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Social Media Analytics by Virtual Operations Support Teams in disaster management: Situational awareness and actionable information for decision-makers

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Virtual Operations Support Teams are groups of institutionalized digital volunteers in the field of disaster management who conduct Social Media Analytics tasks for decision-makers in Emergency Operation Centers (EOCs) during hazard situations such as floods. Through interagency integration into EOC structures, the volunteers provide analytical support using advanced tools and monitoring various social media platforms. The goal of VOSTs is to increase decision-makers' situational awareness through need-oriented analysis and to improve decision-making by providing actionable information in a time-critical work context. In this case study, the data collected during the 2021 flood in Wuppertal, Germany by 22 VOST analysts was processed and analyzed. It was found that information from eight social media platforms could be classified into 23 distinct categories. The analysts' prioritizations indicate differences in the formats of information and platforms. Disaster-related posts that pose a threat to the affected population's health and safety (e.g., requests for help or false information) were more commonly prioritized than other posts. Image-heavy content was also rated higher than text-heavy data. A subsequent survey of EOC decision-makers examined the impact of VOST information on situational awareness during this flood. It also asked how actionable information impacted decisions. We found that VOST information contributes to expanded situational awareness of decision-makers and ensures people-centered risk and crisis communication. Based on the results from this case study, we discuss the need for future research in the area of integrating VOST analysts in decision-making processes in the field of time-critical disaster management.

KEYWORDS

social media analytics, virtual operations support team, risk and crisis communication, situational awareness, disaster management, actionable information, flood, open source intelligence

1 Introduction

In the sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), the authors conclude that the frequency of floods and extreme precipitation has increased in Europe. They note, that their probability will rise even further if global warming reaches two degrees Celsius compared to pre-industrial times (IPCC, 2021). The World Weather Attribution (WWA) also concludes that climate change has increased the likelihood and intensity of extreme rainfall in Western Europe. According to their recent study, the amount of rainfall, i.e. the intensity of extreme precipitation, has increased by between three and 19%, which in turn elevates the resulting risk of flooding (Kreienkamp et al., 2021). Concurrent with these ongoing developments, digital communication are being used to a rising extent during disasters. Eyewitnesses and those affected by disasters intensively utilize social media as interactive platforms to communicate and collaborate in such situations for publicly sharing warnings, psychosocial needs, or rumors, and spontaneously build up community engagement structures (Reuter and Kaufhold, 2018). Systematic analysis of this big crisis data (Castillo, 2016) can thus provide timely and disaster-related information, which can support situational awareness and decision-making in Emergency Operations Centers (EOCs). However, the volume, velocity, and variety of social media data can grow up to a level that EOC staff cannot systematically analyze. With the aim of addressing these challenges by using collaboration technologies, digital volunteers have developed so-called Virtual Operations Support Teams (VOSTs) (St. Denis et al., 2012). These teams work dislocated from the actual disaster area and support EOCs by completing specific tasks using advanced analytical tools and geographic information systems: a VOST identifies, verifies, and visualizes social media data and other publicly available data and creates information products such as evaluation and social media monitoring reports or dashboards of the affected area (St. Denis et al., 2012; Fathi et al., 2020). These information products can be integrated into the EOC's decision-making process, where they contribute to situational awareness or to response actions derived from actionable information. Thus, VOST findings can be used to derive people-centered risk and crisis communication measures that are adapted to the needs of the affected population and take into account the specific disaster situation, e.g. for counterstatements to misinformation (Kutzner and Thust, 2021) or in communicating with those affected (Fire Department Wuppertal, 2021). The German City of Wuppertal was among several districts strongly affected by the July 2021 flooding: Emergency Management Agencies (EMAs) and authorities evacuated parts of the city and set off sirens to warn the public (Zander, 2021). Digital volunteers of the German Federal Agency for Technical Relief's VOST (VOST THW) were virtually integrated as formally trained analysts into the local EOC. This novel interagency participation of digital volunteers as external analysts within an EOC during a flood leads to the following central research question:

How can the integration of Social Media Analytics by Virtual Operations Support Teams in Emergency Operations Centers support situational awareness and generate actionable information for decision-making?

The aim of this work is, on the one hand, to analyze the data generated by a VOST during an operation through a case study and thus to present important findings from the field. On the other hand, we will survey decision-makers from an EOC what impact VOST information has on their situational awareness and actual decisions. The motivation of this research approach consists in the fact that numerous works either address the data analysis of big data from social media, the decision-making processes or the development of machine learning approaches. Therefore, it is essential to better understand practical implementation in this research area in order to obtain valuable insights from implemented solutions. To answer the central research question, we first outline the relevant theoretical background in section 2. We start by looking at the role of social media in disaster management by delineating aspects such as Social Media Analytics (SMA) and risk and crisis communication. We also outline facets of situational awareness, actionable information, and VOSTs before presenting our case study and methods differentiated by the two stages in Section 3. Section 4 illustrates the results of the case study. Section 5 discusses the results, future research approaches, practical considerations for emergency response, and limitations of this work. In the last section 6, we conclude this work and present an outlook.

2 Background

2.1 Social media in disaster management

With the rapid global spreading of digital communication tools, internet access and smartphones, the communication culture has changed fundamentally. Due to immediate availability and transmission, various social media platforms are used in everyday life and increasingly in disaster situations (Reuter and Kaufhold, 2018). Social media are understood as a set of internet-based applications that build on the developments of Web 2.0 and provide opportunities for users to create and share content (Kaplan and Haenlein, 2010). The purposes social media are used for in disaster situations can be differentiated into four areas: information gathering, information dissemination, collaborative problem solving, and processing (Jurgens and Helsloot, 2018). Affected or interested individuals can thus search for reliable information in a complex situation free of charge and on the go. At the same time, information about the current situation can be quickly spread. Studies show that people affected by a disaster share information about roads, weather and traffic conditions, or their emotions and location (Reuter et al., 2017). Interactive social media platforms also offer the opportunity to build spontaneous community engagement structures: The formation of spontaneous volunteer groups is enabled by network functions, who then actively participate in collective disaster response (Nissen et al., 2021; Sackmann et al., 2021). In addition, social media are also used for individual coping, for example in the communication of emotions or as platforms for commemoration (Ebersbach et al., 2016). This bipartite role of passive information consumers and active content producers in social media is described as a prosumer (Ebersbach et al., 2016), which can also be observed in the context of disaster management (Chatfield and Brajawidagda, 2014). Based on this bilateral communication character of social media (Roche et al., 2013) unusual events can be detected at an early stage through the systematic analysis of data using Crisis Informatics approaches (Thom et al., 2016; Rossi et al., 2018; Kersten and Klan, 2020). Crisis Informatics is a growing research area that examines the use of computer-based methods in crises, disasters, and emergencies (Hager, 2006; Palen L. et al., 2007). In the past, numerous fields have been studied in the context of internalizing social media use in disaster management, which Eismann et al. (2021) systematically divide into the following categories: monitoring social media, automatically processing social media data, tapping collective intelligence, accessing information providers, and evaluating crisis response.

Zhang et al. (2019) identify three principal fields in which social media can assist in disaster management: First, they describe the function of using social media to efficiently and effectively generate situational awareness. As a second aspect, they depict the usefulness of networking to engage in coping through self-organized community engagement activities. As a third and final field, they see the ability for EMAs to capture the affected population's sentiment (Zhang et al., 2019). EMAs and other authorities use social media for different purposes: warnings as well as risk and crisis communication with the aim of protective and preventative measures can be disseminated quickly and with wide reach, but EMAs can also gather disaster-related information, such as situational updates (Olteanu et al., 2015; Wu and Cui, 2018). In addition to the use of social media, other approaches also build on new technologies and the use of smartphones applications to reach the public in a disaster situation (Tan et al., 2017; Weyrich et al., 2020) or to communicate bidirectional using mobile crisis apps (Kaufhold et al., 2018). To disseminate information through risk and crisis communication using emerging technologies, there are two aspects that need to be considered in particular: New technologies and machine learning algorithms must be designed for and adapted to human behavior, while their application and use requires learning and training (Kuhaneswaran et al., 2020; Sonntag et al., 2021). In addition, studies show that the public expects that social media will be monitored by EOCs during disasters and that decision-makers will respond to the content (Reuter et al., 2017; Reuter and Spielhofer, 2017). In addition to the general expectation that social media should be monitored (67%), a representative survey of the adult German population by Reuter et al. (2017) indicate that in the event of a disaster, 47% of respondents also expect a response from an EMA on social media within 1 hour. However, systematic analysis of social media poses significant challenges for EOCs in disaster management, which will be discussed next.

2.1.1 Social Media Analytics

Social Media Analytics (SMA) include the design and evaluation of analytics tools to collect, monitor, analyze, summarize and visualize open-access data from social media (Zeng et al., 2010). The objective is to extract intelligence from available data and to identify patterns in order to serve specific needs with information in various areas of interest (Zeng et al., 2010; Stieglitz et al., 2014; Stieglitz et al., 2018a; Stieglitz et al., 2018b). These areas of interest can be quite diverse: besides economics, they might concern journalism, political communication, and especially risk and crisis communication in disaster management (Stieglitz et al., 2018b). Here, Stieglitz et al. see the potential to gather additional previously unknown information from various platforms on which users publish texts, images or videos.

SMA is understood as part of Big Data, with varying terminology being used, such as social big data (Guellil and Boukhalfa, 2015) or social media big data (Lynn et al., 2015). Analyzing such large amounts of data is always fraught with challenges. McAfee and Brynjolfsson (2012) described three often posed key challenges: volume (the amount of data), velocity (the velocity at which the data is available), and variety (different data types, e.g. text, image, video). Additional papers have expanded the challenge collection, e.g. adding veracity (reliability of the data). Lukoianova and Rubin (2014) differentiate this addition into three further levels and describe veracity in objectivity, truthfulness, and credibility.

