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Virtual Operations Support Teams in Disaster Management: Social Media Analytics and the Impact on Decision-Making

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„Do, wo Darwin für alles herhällt,

Ob mer Minsche verdriev oder quält,

Do, wo hinger Macht Jeld ess,

Wo Starksinn die Welt ess,

Vun Kusche un Strammstonn entstellt,

Wo mer Hymnen om Kamm sujar blööß,

Enn barbarischer Gier noh Profit

„Hosianna" un „Kreuzigt ihn" rööf,

Wemmer irjendne Vorteil drin sieht,

Ess täglich Kristallnaach.

Nur noch Kristallnaach." [1]

[1] Niedecken, W. in BAP „Kristallnaach" (1982)

Abstract

Disaster management and civil protection face numerous challenges due to increasing disaster situations, including those caused by climate change, and rapid developments in information and communication technologies. Changes in societal communication due to intensifying use of social media is especially apparent in crises and disaster situations. Individuals affected and eyewitnesses use the interactive opportunities to share relevant information, to communicate and to collaborate. This intensive use generates large and diverse datasets very quickly, likely relevant for rapid and appropriate decision-making in Emergency Operations Centers (EOCs). Aiming to systematically evaluate these datasets through Social Media Analytics (SMA) approaches and to provide resulting information products to decision-makers, digital volunteers have formed and institutionalized Virtual Operations Support Teams (VOSTs). Integrated into the structures of established and governmental Emergency Management Agencies (EMAs), VOST analysts provide support through advanced analysis tools, the verification of relevant information, and visualization of data on digital crisis maps. In doing so, the virtual teams pursue the goal of expanding situational awareness and improving the decision-making process in EOCs. In this time- and safety-critical work environment, also characterized by factors such as urgency and uncertainty, the integration of virtual analysis units as VOSTs is characterized by numerous challenges, so that various questions arise at the level of organization, technology, and human-related analytical capabilities. Parallelly, policymakers and practitioner associations are calling for further expansion of VOST structures and for more intensive implementation during disaster management. Therefore, this dissertation aims to provide answers to the following central research question: How can a VOST be integrated into established disaster management structures, what impact do Social Media Analytics have on situational awareness and decision-making, and what challenges can be identified at the level of human-related data processing and privacy-aware methods? For this purpose, the central research question was operationalized in four studies and examined by applying practice-oriented research methods.

Study I applies a mixed-method-approach including participant observation and focus group discussions with VOST and EOCs decisions-makers to investigate structural, procedural, and technical requirements for collaboration with an interorganizational EOC through a case study. The structural and procedural conceptualization of the VOST in this case, which consisted of 20 digital volunteers, was systematically observed and findings were documented for the first time during a real-time operation. It was found, that forming three working groups of 8-10 members each proved to be suitable group sizing for carrying out SMA, crisis mapping and verification tasks in this operational context. Despite the hierarchical structuring, there was the requirement for spontaneous coordination approaches by VOST group leader during both days. Group leaders dynamically adapted to such approaches according to the work assignments and formed special, short-term working groups. Study I reveals that although the tools assist in carrying out the tasks, neither the user interface, nor the analytical capabilities and the results are trusted by the users, often complicated to use and not easy to comprehend. Based on the results, four areas of technical requirements for future system design improvement are identified.

Study II focuses on the social media data collected by a VOST during the 2021 flood disaster response in Wuppertal, Germany, analyzing what information was identified and when and how VOST analysts prioritized it. In addition, Study II provides answers to how VOST information

contributed to situational awareness and decision-making during disaster management through a survey of decision-makers of the EOC. It was found that information from eight social media platforms could be classified into 23 distinct categories. VOST analysts' prioritizations indicate differences in information formats and social media platforms. Disaster-related posts that pose a threat to the affected population’s health and safety (e.g., false information) were more commonly prioritized than other posts. Image-heavy content was also rated higher than text-heavy data. Surveying EOCs decision-makers revealed that VOST information contributes to expanded situational awareness and ensures people-centered risk and crisis communication.

In Study III, an international workshop experiment with digital volunteers and decision-makers from different EMAs examined human analysis and decision-making capabilities. Multiple phases of a fictitious epidemic scenario in three countries were used to examine how data biases are incorporated into decision-making processes by integrating information products from digital volunteers. It was found that digital volunteers, even if they detect biases, fail to successfully debias data. Subsequently developed biased information products are transmitted to decision-makers, who then base their situational awareness and decision on biased information.

Study IV deals with the key question of how privacy-aware methods can be applied to social media data processing of VOSTs. For this purpose, a focus group discussion with two VOSTs was conducted to investigate the process steps data is collected and analyzed, and which privacy-aware methods can be used in the future. None of the key findings contradicts the assumption that VOSTs can work with processed privacy-aware data. This is possible as the majority of the VOSTs' work is done after potential processing of privacy-aware data. The results indicate that implementing privacy methods in the data collection process does not affect the data analysis process, except for training cases and the verification process. Current analysis methods and data analysis tools could be further developed, e.g., in terms of handling large data sets in a privacy-aware manner, rather than introducing new techniques, as these are already in use and widely accepted.

Overall, these four studies highlight that the utilization of VOSTs is a valuable resource for situational awareness and decision-making in EOCs, providing a wide range of relevant information that would otherwise not or not fully be captured without the integration of VOST analyses. Additionally, organizational and technical requirements for a successful collaboration between a virtual unit and an EOC can be outlined. Furthermore, technical and human capabilities and limitations will be analyzed and discussed against the background of future challenges.

Abstract (German)

Der Bevölkerungsschutz steht aufgrund der Entwicklungen im Bereich der Informations- und Kommunikationstechnologien und zunehmender Katastrophenlagen, auch bedingt durch den Klimawandel, vor zahlreichen Herausforderungen. Die Veränderung der gesellschaftlichen Kommunikation durch die intensive Nutzung sozialer Medien wird insbesondere in Krisen und Katastrophensituationen deutlich: Die Betroffenen und Augenzeuginnen und Augenzeugen nutzen die interaktiven Möglichkeiten zur Verbreitung relevanter Informationen, zur Kommunikation und zur Kollaboration. Durch diese intensive Verwendung entstehen schnell große und vielfältige Datenmengen, die für die richtige Entscheidungsfindung in Krisenstäben relevant sein können. Um diese Datenmengen systematisch durch Social Media Analytics (SMA) auszuwerten und für Entscheiderinnen und Entscheider verfügbar zu machen, haben sich digital Freiwillige zusammengeschlossen und sogenannte Virtual Operations Support Teams (VOSTs) institutionalisiert. Eingebunden in die Strukturen etablierter staatlicher Einsatzorganisationen bieten VOST-Freiwillige Unterstützung durch Analyse-Tools, die Verifizierung relevanter Informationen und die Visualisierung der Daten auf digitalen Karten an. Dabei verfolgen die virtuellen Teams das Ziel, das Lagebewusstsein von Entscheiderinnen und Entscheidern zu erweitern und die Entscheidungsfindung in Krisenstäben somit zu verbessern. In diesem zeit- und sicherheitskritischen Arbeitsumfeld, das auch durch Dringlichkeit und Ungewissheit gekennzeichnet ist, ist die Integration virtueller Analyseeinheiten wie VOSTs besonders herausfordernd. Gleichzeitig fordern Politikerinnen und Politiker und Praxisverbände den weiteren Ausbau von VOST-Strukturen und deren intensivere Integration im operativen Katastrophenschutz. Diese Dissertation verfolgt deshalb das Ziel, Antworten auf die folgende zentrale Forschungsfrage zu geben: Wie können VOSTs in die etablierten Strukturen des Katastrophenschutzes integriert werden, welchen Einfluss haben Erkenntnisse aus sozialen Medien auf das Lagebewusstsein und die Entscheidungsfindung und welche Grenzen und Herausforderungen lassen sich auf der Ebene der menschlichen Datenanalyse und der datenschutzgerechten Auswertung identifizieren? Hierfür wurde die zentrale Forschungsfragen in vier Studien operationalisiert und unter Anwendung unterschiedlicher Forschungsmethoden untersucht.

Studie I nutzt einen Mixed-Method-Ansatz, um die strukturellen, prozeduralen und technischen Anforderungen an die Zusammenarbeit mit einem interorganisationalen Krisenstab anhand einer Fallstudie zu untersuchen. Dabei konnte die strukturelle und prozedurale Konzeptionierung des hier aktiven VOST, das aus 20 digital Freiwilligen bestand, erstmalig bei einem realen Einsatz systematisch beobachtet und somit wichtige Erkenntnisse gewonnen werden. Dabei konnte festgestellt werden, dass eine Gruppengröße von drei Arbeitsgruppen mit jeweils 8-10 Mitgliedern für die Analyse sozialer Medien, der digitalen Kartierung und der Verifikation geeignet war. Trotz der hierarchischen Strukturierung waren an beiden Einsatztagen spontane Koordinationsansätze der VOST-Gruppenleiter erforderlich: Die Gruppenleiter passten je nach Arbeitsauftrag die Strukturen dynamisch an und bildeten spezielle, kurzfristige Arbeitsgruppen. Studie I zeigt, dass die Tools zwar bei der Durchführung der Aufgaben helfen, dass aber weder die Benutzeroberfläche noch die Analysefähigkeiten das vollständige Vertrauen der Benutzer genießen, da sie oft kompliziert zu bedienen sind. Basierend auf den Ergebnissen der Fallstudie wurden vier Bereiche der technischen Anforderungen für zukünftige Verbesserungen identifiziert und analysiert.

Die Studie II fokussiert sich auf die von einem VOST während der Flutkatastrophe 2022 in Wuppertal generierten Daten aus sozialen Medien und analysierte, wann welche Informationen festgestellt und wie diese priorisiert worden sind. Darüber hinaus liefert Studie II durch eine Befragung von Entscheidern des Krisenstabes Antworten darauf, wie VOST-Informationen zum Lagebewusstsein und zur Entscheidungsfindung während der Flutbewältigung beigetragen haben. Es wurde festgestellt, dass die Informationen von acht Plattformen in 23 verschiedenen Kategorien klassifiziert werden konnten. Die Prioritätensetzung der VOST-Analysten weist auf unterschiedliche Schwerpunkte der Informationsformate und Plattformen hin. Posts, die eine Bedrohung für die Gesundheit und Sicherheit der betroffenen Bevölkerung darstellen (z. B. Falschinformationen), wurden höher priorisiert als andere Beiträge. Auch bild-lastige Inhalte wurden höher priorisiert als text-lastige. Die Befragung von Entscheidungsträgern ergab, dass VOST-Informationen zu einem erweiterten Lagebewusstsein beitragen und eine menschenzentrierte Risiko- und Krisenkommunikation gewährleisten.

In Studie III wurde durch ein internationales Workshop-Experiment mit digital Freiwilligen und Entscheiderinnen und Entscheidern aus unterschiedlichen Einsatzorganisationen die menschlichen Analyse- und Entscheidungsfähigkeiten untersucht. In mehreren Schritten einer fiktionalen Epidemie-Ausbreitung über drei Ländern wurde analysiert, inwieweit sich Datenverzerrungen auf die Informationsprodukte der Analysten auswirken und wie diese Eingang in die Entscheidungsprozesse finden. Es wurde festgestellt, dass es digitalen Freiwilligen nicht gelingt, Verzerrungen aus den Daten vollständig zu entfernen, selbst wenn diese identifiziert werden. Daraus folgten verzerrte Informationsprodukte, die an die Entscheiderinnen und Entscheider weitergegeben worden sind und diese so ihr Lagebewusstsein und ihre Entscheidungen auf verzerrte Informationen stützen.

Studie IV beschäftigt sich mit der Frage, wie datenschutzfreundliche Methoden bei der Datenverarbeitung sozialer Medien von VOSTs genutzt werden können. Hierfür wurde durch eine Fokusgruppendiskussion mit zwei VOSTs untersucht, in welchen Prozessschritten Daten erfasst und analysiert werden und wie der Einsatz datenschutzfreundlicher Methoden in Zukunft dabei unterstützen kann. Die Ergebnisse zeigen, dass die Implementierung von datenschutzfreundlichen Analyse-Methoden bei der Datenerhebung den Analyseprozess nicht beeinträchtigt. Die derzeitigen Analysemethoden könnten weiterentwickelt werden, z. B. im Hinblick auf den datenschutzfreundlichen Umgang mit großen Datensätzen, anstatt neue Techniken einzuführen.

Insgesamt zeigen diese vier Studien auf, dass der Einsatz von VOSTs eine gewinnbringende Unterstützung für das Lagebewusstsein der Entscheiderinnen und Entscheider und für die Entscheidungsfindung im Krisenstab ist. So können vielfältige relevante Informationen in die Arbeit integriert werden, die ohne den Einsatz der digital Freiwilligen nicht oder nicht vollständig erfasst worden wären. Gleichzeitig können Antworten über organisatorische und technische Anforderungen an eine erfolgreiche Zusammenarbeit zwischen einer virtuellen Einheit und einem Krisenstab dargelegt werden. Darüber hinaus werden technische und menschliche Fähigkeitsgrenzen analysiert und vor dem Hintergrund der zukünftigen Herausforderungen diskutiert.

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Ramian Fathi

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List of Abbreviations

AI	Artificial Intelligence
AIDR	Artificial Intelligence for Disaster Response
API	Application Programming Interface
BBK	German Federal Office of Civil Protection and Disaster Assistance
CIM	Crisis Information Management
COVID-19	Coronavirus Disease 2019
DHN	Digital Humanitarian Network
DM	Decision-Maker
EA	External Analyst
EMA	Emergency Management Agency
EOC	Emergency Operation Center
FEMA	Federal Emergency Management Agency
GIS	Geographic Information System
HOT	Humanitarian OpenStreetMap Team
ICT	Information and Communication Technology
IPCC	Intergovernmental Panel on Climate Change
NLP	Natural Language Processing
OSINT	Open Source Intelligence
RQ	Research Question
SBTF	Standby Task Force
SMA	Social Media Analytics
THW	German Federal Agency for Technical Relief
V&TC	Volunteer & Technical Community
VGI	Volunteered Geographic Information
VOSG	Virtual Operations Support Group
VOST	Virtual Operations Support Team

Glossary

Actionable Information	Actionable information is defined as information decision-makers need to decide on and respond to (Zade et al., 2018).
Collaboration	Collaboration "[…] must be viewed as an attitude or an organizational culture that characterizes the degree of unity and cooperation that exists within a community. In essence, collaboration creates the environment in which coordination can function effectively." (Federal Emergency Management Agency, 2007).
Coordination	Coordination "[…] refers to a process designed to ensure that functions, roles and responsibilities are identified and tasks accomplished." (Federal Emergency Management Agency, 2007).
Crisis Informatics	Crisis Informatics is a research area that interdisciplinary examines the use of computer-based methods in crises, disasters, and emergencies (Reuter & Kaufhold, 2018).
Decision-Making	Decisions are the results of a decision-making process and a decision-making situation arises when an option can be selected from several possible options based on specific data (Pfister, Jungermann, & Fischer, 2017).
Digital Volunteers	Digital Volunteers are individuals who form Volunteer & Technical Communities for crisis and disaster management. These decentralized groups consists of citizens around the world who collaborate to manage crises and disasters in a collective and innovative way using ICT (Park & Johnston, 2017).
Disaster	According to the German Federal Office of Civil Protection and Disaster Assistance (2022), a disaster is "an event in which the life or health of a large number of people or the natural resources or significant material property are endangered or damaged […]."
Disaster Management	Means "the organization, planning and application of measures preparing for, responding to and recovering from disasters" (United Nations General Assembly, 2016).
Emergency Management	The term "[…] is also used, sometimes interchangeably, with the term disaster management, particularly in the context of biological and technological hazards and for health emergencies. While there is a large degree of overlap, an emergency can also relate to hazardous events that do not result in the serious disruption of the functioning of a community or society" (United Nations General Assembly, 2016).
Emergency Operation Center	EOCs are decision-making units on federal-, state- or local-level and consist of various emergency management agencies' representatives, e.g. fire departments, police and aid organizations (Ryan, 2013).

Emergency Responder	An emergency responder is a member of an authority or organization or an individual responding to the scene of an emergency as first. Emergency responders are for example members of fire and rescue departments, police departments, emergency medical services, or other organizations with public safety responsibilities who respond to rescue and treat victims, and protect the public during an incident (adapted from LINKS, 2022).
Geographic Information System	GIS are "a powerful set of tools for collecting, storing, retrieving at will, transforming, and displaying spatial data from the real world." (Burrough, 1986).
Situational Awareness	Situational awareness can be defined as "[…] perception of the elements in the environment […], the comprehension of their meaning and the projection of their status in the near future." (Endsley, 1988). Situational awareness includes three levels: perception, comprehension, and projection (van de Walle, Brugghemans, & Comes, 2016).
Social Media	Social media is understood as a set of internet-based applications that build on the developments of Web 2.0 and provide interactive opportunities for users to create and share content (Kaplan & Haenlein, 2010).
Social Media Analytics	SMA include the design and evaluation of analytic tools to collect, monitor, analyze, summarize, and visualize open-access data from social media (Zeng, Chen, Lusch, & Li, 2010). The objective is to extract intelligence from available data and to identify patterns in order to serve specific needs with information on various areas of interest (Stieglitz, Bunker, Mirbabaie, & Ehnis, 2018a; Stieglitz, Dang-Xuan, Bruns, & Neuberger, 2014; Stieglitz, Mirbabaie, Ross, & Neuberger, 2018c; Zeng et al., 2010).
Virtual Operations Support Team	A VOST is a group of professionalized and institutionalized digital volunteers who perform data analytics and visualizations tasks and provide disaster-related information products to decision-makers in Emergency Operation Centers (St. Denis, Palen, & Hughes, 2012).
Volunteer & Technical Communities	V&TCs can generally be "understood as volunteer-based communities who apply their technical skills" to support disaster management and humanitarian response (Capelo, Chang, & Verity, 2012).

