimal use of opportunities to ensure sustainable development and well-being (Dehdezi & Sardi, 2016). The common definition of public security is the protection and safety of persons or property against the threat of attack and danger (Manunta, 1999; Ortmeier, 1998). The threat concerns can be criminal or non-criminal. Criminal threats typically arise from non-natural causes such as terrorism, riots, protests, crises, conflicts, accidents and crime. Non-criminal threats, on the other hand, are caused by natural events such as natural disasters, disease outbreaks and pandemics. Ensuring public security is vital for protecting the general public: from significant threats, danger, injury, harm, damage and/or loss of life; whether caused by natural or non-natural events (Bansal, Grover, Saini, & Saha, 2021; Chung & Zeng, 2018; Ortmeier, 1998). These events have seriously threatened human life and safety for a considerable time, causing significant economic and cultural loss.

Opinion mining, also known as sentiment analysis, is the field of study that analyzes people's opinions, sentiments, appraisals, attitudes, and emotions toward entities and their attributes expressed in written text. Although the terms "opinion" and "sentiment" are related, there is a subtle difference between them. Opinion mining primarily deals with a person's concrete view of something, while sentiment refers to an attitude or thought prompted by a feeling. Opinion mining involves two levels of abstraction: a single opinion and a set of opinions, whereas sentiment analysis mainly focuses on opinions that express or imply positive or negative sentiment (B. Liu, 2020). However, the terms “sentiment analysis” and “opinion mining” are used interchangeably as an umbrella for different tasks, such as opinion extraction, sentiment mining, subjectivity analysis, effect analysis, review mining, entity extraction and emotion analysis (Bhatia, Chaudhary, & Dey, 2020; N. Gupta & Agrawal, 2020; Pang & Lee, 2008).

Sentiment analysis and opinion mining were initially used for product review applications but have recently shifted to other tasks, including: stock markets, elections, disasters, healthcare and software engineering (Mäntylä, Graziotin, & Kuutila, 2018). In the context of public security, sentiment analysis and opinion mining have been used to analyze sentiment and public opinion, of an event or disaster, so as to trigger warnings to the public. More generally, sentiment analysis can be said to comprise the analysis of the sentiment, emotions, opinions and attitudes expressed by individuals towards events, phenomena and particular crises. Due to the availability of social media data and the huge amount of sentiment and opinionated data it contains, sentiment analysis and opinion mining have been used in a wide range of domains, such as business, marketing, entertainment, hospitality, politics, social issues, healthcare and disasters. The techniques used have been employed not only by organizations and individuals but also by local and federal governments. The occurrence of events is typically accompanied by public opinion on social media, which serves as a medium for disseminating or expressing sentiment. The content shared across social media platforms provides a valuable source of knowledge about the physical environment and social phenomena (Alfarrarjeh, Agrawal, Kim, & Shahabi, 2017). The availability of textual data from social media platforms has encouraged research on sentiment analysis and opinion mining. As a result, the public security domain has become an important application domain in sentiment analysis and opinion mining.

Researchers have leveraged sentiment analysis and opinion mining to achieve a range of purposes. For example, there is much reported work that utilizes sentiment analysis and opinion mining, directed at social media, to analyze public security threats. This includes the analysis of social media data that expresses opinions and/or sentiment for the monitoring of public security threats and emergency events, as well as the prediction or detection of events from social media acquired data using sentiment analysis. Additionally, researchers have employed geographic location-based sentiment analysis for the detection of public security threats or emergency events (Sattaru, Bhatt, & Saran, 2021).

Several literature reviews and survey papers for sentiment analysis and opinion mining directed at the public security domain have been published. de Carvalho and Seixas Costa (2021) provided a comprehensive review of social web mining and sentiment analysis in public security and proposed a research agenda for future work. Boukabous and Azizi (2020) reviewed the latest trends in learning-based sentiment analysis techniques for security intelligence purposes, with a focus on cyber security, security attacks, crimes, extremism, disasters and hate speech. They suggested a future research direction to consider combining learning-based security for sentiment analysis. Meanwhile, Sharma and Jain (2020) surveyed the sentiment analysis approaches and techniques for social media security and analytics, covering various security domains such as deception detection, anomaly detection, risk management, and disaster relief. Finally, Razali et al. (2021) examined the literature on opinion mining in multiple domains based on text, and highlighting the potential of the Kansei approach in national security research. However, these papers did not provide a descriptive taxonomy of sentiment analysis and opinion mining in the public security domain. A taxonomy categorizes previous work based on specified attributes that could help stake holders to better comprehend the issues involved. Therefore, this survey paper aims to fill this gap by categorizing relevant work, and developing a taxonomy based on the most recent research on sentiment analysis and opinion mining for public security. Additionally, this paper provides an overview and analysis of current trends in sentiment analysis and opinion mining in public security, an overview and analysis not included in previous survey and studies directed at the topic. Finally, the paper discusses the current issues and future directions of sentiment analysis and opinion mining in the public security domain.

This survey paper has three primary objectives: (1) to develop a taxonomy of the current state-of-the-art sentiment analysis and opinion mining techniques that is specifically applicable to the public security domain; (2) to visualize and analyze recent trends in the field; and (3) to identify any remaining issues and suggest potential future research directions. The structure of the paper is as follows: Section 2 outlines the methodology used to conduct this survey, Section 3 provides an overview of sentiment analysis and opinion mining in the context of public security, Section 4 presents the developed taxonomy and provides detailed explanations of each sub-branch within it, Section 5 analyzes trends, research gaps, and remaining issues in the field, and suggests potential future directions for sentiment analysis and opinion mining in public security. Section 6 discusses the critical area reflected to the issues and future direction based on authors opinion and finally, Section 7 concludes the paper.

2. Methodology

In this section, the methodology used to conduct the survey of recent work directed at sentiment analysis and opinion mining for public security is described. Fig. 1 shows the methodology used.

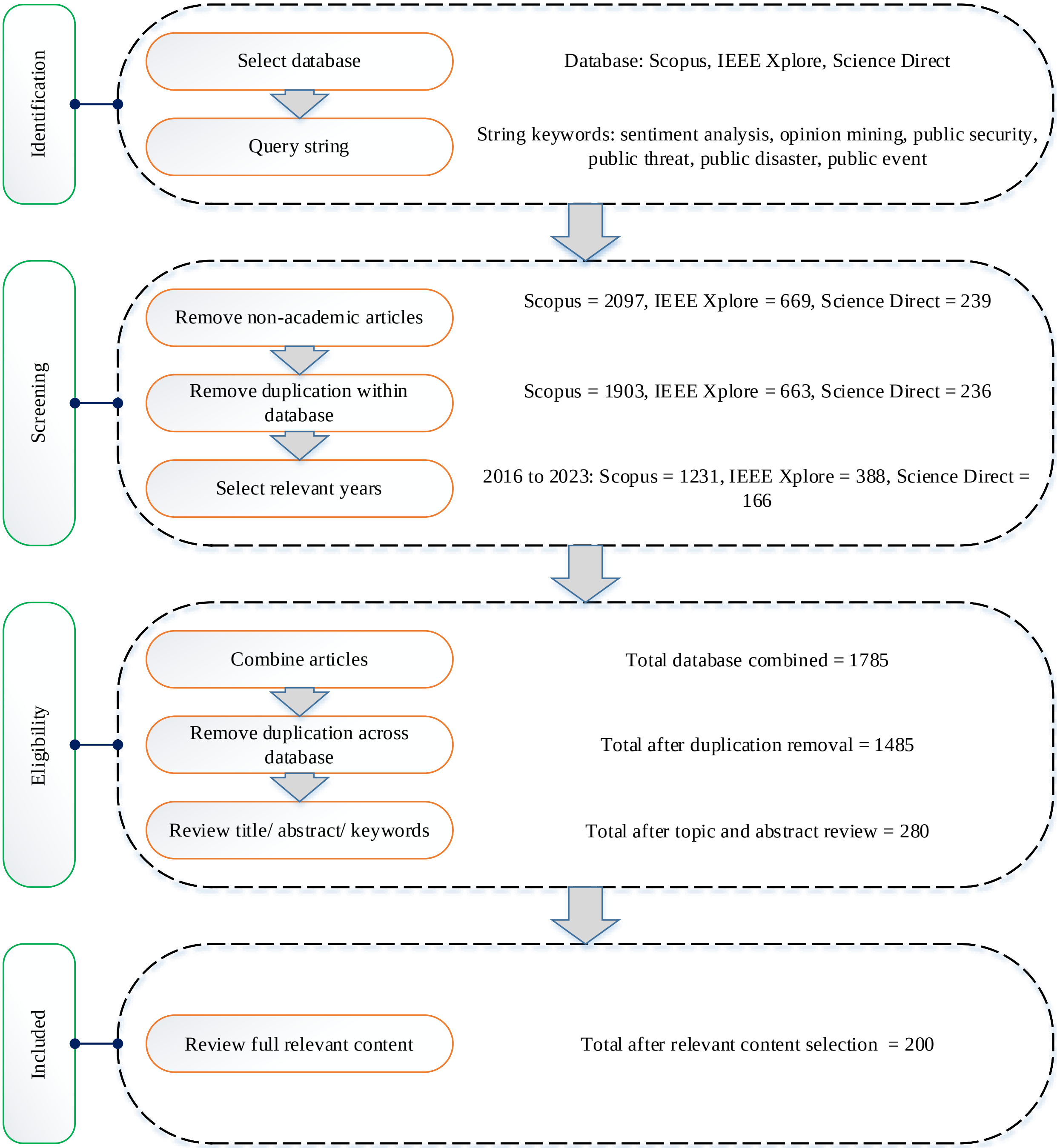


Fig. 1. Methodology used to conduct this survey.

First, several relevant databases of peer-reviewed articles were identified. The Scopus, IEEE Xplore and Science Direct databases were selected due to their wide coverage of scientific peer-reviewed articles and strict evaluations of the journals indexed in their databases. A set of relevant keywords were used to search for all possible articles related to sentiment analysis and opinion mining in public security. Various combinations of terms and operators were used, including "sentiment AND analysis AND public AND security," "opinion AND mining AND public AND security," "sentiment AND analysis AND public AND threat," "opinion AND mining AND public AND threat," "sentiment AND analysis AND public AND disaster," "opinion AND mining AND public AND disaster," "sentiment AND analysis AND public AND event," and "opinion AND mining AND public AND event". The search yielded a total of 2097 articles in Scopus, 669 in IEEE Xplore, and 239 in Science Direct.

Second, a screening process of the articles found for each database was conducted. The non-academic articles were removed. The articles that remained consist of journals, conference proceedings and serials. Duplication of articles found in each of the selected databases was also removed. To ensure only the state-of-the-art work was considered in this paper, only articles published in recent years (2016-2023) were included. After the screening, the remaining number of articles were Scopus: 1903, IEEE Xplore: 663 and Science Direct: 166.

Third, we performed the eligibility filtering process, which involved two sub-processes: (i) the combination of the database and removal of duplicates across the database, and (ii) a brief review of the articles. After removing duplicates, the number of articles was reduced to 1485. Then, we manually reviewed the titles, abstracts, and keywords of each article to identify work that employed sentiment analysis/opinion mining in the public security domain and were written in English. Based on these criteria, we selected a total of 280 articles. We conducted a thorough review of the content of these articles and found 200 articles to be eligible for inclusion in this paper.

3. An Overview of Sentiment Analysis and Opinion Mining for Public Security

This section provides an overview of opinion mining and sentiment analysis in the context of public security. The overview is based on the general framework found in the majority of the articles. Fig. 2 shows the general framework typically adopted when conducting sentiment analysis and opinion mining in the public security domain.

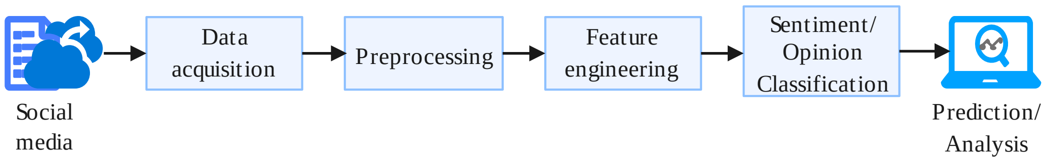


Fig. 2. General sentiment analysis and opinion mining framework in the public security domain.

As noted in the introduction to this paper, the aim of sentiment analysis and opinion mining is to analyze written text to identify sentiments, opinions, attitudes, emotions, and appraisals toward entities and their attributes. In the context of the public security domain, this involves analyzing text related to events that could potentially threaten the public, whether in the form of criminal activity or non-criminal incidents caused by natural or non-natural factors. The initial step in conducting sentiment analysis and opinion mining is to acquire a dataset of text from a social media platform or other relevant sources using keywords, geographic location information, or specific timeframes based on the objectives of the research. In some cases, publicly shared datasets may be used, which eliminates the need for data acquisition. For language-focused events, the relevant social media platform is used to provide insight into the true sentiment of the event.

The acquired dataset undergoes pre-processing using text-processing techniques to transform the raw data into a suitable form. Various approaches such as machine learning-based, lexicon or rule-based, hybrid, or manual coding can be used, depending on the preference of the researcher. However, supervised and semi-supervised machine learning require a data annotation step for data labelling before pre-processing. This pre-processing stage is required to remove noise and irrelevant data in preparation for the feature engineering stage (B. Liu, 2020). Pre-processing techniques commonly used include text cleaning, normalization (Wadawadagi & Pagi, 2021; T. Zhang & Cheng, 2021), replacement (Geeta & Niyogi, 2016), and stopword removal (Mohamed Ridhwan & Hargreaves, 2021).

After pre-processing, the next step is feature engineering, which involves feature extraction, selection, and representation (Eke, Norman, Shuib, & Nweke, 2020). Features are then extracted from the pre-processed data. The extracted features represented the original text in a meaningful form, typically numerical, that is compatible with the algorithms used (Python, Kulkarni, & Shivananda). The techniques used to extract features include statistical, Natural Language Processing (NLP), or rule-based techniques. Deep learning has also been proposed as a feature engineering method, which can learn multiple levels of representation from raw data and reduce the effort required for feature extraction and selection (Bhatia, Chaudhary, & Dey, 2020).

After the feature engineering stage, sentiment or opinion classification can be performed. This is typically conducted using some form of classification algorithm often founded on a lexicon of some kind. In the lexicon-based approach, sentiment classification is based on sentiment resources, such as a lexicon or a corpus database. Usually, as a result of the classification, a sentiment score is calculated and evaluated according to the associated sentiment orientation and strength (Pang & Lee, 2008). Other approaches use topic modeling to categorize the topics within the dataset (J. S. Lee & Nerghes, 2017). The system's performance, using test data, is typically recorded for evaluation purposes.

The evaluation of system performance entails a comprehensive understanding of several key measures. The evaluation metrics used can be categorized based on the approach adopted for analysis. Machine learning based approaches frequently adopt metrics such as accuracy, precision, recall, and F1-measures. Accuracy is the proportion of total predictions that were correctly identified, encompassing both positive and negative sentiments. Precision, on the other hand, indicates the proportion of positive identifications that were actually correct. Recall, also known as sensitivity, is the proportion of actual positives that were correctly identified. The F1-measure provides a balance between precision and recall. The performance measures for lexicon approach usually adopt accuracy based on sentiment score calculation of determined based on the individual sentiment scores of the words or phrases in the text. These sentiment scores are typically derived from a pre-compiled sentiment lexicon, where each word or phrase is associated with a sentiment score (Fan, Farahmend, & Mostafavi, 2020; Thorat & Namrata Mahender, 2019).

Finally, the resulting sentiment analysis is used to provide insight into the event of interest, either by predicting future occurrences or by providing a retrospective analysis of the event.

4. The Taxonomy for Sentiment Analysis and Opinion Mining for Public Security

In this section a taxonomy of the recent work directed at sentiment analysis and opinion mining, derived from the overview discussed in Section 3, is presented. The aim of the taxonomy was to summarize and provide a clear picture of the main concepts expressed, and similarities between the recent works. Seven attributes were identified for inclusion in the taxonomy, represented using the oval shape in Fig. 3. These attributes were chosen as they were consistent across all articles surveyed. The seven attributes are: (1) objectives of the work conducted, (2) the domain of public security, (3) the public security event timeframe, (4) the social media platform used for data acquisition, (5) dataset type, (6) the language of the dataset, and (7) the sentiment analysis or opinion mining approach employed. Sections 4.1 - 4.7 provide a detailed description of each attribute and a survey of relevant works in that area.

4.1. Objective of Sentiment Analysis and Opinion Mining for Public Security

In this survey, the first attribute of the taxonomy is the categorization of recent work based on their objective, as shown in Table 1. The identification of the objective is necessary for understanding the issues addressed and the proposing of potential solutions. It was found that most of the previous work focused on a specific task of sentiment analysis in public security threats, although some work did consider several tasks. The taxonomy categorized the recent works' objectives into four groups: (1) analysis of events, (2) improvement of techniques, (3) corpus generation, and (4) multipurpose. Analysis of events refers to work in which the sentiment analysis or opinion mining was applied to a specific event in order to either: gain insight into the event and mine related information, or analyze the event in order to support disaster and emergency management. The technique improvement objective refers to efforts to improve the performance of sentiment analysis and opinion mining frameworks in general. It can be further divided into feature engineering, classification, or event prediction techniques. Corpus generation objective described work aimed at producing a corpus or dataset in the public security domain. Finally, the multipurpose objective combined both of the preceding objectives or more than one objective from each class. Sub-sections 4.1.1 to 4.1.4 present the attributes and details of each group.

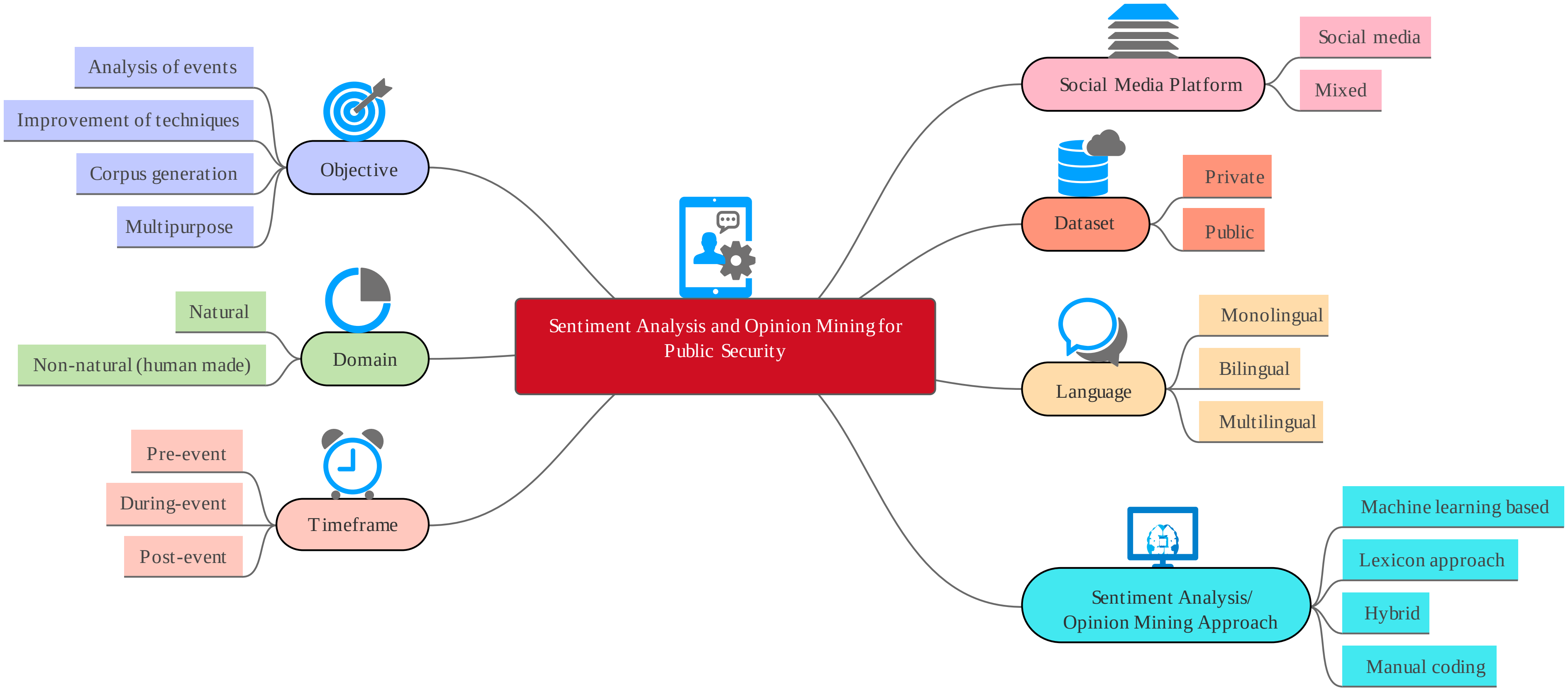


Fig. 3. Taxonomy of sentiment analysis and opinion mining in public security.

4.1.1 Analysis of events

The most common objective of the reviewed work was to perform an analysis of some public security event. Table 1 categorizes this objective into three groups: (i) analysis of a specific event, (ii) disease outbreak or pandemic analysis, and (iii) disaster or emergency management. In the analysis of specific event groups, most work was found to focus on analyzing: natural disasters, war and terrorist activity, crime and chaos. Other analysis included: immigrant and refugee, energy/ nuclear activity, infrastructure and economic threat. The main output of this group was an analytical study that measures and analyzes the sentiment or opinion of the public towards a certain event. It typically included an in depth analysis to better understand: the severity level and demographic (Al-Agha & Abu-Dahrooj, 2019; Chandra, Cambria, & Nanetti, 2020; C. Zhang, Xu, Li, & Hu, 2021), public behaviors and responses (Chung & Zeng, 2016; Gascó, Bayerl, Denef, & Akhgar, 2017; Kostakos, Nykanen, Martinviita, Pandya, & Oussalah, 2018), temporal sentiment analysis (Chaudhary & Bansal, 2021; Kovács, Kovács-Győri, & Resch, 2021; S. Yu, Eisenman, & Han, 2021), event scenarios (Gu, Guo, & Zhuang, 2021; Lian, Liu, & Dong, 2020), and sentiment distribution and visualization (N. Wang, Varghese, & Donnelly, 2016; Z. Wu & Lu, 2017; Xiong, Hswen, & Naslund, 2020).