The actual mass data analysis is conducted in a process with several steps. Fan and Gordon (2014) characterize the process in three successive steps: first, relevant data is collected and preprocessed (capture), followed by analytics, e.g. social network or sentiment analysis (understand), and as a third and final step by the summary and presentation (present). A more detailed model is offered by Stieglitz et al. (2018b), taking into account various studies. The authors distinguish between four steps that build on each other:

(1) Discovery means the (automatic) discovery of latent structures and patterns in text files, whereby text and data mining techniques are often applied (Chinnov et al., 2015).

(2) Tracking includes tactical alignments, for example across social media platforms (e.g., Twitter, Instagram), methodological approaches, and anticipated outcomes (Stieglitz et al., 2014; Stieglitz et al., 2018b).
(3) Preparation differentiates into various approaches, e.g. theme and/or trend-based preparations (Stieglitz et al., 2014).
(4) Analysis comprises e.g. statistical, content, or trend analyses (Stieglitz et al., 2014).

These four steps can be applied to the analysis of data from different social media, where the platforms' interfaces (data crawler) are the Application Programming Interfaces (API) used to apply (partially) automated analysis tools, e.g. for disaster detection (Thom et al., 2016). In the context of disaster management, these tools are used, for example, to identify incidents at an early stage or to conduct sentiment analyses (Fathi et al., 2020). It is particularly important for EOCs to understand communication behavior and current sentiment on social media in order to respond more quickly and efficiently (Stieglitz et al., 2018b).

2.1.2 Risk and crisis communication in social media

Effective risk and crisis communication is crucial to managing disasters. In this context, risk communication needs to be conducted in a people-oriented manner before a disaster occurs to create risk awareness within the population (Basher, 2006; Haer et al., 2016). Affected people do have different information needs, so that a range of approaches for risk communication with the public are required (Fakhruddin et al., 2020). Additionally, these different information needs also change with the different phases of a flood. In the pre-flood phase for example, information is needed on what protective measures to take, how to evacuate, and how to stock food and water. In the dynamic flood situation (response phase), needs shift, for instance, to helping victims, finding emergency shelters or information accompanying siren warnings. In the third, the recovery phase, focus shifts towards topics such as self-organized help of and for the population, protection against epidemics or expressing gratitude towards emergency services (Vongkusolkit and Huang, 2021). Risk communication aims at establishing a long-term relationship of trust between all actors involved in disaster management (Federal Ministry of the Interior, 2014). It intends, on the one hand, to increase the population's awareness of existing risks and hazards and, on the other hand, to inform them about how to deal with risks, and to enable individuals to take preventive measures by providing information and recommendations for action (Federal Ministry of the Interior, 2014). For these purposes, the following aspects must be taken into account: openness, transparency, credibility or consistency, and dialog orientation. Studies show that people-centered flood risk communications can be much more effective than a top-down government communication approach, even if the information reach fewer people (Haer et al., 2016; Haworth et al., 2018; Rahn et al., 2021). Haer et al. (2016) derive from an agent-based model that flood risk communication should aim to use the natural amplification effect of existing offline social networks, in which social media are used deliberately. In addition, EOCs can use the advantages of reaching a wide audience through social media to spread risk-related information via their channels (van Gorp et al., 2015). Haer et al. (2016) identify four different flood risk communication strategies:

(1) Top-down strategy focused on risk.
(2) Top-down strategy focused on risk and coping options.
(3) People-centered strategy focused on risk.
(4) People-centered strategy focused on risk and coping options.

The authors explain the need to have a deep understanding of the factors influencing risk awareness and their relevance for adequate risk communication. Mondino et al. (2020) argue that people-centered risk communication can reduce the population's vulnerability. SMA can be one way to understanding the needs of the affected population, e.g. understanding psychosocial needs. The work of Weyrich et al. (2020) demonstrates that affective response (i.e. feelings) and deliberative appraisal (i.e. understanding of warning) have an impact on the consideration of protective measures, confirming previous findings.

In contrast to risk communication, crisis communication is carried out during or after a disaster has occurred and pursues different goals. Nevertheless, both communication types are closely connected, since risk communication provides the basis for successful crisis communication. However, the main difference consists in the factor of time: while risk communication aims at prevention and preparation, the goal of crisis communication is short-term action to avoid current hazards and to minimize damage (Federal Ministry of the Interior, 2014). For the latter, velocity, veracity, understandability and consistency are crucial (Rahn et al., 2021). These are particularly decisive when authorities and the population affected by a disaster can make intensive use of social media and thus communicate in a dialog-oriented manner.

2.1.3 Building spontaneous community engagement structures

Alongside their potential in risk and crisis communication, social media also offer platforms for spontaneous and self-organized community engagement activities: based on networking functions, e.g. in specific social media groups, spontaneous groups of volunteers can be formed. The general tendency to desire a normalization of the situation after disasters, such as floods, manifests, when thousands of people set up spontaneous structures and participate in collective disaster management for weeks (Sackmann et al., 2021; Bier et al., 2022). However, spontaneous build up community engagement structures in disaster situations are not a new social media phenomenon: Stallings and Quarantelli (1985) described their observation as emergent groups that work collaboratively during an emergency. These groups close a resource gap of professional responders that arises in any large-scale disaster situations. Accordingly, emerging groups pursue common goals in the context of actual or potential disasters, though permanent operational organization structures have not been established (Kaufhold and Reuter, 2014). Nevertheless, with the expansion of social media, the formation of these spontaneous groups of helpers is happening more rapidly and with a wider reach. In the case of heavy rainfalls and subsequent flooding in Germany in 2013 and 2014, it was observed that the first spontaneous groups already became active during the acute hazard conditions (Fathi et al., 2017; Twigg and Mosel, 2017). Large group sizes of several thousands and their agility also created enormous challenges in integrating spontaneous volunteers in disaster management after floods (Sackmann et al., 2021) or earthquakes (Nissen et al., 2021). However, numerous studies allowed for a better understanding of spontaneous volunteers. For example, motivational factors and participation barriers (Fathi et al., 2016) or knowledge and skills transmission in occupational health and safety (Brückner, 2018) were studied. Twigg and Mosel (2017) divide the variety of tasks into search and rescue operations, the transport and distribution of relief supplies, and the provision of food and beverages to victims and responders. Including spontaneous volunteers nevertheless poses considerable organizational challenges for EOCs (Sackmann et al., 2021) as the established operational structures currently do not allow for quick integration (Fathi et al., 2017). This makes it all the more important for EOCs to know about groups developing in social media at an early stage so that they can respond and communicate adequately.

2.2 Situational awareness and actionable information for decision-makers

Decision-making processes in disaster management are complex. They require situational awareness (SA) in a dynamic disaster context and the availability of actionable information in the right time and place. However, these necessary information management processes are influenced by certain challenges and conditions that have already been outlined in the past (van de Walle and Comes, 2015; Comes, 2016). Paulus et al. (2022) describe time pressure, uncertainty, information overload (especially significant in the use of social media), and high stakes (including irreversibility of decisions) as four major challenging elements. These conditions can affect data bias and confirmation bias of analysts' information product which impacts situational awareness and decision-making in disaster management (Paulus et al., 2022). The following two subsections introduce situational awareness for decision-makers in the context of disasters, focusing on the use of social media. Subsequently, we address actionable information for decision-makers in EOC.

2.2.1 Situational awareness for decision-makers

A common description of situational awareness is provided by Endsley (1988) who described it as "the perception of the elements in the environment [. . .], the comprehension of their meaning and the projection of their status in the near future." (S.97). A central aspect in her understanding is the tripartite division of situational awareness into perception, comprehension, and projection. Crisis Informatics also deals with situational awareness, meaning all available information that can be integrated into a coherent picture for the management of a complex disaster situation (Reilly et al., 2007). Hofinger and Heimann (2022) describe situational awareness in the context of disaster management in EOCs as the state of being aware of one's surroundings, the situation, and current processes. They argue that each decision-maker perceives the current operational situation individually. Besides current disaster-related information, this mental model of a disaster situation is also influenced by previous knowledge, experience, and individual evaluations. Therefore, situational awareness is always subjective (even if there is objective situational information, e.g. a crisis maps), varies individually, and can evolve with situational changes (Hofinger and Heimann, 2022). The term situational awareness is closely related to sensemaking, where in the context of information systems it describes the process of how individuals gather and use information and gain a more comprehensive understanding of the current situation (Boin et al., 2014; Stieglitz et al., 2018a).