Preface

This thesis consists of an introduction, summaries of four peer-reviewed studies published in international scientific journals, and a general discussion. The introduction first outlines the current state of relevant research literature in four subsections focusing on decision-making, social media, and digital volunteers amidst disaster management, before introducing the research complex of Virtual Operations Support Teams. The second introductory part presents the research gap to be addressed, subsequent research questions and methods, and the four studies at the core of this thesis. It will additionally highlight the journals having published the studies and the studies' shares attributable to this thesis' author. The subsequent section 2 summarizes the four studies listed below, delineating aims, methods, and results for each study. The last section discusses the results of this thesis in light of the research literature, subsequently deriving implications for practice. Additionally, this thesis' contribution to the literature, future research, and strengths and limitations are covered in this general discussion. The last subsection provides a conclusion of the findings and an outlook prior to the reference list and the appendix including the four studies as published as well as the curriculum vitae. The four studies covered in this thesis are the following:

I. **Study I**
Fathi, R., Thom, D., Koch, S., Ertl, T., & Fiedrich, F. (2020). VOST: A case study in voluntary digital participation for collaborative emergency management. Information Processing & Management. DOI: doi.org/10.1016/j.ipm.2019.102174

II. **Study II**
Fathi, R. and Fiedrich, F. (2022): Social Media Analytics by Virtual Operations Support Teams in Disaster Management: Situational Awareness and Actionable Information for Decision- Makers. Frontiers in Earth Science. DOI: doi.org/10.3389/feart.2022.941803

III. **Study III**
Paulus, D., **Fathi, R.**, Fiedrich, F., van de Walle, B., & Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. An Exploratory Study on Epidemic Response. Information Systems Frontiers. DOI: doi.org/10.1007/s10796-022-10241-0

IV. **Study IV**
Löchner, M., **Fathi, R.**, Schmid, D., Dunkel, A., Burghardt, D., Fiedrich, F. & Koch, S. (2020). Case Study on Privacy-aware Social Media Data Processing in Disaster Management. International Journal of Geo-Information. DOI: doi.org/10.3390/ijgi9120709

1 Introduction

This introduction first provides an overview of the present state of research in subsection 1.1 introducing decision-making, social media and digital volunteers in disaster management, and the concept of Virtual Operations Support Teams (VOSTs). Subsection 1.2 addresses the research gap and underlying research questions (RQs) of this thesis, briefly introducing the methods and including a description of the four different journals having published the four studies and the studies' shares attributable to the author of this thesis.

1.1 Background

In 2021, the average global temperature was 1.11 degrees Celsius above its mean in pre-industrial times (IPCC, 2021). This trend entails enormous implications for current and future disaster management: In addition to prognosticated rise in heat and drought periods, floods and extreme precipitation occur with increasing frequency in Europe. Extreme weather has destroyed lives and property in the past years leading to billions of dollars in economic losses. The Intergovernmental Panel on Climate Change (IPCC) report 2021additionally points out that the last seven years have been the warmest since records began (IPCC, 2021), highlighting the enormous challenges that will affect disaster management and civil protection in upcoming years due to these and other effects of climate change.

Other crises such as uncontrolled infectious disease outbreaks potentially causing major humanitarian crises are also on the rise (Smith et al., 2014). Such outbreaks as the COVID-19 pandemic, in addition to health hazards caused by the consequences of climate change, can exacerbate starvation in the Global South, even adding to increasing poverty in these regions (United Nations, 2021).

Organizational conditions are also changing simultaneously: The volunteer-based model of German disaster management for instance shows to be challenged by demographic change and shifting volunteering requirements (Stephan, Bernhardt, Bäumer, & Fekete, 2018). Climate change-induced developments are additionally challenging these organizational frameworks while the need for innovative processes and structures for future disaster management is emerging concurrently.

Coinciding with these trends, information, and communication technology (ICT), especially internet-based and mobile communication, fundamentally changes communication culture and data availability. Eyewitnesses and those affected by a disaster-situation intensively utilize the interactive opportunity for digital, live communication during disaster situations (Meier, 2015). Social media platforms in particular are widely used to connect with other affected individuals, to collaborate with authorities, to spontaneously establish community engagement structures, and to share disaster-related information such as warnings (Hughes & Tapia, 2015; Kaufhold & Reuter, 2014). Hence, huge amounts of data are rapidly generated during disasters: Castillo (2016) describes this phenomenon as *big crisis data* that cannot be analyzed and visualized by responders without technical and analytical assistance.

However, rapid analysis of such data can provide timely and disaster-related information, which in turn supports situational awareness and decision-making in Emergency Operations Centers (EOCs) (Reuter, Hughes, & Kaufhold, 2018; Reuter & Kaufhold, 2018). Furthermore, ICT allow individuals to engage as digital volunteers in disaster response, alternatively referred as *digital humanitarians* (Meier, 2015) or *voluntweeters* (Starbird & Palen, 2011) as numerous tasks, such as data analysis, crisis mapping or translations do not require physical presence in the respective disaster area.

1.1.1 Decision-Making in Disaster Management

For the purpose of this thesis, *disaster management* is defined as “the organization, planning and application of measures preparing for, responding to and recovering from disasters.” (United Nations General Assembly, 2016). Although the term *emergency management* is sometimes used synonymously with disaster management, its meaning is not limited to this concept and can for instance encompass health emergencies. In contrast to disaster management, this term generally refers to “events that do not result in the serious disruption of the functioning of a community or society” (United Nations General Assembly, 2016).

Disaster management on the other hand is a continuous process in consideration of preventative measures as well as actions needed during a disaster and in its aftermath. This process can be divided into the following four phases: mitigation, preparedness, response, and recovery (German Federal Office of Civil Protection and Disaster Assistance, 2022). This thesis focalizes the response-phase. During this phase, decision-making is crucial for effective disaster management. For this purpose, different Emergency Management Agencies (EMAs), such as fire departments, the police, or relief agencies, form Emergency Operations Centers (EOCs) also referred to as command and control centers in other domains (Ryan, 2013).

In an EOC, a decision-making process, a recurring process of reflection and action preparing and implementing decisions, is applied (Ryan, 2013). This process is divided into four sections as well: situation assessment (including situational awareness), planning (includes evaluating the situation and decision-making), commanding, and control (FwDV 100, 1999; Hofinger & Heimann, 2022). The provision and analysis of information is of crucial significance in this process because “[…] information about the situation and its development must be determined, managed and processed […]” (Comes, Hiete, Wijngaards, & Schultmann, 2011) in order to proceed with the first phase assessing the situation and thus create a factual basis for decision-making. Such decision-making processes in disaster management additionally entail numerous constraints, such as time pressure, complexity, and uncertainty (Drennan, McConnell, & Stark, 2015) challenging decision-making in EOCs (van de Walle & Comes, 2015). The complexity of a decision-making process, depending on its scope, can also be related to the numerous factors (e.g., number of affected population) and stakeholders involved (van de Walle et al., 2016). Uncertainties, especially due to time pressure and complexity, are “largely epistemic” (van de Walle et al., 2016) in the context of disaster management, whereas van de Walle et al. (2016) argue that they can be reduced through data analytics. In addition, the authors describe time pressure in decision-making as a challenge as it limits time for the collection of relevant, disaster-related data for the situation assessment.

The aforementioned factor of complexity additionally affects the situation assessment in the decision-making process as it prolongs actual data analytics (van de Walle et al., 2016). In the working environment of an EOC it is of particular relevance that decision-makers generate situational awareness, also described as a *common picture* or a *common mental model* (Hofinger & Heimann, 2022).

However, said situational awareness of EOC members depends on the information collected, analyzed, and shared within the decision-making process. This requires the verification of information that can in turn be processed and understood promptly, while avoiding conflicting information (van de Walle et al., 2016; Vongkusolkit & Huang, 2021). van de Walle et al. (2016) argue that if such information is shared effectively within the team, an EOC "can make decisions together based on better situational awareness" (van de Walle et al., 2016).

Endsley (1995) defines situational awareness as "the perception of the elements in the environment […], the comprehension of their meaning and the projection of their status in the near future". In her description, she considers three different levels of situational awareness: perception, comprehension, and projection. Hofinger and Heimann (2022) describe situational awareness, specifically referencing decision-making processes in disaster management, as the state of being aware of one's surroundings, the situation, and current processes. However, they also describe the process as subjective, meaning each decision-maker perceiving the ongoing situation from their individual perspective. Besides the disaster-related information obtained, this individual mental model of a disaster situation is influenced by previous knowledge, experience, and individual evaluations. A potential *common mental model* of a disaster situation is thus affected by each decision-maker's previous experience, knowledge, and individual evaluation. Regardless of supposedly objective information, such as a crisis map, being used in the decision-making process, the situational awareness process varies individually and can also change within the disaster situation (Hofinger & Heimann, 2022).

Nonetheless, decision-makers in the EOC are confronted with exceptional conditions described above, such as time pressure, complexity, and uncertainty. Conducting necessary data analytics is therefore especially challenging as required data may not be available or interorganizational accessible. In disaster situations, however, decisions can also be made before extensive data collection and analysis, at the risk of certain regions or social groups being under- or over-represented (Fast, 2017). If such data biases remain undetected, decisions will also be biased. Decisions can also be biased if the decision-maker's cognitive capacity is under particular pressure due to conditions such as urgency and high stakes. In exceptional situations, accompanied by these constraints, the cognitive processes of decision-makers are particularly challenged, tending to cause cognitive biases (Comes, 2016; Phillips-Wren, Power, & Mora, 2019). These biases rest on the idea of *bounded rationality* which Simon (1955) defines as humans being hindered from making purely rational decisions by the complex world that surrounds them.

During disaster management, one of the most important cognitive biases is the confirmation bias (Brooks, Curnin, Owen, & Bearman, 2020; Comes, 2016), which Modgil et al. (2021) have analyzed in the context of social media use during the COVID-19 pandemic. Individuals confronted with a confirmation bias tend to search and choose information confirming their presumptions and prior decisions, while disregarding information that does not confirm them (Nickerson, 1998). Decision-makers and data analysts in the EOC may also be affected by data biases, especially at the time of social media having permanently changed society's communication culture and of people sharing large amounts of data during disasters. Data biases are deviations in datasets negatively influencing data quality and thus potentially causing damage to organizational processes (Storey, Dewan, & Freimer, 2012). In sensitive settings in particular, data bias has been shown to reinforce existing inequities and conditions, such as urgency and overload. In combination with uncertainty, these conditions are frequent drivers of data biases in disaster situations (Fast, 2017).

1.1.2 Social Media in Disaster Management

The global expansion of ICT, including digital communication modes and constant access to the internet, has changed the population's communication culture significantly and permanently. Because of the mobile and constant availability of social media in everyday life, these platforms are also used increasingly for various purposes in disaster situations (Castillo, 2016; Meier, 2015). Via these platforms, information about the current circumstances, warnings, and requests for help can be shared quickly and with wide reach. The interactive *two-way dialogue* (Briones, Kuch, Liu, & Jin, 2011) in social media additionally allows those affected or interested to search for information. Following the 9/11 terrorist attacks in the U.S., pools of information (e.g., wikis) were developed to enable the exchange of information about missing persons (Palen & Liu, 2007). The U.S.-American Federal Emergency Management Agency (FEMA) and the Red Cross also used ICT capabilities for public communication after the 2001 attack (Harrald, Egan, Jefferson, Stok, & Žmavc, 2002). Numerous studies in the sequel studied the user behavior of affected people during various crises, disasters, and emergencies in detail (Reuter & Kaufhold, 2018). These studies indicate that individuals affected by a disaster exchange information about roads, weather and traffic conditions, or their mental state and location (Reuter, Kaufhold, Spielhofer, & Hahne, 2017). Jurgens and Helsloot (2018) identify four categories clustering different behaviors on social media in such disaster situations: information acquisition, information sharing, collaborative problem solving, and processing. Thus, the individual social media user cannot be considered merely a consumer as they would in traditional media.

Ebersbach et al. (2016) describe this bipartite role of active content producers and passive information consumers as *prosume*rs. Besides sharing and consuming information (Weyrich, Scolobig, Walther, & Patt, 2020), social media users increasingly utilize collaboration tools during and after disasters to participate as spontaneous volunteers in disaster response (Kaufhold & Reuter, 2016; Sackmann, Lindner, Gerstmann, & Betke, 2021). The interactivity of social media platforms allow for facilitated networking which in turn enables the founding of spontaneous volunteer groups. The community engagement structures these groups form can comprise more than several thousand spontaneous volunteers (Sackmann et al., 2021), who take on long traveling distances to help for multiple days (Bier et al., 2022). Besides organizing spontaneous responses, social media can also support individual coping, by communicating emotions and publicly sharing condolences for instance (Ebersbach et al., 2016).

Due to the user behavior described, large amounts of data are generated in disaster situations rapidly (Kersten & Klan, 2020). *Crisis Informatics* has thus emerged as an interdisciplinary research field, examining the analysis of mass data and subsequent social implications (Kaufhold, 2021; Palen, Vieweg, Liu, & Hughes, 2009). In this interdisciplinary field, computer-based methods, applications, social media user communication behavior, human-computer interaction, and analytical approaches to analyzing mass data are studied as well as. In an comprehensive meta-study reflecting 15 years of social media in emergency and crisis, Reuter and Kaufhold (2018) identified three different patterns in *Crisis Informatics* research:

1. Usage patterns (interaction in social media, e.g., from citizen to citizen for spontaneous self-coordination)
2. Role patterns (different perspectives, e.g., citizens and authorities)
3. Perception patterns (different perceptions, e.g., authorities' perception of social media)

The authors have not included the numerous technical research analysis approaches in their meta-study as those had been addressed in previous research work. The partially automated analysis of social media for example enabled unusual events or *anomalies* (Thom, Kruger, & Ertl, 2016) to be identified at an early stage (Rossi et al., 2018) in such studies of technical issues around social media utilization.

Furthermore, in a systematic review, Eismann et al. (2021) elaborated five affordances in the technical-organizational use of social media in emergency management: monitoring social media, automatically processing social media data, tapping collective intelligence, accessing information providers, and evaluating crisis response. Another crucial work is that of Zhang et al. (2019) highlighting three different areas in which social media assists disaster management:

1. Using social media to generate situational awareness efficiently and effectively,
2. Usefulness of networking to engage in coping through self-organized community engagement activities, and
3. Ability for EMAs to capture the affected population's sentiment.

Social media is additionally used for warning and risk and crisis communication by EMAs forwarding safety recommendations (Wu & Cui, 2018) as well as warning apps (Rahn, Tomczyk, Schopp, & Schmidt, 2021) or bidirectional disaster-communication apps (Kaufhold, Rupp, Reuter, & Amelunxen, 2018).

The presented research highlights that social media (analytics) can provide a multi-level benefit and an advantage to EMAs and support decision-making in disaster management. Furthermore, it should be noted that studies prior to the COVID-19 pandemic illustrate that the younger population in particular expects social media to be monitored by EMAs and questions asked on these platforms to be responded to within an hour (Reuter et al., 2017; Reuter & Spielhofer, 2017).

Increased user numbers and intensified utilization of social media since the beginning of the COVID-19 pandemic have furthermore increased the expectation towards EMAs assumable (Fathi, Kleinebrahn, Voßschmidt, Polan, & Karsten, 2020a). However, analyzing social media with the goal of integrating available disaster-related information into the work of EOCs and meeting aforesaid expectations poses numerous challenges.

1.1.2.1 Social Media Analytics in Disaster Management

The goal of Social Media Analytics (SMA) is generating information and identifying patterns from available social media data to serve specific information needs in different areas of interest (Stieglitz et al., 2018c; Zeng et al., 2010). This includes not only the use of manual analysis methods, but also the design and evaluation of analytical tools. These tools enable the monitoring of open-access data from social media, but also their analysis, summary, and visualization (Zeng et al., 2010). In addition to their utility in disaster management, SMA are of particular value in journalism, political communication (Stieglitz et al., 2018c), and large scale events, such as music festivals (Sonntag, Fathi, & Fiedrich, 2021). Stieglitz et al. (2018c) see a great value for disaster management in obtaining additional information in different formats (text, images, and videos) from various platforms previously unknown and therefore not integrated into the decision-making process.

Its different designations, such as *big crisis data* (Castillo, 2016), *social big data* (Guellil & Boukhalfa, 2015), or *social media big data* (Lynn et al., 2015), evince that SMA is regarded as part of the age of Big Data. McAfee and Brynjolfsson (2012) describe what they call *the three Vs* as inherent in big data analytics and parallelly posing challenges in SMA: volume (the quantity of data), velocity (the rate at which the data is provided), and variety (various data formats, e.g., text, image, and video). In SMA in particular, the credibility of data plays a major role, as subjective and false information can be shared, contrasting other datasets generated in controlled settings. Consequently, Lukoianova and Rubin (2014) add the fourth challenge of veracity, comprising objectivity, truthfulness, and credibility defining as sub areas.

Considering these four challenges, SMA can be depicted by process stages. The basic representation by Fan and Gordon (2014) characterizes SMA in three successive steps: capture (collecting and preprocessing the relevant social media data), understand (analytical approaches, e.g. sentiment analysis) and present (visualization and summary of the SMA). By considering various studies, Stieglitz et al. (2018c) have developed a more detailed process spanning four steps:

1. Discovery*:* identification of structures and patterns in social media data, whereby data mining approaches can be applied (Chinnov, Kerschke, Meske, Stieglitz, & Trautmann, 2015).
2. Tracking: tactical alignments, e.g., selection of social media platforms, methodological approaches, and anticipated outcomes (Stieglitz et al., 2014; Stieglitz et al., 2018c).
3. Preparation: e.g. trend-based preparations (Stieglitz et al., 2014).
4. Analysis: comprises e.g. content analyses (Stieglitz et al., 2014).