In the analysis of the disease outbreak and pandemic group, the aim was to analyze diseases and pandemics that threatened the public, such as the Middle East Respiratory Syndrome (MERS), Zika virus, multiple diseases, monkeypox and recent Coronavirus (COVID-19). The objectives include sentiment analysis and topic modelling of COVID-19. Unlike the first group described in the foregoing paragraph, this group only focused on analyzing pandemics or disease outbreaks. Thus, the output of this group was an analytical study of an outbreak or pandemic that included outbreak identification (X. Yu, Zhong, Li, & Xu, 2020; S. Zhao, Chen, Liu, Yu, & Han, 2022), tracking pandemic (Arias, Guerra-Adames, Zambrano, Quintero-Guerra, & Tejedor-Flores, 2022; Fakhry, Kassam, & Asfoura, 2020), and statistical analysis during a pandemic (Ghanem et al., 2021; C. Zhang et al., 2021).

For the disaster or emergency management group, some of the work considered focused on improving disaster management and exploring emergency management of a specific event. The output of this group was typically an analysis of emergency and disaster events that might include: a sentiment and disaster concern index (Bai & Yu, 2016), an event urgency level (Y. Chen & Ji, 2021; Subramaniyaswamy, Logesh, Abejith, Umasankar, & Umamakeswari, 2017), a quantitative analysis of public resilience during emergency events (Fan, Farahmend, & Mostafavi, 2020; L. Li, Ma, & Cao, 2020; L. Zhang, Wei, & Boncella, 2020), and decision support systems for improving disaster management (Behl, Rao, Aggarwal, Chadha, & Pannu, 2021; Obiedat, Harfoushi, Qaddoura, Al-Qaisi, & Al-Zoubi, 2021; Xu, Liu, & Shang, 2017).

4.1.2 Improvement of Techniques

The second objective of recent work that was found was to improve the techniques used for sentiment analysis and opinion mining systems. Proposed improvements have focused on three main areas: (i) feature engineering, (ii) classification improvement, and (iii) event prediction. Table 1 lists the work considered related to these technique improvements. Each is described in the following paragraphs.

For the feature engineering improvement, the surveyed work tended to be focused on feature enhancement and representation techniques. In this context, features refer to input variables or attributes derived from distinct raw data (Guyon, Gunn, Nikravesh, & Zadeh, 2008). The goal of improving features is to find a good representation of data relevant to a specific domain and associated measurement. The surveyed work identified two potential means for enhancing features: information enrichment and expansion of lexicon. For the information enrichment, all relevant work considered geographical and location information from harvested social media data. Specifically, proposed approaches included: the development of geographical sentiment models, exploration of spatio-temporal factors, geographical sentiment analysis with topic modelling and framework for analyzing social media using geographic locations during disasters. The objective of lexicon expansion, on the other hand, is more focused on improving the vocabulary and dictionary to tackle the rapid evolution of language. This particular task presents greater challenges, resulting in a comparatively lower distribution for this objective. The output for this group tended to be a methodology for sentiment or opinion analysis from a geographic location perspective, including geographic location-based sentiment models (Dahal, Kumar, & Li, 2019; Fakhry, Kassam, & Asfoura, 2020; S. Yue, Kondari, Musave, Smith, & Yue, 2018), and spatio-temporal approaches for sentiment analysis in the public security domain (Dahal, Kumar, & Li, 2019; Karami, Shah, Vaezi, & Bansal, 2020; T. Zhang & Cheng, 2021).

Regarding lexicon expansion, the aim here was to enrich or enlarge the lexicon to improve sentiment analysis performance. A sentiment dictionary was built to address the shortage of sentiment analysis on hot events in social media. Improvement of short text classification using domain sentiment lexicon expansion with sentiment orientation analysis also has been experimented. In addition, an emoji lexicon developed for sentiment polarity sign and intensity scores. Other work has been directed at generating corpora based on domain or language used. The main output of this group include: feature combination sets derived from expanded lexicons (Abid, Ameur, Mbarek, Rekik, Jamoussi, & Ben Hamadou, 2017; Bai & Yu, 2016; P. Li & Wang, 2021), features sets based on the language used (Anuratha, Joshi, Sharmila, Nandhini, & Paravthy, 2021; Fuadvy & Ibrahim, 2019; Laudy, Ruini, Zanasi, Przybyszewski, & Stachowicz, 2017), lexical and semantic feature combinations for deep learning (J. Li, Wang, & Wang, 2021), multi-feature based deep learning frameworks for classification (R. Sun, An, Li, & Yu, 2022) and textual feature sets based on disaster visual content (Amin, Ahn, & Choi, 2021; Sadiq, Ahn, & Choi, 2020).

For the improvement of classification techniques, most of the surveyed work was focused on the modification of the classifiers used to generate the classification models using machine learning, deep learning, and hybrid/ ensembles. Some other work has also contributed to the improving associated techniques for: annotation, pipeline and parsing, utilization of lexicons for classification, topic modelling, and multi-task or multi-level classification. The output for this group was typically either: a technique or model (Bansal et al., 2021; Bashar, 2022; J. Li, Wang, & Wang, 2021), a framework (Mendon, Dutta, Behl, & Lessmann, 2021; Thukral, Varshney, & Gaur, 2021; Wahid, Hussain, Wang, Wu, Shi, & Gao, 2021) and an algorithm of some kind (Jiang, Luo, Xuan, & Xu, 2017; Moraes Silva, Valêncio, Donegá Zafalon, & Columbini, 2022; K. Wang, Qiu, Wu, & Qiu, 2020) for sentiment analysis or opinion mining in public security domain.

For the event prediction technique, the surveyed work focused on the improvement of the technique used to detect and predict an event according to their timeframe. Some of the objectives included: the detection of an emergency event and early event detection, and real-time monitoring of the progress of an event. The ability to predict or detect events early can significantly enhance response times and potentially mitigate harm or damage. The output for this group tended to be an improved approach to the detection and prediction of an emergency/disaster event related to the public security domain before the event occurred (An, Han, Yi, Li, & Yu, 2021; Duan, Zhai, & Cheng, 2020; Zhong, 2021).

4.1.3 Corpus generation

The third objective was corpus generation whereby a specific corpus or dataset related to the respective domain was produced. The generation divided into initiation of the corpus and technique enhancement. The former created new corpus from scratch or adding new data to an existing corpus while the later refined and enhance existing technique to better curate data. The outputs from this objective include: compiled corpora of texts concerning specific events related to public security (Backfried & Shalunts, 2016; Effrosynidis, Karasakalidis, Sylaios, & Arampatzis, 2022; Thorat & Namrata Mahender, 2019), annotated corpora (de Carvalho, Nepomuceno, & Costa, 2020; Mamta, Ekbal, Bhattacharyya, Srivastava, Kumar, & Saha, 2020), data collection methodology (Abid et al., 2017) and dataset manipulation (Olusegun, Oladunni, Audu, Houkpati, & Bengesi, 2023).

4.1.4 Multipurpose

The multipurpose objectives refer to work that addressed more than one issue concurrently, such as analysis of a specific event, and improvement of features or techniques. For example, the work presented in (P. Li & Wang, 2021; Mendon et al., 2021; Mohamed Ridhwan & Hargreaves, 2021; Moraes Silva et al., 2022; T. Qin, Wang, Liu, Chen, & Ding, 2022) proposed improved classification and feature extraction techniques to enhance the quality of their models. Other work proposed new frameworks that addressed several issues pertaining to the domain of interest (Adamu, Lutfi, Malim, Hassan, Di Vaio, & Mohamed, 2021; Garcia & Berton, 2021; Kovács, Kovács-Győri, & Resch, 2021; S. Yu, Eisenman, & Han, 2021; C. Zhang et al., 2021).

Table 1
Natural domain's event of related works.

Objectives	Details	Related works
Analysis specific event	Natural disasters	Astuti, Widagdo, Tanro, Cahyadi, and Suntara (2023); Becken, Stantic, Chen, and Connolly (2022); Chenxi, Jilin, Meng, and Zhonghao (2022); Du, Li, Li, Zhou, and Cui (2023); Dudani, Srividya, Sneha, and Tripathy (2020); Hasegawa et al. (2020); He, Wen, and Zhu (2019); Henríquez-Coronel, García García, and Herrera-Tapia (2019); Karami et al. (2020); Karimiziarani and Moradkhani (2023); Lian, Liu, and Dong (2020); Loureiro and Alló (2020); X. Ma et al. (2020); Mendon et al. (2021); Mustakim, Fauzi, Mustafa, Abdullah, and Rohayati (2021); Ray and Kumar (2023); Uthirapathy and Sandanam (2023); D. Wu and Cui (2018); Xiong, Hswen, and Naslund (2020); Yuan and Liu (2020); S. Yue et al. (2018); Zander, Garnett, Ogie, Alazab, and Nguyen (2023); Zeng (2022)
	Non-natural disasters	Abdul Reda, Sinanoglu, and Aboussalah (2023); Al-Agha and Abu-Dahrooj (2019); Backfried and Shalunts (2016); Berhoum, Meftah, Laouid, and Hammoudeh (2023); Chandra, Cambria, and Nanetti (2020); Chaudhary and Bansal (2021); Chung and Zeng (2016); Duan, Zhai, and Cheng (2020); Gascó et al. (2017); Geeta and Niyogi (2016); Gong, Wang, Wei, and Yu (2022); Gu, Guo, and Zhuang (2021); Khatua, Cambria, Ho, and Na (2020); Kostakos et al. (2018); Kovács, Kovács-Győri, and Resch (2021); Koytak and Celik (2022); N. Kumar (2018); J. S. Lee and Nerghes (2017, 2018); M. J. Lee, Lee, Lee, Jang, and Kim (2020); L. Li, Ma, and Cao (2020); N. Li, Akin, Yi-Fan, Brossard, Xenos, and Scheufele (2016); S. Lyu and Lu (2023); Pope and Griffith (2016); Prathap and Ramesha (2019); Pu, Jiang, and Fan (2022); Qi, Jiang, Bu, Zhang, and Shim (2019); Tan, Xie, and Lin (2021); N. Wang, Varghese, and Donnelly (2016); Z. Wu and Lu (2017); Zhou and Jing (2020)
Analyze outbreak/ pandemic	Epidemic/ pandemic/ coronavirus	Abusaqer, Benaoumeur Senouci, and Magel (2023); Adamu et al. (2021); Ali, Irfan, and Lashari (2023); Anuratha and Parvathy (2023); Arias et al. (2022); Azmi, Abidin, Mutalib, Zawawi, and Halim (2022); Bashar (2022); Cai, Luo, and Cui (2021); G. Cao et al. (2021); Che, Wang, Zhang, and Kim (2023); X. Chen, Zeng, Xu, and Di (2021); Dimitrov et al. (2020); Fakhry, Kassam, and Asfoura (2020); Garcia and Berton (2021); Ghanem et al. (2021); Gu, Guo, and Zhuang (2021); M. Gupta, Bansal, Jain, Rochelle, Oak, and Jalali (2021); Han, Cao, Zhang, Zhang, Aoki, and Ogasawara (2022); Hu (2022); Iksan, Widodo, Sunarko, Udayanti, and Kartikadharma (2021); Khandelwal and Chaudhary (2022); X. Li, Li, and Tian (2021); R. Liu, Liu, Li, and Wu (2023); X. Liu, Zheng, Jia, Qi, Yu, and Wang (2021); X. Lyu, Chen, Wu, and Wang (2020); Mathayomchan, Taecharungroj, and Wattanacharoensil (2022); Mohamed Ridhwan and Hargreaves (2021); Pan, Han, Li, Zhang, and He (2022); Pran, Bhuiyan, Hossain, and Abujar (2020); Praveen, Ittamalla, and Subramanian (2022); Quach et al. (2022); Rathke, Yu, and Huang (2023); Samaras, García-Barriocanal, and Sicilia (2023); Sari and Ruldeviyani (2020); Sukhwal and Kankanhalli (2022); J. Sun, Zeng, Li, and Sun (2023); R. Sun et al. (2022); Tsao, MacLean, Chen, Li, Yang, and Butt (2022); Xie and Chen (2022); S. Yu, Eisenman, and Han (2021); X. Yu et al. (2020); B. Zhang et al. (2022); C. Zhang et al. (2021); S. Zhao et al. (2022); Y. Zhao, Cheng, Yu, and Xu (2020); Zhu, Zheng, Liu, Li, and Wang (2020)
	Disease outbreak	Hyo Jin, Chae-Gyun, You Jin, and Ho-Jin (2016); Olusegun et al. (2023); Z. Qin and Ronchieri (2022); Su and Li (2018); Zhou and

		Zhang (2017)
Disaster/ emergency management	Improve disaster management	Alomari, Mehmood, and Katib (2020); Behl et al. (2021); Y. Chen and Ji (2021); Chung and Zeng (2018); Dong, Meng, Christenson, and Fulton (2021); Fan, Farahmend, and Mostafavi (2020); R. Liu et al. (2023); Obiedat et al. (2021); Subramaniyaswamy et al. (2017); Xu, Liu, and Shang (2017); L. Zhang, Wei, and Boncella (2020)
	Explore disaster/ emergency management	Bai and Yu (2016); El Ali, Stratmann, Park, Schöning, Heuten, and Boll (2018); Fang et al. (2022); Gangadhari, Khanzode, and Murthy (2021); L. Li, Ma, and Cao (2020); Zhou (2021, 2023a, 2023b); Zhuang, Li, Tan, Xing, and Lu (2021)
Feature engineering	Information enrichment	Alfarrarjeh et al. (2017); Bala, Srinivasa Rao, and Ramesh Babu (2017); S. Chen, Mao, and Li (2019); Dahal, Kumar, and Li (2019); Du et al. (2023); Fakhry, Kassam, and Asfoura (2020); Karami et al. (2020); Laudy et al. (2017); Litvak, Vanetik, Levi, and Roistacher (2016); Mohamed Ridhwan and Hargreaves (2021); J. Sun et al. (2023); To, Agrawal, Kim, and Shahabi (2017); Yan, Chen, and Wang (2020); S. Yu, Eisenman, and Han (2021); S. Yue et al. (2018); T. Zhang and Cheng (2021); Zhu et al. (2020)
	Lexicon expansion	Abid et al. (2017); Bai and Yu (2016); L. Li and Wang (2022); P. Li and Wang (2021); S. Li and Sun (2023); L. Ma, Zhang, Yang, and Luo (2016); Moraes Silva et al. (2022); T. Qin et al. (2022); Samaras, García-Barriocanal, and Sicilia (2023); Sufi and Khalil (2022); R. Sun et al. (2022); Xie and Chen (2022); Yin, Beibei, Su, and Chai (2017); Zhou (2021)
Classification	Dual/ multilevel sentiment	Adamu et al. (2021); Al-Agha and Abu-Dahrooj (2019); Anuratha et al. (2021); Anuratha and Parvathy (2023); Backfried and Shalunts (2016); Fuadvy and Ibrahim (2019); Geeta and Niyogi (2016); Laudy et al. (2017); X. Lyu et al. (2020); Olusegun et al. (2023); Pope and Griffith (2016); Theja Bhavaraju, Beyney, and Nicholson (2019); Thukral, Varshney, and Gaur (2021); X. Zhang and Xu (2021); Zhou and Zhang (2017)
	Deep learning	Amin, Ahn, and Choi (2021); Andhale, Mane, Vaingankar, Karia, and Talele (2021); Bansal et al. (2021); H. Cao and Lian (2020); Fattoh, Kamal Alsheref, Ead, and Youssef (2022); J. Li, Wang, and Wang (2021); Lin and Moh (2021); Lydiri, El Mourabit, El Habouz, and Fakir (2023); Srikanth, Damodaram, Teekaraman, Kuppusamy, and Thelkar (2022); Wadawadagi and Pagi (2021)
	Classification technique	Akbar, Santoso, Putra, and Budi (2021); Bashar (2022); Bhullar, Khullar, Kumar, Sharma, Pannu, and Malhi (2022); Y. Chen, Ji, and Wang (2019); Chenxi et al. (2022); Chouhan (2021); Dimitrov et al. (2020); Jiang et al. (2017); S. Li and Sun (2023); Y. Li, Zhou, Sun, and Zhang (2016); Mendon et al. (2021); Moraes Silva et al. (2022); T. Qin et al. (2022); Sadiq, Ahn, and Choi (2020); Sliva, Shu, and Liu (2019); Tsai and Wang (2020); Wahid et al. (2021); K. Wang et al. (2020); Huosong Xia, An, Li, and Zhang (2022); X. Zhang and Ma (2023)
	Topic modeling geo-related	Choirul Rahmadan, Nizar Hidayanto, Swadani Ekasari, Purwandari, and Theresiawati (2020); Kovács, Kovács-Győri, and Resch (2021); Tan, Xie, and Lin (2021); Tang, Xu, Rui, Heng, and Song (2022); Xiong, Hswen, and Naslund (2020); Yan, Chen, and Wang (2020); Yuan, Li, and Liu (2020); Zhuang et al. (2021)
	Annotation and pipeline	Wei Zhang, Wang, and Zhu (2020); W. Zhang, Zhu, and Wang (2019)
Event prediction	Early event detection	Adamu et al. (2021); Almehmadi, Joudaki, and Jalali (2017); Alomari, Mehmood, and Katib (2020); An, Han, Yi, and Li (2019); An et al. (2021); Bai and Yu (2016); Barachi, Mathew, and Alkhatib (2022); Chowdhury, Basu, and Maulik (2022); Daou (2021); Duan, Zhai, and Cheng (2020); R. Lamsal, Harwood, and Read (2022); X. Li, Wang, Gao, and Shi (2017); Z. Li and Liu (2020); Litvak et al. (2016); Luna, Guerrero, Gonzalez, and Akundi (2022); Nagapudi, Agrawal, and Bulusu (2021); Shi et al. (2021); Smith, McCreadie, Macdonald, and Ounis (2018); Tang et al. (2022); M. Wang, Wu, Zhang, and Zhu (2020); D. Wu and Cui (2018); Xu,

		Liu, and Shang (2017); X. Yu, Ferreira, and Paulovich (2021); Zhong (2021)
	Real-time monitoring	Al-khateeb and Agarwal (2016); Albayrak and Gray-Roncal (2019); Ali, Irfan, and Lashari (2023); Kabbani, Klumpenhouwer, El-Diraby, and Shalaby (2022); Laudy et al. (2017); Sattaru, Bhatt, and Saran (2021); Sufi and Khalil (2022)
Corpus generation	Corpus initiation	Backfried and Shalunts (2016); de Carvalho, Nepomuceno, and Costa (2020); Effrosynidis et al. (2022); M. Imran, Qazi, and Ofli (2022); L. Li and Wang (2022); Mamta et al. (2020)
	Generation technique enhancement	Abid et al. (2017); Bai and Yu (2016); de Carvalho and Costa (2022); L. Ma et al. (2016); Olusegun et al. (2023); Tsai and Wang (2020); Zhou (2021)
Multipurpose	Abid et al. (2017); Adamu et al. (2021); Al-Agha and Abu-Dahrooj (2019); Ali, Irfan, and Lashari (2023); Alomari, Mehmood, and Katib (2020); Anuratha and Parvathy (2023); Backfried and Shalunts (2016); Bai and Yu (2016); Bashar (2022); Chenxi et al. (2022); Dimitrov et al. (2020); Du et al. (2023); Duan, Zhai, and Cheng (2020); Fakhry, Kassam, and Asfoura (2020); Geeta and Niyogi (2016); Karami et al. (2020); Kovács, Kovács-Győri, and Resch (2021); Laudy et al. (2017); L. Li, Ma, and Cao (2020); L. Li and Wang (2022); S. Li and Sun (2023); Litvak et al. (2016); R. Liu et al. (2023); X. Lyu et al. (2020); Mendon et al. (2021); Mohamed Ridhwan and Hargreaves (2021); Moraes Silva et al. (2022); Olusegun et al. (2023); Pope and Griffith (2016); T. Qin et al. (2022); Samaras, García-Barriocanal, and Sicilia (2023); Sufi and Khalil (2022); J. Sun et al. (2023); R. Sun et al. (2022); Tan, Xie, and Lin (2021); Tang et al. (2022); D. Wu and Cui (2018); Xie and Chen (2022); Xiong, Hswen, and Naslund (2020); Xu, Liu, and Shang (2017); Yan, Chen, and Wang (2020); S. Yu, Eisenman, and Han (2021); S. Yue et al. (2018); C. Zhang et al. (2021); Zhou (2021); Zhu et al. (2020); Zhuang et al. (2021)	

4.2. Domain of Interest in Public Security

The second attribute of the taxonomy is the domain of the public security work identified. Based on the survey, the domain was divided into two: the natural and the non-natural security threat domains. Sub-sections 4.2.1 and 4.2.2 briefly explain each group.

4.2.1 Natural

The domain of natural events is defined by the underlying natural causes that trigger an event, which included natural disasters and public health crises, provides in Table 2. Examples of the natural disaster events that have been studied were earthquake, flood, wildfire, hurricane, storm, rainstorm, tornado, drought, tsunami, climate change and blizzards. Examples of public health related events include: disease outbreaks such as Zika virus, monkeypox and Avian influenza, epidemics and pandemics of COVID-19. A few studies have also explored events that span multiple categories.). For example, the combination of earthquakes and the Swine Influenza pandemic has been explored (X. Li et al., 2017). Similarly, the joint occurrence of floods, earthquakes, and Influenza spread have been studied (Albayrak & Gray-Roncal, 2019).

Table 2

Natural domain's event of related works.

Domain	Natural disaster events	Related works
Natural disaster	Earthquake	Y. Chen, Ji, and Wang (2019); Chenxi et al. (2022); Laudy et al. (2017); Xu, Liu, and Shang (2017); S. Yue et al. (2018)
	Flood	Choirul Rahmadan et al. (2020); Dudani et al. (2020); He, Wen, and Zhu (2019); Karami et al. (2020)
	Wildfire	Astuti et al. (2023); Zander et al. (2023)
	Hurricane	D. Wu and Cui (2018); Yuan, Li, and Liu (2020); L. Zhang, Wei, and Boncella (2020)
	Storm	Theja Bhavaraju, Beyney, and Nicholson (2019)
	Rainstorm	X. Zhang and Ma (2023)
	Tornado	Sadiq, Ahn, and Choi (2020)
	Drought	Thorat and Namrata Mahender (2019)
	Tsunami	S. Chen, Mao, and Li (2019)
	Climate change	Becken et al. (2022); Effrosynidis et al. (2022); Lydiri et al. (2023); Zeng (2022)
	Blizzards	Dong et al. (2021); Theja Bhavaraju, Beyney, and Nicholson (2019)
Public health crises	Disease outbreaks	Hyo Jin et al. (2016); Olusegun et al. (2023); Z. Qin and Ronchieri (2022); Su and Li (2018); Zhou and Zhang (2017)
	Pandemics/ COVID-19	Rathke, Yu, and Huang (2023); Samaras, García-Barriocanal, and Sicilia (2023); Shi et al. (2021); Srikanth et al. (2022); Sukhwal and Kankanhalli (2022); J. Sun et al. (2023); R. Sun et al. (2022); Tsao et al. (2022); Wahid et al. (2021); Huosong Xia et al. (2022); Xie and Chen (2022); X. Yu, Ferreira, and Paulovich (2021); B. Zhang et al. (2022); S. Zhao et al. (2022); Zhuang et al. (2021)

4.2.2 Non-natural (human-made)

Non-natural events are those caused by humans or are human-made. This includes the following categories: emergencies, chaos, crises and cyber or technology threats, provides in Table 3. The emergency category includes energy-related incidents, nuclear accidents, electricity/ power issues, transportation/ airlines incidents, emergency traffic issues, infrastructure collisions, crowd accidents that triggered emergencies, water crises and local public emergency issues. The chaos category includes terrorism, riot, protest and crime. The crises category included:

conflicts between countries, immigrant issues and economic crises. The cyber and technology threat category included computer hacking, data privacy issues, and internet-related incidents. Mamta et al. (2020) reported a study that encompassed multiple non-natural domains, including terrorism, cyber-attacks, and crime. Recently a review of sentiment analysis in the context of public security was reported in de Carvalho and Seixas Costa (2021) that concentrated on the conceptual framework of sentiment analysis for public emergency events.