In 2010, Vieweg et al. investigated how social media, in this case Twitter, can contribute to situational awareness. Based on two scenarios (Red River flood and Oklahoma grassfire, both 2009), the authors classified Twitter posts into 13 categories to provide a better overview. They coded tweets into these categories, each consisting of at least five tweets: warning, preparatory activity, fire line/hazard location, flood level, weather, wind, visibility, road conditions, advice (i.e. advice on how to cope with the emergency), evacuation information, volunteer information, animal management, and damage/injury reports (Vieweg et al., 2010). The categories vary significantly within the two scenarios, which in turn consist of the different scenario-parameters (area, number of people affected, and duration). In the case of flooding, the most frequent categories are preparatory activity, flood level, weather and volunteer information. To automatize such analyses, numerous text mining and natural language methods have been developed to classify social media content (Vongkusolkit and Huang, 2021). The goal is to separate disaster-related information from unimportant information in order to support situational awareness through categorization. Previous studies have examined whether SMA could improve situational awareness in different scenarios, such as floods, hurricanes, tsunamis, wildfires, or terroristic attacks (Fathi et al., 2020; Vongkusolkit and Huang, 2021). Since machine-learning approaches were usually applied to one singular scenario, Yu et al. (2019) developed a cross-event classification analysis method. Further approaches have also been developed to automatize the classification and analysis of images based on artificial intelligence (AI) for disaster management, e.g. the platform AIDR (Artificial Intelligence for Disaster Response) (Imran et al., 2014; Imran et al., 2018). In the literature review conducted by Vongkusolkit and Huang (2021), the majority of studies to date (64%) have been limited exclusively to the microblogging platform Twitter due to the simplified automated analysis procedures. In view of the heterogeneous use of social media, the focus on just one platform does not exactly represent their real-world usage. In Germany, Twitter was used by eight percent of the population in 2021 (4% daily or weekly, 4% monthly or less frequently), with other platforms such as Facebook (38%) (28% daily or weekly, 10% monthly or less frequently) or Instagram (33%) (26% daily or weekly, 7% monthly or less frequently) being used more often (Krupp and Bellut, 2021). Thus, cross-platform SMA enables improved situational awareness: By classifying social media data into categories, the most frequent themes, issues, and communication priorities can be identified and made usable for decision-makers, so that information on people-centered needs or social coping activities can be understood and utilized for situational awareness (Vongkusolkit and Huang, 2021). People-centered needs and sentiments can be differentiated into various subcategories, such as fear, anger, worry, or gratitude (Buscaldi and Hernandez-Farias, 2015; Vongkusolkit and Huang, 2021). Vongkusolkit and Huang (2021) further found that the approach of temporal classification, which means categorizing social media posts according to the time it was published in relation to the disaster phase, is particularly used in studies for hurricanes (36%), followed by a tie between floods and several other events (14%). However, evaluating and applying such categorization in disaster management poses numerous challenges. For example, during a dynamic flood situation, the focus may shift, necessitating supplemental information for situational awareness (Rossi et al., 2018). Furthermore, emergencies can arise and spread via social media, especially in the response phase. Additionally, actionable information must also be considered and evaluated by decision-makers.

2.2.2 Actionable information for decision-makers

Decision-making in EOCs can rely on both joint situational awareness and actionable information. We draw on Zade et al. (2018), to define and delineate actionable information, which they define as information on which decision-makers need to respond and decide. In our work we especially apply short-term actionable information as defined by Mostafiz et al. (2022), because we address the issue of immediate response with flood hazards. Mostafiz et al. (2022) understand long-term actionable information as information that can help coping with hazards in the preparation or recovery phase. Especially concerning short-term actionable information, producing the right information to the right decision-makers at the right time helps members of an EOC overcome multiple challenges such as limited resources in SMA, and information overload in a time- and safety-critical work environment. In a survey of emergency and disaster managers, Zade et al. (2018) illustrated that the interviewees have a broad understanding of actionable information, which might also be information that directly affects them or their organization. In such cases, actionable information can assist, enact or expedite problem-solving, even if the problem is merely theoretical or potential (Zade et al., 2018). However, information gathered during dynamic disaster situations may be or become relevant in the future. Yet, not all information needs to be directly followed by immediate response action. Thus, Zade et al. (2018) state in their conclusion, that all information is important, but only some is actionable. We also argue based on this conclusion: the distinction between actionable information and situational awareness is crucial. Social media data can support decision-making by both contributing to situational awareness and providing actionable information. However, EOCs face challenges such as limited resources in SMA or information overload (Stieglitz et al., 2018b). Digital volunteers have formed VOSTs to support EOCs in addressing these challenges.

2.3 Virtual Operations Support Team

Due to a lack of resources competence, EOCs cannot perform SMA task fully during disasters, which creates a gap in situational awareness. Virtual Operations Support Teams (VOSTs) are being established as a way to fill this gap, with digital volunteers conducting the monitoring and analysis, using semi-automated tools and visualizing mass data (St. Denis et al., 2012; Cobb et al., 2014; Martini et al., 2015). The idea of creating a VOST was born in 2011 in the United States by emergency manager Jeff Philipps with the intention of better integrating the work of digital volunteers into existing structures of EOCs to enable the identification and direct integration of disaster-related information from social media into disaster response by using volunteer work. These VOST analysts are verified digital volunteers of official EMAs who work on a voluntary basis and take on specific tasks, such as the analysis of large amounts of social media data, translations, or the mapping of affected areas. The capability spectrum of VOST can be divided into three main working fields:

- Digital Operation Investigation
  - Information retrieval, processing and visualization from publicly available sources using Open Source Intelligence (OSINT) approaches (Böhm and Lolagar, 2021)
  - Verification and falsification, e.g. identification of false information and rumors
- Crisis Mapping
  - Creating digital maps of affected areas and processing those with additional information (e.g. access routes, flooded area)
  - Visualization, geolocalization and spatial analysis using geographic information systems
- Volunteer Coordination and Cooperation
  - Interface with other national and international teams
  - Establishing technical and collaborative frameworks to enable cooperation

The informational results are prepared by the VOST team leaders and provided to the EOC in different information products, such as situation reports or crisis maps. This work of the team leaders is accompanied for example by the following other activities:

- Information selection, prioritization, and dissemination of actionable information to decision-makers
- Advising EOC staff on the use of social media in risk and crisis communication
- Cooperation with other digital networks and VOSTs

After the first VOST was established in the United States, an overarching umbrella organization called Virtual Operations Support Group (VOSG) formed to help teams in their development and guide new VOSTs in there structuring in an advisory role. At the transnational level, regional associations such as VOST Europe, VOST Oceania and VOST America have subsequently been established.

2.3.1 Virtual Operations Support Team, German Federal Agency

The first German VOST was initiated in 2016 as a pilot project by the German Federal Agency for Technical Relief (THW), subordinated to the German Federal Ministry of the Interior (Fathi and Hugenbusch, 2020). With nearly 80.000 volunteers in 668 local sections, the THW is particularly engaged in disaster management following natural disasters, civil protection, and civil defense tasks (Federal Agency for Technical Relief, 2021). Since 2018, additional VOST groups have been established at the level of federal states, districts, or cities. The THW's goal was to evaluate the operational options and the tactical value of a VOST. This digital unit, which is not tied to a specific location, also provided the first opportunity to test a new form of volunteer commitment for the THW. The VOST THW is a team of 46 specifically qualified THW volunteers who collect disaster-related information from publicly available sources such as social media using advanced analytical software and competencies. The VOST THW's goal is to make information technologies and new potentials of digital networking usable for the operational structure of the THW and other EMAs, which can request this team for specific tasks (Fathi and Hugenbusch, 2020). With the exception of the liaison officer, who brings together the VOST and the decision-makers in an EOC, VOST analysts are not tied to any specific location (Martini et al., 2015). During an operation, they network via their own IT infrastructure and thus do not become active at the operation site, so that they can perform their tasks distributed across the entire federal territory. The liaison officer is usually attached to the situational awareness section in the EOC ensuring that time-critical and actionable information from a VOST can be directly taken into account in the staff's decision-making process. Situation-adapted and additional tasks can also be forwarded to the team immediately. Since 2017, VOST THW has been requested more than 45 times by various EMAs (Fathi and Hugenbusch, 2020) for a spectrum of operational situations ranging from large-scale events to natural disasters. Primary requesters of the VOST are EOCs of districts, municipalities, and federal states. Within the scope of these operations, the following tasks were carried out, for example:

- Classification of disaster-related information that allows for conclusions about the current situation on-site
- Crisis Mapping and image analysis
- Identification of false information
- Advice on situation- and people-centered risk and crisis communication in social media

This new form of digital support requires a variety of adaptations within the operational organizations and an in-depth understanding of the decision-making processes within new VOST units.

2.4 Research gap and research questions

The academic investigation of this topic has so far been carried out in limited depth only. Aspects, such as the challenge of automated analysis of large social media text-data sets using approaches like Natural Language Processing (Buscaldi and Hernandez-Farias, 2015) or machine learning algorithms such as Random Forests (Nair et al., 2017) have been widely researched. In recent years, international research was focused on big data analysis particularly of Twitter (Vongkusolkit and Huang, 2021) and some other social media platforms such as Flickr (Cervone et al., 2016) in disaster situations. Based on this work, a new research area developed under the umbrella of Crisis Informatics (Palen et al., 2007b; Reuter and Kaufhold, 2018).

Crisis Informatics addresses the challenges portrayed mainly using technical approaches, although a number of other studies explore organizational collaboration with digital volunteers. In their work, Soden and Palen (2018) outline how innovative and participatory approaches have found their way into the field of disaster management. Drawing on four recent cases, they explain how information and communication technology has changed the way natural hazards are perceived and responded to, including in the field of research. Soden and Palen (2018) argue that informing affected people, i.e., risk and crisis communication, is not limited to the neutral depiction of disaster situations through data. They base their argument on two theses: On the one hand, they state that the academic discussion of crisis is dominated by technical solution approaches. On the other hand, communities of research institutions, practitioners, and funding agencies dominate the development of solution approaches to scientific problems they formulate. Nevertheless, practical applications of scientific approaches are also taking place in experimental or real-world environments in numerous fields. For example, Kaufhold et al. (2020) presented results from field trials with EMAs in a paper that evaluated a system for cross-platform monitoring of social media that also included automated alerting based on advanced algorithmic analysis. Current work is investigating requirements for dashboards to visualize social media information for instance (Basyurt et al., 2021). The impact of information products generated by virtual communities of volunteers on situational awareness and on decision-making processes of EOCs have not yet been researched in depth. Furthermore, there is a lack of research studies examining necessary organizational requirements for the integration of these digital volunteer units. Initial work has addressed this gap: a case study systematically analyzed organizational, procedural, and technical requirements for the integration of a VOST when collaborating in an EOC during a large-scale event (Fathi et al., 2020). In light of the COVID-19 pandemic and the 2021 flood in Western Germany, various institutions call for strengthened VOST structures and intensified mobilization and utilization of such teams. In Germany, both the Ministry of the Interior of North Rhine-Westphalia, (2022) and the Association of Fire Departments in North Rhine-Westphalia (2021) are advocating the integration of VOSTs in risk and crisis communication activities, including information collection from social media. Parliamentarians of the German Bundestag also call for further strengthening of VOSTs, e.g. to identify false information at an early stage in disasters (Mihalic et al., 2021; Bündnis, 2022). At the same time, a research gap on digital VOST-analysts work, its impact on decision-makers' situational awareness and subsequent decision-making in disaster management persists. To initiate closing this research gap, we conduct a scenario-based case study to examine findings about a VOST's work and the impact of subsequent VOST information in a specific hazard situation. Due to the broad range of topics, this work addresses the following research questions (RQ):

RQ 1: Which categories of information have been identified, prioritized, and contextualized in relation to the specific flood situation, taking into account the factor of time?