To conduct SMA, numerous (partially) automated tools are used in the field of disaster management, for example to identify incidents at an early stage or to conduct sentiment analyses (Bosch et al., 2011; Kersten & Klan, 2020). The majority (64 %) of SMA studies are limited to the microblogging platform *Twitter* (Vongkusolkit & Huang, 2021), as sufficient data for automated analysis is collected via Application Programming Interfaces (API). This limitation simplifies the analysis. However, only 8 % of the German population do use this specific platform, with other platforms such as *Facebook* (38 %) or *Instagram* (32 %) being used much more intensively (Krupp & Bellut, 2021). Due to data limitations, (partially) automated SMA approaches can only operate to a limited extent or not at all, meaning that manual analysis methods need to be used frequently for other platforms (Gramm & Harnisch, 2022; Sonntag et al., 2021).

However, analyzing data from the numerous platforms is not the only challenge, but privacy-aware data collection can also pose obstacles in analyzing data of individuals affected by a disaster. Depending on the circumstances, these people form a vulnerable group potentially dependent on social media use for sharing private information. When searching for missing relatives, personal data (e.g. real names, addresses or personal pictures) are published (Park & Johnston, 2017). In other cases, additional personal data of affected individuals such as pictures of injured or deceased people can be shared publicly. Further privacy challenges may arise when social media users join public groups or communicate publicly with authorities on social media (Kuner & Marelli, 2020).

1.1.2.2 Social Media and Situational Awareness in Disaster Management

The emerging research field of *Crisis Informatics* also deals with situational awareness. Scholars analyzed in 2010 already how *Twitter* can contribute to the situational awareness of decision-makers (Vieweg, Hughes, Starbird, & Palen, 2010). The authors of this study selected two different disaster situations (a flood and a grassfire, both in 2009) as case studies and classified the social media data derived from *Twitter* into 13 categories. With this approach, they aimed to obtain a better overview of the key topics addressed. They identified disaster-related information from the social media data and classified it in categories such as warning, flood level, road conditions, or volunteer information with at least five *Twitter* posts per category (Vieweg et al., 2010). Due to the variety of scenarios, Vieweg et al. (2010) found that the frequency of categories is related to the underlying disaster circumstances, such as the number of people affected by or the duration of the disaster.

However, in some circumstances, the amount of data on social media platforms increases in such a short time that manual evaluations are inappropriate (Thom et al., 2016). Automation approaches of SMA aim to support situational awareness in view of this challenge by identifying and categorizing disaster-related information via numerous text mining and natural language methods (Vongkusolkit & Huang, 2021). For example, Yu et al. (2019) developed a machine-learning approach for cross-event classification of social media data. Moreover, Imran et al. (2018) developed an Artificial Intelligence (AI) based classification and analysis tool for social media images. Vongkusolkit and Huang (2021) show that cross-platform SMA can expand the situational awareness of decision-makers by detecting disaster-related information (e.g., sentiments, issues of the affected population) and thereby making social media data usable for decision-makers.

Furthermore, relevant information that would otherwise be difficult or impossible to include in the EOC processes can be obtained through this approach: Through a more in-depth analysis, subcategories such as anxiety, anger, or worries of those affected can be identified (Buscaldi & Hernandez-Farias, 2015; Vongkusolkit & Huang, 2021). According to Vongkusolkit and Huang (2021), temporal categorization of social media data has also been conducted, mainly for scenarios such as hurricanes (36 %) and floods or other events (14 %). Nevertheless, utilizing automated SMA tools is fraught with challenges (Kaufhold, 2021). Besides the constraints described in subsection 1.1.1 making data analytics more difficult, the decision-makers' focus can change dynamically in disaster situations (Rossi et al., 2018). New disaster situations may arise and consequently be shared on social media, especially during the response phase of a disaster, leaving no time for extensive data analytics.

Additionally, actionable information, meaning information decision-makers need to respond to and decide immediately, needs to be identified and evaluated (Zade et al., 2018). In the response-phase, this particularly applies to *short-term actionable information* (Mostafiz, Rohli, Friedland, & Lee, 2022) i.e. producing the right information to the right decision-maker of an EOC at the right time. Actionable information in this case is so urgent that immediate measures need to be derived and implemented. Zhang et al. (2019) argue that during a disaster, all information can be considered important, but only a fraction of it as actionable. The distinction of non-time-critical information adding to the general situational awareness process and actionable information allowing for the derivation immediate decisions and measures is thus relevant in this context. Decisions and measures derived from actionable information can be, for example, people-centered risk and crisis communication.

1.1.2.3 Risk and Crisis Communication in Disaster Management

Open, transparent, consistent, and dialog-oriented communication is essential for successful disaster management (Federal Ministry of the Interior, 2014; Haer, Botzen, & Aerts, 2016). To achieve this goal, two different forms of communication need to be distinguished: risk communication and crisis communication. Risk communication, in contrast to crisis communication, is administered before a disaster occurs. Its aim is to raise risk awareness among the population, considering all different information needs. To address these needs, a people-centered approach to risk communication is necessary in order to provide appropriate information about different risks (Fakhruddin, 2018; Vongkusolkit & Huang, 2021). Numerous studies have illustrated that people-centered risk communication is more effective than top-down communication by the government (Haer et al., 2016; Haworth, Bruce, Whittaker, & Read, 2018). This can be achieved, for instance, by using of social media in a dialog-oriented approach and by integrating existing social networks (Haer et al., 2016). SMA can be an approach to conduct people-centered risk communication, promoting an understanding of the affected population's needs by e.g., capturing psychological needs and sentiments.

The main distinctive feature between risk and crisis communication is the time factor. While risk communication aims at preventing and preparing in the medium and long term, the goal of crisis communication is to act in the short term to avoid current dangers and to mitigate damage by warning (Federal Ministry of the Interior, 2014). However, warnings are perceived differently by diverse population groups (Rahn et al., 2021), which means that crisis communication via social media also needs to be adapted to specific users' needs, groups and behavior. Several studies highlight that in addition to a significant part of the population expecting social media monitoring (67 %) by an EMA, 47 % expect to be responded to on social media within an hour during a disaster (Reuter et al., 2017; Reuter & Spielhofer, 2017).

In disaster situations, however, EMAs do not have sufficient technical resources and competencies to implement systematic SMA, mapping of the disaster area, providing verified information or conducting people-centered crisis communication (Castillo, 2016). In 2011, Starbird and Palen defined *voluntweeters* as self-organized digital volunteers, who formed Volunteer & Technical Communities (V&TCs) to close the competence gap in disaster management by offering digital support for established and formal EMAs.

1.1.3 Digital Volunteers in Disaster Management

Following the severe earthquake in Haiti in January 2010, the first group of digital volunteers in disaster management emerged to assist in response efforts, dislocated from the actual event (Meier, 2015; Starbird & Palen, 2011). These digital volunteers analyzed social media, mapped the earthquake region, and translated content from social media into different languages (Fathi, Polan, & Fiedrich, 2017). Over time, the group expanded and the information products were made available to the established EMAs, e.g. for search and rescue operations (Fathi et al., 2017). In the aftermath of the Haiti disaster response, these groups specialized and formed so-called Volunteer & Technical Communities (V&TCs) (Meesters & van de Walle, 2013). In 2012, the Digital Humanitarian Network (DHN), an umbrella organization for 16 different V&TCs, was established as an interface between V&TCs and formalized humanitarian actors (Butler, 2013). The digital volunteers' skills varied from mapping and spatial analysis, statistical analysis, geographical information systems, and translation (Fiedrich & Fathi, 2021). Based on Park and Johnston's (2017) definition, digital volunteers are thus individuals who form a V&TC for crisis and disaster management as a decentralized group consisting of citizens around the world collaborating to manage disasters and crises collectively and innovatively using ICT. Integrating these novel organizational structures, however, has been described by established EMAs as challenging in many studies (Kaufhold & Reuter, 2016; Park & Johnston, 2017; Starbird & Palen, 2011). The difficulty of integrating purely virtual V&TCs with volunteers from around the world into established operational structures working in a safety and disaster management context is only one example in a study of Park and Johnston (2017).

van Gorp (2014) additionally analyzes various organizational and inter-organizational barriers of the V&TCs' integration in humanitarian aid and disaster management. She notes that the engagement of digital volunteers in V&TCs can differ from formalized emergency responders in EMAs. However, initial studies show that the motivation of digital volunteers is primarily based on altruistic values (Fathi & Fiedrich, 2020), similarly to formalized volunteer response teams. van Gorp (2014) further argues that formal EMAs have a more comprehensive disaster overview, whereas V&TCs mostly focus on supporting the affected population. There are also significant differences in working structures: While EMAs train and work within established hierarchies, V&TCs tend to be rather loose networks with flat and decentralized structures (Capelo et al., 2012), potentially complicating collaboration. Because of these differences, the specialized knowledge and skills of V&TCs might remain unknown to decision-makers. These results highlight the organizational gap among EMAs and V&TCs (van Gorp, 2014).

Despite these differences and collaboration barriers, V&TCs have had a major impact on disaster management practice in recent years. Several V&TCs such as the Standby Task Force (SBTF) (Hichens, 2012) or the Humanitarian OpenStreetMap Team (HOT) (Herfort, Lautenbach, Porto de Albuquerque, Anderson, & Zipf, 2021) have produced large amounts of Volunteered Geographic Information (VGI) to improve disaster response efforts particularly in humanitarian aid, but also in disaster management. Over time, V&TC structures have professionalized, permanent structures have been developed and cooperation with EMAs has been formalized, so that the umbrella organization DHN has withdrawn from operational activities (Fiedrich & Fathi, 2021). In line with these developments, EMAs have begun to build their own digital competencies and to establish structures of digital volunteers as *trusted agents* (St. Denis et al., 2012) with VOSTs. Compared to the more loosely organized digital volunteers, *trusted agents* organized in VOSTs are part of established EMAs and thus known to decision-makers. Moreover, the operational structures are comparable (Martini, Fathi, Voßschmidt, Zisgen, & Steenhoek, 2015; Roth & Prior, 2019).

1.1.4 Virtual Operations Support Teams

During disaster situations, conducting SMA tasks is challenging for EOCs due to a lack of resource expertise, tools, and volunteers creating a gap in situational awareness. VOSTs thus aim at integrating digital volunteers as part of the operational structures of an EMA in order to fill this gap. In

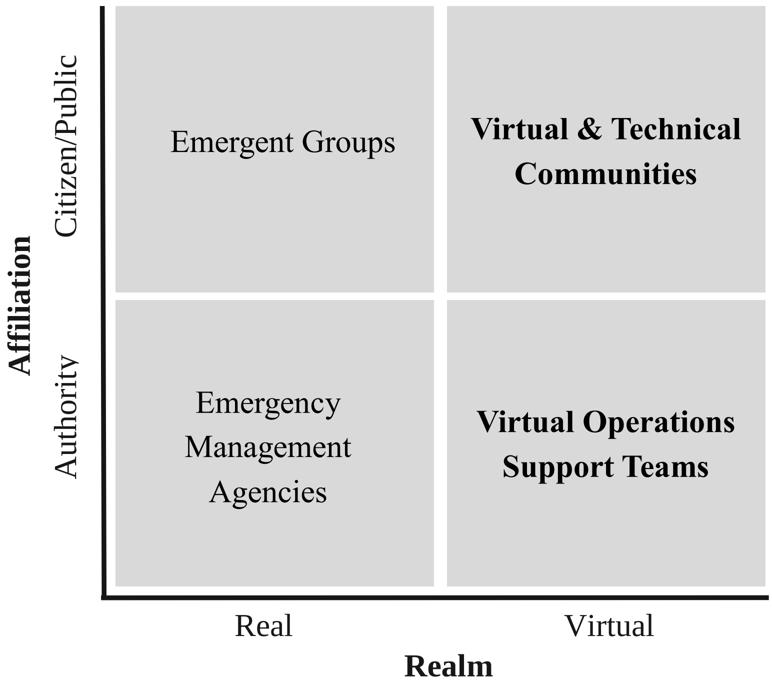

Figure 1: Role typology based on Reuter and Kaufhold (2018)

2011, Jeff Phillips, an emergency manager from Los Ranchos de Albuquerque (New Mexico) announced the idea of setting up a VOST at a conference (St. Denis et al., 2012). Phillips' goal was to improve structural integration of digital volunteers' work into the EMAs and thus to consider information products more effectively in decision-making processes. The idea was to incorporate digital volunteers as a part of established EMAs, as opposed to V&TCs tending to operate as loose digital volunteers as described above (Capelo et al., 2012). A further distinction is that VOST analysts, as *trusted agents*, have operational experience in disaster management combined with analytical and communication skills (Roth & Prior, 2019; St. Denis et al., 2012). This integration of VOST analysts and their analysis, Geographic Information System (GIS), and communication skills into EMA allows them to act as an integral part of disaster management (Martini et al., 2015).

These plans attracted considerable international interest, so that such teams within EMAs were formed worldwide. Subsequently, the Virtual Operations Support Group (VOSG) formed as a worldwide umbrella organization of all VOSTs with the objective of advising on the development of new teams and helping with their structuring (Susaeta, Lane, Tondorf, & Tymen, 2017). In addition, three transnational organizations were founded under the VOSG: VOST Europe, VOST Oceania and VOST America (Susaeta et al., 2017).

Based on the role typology of Reuter and Kaufhold (2018), Figure 1 illustrates the differences between V&TCs and VOSTs: While both exist and operate exclusively virtually in the event of a disaster, VOSTs are part of an EMA and thus an authority, while V&TCs can be assigned to the citizens/public spectrum (see Figure 1).

However, the tasks conducted by volunteers in both modes of digital participation are comparable: Both use publicly available data for evaluation and visualization during a disaster and additionally utilize the networking functions of social media for collaboration.

The competence and capability fields of VOSTs can be divided into three areas:

1. Digital operation investigation:
    - Conducting SMA tasks including data retrieval, processing and visualization using Open Source Intelligence (OSINT) approaches (Böhm & Lolagar, 2021) and
    - Applying verification and falsification approaches to identify rumors and false information.
2. Crisis mapping:
    - Developing digital crisis maps and dashboards of the disaster-affected region and processing these maps with additional data (e.g., access routes) and
    - Geolocating social media data and applying GIS for spatial analysis.
3. Volunteer coordination and cooperation:
    - Coordinating and cooperating with national and international (volunteer) EMAs and
    - Providing a technical and collaborative platform for collaboration and information sharing.

With the aim of institutionalizing and professionalizing these capabilities in governmental civil protection and disaster management structures in Germany, the German Federal Agency for Technical Relief (THW), subordinated to the German Federal Ministry of the Interior, launched a VOST THW pilot project in 2016 (Fathi & Hugenbusch, 2020). The THW is an EMA founded in 1950 consisting of approximately 80,000 volunteers, organized in 668 local units nationwide. The primary task of these volunteers is to provide technical assistance in disaster management after natural disasters and civil protection (German Federal Agency for Technical Relief, 2021). To integrate a team of VOST analysts into existing disaster management structures, the operational options and the tactical value were initially assessed in a five-year period of operations (German Federal Agency for Technical Relief, 2022).

The unit, existing solely virtually, additionally provided a first opportunity to explore a new form of participation: digital volunteering in a governmental structure. The team of 46 especially qualified analysts uses advanced analytical software and GIS and can be engaged by the THW as well as other EMAs in the event of a disaster (Fathi & Hugenbusch, 2020). The team has been requested over 45 times by various EMAs since project piloting began and since July 2022, the VOST THW supports the operational spectrum of the THW as a formal unit (German Federal Agency for Technical Relief, 2022). In line with the primary tasks of *Digital Operation Investigation* and *Crisis Mapping*, the 46 VOST analysts are divided into two working groups, each led by two group leaders. Furthermore, the organizational structure consists of two VOST leaders and a liaison officer. All analysts collaborate virtually, with the exception of the liaison officer acting as the information manager on-site in the EOC (Martini et al., 2015).