Table 3

Non-natural domain's event of related works.

Domain	Non-natural disaster events	Related works
Emergency	Energy incident	Gangadhari, Khanzode, and Murthy (2021); Pu, Jiang, and Fan (2022); Tan, Xie, and Lin (2021); Z. Wu and Lu (2017)
	Nuclear accidents	Gu, Guo, and Zhuang (2021); Hasegawa et al. (2020); N. Li et al. (2016)
	Electricity/ power issue	L. Li, Ma, and Cao (2020)
	Transportation/ airlines incidents	Jiang et al. (2017); M. J. Lee et al. (2020); P. Li and Wang (2021); Y. Li et al. (2016); L. Ma et al. (2016); Moraes Silva et al. (2022); Yin et al. (2017); Zhou and Jing (2020)
	Emergency traffic issue	Alomari, Mehmood, and Katib (2020); Y. Chen and Ji (2021); Kabbani et al. (2022); Z. Li and Liu (2020)
	Infrastructure collisions	Gu, Guo, and Zhuang (2021); Subramaniyaswamy et al. (2017)
	Crowd accidents	Daou (2021); Wei Zhang, Wang, and Zhu (2020)
	Water crises	Xiong, Hswen, and Naslund (2020)
	Local public emergency	H. Cao and Lian (2020); Duan, Zhai, and Cheng (2020); Zhong (2021); Zhou (2021)
Chaos	Terrorism	Abid et al. (2017); An et al. (2019); An et al. (2021); Chaudhary and Bansal (2021); Chouhan (2021); El Ali et al. (2018); Geeta and Niyogi (2016); Kostakos et al. (2018); Smith et al. (2018)
	Riot	Gascó et al. (2017),
	Protest	Kovács, Kovács-Győri, and Resch (2021); Qi et al. (2019)
	Crime	Almehmadi, Joudaki, and Jalali (2017); de Carvalho and Costa (2022); de Carvalho, Nepomuceno, and Costa (2020); J. Li, Wang, and Wang (2021); L. Li and Wang (2022); Prathap and Ramesha (2019); N. Wang, Varghese, and Donnelly (2016); W. Zhang, Zhu, and Wang (2019)
Crises	Countries' conflict	Al-Agha and Abu-Dahrooj (2019); Backfried and Shalunts (2016); J. S. Lee and Nerghes (2017); Litvak et al. (2016)
	Immigrant	Arias et al. (2022); Chung and Zeng (2016); Koytak and Celik (2022); J. S. Lee and Nerghes (2018)
	Economic crises	Chandra, Cambria, and Nanetti (2020); N. Kumar (2018)
Cyber/ technology	Computer hacking	Abusaqer, Benaoumeur Senouci, and Magel (2023); Sliva, Shu, and Liu (2019)
	Data privacy	Al-khateeb and Agarwal (2016)
	Internet-related incident	K. Wang et al. (2020)

4.3. Public Security Event Timeframe

The public security event timeframe refers to the time when the sentiment analysis was used in any event related to public security. The timeframe is divided into pre-event, during-event, and post-event. Fig. 4 depicts the chronology of this timeframe. Sub-section 4.3.1 to 4.3.3 provide an explanation for each attribute.

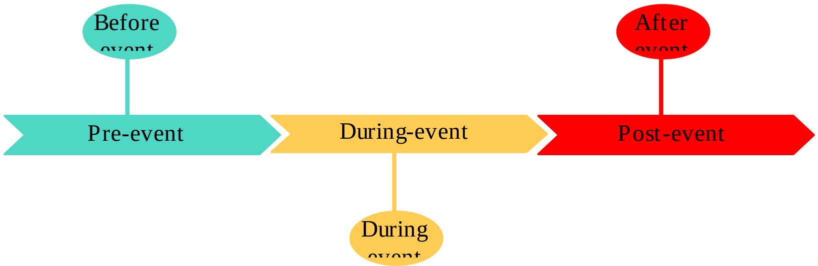


Fig. 4. Public security event timeframe chronology.

4.3.1 Pre-event

The pre-event timeframe covered sentiment analysis and opinion mining, related to natural and non-natural disasters or events, prior to their occurrence. This timeframe has been the least explored in the literature. It holds significant potential for enabling governments and law enforcement agencies to remain vigilant based on predicted potential threats or unrest. The idea is to leverage previous and current datasets to analyze and predict events, allowing for the implementation of necessary precautions or preventive measures. For instance, Abid et al. (2017) proposed a methodology to extract, annotate and unify suspicious social media content to predict potential threats to public security. They focused on terrorism related to ISIS and Daesh using platforms such as Twitter, Facebook and YouTube. Similarly, Almehmadi, Joudaki, and Jalali (2017) used Twitter public data to predict crime rates in Houston and New York City. They collected offensive and non-offensive Tweets based on geographic location and analyzed the relationship between tweet classification and crime rates. Similar work, utilizing geolocation data and sentiment analysis was reported to monitor and predict disasters in Albayrak and Gray-Roncal (2019); Sufi and Khalil (2022).

4.3.2 During-event

The during-event timeframe is where sentiment analysis or opinion mining is conducted in real-time during an ongoing event. From the survey, the during-event timeframe is the second most common area of study in social media sentiment analysis related to public security. This approach is particularly useful for time-sensitive issues with a large social media following, as it enables real-time insights into public sentiment. For instance, analyzing public sentiment during the 2011 Egyptian revolution in real-time provided more valuable insights than retrospective data from previous years. The amount of data acquired before any analysis can be performed is event-oriented. For example, an emergency event may necessitate the collection of social media data from the event's inception through to the recovery period, while for disasters such as earthquakes, floods, and tsunamis, the timespan could be shorter. In contrast, public health events, such as disease outbreaks, require a longer time span for data collection. Once the data is collected within the specified timeframe, it can be analyzed to support relief and disaster management efforts. Various studies have utilized the during-event timeframe to analyze specific events, such as disease outbreaks and the coronavirus pandemic, as reported in Garcia and Berton (2021); Koytak and Celik (2022); S. Yu, Eisenman, and Han (2021). Some reported work adopted a longer timeframe, including data collected prior to the known occurrence of an event, to fully utilize available data for analysis (Fakhry, Kassam, & Asfoura, 2020; Quach et al., 2022; S. Zhao et al., 2022).

4.3.3 Post-event

Based on the survey, post-event sentiment analysis or opinion mining is the most prevalent type of study in the field of public security. This approach involves analyzing data after a specific event has occurred, either using the event date itself, or data from an earlier time frame that triggered the public security threat. The purpose of the analysis is usually to relook at issues related to public security and provide insight into what happened (Geeta & Niyogi, 2016; N. Li et al., 2016; L. Ma et al., 2016) and to prepare for future endeavors (Alfarrarjeh et al., 2017; N. Wang, Varghese, & Donnelly, 2016). The analysis also provides support for policy making (Chung & Zeng, 2016; de Carvalho & Costa, 2022) and management (Gascó et al., 2017). Examples of events analyzed using post-event sentiment analysis include immigration and border security breaches (Chung & Zeng, 2016), shooting incidents (N. Wang, Varghese, & Donnelly, 2016), collision accidents (Y. Li et al., 2016; L. Ma et al., 2016), nuclear accidents (N. Li et al., 2016), hurricane and earthquake disasters (Alfarrarjeh et al., 2017).

4.4. Social Media Platform

The fourth attribute of the recent work on social media sentiment analysis and opinion mining for public security was the platform of social media used. The attribute can be grouped into those using a single social media platform and those using multiple platforms mixed. Most of the recent work in the public security domain used a dataset from a single social media platform. From the survey, it was found that Twitter and Sina Weibo were the most utilized, followed by YouTube, Facebook and other microblogs. Only few instances of reported work used multiple platforms, or combined them with web feeds. There were examples of work that combined: Twitter, Facebook and web feeds (Backfried & Shalunts, 2016), Twitter, Facebook and Youtube (Ghanem et al., 2021), Twitter and Flickr (Alfarrarjeh et al., 2017), Twitter and Reddit (Qi et al., 2019), Twitter and ReliefWeb (X. Li et al., 2017), Twitter and Sina Weibo (X. Ma et al., 2020), Twitter/ Sina Weibo and online news feed (de Carvalho & Costa, 2022; Xu, Liu, & Shang, 2017; X. Yu et al., 2020), and, Sina Weibo and WeChat (Lian, Liu, & Dong, 2020; X. Liu et al., 2021). Among these platforms, Twitter was found to be the most commonly used, followed by Sina Weibo. One of the reasons for their popularity is their real-time information dissemination and data acquisition tools (Al-khateeb & Agarwal, 2016; Bai & Yu, 2016). Platforms that prohibit data acquisition, such as Facebook, are less popular. It is argued that a combination of social media platforms is required to improve sentiment analysis system performance and present the actual sentiment or opinion of the public on a larger scale (Dahal, Kumar, & Li, 2019; Mendon et al., 2021; Mohamed Ridhwan & Hargreaves, 2021).

4.5. Dataset

The fifth attribute of the taxonomy pertains to the type of dataset used in sentiment analysis and opinion mining for public security. The dataset attribute can be grouped into two types: (i) public datasets, and (ii) private datasets. Public datasets, as the name suggests, are in the public domain. Public datasets are important because they allow researchers to compare results. They are also useful with respect to transfer learning (Anuratha et al., 2021; Bansal et al., 2021). However, due to the shortage of public datasets, the majority of the work conducted on sentiment analysis and opinion mining has been conducted using private datasets. Furthermore, researchers prefer to acquire their own private dataset in order to achieve a specific objective or conduct an analysis based on a specific event. Table 4 presents a summary of accessible public dataset used for sentiment analysis and opinion mining in the public security domain. Some of the existing public datasets include geotagged tweets related to disasters including: disasters within the United States (Pfeffer & Morstatter, 2016), the Hurricane Harvey Twitter Dataset (Phillips, 2017), earthquakes from the Nepal-quake and Italy-quake (Basu, Shandilya, Khosla, Ghosh, & Ghosh, 2019), the international disaster dataset (Guha-Sapir, Below, & Hoyois, 2016), climate change (Effrosynidis et al., 2022; Qian, 2019), and an emotion dataset of internet users during the epidemic period from DataFountain (X. Zhang & Xu, 2021). Most of the public dataset available for the public health domain are COVID-19 related (Banda et al., 2021; Dimitrov et al., 2020; S. Kumar, 2020; Rabindra Lamsal, 2020a, 2020b; X. Lyu et al., 2020; Pfeffer & Morstatter, 2016). Some authors have shared their dataset with the public. Examples include: the refugee crisis (J. S. Lee & Nerghes, 2017), the Palestinian-Israeli conflict (Al-Agha & Abu-Dahrooj, 2019), the Sewol Ferry Disaster (M. J. Lee et al., 2020), terrorism and cyber security (Mamta et al., 2020) and the Typhoon Haiyan disaster (T. Zhang & Cheng, 2021). Recent efforts have also utilized public dataset for multi-domain purposes (Mamta et al., 2020; Rudra, Ghosh, Ganguly, Goyal, & Ghosh, 2015).

Table 4

Summary of public datasets used for sentiment analysis and opinion mining in public security domain.

Author	Domain	Description	Link
Muhammad Imran, Elbassuoni, Castillo, Diaz, and Meier (2013)	Natural disaster	Human-labelled tweets collected during 2012 Hurricane Sandy and 2011 Joplin tornado	https://crisisnlp.qcri.org/#
Alam, Joty, and Imran (2018)	Natural disaster	Human-labelled tweets collected from 2015 Nepal earthquake and 2013 Queensland floods	https://crisisnlp.qcri.org/#
Pfeffer and Morstatter (2016)	Natural disaster	United States geotagged Twitter daily posts from June to November 2014 and 2015	https://search.gesis.org/research_data/SDN-10.7802-1166?doi=10.7802/1166

T. Zhang and Cheng (2021)	Natural disaster	Internet archive database for historical tweets using hashtag related Typhoon Haiyan from October to December 2013	https://archive.org/
Phillips (2017)	Natural disaster	Hurricane Harvey Twitter dataset from August to September 2017	https://digital.library.unt.edu/ark:/67531/metadc993940/
Basu et al. (2019)	Natural disaster	Tweets collected during Nepal Earthquake 2015 and Italy Earthquake 2016	https://zenodo.org/record/2649794#.YzL5iXZByv8
Qian (2019)	Natural disaster	Tweets related to climate change sentiment dataset form April 2015 to February 2018	https://www.kaggle.com/datasets/edqian/twitter-climate-change-sentiment-dataset
Effrosynidis et al. (2022)	Natural disaster	Climate change Twitter dataset from June 2006 to October 2019	https://data.mendeley.com/datasets/mw8yd7z9wc/
S. Li and Sun (2023)	Natural disaster	Twitter public opinion comments about natural disasters from August 2013 to June 2014	https://figshare.com/articles/dataset/tweets_csv_gz/3465974/2
M. J. Lee et al. (2020)	Emergency	Mixed platform post related to Sewol Ferry Disaster from April 2014 to March 2015	https://www.frontiersin.org/articles/10.3389/fpsyt.2020.505673/full#supplementary-material
Moraes Silva et al. (2022)	Emergency	Twitter US Airline Sentiment in February 2015	https://www.kaggle.com/datasets/crowdflower/twitter-airline-sentiment
Al-Agha and Abu-Dahrooj (2019)	Chaos	Tweets related terrorism keywords from December 2015 to 2106 in United States and European country	https://github.com/odahroug2010/2017
Berhoum et al. (2023)	Chaos	Tweets originating from Pro-ISIS supporters since November 2015 Paris Attack	https://www.kaggle.com/datasets/fifthtribe/how-isis-uses-twitter
Rudra et al. (2015)	Multi-domain	Tweets related to 5 different event of public security domain	http://cse.iitkgp.ac.in/~krudra/disaster_dataset.html
Guha-Sapir, Below, and Hoyois (2016)	Multi-domain	International Disaster Database for public access (multi-domain)	https://www.emdat.be/
Mamta et al. (2020)	Multi-domain	Tweets related to public security domain keywords from January to April 2019	https://www.iitp.ac.in/~ai-nlp-ml/resources.html
Dimitrov et al. (2020)	Public health	Semantically annotated corpus COVID-19 related tweets	https://data.gesis.org/tweetscov19/
X. Lyu et al. (2020)	Public health	Weibo labelled and unlabeled sentiment post about COVID-19 from January to May 2020	https://github.com/COVID-19-Weibo-data/COVID-19-sentiment-analysis-dataset-Weibo
S. Kumar (2020)	Public health	COVID-19 related sentiment labelled dataset collected in India from March to July 2020	https://www.kaggle.com/datasets/surajkum1198/twitterdata
X. Zhang and Xu (2021)	Public health	Emotional dataset during epidemic period	https://www.datafountain.cn/datasets
E. Chen, Lerman, and Ferrara (2020)	Public health	Multilingual COVID-19 Twitter dataset collected from January to March 2020	https://github.com/echen102/COVID-19-TweetIDs
Rabindra Lamsal (2020b)	Public health	Daily updated COVID-19 tweets dataset	https://ieee-dataport.org/open-access/coronavirus-covid-19-tweets-dataset

Rabindra Lamsal (2020a)	Public health	Daily updated COVID-19 geo-tagged tweets dataset	https://ieee-dataport.org/open-access/coronavirus-covid-19-geo-tagged-tweets-dataset
Mathayomchan, Taecharungroj, and Wattanacharoensil (2022)	Public health	Pandemic tweets dataset mentioned the SEA countries from January 2020 to July 2021	https://github.com/viriyatae/pandemictweets
Banda et al. (2021)	Public health	Large scale COVID-19 Twitter dataset from January 2020 to June 2021	https://zenodo.org/record/7179601#.Y0Th43ZByv8
M. Imran, Qazi, and Ofli (2022)	Public health	Two billion multilingual tweets related to the COVID-19 pandemic from February 2020 to March 2021	https://crisisnlp.qcri.org/tbcov

4.6. Language

The sixth attribute of the taxonomy pertains to the language of the dataset used. The language attribute can be grouped into three: (i) monolingual, (ii) bilingual, and (iii) multilingual. A monolingual dataset is composed of text in a single language, while a bilingual dataset comprises two languages, and a multilingual dataset includes three or more languages. In terms of pre-processing and feature extraction support, with respect to the tools available and the source of the lexicon, monolingual has an advantage over the others. To fully exploit this benefit, some reported work has excluded text in languages other than the preferred language, such as keeping only English tweets and discarding others (Almehmadi, Joudaki, & Jalali, 2017; Subramaniyaswamy et al., 2017). However, removing data in other languages may hamper the sentiment detection, which could provide critical information about the disaster or events (N. Li et al., 2016). The most common language used in the public security domain is English, followed by Chinese. Other languages include Indonesian, Arabic, Indian, Japanese, Korean, Bangla, Telugu, Vietnamese, Germany and Portuguese.

Bilingual datasets typically comprise English combined with some other language, such as Chinese, Filipino, Malay, Hindi, German, Portuguese, and Spanish. In existing works, translation is often performed from one language into another, such as translating written text in Filipino to English (T. Zhang & Cheng, 2021) and Malay to English (Azmi et al., 2022), before the sentiment analysis is conducted. Some reported work has combined a language with another translated language to maximize the available resources for representing features (Fuadvy & Ibrahim, 2019). However, communication that uses dual language presents a challenge in bilingual datasets where different languages are compounded in a single sentence or comment (Farzindar & Inkpen, 2020), referred to as "code-switched" or "code-mixed" data. This type of data presents a new research challenge in terms of filtering the language, preprocessing, and feature representation, based on each language, while maintaining contextual meaning. Examples of work that uses code-mixed datasets are Malay with English (Fuadvy & Ibrahim, 2019), Filipino with English (T. Zhang & Cheng, 2021), Indonesian with English (Yan, Chen, & Wang, 2020), and Nigerian with English (Adamu et al., 2021).

Sentiment analysis and opinion mining for public security that has been conducted using multilanguage settings include combinations of: English, French and German (Smith et al., 2018), English, Arabic, French and German (El Ali et al., 2018), and English with conjunctions of European languages (Kovács, Kovács-Győri, & Resch, 2021; Laudy et al., 2017). Additionally, there have been studies that utilized multilingual datasets from 218 countries worldwide (M. Imran, Qazi, & Ofli, 2022). However, this reported work commonly used separate datasets for each language and generated separate models based on each dataset. In some countries, nevertheless, it was observed multilingualism is used in a single dataset instead (Suhaimin, Hijazi, Alfred, & Coenen, 2017, 2019).

4.7. Sentiment Analysis and Opinion Mining Approach

The seventh and last attribute of the taxonomy is the approach used to perform sentiment analysis and opinion mining. It is critical to select an appropriate approach to achieve the objectives described in Section 4.3 and guide each methodology in completing the analysis or mining. According to the taxonomy, the recent approaches found in the surveyed work, in the public security domain, can be divided into machine learning-based, lexicon-approaches, hybrid, and manual coding groups. Sub-section 4.7.1 to 4.7.4 present a detailed explanation of each group, and includes some surveyed works that have used each approach.

4.7.1 Machine Learning Based

The machine learning method is divided into five: (i) supervised learning, (ii) unsupervised learning, (iii) semi-supervised learning, (iv) ensemble learning, and (v) deep learning. The following sub-section describes the details of each.

i. Supervised Learning

Supervised learning uses labelled data to learn and classify the sentiment from opinionated text. It involves preprocessing textual data and extracting features (Razali et al., 2021). The tasks include the removal of special characters and leaving only specific, meaningful words before features, such as Bag Of Words (BOW) and Word2Vec features, are extracted. Recent work in the public security domain has shown that supervised learning is the most popular approach. The algorithms that have been most frequently employed include: Random Forest (RF), Support Vector Machine (SVM), Naïve Bayes (NB), K-Nearest Neighbor (K-NN), Logistic Regression (LR) and Maximum Entropy (ME). The researchers usually experimented with multiple algorithms coupled with the extracted features to find the best performing classifier (N. Wang, Varghese, & Donnelly, 2016). Bai and Yu (2016) showed that RF with a Distribution Representation of Words (DRW) performed the best in the detection of messages related to disaster. S. Yue et al. (2018) found that RF and SVM algorithms were the best in mapping different event correlations with social media data. An et al. (2019) predicted the influence of social media in the context of terrorist events with multiple algorithms and concluded that LR algorithms produced the best prediction model. The work presented in Fakhry, Kassam, and Asfoura (2020) evaluated COVID-19 cases using social media data and its geographic location, and found that NB produced the best performance. M. Gupta et al. (2021) analyzed social media data for public perception on COVID-19 issues using various classification models and found that the SVM model performed the best.