RQ 2: How are categories, information format, prioritizations, and platforms related?

RQ 3: How do the information provided by VOSTs impact the situational awareness and response actions based on actionable information in EOCs decision-making?

To examine these research questions, we used two different methods in our case study, which are described in detail in the next section.

3 Case study and methods

This case study uses different research methods to explore the three research questions described above. We proceed in two stages to address the three research questions. In the first stage addressing RQ 1 and RQ 2, we examine the data generated by the VOST during the flood response. In the second stage, we address RQ 3, focusing on the perspective of decision-makers in the EOC. By surveying these decision-makers, we study the impact of VOST information on situational awareness and decisions, as well as risk and crisis communication. A graphical illustration of this case study used along with corresponding stages, research questions, data material, and methods will allow for a structured overview in Figure 1. As we have been scientifically supervised VOST THW since the project was piloted in 2016, we were provided with the VOST data for conducting this research. Furthermore, there are several personnel overlaps between our university and the VOST THW, for example, the first author of this case study is a volunteer in the VOST. In addition to the VOST data, operations orders were also provided that could be used to track the integration of VOST operations into the EOC. This includes the precise times of the alert, the end of the operation and the task priorities. In the following section 3, we first explain our case study concerning the flooding event in July 2021 in Wuppertal, Germany including the interagency setting in which the VOST THW was integrated into the EOC. Following these explanations, the two methods of data analysis and surveying decision-makers are described in detail.

3.1 Case study

3.1.1 Flooding event 2021

Flooding in Germany on July 14 and 15 in 2021 severely damaged several areas in the federal states of North Rhine-Westphalia and Rhineland-Palatinate. Due to exceptionally heavy precipitation, floods were induced that caused substantial damage, especially in the Ahr valley (Kreienkamp

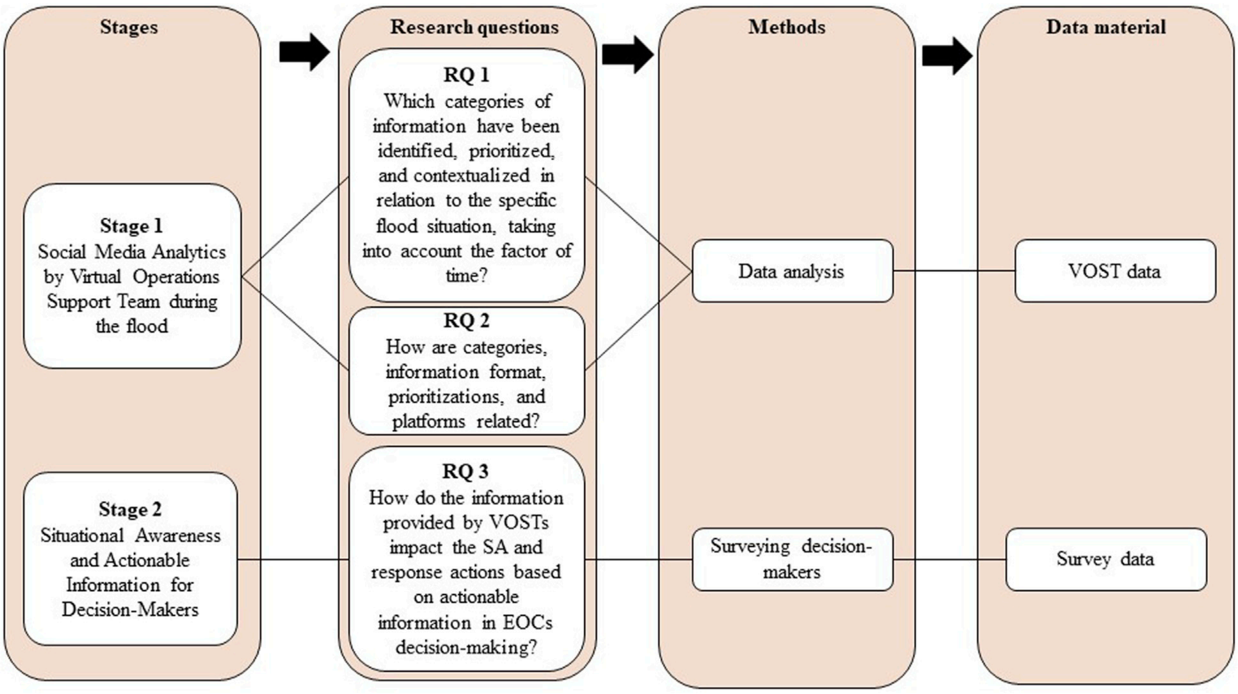

FIGURE 1
Research design.

et al., 2021) and the death of 184 people. The North Rhine-Westphalian city of Wuppertal (361,550 inhabitants) was also seriously affected by strong precipitation (up to 151.5 L/m^2) with subsequent floods on 14 July 2021 (Zander, 2021). The EOC, led by the fire department and including other decision-makers from several EMAs, began its work at 5:00 p.m. on July 14. At about 23:35, the Wupperverband (responsible for water management in the Wupper river catchment) registered uncontrolled overflow of 2 dams (Zander, 2021). The EOC declared a state of emergency in the entire city area due to the amount of precipitation, uncontrolled overflow at the dams and the overflow of the river Wupper. Floods were expected to reach the city area during the night. Due to numerous floods and power outages, the EOC received 4,973 emergency calls within 24 h (Zander, 2021). According to Zander (2021) various approaches were used to warn the population. Besides the involvement of radio and press, the governmental warning app *Nina* was used as well as mobile warning by vehicles, social media and the siren was set off at 00:38 a.m. Thirteen sirens were activated and seven mobile warning vehicles were deployed throughout the city. At 00:20 a.m., the highest warning level 1 was declared. This level includes, for example, media broadcasting the warning immediately and unaltered, and radio programs stopping their shows to warn. In the following days, all emergency sites were processed. Additional to all available staff of the Wuppertal fire department other EMAs were also involved. Approximately 1,125 emergency staff were deployed over a period of 72 h. In Wuppertal, there were no serious personal injuries caused by the flood. The fire department and city authorities were involved in rebuilding and recovery response for several months.

3.1.2 Integration of VOST in an EOC

EOCs are decision-making units of public authorities and EMAs such as fire departments and aid organizations. Due to the professionalization and institutionalization of digital volunteers in the VOST THW described in section 2.3.1, this VOST can be activated rapidly in unexpected ad-hoc situations. The team was alerted by the EOC in Wuppertal at 8:32 p.m. on 14 July 2021 and set up its digital operating structures immediately. These structures primarily stipulate two elements: On the one hand, a liaison officer is sent to the EOC to forward VOST information to decision-makers and to ensure collaboration between the virtual team and the operating EOC. On the other hand, VOST team leaders simultaneously build up the team structure. This includes the coordination of work procedures, information products, and the distribution of tasks. For the development of information products, task priorities and information needs were defined for SMA with EOC decision-makers and the liaison officer as follows:

(1) Information on damages and the current flood situation,
(2) Helpless people and people in danger,

(3) Identification of disaster-related information for risk and crisis communication (including false information and rumors),
(4) Psychosocial needs of the affected population, and
(5) Development of spontaneous build up community engagement structures.

Additionally, it was determined that information prioritized as high by VOST analysts within these five categories would immediately be forwarded by the liaison officer to the appropriate decision-makers in the EOC. Low and medium priority information was forwarded in chronological listings at regular intervals to contribute to situational awareness. Twenty-two VOST analysts were involved in the operation over the specific period until the interagency collaboration with the EOC ended on 16 July 2021 at 02:30 a.m.

3.2 Methods

3.2.1 Stage 1: Analysis of VOST data

In the first stage of this study (concerning RQ 1 and RQ 2), various analyses were conducted based on VOST data. VOST analysts collected social media data from different social media platforms during the operation. Platforms were selected by VOST and included eight different social media: Twitter, Facebook, Jodel, Instagram, YouTube, TikTok, Snapchat and Telegram. In addition to these platforms, websites were captured if, for example, links to news pages were shared on social media. The original source (website) was collected. To acquire this data, some manual search methods were used as well as the semi-automated SMA software ScatterBlogs (Bosch et al., 2011). For the selection of relevant, disaster-related social media posts, VOST analysts used keywords (e.g. wuppertal or "wupper" and hashtags (e.g. #wuppertal or #w1407) as well as the location search. The SMA tool autonomously locates Twitter posts in regions using advanced analytics (Thom et al., 2016). All data was entered into an aggregate file, which we name "VOST data" for the purposes of this case study. VOST analysts separated disaster-related information from unimportant information, applying the task priorities (see five points in section 3.1.2). Data considered relevant was then collected in a central file accessible for all analysts, which we used for the research depicted in this paper. During the flood, VOST classified 536 social media posts as relevant and subsequently evaluated and categorized their relevance into three levels (high, medium, low), first by team member and then by team leaders. In line with the task priorities, the social media posts (text, images and videos) are evaluated on the basis of two factors: first, how important the information is for the decision-makers and, second, whether it is also urgent (e.g., because dangers or changes in the situation may emanate from it). Because the prioritization of data is subjective and depends on the current disaster situation, which in turn can change within a short period, a team leader performs an additional evaluation. The file of data collected during the flood, however, was partially incomplete. To complete the VOST data and for subsequent analysis, we proceeded in the following four steps:

(1) Data cleaning: adding missing metadata (times of posts, information format, and platform)
(2) Summary of categories (e.g. misinformation and disinformation combined in the category false information)
(3) Visualization of the data
(4) Comparative quantitative analysis and contextualization of the data

In addition to analyzing the distributions of the categories (RQ 1), different parameters from the data set were used for more in-depth analyses. These parameters are the prioritization of social media posts by VOST analysts, the format of information (text, image, and video), and the source (social media platform). For answering RQ 2, we have quantified the three levels of prioritization (high = 3, medium = 2, and low = 1) and calculated the mean value for each category. This dataset is unique because it was collected during a real-world flood operation and not during a training or scenario-based simulation. Furthermore, 22 skilled VOST analysts conducted the data collection, so the data collected was always preceded by an evaluation. Compared to datasets from other works, a variety of data from several social media platforms was included here.