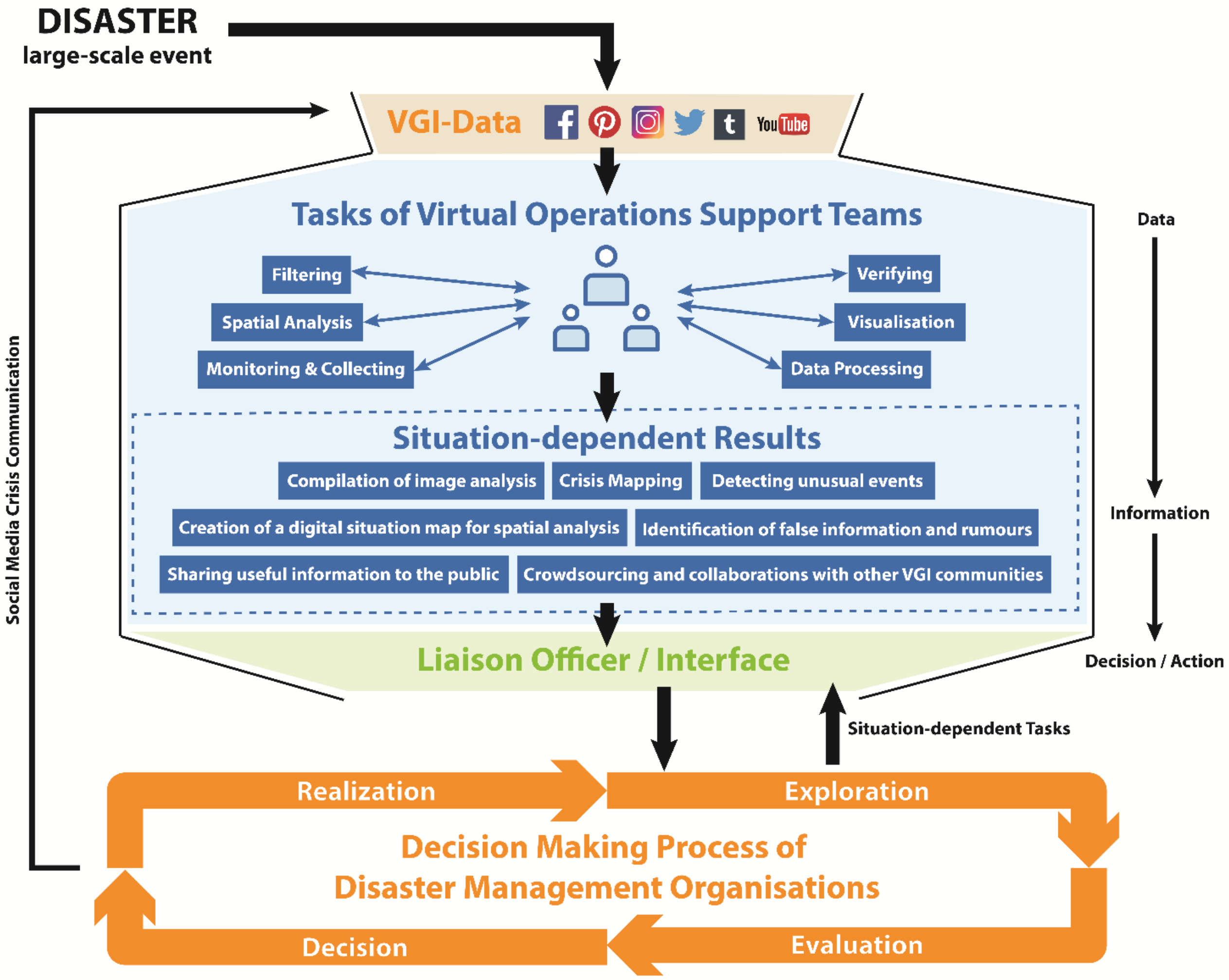

Figure 2: Integrating VOST into the decision-making process in Fathi et al. (2020b)

The VOST liaison officer's function is usually attached to the communications or situational awareness section within the EOC. Thus, actionable information can reach the right decision-maker immediately. Simultaneously, tasks arising from the situation can be forwarded to the VOST members. The information products, i.e., analysis reports, crisis maps, statistical evaluations, or dashboards, are prepared by VOST leaders and passed on into the decision-making process by the liaison officer (see Figure 2). Figure 2 additionally shows that disaster-related social media data is filtered, verified, and processed by VOST analysts before the liaison officer feeds situation-dependent results into the EOCs decision-making process.

Following the initiation of the VOST THW at the federal level, other VOSTs have been formed in Germany at since 2018 at federal state and local levels. For example, the Ministry of the Interior of the State of Baden-Württemberg has established VOSTbw (Ministry of the Interior, Digitalisation and Local Government of Baden-Württemberg, 2022), and the Hamburg Fire Department (VOSThh) or the district of Bad Kreuznach (VOST-Team Medien) have set up similar teams (Fathi & Hugenbusch, 2020).

In the context of the COVID-19 pandemic and especially the 2021 flood in Western Germany, several institutions and parliamentarians are urging for the expansion and strengthening of VOST structures and increased deployment of VOSTs in disaster and crisis management as well as civil protection. Parliamentarians in the German Bundestag of the governing party *Bündnis 90/Die Grünen* call for further strengthening of the VOST THW (Bündnis 90/ Die Grünen, 2022), e.g., for early identification of false information during crises and disasters (Mihalic, Dahmen, Schäffer, & Höller, 2021). In addition, the Ministry of the Interior of North Rhine-Westphalia (NRW) (2022) and the Association of Fire Departments in North Rhine-Westphalia (2021) demand the expansion of VOST structures and their integration into the EOCs following the flood of 2021.

However, there is a significant research gap in this area, such as which requirements the interorganizational collaboration between a virtual unit and an EMA entail. From a theoretical point of view, integrating a virtual team into existing, established, and non-virtual structures of EMAs poses challenges on several levels. Thus, a VOST analyst working remotely requires that communication channels are established, specifications and rules are known, and team and group leaders can delegate tasks. The theory of organizational structural dimensions introduced by Kieser and Walgenbach (2010) – consisting of specialization, coordination, configuration, delegating decisions, and formalization – can be applied as a basis for organizational analysis. Due to their widespread and established adaptation by EMAs, these dimensions are suitable for application to the virtual work of VOST.

1.2 Research Questions and Scope of the Thesis

Although the development of professionalized and institutionalized digital volunteers organized in VOSTs can be observed worldwide, there is a lack of in-depth research approaches to this topic. The previously outlined research field of *Crisis Informatics* mainly examines technical aspects of data analytics in particular, using approaches like Natural Language Processing (NLP) (Buscaldi & Hernandez-Farias, 2015) or machine learning algorithms such as Random Forests (Nair, Ramya, & Sivakumar, 2017; Sonntag et al., 2021). Additionally, data from only one platform in particular (*Twitter*) was used for the analyses (Vongkusolkit & Huang, 2021), although only 8 % of the German population uses this social media (Krupp & Bellut, 2021). The resulting imbalance in existing research can thus lead to biases especially due to under- or overrepresentation of the data.

Even though *Crisis Informatics* primarily examines technical approaches, some studies have analyzed organizational collaboration with digital volunteers. For example, Soden and Palen (2018) have examined the use of innovative and participatory approaches in disaster management, including the contribution of ICT to addressing hazards and disasters differently. They also note that academic research and discussion focus in this field is highly technology-heavy while research institutions, practitioners, and funding agencies dominate the development of new approaches (Soden & Palen, 2018).

Nevertheless, scientific approaches can be observed to finding their way into disaster management. Kaufhold et al. (2020) analyzed results from field studies evaluating a system for social media monitoring of different platforms, including automated alerting based on advanced algorithms. The visualization of SMA results in dashboards, is another field of research currently finding its way into practical implementation (Basyurt, Marx, Stieglitz, & Mirbabaie, 2021). Additionally, organizational issues such as those of EOCs' work, performance, and success, are explored in a practice-oriented approach by Gißler (2019).

1.2.1 Aim

This thesis aims to answer questions concerning the role of institutionalized and professionalized digital volunteers organized in a Virtual Operations Support Team. Therefore, various issues will be addressed: The requirements for collaboration with decision-makers in Emergency Operations Centers will be analyzed as well as analytical aspects, such as the impact of informational results on situational awareness and decision-makers in EOCs, but also potential biases in the decision-making process and privacy-aware approaches.

1.2.2 Research Gap and Research Questions

As presented in section 1.1, numerous studies in the field of *Crisis Informatics* have examined multiple questions of technical approaches in automated data analytics, communicative efforts through social media by EMAs, and the virtual work by digital volunteers in V&TCs in humanitarian aid. However, questions challenges of professionalized VOST analysts as part of EMAs in disaster management structures remain unaddressed. This research gap illustrates that organizational requirements for integrating VOSTs into disaster management, technical challenges, and human-related analytical capabilities are yet to be addressed. The integration of VOST information into the decision-making processes of an EOC has not been investigated to date, just as its impact on situational awareness and decision-making. Investigating how VOST analysts conduct data analytics approaches manually during a disaster, how disaster-related social media is categorized, and how it is prioritized is crucial as well, especially to understand the analytical value. Additionally, the effect of data bias on the work of digital volunteers, in this case VOST analysts, and their potential impact on decision-making remain to be researched. Privacy-aware methods integrable into the work of VOSTs have not yet been investigated either. This substantial research gap gives rise to technical, organizational, and analysts-related research questions (RQs) that can be subsumed under the following overarching central RQ of this thesis:

How can a VOST be integrated into established disaster management structures, what impact do Social Media Analytics have on situational awareness and decision-making, and what challenges can be identified at the level of human-related data processing and privacy-aware methods?

To answer this question, four operationalized RQs were derived:

1. RQ 1: What are the structural, procedural, and technical requirements for a successful collaboration between a VOST and interagency disaster management?
2. RQ 2: What information is analyzed in which disaster phase and how does the information provided by VOSTs impact situational awareness and response actions based on actionable information in decision-making?
3. RQ 3: How do external analysts and decision-makers jointly handle data biases in the decision-making process?
4. RQ 4: What are the opportunities and challenges for privacy-aware social media data processing by VOSTs in disaster management?

These four questions were addressed in four studies, with further differentiation of the RQs mentioned above within each study (see Table 1).

Table 1: Research questions according to the four studies

Studies	Research Questions
Study I (RQ 1) VOST: A case study in voluntary digital participation for collaborative emergency management	1. Which structural and procedural requirements for a successful collaboration between a VOST and emergency management agencies can be identified? 2. Which technical requirements can be identified and how can the existing technical tools for real-time social media monitoring be evaluated? 3. How can the actual tasks performed by a VOST during the real-world deployment be analyzed? 4. What organizational, structural, and technical implications can be derived for future systems used in the decision-making process of an EOC?
Study II (RQ 2) Social Media Analytics by Virtual Operations Support Teams in Disaster Management: Situational Awareness and Actionable Information for Decision- Makers	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? 2. How are categories, information format, prioritizations, and platforms related? 3. How do the information provided by VOSTs impact the situational awareness and response actions based on actionable information in EOCs decision-making?
Study III (RQ 3) On the Interplay of Data and Cognitive Bias in Crisis Information Management	1. Is surging external analysis capacity effective in identifying and mitigating data bias? 2. How do external analysts and decision-makers jointly handle data bias in the decision process? 3. Does confirmation bias create path dependencies whereby biased assumptions persist in sequential decisions?
Study IV (RQ 4) Case Study on Privacy-aware Social Media Data Processing in Disaster Management	1. What are opportunities and challenges for privacy-aware Social Media Data Processing by VOSTs in Disaster Management?

1.2.3 Methods

Due to the variety of research questions, a mixed-method-approach was applied. To answer RQ 1 and RQ 2, two case studies were conducted. For RQ 1, the underlying scenario was a large sports event, where the VOST was integrated into the interagency EOC structures. Several methods were used to investigate the structural, procedural, and technical requirements for successful collaboration between a VOST and the EOC: Participant observation, focus group discussions and interviews, analysis of the transcripts, and log files. To analyze RQ 2, another case study was conducted based on the scenario of the dynamic flood in 2021 in Wuppertal, Germany. Here, the VOST data collected was analyzed and the EOC decision-makers were interviewed about the impact of VOST information in the aftermath of the VOST operation. For RQ 3, a two-day experimental workshop was conducted with external analysts (including VOST analysts) and decision-makers. This study included two experiment stages based on an epidemic outbreak scenario, systematically observed through participatory and structured observations. The final research question (RQ 4) was explored using focus group discussions with the two VOSTs in Germany, VOST THW and VOSTbw.

1.2.4 Studies

This thesis consists of four studies published in different international peer-reviewed journals. The full studies are appended:

I. **Study I**
Fathi, R., Thom, D., Koch, S., Ertl, T., & Fiedrich, F. (2020). VOST: A case study in voluntary digital participation for collaborative emergency management. Information Processing & Management. DOI: doi.org/10.1016/j.ipm.2019.102174

II. **Study II**
Fathi, R. and Fiedrich, F. (2022): Social Media Analytics by Virtual Operations Support Teams in Disaster Management: Situational Awareness and Actionable Information for Decision- Makers. Frontiers in Earth Science. DOI: doi.org/10.3389/feart.2022.941803

III. **Study III**
Paulus, D., **Fathi, R.**, Fiedrich, F., van de Walle, B., & Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. An Exploratory Study on Epidemic Response. Information Systems Frontiers. DOI: doi.org/10.1007/s10796-022-10241-0

IV. **Study IV**
Löchner, M., **Fathi, R.**, Schmid, D., Dunkel, A., Burghardt, D., Fiedrich, F. & Koch, S. (2020). Case Study on Privacy-aware Social Media Data Processing in Disaster Management. International Journal of Geo-Information. DOI: doi.org/10.3390/ijgi9120709

Addressing the research gap described in section 1.2.2, this thesis explores different fields of interest and pursues an interdisciplinary research approach. Due to the variety of research questions, a deeper background and theory section is presented for each study. The empirical results of the studies are structured differently due to the diverse methods, although some of them complement each other and build on each other. A brief summary of the studies, including methods and results sections, is introduced in section 2. An overarching and general discussion deriving implications for practice and the contribution to the literature is presented in section 3. The selection of four different peer-reviewed journals underlines the interdisciplinary character of the research subject and this thesis.

Study I (Fathi et al., 2020b) was published in the journal *Information Processing & Management* (Elsevier). This journal is a publisher of "[…] cutting-edge original research at the intersection computing and information science concerning theory, methods, or applications in a range of domains, including but not limited to advertising, business, health, information science, information technology marketing, and social computing." (Elsevier, 2022).

The Journal *Frontiers in Earth Science – Section Geohazards and Georisks* (Frontiers) in which Study II (Fathi & Fiedrich, 2022) was published is an interdisciplinary journal with a focus on practical applications in the field of geohazards and georisks, including various research areas, such as civil engineering and risk management (Frontiers, 2022).

Study III (Paulus, Fathi, Fiedrich, van de Walle, & Comes, 2022) was published in the Springer Nature journal *Information Systems Frontiers* focusing on information systems and information technology. Apart from technological approaches, however, it also covers behavioral and analytical perspectives (Springer Nature, 2022).

The Study IV (Löchner et al., 2020) with the title "Case Study on Privacy-aware Social Media Data Processing in Disaster Management" was published in the *International Journal of Geo-Information* (MDPI), which particularly covers topics of science and technology in the field of geographical information. It focuses on areas such as the spatial data modeling, spatial analysis and decision-making, but also on citizen science approaches, crowdsourcing and VGI (MDPI, 2022).

In two of the studies, the author of this thesis Ramian Fathi (RF) is the first author, and in the other two, the second author. Study I was designed and conducted by RF. The focus group discussions and the planning of the operational observations were also conceptualized and conducted by RF. Participant observation in the field was applied jointly with the second author (DT). Except for section 5, which was written by DT, the author of this thesis conducted the analysis and writing of the manuscript and the revised versions. The other authors have supervised the writing of the inter-university and interdisciplinary study. Regarding Study II, RF designed the study, conceptualized it, conducted the multilevel analyses of the data, designed, conducted, and analyzed the survey and wrote the manuscript. The second author Frank Fiedrich (FF) accompanied the work as a critical reviewer with a supervisor role. Study III was again an interuniversity and interdisciplinary collaboration. RF and the first author (DP) carried out the workshop experiments. DP developed the experiment materials including datasets and survey questions. RF designed the observation methodology for the three-stage workshop experiment. DP coded the collected data in the first iteration. The resulting codes and corresponding observational notes were discussed with RF in the second iteration and adjusted after that. RF conducted the analysis of research question 2 (see Table 1: Research questions according to the four studies) and DP focused the analysis of research question 1 and 3. RF and DP discussed the results and limitations and wrote the conclusion. The last author Tina Comes (TC), the fourth author Bartel Van de Walle (BVDW), and FF supported the workshop design and organization, critically reviewed the paper, and approved the final version. In Study IV, the authors' contribution has been published with the manuscript (see section 5.1.4).

2 Summary of the Studies

2.1 Study I

Fathi, R., Thom, D., Koch, S., Ertl, T., & Fiedrich, F. (2020). VOST: A case study in voluntary digital participation for collaborative emergency management. Information Processing & Management. DOI: doi.org/10.1016/j.ipm.2019.102174

2.1.1 Aim

The aim of this case study was to analyze structural, procedural, and technical requirements of a VOST collaborating during the Grand Départ of the Tour de France 2017 in Düsseldorf with an EOC. VOST analysts conducted real-time tasks such as SMA, information verification, and crisis mapping in three separate groups. This study provides insights into the practical implementation of structural, procedural, and technical concepts applied in a real-world operation of a VOST. Study I also gives insights into the decision-making processes by integrating a VOST into the workflow of an EOC. Previous research in the context of C*risis Informatics* has mainly focused on technology usage or on the analysis of singular social media platforms, mainly *Twitter*, during disasters. Even though some field-trial studies have considered multiple social media platforms, EOC-integrated VOST operations in real-world environments were not analyzed by any of them. Analyzing and understanding the requirements for integrating 20 VOST analysts into the disaster management structure provides valuable insights and contributes to future research and practical implications. The time- and safety-critical realistic setting of the operation in Study I allows for findings not obtainable otherwise.

2.1.2 Methods

The case study draws on different data as different methods were used for data collection and analysis:

- Focus group discussions and informal interviews with VOST analysts and decision-makers of the EOC before, during and after the operation,
- Participant observation of the VOST collaboration with the EOC during the operational days, and
- Transcript and log file analysis of the data collected by the VOST before and during the operation.