Supervised learning has the advantage of using labelled or annotated data to train the classifier, enabling the extraction of patterns to provide more accurate predictions. However, a notable disadvantage of this approach is that it is domain-dependent, which means that the performance of the classifier is impacted if it encounters data outside of its domain or was not seen during the learning stage (An et al., 2019; To et al., 2017). A further disadvantage is the effort required to create the training set for inference process (Gu, Guo, Zhuang, Du, & Qian, 2022; Xie & Chen, 2022).

ii. Unsupervised Learning

The unsupervised learning approach does not require labeled training data. It leverages hidden structures or semantic associations in unlabeled data and can be applied to text data without manual intervention (Aggarwal & Zhai, 2012; Pedrycz & Chen, 2016). Two common unsupervised approaches used in sentiment analysis and opinion mining for public security are clustering and topic modeling. Clustering is the process of grouping data into distinct classes or clusters so that items belonging to the same cluster have a high degree of similarity while objects belonging to separate clusters exhibit a high degree of variety (L. Yue, Chen, Li, Zuo, & Yin, 2019). Clustering has been employed to assess the impact of topics in the context of predicted events (An et al., 2019). In sentiment analysis, researchers have set thresholds for keyword frequency in documents related to an event (Xu, Liu, & Shang, 2017) or orientation of the sentiment (L. Ma et al., 2016). In recent work, the K-Means, K-Medoids and Density-Based Spatial Clustering of Application with Noise (DBSCAN) algorithms are the most commonly used. In clustering public opinion on natural disasters, Mustakim et al. (2021) compared K-Medoids and DBSCAN and found that DBSCAN performed better with a higher Silhouette Index (SI). In Bansal et al. (2021) it was also found that DBSCAN outperformed other algorithms in clustering multi-domain non-natural events. Topic modeling has been achieved through Latent Dirichlet Allocation (LDA), a commonly used model found in this survey. Y. Li et al. (2016) proposed an unsupervised topic sentiment for the automatic classification of Chinese social media data. Gu, Guo, and Zhuang (2021) used the LDA model to extract emerging topics amongst Weibo users during an emergency, and G. Cao et al. (2021) used the LDA model for categorizing topics in social media posts during Wuhan lockdown.

The advantage of unsupervised learning is it does not require labelled or annotated data. This approach also outperforms manual selection of keywords for sentiment analysis in identifying event-related keywords for public security purposes (X. Li et al., 2017). However, unsatisfactory results have been reported in sentiment analysis for non-dependent features or out-of-domain keywords (de Carvalho & Costa, 2022; Y. Li et al., 2016).

iii. Semi-supervised Learning

The semi-supervised learning uses a small amount of labeled or annotated data along with a larger amount of unlabeled data for classification. However, this approach has been the least used in the recent work considered in the review reported here due to its lower classification performance results. (Sharma & Jain, 2020). L. Zhang, Wei, and Boncella (2020) leveraged a semi-supervised SVM to train a model using only on a small training set of labeled data to classify emotions in the emergency situation of Hurricane Irma. Recently, Z. Qin and Ronchieri (2022) utilized

20% of labeled data to predict the classes of the remaining data and produce a classification model for sentiment related to pandemic events.

Semi-supervised learning takes advantage of the small amount of labeled data to automate the data labeling process and overcome the expense of data labeling and annotation. However, semi-supervised learning is not applicable to all sentiment analysis problems, especially for data that require rule-based feature extraction (Behl et al., 2021).

iv. Ensemble Learning

The ensemble approach idea is to combine outputs from multiple base learners to produce a single output that yields better classification performance (Guyon et al., 2008). Among the most commonly implemented types of ensembles are bagging and boosting, in addition to stacking and RF (Bhosale & Patnaik, 2023; Hung, Alfred, Ahmad Hijazi, Ibrahim, & Asri, 2015). Bagging trains each base learner on a different bootstrap sample taken from the input data, while boosting builds a model incrementally by adding weights to the data misclassified by the base classifiers (Zong, Xia, & Zhang, 2021). Chouhan (2021) developed a gradient boosting classifier for differentiate types of non-situational tweets during the Pulwama Terrorist Attack. Tsai and Wang (2020) proposed an ensemble method by combining pre-trained and early-trained models for COVID-19 related tweet analysis. Mamta et al. (2020) perform sentiment analysis on multi-domain sentiment corpora of crime, emergency, terrorism and cyber security using an ensemble of Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU).

Ensemble learning presents a robust strategy for addressing challenges associated with multiple learning models by facilitating the creation of intelligently integrated models (Bhosale & Patnaik, 2023). It has been shown to improve sentiment analysis performance in recent work, with boosting generally outperforming bagging (Chouhan, 2021; Tsai & Wang, 2020; N. Wang, Varghese, & Donnelly, 2016). However, ensemble methods require a deeper understanding of the dataset for feature extraction and may require complex architectures (Mamta et al., 2020).

v. Deep Learning

Deep learning is a subset of machine learning that employs deep neural networks and data learning presentations (Razali et al., 2021; L. Yue et al., 2019). Deep learning can be utilized in supervised, partially supervised or unsupervised learning settings (N. Gupta & Agrawal, 2020). In machine learning methods, deep learning offers solutions to complex problems by deriving insightful knowledge from straightforward representations. The prominence of neural network approaches is largely due to their ability to learn precise representations, a critical structural feature (Bhosale & Patnaik, 2022). In the field of sentiment analysis and opinion mining for public security, researchers have shown a growing interest in applying deep learning techniques. For instance, Gu, Guo, and Zhuang (2021) proposed a Bi-Directional Long Short-Term Memory (Bi-LSTM) to identify a positive, negative or neutral sentiment from social media activities during emergency events. Pran et al. (2020) compared CNN and LSTM for sentiment analysis towards COVID-19 using the Bangla language and found that CNN performed better in accuracy. X. Chen et al. (2021) experimented with a deep transformer network, namely the Bidirectional Encoder Representations from Transformers (BERT), with Neural Network (NN) for sentiment classification both before and after the COVID-19 pandemic. Recently, B. Zhang et al. (2022) fine-tuned the BERT inspired model, ERNIE, on pandemic outbreak datasets to achieve better classification performance.

The deep learning approach has the advantage of producing better classification performance results using the coarse grain and deep features of the dataset (Chandra, Cambria, & Nanetti, 2020; Garcia & Berton, 2021). The deep learning approach, specifically in domain-related tasks, can perform better with a few adjustments made at the feature extraction level (Lin & Moh, 2021). However, the disadvantage of deep learning is the large amount of data required to generate the model (Behl et al., 2021; El Ali et al., 2018) and the high cost of training to build the model (Lin & Moh, 2021; Sadiq, Ahn, & Choi, 2020).

4.7.2 Lexicon Approaches

Based on the recent work surveyed, another approach for sentiment analysis and opinion mining for public security is the lexicon-based approach. The lexicon-based is divided into two: dictionary-based and corpus-based. The following subsections describe the details of each approach.

i. Dictionary-Based

Dictionary-based lexicon approaches utilizes a dictionary that integrates the polarity of the terms. When a word is discovered in a text, a lookup in the dictionary is conducted, and then the sentiment score is calculated. From the survey, many dictionaries have been used such as Valence Aware Dictionary and Sentiment Reasoner (VADER) (Hutto & Gilbert, 2014), WordNet (Miller, 1995), SentiWordNet (Baccianella, Esuli, & Sebastiani, 2010), SentiStrength (Thelwall, 2017), Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Francis, & Booth, 2001), AFINN (Nielsen, 2011), Word-Emotion Association Lexicon (EmoLex) (Mohammad & Turney, 2013), and TextBlob (Loria, Keen, Honnibal, Yankovsky, Karesh, & Dempsey, 2014). For Chinese sentiment analysis during the COVID-19 pandemic, BosonNLP (Min, Ma, Zhao, & Li, 2015), a sentiment dictionary constructed from labeled Weibo, news and forum data, was used (X. Yu et al., 2020). Additionally, HowNet (a large-scale knowledge database of Chinese) was used for feature engineering to feed into deep learning model for emergency event detection (P. Li & Wang, 2021).

The advantage of the dictionary-based method is that it is simple to implement and does not rely on labeled or annotated data (Becken et al., 2022). However, the sentiment analysis performance of a dictionary-based method is limited by the quality of the rules that integrate the polarity and lexicons in the dictionary (Y. Chen & Ji, 2021; L. Li, Ma, & Cao, 2020; T. Zhang & Cheng, 2021). Additionally, the coverage of social media words in existing dictionaries is often incomplete and requires expansion (Pan et al., 2022; T. Qin et al., 2022).

ii. Corpus-Based

The corpus-based lexicon approach relies on co-occurrence patterns and a seed list of words to find other sentiment words in a large corpus (B. Liu, 2011). Hence the corpus-based approach requires a large training corpus to compute the polarity of the words (Agarwal & Mittal, 2016). In the survey presented in Zhou (2021), microblog corpora were obtained for multiple emergency events by retrieving event keywords and then measuring the influence of the event using a calculated equation. The work presented in Abid et al. (2017) adopted diverse data sources to produce heterogeneous content to improve a corpus. The authors later obtained other XML data structures from different social media and unified them into a single structure, targeting the detection of suspicious content circulated on social media that could threaten public security. Jiang et al. (2017) proposed the Word Emotion Association Network (WEAN) to compute the emotion of words based on nouns, verbs, adjectives and cyber words in the corpus acquired. The results produced better sentiment analysis performance when applied to the emergency event of The Malaysia Airlines MH370 dataset from Sina Weibo. Thorat and Namrata Mahender (2019) created a corpus based on drought synonym tweets and later generated patterns for predicting tweet polarity.

The advantage of the corpus-based approach is that it provides better performance for the specific domain for which it was developed (Abid et al., 2017; Thorat & Namrata Mahender, 2019). However, it requires a large amount of data to build an informative corpus (Sufi & Khalil, 2022; Theja Bhavaraju, Beyney, & Nicholson, 2019). Furthermore, the performance of sentiment analysis in a domain-specific corpus is usually low if transferred to other domains (Zhou, 2021; Zong, Xia, & Zhang, 2021).

4.7.3 Hybrid

From the literature, some of the reported work has adopted a hybrid approach to analyze sentiment concerning public threat, which combines the machine learning and lexicon-based approaches. This method was developed to compensate for the shortcomings of machine learning and lexicon-based approaches when used separately, and is the most preferred approach after supervised learning. The reported work directed at hybrid approaches tends to leverage lexicons to extract features and use machine learning to classify the sentiment, rather than the calculation of the polarity based on the lexicon only. For example, Akbar et al. (2021) extracted a feature set based on the corpus lexicon of COVID-19 lockdown public opinion before applying a series of supervised machine learning classifiers to analyze the sentiment. The result using Bernoulli NB achieved optimal values over other classifiers. Recently, Pan et al. (2022) expanded the corpus-based lexicon for the Weibo COVID-19 dataset before experimenting with several machine learning algorithms. The RF showed the highest classification performance among all tested algorithms.

The advantage of the hybrid approach is it improves the performance of the sentiment analysis compared to using only either the lexicon or machine learning approach alone (An et al., 2019; Chandra, Cambria, & Nanetti, 2020; Garcia & Berton, 2021; W. Zhang, Zhu, & Wang, 2019). However, the hybrid approach requires a complex framework or structure to implement (Y. Chen, Ji, & Wang, 2019; Khatua et al., 2020; Tang et al., 2022; H. Xia, An, Li, & Zhang, 2020).

4.7.4 Manual Coding

Manual coding is an approach that relies on human coders to read and code subsampled datasets using pre-defined rules (N. Li et al., 2016). The particular rules can be performed repeated or differently. For example, manual coding was performed separately for positive statements and negative statements (Gascó et al., 2017). The manual codes were then verified before being assigned, and then used for training and testing using a larger dataset (Henríquez-Coronel, García García, & Herrera-Tapia, 2019).

The advantage of manual coding is that specific rules can be applied to produce a better performance analysis system. Despite being expensive, this approach has the potential to overcome the problem of scalability and replicability by providing deeper insights into each task (Van Atteveldt, van der Velden, & Boukes, 2021). The disadvantage is it is time consuming and not easily transferable to other problems or domains.

5. Analysis of Trend, Issues and Future Directions of Sentiment Analysis and Opinion Mining for Public Security

This section presents the trend analysis of work considered in this survey. The trend for each of the aforementioned attributes is presented with the goal of demonstrating the progress of the work and the direction in which the researchers have moved over the last seven years. Based on the selected works in this survey, a threshold of five articles is considered for each year to be included for better trend visualization. Consideration was also needed to ensure the representativeness of articles against the practical limitation of the considered work (Groves, Fowler Jr, Couper, Lepkowski, Singer, & Tourangeau, 2011), and to make meaningful conclusions about trends or patterns in the data (Cohen, 1988). The demonstrated trends may be useful in determining the direction of future research in this domain. Section 5.1 to 5.7 present the analysis of the trends within the work considered in this survey. Section 5.8. identifies some remaining issues that the authors deem pertinent and describes possible future directions for research in social media sentiment analysis and opinion mining in public security.

5.1. Trend Analysis of Sentiment Analysis and Opinion Mining Objectives for Public Security

Fig. 5a depicts the trend associated with the objectives attribute. The analysis of events and improvement of techniques have emerged as the primary areas of interest within the research community, with the number of publications focused on these objectives showing an upward trend since 2019. This trend could be caused by the COVID-19 pandemic, whereby most work focused on efforts to understand events and explore techniques for mitigating them. Meanwhile, the number of multipurpose publications has slightly increased since 2020, while corpus generation remaining limited over time.

Fig. 5b depicts the distribution of the objectives from 2016 to 2023. Analysis of events and technique improvement are the most common, accounting for 41% and 39% of the existing work respectively. This observation demonstrates that researchers were interested in understanding events by analyzing them and proposing techniques to improve the detection or the prediction ability of models. The distribution of multipurpose objectives came third at 16%. In contrast, corpus generation is the least common objective, due to most of the published work considered using existing corpora to validate and verify their proposed techniques (Backfried & Shalunts, 2016; Kostakos et al., 2018; N. Wang, Varghese, & Donnelly, 2016).

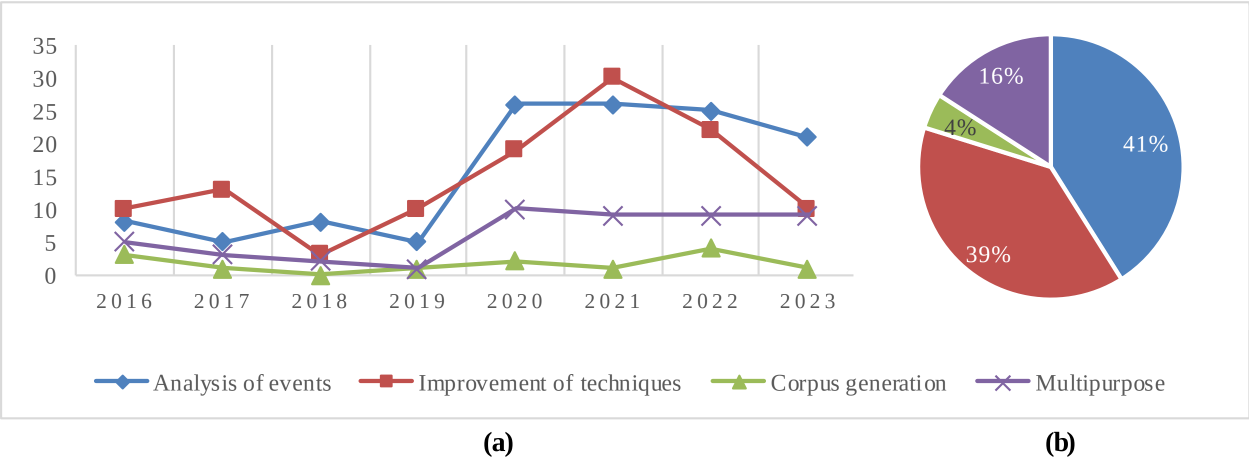
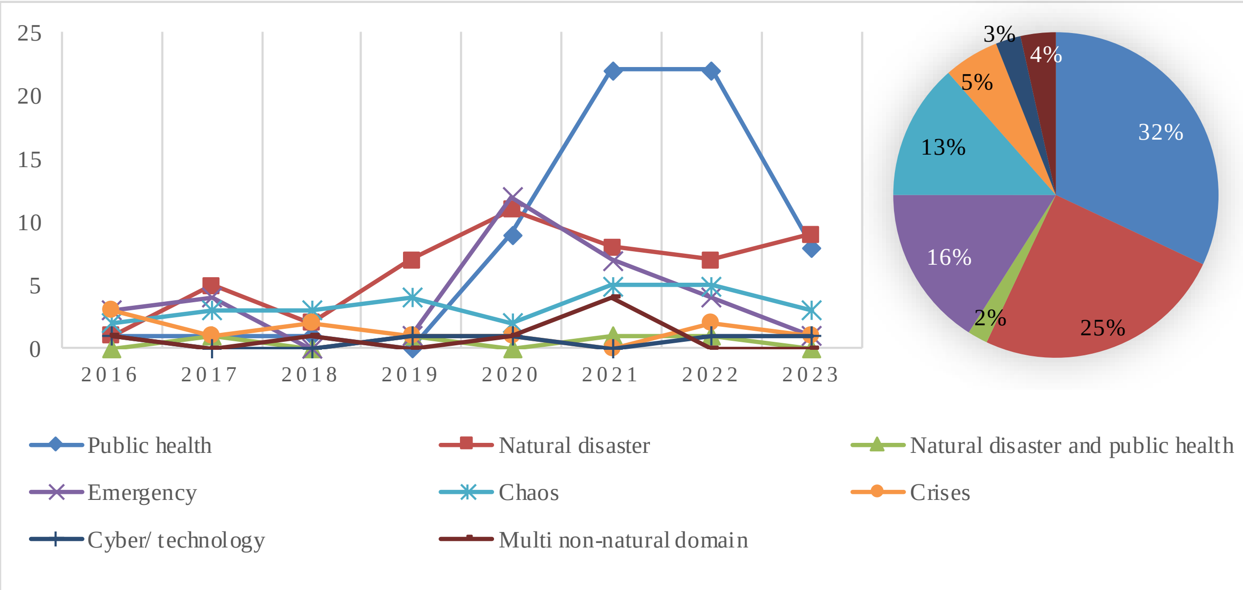


Fig. 5. (a) The trend of published work for the objectives in social media sentiment analysis and opinion mining for public security in recent years and **(b)** the distribution of the objectives in recent years.

5.2. Trend Analysis of Domain of Interest in Public Security

Fig. 6a depicts the trend of work that concentrated on public security in the natural and non-natural domain. From the figure, compared to other domains, it can be seen that the natural disaster domain increased linearly until 2020, before it decreased. Meanwhile, the public health domain has experienced a sudden increase from 2020 until recently. This is due to the sudden demand for research on the COVID-19 pandemic, which can be seen in public health domain surge from 2020. Compared to other domains, the non-natural domain of emergency demonstrated a rapid increase from 2019 to 2020. This category's focus groups included emergency situations, accidents, and energy incidents. However, it decreased in 2021 and 2022, while chaos and multi-domain interests increased, indicating a desire to combine multiple domain types for the analysis of multiple events.

Fig. 6b depicts the distribution of recent work in the public security domain. Public health and natural disasters have dominated the recent work, accounting for 32% and 25% of the total work respectively. The majority of the works focus on the emergency domain (16%), which is followed by chaos (13%). The high percentage of works in the emergency domain could be due to the frequent sharing of data related to emergency events on social media. Crisis comes in fifth place with 5%, followed by multi-domain with 4%. The cyber and technology domain has the second lowest percentage at 3%, which could be because only a small number of people directly involved in the cyber security domain share or discuss related topics. However, the number of published works that integrate both natural disaster and public health remain limited, comprising only 2% of the total. This is could be due to lack of work that connects the two domains based on public reaction. Moreover, combining both domains also leads to large-scale data coverage (Albayrak & Gray-Roncal, 2019; X. Li et al., 2017).



(a) **(b)**

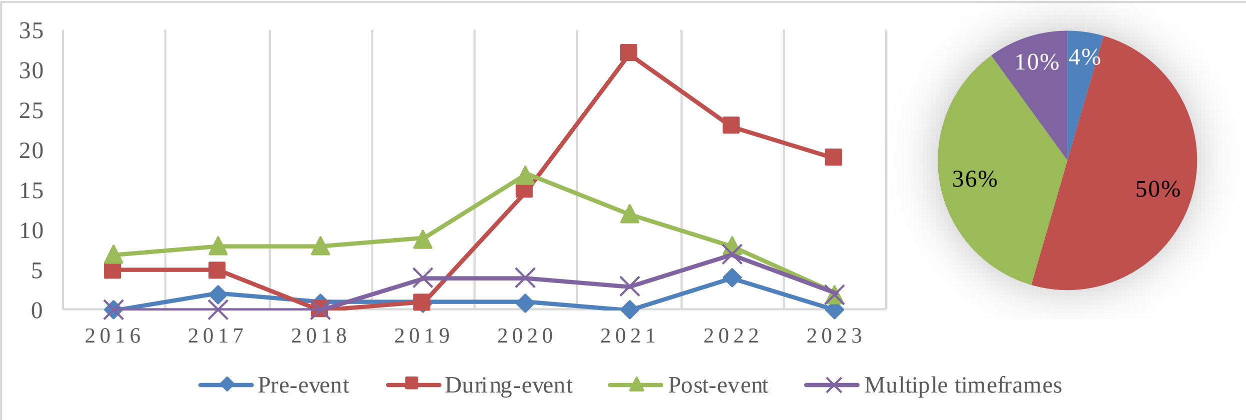
Fig. 6. **(a)** The trend of recent published work in the non-natural public security domain and **(b)** the distribution of the works in the domain.

5.3. Trend Analysis of Event Timeframe

Fig. 7a depicts the trend of the event timeframe attribute. From the figure it can be seen that the post-event timeframe attracted the most interest up until 2020, when the during-event timeframe featured significant increase. This increase is caused by the emergence of the COVID-19 pandemic, which led to a shift in research attention towards the existing pandemic-focused public health domain. The trend of work concerning the pre-event timeframe remains low throughout the sample period considered.

Fig. 7b depicts the distribution of published work across different timeframes. In recent years, a high number of publications have been dedicated to the during-event and post-event timeframes, which account for 50% and 36%, respectively. Meanwhile, the number of publications that cover the multiple and pre-event timeframes were low at

10% and 4% respectively. Thus, indicating that current work focused on addressing the public needs for a specific event after it has occurred, with less emphasis on prediction or early detection of events.