3.2.2 Stage 2: Survey of decision-makers

One of the characteristics of the German disaster management system is that it is organized on a regional basis, with local EOCs taking over the management. This means that a large number of EOCs exist for disasters that affect several regions at the same time. In our case study, we only examined the one EOC that collaborated with the VOST THW. In stage 2, an online survey was designed using the application LimeSurvey to answer RQ 3. The objective was to interview all EOC decision-makers who had worked with the VOST THW during the flood in Wuppertal. In selecting these participants, it was also important that they had worked directly with VOST information and thus based their situational awareness and/or decisions on it. A total of nine persons were identified as eligible for this survey. All nine decision-makers from the EOC participated in the survey conducted from Jan. 7 to 21, 2022, preceded by six online pretests. First, demographic data and respondents' roles in the EOC were asked, followed by a matrix of six questions about whether and how VOST information impacts situational awareness. These questions addressed the results gained in stage 1 and examined whether categorizing, filtering, and prioritizing the collected data contributed to situational awareness. Subsequently, another matrix of six questions examined how actionable information influenced decision-making by asking whether faster and better decisions were made based on this actionable information. We also examined whether such information contributed to greater certainty in decision-making and how it impacted people-centered risk and crisis communication. Both question matrixes needed to be rated by the nine decision-makers on a five-point Likert scale. Subsequently, the mean value of these ratings was calculated in order to be able to make a quantitative comparison of the ratings. The calculated mean was categorized as follows (5–1): strongly agree = 5; agree = 4; partially agree = 3; disagree = 2; strongly disagree = 1. Using Likert scales is an established method in the research literature of summated scores to translate individual respondent ratings into an aggregate score (e.g., impact on situational awareness or decision-making) (Schnell et al., 2011). This case study utilizes the five-point Likert scale as a metric scale (strongly agree = 5; strongly disagree = 1) defined as an interval scale with equally spaced units (Backhaus et al., 2021). Therefore, this scaling is appropriate for our survey to use a quantitative research approach to answer the RQ 3 and determine the impact of VOST information on situational awareness and decisions based on actionable information. For this purpose, we apply the descriptive statistics approach in the following section 4. We ended the survey with general questions about information product design and future cooperation with VOST. The following Figure 1 presents our methodological approach in a schematic illustration of our two stages, the respective research questions, the methods and the data material.

4 Results

4.1 Stage 1: Social Media Analytics by Virtual Operations Support Team during the flood

A total of 536 posts from various social media platforms were identified and collected. 56% of these disaster-related posts were shared on Twitter, 15% on Facebook, nine percent on Jodel and seven percent on Instagram. Three percent of the analyzed information was posted on YouTube and one percent on TikTok. In addition to this social media data, 42 datasets from websites were gathered. Almost all posts were in German; only three posts (translations of EOC warnings by social media users) were in English, Turkish, and Russian. The posts' formats were collected as well: More than half (58%) of the information was posted in text-only format, 22% of the posts were images, and 20% were videos. The types of accounts that forwarded the information previously shared on social media were identified as follows: 77% of the posts were shared through citizens' private accounts, 17% by media and press accounts and five percent by EMAs. Other types such as public transport agencies, accounted for the remainder.

4.1.1 Categories

To answer RQ 1, VOST data collected during the flood were analyzed and contextualized in the respective flood situation. For this purpose, data collected by the 22 VOST analysts who classified disaster-related information from the flood into categories during the flood operation were summarized. Categories described with different terms (e.g. spontaneous volunteer and spontaneous helpers combined in the category spontaneous community engagement or misinformation and disinformation combined in the category false information) were merged for a better understanding. This analysis indicated that the information gathered from social media could be summarized into 23 different categories for the examined period. Figure 2 shows these categories and their proportional distribution for the entire operation period in percent. It illustrates that the first five categories' distributions closely resemble one another and account for over half of all identified posts (51.9%). The results also show that four of the five categories (level of the river, warning, flooded traffic roads and power outage) are related to the hazard flood situation. However, the largest category mainly concerns the time after the hazard flood situation (spontaneous community engagement). With regard to the information needs of the decision-makers in the EOC, defined as task priorities (see section 3.1.2), Figure 2 illustrates that information could be found on all aspects. Subdivided into 23 categories, information was found on the extent of damage, level of the river, hazards, and findings for risk and crisis communication, psychosocial needs, and spontaneous build up community engagement structures.

Due to the hazard and dynamic flood situation, which consists of various different elements (e.g. power failure, activation of warning sirens, evacuation), the analysis of the categories under the factor of time plays an essential role for the overall understanding of the summarized categories. To visualize the five most frequent categories, we made use of the posts' timestamps to analyze when they were published on social media (see Figure 3). In addition to these first five categories, the posts about sirens were added. With about four percent of all posts, this category plays a minor role overall. However, looking at the distribution of posts over time, it becomes clear, that the siren warning was a relevant topic of interest. Its activation at 00:38 a.m. is distinctly visible within the data. During the dynamic flood situation, posts about flooded roads and information about the level of the river dominated particularly. This was followed by posts about warnings via various methods (sirens, warning vehicles, and warning app) during the night and in some cases power outages, which were discussed intensively altogether. With the abatement of the hazard flood situation, from the following day on July 15, the flood response of so-called spontaneous volunteers predominated as spontaneous community engagement structures formed in social media especially (see Figure 3). As the day progressed, this topic increasingly dominated social media, partly due to a call to the public by the EOC to participate in disaster response.

4.1.2 Relationships between categories, prioritizations, information format, and platforms

In addition to summarizing the categories and analyzing them with the consideration of time, our processing of RQ

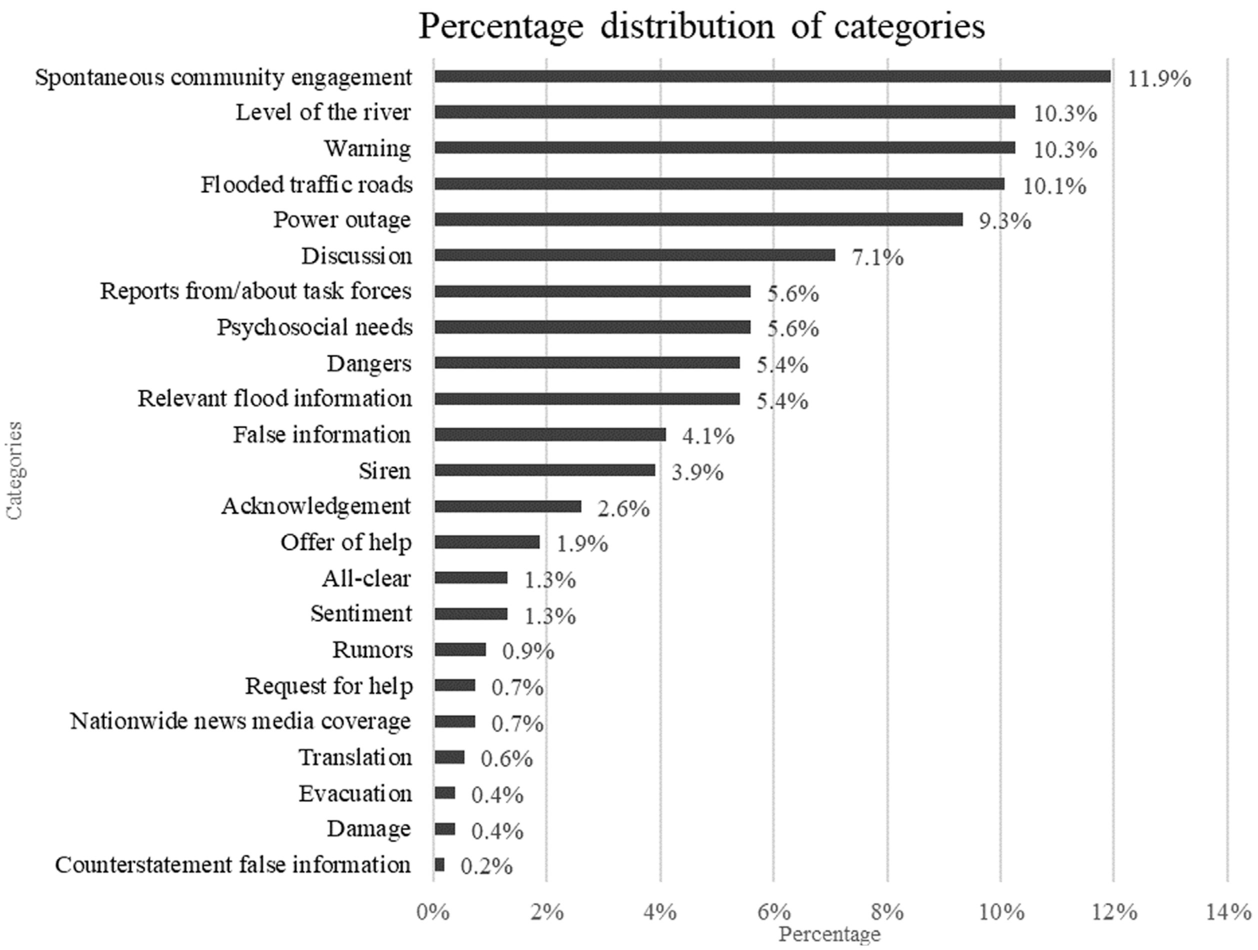

FIGURE 2
Percentage distribution of categories.