This work is designed as an exploratory case study, for which the EOC of the major event Grand Départ of the Tour de France 2017 in Düsseldorf served as a test environment. The EOC consists of multiple EMAs, such as the fire department, police, aid organizations, and the event organizer. In this interorganizational and interdisciplinary operations environment, numerous information processes, structuring approaches, and communication paths exist, so that cooperation and collaboration forms become increasingly relevant. Due to these framework settings, engaging the various stakeholders through focus group discussion prior to the mass event was necessary. The focus group discussions were designed to ensure that all relevant stakeholders and organizations could participate. The fire brigade in charge, the organizers of the Grand Départ 2017, the THW, VOST team leaders and the first and fifth authors of this study were involved. There were three preparatory and one debriefing focus group sessions with the same participants. The aim of these discussions was to identify (inter-)organizational requirements for structures, procedures, and technology, and to define task priorities. The focus group discussions also delineated scenario-dependent tasks for the VOST by analyzing the EOC's scenario-specific information requirements as well as the VOST's capabilities. For the course of the event, decision-makers of the EOC defined their informational needs and working priorities as follows:

- Identification of critical crowd densities and crowd flows;
- Detecting unusual events, false information, and rumors;
- Social media image analysis; and
- Creation of a digital situation map for spatial analysis (crisis mapping).

The agreement following this process was that VOST findings would be summarized and visualized in situational reports so that they can find their way into the situational awareness of decision-makers in the EOC. The VOST liaisons officer, on the other hand, should forward actionable information immediately to the right decision-maker in the EOC at the right time to avoid delays. To guarantee functioning communication channels in the case of an emergency, potential scenarios were identified and discussed. This delineation of task priorities allowed the information needs of the decision-makers to be served while simultaneously examining structural, procedural, and technical requirements. During the two-day operation, structures and processes were systematically observed and noted by the first two authors. In addition, transcripts and log files generated by the 20 VOST analysts before and during the operation were analyzed.

2.1.3 Results

The analyses of this case study show that the integration of a VOST into the disaster management structures as part of an interorganizational collaboration in the EOC for this large-scale two-day event was successful and beneficial. The virtual team consisting of 20 VOST analysts was able to quickly find disaster-related information, verify and provide it in an appropriate and effective manner to the decision-makers in the EOC at the right place and in time. One of the main reasons found is the division of the team into three defined working groups, which were able to take independent tactical decisions due to the decentralization. Despite the digital participation and decentralization of VOST decision-making, a one-line system was implemented as a hierarchical structure. Due to the similar structures within the EOC, actionable information was distributed via direct channels.

The liaison officer position in the EOC was identified as a key position for the success of operations management. With constant presence at the EOC, the VOST liaison officer served to relay actionable information to decision-makers immediately and to intervene in an advisory capacity. In addition, the liaison officer communicated ad-hoc changes in task priorities to the 20 VOST analysts in a timely manner. Thus, disaster-related VOST information was found to be particularly insightful in combination with that from other information sources (such as field response). This allowed for information differences and gaps in situational awareness to be identified and developments to be detected earlier than through established methods. This enabled the identification of information differences and gaps in situational awareness as well as earlier detection of developments than through conventional methods. Overall, the informational needs and working priorities defined by the decision-makers were served with VOST information.

In view of the structural and procedural requirements, forming three working groups of 8-10 members each proved to be suitable group sizing for carrying out the tasks in this operational context. Tasks were thus communicated directly to VOST analysts, especially during workload peaks, without management tasks interfering. Nevertheless, greater coordination efforts due to digital communication and distributed work methods challenged the team and group leaders: The time- and safety-critical dynamic way of working within the EOC caused spontaneous coordination approaches by VOST group leader during both days. Group leaders, despite hierarchical structures, dynamically adapted to such approaches according to the work assignments and formed special, short-term working groups. These groups performed specific assignments independently and upon completion of their tasks, such as verifying and geolocating distinct challenging disaster-related information from social media, the VOST analysts returned to the original structure. Similar dynamic group member structuring was also conducted during periods of high workload and in numerous cases, individual analysts initiated restructuring. Dynamic structural adjustment allowed for adaption to unexpected developments during the operation and for the allocation of new tasks. These findings are consistent with those from the 2011 observation of the integration of digital volunteers at a wildland fire in the US Pacific Northwest (St. Denis et al., 2012). The necessity to adapt structures dynamically by moving VOST analysts between groups in work-intensive phases mandatorily requires functioning communication channels between group leaders.

For communication and information exchange, procedural steps were defined within the VOST and between VOST and EOC: Situation reports were to be written in defined time windows to be integrable into the situational awareness process of the EOC decision-makers. Although such situation reports can be suitable in non-emergency situations as a procedural requirement, it was shown that their time-intensive preparation ties up team leaders. The focus group discussions highlighted that communication channels need to be modified to cater changing needs in time-critical, acute emergencies and to transmit actionable information without time-consuming preparation directly via the liaison officer to the respective decision-makers. The participant observation conducted during the operation evinced numerous queries asked decision-makers after the transmission of actionable information in time-critical circumstances: These were e.g. the respective post´s publication date, its geolocalization, verification, or consistency with other sources. These information needs of decision-makers manifested in their questions posed should be considered as procedural requirements in future operations, especially during disasters.

This case study also examines technical requirements for collaborative SMA and teamwork in the virtual team. This allowed working out that VOST analysts need to trust the tools applied, especially in time-critical situations while refraining from further increase of their high cognitive workload. Additionally, automated SMA tools were found to not be needed for all tasks: For specific analysis activities, such as verification and monitoring, mostly manual search methods were used. However, automated tools were particularly applied for comprehensive SMA. The observation sheets analogically show that tools need to be carefully designed to provide reliable utility and concomitantly address the specific operational scenarios of a VOST. Based on the case study results, four areas of technical requirements for future system design improvement are identified:

1. Support for collaborative work: Collaborative approaches can reduce communication efforts while improving analysis results by linking multiple files.
2. Support for visual information sharing: Automated processing of disaster-related information

and analytical insights for situation reports or digital maps to inform decision-makers should be automated further.

3. Support for image analysis: In relation to text-heavy information, images and videos engage VOST analysts longer due to the large amount of information comprised, so further automation, e.g., by clustering and verifying the images, can be beneficial.
4. Interoperability vs. holistic systems: Multiple different tools (e.g., for communication, analysis, documentation, crisis mapping) complicate achieving a comprehensive overview, so a proposed solution should be both practical to implement and holistically designed.

2.2 Study II

Fathi, R. and Fiedrich, F. (2022): Social Media Analytics by Virtual Operations Support Teams in Disaster Management: Situational Awareness and Actionable Information for Decision-Makers. Frontiers in Earth Science. DOI: doi.org/10.3389/feart.2022.941803

2.2.1 Aim

VOST analysts provide analytical support using advanced tools and monitoring social media platforms by interagency integration into EOC structures. The goal of VOSTs is to increase decision-makers' situational awareness by need-oriented analysis and to improve decision-making in a time-critical work environment by providing actionable information. A VOST's digital volunteers are organized into novel governmental structures and dispersed dislocated from the actual disaster. The aim of this study was to investigate what information is analyzed by VOSTs, which information is available when and how VOST analysts prioritize it. Besides these aims, identifying which information categories and formats (text, images, and videos) are analyzed during the disaster management process was of central interest as well as answering the key question of what impact VOST efforts have on situational awareness and on decision-making. For the latter purpose, decision-makers of an EOC were surveyed. These objectives were addressed by processing and analyzing data collected by 22 VOST analysts during the 2021 flood in Wuppertal, Germany. A subsequent survey of nine EOC decision-makers looked into the impact of VOST information on situational awareness during the flood in particular and the effect of actionable information on decisions in general.

2.2.2 Methods

To investigate the research questions 2 (What information is analyzed in which disaster phase and how does the information provided by VOSTs impact situational awareness and response actions based on actionable information in decision-making?), this case study applies quantitative and qualitative research methods. The three research questions of this Study II (see Table 1: Research questions according to the four studies) were addressed in two stages: The data generated by the VOST during the flood response was examined in Stage 1. Stage 2 focused on the perspectives of EOC decision-makers. The impact of VOST information on situational awareness, decisions, and risk and crisis communication was studied by surveying aforesaid decision-makers.

The selected underlying scenario is the VOST operation during the 2021 flood disaster in Wuppertal, Germany. Flooding on July 14 and 15, 2021 in Germany caused severe damage in numerous regions in the federal states of North Rhine-Westphalia and Rhineland-Palatinate. Wuppertal with

361,550 inhabitants in North Rhine-Westphalia was also strongly affected by heavy precipitation up to 151.5 l/m^2 with subsequent flooding on July 14, 2021 (Zander, 2021). EOC, led by the fire department and comprising decision-makers from several EMAs, began its work on July 14 at 5:00 p.m. (Zander, 2021). The VOST THW was alerted by the EOC in Wuppertal at 8:32 p.m. on July 14, 2021, and immediately established its virtual operating structures.

Various analyses of VOST data were performed in Stage 1 of this study. Throughout the flood response, VOST analysts collected social media data from different social media platforms using manual search methods and semi-automated SMA software. The team applied different methods to identify relevant disaster-related social media posts, for example via keywords and hashtags (e.g., "wupper" or #w1407) and location search approaches. The analysts distinguished disaster-related information from unimportant information by using task priorities of EOCs decision-makers. The relevant data was collected in a central file accessible to all analysts, later used for the research depicted in this study. During the flood, the virtual team identified 536 social media posts as relevant, categorized and subsequently prioritized them in three levels of relevance (high, medium, low).

An online survey was developed in Stage 2 using the application *LimeSurvey* to conduct interviews with all EOC decision-makers who had worked with VOST during the flood. The participants were selected based on their direct work with VOST information who had thus grounded their situational awareness and decisions in it. All nine EOC decision-makers selected took part in the survey, which ran from January 7 to 21, 2022, and was preceded by six online pretests. The first set of questions focused on demographic information and the respondents' roles in the EOC, followed by a matrix of statements to evaluate whether and how VOST information impacted their situational awareness. These statements were derived from the findings in Stage 1 and examined whether the categorization, filtering, and prioritization of the collected data supported situational awareness. Following that, another set of statements investigated how actionable information impacted decision-making by asking whether faster and better decisions were made as a result of the actionable information provided by the VOST. It was also examined whether such information contributed to greater decision-making certainty and whether and how it impacted people-centered risk and crisis communication. The survey concluded with general questions about the design of information products and future collaboration with VOST.

The nine EOC decision-makers rated the statements about situational awareness and decision-making on a five-point Likert scale. The mean calculated allowed for the quantitative comparison of the individual ratings. Therefore, the qualitative ratings were categorized as follows: strongly agree = 5; agree = 4; partially agree = 3; disagree = 2; strongly disagree = 1. To translate individual decision-makers' ratings into an overall score, Likert scales are established (Schnell, Hill, & Esser, 2011). The metric scale (strongly agree = 5; strongly disagree = 1) serves as an interval scale with equally distributed units (Backhaus, Erichson, Gensler, Weiber, & Weiber, 2021). Thus, using a quantitative research approach, this scaling is suitable for determining the effects of VOST information on situational awareness and decisions based on actionable information.

2.2.3 Results

The VOST identified and collected 536 disaster-related posts from various social media platforms.

56 % of these were shared on *Twitter*, 15 % on *Facebook*, 9 % on *Jodel*, and 7 % on *Instagram*. More than half of the information (58 %) was uploaded in text-only format, 22 % as images, and 20 % in video format. The analysis revealed that the VOST data gathered from social media can be classified into 23 different categories for the analyzed time period. The distributions of the five most common categories are mostly similar and account for more than half of all identified posts (51.9 %). The findings also show that four of the top five categories (level of the river, warnings, flooded traffic roads, and power outages) are directly associated with the acute flood situation. However, the largest category is primarily concerned with the aftermath of the acute flood situation (spontaneous community engagement). The EOC decision-makers' needs were classified analogically to these five categories: Their task prioritization asked for information on the damage extent and level of the river, hazards, risk and crisis communication, psychosocial needs, and spontaneous build up community engagement structures.

Because of the hazardous and dynamic flood situation entailing a variety of different elements such as power failure, activation of warning sirens, or evacuation, analyzing previously mentioned categories under the factor of time is crucial for a profound understanding of the disaster situation. Consequently, the posts' timestamps were used to visualize the five most common categories in relation to the respective publishing time. During the dynamic flood situation, posts about flooded roads and river level information particularly dominated, followed by posts about nighttime warnings via different approaches (sirens, warning vehicles, and warning apps) and, in some cases, power outages. After the acute flood situation had waned, potential spontaneous volunteers' reactions prevailed on social media. As the second flood-day progressed, this topic became more prominent, due in part to the EOC's call for the public to participate in disaster response activities.

In answering the second research question of this case study, the relation between the categories and other variables such as VOST analysts' prioritization of social media posts, information format (text, image, and video), and source (social media platform) was investigated. Three priority levels were quantified (high = 3, medium = 2, and low = 1) enabling the determination of the mean value for each category. Comparing the categories' frequency and prioritization reveals that none of the five most frequent categories was assigned the highest mean priority, whereas all posts labeled as false information, rumors, and requests for help were consistently prioritized with the highest level of 3.00. Except for the category power outage (n=50; M=1.92), the five most frequent categories were rated high to medium priority: spontaneous community engagement (n=64; M=2.03), river level (n=55; M=2.18), warning (n=55; M=2.07), and flooded traffic roads (n=54; M=2.43). Information with potential major impact on human health and the affected population' safety (e.g., a request for help or false information) was on average rated higher than other content. All high impact on human health posts were subsequently classified as actionable information and thus forwarded directly to the EOC's decision-makers.

In addition, different information formats were examined in relation to prioritization. Social media posts in the format of videos (n=105; M=2.25) were generally assigned higher priority than other formats, such as images (n=117; M=2.09), and text (n=313; M=1.90). A further evaluation reveals that eight different platforms were used for collecting disaster-related social media data. Disaster-related information from platforms that primarily publish images and videos were prioritized higher (e.g., *YouTube*: n=16; M=2.44) than those from text-heavy platforms (e.g., *Twitter*: n=300; M=1.95).

Stage 2 addresses the questions of how VOST analyses impact decision-makers' situational awareness and how actionable information contributes to decision-making in EOCs. For this purpose, an online survey was conducted to interview all nine EOC decision-makers who had worked with VOST analysis. The decision-makers were all male, between 32 and 54 years of age (M=41.7), and with an average of 21 years of work experience in EOC structures and decision-making. Three respondents were EOC directors and six responsible of specific subject areas (e.g., warning). To investigate how VOST information contributed to situational awareness during the flood, six statements were evaluated on a five-point *Likert Scale*. All six statements were rated with strong agreement (n=9; M=4.46), with the highest approval expressed for the statement that VOST information contributes to expand situational awareness (n=9; M=4.78). Seven EOC decision-makers rated the statement with strong agreement, and two with agreement. VOST analysis of the data, e.g., through categorizing and prioritizing, also contributed to gain better situational awareness (n=9; M=4.67) while the physical presence of a VOST liaison officer appears to be required to communicate VOST results to the EOC (n=9; M=4.22).

Immediate decision-making in the EOC is thus based on actionable information, i.e., high priority VOST information. To analyze the impact of the VOSTs actionable information on EOCs decision-making, the same respondents were asked to rate six further statements on a five-point *Likert Scale*. The statement receiving the highest level of agreement (n=9; M=4.56) compared to all others was the statement that actionable information provided by the VOST enabled people-centered risk and crisis communications. Furthermore, VOST information contributes to confidence in decision-making (n=9; M=4.44), to better decisions (n=9; M=4.33), and to identifying alternative decision paths (n=9; M=4.11). All three statements aimed at projecting the disaster situation to future developments however (e.g., *The information from VOST helps me to forecast developments of future situations*, n=9; M=3.89), were rated between *agree* and *partially agree* and thus lower than the other statements.

2.3 Study III

Paulus, D., **Fathi, R.**, Fiedrich, F., van de Walle, B., & Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. An Exploratory Study on Epidemic Response. Information Systems Frontiers. DOI: doi.org/10.1007/s10796-022-10241-0

2.3.1 Aim

Disaster situations increasingly pose challenges for crisis information management (CIM). Multiple aspects characterize the straining environment CIM is used in by digital volunteers and decision-makers: uncertainty about the situation, urgency to respond, limited resources, high stakes, and a high level of cognitive load. These challenges are of particular relevance due to the large amount of disaster-related data available within a narrow time period due to ICT developments, especially in social media. The sheer data volume makes both digital volunteers (in this Study III called "external analysts") and decision-makers prone to data biases in crises and disaster situations. Without established structures to detect data biases, there is a risk of decisions being made based on biased information products of external analysts. Consequently, a workshop experiment on fictitious epidemic response was conducted with practitioners in disaster decision-making and external analysts to examine previously mentioned challenges.

2.3.2 Methods

To answer RQ 3 (How do external analysts and decision-makers jointly handle data biases in the decision-making process?), an exploratory study of a fictitious epidemic response was conducted. The scenario-based workshop experiment was addressed at experienced practitioners in both decision-making and external analysis (e.g., VOST analysts) for CIM assistance.

The experiment provides a controlled environment for observing data analytics, crisis information management, and decision-making. Three separate groups were formed in the experiment, allowing for structured observation. By setting realistic time constraints, information flows, and standard tools, the scenario was created sufficiently realistic to encourage work modes similar to the ones exhibited by external analysts and decision-makers in real disaster management and especially during an epidemic response. The participants' activities, communications, and interactions within and across groups were systemically observed in this environment.

The scenario-based workshop experiment was conducted at the TU Delft campus in The Hague, Netherlands, in January 2020. The precondition to be eligible as participants was a record of previous experience as external analysts or decision-makers in disaster management. The recruitment process focused on the skills needed to complete the tasks relevant for the experiment. These skills comprise technical skills i.e. aggregating tabular data and creating and comprehending disaster information products such as crisis maps and disaster situation reports. Participants were also required to be affiliated to an established EMA, V&TC, or disaster management research institute. They were selected from a global pool from various countries. The experiment included 24 participants, 21 of whom had previous disaster management experience (11 external analysts and 10 decision-makers), while three were students. The latter three participants bring the group composition closer to reality since disaster response teams commonly experience staff turnover and thus need to integrate new and inexperienced staff frequently.