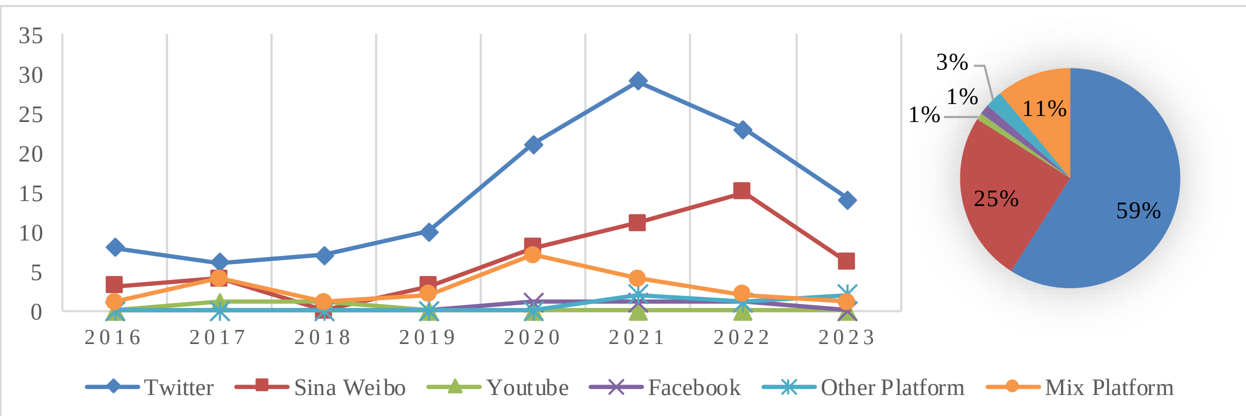
(a) **(b)**

Fig. 7. (a) The trend of published work in the event timeframe in public security in recent years and **(b)** the distribution of the work in recent years.

5.4. Trend Analysis of Social Media Platforms Used

Fig. 8a shows the trend of the social media platforms used for research in the public security domain. Twitter and Sina Weibo have grown in popularity over the years for communication and message dissemination. These platforms offer researchers an easy way to acquire data, and several publicly available datasets harvested from these platforms have been made available by researchers (Mathayomchan, Taecharungroj, & Wattanacharoensil, 2022; Nagapudi, Agrawal, & Bulusu, 2021). The mixed platforms recorded similar popularity to Sina Weibo, however, demonstrated a slight decrease started in 2021. This could be due to users' preference to use a single social media platform to share news.

Fig. 8b depicts the distribution of the social media platforms used for sentiment analysis and opinion mining in public security. Twitter was found to be the dominant platform, with 59% of the published work considered. Sina Weibo comes in second with 25%, followed by mixed platforms with 11%. In contrast, Facebook, YouTube, and other platforms are still underutilized for public security data acquisition. This could be due to the low popularity of these platforms for real-time discussion and the difficulty of acquiring data from these platforms for research purposes.



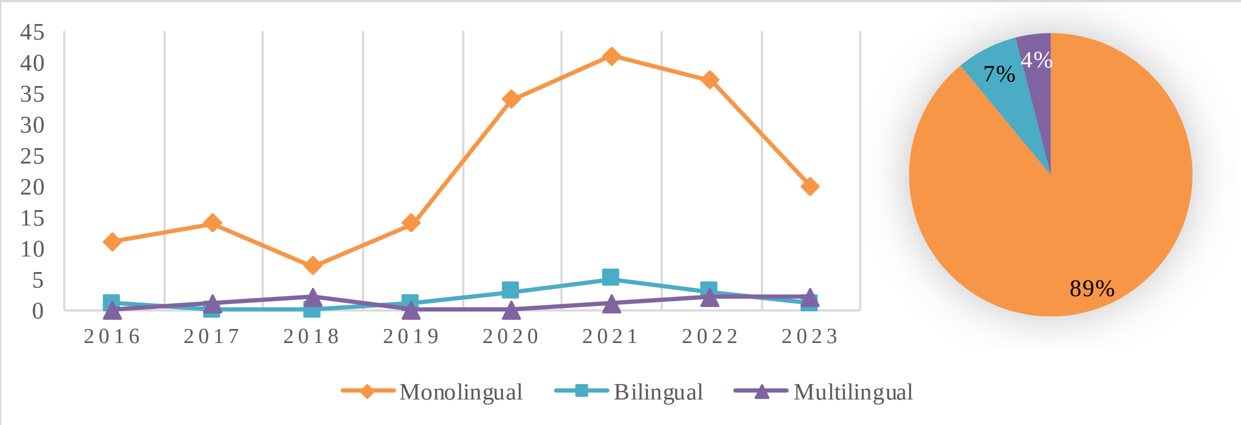
(a) **(b)**

Fig. 8. (a) The trend of platforms used for published work in social media sentiment analysis and opinion mining for public security in recent years and **(b)** the distribution of the platform used in recent years.

5.5. Trend Analysis of Language of Dataset Used

Fig. 9a depicts the language of the datasets used in the context of the considered published work in sentiment analysis and opinion mining for public security. The use of monolingual datasets has steadily increased over time. This trend can be attributed to the wide availability of pre-processing approaches and resources for feature engineering specific to monolingual data. Based on the trend, the study of bilingual and multilingual public security are low. However, the trend is gradually increasing since 2020, although interest remains relatively low compared to the monolingual work. This trend suggested a growing interest among researchers in investigating sentiment analysis and opinion mining across different languages, in particular in the bilingual context, within the public security domain. It was found that bilingual studies were conducted because there was a need for the analysis of compounding language in the dataset as a result of the uniqueness of the language itself. This is particularly relevant as bilingual comments are common among the public, making them a valuable source of information for sentiment analysis and opinion mining.

Fig. 9b depicts the language distribution of the dataset used. Monolingual datasets dominate the work surveyed, comprising 89% of the total. The bilingual and multilingual datasets remain significantly low, at 7% and 4%, respectively.



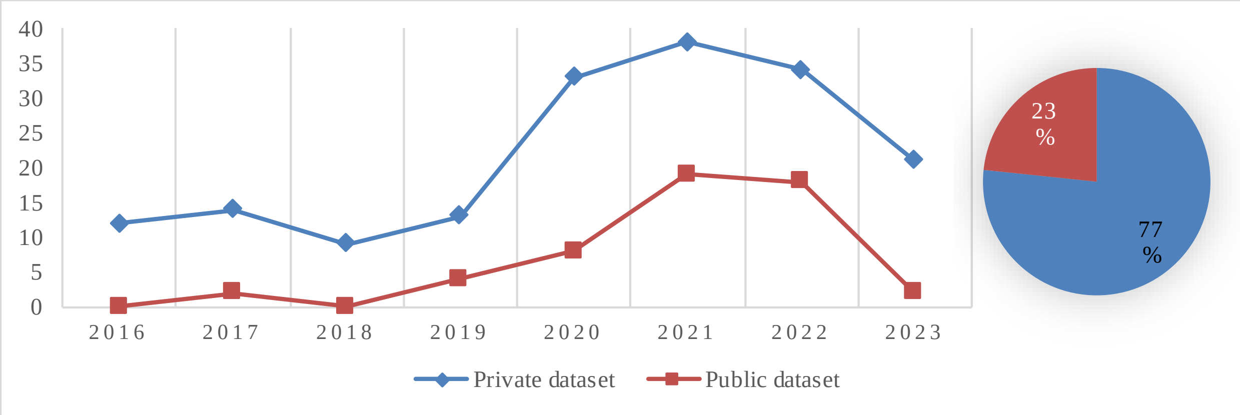
(a) (b)

Fig. 9. (a) The trend of the language of the dataset used for published work in social media sentiment analysis and opinion mining for public security in recent years and **(b)** the distribution of the language used in recent years.

5.6. Trend Analysis of Dataset Type Used

Fig. 10a depicts the trend in the types of datasets used with respect to published work in sentiment analysis and opinion mining for public security. Private datasets have exhibited a steady increase in usage over the years, whereas the use of public datasets has remained constant with a slight increase in recent years. This trend suggests that researchers in the public security domain prefer to use their own datasets for analysis and testing their sentiment analysis approach, which may raise concerns about the generalizability of the output. The marginal increase in the usage of public datasets in 2020 and 2021 can be attributed to the wide availability and sharing of COVID-19 datasets for urgent global analysis.

The distribution of dataset types used is illustrated in Fig. 10b. The chart shows that the vast majority of the surveyed work, 77% used private datasets, while only 23% used public datasets.



(a) (b)

Fig. 10. **(a)** The trend of the dataset type used for published work in social media sentiment analysis and opinion mining for public security in recent years and **(b)** the distribution of the dataset type used in recent years.

Despite the predominance of private datasets over public ones, the public datasets that see the most use are predominantly from the public health domain, followed by natural disaster. Fig. 11 shows the overall dataset usage distribution among related works in the public security domain. Public health datasets constitute the major chunk, amounting to 38% of overall use, followed by natural disaster datasets at 35%. The most frequently used public health dataset is the daily updated COVID-19 tweets dataset (Rabindra Lamsal, 2020b), while the Nepal Earthquake 2015 and Italy Earthquake 2016 datasets (Basu et al., 2019) top the list for natural disasters. The popularity of these datasets can be attributed to their early availability as large-scale public resources within their respective domains, making them highly valuable for sentiment analysis and opinion mining during and in the aftermath of specific events.

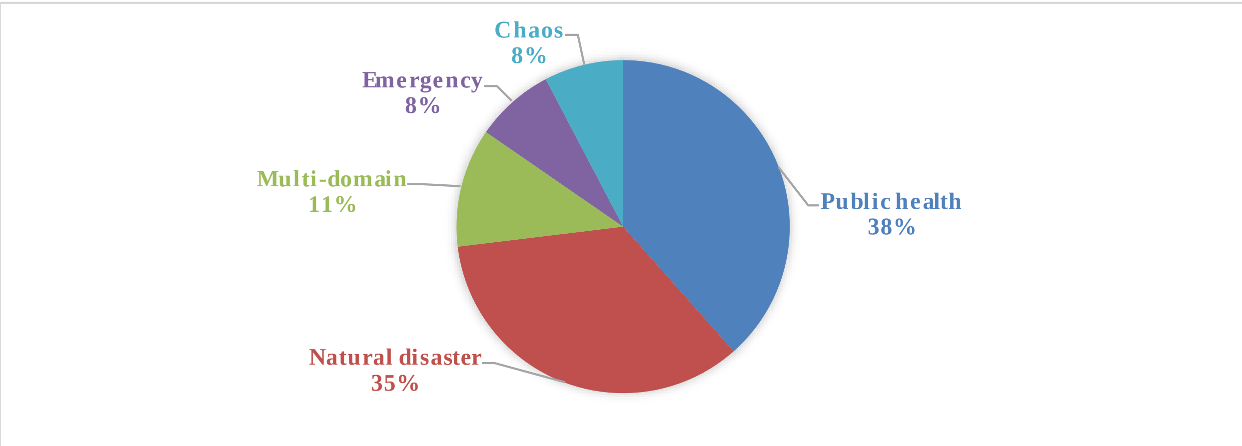


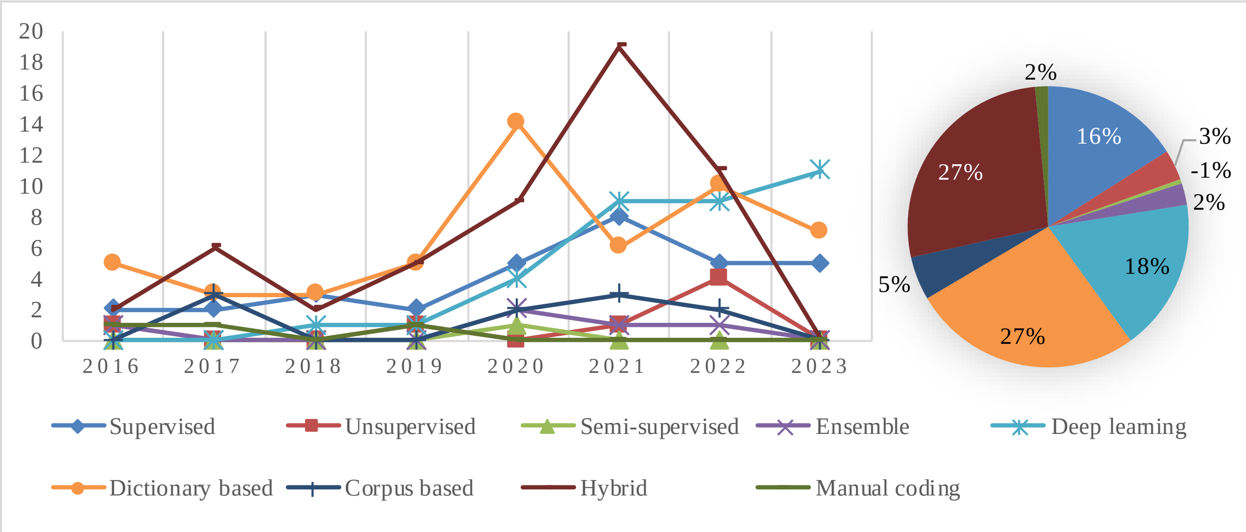
Fig. 11. Distribution of public dataset usage by public security domain.

5.7. Trend Analysis of Approaches for Sentiment Analysis and Opinion Mining in Public Security

Fig. 12a depicts the approaches evident from the considered published work on sentiment analysis and opinion mining for public security. The dictionary-based approach was found to be the most preferred; the number of publications increased steadily over time. Meanwhile, the rise in popularity of the hybrid and deep learning approaches since 2020 suggests that researchers are taking advantage of the availability of high-end processing hardware capable of multitasking, which may not be easily accessible before. Supervised learning has been consistently used over the years, while the unsupervised learning and other approaches have seen slower growth.

Fig. 12b depicts the recent distribution of the approaches considered. The dictionary and hybrid-based was found to be the most common approach used both at 27%. The deep learning approach ranks second with 18%, and the supervised learning approach ranks third with 16%. Corpus-based learning comes in fourth with 5%, followed by unsupervised learning with 3%. Other approaches were found to have a lower distribution over time, namely:

ensemble, semi-supervised, and manual coding. This suggests that, among the available algorithms, the ensemble and semi-supervised approaches are still underutilized for sentiment analysis and opinion mining in public security.



(a) **(b)**

Fig. 12. (a) The trend of the main approach used for social media sentiment analysis and opinion mining for public security in recent years and **(b)** the distribution of the approach used in recent years.

5.8. Issues and Future Direction of Social Media Sentiment Analysis and Opinion Mining for Public Security

This section presents the remaining issues, as well as potential future directions, of research work in social media sentiment analysis and opinion mining for public security. The state-of-the-art social media sentiment analysis for the public is plagued by several issues that can be identified from the presented trend analysis and highlighted in this survey. The issues are presented in Subsection 5.8.1, and potential future work is presented in Subsection 5.8.2.

5.8.1 Issues

Based on the surveyed articles, there were five major issues identified: (i) shortage of multi-class and different level analysis approaches; (ii) insufficient availability of public security domain-independent datasets; (iii) inadequate prediction based on timeframe coverage; (iv) lack of supporting approaches for variations across different languages; and (v) limited information availability.

(i) Shortage of multi-class and different level analysis approaches: When dealing with multi-objective studies, researchers can benefit from multi-level sentiment analysis and opinion mining. Such scenarios encounter challenges in multi-class classification (Bashar, 2022; M. Gupta et al., 2021). Specifically, tri-class classification can be problematic, as some data points may straddle the border of multiple categories (Bhullar et al., 2022; Garcia & Berton, 2021; M. Gupta et al., 2021). In addition, different level of analysis, such as fine-grained emotion analysis, may lead to low classification performance (Zhou & Zhang, 2017). Furthermore, addressing each problem may require distinct techniques (Zhou & Jing, 2020).

(ii) Insufficient availability of public security domain-independent datasets: As sentiment analysis and opinion mining are increasingly applied to public security domains, it is crucial to have a domain-independent dataset to ensure reliable results (de Carvalho & Costa, 2022). However, the availability of training and validation datasets for events that threaten public security is minimal (Behl et al., 2021; Zhou, 2021). The trend analysis of dataset types revealed a lack of public dataset availability in the public security domain, and recent work was found to often rely on datasets from other domains for training (Fuadvy & Ibrahim, 2019; To et al., 2017). This presents a challenge for sentiment analysis and opinion mining models as using corpora based on other domains is typically larger than a domain-specific corpus, potentially leading to reduced performance.

(iii) Inadequate prediction based on timeframe coverage: The published work that has focused on trend analysis for automatic detection or prediction at the pre-event timeframe, as described in Section 4.2.1, is very limited. The detection of an event's starting point, such as a natural disaster or emergency event, or an outbreak of a disease or a pandemic, is the most important key factor for early warning and forecasting of public threats (R. Lamsal, Harwood, & Read, 2022). The problem of misinformation that creates noise or false detection was found to often hinder prediction performance (Fang et al., 2022; Luna et al., 2022; Sufi & Khalil, 2022).

(iv) Lack of supporting approaches for variations across different languages: The language perspectives has become a major issue that has hampered sentiment analysis and opinion model performance for public security. Multi-language variation across different regions (Dahal, Kumar, & Li, 2019; Geeta & Niyogi, 2016; Kostakos et al., 2018; N. Li et al., 2016), figurative language such as irony and sarcasm (Andhale et al., 2021; M. Gupta et al., 2021; Tsao et al., 2022), and non-English processing (Y. Li et al., 2016; Lin & Moh, 2021) are among the language-related issues identified. In addition, the limited lexicon sources, and analysis approaches, have served to further complicate this issue. The problem is also hampered by the limitations of feature extraction techniques (Andhale et al., 2021; de Carvalho & Costa, 2022; Mohamed Ridhwan & Hargreaves, 2021).

(v) Limited information availability: The unavailability of comprehensive data was a major limitation found in the study, attributed to users withholding crucial information or restrictions imposed by social media platforms. Users refrained from disclosing important details, such as the geographical location or event-related references (Sattaru, Bhatt, & Saran, 2021). While platform restrictions such as limited access to user profiles and data acquisition timeframes added to the scarcity of information. These constraints within the message content have adversely impacted the overall sentiment distribution (Alomari, Mehmood, & Katib, 2020; Chowdhury, Basu, & Maulik, 2022; D. Wu & Cui, 2018). Consequently, imbalanced sentiment distribution has resulted in flawed analyses (Zhu et al., 2020), limiting the accuracy and reliability of the findings.

5.8.2 Potential Future Works

This sub-section outlines potential work for further advancement in the field of social media sentiment analysis and opinion mining, specifically in relation to public security. These projections are based on the trend analysis and issue identification discussed in the preceding section. The recommended future works focus on intensifying analysis levels, improving the relevance of the dataset, utilizing variations of features to enhance outbreak detection, offering better language/lexicon support, and mitigating information exhaustion. It is anticipated that addressing these focal points may tackle critical challenges in the public security domain, thereby contributing substantively to the evolution of sentiment analysis and opinion mining. The suggested future work is enumerated as follows:

(i) More extensive multi-class and multi-level analysis: Multitasking with multidimensional sentiment analysis and opinion mining could overcome the unspecified approach for problem domain. It also can overcome the difficulties for researchers who need to analyze a specific event quickly. According to the trend analysis of the objectives of the published work considered, the number of multipurpose objectives is still low when compared to other studies. This highlights a significant gap in the current research, where the value of nuanced, detailed analysis is not being fully realized. Future work must focus extensively on multi-class and multi-level approaches, especially to address subtle class and level differences. Pre-trained transformers with unique embeddings can be experimented with, as they offer a superior classification approach in language models to enhance comprehensive multi-class and multi-level analysis (R. Sun et al., 2022; Huosong Xia et al., 2022). Utilizing these advanced computational tools can yield more detailed and nuanced sentiment analysis, enabling the capture subtleties in public opinion that might otherwise go unnoticed.

(ii) Production of a multi-domain public security datasets: As noted earlier in this survey, much existing published work used private datasets for specific events. Extra effort is required to obtain a larger dataset that encompasses multiple public security domains. The rationale for this is that larger datasets provide more representative and diverse samples that can help in improving the robustness and generalizability of the models. Access to more data can substantially enhance the performance of sentiment analysis and opinion models (Alfred & Obit, 2021). Additionally, the diversity of data will also serve as a catalyst for the development of new relevant techniques. Having access to a wider variety of data enables researchers to gain insights into different types of public sentiment, which can lead to the creation of more effective and tailored strategies for each sub-domain.

(iii) Utilization of a greater variety of features and techniques for automatic detection of outbreaks: Due to the limited data for the pre-event timeframe, it is essential to employ diverse features and prediction techniques to build better models. Utilizing data from multiple domains, as recommended in (i), can yield diverse datasets to facilitate feature extraction and transfer learning for detection and implementation. Moreover, network-based studies can be used to monitor scenarios within a short event window. Dissemination networks, such as social network analysis, provide monitoring tools based on structures and relationships to identify key nodes. This is essential as key nodes often play pivotal roles in information propagation, and early detection of unusual activity may serve as an indicator of potential security threats. Such studies can simulate changes in community activity and explain the virality phenomenon within the designated timeframe (Chung & Zeng, 2018; X. Ma et al., 2020), providing valuable insight for predicting and detecting outbreaks in a timely manner.

(iv) Establishment of cross-language corpora and supporting approaches: Cross-language lexicon corpus from corresponding language datasets and larger datasets for validation could be used to address language processing issues. This becomes increasingly important considering the global nature of social media and public security issues. Different communities, cultures, and countries express sentiments in unique ways, and it is important to account for these linguistic differences to ensure accurate sentiment analysis and opinion mining. According to the objective trend analysis presented in Fig. 12, there has been a lack of work focusing on corpus generation. For the development of sentiment analysis and opinion mining for public security, an approach that does not rely solely on translation accuracy must be investigated. NLP features can be diversified with domain corpus for the feature extraction. A modification of transfer learning that supports multilanguage in public security domain can also be proposed. This approach could potentially create a more inclusive model, capable of understanding a wider range of sentiment from various linguistic communities, thereby improving the overall effectiveness and reach of sentiment analysis and opinion mining in the public security domain.

(v) Expansion of data acquisition and geographical coverage: Addressing the issues of limited data availability and imbalanced sentiment data distribution requires expanding data acquisition across multiple platforms. This can not only provide a larger pool of data but also help in achieving a more representative sample, capturing a broader array of sentiments from various demographics and geographical locations. Geographical coverage areas can be extended, for instance, by increasing the radius of the area (Yuan & Liu, 2020). Furthermore, acquiring more data and integrating the Named Entity Recognition (NER) approach in the pre-processing stage for location detection in message dissemination can also improve sentiment data distribution (Barachi, Mathew, & Alkhatib, 2022). Expanding geographical coverage and improving data acquisition can lead to more accurate sentiment analysis, as it accounts for regional differences in sentiment expression. The integration of NER can help identify the origin of sentiments, which is critical for public security agencies in developing localized and effective strategies.

6. Discussion

This survey paper set out with the aim of constructing a taxonomy for state-of-the-art sentiment analysis and opinion mining methods applicable to the public security domain, analyzing recent trends, and identifying gaps and potential future areas of research.