2 examined what relationships exist between the categories and other parameters. Table 1 lists the categories (number of posts in brackets) and the mean value of the respective prioritization assigned by VOST. The comparison of the categories' frequency and their prioritization shows that none of the five most common categories discussed above (see Figure 2) were assigned the highest mean priority, while all posts in the categories of false information and rumors (and the one counterstatement) or damage and requests for help were consistently prioritized with the highest level of 3. The top five most frequent categories were rated between medium to high priority (in average M = 2.13): spontaneous community engagement (n = 64; M = 2.03), level of the river (n = 55; M = 2.18), warning (n = 55; M = 2.07), flooded traffic roads (n = 54; M = 2.43)) only with the exception of the category power outage (n = 50; M = 1.92).

Posts in categories that could have had a direct impact on the health and safety of the affected population (e.g., request for help or false information) were on average rated higher than others. All such posts were classified as actionable information and thus directly forwarded to the decision-makers in the EOC. In flood situations, f alse information can lead the affected population to take wrong and dangerous actions, such as fleeing reactions. While the flood situation was still dynamic in Wuppertal for example, a video supposedly showing the Wuppertal Dam was shared, picturing rushing muddy water and various steel constructions as well as a conveyor belt. It was first published on the evening of July 15 claiming the Wuppertal Dam had busted, and subsequently shared on various social media platforms such as Twitter, Facebook, Telegram and YouTube with wide reach. However, the video does not show the location indicated, but in fact the Inden strip mine 120 km from the Wuppertal Dam. This mine had been flooded by the river Inde due to the heavy rainfall on July 15 indeed causing great damage, but not in Wuppertal.

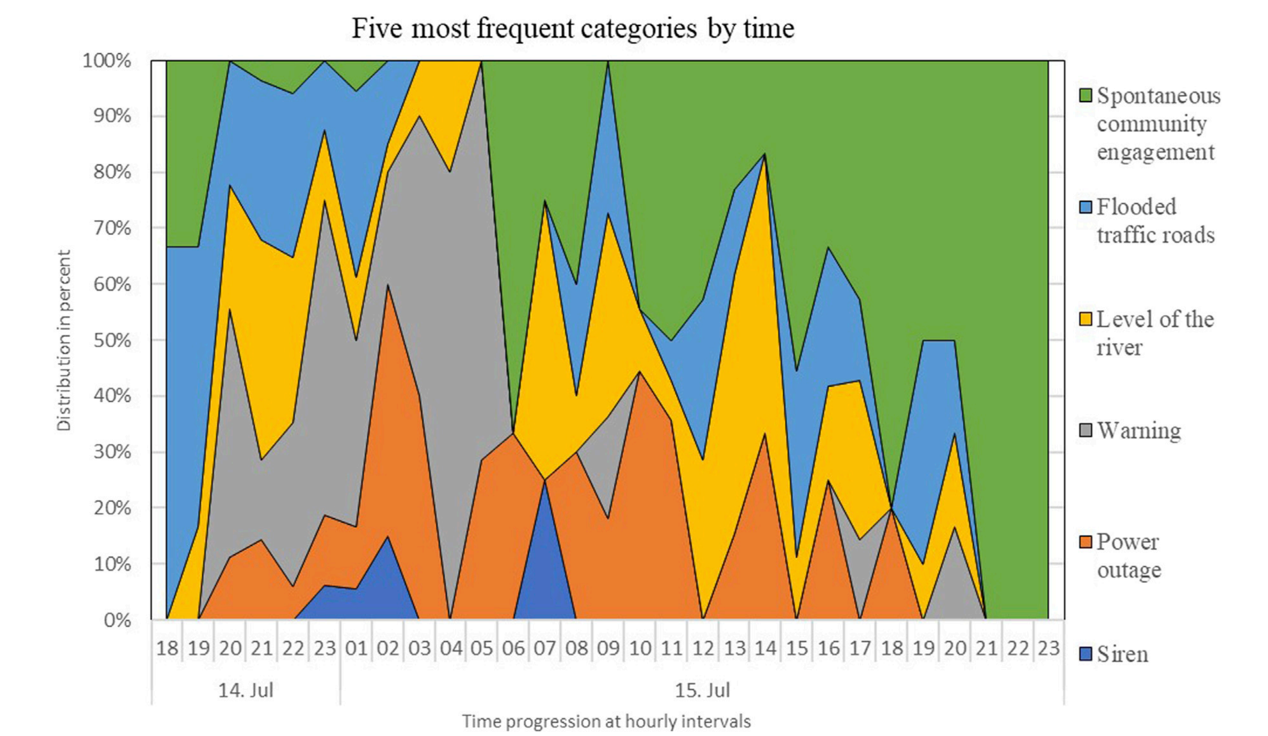

FIGURE 3
Five most frequent categories by time.

Although the situation at the Wuppertal Dam was difficult as described in section 3.1.1, it was not as critical endangering large parts of the population. In a further step to answer RQ 2, we analyzed how the different formats of information can be classified into the categories. Four different formats were identified in the dataset of 536 social media posts: text, image, video, and one gif. Table 2 lists these formats and their mean value of prioritization.

This comparative analysis shows that, on average, information in the format of videos (n = 105; M = 2.25) has a higher priority than information in other formats such as images (n = 117; M = 2.09) and text (n = 313; M = 1.90). Following on from this analysis, we conducted a comparative analysis of the prioritization of the data and the sources on which the information was published (see Table 3). Eight different social media platforms were identified, with disaster-related information from websites also listed (n = 42).

Table 3 illustrates that information from social media platforms that mainly contain images and videos is prioritized higher (e.g. YouTube: n = 16; M = 2.44) than that from text-heavy platforms (e.g. Twitter: n = 300; M = 1.95), with a large difference in distribution within platforms.

Our analysis from various social media platforms indicates that the information can be summarized into 23 categories of which the five most frequently occurring categories have a similar distribution. However, a chronological analysis reveals that the prevalence of categories varies over time: posts about spontaneous community engagement increase strongly as the hazard flood situation passes and finally dominate completely. The investigation of the prioritization by VOST analysts also leads to important findings: Posts with a potential impact on the health and safety of the affected people, such as request for help or false information, are given high priority. Furthermore, it could be established that in the mean prioritization value of all 536 posts, videos are prioritized higher than other formats of information. This is also reflected in the selection of social media platforms: information from those that are more image-heavy are prioritized higher than text-heavy ones.

4.2 Stage 2: Situational awareness and actionable information for decision-makers

In stage 2 of this case study, we examine RQ 3, addressing the question of how VOST information impact decision-makers' situational awareness and how actionable information contributes to decisions. In an online survey, we systematically interviewed all nine decision-makers who had worked with VOST information during the flood. All respondents were men between 32 and 54 years

TABLE 1 Categories and prioritization.

Categories	Mean of Prioritization (M)	Standard Deviation (SD)
Rumors (n = 5)	3.00	0.00
Request for help (n = 4)	3.00	0.00
False information (n = 22)	3.00	0.00
Counterstatement false information (n = 1)	3.00	-
Damage (n = 2)	3.00	0.00
Dangers (n = 29)	2.79	0.49
Nationwide news media coverage (n = 4)	2.50	0.58
Flooded traffic roads (n = 54)	2.43	0.69
Level of the river (n = 55)	2.18	0.75
Warning (n = 55)	2.07	0.66
Spontaneous community engagement (n = 64)	2.03	0.71
Translation (n = 3)	2.00	0.00
All-clear (n = 7)	2.00	0.58
Evacuation (n = 2)	2.00	0.00
Psychosocial needs (n = 30)	1.93	0.78
Power outage (n = 50)	1.92	0.70
Siren (n = 21)	1.90	0.62
Relevant flood information (n = 29)	1.62	0.56
Offer of help (n = 10)	1.60	0.70
Sentiment (n = 7)	1.57	0.53
Reports from/about task forces (n = 30)	1.30	0.65
Discussion (n = 38)	1.16	0.37
Acknowledgement (n = 14)	1.00	0.00

TABLE 2 Information format and prioritization.

Information Format	Mean of Prioritization (M)	Standard Deviation (SD)
Video (n = 105)	2.25	0.72
Image (n = 117)	2.09	0.82
Text (n = 313)	1.90	0.78
Gif (n = 1)	1.00	-

of age (M = 41.7), with an average of 21 years of work experience in EOCs. Three of the interviewees were EOC directors; the other six were executives of specific subject areas (e.g. communication or warning) within the EOC.

4.2.1 VOST impact on situational awareness

In the first step of this second stage, we examined how VOST information contributed to decision-makers' situational awareness during the flood. All statements were generally rated with a strong agreement overall (M = 4.46). The highest level of agreement was expressed for the statement that VOST information contributes to increased situational awareness, with two decision-makers rating the statement with agree and all others with strongly agree (n = 9; M = 4.78). Categorizing, prioritizing, and filtering social media data by VOST analysts also contributes to situational awareness, according to the decision-makers interviewed (see Table 4).