Three groups of respectively seven to nine participants were formed. These group sizes correspond to realistic team sizes of CIM processes supported by external analysts (St. Denis et al., 2012). In addition, Bradner et al. show that members of locally dispersed teams of less than ten people are more actively engaged, and more conscious of the group goals than members of larger teams (Bradner, Mark, & Hertel, 2003). The group composition ensured that comparably experienced mapping and data analysts were represented in each group as well as participants with complementary skills and knowledge. Therefore, both the total number of participants and the composition of the groups reflect realistic teams in the field.

In the experiment, an outbreak of a fictitious epidemic in three countries concurrently was assumed, based on data from the 2014 Ebola outbreaks in Guinea, Liberia, and Sierra Leone. The three groups had to evaluate the situation in the countries assigned based on the data provided to decide on the location of treatment centers. The experiment was designed to represent the key challenges of decision-making in disaster management. Therefore, participants were put under time pressure (urgency), provided with deficient and low-quality datasets (uncertainty), forced to decide on treatment center placements under intense time pressure, and obliged to do so with a lack of resources.

One observer per group recorded information on management procedures, communications, and interactions using protocol sheets with guiding questions. Additionally, photos, for example of notes on the printed maps, were taken to record the processes and outcomes. The files of information products developed by the group participants were saved on their laptops and examined after the workshop experiment.

2.3.3 Results

The three external analyst groups noted discrepancies between their respective datasets and found inaccuracies in the datasets providing infection counts. As a result, the information products mostly targeted the outbreak situation while ignoring existing capacities. Each group's final information product for the decision-making process revealed lower infection rates in the areas affected most than the comprehensive and unbiased statistics obtainable by dataset combination. Based on these findings, this thesis studies how these biased information products were handled in the decision-making process in the second stage of the experiment with decision-makers from various EMAs.

External analysts informed the decision-makers in an initial briefing of the epidemic situation using the biased infection numbers. While doing so, the external analysts communicated the limitations of the data. This led to a common awareness that the information products are unreliable. Beginning with the second interval, decision-making discussions about allocation strategies dominated. They peaked during the penultimate interval, when 35 % of the discussions revolved around allocation approaches. Consequently, all three groups based their treatment center placement decisions on the resulting biased information products. The participants showed the strongest debiasing behavior at the beginning of the experiment, in which the data limitations were discussed. However, this focus ceased as the decision-making processes dominated. The debiasing behavior increased slightly only in the last time interval.

During the information product development, the data bias in regarding the number of beds was not detected by any group. As a result, detailed capacity information was not provided to the decision-makers, who made their allocation decisions without this information. Decision-makers acted as *advocatus diabolic* by closely analyzing the information products´ database. In their function as decision-makers, they exerted pressure regarding data gaps and quality issues on the analysts in an early experiment stage. However, the decision-makers did not put enough pressure on the groups to detect potential data biases. Instead, they urged the groups to assign treatment centers based on priorities. Although it was made clear to participants that no more datasets would be provided during the experiment, requests for more data were made and remained constant at subsequent intervals. This behavior indicates a strong reliance on more data and an assumption that additional data would improve the decision-making process, although its quality is unknown and potentially uncertain if the data available is of low quality.

Creating a shared situational awareness carried more weight than interpreting the external analysts' information products. This demonstrates that decision-makers rely on their previous operational experience to assess disaster situations rather than basing their presumptions on the information products known to be limited. Altogether, the combined decision-making process including external analysts was insufficient in terms of debiasing, and epidemic response measures were based on biased information.

2.4 Study IV

Löchner, M., **Fathi, R.**, Schmid, D., Dunkel, A., Burghardt, D., Fiedrich, F. & Koch, S. (2020). Case Study on Privacy-aware Social Media Data Processing in Disaster Management. International Journal of Geo-Information (ISPRS). DOI: doi.org/10.3390/ijgi9120709

2.4.1 Aim

Virtual Operations Support Teams analyze data from social media to capture the situation during disasters and decide on how to proceed with the information derived. Privacy issues are often considered to be of secondary concern in such disaster situations, even though those affected by disasters are particularly vulnerable. The privacy of social media users must be protected to prevent future misuse, leakage, or disclosure of the datasets collected. Although a variety of technical and methodic approaches is available, their application in disaster management is either unsuitable or requires specific adaptations, limiting their utility. This case study investigates the analytical processes by VOST for integrating privacy-aware methods and algorithm into disaster management operations. As it allows streaming data in a format usable only for the purposes it was developed for, a privacy-aware method or algorithm is particularly suitable for the disaster management domain. To analyze the potential of such adoptions, two different VOSTs participated in a focus group discussion. The goal was to compare privacy-aware with traditional data analytics methods and to identify opportunities and challenges of using a privacy-aware social media data format.

2.4.2 Methods

In disaster management, the discussion of privacy and data protection often remains unresolved. The feasibility of integrating privacy-aware methods into the VOST workflow was therefore explored in a focus group discussion among VOST analysts. Participants included the first three authors of this study, one observer, and two teams of VOST analysts (THW and Baden-Württemberg). The research design included guideline-based questions based on pandemic scenarios ensuring the structured documentation of this discussion (Nyumba, Wilson, Derrick, & Mukherjee, 2018). The focus group discussion was aimed at capturing participants' experiences as social media analysts in disaster management. The method chosen was prompted by the diversity of VOST analysts: Among other factors, they differ in their knowledge levels, working and analytical methods, and work cultures.

A general overview of the concept of privacy and of a privacy-aware data structure in social media started the discussion. A dataset containing both raw and processed data was subsequently presented. Hereinafter, VOST analysts were introduced with three fictitious pandemic scenarios and requested to describe their particular social media analysis approaches for each scenario. The scenario catalog, serving as a roadmap for the focus group discussion, was created with the intent of establishing a discussion format and examining the analysis approaches. The key operational difference between the three scenarios were the operational levels: national, regional, or local. All three scenarios rest on the pandemic spreading of the coronavirus as the primary operational scenario. These differences in operational levels were made on the assumption that different privacy issues would arise at of VOST analysis of social media data. For the analysis within this study, the focus group discussion was recorded, transcribed and subsequently analyzed systematically.

2.4.3 Results

The VOST analysts in the focus group discussion considered the privacy-aware data processing technology presented less important stating that they would rarely interact with it. Comprehensive data availability is of much greater value for them, as is good interface usability and processing speed. Both access issues and loss of data can pose serious problems, especially in disaster scenarios where human lives are at risk. VOST analysts additionally stated that handling social media data could be difficult due to the total volume, which negatively affects storage space and processing performance.

The findings from the focus group discussion refute the assumption that big data analytics is the mainstay of VOSTs' operations. However, most of VOST analysts' work consists of analyzing social media data such as singular images and videos. In a time- and safety-critical work environment, an intuitive user interface for the analytics software used is a vital requirement. However, in some operation situations open-ended social media monitoring, with VOST analysts not initially knowing exactly what they are looking for, is not uncommon without using data analytics software.

Participants from both VOSTs considered one of their most prominent tasks as verifying the information contained in a post by looking at the post's metadata (e.g., the time, location). This allows VOST members to identify whether the information in a post, respectively the account it was published with on social media is trustworthy. Important indicators for such credibility included the time of the user's account exists, the language(s) typically used, the time period posts are published in (e.g., does the user sleep regularly), and the follower count, likes, and shares. The discussion participants also emphasized that standard operating procedures are not significantly affected by the scope of a disaster or the level an operation is conducted at. In addition, they argued that qualitative analysis should be conducted alongside quantitative research, for example, to assess whether a social media post is relevant to decision-makers. In this case, an account's metadata can be critical as well.

VOST analysts might encounter archived datasets as part of exercises and trainings. This contradicts the notion that processed privacy-aware data is expendable, that it cannot be used to extract information other than originally intended. As a result, it became apparent that managing the vast amounts of data in social media and the time processing it requires poses a common challenge. VOST analysts additionally underlined concerns about potential inaccessibility or loss of disaster-related information relevant to their work, for example, due to privacy regulations.

Although they are aware of privacy issues, the analysts expect intricacies in applying them in their day-to-day work, particularly during operations in disaster management. This would indubitably pose substantial challenges, especially when human lives are affected. Other situations, such as analyzing pandemic disinformation, do not necessitate time-critical decisions and enable in-depth investigation.

None of these key findings contradicts the presumption that VOSTs can work with processed privacy-aware data. This is possible as the majority of the VOSTs' analyses is conducted after processing potential privacy-aware data. This indicates that implementing privacy methods in data collection does not affect SMA, except in training cases and the verification process. Current analysis methods and data analysis tools could be further developed, e.g., in terms of handling large data sets in a privacy-aware manner, rather than introducing new techniques, as these are already in use and widely accepted.

3 General Discussion

To contextualize these findings within the greater reference frame of this thesis as presented in chapter 1, this section provides a general discussion of the results generated in the four studies regarding the four central research questions. The first subsection discusses the results considering organizational requirements for the collaboration between VOSTs and EOCs and thus aims at answering RQ 1. Two subsequent subchapters discuss RQ 2, concerning Social Media Analytics during disaster management and its impact on decision-making, as well as RQ 3 aimed at understanding data biases in the decision-making process including digital volunteers. The last research question is addressed in chapter 3.1.4, reviewing findings concerning privacy-aware social media data processing (RQ 4). Subsequently, the scope of this thesis is discussed in section 3.2, first deducing its implications for practice and contextualizing them concerning relevant contribution to the literature and highlighting strengths and limitations. The final chapter concludes this thesis and provides an outlook.

3.1 Discussion of the Results

3.1.1 Organizational Requirements for VOST Collaboration with an EOC

The first research question (RQ 1) addresses the structural, procedural, and technical requirements for a successful collaboration between a VOST and interagency disaster management. A crucial element of VOSTs is their close organizational integration into EOCs and thus into the decision-making process of disaster management. This allows for faster implementation of the VOST information products and their efficient integration into the EOC's work, especially in time-critical situations. Therefore, VOST analysts are integrated considerably closer both structurally and procedurally than V&TCs. In contrast to the loosely bound digital volunteers in the humanitarian sector described in section 1.1.3, VOSTs are part of established governmental EMAs. A resulting essential difference is therefore that digital volunteers in a VOST are verified analysts (*trusted agents* (St. Denis et al., 2012)) and that their volunteering is formalized, thus entailing obligations to participate in operations and trainings. Nevertheless, integrating a new virtual team into the operational structures of established EMAs is challenging because digital volunteers for example work exclusively remotely and computer-based contrary to rather traditional emergency responders. Considering that the virtual team operates in time- and safety-critical environments in emergency and disaster situations, the need for reliable structures and procedurals is apparent. Therefore, it is particularly crucial to study the requirements for the following three areas of virtual teams' organizational designs: structure, procedure, and technology.

3.1.1.1 Structural and Procedural Requirements

Initial studies already examined structural and procedural factors crucial for the success of a virtual team: Besides the respective project's duration, the leadership and size of a team are also decisive parameters for its operation (Hiltz, Fjermestad, Ocker, & Turoff, 2006). The advantages of smaller virtual teams, i.e., between four and nine versus 14-18 members, were described by Bradner et al. (2003) in five dimensions: more active participation, more involvement of the team members, more awareness of team goals, more familiarity with the characteristics of the other team members, increased sense of engagement. Another parameter related to the success of a virtual team that Hiltz et al. (2006) addressed is aforesaid duration of the project. Walther et al. (2002) were able to derive a correlation between rather positive relationships within a virtual team and the length of a project. In addition to these two aspects, the function of the digital team leader is a crucial factor in successfully managing a virtual team. In another key paper on virtual team success, Kayworth and Leidner (2002) found that leaders of successful teams communicated effectively, communicated roles and responsibilities across members, and also carried out their authority in a way that members viewed as positive.

Nevertheless, there is a gap in the research of virtual teams in disaster management that are part of an established EMA, perform analytical tasks only, and are closely integrated into the decision-making processes of an EOC. To address this research gap, in Study I, existing research and organizational theory approaches were applied to structure VOST and to integrate the team into an EOC. For the purpose of analyzing the structures and procedures, an established theory by Kieser and Walgenbach (2010) was applied to the virtual work of VOST, theoretically conceptualized, and systematically analyzed in the practical operational environment during a two-day operation in Study I. The five organizational structure dimensions of specialization, coordination, configuration, delegating decisions, and formalization were thus investigated in depth. The aim was to adapt existing structures and procedures in disaster management modifying them in such a way that effective collaboration can be achieved in the event of a disaster. Consequently, an organizational structure was established in harmony with the other EMA structures integrated in the EOC by dividing the tasks and responsibilities in a one-line system. Nevertheless, flexible in structures were needed to enable adaptation of said structures and procedures to the specific needs of the acute operational situation. Therefore, the team's fundamental internal structure was primarily based on the subgroups' specialization and subsequent tasks as follows:

- *Digital Deployment Investigation*,
- *Crisis Mapping* and,
- *Verification and Geolocation*.

The various analyses in Study I highlight that the groups' sizes (8-10 member) were suitable for coordinating the procedurals, which is in line with the findings on virtual teams by Bradner et al. (2003) and those specifically concerning VOSTs by St. Denis et al. (2012). All three subgroups consist of both VOST group leaders and analysts. The superordinate structure took leadership of the entire VOST operation and sent a liaison officer to the EOC. This enabled the group leaders to focus on their respective group's work, to distribute tasks to the VOST analysts within the group and to leave higher-level management tasks, such as communication and information transfer with the EOC, to the overarching management group.

During the operation, the need to form temporary specialized subgroups for specific tasks arose. This allowed group leaders to outsource resource-intensive and time-consuming tasks to a temporary subgroup, which dissolved after finishing the tasks with the respective analysts returning to their ordinary subgroup. The capability to dynamically reorganize and react to situations was described as highly beneficial as well. This approach is potentially in conflict with a desire for continuity (St. Denis et al., 2012) in the structures and duration of a project (Walther et al., 2002). The increased communication efforts needed to effectively communicate newly raised temporary subgroups, roles, and responsibilities to all members (Kayworth & Leidner, 2002), including those who were absent when these decisions were made, might pose an additional challenge for the team leaders.

However, the previously mentioned studies did not investigate virtual teams in time- and safety-critical circumstances when integrated into EOC structures in disaster management. Regarding the duration of the project, it must be taken into account that, although the operation and integration to the EOC spanned two days only, the team existed beforehand and continued to regularly train and complete operations afterwards demonstrating continuity and consistency.

The general indicators for successful virtual teamwork elucidated in this chapter thus need to be refined and specified in view of realistic disaster management conditions. This raises the question whether such insights are transferable to other operational scenarios such as long-lasting crises (e.g., a pandemic), or major international disasters. Consequently, and in line with Berry (2011), standardized operating processes need to be implemented in virtual teams to reduce the time needed for repetitive tasks and to conduct operations procedures effectively without having to repeatedly reinvent them for any new project.

Berry (2011) further describes the relevance of face-to-face communication: Nonverbal cues such as facial expressions and gestures allowing listeners to (mis)understand the speaker's intention may be lacking when communicating via ICT only. Establishing a VOST liaison officer ensuring face-to-face communication with EOC decision-makers has proven to be the key to success for both sides. The permanent presence of the liaison officer in the EOC allows the virtual team to be closer to the scene, to inform decision-makers directly in regularly held situation meetings and immediately about relevant findings, and to introduce the team and its procedures to the decision-makers for improved collaboration. The benefit of direct communication between the VOST and decision-makers via a liaison officer were also confirmed in Study II (Fathi & Fiedrich, 2022). The statement, *A VOST liaison officer is necessary for the transmission of information within the EOC.* received an average rating within the Likert scale of 4.22 from the nine decision-makers interviewed.

However, numerous additional challenges arise due to the virtual remote work: For example, occupational health and safety issues may arise when analyzing disaster-related material alone, potentially causing emotional and psychological stress. Tutt (2021) developed psychosocial assistance structures for the virtual conditions of VOST analysts´ work that can be used in the field providing support in such stressful situations.

The exclusively analytical nature of VOST work also raises new questions, for instance, about which information products are to be used at which disaster phase. Study I indicates that the needs concerning the form in which information is transmitted might also change over time. While individual preferences can be pivotal, different requirements also arise from the specific role the VOST is assigned within the EOC depending on, among other factors, which decision-maker the VOST is working for (e.g., chief of staff, communications section, or situational awareness section).

3.1.1.2 Technical Requirements

The technical requirements for collaboration must be considered from both internal and external perspectives: Internal communication technologies are particularly used for communication, collaboration, and data transfer using a wide range of analysis tools. External communication techniques are primarily used for collaboration with decision-makers in the EOC. Thus, a variety of different tools needed to be analyzed in Study I. However, although the interactive and collaborative functions of ICT used in virtual teams overcome many complexities caused by the members' dislocated work, Berry (2011) sees these technologies as mere communication and collaboration tools, rather than communication or collaboration itself.

Study I allowed for key insights into a VOSTs analytical approach and for an operational analysis of the tools used. Collecting, filtering, and classifying disaster-related information from multiple platforms proved to be the most time-intensive VOST tasks, even if relevant hashtags and keywords had already been collected previously. These tasks evidently put additional pressure onto the analysts because of mental challenges caused by the repetitive assignments as well as the *Digital Deployment Investigation* group's internal demand to identify all relevant data. Thus, a VOST analyst was only able to perform the tasks for a limited period of time until another analyst needed to replace him. Since these tasks are conducted in a both time- and safety-critical EOC circumstances affecting the analysts' work (Comes (2016), they can only be performed effectively founded on substantial preparation and backed by advanced analytics tools (Imran et al., 2018).