First, the objective trends in sentiment analysis and opinion mining within the public security domain are projected to display an increasing focus on specific events, following the trends indicated in Section 5.1. This shift may be due to the growing realization that event-specific approaches allow for fine-tuned analytics that can provide nuanced and actionable insights. However, this requires advancements in the system's flexibility and adaptability to different events, thus indicating a key area for future innovation. Despite the need for larger and more varied datasets, the generation of new corpora is predicted to remain low, primarily due to high computational costs and challenges associated with multi-domain and multilingual data. However, this gap presents an opportunity for future research to explore more efficient and effective data generation methods.

Second, regarding the focus within the public security domain, an anticipated surge is expected in the domain of public health. This projection is informed by trend analyses discussed in Section 5.2 and is further reinforced by a substantial amount of related work concentrating on during-event scenarios, such as COVID-19. This assumption is grounded in the continued global emphasis on public health and the potential of sentiment analysis to provide real-time public reactions and insights, a resource crucial for responsive and efficient policy-making.

Third, as for the utilization of social media platforms, Twitter and Sina Weibo are likely to maintain their dominance as indicated in Section 5.4. This trend is likely to persist due to their ease of data acquisition, extensive user base, and the availability of robust analytical tools, enabling more comprehensive sentiment analysis and opinion mining.

Fourth, in terms of the language used in datasets, as discussed in Section 5.5, monolingual data is expected to continue to dominate over bilingual and multilingual data. However, as methods for monolingual analysis become more established, research interest in bilingual and multilingual data is likely to grow. This shift will be crucial in the globalized context of social media, where public opinion is diverse and multilingual. On the topic of dataset usage in the public security domain in Section 5.6, although private datasets are often employed, it is expected that public datasets will be shared more frequently as they are studied and analyzed. This shift can enhance transparency and enable collaborative efforts across different studies.

Fifth, as discussed in Section 5.7, the hybrid approach for sentiment analysis and opinion mining will likely remain popular due to its proven effectiveness in combining multiple approaches. However, with the exponentially advancements in deep learning, an increase in research interest is expected in this area. This prediction is based on the recent surge in computational power and the potential of deep learning to automate and enhance sentiment analysis. In light of this trend, future taxonomies or surveys on sentiment analysis and opinion mining in the public security domain may focus on deep learning methods. This shift could catalyze further innovations in the field and provide valuable insights into the evolving landscape of sentiment analysis.

While this survey has made significant strides in mapping the landscape of sentiment analysis and opinion mining in the domain of public security, it is important to acknowledge its limitations. Primarily, this survey has not extensively covered public security within the domain of cyber security. The nexus of cyber security and public safety is indeed significant and increasingly salient in an ever-more digitally connected world. However, the availability of related works specific to this intersection was limited based on search queries' result. Moreover, this area was not within the intended scope of this survey. Future surveys could look to address this by specifically including cyber security within their purview. A second limitation lies in the lack of a comparative evaluation of the performance of machine learning and lexicon-based approach. The works under consideration differed considerably in their objectives, methodologies, and levels of detail provided. For instance, while some research focused on the successful application of an approach, they did not necessarily provide detailed results from their experiments or implementations. In other cases, the focus was primarily on statistical analysis, informed by the specific objectives of the study. The heterogeneity in the focus and depth of the analyzed studies precluded a thorough head-to-head comparison of these techniques. By acknowledging these limitations, additional review works could be useful to yield further valuable insights on the performance comparison of the existing work.

7. Conclusions

More research work on sentiment analysis and opinion mining for public security domain has been conducted over the years. However, there have been limited systematic surveys on the current state of this work. Therefore, a more systematic survey, supported by a descriptive taxonomy, was presented here; a taxonomy that classifies attributes.

This survey papers summarize the key concepts of the existing work on social media sentiment analysis and opinion mining for public security by organizing a taxonomy. Relevant indexed articles from Scopus, IEEE Xplore, and Science Direct are extracted using keyword searching. Related journals, conference proceedings, and serials underwent identification, screening, and review for inclusion in this survey. The taxonomy includes seven key attributes; objectives of the work conducted, the domain of public security, the public security event timeframe, the social media platform of the data acquisition, the dataset type, language of the dataset, and the sentiment analysis or opinion mining approach used. An analysis of the trends featured in the recent work considered, and the distribution on topics based on the identified attributes from the taxonomy, was also presented.

The remaining issues and future direction of social media sentiment analysis and opinion mining for public security were established and described in the second half of the survey. Five issues were identified; (i) shortage of multi-class and different level analysis approaches; (ii) insufficient availability of public security domain-independent datasets; (iii) inadequate prediction based on timeframe coverage; (iv) lack of supporting approach for variation across different languages; and (v) limited information availability. Five potential areas of future work for social media sentiment analysis and opinion mining, within the public security domain, were suggested: (i) more extensive multi-class and multi-level analysis; (ii) production of multi-domain public security datasets; (iii) utilization of greater variety of features and technique for automatic detection of outbreaks; (iv) establishment of cross-language corpora and supporting approaches; and (v) expansion of data acquisition and geographical coverage.

To conclude, recent work on social media sentiment analysis and opinion mining needs extra effort and extensive work with respect to the public security domain, to ensure the development of the study in the domain and delivery of related applications for the public benefit. The presented taxonomy could be used by other researchers to plan their works and research activities. The potential future directions suggested could further improve the existing approach or addresses the remaining gaps.

Conflict of interest

The authors declare that they have no conflicts of interest.

Author Contributions

All authors contributed to the paper conceptualization and design. Material preparation and analysis were performed by M.S.M.S and M.H.A.H. Writing of the original draft was conducted by M.S.M.S., M.H.A.H. and E.G.M. The writing review and editing were performed by P.N.E.N. and S.C., supervised by F.C. All authors have read and agreed to the published version of the manuscript.

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References

Abdul Reda, A., Sinanoglu, S., & Aboussalah, A. (2023). Out of sight, out of mind: The impact of lockdown measures on sentiment towards refugees. *Journal of Information Technology and Politics*. doi:10.1080/19331681.2023.2183301

Abid, A., Ameur, H., Mbarek, A., Rekik, A., Jamoussi, S., & Ben Hamadou, A. (2017). *An extraction and unification methodology for social networks data: An application to public security*. Paper presented at the ACM International Conference Proceeding Series.

Abusaqer, M., Benaoumeur Senouci, M., & Magel, K. (2023). *Twitter User Sentiments Analysis: Health System Cyberattacks Case Study*. Paper presented at the 5th International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2023.

Adamu, H., Lutfi, S. L., Malim, N. H. A. H., Hassan, R., Di Vaio, A., & Mohamed, A. S. A. (2021). Framing twitter public sentiment on Nigerian government COVID-19 palliatives distribution using machine learning. *Sustainability (Switzerland), 13*(6). doi:10.3390/su13063497

Agarwal, B., & Mittal, N. (2016). *Prominent feature extraction for sentiment analysis*: Springer.

Aggarwal, C. C., & Zhai, C. (2012). *Mining text data*: Springer Science & Business Media.

Akbar, A. F., Santoso, A. B., Putra, P. K., & Budi, I. (2021). A classification model to identify public opinion on the lockdown policy using Indonesian tweets. *Journal of Theoretical and Applied Information Technology, 99*(14), 3394-3402. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85111596289&partnerID=40&md5=a7e6e851c96f32b1b426cbfd50525da9

Al-Agha, I., & Abu-Dahrooj, O. (2019). Multi-level analysis of political sentiments using twitter data: A case study of the Palestinian-Israeli conflict. *Jordanian Journal of Computers and Information Technology, 5*(3), 195-215. doi:10.5455/jjcit.71-1562700251

Al-khateeb, S., & Agarwal, N. (2016, 18-21 Aug. 2016). *The rise & fall of #NoBackDoor on Twitter: The apple vs. FBI case*. Paper presented at the 2016 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM).

Alam, F., Joty, S., & Imran, M. (2018). Domain adaptation with adversarial training and graph embeddings. *arXiv preprint arXiv:1805.05151*.

Albayrak, M. D., & Gray-Roncal, W. (2019). *Data Mining and Sentiment Analysis of Real-Time Twitter Messages for Monitoring and Predicting Events*. Paper presented at the 2019 9th IEEE Integrated STEM Education Conference, ISEC 2019.

Alfarrarjeh, A., Agrawal, S., Kim, S. H., & Shahabi, C. (2017). *Geo-spatial multimedia sentiment analysis in disasters*. Paper presented at the Proceedings - 2017 International Conference on Data Science and Advanced Analytics, DSAA 2017.

Alfred, R., & Obit, J. H. (2021). The roles of machine learning methods in limiting the spread of deadly diseases: A systematic review. *Heliyon, 7*(6), e07371.

Ali, M. F., Irfan, R., & Lashari, T. A. (2023). Comprehensive sentimental analysis of tweets towards COVID-19 in Pakistan: a study on governmental preventive measures. *PeerJ Computer Science, 9*. doi:10.7717/PEERJ-CS.1220

Almehmadi, A., Joudaki, Z., & Jalali, R. (2017). *Language Usage on Twitter Predicts Crime Rates*. Paper presented at the ACM International Conference Proceeding Series.

Alomari, E., Mehmood, R., & Katib, I. (2020) Sentiment analysis of arabic tweets for road traffic congestion and event detection. In *EAI/Springer Innovations in Communication and Computing* (pp. 37-54).

Amin, M. S., Ahn, H., & Choi, Y. B. (2021). *Human Sentiments and Associated Physical Actions Detection in Disasters with Deep Learning*. Paper presented at the 3rd International Conference on Artificial Intelligence in Information and Communication, ICAIIC 2021.

An, L., Han, Y., Yi, X., & Li, G. (2019). *Prediction of microblogging influence and measuring of topical influence in the context of terrorist events*. Paper presented at the 17th International Conference on Scientometrics and Informetrics, ISSI 2019 - Proceedings.

An, L., Han, Y., Yi, X., Li, G., & Yu, C. (2021). Prediction and Evolution of the Influence of Microblog Entries in the Context of Terrorist Events. *Social Science Computer Review*. doi:10.1177/08944393211029193

Andhale, S., Mane, P., Vaingankar, M., Karia, D., & Talele, K. T. (2021). *Twitter Sentiment Analysis for COVID-19*.

Paper presented at the Proceedings - International Conference on Communication, Information and Computing Technology, ICCICT 2021.
Anuratha, K., Joshi, S., Sharmila, P., Nandhini, J. M. N., & Paravthy, M. (2021). *Topical Sentiment Classification to Unmask the Concerns of General Public during COVID-19 Pandemic using Indian Tweets*. Paper presented at the Proceedings of the 2021 4th International Conference on Computing and Communications Technologies, ICCCT 2021.
Anuratha, K., & Parvathy, M. (2023). Multi-label Emotion Classification of COVID-19 Tweets with Deep Learning and Topic Modelling. *Computer Systems Science and Engineering, 45*(3), 3005-3021. doi:10.32604/csse.2023.031553
Arias, F., Guerra-Adames, A., Zambrano, M., Quintero-Guerra, E., & Tejedor-Flores, N. (2022). Analyzing Spanish-Language Public Sentiment in the Context of a Pandemic and Social Unrest: The Panama Case. *International Journal of Environmental Research and Public Health, 19*(16). doi:10.3390/ijerph191610328
Astuti, I. F., Widagdo, P. P., Tanro, M. L. R., Cahyadi, D., & Suntara, A. A. (2023). *Sentiment analysis on land and forest fire management in Twitter using Naïve Bayes method*. Paper presented at the AIP Conference Proceedings.
Azmi, P. A. R., Abidin, A. W. Z., Mutalib, S., Zawawi, I. S. M., & Halim, S. A. (2022, 7-8 Sept. 2022). *Sentiment Analysis on MySejahtera Application during COVID-19 Pandemic*. Paper presented at the 2022 3rd International Conference on Artificial Intelligence and Data Sciences (AiDAS).
Baccianella, S., Esuli, A., & Sebastiani, F. (2010). *Sentiwordnet 3.0: An enhanced lexical resource for sentiment analysis and opinion mining*. Paper presented at the Proceedings of the Seventh International Conference on Language Resources and Evaluation (LREC'10).
Backfried, G., & Shalunts, G. (2016) Sentiment analysis of media in German on the refugee crisis in Europe. In *: Vol. 265. Lecture Notes in Business Information Processing* (pp. 234-241).
Bai, H., & Yu, G. (2016). A Weibo-based approach to disaster informatics: incidents monitor in post-disaster situation via Weibo text negative sentiment analysis. *Natural Hazards, 83*(2), 1177-1196. doi:10.1007/s11069-016-2370-5
Bala, M. M., Srinivasa Rao, M., & Ramesh Babu, M. (2017). Sentiment trends on natural disasters using location based twitter opinion mining. *International Journal of Civil Engineering and Technology, 8*(8), 9-19. Retrieved from https://www.scopus.com/inward/record.uri?eid=2-s2.0-85028308036&partnerID=40&md5=477be37d86174572cf160dcdda832d71
Banda, J. M., Tekumalla, R., Wang, G., Yu, J., Liu, T., Ding, Y., . . . Chowell, G. (2021). A large-scale COVID-19 Twitter chatter dataset for open scientific research—an international collaboration. *Epidemiologia, 2*(3), 315-324.
Bansal, D., Grover, R., Saini, N., & Saha, S. (2021). GenSumm: A Joint Framework for Multi-task Tweet Classification and Summarization using Sentiment Analysis and Generative Modelling. *IEEE Transactions on Affective Computing*. doi:10.1109/TAFFC.2021.3131516
Barachi, M. E., Mathew, S. S., & Alkhatib, M. (2022). *Combining Named Entity Recognition and Emotion Analysis of Tweets for Early Warning of Violent Actions*. Paper presented at the 2022 7th International Conference on Smart and Sustainable Technologies, SpliTech 2022.
Bashar, M. K. (2022). A Hybrid Approach to Explore Public Sentiments on COVID-19. *SN Computer Science, 3*(3). doi:10.1007/s42979-022-01112-1
Basu, M., Shandilya, A., Khosla, P., Ghosh, K., & Ghosh, S. (2019). Extracting resource needs and availabilities from microblogs for aiding post-disaster relief operations. *IEEE Transactions on Computational Social Systems, 6*(3), 604-618.
Becken, S., Stantic, B., Chen, J., & Connolly, R. M. (2022). Twitter conversations reveal issue salience of aviation in the broader context of climate change. *Journal of Air Transport Management, 98*, 102157. doi:https://doi.org/10.1016/j.jairtraman.2021.102157
Behl, S., Rao, A., Aggarwal, S., Chadha, S., & Pannu, H. S. (2021). Twitter for disaster relief through sentiment analysis for COVID-19 and natural hazard crises. *International Journal of Disaster Risk Reduction, 55*. doi:10.1016/j.ijdrr.2021.102101
Berhoum, A., Meftah, M. C. E., Laouid, A., & Hammoudeh, M. (2023). An Intelligent Approach Based on Cleaning up of Inutile Contents for Extremism Detection and Classification in Social Networks. *ACM Transactions on Asian and Low-Resource Language Information Processing, 22*(5). doi:10.1145/3575802
Bhatia, S., Chaudhary, P., & Dey, N. (2020). *Opinion mining in information retrieval*: Springer.

Bhosale, Y. H., & Patnaik, K. S. (2022). Application of deep learning techniques in diagnosis of covid-19 (coronavirus): a systematic review. *Neural Processing Letters*, 1-53.

Bhosale, Y. H., & Patnaik, K. S. (2023). PulDi-COVID: Chronic obstructive pulmonary (lung) diseases with COVID-19 classification using ensemble deep convolutional neural network from chest X-ray images to minimize severity and mortality rates. *Biomedical Signal Processing and Control, 81*, 104445.

Bhullar, G., Khullar, A., Kumar, A., Sharma, A., Pannu, H. S., & Malhi, A. (2022). Time series sentiment analysis (SA) of relief operations using social media (SM) platform for efficient resource management. *International Journal of Disaster Risk Reduction, 75*, 102979. doi:https://doi.org/10.1016/j.ijdrr.2022.102979

Boukabous, M., & Azizi, M. (2020). *Review of Learning-Based Techniques of Sentiment Analysis for Security Purposes*. Paper presented at the The Proceedings of the Third International Conference on Smart City Applications.

Cai, M., Luo, H., & Cui, Y. (2021). A Study on the Topic-Sentiment Evolution and Diffusion in Time Series of Public Opinion Derived from Emergencies. *Complexity, 2021*. doi:10.1155/2021/2069010

Cao, G., Shen, L., Evans, R., Zhang, Z., Bi, Q., Huang, W., . . . Zhang, W. (2021). Analysis of social media data for public emotion on the Wuhan lockdown event during the COVID-19 pandemic. *Computer Methods and Programs in Biomedicine, 212*, 106468. doi:https://doi.org/10.1016/j.cmpb.2021.106468

Cao, H., & Lian, S. (2020, 11-13 Dec. 2020). *Internet Forum Texual Information Filtering Mechanism for Emergency based on Bi-LSTM Neural Network*. Paper presented at the 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC).

Chandra, J. K., Cambria, E., & Nanetti, A. (2020). *One Belt, One Road, One Sentiment? A Hybrid Approach to Gauging Public Opinions on the New Silk Road Initiative*. Paper presented at the IEEE International Conference on Data Mining Workshops, ICDMW.

Chaudhary, M., & Bansal, D. (2021) Agitation on Social Media Amid Terrorist Attacks: A Case Study on Jammu and Kashmir. In*: Vol. 62. Lecture Notes on Data Engineering and Communications Technologies* (pp. 383-391).

Che, S. P., Wang, X., Zhang, S., & Kim, J. H. (2023). Effect of daily new cases of COVID-19 on public sentiment and concern: Deep learning-based sentiment classification and semantic network analysis. *Journal of Public Health (Germany)*. doi:10.1007/s10389-023-01833-4

Chen, E., Lerman, K., & Ferrara, E. (2020). Tracking social media discourse about the covid-19 pandemic: Development of a public coronavirus twitter data set. *JMIR Public Health and Surveillance, 6*(2), e19273.

Chen, S., Mao, J., & Li, G. (2019) Spatiotemporal Analysis on Sentiments and Retweet Patterns of Tweets for Disasters. In*: Vol. 11420 LNCS. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 436-443).

Chen, X., Zeng, H., Xu, H., & Di, X. (2021). *Sentiment Analysis of Autonomous Vehicles after Extreme Events Using Social Media Data*. Paper presented at the IEEE Conference on Intelligent Transportation Systems, Proceedings, ITSC.

Chen, Y., & Ji, W. (2021). Public demand urgency for equitable infrastructure restoration planning. *International Journal of Disaster Risk Reduction, 64*. doi:10.1016/j.ijdrr.2021.102510

Chen, Y., Ji, W., & Wang, Q. (2019, 8-11 Dec. 2019). *A Bayesian-Based Approach for Public Sentiment Modeling*. Paper presented at the 2019 Winter Simulation Conference (WSC).

Chenxi, L., Jilin, F., Meng, H., & Zhonghao, W. (2022, 6-8 May 2022). *Research on Post Earthquake Public Opinion Analysis Based on XLNet-BiGRU-A Algorithm*. Paper presented at the 2022 IEEE 2nd International Conference on Computer Communication and Artificial Intelligence (CCAI).

Choirul Rahmadan, M., Nizar Hidayanto, A., Swadani Ekasari, D., Purwandari, B., & Theresiawati. (2020). *Sentiment Analysis and Topic Modelling Using the LDA Method related to the Flood Disaster in Jakarta on Twitter*. Paper presented at the Proceedings - 2nd International Conference on Informatics, Multimedia, Cyber, and Information System, ICIMCIS 2020.

Chouhan, R. L. (2021) Sentiment analysis of pulwama attack using twitter data. In*: Vol. 135. Lecture Notes in Networks and Systems* (pp. 119-126).

Chowdhury, S. R., Basu, S., & Maulik, U. (2022). Disastrous Event and Sub-Event Detection From Microblog Posts Using Bi-clustering Method. *IEEE Transactions on Computational Social Systems*, 1-0. doi:10.1109/TCSS.2022.3213794

Chung, W., & Zeng, D. (2016). Social-media-based public policy informatics: Sentiment and network analyses of U.S. Immigration and border security. *Journal of the Association for Information Science and Technology, 67*(7), 1588-1606. doi:10.1002/asi.23449

Chung, W., & Zeng, D. (2018) Social-media-based policy informatics: Cyber-surveillance for homeland security and public health informatics. In*: Vol. 25. Public Administration and Information Technology* (pp. 363-385).
Cohen, J. (1988). Stafisfical power analysis for the behavioral sciences.(rev. edn.). In: Orlando, FL: Academic Press.
Dahal, B., Kumar, S. A. P., & Li, Z. (2019). Topic modeling and sentiment analysis of global climate change tweets. *Social Network Analysis and Mining, 9*(1). doi:10.1007/s13278-019-0568-8
Daou, H. (2021). Sentiment of the public: the role of social media in revealing important events. *Online Information Review*, *45*(1), 157-173. doi:10.1108/OIR-12-2019-0373
de Carvalho, V. D. H., & Costa, A. P. C. S. (2022). Towards corpora creation from social web in Brazilian Portuguese to support public security analyses and decisions. *Library Hi Tech*. doi:10.1108/LHT-08-2022-0401
de Carvalho, V. D. H., Nepomuceno, T. C. C., & Costa, A. P. C. S. (2020) An Automated Corpus Annotation Experiment in Brazilian Portuguese for Sentiment Analysis in Public Security. In*: Vol. 384 LNBIP. Lecture Notes in Business Information Processing* (pp. 99-111).
de Carvalho, V. D. H., & Seixas Costa, A. P. C. (2021). Public Security Sentiment Analysis on Social Web: A Conceptual Framework for the Analytical Process and a Research Agenda. *International Journal of Decision Support System Technology, 13*(1), 1-20. doi:10.4018/IJDSST.2021010101
Dehdezi, A. K., & Sardi, F. K. Q. (2016). The Role of Public Security in Society. *International Journal of Humanities and Cultural Studies (IJHCS) ISSN 2356-5926*, 2090-2096.
Dimitrov, D., Baran, E., Fafalios, P., Yu, R., Zhu, X., Zloch, M., & Dietze, S. (2020). *TweetsCOV19 - A Knowledge Base of Semantically Annotated Tweets about the COVID-19 Pandemic*. Paper presented at the International Conference on Information and Knowledge Management, Proceedings.
Dong, Z. S., Meng, L., Christenson, L., & Fulton, L. (2021). Social media information sharing for natural disaster response. *Natural Hazards, 107*(3), 2077-2104. doi:10.1007/s11069-021-04528-9
Du, Q., Li, Y., Li, Y., Zhou, J., & Cui, X. (2023). Data mining of social media for urban resilience study: A case of rainstorm in Xi'an. *International Journal of Disaster Risk Reduction*, *95*, 103836. doi:https://doi.org/10.1016/j.ijdrr.2023.103836
Duan, J., Zhai, W., & Cheng, C. (2020). Crowd detection in mass gatherings based on social media data: A case study of the 2014 shanghai new year's eve stampede. *International Journal of Environmental Research and Public Health*, *17*(22), 1-14. doi:10.3390/ijerph17228640
Dudani, A., Srividya, V., Sneha, B., & Tripathy, B. K. (2020) Sentiment Analysis on Kerala Floods. In*: Vol. 1087. Advances in Intelligent Systems and Computing* (pp. 107-124).
Effrosynidis, D., Karasakalidis, A. I., Sylaios, G., & Arampatzis, A. (2022). The climate change Twitter dataset. *Expert Systems with Applications, 204*, 117541. doi:https://doi.org/10.1016/j.eswa.2022.117541
Eke, C. I., Norman, A. A., Shuib, L., & Nweke, H. F. (2020). Sarcasm identification in textual data: systematic review, research challenges and open directions. *Artificial Intelligence Review, 53*(6), 4215-4258.
El Ali, A., Stratmann, T. C., Park, S., Schöning, J., Heuten, W., & Boll, S. C. J. (2018). *Measuring, understanding, and classifying news media sympathy on Twitter after crisis events*. Paper presented at the Conference on Human Factors in Computing Systems - Proceedings.
Fakhry, N. N., Kassam, G., & Asfoura, E. (2020). Tracking coronavirus pandemic diseases using social media: a machine learning approach. *International Journal of Advanced Computer Science and Applications, 11*(10), 211-219. doi:10.14569/IJACSA.2020.0111028
Fan, C., Farahmend, H., & Mostafavi, A. (2020). *Rethinking infrastructure resilience assessment with human sentiment reactions on social media in disasters*. Paper presented at the Proceedings of the Annual Hawaii International Conference on System Sciences.
Fang, F., Wang, T., Tan, S., Chen, S., Zhou, T., Zhang, W., . . . Lu, X. (2022). Network Structure and Community Evolution Online: Behavioral and Emotional Changes in Response to COVID-19. *Frontiers in Public Health, 9*. doi:10.3389/fpubh.2021.813234
Farzindar, A. A., & Inkpen, D. (2020). Natural language processing for social media. *Synthesis lectures on human language technologies, 13*(2), 1-219.
Fattoh, I. E., Kamal Alsheref, F., Ead, W. M., & Youssef, A. M. (2022). Semantic Sentiment Classification for COVID-19 Tweets Using Universal Sentence Encoder. *Computational Intelligence and Neuroscience, 2022*. doi:10.1155/2022/6354543
Fuadvy, M. J., & Ibrahim, R. (2019). *Multilingual Sentiment Analysis on Social Media Disaster Data*. Paper presented at the ICEEIE 2019 - International Conference on Electrical, Electronics and Information Engineering: Emerging Innovative Technology for Sustainable Future.