There was also strong agreement with the statement that a liaison officer is necessary to report information from VOST to the EOC (n = 9; M = 4.22). The statement that VOST information forecasts developments of future situations received the proportionally lowest level of agreement (n = 9; M = 3.89).

TABLE 3 Sources and prioritization.

Sources	Mean of Prioritization (M)	Standard Deviation (SD)
Telegram (n = 2)	2.50	0.71
YouTube (n = 16)	2.44	0.63
Snapchat (n = 3)	2.33	0.58
Facebook (n = 83)	2.25	0.71
Instagram (n = 38)	2.11	0.86
Jodel (n = 46)	2.00	0.79
Twitter (n = 300)	1.95	0.80
Website (n = 42)	1.74	0.63
TikTok (n = 6)	1.67	0.82

TABLE 4 VOST impact on situational awareness.

Statement	Mean (M)[a]	Standard Deviation (SD)
1. Information from VOST contributes to expanded situational awareness.	4.78	0.42
2. Categorizing the information (e.g., into “spontaneous volunteers” or “false information”) by VOST members helps me gain a better awareness of the current situation.	4.67	0.47
3. Prioritization of information by VOST members helps me maintain a better awareness of the current situation.	4.67	0.47
4. The filtering and evaluation of information by VOST members contributes to an expanded situational awareness.	4.56	0.50
5. A VOST liaison officer is necessary for the transmission of information within the EOC.	4.22	0.79
6. The information from VOST helps me to forecast developments of future situations.	3.89	0.74
Total	4.46	0.14

[a]Explanation Mean (M): The calculated mean was categorized as follows (5–1): strongly agree = 5; agree = 4; partially agree = 3; disagree = 2; strongly disagree = 1.

Overall, the battery of questions on situational awareness was strongly agreed to (n = 9; M = 4.46) with minor differences between strongly agree, agree and partially agree within the statements. However, VOST information products not only contributed to situational awareness, decisions were also made based on actionable information.

4.2.2 VOST impact on decision-making

Decision-making processes are complex in disaster management. In a short period, a large amount of information is available from various sources, so decision-makers need to quickly identify, process, and verify information and derive specific decisions from it. The previous sections show what kind of information from social media is identified, categorized, and prioritized by a VOST and how it impacts situational awareness. In contrast to the more general, medium-priority information that contributes to situational awareness, direct decision-making in the EOC is derived from so-called actionable information. We developed a battery of statements to determine the impact of this actionable information on decision-making. As in section 4.2.1, the statements were rated by the same group of decision-makers (n = 9) in a five-point Likert Scale (see Table 5).

According to these decision-makers’ assessments, the VOST’s provision of actionable information has helped to enable the implementation of people-centered risk and crisis communication. This statement was most strongly agreed to compared to the others (n = 9; M = 4.56).

The statements that VOST information contributes to confidence in decision-making (n = 9; M = 4.44), to make better decisions (n = 9; M = 4.33), and to identifying alternative decision paths (n = 9; M = 4.11) were also on average rated between strongly agree and agree. Only the last two statements have an average agreement value between three and four: the decision-makers thus do not agree as strongly with the statements that VOST information leads to faster decision-making and reduces complexity as with the first three (see Table 5).

The results stress that VOST information supports decision-making at different levels. Thus, actionable information contributes in particular to the ability to ensure people-centered risk and crisis communication. According to the EOC decision-makers interviewed, VOST information

TABLE 5 VOST impact on decision-making.

Statement	Mean (M)[a]	Standard Deviation (SD)
1. The information from VOST helped to ensure more people-centered risk and crisis communication.	4.56	0.50
2. The information from VOST has contributed to confidence in decision-making.	4.44	0.68
3. The information from VOST has helped to make better decisions.	4.33	0.67
4. Through the information from VOST, alternative decision paths became apparent to me.	4.11	0.74
5. The information from VOST has contributed to faster decisions.	3.89	0.74
6. Information from VOST helps reduce complexity in decision-making.	3.78	1.03
Total	4.19	0.16

[a]Explanation Mean (M): The calculated mean was categorized as follows (5–1): strongly agree = 5; agree = 4; partially agree = 3; disagree = 2; strongly disagree = 1.

contributes to confidence in their own actions when making decisions. This is particularly important in view of potential long-term consequences of decisions in disaster management that need to be considered.

5 Discussion and limitations

5.1 Discussion

Information is crucial for effective disaster management, including decision-making and people-centered risk and crisis communication. However, in a hazard and dynamic flood situation, EOCs are often challenged by the conditions (Comes, 2016) and the enormous amount of data (McAfee and Brynjolfsson, 2012) available on social media. Previous research focused on technological, communicative, and organizational issues, as shown in section 2. Although a few papers investigated other issues, the analysis of such a cross-platform dataset from an urgent hazard situation, collected by 22 VOST analysts with a subsequent survey of decision-makers of an EOC, has not yet been investigated, even though it is crucial to understand how integrating VOSTs impact the situational awareness and decision-making of EOCs. First, this section discusses social media data analysis durin the flood response and subsequently the impact on situational awareness and decision making in light of the relevant literature. Following this, approaches for future research and practical considerations are derived from the findings and outlined.

5.1.1 Stage 1: The data analysis

Through our approach of data analysis of VOST data from an operation, important insights could be gained. Thus, to answer RQ 1 and RQ 2, it was possible to classify a large number (23) of categories of information from eight social media platforms which was relevant to the decision-makers. This allowed the classification of information that played a minor quantitative role but gained relevance to the flood response through prioritization by VOST analysts (e.g. rumors and false information). Other approaches have identified fewer categories (13), also requiring at least five tweets per category (Vieweg et al., 2010) and limiting them to just one platform (Cervone et al., 2016; Vongkusolkit and Huang, 2021). The percentage distribution of categories illustrates that not only information about the flood is communicated and exchanged, but that social media is used intensively for the creation of spontaneous build up community engagement structures, which is in line with results from Nissen et al. (2021) or Sackmann et al. (2021). The increase in spontaneous volunteering over time (Sackmann et al., 2021) is also an observation that has been noted in the past and that we have been able to illustrate in Figure 3 regarding social media content. Another crucial factor of our approach also consists of the prioritization of the data by VOST analysts, which allowed us to analyze how all 536 datasets were actually evaluated. The prioritization of the posts by trained VOST analysts, enables to draw conclusions on how important and urgent social media information was during the flood response, without machine learning approaches taking over this evaluation (Rossi et al., 2018). Furthermore, the results of our case study were not limited to text messages (Buscaldi and Hernandez-Farias, 2015; Nair et al., 2017), images and videos were also included into the analysis. The analysis of images and videos assumes an important part, as these can be time-consuming by human analysts. The content has to be verified, geolocated and interpreted, which can tie up several analysts at the same time; in a VOST operation during a mass-event 2017, a separate group has been formed for this tasks (Fathi et al., 2020). Automated tools, such as the AI-supported AIDR presented in section 2.2.1, are not yet widely implemented (Reuter et al., 2016). In their survey of 761 emergency responders, Reuter et al. (2016) determined that only 23% were using social media to expand situational awareness and some EMA were experimenting with different tools. At the same time, the study by Krupp and Bellut (2021) shows that in Germany, especially among the younger population, image-heavy platforms (such as Instagram) are used instead of text-heavy platforms (such as Twitter). The approach of analyzing and prioritize large mass data by VOST analysts also has its risks. Due to the close integration into an

EOC, the digital volunteers in the VOST are exposed to similar conditions (time pressure, uncertainty, information overload, high stakes) as the decision-makers in the EOC, despite the virtual working methods (Comes, 2016; Paulus et al., 2022). This can cause data bias and confirmation bias to affect the analysts' information products for decision-maker (Paulus et al., 2022). In addition, analyzing disaster-related social media information (e.g., traumatizing images and videos) and working alone creates the possibility of psychosocial burdens on VOST analysts. Due to the integration in an EMA, established structures of psychosocial help also exist for digital volunteers, which Tutt (2021) described in a paper due to the special virtual conditions.

5.1.2 Stage 2: The impact on decision-making

As described in section 2.2.1, Endsley (1988) understands situational awareness in three distinct parts with the aspects of perception, comprehension, and projection. Applied to our survey, the results indicate that perception and comprehension especially are influenced positively. Using the calculated mean, it can be seen in the results Table 4 and Table 5 that most statements receive a high level of agreement from the decision-makers (nine out of a total of twelve statements have a value above $M = 4.00$) and thus contribute to a wider perception. Even though situational awareness is always subjective (although there is objective situational information, e.g., in our case VOST information) (Hofinger and Heimann, 2022) we were able to transform individual respondent ratings into an aggregate score (Schnell et al., 2011). The results illustrate that the interagency integration of a VOST into EOC structures contributes to expanded situational awareness ($M = 4.78$). The high agreement in the use of SMA approaches, such as categorization ($M = 4.67$), prioritization ($M = 4.67$), filtering and evaluation ($M = 4.56$), highlight this result. Thus, our results are in line with Vongkusolkit and Huang (2021) who previously highlighted that SMA can improve situational awareness for decision-makers in disaster management. The high level of agreement indicates that the perceptions of decision-makers at the EOC have been positively impacted. The second part of the survey focused on decision-making based on short-term actionable information (Mostafiz et al., 2022). Decision-making based on actionable information requires that information reaches the right decision-maker in the EOC at the right time and that the decision-maker comprehends it (Zade et al., 2018). Applied to the second of three aspects of the definition by Endsley (1988) our results suggest that VOST information can also make an impactful contribution. This can be argued especially because important decisions could be made based on VOST information (e.g., ensure more people-centered risk and crisis communication, $M = 4.56$) or that information from VOST helped to make better decisions ($M = 4.33$). Collecting data in the decision-makers task priority spontaneous build up community engagement structures contributed to a better assessment of the resource potential within the population and allowed to derive focused measures, such as an active call on social media by the EOC for spontaneous participation in disaster management. According to the four different flood risk communication strategies by Haer et al. (2016) introduced in section 2.1.2, it can be deduced that this approach enabled a people-centered communication strategy focused on risk and coping options. Compared to perception and comprehension, the results of the survey that can be assigned to third field from the situational awareness definition by Endsley (1988), projection, are less strongly positive. Thus, the statements that VOST information helps me to forecast developments of future situations ($M = 3.89$), has contributed to faster decisions ($M = 3.89$), and helps reduce complexity in decision-making ($M = 3.78$) are only in a range between partially agree and agree. Even though the decision-makers at the EOC are experienced disaster management responders with an average of 21 years of work experience in EOCs, the conditions (e.g., uncertainty and high stakes) (Comes, 2016) during such a situation affect them. In addition to these conditions, there is the severity of the flood (Zander, 2021), the night time and uncertain situation developments (see description in 3.1.1). These factors may have contributed to the VOST information not being as positive as the other two aspects (perception and comprehension) in projecting the future. Based on our survey, VOST information contributes in particular to perception and comprehension. Both the expansion of situational awareness and the deduction of immediate measures are indicators for this. Statements, which are concerned with forecast developments of future situations, faster decision-making and reduction of complexities, received less approval. The projection seems to be improvable, e.g. by exercises.