In addition, the activities in the other two groups (*Crisis Mapping* and *Verification and Geolocation*) revealed issues that need to be addressed in the future. Their tasks were based on the datasets generated by the first group, which they processed and mapped, but these activities were performed under different conditions: The VOST analysts in these two groups were for example not exposed to the permanent stream of a large social media dataset, they instead had to cater to the needs of the EOC decision-makers. Study I revealed that these two groups had an increased need for teamwork and thus intensive communication and collaboration within the group. These circumstances differ from the *Digital Deployment Investigation* group, rather depending on a specific number of VOST analysts to perform isolated data analytic tasks.

In addition to these internal ICT aspects, VOST utilizes analytical tools for the semi-automated evaluation of social media. Study I reveals that although the tools assist in carrying out the tasks, neither the user interface, nor the analytical capabilities and the results are trusted by the users, often complicated to use and not easy to comprehend. Nevertheless, it is important to make the tools transparent for the analysts' acceptance and trust, which is in line with findings of Kaufhold et al. (2020) who propose a white-box-approach. Study I additionally demonstrates that when using analytics tools, a bottom-up approach to development is rather helpful compared to the widely used top-down approach.

In addition, tools supporting the detailed requirements of VOST analysts need to be developed, allowing and facilitating tasks such as the verification and geolocalization of social media posts. Stieglitz et al. (2018b) also conclude that analytics tools only find the analysts´ trust and acceptance when adapted to their specific needs. When designing such tools however, the findings obtained in Study I need to be considered as they indicate that if usability barriers are too high, the tools are used less and replaced by time-intensive manual analysis methods. Due to the volume of social media data available, this poses the potential risk that important disaster-related posts will not be detected. The technical requirements for VOST work can thus be summarized into four key elements:

1. Support for collaborative research:
   The pre-deployment work of collecting relevant keyword and hashtag lists can be facilitated by an interactive collaborative technology. Such a system automatically analyzes previous, comparable events and derive potentially relevant keywords and hashtags for later analysis. For example, it compiles keywords and hashtags lists used comparatively frequently, indicating that they might be of particular importance to the disaster scenario. Interaction and communication capabilities specifically aligned with collaboration in VOSTs, including managing keyword lists and examining results, can additionally enhance the system. VOST-adapted approaches can incorporate, for example, better role-based editing rights, change alerts, more interactive need-based task division, and options for exporting and importing data.

2. Support for visual information sharing:
   The most time-intensive tasks for a VOST's group and team leaders include the manual summary of analytical results in the crisis map and the preparation of situation reports. The visual preparation of the information can be improved by automated support. For example, relevant posts needed in the situation reports can be summarized automatically in a separate document. Organizational information to be included in a crisis map or situation report can also be collected automatically. For instance, information about the current number of VOST analysts working during the operation, deployment times, keyword and hashtag lists can be integrated.

3. Support for image analysis:
   Both Study I and Study II (Fathi & Fiedrich, 2022) revealed that images and videos are the most valuable sources for disaster-related information. In contrast to merely text-based information, image-heavy posts from social media offer better starting points for verification. Images and videos open the opportunity to localize and verify them using place and time indicators. The verification effort however is a particularly time-consuming task for VOST analysts during disaster management. Currently, manual analysis methods such as reverse image search or landmark analysis are used to verify an image, which could prospectively be automated and integrated into existing tools and platforms. The work of Imran et al. (2018) (see section 1.1.2) already offers initial approaches to be pursued further.

4. Interoperability vs. holistic systems:
   VOST analysts utilize a wide range of different tools for various tasks during an operation. Thus, several tools are used for analytics, documentation, internal and external communication, verification, and geolocation and for crisis mapping. Developing a platform covering all these tools will probably not be promising as many of these tools are constantly being improved and developed, so that each individual tool would be preferable to an overall system. Furthermore, not every tool is needed for every operation. Therefore, VOST analysts will assumably rely on the specialized tools for tangible tasks, instead of an overarching platform potentially causing integration and compatibility issues. This is consistent with findings from Study III (Paulus et

al., 2022), where digital volunteers quickly selected their preferred tools for data analytics. Nevertheless, data collection is the essential core task based on which further analyses and visualizations are built. According to these findings, an analysis tool allowing the integration of existing tools (commercial, but also open source) and taking research approaches into account would be highly beneficial.

3.1.2 Social Media Analytics and the Impact on Situational Awareness and Decision-Making

In addition to the collaboration requirements discussed in section 3.1.1 (RQ 1), this thesis studied what information is analyzed in which disaster phase and how the information provided by VOSTs impacts situational awareness and decision-making (RQ 2). Numerous previous studies have focused on technical and organizational issues related to the use and analysis of social media in disaster management. However, as described, these previous studies cannot be fully applied to the work of a VOST. Understanding the impact of VOSTs on the decision-making processes of EOCs, however, is of particular relevance, as the units are deployed in multiple disasters and emergencies by different authorities in various countries (see section 1.1.4).

3.1.2.1 Social Media Analytics

Building on the findings of Study I (Fathi et al., 2020b), Study II was conducted focusing on the analytical data collected during the flood disaster situation 2021 in Germany and on the impact of VOST information on situational awareness and decision-making processes. This enabled important field insights to a VOST operation, not achievable through approaches of exclusively automated SMA. Numerous platform providers offer limited or no access to the Application Programming Interface (API) at all, so most SMA steps are performed manually requiring different analysis methods of each VOST member, e.g., for verification of social media data.

This approach of VOST data analytics, allowed for the evaluation of data from eight different social media platforms in Study II. As introduced in section 1.1.2, most previous research in the context of SMA during disaster management is based solely on the analysis of *Twitter* data (Cervone et al., 2016; Vongkusolkit & Huang, 2021) and thus do not represent the diverse user behaviors during disaster situations. The VOST's approach during the flood operation thus allowed for a considerably broader analysis of websites (especially local news sites with news tickers) as well as eight social media platforms. Subsequently, 23 different categories of information were classified. Other previous approaches of classification defining fewer categories, although capturing at least five social media posts per category as well (Vieweg et al., 2010) and only built on *Twitter* data. In addition, in Study II, analyzing the distribution of the categories over time provided important insights into which topics were communicated when via social media during the flood. This showed that the topics varied over time: A large increase of posts about spontaneously built up community engagement structures became apparent. The rapid short term organization of spontaneous volunteers using social media is line with Nissen et al. (2021) or Sackmann et al. (2021) in addition, has been observed in other disaster situations in the past.

Furthermore, analytical parameters resulting from VOST data were considered: Each social media post was prioritized on a three-level qualitative scale (high, medium, low) enabling statistical analyses. Particularly relevant categories for disaster management (e.g., request for help or false information) became statistically visible, even if these categories played a minor role in quantitative measurements. This procedure allowed for the integration of situational factors (e.g., EOC task priorities) and contextual information into the prioritization process without machine learning techniques taking over this evaluation (Rossi et al., 2018). The relevance of image-heavy social media content discussed in section 3.1.1 also became apparent in the comparative analysis of the formats and prioritization. The dataset was not limited to textual information, unlike in many other analysis (Buscaldi & Hernandez-Farias, 2015; Nair et al., 2017), but rather included texts, images, and videos. This analytical approach revealed that VOST analysts prioritized image-heavy posts higher than text-heavy posts. Studies further show that younger population groups use image-heavy platforms such as *Instagram* and *YouTube* instead of text-heavy platforms (such as *Twitter*) as opposed to older generations (Krupp & Bellut, 2021), indicating that the relevance of these platforms will increase rather than decrease.

Against the backdrop of disinformation campaigns using *deep fakes* (Verdoliva, 2020), manual methods will assumably reach their limits in verifying such information. Although initial approaches for automated evaluation, e.g., AI-supported image analysis software (see section 1.1.2.2), are being researched, they are not yet widely applied in the field of disaster management. The evaluation and prioritization of posts by individual analysts is fraught with risks as well: VOST analysts, for example, are exposed to similar conditions of time pressure, uncertainty, information overload, and high stakes as EOC decision-makers due to their close integration into the structures of disaster management. These conditions can impact the evaluation of information as for example data biases can affect data analysis and consequently the decision-making process as well (see section 3.1.3 Data Bias in the Decision-Making Process).

In future research, more attention needs to be paid to the highly heterogeneous use of social media of the affected population, among other factors depending on differences in age structures (Krupp & Bellut, 2021). If research continues to be limited to individual platforms, important disaster-related information can be lost and the wrong measures derived. Furthermore, categorization models for various disaster scenarios can be inferred from these findings facilitating machine-learning approach training and improvement while providing decision-makers in the EOC with reliable information. AI-based research approaches such as Artificial Intelligence for Disaster Response (AIDR) (Imran et al., 2018) can additionally assist in providing valuable analysis of data previously generated from disaster management operations. As elaborated in this thesis, image-heavy information plays an essential role in the analysis of social media data. AI research thus needs to be developed further to support the verification, geolocation, and interpretation of image content in a useful manner. The prioritization of disaster-related information can be enhanced by automated evaluations, e.g., sentiment analyses, as well, objectifying VOST analysts' ratings. In addition, the analysis of VOST data over time has shown that there is a need for further research into the psychosocial needs of the population during disasters. Qualitative research approaches for instance could examine what content was communicated in the "warning" category, improving the people-centered decision-making by making it more need-oriented.

3.1.2.2 Impact on Situational Awareness and Decision-Making

With the aim of examining the impact of VOST information on situational awareness and decision-making during the 2021 flood disaster, a survey of decision-makers was conducted. These insights are crucial, as the close integration of VOSTs has not yet been analyzed with regard to its impact on decision-making. In addition, Study II can be used to discuss firsthand findings from a dynamic operational situation without the trade-offs an artificial environment such as tabletop exercise or experiments would entail.

As highlighted in section 1.1.1, Endsley's (1988) definition of situational awareness consists of three aspects: perception, comprehension, and projection. In her research, Endsley refers to the situational awareness of aircraft pilots describing that the quality of situational awareness depends on capabilities, individual experience, and training (Endsley, 1988). Her analysis shows that situational awareness and subsequent decisions depend on individual factors. For the specific context of disaster management, Hofinger and Heimann (2022) similarly describe situational awareness as always subjective, although potentially based on objective situational information, e.g., crisis maps.

To systematically determine the VOST impact on situational awareness and decision-making and thus address RQ 2 of this thesis, several EOC decision-makers were surveyed. The decision-makers had to rate statements structured in two matrixes were (six statements each). Transferring the understanding of situational awareness by Endsley (1988) to the survey results reveals that particularly perception and comprehension are positively impacted by VOST information. Notably, the statements related to the impact on situational awareness (e.g., *Information from VOST contributes to expanded situational awareness*, M=4.78) generally received high agreement rates. This is underlined by further findings as well: The SMA steps such as categorization (M=4.67), prioritization (M=4.67), or filtering and evaluation (M=4.56), assist the decision-makers during the flood disaster to get a better situational awareness. The results are thus in line with other work, such as Vongkusolkit and Huang's findings (2021) who conclude that situational awareness in disaster management can be enhanced by SMA approaches. The survey findings strongly indicate that VOST information contributes positively to the perception of the operational situation.

Further survey statements focused on decision-making, e.g., based on short-term actionable information (Mostafiz et al., 2022). Effective decision-making requires comprehensible information, especially when high-priority VOST information, thus actionable information, reaches decision-makers immediately (Zade et al., 2018). The survey results demonstrate that the second aspect of the definition by Endsley (1988), comprehension, is also strongly influenced by the integration of a VOST. Both important measures during the dynamic flood situation were either based on VOST information (e.g., ensure more people-centered risk and crisis communication, M=4.56) or VOST information has contributed to strong confidence in making this decision (M=4.44). These high approval rates might however also depend on the task priorities set by the decision-makers. As a result, the VOST information matched the informational needs of the decision-makers, high agreement rates can therefore be expected in this matrix. Thus, information on decision-makers' task priorities concerning spontaneously built up community engagement structures was collected, allowing the decision-makers to prepare for unexpected spontaneous volunteers in the affected flood area.

Social media enabled the EOC to communicate with potential spontaneous volunteers appropriately. Counterstatements to false information, which the VOST identified, verified, and disseminated to decision-makers as high-priority actionable information, can also be considered as valuable crisis communication measures. Applied to the four flood risk communication strategies described by Haer et al. (2016) – top-down strategy focused on risk, top-down strategy focused on risk and coping options, people-centered strategy focused on risk, and people-centered strategy focused on risk and coping options – it can be concluded that, the last strategy describes the underlying measures of the EOC's manifold approaches most accurately.

The third aspect of the definition by Endsley (1988), the projection of the situation in future developments, is particularly relevant in disaster management because of the potentially serious impact on human life. The results indicate that the statements attributed to projection are less strongly agreed to than those attributed to perception and comprehension are. 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) all have a mean agreement value below 4.00 and thus only range between partially agree and agree. The cause for these results might be that, due to the dynamic and ambiguous flood situation, the overall operation development was difficult to project and thus VOST information especially impacted acute tactical operation.

Despite their considerable work experience (21 years on average), the decision-makers are simultaneously affected by the conditions described by Comes (2016), such as lacking and uncertain information and a continuous stream of requests for help causing an extreme cognitive load. In addition, factors such as the unique severity of the flood, the nighttime, and uncertain developments in neighboring cities (Zander, 2021) made it difficult to realistically project future developments. The integration of VOST information for decision-making in such a flood situation may not have facilitated projection as much as it contributed to perception and comprehension.

To conclude, the integration of VOST supports the decision-makers in perception and comprehension considerably. VOST information can thus aid in expanding situational awareness as well as deriving immediate measures, which are leading factors for this conclusion. Statements related to projecting the flood situation and the contribution of VOST information to this issue received less agreement. There is a need for further research in this area, e.g., how trainings can help improve projection capabilities using VOST information in the future. This discussion highlights that without VOST information, the EOC's situational awareness would not be expanded, and their decisions would have been made with more uncertainty and at a slower speed. However, human analysis capabilities are subject to limitations, especially to biases that can find their way into the development of information products. Hence, potential data biases can affect the decision-making process in EOCs, who might thus base their decisions on biased information.

3.1.3 Data Bias in the Decision-Making Process

The working environment of EOC decision-makers and VOST analysts is characterized by numerous challenging conditions: Decisions by EOC members and analyses by VOST volunteers must be completed rapidly, exposing both to great uncertainty while facing pronounced resource constraints (Comes, van de Walle, & van Wassenhove, 2020). These characteristics entail a high cognitive load on those involved given the urgency of the situation and poses two challenges: The necessary data can be unavailable or biased due to data collection limitations, or the available data may be uncertain or even contradictory (Comes, 2016). In such situations when urgency, uncertainty, and risk characterize the operation, people tend to cognitive biases (Comes, 2016; Phillips-Wren et al., 2019). Therefore, this thesis addressed in RQ 3, how external analysts and decision-makers jointly handle data biases in the decision-making process.

A workshop experiment with digital volunteers (including VOST analysts) and decision-makers from the disaster management field was conducted in Study III to investigate the extent to which data biases influence the decision-making process. The results reveal that digital volunteers used biased data in the analysis process and that the resulting biased information products found their way into the situational awareness and decision-making process. One reason for the insufficient debiasing efforts was the time-critical disaster management environment created by the scenario of a fictitious epidemic. In addition, pronounced group cohesion became apparent, causing insufficient critical data evaluation in the initial analysis steps. Although individual debiasing approaches were observed at the beginning, they abated with increasing time pressure. External analysts thus accepted the datasets provided as sufficient to develop information products for the decision-makers rapidly. At the same time, the efforts were not aimed at using alternative data sources and comparing them with each other. As data biases remained undetected in all three groups, they influenced subsequent decisions.

These findings contribute to the theoretical understanding of data biases in disaster management decision-making (Mirbabaie, Bunker, Stieglitz, Marx, & Ehnis, 2020; Ogie, Forehead, Clarke, & Perez, 2018). The observation during the experiment that the biased data was identified but not eliminated permits the assumption that more digital volunteers serving as analysts would not help to counter this challenge. Despite these challenges, digital volunteers take on a significant role in disaster management, for instance due to their specialized capabilities and tools as well as their personal commitment and effort, as analyzed in previous literature (Fathi & Fiedrich, 2020; Herfort et al., 2021).

Applied to real-world operations of VOST analysts in EOCs, see Study I (Fathi et al., 2020b) or Study II (Fathi & Fiedrich, 2022), the experiment's findings indicate that biases, e.g., in the selection of relevant social media posts and their prioritization, emerge due to the described challenges. The manual classification of social media data into categories may additionally be affected by preliminary conjectures. This may be evident for instance in disaster-related posts classifiable into multiple categories simultaneously (e.g., flooded roads and simultaneously hazards to emergency responders). In such cases, the analyst is in charge of selecting the category, potentially impacting situational awareness and decision-making in the EOC. In addition, data biases can occur when single social media platforms are over- or under-represented in the SMA process. The VOST approach of selecting diverse platforms for analysis can counteract such biases, but the risk of representational biases persists (Weidinger, Schlauderer, & Overhage, 2018), e.g., when social groups distributing content in a different language fall through the raster.

The findings of Study III also show that mere awareness of the challenges is not sufficient. The conditions in disaster management (urgency, uncertainty, and resource-constraint context) compel permanent adaptation of measures and data analytic approaches. Future research approaches need to explore these challenges of data biases in disaster management in depth while developing methods to address them in a user-oriented manner. While the demanding conditions of decision-making in disaster management will presumably persist, future developments will increase the need for data analytics simultaneous to the analysts' cognitive load: Prospectively, more data will be available parallel to increasing necessity of privacy-aware approaches (see Study IV, (Löchner et al., 2020)), complexity and variety of analysis, communication, and collaboration tools. Thus, the pressure on digital volunteers might grow, potentially increasing their vulnerability to biases.