Gangadhari, R. K., Khanzode, V., & Murthy, S. (2021). *Disaster impacts analysis using social media data.* Paper presented at the 2021 International Conference on Maintenance and Intelligent Asset Management, ICMIAM 2021.

Garcia, K., & Berton, L. (2021). Topic detection and sentiment analysis in Twitter content related to COVID-19 from Brazil and the USA. *Applied Soft Computing, 101*. doi:10.1016/j.asoc.2020.107057

Gascó, M., Bayerl, P. S., Denef, S., & Akhgar, B. (2017). What do citizens communicate about during crises? Analyzing twitter use during the 2011 UK riots. *Government Information Quarterly, 34*(4), 635-645. doi:https://doi.org/10.1016/j.giq.2017.11.005

Geeta, & Niyogi, R. (2016). *Demographic analysis of Twitter users.* Paper presented at the 2016 International Conference on Advances in Computing, Communications and Informatics, ICACCI 2016.

Ghanem, A., Asaad, C., Hafidi, H., Moukafih, Y., Guermah, B., Sbihi, N., . . . Baina, K. (2021). Real-time infoveillance of moroccan social media users' sentiments towards the covid-19 pandemic and its management. *International Journal of Environmental Research and Public Health, 18*(22). doi:10.3390/ijerph182212172

Gong, P., Wang, L., Wei, Y., & Yu, Y. (2022). Public attention, perception, and attitude towards nuclear power in China: A large-scale empirical analysis based on social media. *Journal of Cleaner Production, 373*. doi:10.1016/j.jclepro.2022.133919

Groves, R. M., Fowler Jr, F. J., Couper, M. P., Lepkowski, J. M., Singer, E., & Tourangeau, R. (2011). *Survey methodology*: John Wiley & Sons.

Gu, M., Guo, H., & Zhuang, J. (2021). Social media behavior and emotional evolution during emergency events. *Healthcare (Switzerland), 9*(9). doi:10.3390/healthcare9091109

Gu, M., Guo, H., Zhuang, J., Du, Y., & Qian, L. (2022). Social Media User Behavior and Emotions during Crisis Events. *International Journal of Environmental Research and Public Health, 19*(9). doi:10.3390/ijerph19095197

Guha-Sapir, D., Below, R., & Hoyois, P. (2016). EM-DAT: the CRED/OFDA international disaster database.

Gupta, M., Bansal, A., Jain, B., Rochelle, J., Oak, A., & Jalali, M. S. (2021). Whether the weather will help us weather the COVID-19 pandemic: Using machine learning to measure twitter users' perceptions. *International Journal of Medical Informatics, 145*. doi:10.1016/j.ijmedinf.2020.104340

Gupta, N., & Agrawal, R. (2020). Application and techniques of opinion mining. In *Hybrid Computational Intelligence* (pp. 1-23): Elsevier.

Guyon, I., Gunn, S., Nikravesh, M., & Zadeh, L. A. (2008). *Feature extraction: Foundations and applications* (Vol. 207): Springer.

Han, F., Cao, Y. D., Zhang, Z. H., Zhang, H. J., Aoki, T., & Ogasawara, K. (2022). Weibo users perception of the COVID-19 pandemic on Chinese social networking service (Weibo): sentiment analysis and fuzzy-c-means model. *Journal of Medical Artificial Intelligence, 5*. doi:10.21037/jmai-21-36

Hasegawa, S., Suzuki, T., Yagahara, A., Kanda, R., Aono, T., Yajima, K., & Ogasawara, K. (2020). Changing emotions about fukushima related to the fukushima nuclear power station accident-how rumors determined people's attitudes: Social media sentiment analysis. *Journal of Medical Internet Research, 22*(9). doi:10.2196/18662

He, Y., Wen, L., & Zhu, T. (2019). *Area Definition and Public Opinion Research of Natural Disaster Based on Micro-blog Data.* Paper presented at the Procedia Computer Science.

Henríquez-Coronel, P., García García, J., & Herrera-Tapia, J. (2019) Management of Natural Disasters Based on Twitter Analytics. 2017 Mexico Earthquake. In*: Vol. 918. Advances in Intelligent Systems and Computing* (pp. 3-12).

Hornby, A. S., & Cowie, A. P. (1995). *Oxford advanced learner's dictionary* (Vol. 1428): Oxford university press Oxford.

Hu, N. (2022). Sentiment Analysis of Texts on Public Health Emergencies Based on Social Media Data Mining. *Computational and Mathematical Methods in Medicine, 2022*. doi:10.1155/2022/3964473

Hung, L. P., Alfred, R., Ahmad Hijazi, M. H., Ibrahim, A., & Asri, A. (2015). A review on the ensemble framework for sentiment analysis. *Advanced Science Letters, 21*(10), 2957-2962.

Hutto, C., & Gilbert, E. (2014). *Vader: A parsimonious rule-based model for sentiment analysis of social media text.* Paper presented at the Proceedings of the international AAAI conference on web and social media.

Hyo Jin, D., Chae-Gyun, L., You Jin, K., & Ho-Jin, C. (2016, 18-20 Jan. 2016). *Analyzing emotions in twitter during a crisis: A case study of the 2015 Middle East Respiratory Syndrome outbreak in Korea.* Paper presented at

the 2016 International Conference on Big Data and Smart Computing (BigComp).
Iksan, N., Widodo, D. A., Sunarko, B., Udayanti, E. D., & Kartikadharma, E. (2021). *Sentiment Analysis of Public Reaction to COVID19 in Twitter Media using Naïve Bayes Classifier*. Paper presented at the InHeNce 2021 - 2021 IEEE International Conference on Health, Instrumentation and Measurement, and Natural Sciences.
Imran, M., Elbassuoni, S., Castillo, C., Diaz, F., & Meier, P. (2013). *Practical extraction of disaster-relevant information from social media*. Paper presented at the Proceedings of the 22nd international conference on world wide web.
Imran, M., Qazi, U., & Ofli, F. (2022). TBCOV: Two Billion Multilingual COVID-19 Tweets with Sentiment, Entity, Geo, and Gender Labels. *Data, 7*(1). doi:10.3390/data7010008
Jiang, D., Luo, X., Xuan, J., & Xu, Z. (2017). Sentiment computing for the news event based on the social media big data. *IEEE Access, 5*, 2373-2382. doi:10.1109/ACCESS.2016.2607218
Kabbani, O., Klumpenhouwer, W., El-Diraby, T., & Shalaby, A. (2022). What do riders say and where? The detection and analysis of eyewitness transit tweets. *Journal of Intelligent Transportation Systems: Technology, Planning, and Operations*. doi:10.1080/15472450.2022.2026773
Karami, A., Shah, V., Vaezi, R., & Bansal, A. (2020). Twitter speaks: A case of national disaster situational awareness. *Journal of Information Science, 46*(3), 313-324. doi:10.1177/0165551519828620
Karimiziarani, M., & Moradkhani, H. (2023). Social response and Disaster management: Insights from twitter data Assimilation on Hurricane Ian. *International Journal of Disaster Risk Reduction, 95*. doi:10.1016/j.ijdrr.2023.103865
Khandelwal, S., & Chaudhary, A. (2022). COVID-19 pandemic & cyber security issues: Sentiment analysis and topic modeling approach. *Journal of Discrete Mathematical Sciences and Cryptography, 25*(4), 987-997. doi:10.1080/09720529.2022.2072421
Khatua, A., Cambria, E., Ho, S. S., & Na, J. C. (2020). *Deciphering Public Opinion of Nuclear Energy on Twitter*. Paper presented at the Proceedings of the International Joint Conference on Neural Networks.
Kostakos, P., Nykanen, M., Martinviita, M., Pandya, A., & Oussalah, M. (2018). *Meta-terrorism: Identifying linguistic patterns in public discourse after an attack*. Paper presented at the Proceedings of the 2018 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining, ASONAM 2018.
Kovács, T., Kovács-Győri, A., & Resch, B. (2021). #allforjan: How twitter users in europe reacted to the murder of ján kuciak—revealing spatiotemporal patterns through sentiment analysis and topic modeling. *ISPRS International Journal of Geo-Information, 10*(9). doi:10.3390/ijgi10090585
Koytak, H. Z., & Celik, M. H. (2022). A Text Mining Approach to Determinants of Attitude Towards Syrian Immigration in the Turkish Twittersphere. *Social Science Computer Review*. doi:10.1177/08944393221117460
Kumar, N. (2018). *Sentiment Analysis of Twitter Messages: Demonetization a Use Case*. Paper presented at the 2nd International Conference on Computational Systems and Information Technology for Sustainable Solutions, CSITSS 2017.
Kumar, S. (2020). *Covid 19 Indian Sentiments on covid19 and lockdown*. Retrieved from: https://www.kaggle.com/datasets/surajkum1198/twitterdata
Lamsal, R. (2020a). *Coronavirus (COVID-19) geo-tagged tweets*. Retrieved from: https://ieee-dataport.org/open-access/coronavirus-covid-19-geo-tagged-tweets-dataset
Lamsal, R. (2020b). Coronavirus (COVID-19) tweets dataset. *IEEE Dataport, 10*.
Lamsal, R., Harwood, A., & Read, M. R. (2022). Twitter conversations predict the daily confirmed COVID-19 cases. *Applied Soft Computing, 129*. doi:10.1016/j.asoc.2022.109603
Laudy, C., Ruini, F., Zanasi, A., Przybyszewski, M., & Stachowicz, A. (2017). *Using social media in crisis management: SOTERIA fusion center for managing information gaps*. Paper presented at the 20th International Conference on Information Fusion, Fusion 2017 - Proceedings.
Lee, J. S., & Nerghes, A. (2017). *Labels and sentiment in social media: On the role of perceived agency in online discussions of the refugee crisis*. Paper presented at the ACM International Conference Proceeding Series.
Lee, J. S., & Nerghes, A. (2018). Refugee or Migrant Crisis? Labels, Perceived Agency, and Sentiment Polarity in Online Discussions. *Social Media and Society, 4*(3). doi:10.1177/2056305118785638
Lee, M. J., Lee, T. R., Lee, S. J., Jang, J. S., & Kim, E. J. (2020). Machine Learning-Based Data Mining Method for Sentiment Analysis of the Sewol Ferry Disaster's Effect on Social Stress. *Frontiers in Psychiatry, 11*. doi:10.3389/fpsyt.2020.505673
Li, J., Wang, Y., & Wang, J. (2021). An analysis of emotional tendency under the network public opinion: Deep

learning. *Informatica (Slovenia), 45*(1), 149-156. doi:10.31449/inf.v45i1.3402
Li, L., Ma, Z., & Cao, T. (2020). Leveraging social media data to study the community resilience of New York City to 2019 power outage. *International Journal of Disaster Risk Reduction, 51*. doi:10.1016/j.ijdrr.2020.101776
Li, L., & Wang, X. T. (2022). Nonverbal communication with emojis in social media: dissociating hedonic intensity from frequency. *Language Resources and Evaluation*. doi:10.1007/s10579-022-09611-6
Li, N., Akin, H., Yi-Fan, L., Brossard, D., Xenos, M., & Scheufele, D. A. (2016). Tweeting disaster: An analysis of online discourse about nuclear power in the wake of the Fukushima Daiichi nuclear accident. *Journal of Science Communication, 15*(5), 1-20. doi:10.22323/2.15050202
Li, P., & Wang, Q. (2021). A Multichannel Model for Microbial Key Event Extraction Based on Feature Fusion and Attention Mechanism. *Security and Communication Networks, 2021*. doi:10.1155/2021/7800144
Li, S., & Sun, X. (2023). Application of public emotion feature extraction algorithm based on social media communication in public opinion analysis of natural disasters. *PeerJ Computer Science, 9*. doi:10.7717/PEERJ-CS.1417
Li, X., Li, Z., & Tian, Y. (2021). Sentimental knowledge graph analysis of the covid-19 pandemic based on the official account of chinese universities. *Electronics (Switzerland), 10*(23). doi:10.3390/electronics10232921
Li, X., Wang, Z., Gao, C., & Shi, L. (2017). Reasoning human emotional responses from large-scale social and public media. *Applied Mathematics and Computation, 310*, 182-193. doi:10.1016/j.amc.2017.03.031
Li, Y., Zhou, X., Sun, Y., & Zhang, H. (2016). Design and implementation of Weibo sentiment analysis based on LDA and dependency parsing. *China Communications, 13*(11), 91-105. doi:10.1109/CC.2016.7781721
Li, Z., & Liu, W. (2020) Automatic decision support for public opinion governance of urban public events. In *: Vol. 1031 AISC. Advances in Intelligent Systems and Computing* (pp. 47-53).
Lian, Y., Liu, Y., & Dong, X. (2020). Strategies for controlling false online information during natural disasters: The case of Typhoon Mangkhut in China. *Technology in Society, 62*, 101265. doi:https://doi.org/10.1016/j.techsoc.2020.101265
Lin, H. Y., & Moh, T. S. (2021). *Sentiment analysis on COVID tweets using COVID-Twitter-BERT with auxiliary sentence approach*. Paper presented at the Proceedings of the 2021 ACMSE Conference - ACMSE 2021: The Annual ACM Southeast Conference.
Litvak, M., Vanetik, N., Levi, E., & Roistacher, M. (2016). *What's up on Twitter? Catch up with TWIST!* Paper presented at the COLING 2016 - 26th International Conference on Computational Linguistics, Proceedings of COLING 2016: System Demonstrations.
Liu, B. (2011). *Web data mining: exploring hyperlinks, contents, and usage data* (Vol. 1): Springer.
Liu, B. (2020). *Sentiment analysis: Mining opinions, sentiments, and emotions*: Cambridge University Press.
Liu, R., Liu, M., Li, Y., & Wu, L. (2023). Crisis Management Experience from Social Media: Public Response to the Safety Crisis of Imported Aquatic Products in China during the Pandemic. *Foods, 12*(5). doi:10.3390/foods12051033
Liu, X., Zheng, L., Jia, X., Qi, H., Yu, S., & Wang, X. (2021). Public Opinion Analysis on Novel Coronavirus Pneumonia and Interaction With Event Evolution in Real World. *IEEE Transactions on Computational Social Systems, 8*(4), 1042-1051. doi:10.1109/TCSS.2021.3087346
Loria, S., Keen, P., Honnibal, M., Yankovsky, R., Karesh, D., & Dempsey, E. (2014). Textblob: simplified text processing. *Secondary TextBlob: simplified text processing, 3*.
Loureiro, M. L., & Alló, M. (2020). Sensing climate change and energy issues: Sentiment and emotion analysis with social media in the U.K. and Spain. *Energy Policy, 143*. doi:10.1016/j.enpol.2020.111490
Luna, S., Guerrero, A., Gonzalez, K., & Akundi, A. (2022). *Social media and pandemic events: challenges for alert-warning systems*. Paper presented at the 2022 17th Annual System of Systems Engineering Conference, SOSE 2022.
Lydiri, M., El Mourabit, Y., El Habouz, Y., & Fakir, M. (2023). A performant deep learning model for sentiment analysis of climate change. *Social Network Analysis and Mining, 13*(1). doi:10.1007/s13278-022-01014-3
Lyu, S., & Lu, Z. (2023). Exploring Temporal and Multilingual Dynamics of Post-Disaster Social Media Discourse: A Case of Fukushima Daiichi Nuclear Accident. *Proceedings of the ACM on Human-Computer Interaction, 7*(CSCW1). doi:10.1145/3579484
Lyu, X., Chen, Z., Wu, D., & Wang, W. (2020) Sentiment Analysis on Chinese Weibo Regarding COVID-19. In*: Vol. 12430 LNAI. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 710-721).
Ma, L., Zhang, D., Yang, J., & Luo, X. (2016, 10-11 Dec. 2016). *Sentiment orientation analysis of short text based*

on background and domain sentiment lexicon expansion. Paper presented at the 2016 5th International Conference on Computer Science and Network Technology (ICCSNT).

Ma, X., Liu, W., Zhou, X., Qin, C., Chen, Y., Xiang, Y., . . . Zhao, M. (2020). Evolution of online public opinion during meteorological disasters. *Environmental Hazards, 19*(4), 375-397. doi:10.1080/17477891.2019.1685932

Mamta, Ekbal, A., Bhattacharyya, P., Srivastava, S., Kumar, A., & Saha, T. (2020). *Multi-domain tweet corpora for sentiment analysis: Resource creation and evaluation*. Paper presented at the LREC 2020 - 12th International Conference on Language Resources and Evaluation, Conference Proceedings.

Mäntylä, M. V., Graziotin, D., & Kuutila, M. (2018). The evolution of sentiment analysis—A review of research topics, venues, and top cited papers. *Computer Science Review, 27*, 16-32. doi:10.1016/j.cosrev.2017.10.002

Manunta, G. (1999). What is security? *Security Journal, 12*(3), 57-66.

Mathayomchan, B., Taecharungroj, V., & Wattanacharoensil, W. (2022). Evolution of COVID-19 tweets about Southeast Asian Countries: topic modelling and sentiment analyses. *Place Branding and Public Diplomacy*. doi:10.1057/s41254-022-00271-5

Mendon, S., Dutta, P., Behl, A., & Lessmann, S. (2021). A Hybrid Approach of Machine Learning and Lexicons to Sentiment Analysis: Enhanced Insights from Twitter Data of Natural Disasters. *Information Systems Frontiers*. doi:10.1007/s10796-021-10107-x

Miller, G. A. (1995). WordNet: a lexical database for English. *Communications of the ACM, 38*(11), 39-41.

Min, K., Ma, C., Zhao, T., & Li, H. (2015). BosonNLP: An ensemble approach for word segmentation and POS tagging. In *Natural language processing and chinese computing* (pp. 520-526): Springer.

Mohamed Ridhwan, K., & Hargreaves, C. A. (2021). Leveraging Twitter data to understand public sentiment for the COVID‐19 outbreak in Singapore. *International Journal of Information Management Data Insights, 1*(2), 100021. doi:https://doi.org/10.1016/j.jjimei.2021.100021

Mohammad, S. M., & Turney, P. D. (2013). Crowdsourcing a word–emotion association lexicon. *Computational intelligence, 29*(3), 436-465.

Moraes Silva, L. M., Valêncio, C. R., Donegá Zafalon, G. F., & Columbini, A. C. (2022). *Feature Selection with Hybrid Bio-inspired Approach for Classifying Multi-idiom Social Media Sentiment Analysis*. Paper presented at the International Conference on Enterprise Information Systems, ICEIS - Proceedings.

Mustakim, Fauzi, M. Z., Mustafa, Abdullah, A., & Rohayati. (2021). *Clustering of Public Opinion on Natural Disasters in Indonesia Using DBSCAN and K-Medoids Algorithms*. Paper presented at the Journal of Physics: Conference Series.

Nagapudi, V., Agrawal, A., & Bulusu, N. (2021, 23-27 Aug. 2021). *Extracting Physical Events from Digital Chatter for Covid-19*. Paper presented at the 2021 IEEE International Conference on Smart Computing (SMARTCOMP).

Nielsen, F. Å. (2011). A new ANEW: Evaluation of a word list for sentiment analysis in microblogs. *arXiv preprint arXiv:1103.2903*.

Obiedat, R., Harfoushi, O., Qaddoura, R., Al-Qaisi, L., & Al-Zoubi, A. M. (2021). An evolutionary-based sentiment analysis approach for enhancing government decisions during covid-19 pandemic: The case of Jordan. *Applied Sciences (Switzerland), 11*(19). doi:10.3390/app11199080

Olusegun, R., Oladunni, T., Audu, H., Houkpati, Y., & Bengesi, S. (2023). Text Mining and Emotion Classification on Monkeypox Twitter Dataset: A Deep Learning-Natural Language Processing (NLP) Approach. *IEEE Access, 11*, 49882-49894. doi:10.1109/ACCESS.2023.3277868

Ortmeier, P. J. (1998). *Public safety and security administration*: Gulf Professional Publishing.