5.1.3 Future research

These results illustrate that a variety of disaster-related information can be found on several different platforms, in this case study eight different platforms and additionally information from websites. Our approach allowed us to analyze in detail a wide range of relevant disaster-related information in social media, in different disaster phases. For future research approaches, more attention should be paid to the fact that the affected population's communication is not confined to only one social media platform, so that detailed insights can be derived that remain hidden when focusing on a single platform. This circumstance must also be taken into account in EMAs people-centered risk and crisis communication, since different age groups, for example, use differing platforms intensively (Krupp and Bellut, 2021). In addition, future approaches designing categorization frameworks for different disaster scenarios from social media data could simplify the classification of these large amounts of data. In addition, exploring the use of AI in the analysis and visualization of big data volumes and creating it to support decision-making is crucial. In particular, research approaches for the use of AI need to be further developed, such as the platform Artificial Intelligence for Disaster Response (AIDR) described in section 2.1.1, particular in the automated analysis of images and videos.

In addition, machine learning approaches need to be explored further, for example, such as those that cluster text messages (Sonntag et al., 2021) or analyze the data of social media comparatively with those of news sites and intend to verify with this approach (Kuhaneswaran et al., 2020). The results revealed that several categories were of particular priority during the hazardous flood situation. Future AI approaches can follow up on this research by capturing information needs of decision-makers and developing automated prioritization methods and algorithm for various disaster scenarios.

The visualization of categories by time enabled us to show that immediate actions, e.g. siren warning, are publicly discussed in social media (see Figure 3). Here, a more comprehensive and in-depth analysis of the affected population's psychosocial needs could help decision-makers in improving their people-centered risk communication. Our results additionally illustrate that image-heavy information is prioritized higher by VOST analysts than text-heavy posts (M_{Video} = 2.25 and M_{Text} = 1.90). In order to understand potential biases in the perceptions and ratings by individual VOST analysts, research into the individual reasons that lead to a lower or higher prioritization can be beneficial.

The results illustrate that the situational awareness is expanded by VOST information (M = 4.78) so that it can be argued that without the integration of a VOST, the information available would not or not completely be integrated into situational awareness. The scope of this situational awareness expansion however, has not yet been examined. To investigate this issue, participatory observations and interviews during future operations or interagency exercises can be used to qualitatively examine both information management and the detailed processes used to gain situational awareness.

Furthermore, we can contribute to improving the understanding of data analytics impact on human performance, in our case situational awareness. Linking data analytics and real-world impact is particularly important in order to realize needs-based analytics. In this regard, a more in-depth study of the information needs of individual decision-makers' work areas (e.g. communication) in EOCs will be valuable.

5.1.4 Practical considerations for disaster management

Based on the results of the two stages, it can be deduced that the analysis of social media offers an opportunity to derive information about the current situation and the needs of the affected population. The integration of VOST analysts in an EOC can help to find and integrate relevant disaster-related information in disaster management, expand decision-makers' situational awareness and enable people-centered risk and crisis communication.

To maintain these positive effects in the future, it seems necessary for EOCs to practice with VOSTs (e.g., tabletop exercise), especially before the need to expand projection skills described in Section 5.1.2. Moreover, as the affected population uses various social media platforms for communication, EMAs ought to observe the trends of different platforms closely for future people-centered risk communication, so that individuals can be reached in a multimedia and dialog-oriented approach. This indicates the necessity, especially in light of the climate change-related challenges for disaster management, that EMAs develop and establish their own analytical, risk and crisis communication competencies. Large-scale disasters, such as the 2021 flood in Germany, demonstrate that the analysis resources of a VOST are not sufficient to parallelly provide all EOCs with appropriate information products.

5.2 Limitations

Two different methods were used in two stages to study RQ 1, RQ 2 and RQ 3. For this case study, the data collected by the VOST during the dynamic hazard situation for the purpose of collaboration among the 22 analysts were studied. To investigate the VOST information's impact on situational awareness, but also for a deeper understanding of actionable information affecting EOCs decision-making, a survey was conducted for this paper. With a subsequent analysis, the results of the two methods used were examined and discussed in the context of previous work. The combination of the two stages in our research approach remains at the level of linking the separate findings so that the results can also be collected and analyzed in isolation and independently of each other. This approach, based on innovative analysis approaches (analyzing operational VOST data) as well as established research methods (survey), ensures that this work contributes to the scientific debate and to the practical discussion in this strongly interdisciplinary research area. The scientific value of this methodological approach is based on the fact that, despite the time- and safety-critical working environment in disaster management, important real world and unique findings could be obtained.

Due to the nature of a case study, there are limitations in generalizing the results to other hazard scenarios and interagency collaborations. It should be noted that integrated SMA by a VOST depends on the task priorities and information needs set by the respective EOC as they can vary according to the particular focus of an EOC. The timing of a VOST operation in a hazard situation is also crucial. During the response phase, information needs differ from those during the recovery phase of a disaster. This becomes visible in the depiction of the identified categories over time, where different task priorities dominate over the course of the acute hazard situation (see Figure 3). Additionally, even if the prioritization was performed by more than one person (VOST analyst and VOST team leader), there is a possibility of cognitive or data bias (Paulus et al., 2022). The dataset is also not representative of all data posted on social media during the flood situation, but rather reflects what the 22 VOST analysts were able to collect in this particular hazard flood scenario based on the EOC task priorities. Despite the cross-platform data, over half (56%) of the disaster-related information comes from Twitter, thus, similar to other papers (Vongkusolkit and

Huang, 2021), a data bias has to be noted here. In addition to data from social media, 42 information shared on websites were also analyzed. For the purpose of completeness, this data was also included in this case study. While it was possible to examine that VOST information contribute to an expanded situational awareness by surveying EOCs decision-makers, detailed insights are missing due to the common limitations of a survey. Additional guided interviews would allow a deeper understanding of situational awareness among individual decision-makers to be explored. In addition, only nine decision-makers from a single EOC were surveyed, interviewing members of different EOCs would also be helpful for detailed findings.

6 Conclusion and outlook

Integrating SMA conducted by a VOST into the decision-making process in disaster management is challenging: On the one hand, VOSTs work on a volunteer basis and are exclusively virtual. On the other hand, virtual work in time-critical environments has not been explored sufficiently, although without the volunteer work of a VOST, SMA could not be conducted in-depth. Thus, VOST information have revealed a new or complementary view of the flood situation to the EOC. Through the unique approach of analyzing VOST data and also surveying the EOC decision-makers who worked with VOST information during the flood response, we were able to gain important insights. Thus, it was shown that VOST analysts utilized a variety of different social media platforms for analysis and was not limited to Twitter. Furthermore, it could be shown that image-heavy posts are prioritized higher than text-heavy posts and that the percentages of the categories change heavily in the course of the flood. The survey highlights that VOST information helps to increase situational awareness and resulting actionable information contributes to the EOC's decision-making. This includes in particular the realization of people-centered risk and crisis communication during a hazard situation. Integration VOST information into the EOC has a positive impact on the perception and comprehension of the disaster situation by the decision-maker overall, although the projection on future developments needs to be improved. This case study demonstrated that the need for SMA does exist and that information can be generated by an interagency collaboration and subsequently integrated into decision-making contributing to operational success.

The research focus of this paper was to investigate the VOST data generated during a hazard flood and its impact on situational awareness and decision-making in disaster management. Thus, this case study with its three research questions contributes to developing a scientifically substantiated understanding of virtual work with social media data in time-critical environments and to exploring its impact on decision-making in an EOC. While previous research was mainly focused on technical aspects of SMA, this case study allows the practical assessment of such teams by analyzing a VOST operation during a flood and by interviewing decision-makers. Furthermore, this work contributes to further developing the understanding of digital participation in disaster management and to generate a foundation for future research, both in technical and social sciences. For the future integration of professionalized digital volunteers, it appears necessary that decision-makers in EOCs more deeply understand the relevance, velocity, and fundamental change in the communication culture due to social media develop their own competencies and resources.

Data availability statement

The datasets presented in this article are not readily available because operational data from VOST cannot be published. Anonymized survey data, in contrast, can be published. Requests to access the datasets should be directed to fathi@uni-wuppertal.de.

Ethics statement

Ethical review and approval was not required for the study on human participants in accordance with the local legislation and institutional requirements. The patients/participants provided their written informed consent to participate in this study.

Author contributions

RF developed the paper concept and the methodology, analyzed the data and wrote the manuscript. FF supervises this project.

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Conflict of interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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