Pan, W., Han, Y., Li, J., Zhang, E., & He, B. (2022). The positive energy of netizens: development and application of fine-grained sentiment lexicon and emotional intensity model. *Current Psychology*. doi:10.1007/s12144-022-03876-4

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. *Foundations and Trends® in Information Retrieval, 2*(1–2), 1-135. doi:10.1561/1500000011

Pedrycz, W., & Chen, S.-M. (2016). Sentiment Analysis and Ontology Engineering. *Studies in Computational Intelligence, 639*.

Pennebaker, J. W., Francis, M. E., & Booth, R. J. (2001). Linguistic inquiry and word count: LIWC 2001. *Mahway: Lawrence Erlbaum Associates, 71*(2001), 2001.

Pfeffer, J., & Morstatter, F. (2016). Geotagged Twitter posts from the United States: A tweet collection to investigate representativeness. Version: 1. GESIS Data Archive. Dataset. In.

Phillips, M. E. (2017). Hurricane harvey twitter dataset. *Univ. North Texas, Denton, TX, USA, Tech. Rep. ark:/67531/metadc993940*.

Pope, D., & Griffith, J. (2016). *An analysis of online twitter sentiment surrounding the european refugee crisis*. Paper presented at the IC3K 2016 - Proceedings of the 8th International Joint Conference on Knowledge Discovery, Knowledge Engineering and Knowledge Management.

Pran, M. S. A., Bhuiyan, M. R., Hossain, S. A., & Abujar, S. (2020, 1-3 July 2020). *Analysis Of Bangladeshi People's Emotion During Covid-19 In Social Media Using Deep Learning*. Paper presented at the 2020 11th International Conference on Computing, Communication and Networking Technologies (ICCCNT).

Prathap, B. R., & Ramesha, K. (2019). *Twitter sentiment for analysing different types of crimes*. Paper presented at the Proceedings of the 2018 International Conference On Communication, Computing and Internet of Things, IC3IoT 2018.

Praveen, S. V., Ittamalla, R., & Subramanian, D. (2022). Challenges in successful implementation of Digital contact tracing to curb COVID-19 from global citizen's perspective: a text analysis study. *International Journal of Pervasive Computing and Communications, 18*(5), 491-498. doi:10.1108/IJPCC-09-2020-0147

Pu, X., Jiang, Q., & Fan, B. (2022). Chinese public opinion on Japan's nuclear wastewater discharge: A case study of Weibo comments based on a thematic model. *Ocean and Coastal Management, 225*. doi:10.1016/j.ocecoaman.2022.106188

Python, D. L. U., Kulkarni, A., & Shivananda, A. Natural Language Processing Recipes.

Qi, H., Jiang, H., Bu, W., Zhang, C., & Shim, K. J. (2019). *Tracking Political Events in Social Media: A Case Study of Hong Kong Protests*. Paper presented at the Proceedings - 2019 IEEE International Conference on Big Data, Big Data 2019.

Qian, E. (2019). *Twitter Climate Change Sentiment Dataset*. Retrieved from: https://www.kaggle.com/datasets/edqian/twitter-climate-change-sentiment-dataset

Qin, T., Wang, B., Liu, Z., Chen, Z., & Ding, J. (2022). High-quality tweet generation for online behavior security management based on semantics measurement. *Transactions on Emerging Telecommunications Technologies, 33*(6). doi:10.1002/ett.3811

Qin, Z., & Ronchieri, E. (2022). Exploring Pandemics Events on Twitter by Using Sentiment Analysis and Topic Modelling. *Applied Sciences (Switzerland), 12*(23). doi:10.3390/app122311924

Quach, H. L., Pham, T. Q., Hoang, N. A., Phung, D. C., Nguyen, V. C., Le, S. H., . . . Nguyen, C. K. (2022). Using 'infodemics' to understand public awareness and perception of SARS-CoV-2: A longitudinal analysis of online information about COVID-19 incidence and mortality during a major outbreak in Vietnam, July—September 2020. *PLoS ONE, 17*(4 April). doi:10.1371/journal.pone.0266299

Rathke, B., Yu, H., & Huang, H. (2023). What Remains Now That The Fear Has Passed? Developmental Trajectory Analysis of COVID-19 Pandemic for Co-occurrences of Twitter, Google Trends, and Public Health Data. *Disaster Medicine and Public Health Preparedness*. doi:10.1017/dmp.2023.101

Ray, S., & Kumar, A. M. S. (2023, 5-6 April 2023). *Prediction and Analysis of Sentiments of Reddit Users towards the Climate Change Crisis*. Paper presented at the 2023 International Conference on Networking and Communications (ICNWC).

Razali, N. A. M., Malizan, N. A., Hasbullah, N. A., Wook, M., Zainuddin, N. M., Ishak, K. K., . . . Sukardi, S. (2021). Opinion mining for national security: techniques, domain applications, challenges and research opportunities. *Journal of Big Data, 8*(1). doi:10.1186/s40537-021-00536-5

Rudra, K., Ghosh, S., Ganguly, N., Goyal, P., & Ghosh, S. (2015). *Extracting situational information from microblogs during disaster events: a classification-summarization approach*. Paper presented at the Proceedings of the 24th ACM international on conference on information and knowledge management.

Sadiq, A. M., Ahn, H., & Choi, Y. B. (2020). Human sentiment and activity recognition in disaster situations using social media images based on deep learning. *Sensors (Switzerland), 20*(24), 1-26. doi:10.3390/s20247115

Samaras, L., García-Barriocanal, E., & Sicilia, M.-A. (2023). Sentiment analysis of COVID-19 cases in Greece using Twitter data. *Expert Systems with Applications, 230*, 120577. doi:https://doi.org/10.1016/j.eswa.2023.120577

Sari, I. C., & Ruldeviyani, Y. (2020). *Sentiment Analysis of the Covid-19 Virus Infection in Indonesian Public Transportation on Twitter Data: A Case Study of Commuter Line Passengers*. Paper presented at the 2020 International Workshop on Big Data and Information Security, IWBIS 2020.

Sattaru, J. S., Bhatt, C. M., & Saran, S. (2021). Utilizing Geo-Social Media as a Proxy Data for Enhanced Flood Monitoring. *Journal of the Indian Society of Remote Sensing, 49*(9), 2173-2186. doi:10.1007/s12524-021-

01376-9
Sharma, S., & Jain, A. (2020). Role of sentiment analysis in social media security and analytics. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 10*(5), e1366.
Shi, J., Li, W., Yang, Y., Yao, N., Bai, Q., Yongchareon, S., & Yu, J. (2021) Automated Concern Exploration in Pandemic Situations - COVID-19 as a Use Case. In*: Vol. 12280 LNAI. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)* (pp. 178-185).
Sliva, A., Shu, K., & Liu, H. (2019) Using social media to understand cyber attack behavior. In*: Vol. 783. Advances in Intelligent Systems and Computing* (pp. 636-645).
Smith, K. S., McCreadie, R., Macdonald, C., & Ounis, I. (2018). Regional Sentiment Bias in Social Media Reporting During Crises. *Information Systems Frontiers, 20*(5), 1013-1025. doi:10.1007/s10796-018-9827-x
Srikanth, J., Damodaram, A., Teekaraman, Y., Kuppusamy, R., & Thelkar, A. R. (2022). Sentiment Analysis on COVID-19 Twitter Data Streams Using Deep Belief Neural Networks. *Computational Intelligence and Neuroscience, 2022*. doi:10.1155/2022/8898100
Stevens, D., & Vaughan-Williams, N. (2016). Citizens and Security Threats: Issues, Perceptions and Consequences Beyond the National Frame. *British Journal of Political Science, 46*(1), 149-175. doi:10.1017/s0007123414000143
Su, C. J., & Li, Y. (2018). *Sentiment analysis and information diffusion on social media: The case of the Zika virus.* Paper presented at the International Conference on Biological Information and Biomedical Engineering, BIBE 2018.
Subramaniyaswamy, V., Logesh, R., Abejith, M., Umasankar, S., & Umamakeswari, A. (2017). Sentiment analysis of tweets for estimating criticality and security of events. *Journal of Organizational and End User Computing, 29*(4), 51-71. doi:10.4018/JOEUC.2017100103
Sufi, F. K., & Khalil, I. (2022). Automated Disaster Monitoring From Social Media Posts Using AI-Based Location Intelligence and Sentiment Analysis. *IEEE Transactions on Computational Social Systems*, 1-11. doi:10.1109/TCSS.2022.3157142
Suhaimin, M. S. M., Hijazi, M. H. A., Alfred, R., & Coenen, F. (2017). *Natural language processing based features for sarcasm detection: An investigation using bilingual social media texts.* Paper presented at the 2017 8th International conference on information technology (ICIT).
Suhaimin, M. S. M., Hijazi, M. H. A., Alfred, R., & Coenen, F. (2019). Modified framework for sarcasm detection and classification in sentiment analysis. *Indonesian Journal of Electrical Engineering and Computer Science, 13*(3), 1175-1183.
Sukhwal, P. C., & Kankanhalli, A. (2022). Determining containment policy impacts on public sentiment during the pandemic using social media data. *Proceedings of the National Academy of Sciences of the United States of America, 119*(19). doi:10.1073/pnas.2117292119
Sun, J., Zeng, Z., Li, T., & Sun, S. (2023). Analyzing the spatiotemporal coupling relationship between public opinion and the epidemic during COVID-19. *Library Hi Tech*. doi:10.1108/LHT-10-2022-0462
Sun, R., An, L., Li, G., & Yu, C. (2022). Predicting social media rumours in the context of public health emergencies. *Journal of Information Science*. doi:10.1177/01655515221137879
Tan, K., Xie, L., & Lin, L. (2021). *Research on the Evolution Path of Public Opinion in Environmental Emergencies.* Paper presented at the E3S Web of Conferences.
Tang, H., Xu, H., Rui, X., Heng, X., & Song, Y. (2022). The Identification and Analysis of the Centers of Geographical Public Opinions in Flood Disasters Based on Improved Naïve Bayes Network. *International Journal of Environmental Research and Public Health, 19*(17). doi:10.3390/ijerph191710809
Theja Bhavaraju, S. K., Beyney, C., & Nicholson, C. (2019). Quantitative analysis of social media sensitivity to natural disasters. *International Journal of Disaster Risk Reduction, 39*. doi:10.1016/j.ijdrr.2019.101251
Thelwall, M. (2017). The Heart and soul of the web? Sentiment strength detection in the social web with SentiStrength. In *Cyberemotions* (pp. 119-134): Springer.
Thorat, S., & Namrata Mahender, C. (2019) Domain-specific fuzzy rule-based opinion mining. In*: Vol. 56. Lecture Notes in Networks and Systems* (pp. 287-294).
Thukral, T., Varshney, A., & Gaur, V. (2021). Intensity quantification of public opinion and emotion analysis on climate change. *International Journal of Advanced Technology and Engineering Exploration, 8*(83), 1351-1366. doi:10.19101/IJATEE.2021.874417
To, H., Agrawal, S., Kim, S. H., & Shahabi, C. (2017). *On Identifying Disaster-Related Tweets: Matching-Based or*

Learning-Based. Paper presented at the Proceedings - 2017 IEEE 3rd International Conference on Multimedia Big Data, BigMM 2017.

Tsai, M. H., & Wang, Y. (2020). *A New Ensemble Method for Classifying Sentiments of COVID-19-Related Tweets*. Paper presented at the Proceedings - 2020 International Conference on Computational Science and Computational Intelligence, CSCI 2020.

Tsao, S. F., MacLean, A., Chen, H., Li, L., Yang, Y., & Butt, Z. A. (2022). Public Attitudes During the Second Lockdown: Sentiment and Topic Analyses Using Tweets From Ontario, Canada. *International Journal of Public Health, 67*. doi:10.3389/ijph.2022.1604658

Uthirapathy, S. E., & Sandanam, D. (2023). Topic Modelling and Opinion Analysis On Climate Change Twitter Data Using LDA And BERT Model. *Procedia Computer Science, 218*, 908-917. doi:https://doi.org/10.1016/j.procs.2023.01.071

Van Atteveldt, W., van der Velden, M. A., & Boukes, M. (2021). The validity of sentiment analysis: Comparing manual annotation, crowd-coding, dictionary approaches, and machine learning algorithms. *Communication Methods and Measures, 15*(2), 121-140.

Wadawadagi, R., & Pagi, V. (2021) Disaster Severity Analysis from Micro-Blog Texts Using Deep-NN. In*: Vol. 1176*. *Advances in Intelligent Systems and Computing* (pp. 145-157).

Wahid, J. A., Hussain, S., Wang, H., Wu, Z., Shi, L., & Gao, Y. (2021). *Aspect oriented sentiment classification of COVID-19 twitter data; An enhanced LDA based text analytic approach*. Paper presented at the Proceedings - 2021 International Conference on Computer Engineering and Artificial Intelligence, ICCEAI 2021.

Wang, K., Qiu, Q., Wu, M., & Qiu, J. (2020). *Topic analysis of internet public opinion on natural disasters based on time division*. Paper presented at the Proceedings - 2020 3rd International Conference on Advanced Electronic Materials, Computers and Software Engineering, AEMCSE 2020.

Wang, M., Wu, H., Zhang, T., & Zhu, S. (2020). Identifying critical outbreak time window of controversial events based on sentiment analysis. *PLoS ONE, 15*(10 October 2020). doi:10.1371/journal.pone.0241355

Wang, N., Varghese, B., & Donnelly, P. D. (2016, 23-27 Oct. 2016). *A machine learning analysis of Twitter sentiment to the Sandy Hook shootings*. Paper presented at the 2016 IEEE 12th International Conference on e-Science (e-Science).

Wu, D., & Cui, Y. (2018). Disaster early warning and damage assessment analysis using social media data and geo-location information. *Decision Support Systems, 111*, 48-59. doi:10.1016/j.dss.2018.04.005

Wu, Z., & Lu, Y. (2017). *A study on micro-blog sentiment analysis of public emergencies under the environment of big data*. Paper presented at the Proceedings of the 29th Chinese Control and Decision Conference, CCDC 2017.

Xia, H., An, W., Li, J., & Zhang, Z. (2022). Outlier knowledge management for extreme public health events: Understanding public opinions about COVID-19 based on microblog data. *Socio-Economic Planning Sciences, 80*, 100941. doi:https://doi.org/10.1016/j.seps.2020.100941

Xia, H., An, W., Li, J., & Zhang, Z. J. (2020). Outlier knowledge management for extreme public health events: Understanding public opinions about COVID-19 based on microblog data. *Socio-Economic Planning Sciences*. doi:10.1016/j.seps.2020.100941

Xie, X. H., & Chen, L. (2022, 25-27 March 2022). *Analysis of Sentiment Tendency Based on Major Public Health Events*. Paper presented at the 2022 4th International Conference on Natural Language Processing (ICNLP).

Xiong, J., Hswen, Y., & Naslund, J. A. (2020). Digital surveillance for monitoring environmental health threats: A case study capturing public opinion from twitter about the 2019 Chennai water crisis. *International Journal of Environmental Research and Public Health, 17*(14), 1-15. doi:10.3390/ijerph17145077

Xu, W., Liu, L., & Shang, W. (2017). Leveraging cross-media analytics to detect events and mine opinions for emergency management. *Online Information Review, 41*(4), 487-506. doi:10.1108/OIR-08-2015-0286

Yan, Y., Chen, J., & Wang, Z. (2020). Mining public sentiments and perspectives from geotagged social media data for appraising the post-earthquake recovery of tourism destinations. *Applied Geography, 123*. doi:10.1016/j.apgeog.2020.102306

Yin, F., Beibei, Z., Su, P., & Chai, J. (2017). *Research on the text sentiment classification about the social hot events on Weibo*. Paper presented at the Proceedings of 2016 IEEE Advanced Information Management, Communicates, Electronic and Automation Control Conference, IMCEC 2016.

Yu, S., Eisenman, D., & Han, Z. (2021). Temporal dynamics of public emotions during the COVID-19 pandemic at the epicenter of the outbreak: Sentiment analysis of weibo posts from Wuhan. *Journal of Medical Internet Research, 23*(3). doi:10.2196/27078

Yu, X., Ferreira, M. D., & Paulovich, F. V. (2021). Senti-COVID19: An interactive visual analytics system for detecting public sentiment and insights regarding COVID-19 from social media. *IEEE Access, 9*, 126684-126697. doi:10.1109/ACCESS.2021.3111833

Yu, X., Zhong, C., Li, D., & Xu, W. (2020). *Sentiment analysis for news and social media in COVID-19*. Paper presented at the Proceedings of the 6th ACM SIGSPATIAL International Workshop Emergency Management using GIS 2020, EM-GIS 2020.

Yuan, F., Li, M., & Liu, R. (2020). Understanding the evolutions of public responses using social media: Hurricane Matthew case study. *International Journal of Disaster Risk Reduction, 51*. doi:10.1016/j.ijdrr.2020.101798

Yuan, F., & Liu, R. (2020). Mining Social Media Data for Rapid Damage Assessment during Hurricane Matthew: Feasibility Study. *Journal of Computing in Civil Engineering, 34*(3). doi:10.1061/(ASCE)CP.1943-5487.0000877

Yue, L., Chen, W., Li, X., Zuo, W., & Yin, M. (2019). A survey of sentiment analysis in social media. *Knowledge and Information Systems, 60*(2), 617-663.

Yue, S., Kondari, J., Musave, A., Smith, R., & Yue, S. (2018). *Using twitter data to determine hurricane category: An experiment*. Paper presented at the Proceedings of the International ISCRAM Conference.

Zander, K. K., Garnett, S. T., Ogie, R., Alazab, M., & Nguyen, D. (2023). Trends in bushfire related tweets during the Australian 'Black Summer' of 2019/20. *Forest Ecology and Management, 545*. doi:10.1016/j.foreco.2023.121274

Zeng, L. (2022). Chinese Public Perception of Climate Change on Social Media: An Investigation Based on Data Mining and Text Analysis. *Journal of Environmental and Public Health, 2022*. doi:10.1155/2022/6294436

Zhang, B., Lin, J., Luo, M., Zeng, C., Feng, J., Zhou, M., & Deng, F. (2022). Changes in Public Sentiment under the Background of Major Emergencies—Taking the Shanghai Epidemic as an Example. *International Journal of Environmental Research and Public Health, 19*(19). doi:10.3390/ijerph191912594

Zhang, C., Xu, S., Li, Z., & Hu, S. (2021). Understanding concerns, sentiments, and disparities among population groups during the COVID-19 pandemic via twitter data mining: Large-scale cross-sectional study. *Journal of Medical Internet Research, 23*(3). doi:10.2196/26482

Zhang, L., Wei, J., & Boncella, R. J. (2020). Emotional communication analysis of emergency microblog based on the evolution life cycle of public opinion. *Information Discovery and Delivery, 48*(3), 151-163. doi:10.1108/IDD-10-2019-0074

Zhang, T., & Cheng, C. (2021). Temporal and spatial evolution and influencing factors of public sentiment in natural disasters-a case study of typhoon haiyan. *ISPRS International Journal of Geo-Information, 10*(5). doi:10.3390/ijgi10050299

Zhang, W., Wang, M., & Zhu, Y.-c. (2020). Does government information release really matter in regulating contagion-evolution of negative emotion during public emergencies? From the perspective of cognitive big data analytics. *International Journal of Information Management, 50*, 498-514. doi:https://doi.org/10.1016/j.ijinfomgt.2019.04.001

Zhang, W., Zhu, Y. C., & Wang, J. P. (2019). An intelligent textual corpus big data computing approach for lexicons construction and sentiment classification of public emergency events. *Multimedia Tools and Applications, 78*(21), 30159-30174. doi:10.1007/s11042-018-7018-x

Zhang, X., & Ma, Y. (2023). An ALBERT-based TextCNN-Hatt hybrid model enhanced with topic knowledge for sentiment analysis of sudden-onset disasters. *Engineering Applications of Artificial Intelligence, 123*. doi:10.1016/j.engappai.2023.106136

Zhang, X., & Xu, Z. (2021, 14-16 May 2021). *Research on Sentiment Analysis and Entity Recognition of COVID-19 Based on Multi-task Sentiment Analysis Model in Artificial Intelligence*. Paper presented at the 2021 International Conference on Artificial Intelligence and Electromechanical Automation (AIEA).

Zhao, S., Chen, L., Liu, Y., Yu, M., & Han, H. (2022). Deriving anti-epidemic policy from public sentiment: A framework based on text analysis with microblog data. *PLoS ONE, 17*(8 August). doi:10.1371/journal.pone.0270953

Zhao, Y., Cheng, S., Yu, X., & Xu, H. (2020). Chinese public's attention to the COVID-19 epidemic on social media: Observational descriptive study. *Journal of Medical Internet Research, 22*(5). doi:10.2196/18825

Zhong, Z. (2021). *Computer Intelligent Prediction Method for Hot Event by Long Short-Term Memory Model*. Paper presented at the Proceedings of 2021 IEEE International Conference on Emergency Science and Information Technology, ICESIT 2021.

Zhou, Q. (2021). Detecting the public's information behaviour preferences in multiple emergency events. *Journal of*

Information Science. doi:10.1177/01655515211027789
Zhou, Q. (2023a). Fine-grained detection on the public's multi-dimensional communication preferences in emergency events. *Heliyon, 9*(6). doi:10.1016/j.heliyon.2023.e16312
Zhou, Q. (2023b). Support towards emergency event processing via fine-grained analysis on users' expressions. *Aslib Journal of Information Management*. doi:10.1108/AJIM-05-2022-0263
Zhou, Q., & Jing, M. (2020). Multidimensional mining of public opinion in emergency events. *Electronic Library, 38*(3), 545-560. doi:10.1108/EL-12-2019-0276
Zhou, Q., & Zhang, C. (2017). Emotion evolutions of sub-topics about popular events on microblogs. *Electronic Library, 35*(4), 770-782. doi:10.1108/EL-09-2016-0184
Zhu, B., Zheng, X., Liu, H., Li, J., & Wang, P. (2020). Analysis of spatiotemporal characteristics of big data on social media sentiment with COVID-19 epidemic topics. *Chaos, Solitons and Fractals, 140*. doi:10.1016/j.chaos.2020.110123
Zhuang, M., Li, Y., Tan, X., Xing, L., & Lu, X. (2021). Analysis of public opinion evolution of COVID-19 based on LDA-ARMA hybrid model. *Complex and Intelligent Systems, 7*(6), 3165-3178. doi:10.1007/s40747-021-00514-7
Zong, C., Xia, R., & Zhang, J. (2021). *Text Data Mining* (Vol. 711): Springer.