Especially data from the population affected can contain a variety of biases. In future developments of automated analysis tools and machine learning approaches, this aspect is of crucial relevance if social media data from individual users is to be transformed into information products for decision support and thus impacting decision-making. Research approaches have examined how technical implementations in information systems, such as nudging in disaster management, can support this process (Mirbabaie et al., 2020). However, considering the conditions of analysts' and decision-makers' work and the diversity of tools already in use is necessary for such approaches (see the discussion of Study I (Fathi et al., 2020b)).

At the same time, research has shown that debiasing interventions can be effective, for example, through intensive education and training (Sellier, Scopelliti, & Morewedge, 2019). VOST analysts as well as decision-makers in EOCs, can thus be trained to actively search for information contradicting their initial assumptions (Lidén, Gräns, & Juslin, 2019). Accompanying research can consequently examine the effectiveness of such approaches.

3.1.4 Privacy-Aware Social Media Data Processing

Data protection plays a particularly relevant role during and after a disaster as the affected population is especially vulnerable in such situations (Kuner & Marelli, 2020). Therefore, this thesis also studied what the opportunities and challenges for privacy-aware social media data processing by VOSTs in disaster management are (RQ 4). Social media is an important resource for people to consume and disseminate information, but also to search for relatives (with photos and real names), as exerted during the Haiti earthquake 2010 (Meier, 2015). When such data is analyzed, there is a risk that private user data is collected. In order to avoid such breaches preventatively, Study IV investigated to what extent a privacy-aware approach can be integrated into a VOST's SMA procedures.

The research question focused on the opportunities and challenges VOSTs would face if they were to use privacy-aware data, and what barriers might prevent practical implementation. The results show that VOST analysts consider privacy-aware methods to be less important for their work during operations, since they rarely encounter them in practice. In line with the results from Study I (Fathi et al., 2020b), it was confirmed that good interfaces, usability, and analysis speed in turn have a particularly high priority for the analysts. However, this does not contradict a privacy-aware presentation of the necessary social media findings. Study IV again demonstrated the value of images and videos in SMA during disaster management, just as Study I (Fathi et al., 2020b) and Study II (Fathi & Fiedrich, 2022) had shown. Privacy-aware approaches currently do not allow for the analysis of images and videos in a way that captures their individual operation context, although such information might be essential for situational awareness. In addition, presently developed algorithms are not effective during realistic operations in which VOST work rely on social media monitoring rather than systematic big data analytics. Moreover, privacy-aware approaches in time-critical disaster situations, such as a flood, can even lead to more arduous and strenuous investigations further elevating the high cognitive load of the analysts (see Study III (Paulus et al., 2022)).

However, in some application scenarios providing a method for deploying an infrastructure for

SMA in disaster management with the help of appropriate privacy-aware methods. Thus, in VOST operations in which time criticality plays a subordinate role, e.g., the analysis of false information during the COVID-19 pandemic, more time can be spent on verification and research. Thus, social media data can be previously stored in a privacy-aware format before the false information analysis is conducted. Sentiment analyses based on text messages using only actual words (e.g., from *Twitter* posts) can potentially be conducted automatically using advanced privacy-aware methods. Establishing such support methods can have a relieving effect on VOST analysts during operations, as factors such as information overload (see Study III (Paulus et al., 2022)) or the pressure to operate in a privacy-compliant manner can be mitigated.

It can be stated that valuable use cases do exist, especially because a substantial part of the analysis (crisis mapping and verification) happens after data collection (see Study I (Fathi et al., 2020b)), so that privacy-aware methods could process the data beforehand. Nevertheless, there is a great need for research, as in this Study IV only two German VOSTs participated, although being the two largest teams in Germany. There is an additional need to interview the EMA decision-makers in this context. Exercises in which privacy-aware datasets are used and differentiated by scenario (e.g., into time-critical and non-time-critical) to observe the VOST analyses can be of great benefit. In addition, the decision-makers' perspective can be used to determine at which steps of the decision-making process what details of social media posts are necessary.

3.2 Discussion of the Scope

The following subsection highlights the scope of this thesis, discussing implications for practice, contribution to the literature with future work, and strengths and limitations.

3.2.1 Implications for Practice

The emerging and expanding digitalization poses great challenges to EMAs, as innovative ICT concerns their respective organization on the one hand and on the other hand, societal technology use has changed and is changing fundamentally within very short period. At the same time, EMAs face climate change increasing the frequency of severe disasters due to extreme weather conditions in the future, which requiring additional organizational and technical adjustments. Based on the practice-oriented research approaches applied in this thesis, the results generated can be transferred to the practice of disaster management.

Since the onset of the COVID-19 pandemic in early 2020 at the latest, EMAs had to change work practices towards remote work, including in EOCs. This thesis shows that the organizational requirements for collaboration with virtual teams correspond to those of established concepts, even if their rather unique characteristics need to be considered. By taking this into account, effectively integrating the competencies of VOST analysts operating as part of an established EMA can be ensured.

Integrating a virtual team into EOC structures can thus be effective, even in time- and safety-critical interorganizational environments with numerous actors involved, if the aspects outlined are considered. Particularly the results of Study II highlight that a VOST can bring considerable value to decision-makers and that a wide range of disaster-related information can be integrated into the situational awareness and decision-making processes. Maintaining Social Media Analytics, visualization and verification skills can therefore be crucial for operational success as EOCs will not be able to perform SMA tasks in depth without integrating the virtual teams' capabilities. This indicates a need for practitioners to expand EMA's data analytics and digital crisis mapping capabilities in future.

The German disaster management system, however, is organized on a federal state level, with fire departments operating on a local level. This poses the potential risk that many isolated and individual solutions are established complicating collaboration during major disasters when it is existential. Nationwide coordination across organizational boundaries is thus needed to develop such competencies. Reasonable authority levels for the establishment and implementation of VOST units needs to be discussed as well since a significant advantage of virtual teams is the dislocated mode of operation. Due to the physical distance, teams are less vulnerable to the effects of a disaster such as a local power outage.

Nevertheless, expanding VOST capabilities alone is not sufficient for effective disaster management, as analysts and decision-maker can additionally be affected by data biases, in turn affecting decision-making. Bias-awareness training for VOST analysts and decision-makers can bring important progress, e.g., by developing guidelines and standardized processes. Standardized debriefings after disaster response conducted both internally and externally with EOCs and other EMAs involved can create additional awareness for bias issues. Consequent critical analysis of existing structures, processes, and operational documents for instance allows for beneficial improvements. Such adaptations can subsequently be practiced in joint disaster response exercises in which debiasing efforts are actively trained and evaluated afterwards. Debiasing efforts can also assist analysts and decision-makers in their work by making use of technical information systems and algorithms. These three consecutive steps (training, standardized debriefings, and joint disaster response exercises) are further applicable to other relevant areas, e.g., in the conceptual design of privacy-aware data analytics methods for disaster management. In light of the fast-changing and heterogeneous use of various social media platforms, interorganizational risk and crisis communication exercises targeting people-centered communication in emergency and disaster situations yield additional advantages.

3.2.2 Contribution to Literature and Future Work

This thesis provides experimental evidence for specific requirements of collaboration with virtual team in a time- and safety-critical work environment. In addition, the challenges of both the internal technology use and the diverse use of various analytics tools were analyzed. The results address a relevant research gap by systemically answering organizational collaboration issues in a two-day VOST operation in Study I (Fathi et al., 2020b). These findings thus form a basis for future investigation of organizational questions, such as how analysis methods can be defined and standardized, or what kind of information products are most suitable for which operational scenario in which disaster phase. Another research contribution of this thesis is the content analysis of operational VOST data. This method, unlike the majority of studies only referring to *Twitter*, allows the presentation of cross-platform insights' distribution across several social media platforms during a disaster situation and subsequent visualization of which categories occurred in which response phase.

The prioritization of datasets by trained VOST analysts allows for the analysis of evaluated and therefore unique datasets. These datasets yield valuable findings about the importance of disaster-related information for analysts and decision-makers. Thus, this thesis contributes to the broader comprehension of the relevance of different information formats (text, images, and videos) and categories (e.g., false information) from social media during disasters. The acquired insights can be used for future disaster scenarios, for example, by developing category clusters and improving automated image analysis techniques, possibly using AI-supported analysis methods. These research approaches can be accompanied by studies investigating automated verification, falsification and geolocation methods of social media data including different information formats.

In addition to these data analysis methods, this thesis contributes to expanding the academic discussion of decision-makers' situational awareness with the use of social media data. The results highlight that situational awareness and the decision-making processes are effectively supported by VOST information and demonstrate the areas requiring further improvement. Future research should address additional decision-making aspects, e.g., the impact of the numerous different social media platforms on risk and crisis communication. It is also relevant to analyze the specific information needs of the distinct positions in the EOC more comprehensively, considering the disaster phase, and to investigate how VOSTs can serve these needs in the future.

However, future research needs to investigate these analyses in depth in order to analyze the impact of VOST information and its specific impact on decision-makers and thus estimate the effect more precisely. For this purpose, it is appropriate to collect qualitative data through participant observation during future operations or interagency exercises and guided interviews with decision-makers and VOST analysts. Including different disaster scenarios and decision-makers with different work experience in the research to generate a realistic picture of disaster management would be of additional benefit.

Furthermore, this thesis demonstrates that digital analysts as well as decision-makers are exposed to data biases impacting decision-making. This knowledge is essential for the deeper understanding of data analytics in the decision-making process: Expanding VOSTs' integration could become inefficient if disaster management measures are based on biased information. Especially in light of political calls to further strengthen VOST units, conducting more in-depth research on the capabilities and limitations of analysts' and decision-makers' cognitive capacities in disaster management situations is necessary. This thesis has furthermore contributed to broadening the academic discussion on privacy-aware processing of social media data with findings drawn from the practical field of VOSTs in disaster management and subsequent identification of limitations and potentials in privacy-aware methods. These contributions point to future research needs, e.g., in the precise delineation of the usability and acceptance of privacy-aware methods.

3.2.3 Strengths and Limitations

A mixed-methods-approach was applied in this thesis to investigate numerous research questions (see section 1.2.2) allowing for the examination of multiple research fields. Thus, the four studies provide valuable insights into practice-relevant research questions of disaster management. The interdisciplinary research field enabled the investigation of both technical and organizational issues, as well as questions related to human-related analytical capabilities, situational awareness, and decision-making. The observation of a real-world VOST operation, its analysis as a case study (Study I), and subsequent examination of the data obtained and interviews of decision-makers (Study II) generated findings with elaborate methods in an innovative research field. The challenges of conducting practical research in the time- and safety-critical context of disaster management further highlight this thesis' value. Study I for instance required extensive preliminary consultations with various stakeholders of the EOC to build confidence so that observations could be carried during the operation.

The elaborate and unique workshop experiment conducted in Study III required international collaboration with another university and V&TCs allowing the recruitment of experienced analysts and decision-makers from different countries in Europe and the USA. The valuable findings gained provide experimental evidence with practitioners. The innovative research methods applied to address various research questions and provide urgent answers thus provides considerable additional value to this field of research. The bottom-up approach used in Study IV to gain further insights allows for future technical development aligned with the specific needs of VOST analysts. Subsequent identification of the work processes of the VOST privacy-aware methods are applicable in, and in which it is not possible or necessary.

The case study nature poses challenges to potential replication of the exact results. Nevertheless, the combination of results from diverse studies confirming the findings and the discussions in consideration of relevant research literature offers the potential to derive universally valid findings. For feasibility reasons however, the studies were conducted exclusively with digital volunteers from VOSTs and decision-makers (apart from Study III) from Germany only. An international view of this research area will bring further insights, potentially in cross-reference with these finding for Germany. While the analysis of post-operational VOST data conducted in Study II has revealed some important initial findings about the SMA done during a flood disaster, it has not yet been applied to other scenarios involving VOSTs. Extending this approach to different VOST scenarios may yield cross-scenario results.

Another limitation lies in the descriptive form of the results presentation in Study II: Further analytical steps, e.g., in differentiating the categories in more detail, can provide additional value. In addition, interviewing nine decision-makers from only one EOC limits the scope of the findings. While all interviewees in the case study used VOST information for situational awareness and decision-making, a survey of multiple EOCs and their decision-makers is necessary to get a broader picture of VOST impact, especially due to the diverse VOST assignments and integration levels. Furthermore, prospectively understanding if there are differences between different agencies in the EOC, and if so, what those differences are is important.

3.3 Conclusion and Outlook

With the emergence of innovative ICT solutions and new data sources, such as social media, the work of EMAs has fundamentally changed. Increasingly frequent climate change related disasters challenge EMAs additionally, as both aspects can require organizational, technical, and personal adaptations. The results of the four studies have provided new insights into the work of analysts and decision-makers in disaster management. As shown in this thesis, digital volunteers organized in VOSTs use the ICT capabilities to organize virtually, collaborate with each other, and support emergency responders in EOCs in disaster management.

The virtual organization of a new dislocated team of analysts poses a major challenge in terms of collaboration, analysis, and integration into existing structures. However, the teams also offer the opportunity to gain from the digital volunteers' potential, especially in tasks that cannot be performed by an EOC. The fundamental change in social communication via social media and the intensive use of ICT pose a great challenge for evaluation, verification, and visualization, but also a novel opportunity to obtain disaster-related information for decision-making. The analysis of social media by VOSTs can provide new and complementary information to decision-makers, expanding their situational awareness, improving decision-making, and thus providing faster and better help to the disaster-affected population.

This thesis demonstrates that VOSTs can help combine human-related analytics capabilities and technical processing to integrate social media data into decision-making in disaster situations. However, there are crucial organizational, technical, and human factors to consider: The integration and understanding of virtual units like VOSTs, automated data analytics approaches utilizing privacy-aware methods, and the analysts' and decision-makers' capabilities are key areas. Nevertheless, VOSTs contribute to the acquisition of new volunteer resources and new population groups for volunteered disaster management. Their prerequisites for volunteers are different to those of traditional EMAs due to their virtual and exclusively analytical nature of work. This results in great potential for established government EMAs to profitably leverage digitalization capabilities for their own organization, thus strengthening community engagement and resilience.

Nevertheless, there is also a need for increased understanding of the motivational factors and participation barriers among VOST analysts. While these have been studied for digital volunteers in V&TCs (Fathi & Fiedrich, 2020; Hichens, 2012), generating evidence about VOST analysts is crucial for a more comprehensive understanding of digital volunteering in the institutionalized VOST context.

For emergency responders and other stakeholders in disaster and emergency management and civil protection, this work reveals that VOSTs can effectively support their work and contribute value to decision-making. At the same time, however, capacity constraints must be considered, raising the question of which EMAs will build their own virtual analysis team in the future and integrate them into their organization. In this particular interdisciplinary field, interorganizational approaches beyond singular EMAs are feasible in terms of setting up teams in a resource-efficient manner. Established teams can support this structuring process with their empirical knowledge, but also the results of this thesis can be used for this purpose.

While policy makers are already calling for strengthening VOST structures, this work suggests that additional efforts in training analysts and decision-makers are needed as well as in investigating in-depth research questions and developing analytical support. In light of the fundamental changes in social communication through social media and simultaneous global crises and disasters, it appears necessary to expand capabilities in risk and crisis communication by EMAs. Due to the heterogeneous use of various platforms, reaching the population in a multimedia way is necessary as well. Policy makers can help raise awareness by increasing the self-help capacity and thus reducing the impact of future disasters on the population.

In conclusion, this thesis highlights the opportunities, advantages, limitations, and challenges of digital collaboration between VOST analysts and decision-makers in disaster management. The research presented in the four studies contributes to a broader and more substantial understanding of virtual units in a time- and safety-critical work environment, thus allowing for further practical and scientific work in the future.

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5 Appendix

5.1 Studies

5.1.1 Study I

Fathi, R., Thom, D., Koch, S., Ertl, T., & Fiedrich, F. (2020). VOST: A case study in voluntary digital participation for collaborative emergency management. Information Processing & Management. DOI: doi.org/10.1016/j.ipm.2019.102174

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VOST: A case study in voluntary digital participation for collaborative emergency management

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A R T I C L E I N F O

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A B S T R A C T

Virtual Operations Support Teams (VOSTs) are a novel form of organized intelligence-gathering effort that has recently appeared in the emergency management and disaster response domain. Using novel organizational strategies and advanced algorithmic tools, such teams are set up to master the challenge of data overload and to turn it into increased situational awareness for decision-makers. This paper contains an analysis of the structural, procedural and technical requirements of VOSTs for the collaborative deployment with emergency management agencies during the *Grand Départ* of the Tour de France 2017 in Düsseldorf. We had the unique opportunity to participate in the creation and initial deployments of a VOST, a new team assembled by the German Federal Agency for Technical Relief (THW). Based on our observations we will provide a structured investigation into the various tasks of a VOST, such as social media monitoring, information verification, and crisis mapping. Due to the specific nature of the challenges faced by a VOST, which inherently involve big data processing, we will discuss the technical requirements and future prospects of data mining tools developed for and employed within this context.

1. Introduction

In recent years, social media data and particularly Volunteered Geographic Information (VGI) have played a novel and increasingly important role in the emergency management and disaster response domain. Digital volunteers, who network and collaborate virtually with each other, have the potential to improve decision-making processes by collecting, assessing, analyzing and verifying valuable crisis-related information from services such as Twitter, Facebook or YouTube. At the same time, social media and the rise of Volunteer and Technical Communities (V&TCs) have also led to changes in approaches to handling spatial data in crisis analytics efforts. Already in 2011, Starbird and Palen analyzed so-called ``voluntweeters", i.e. self-organizing digital volunteers. The focus was on the analysis of products and activities, but a survey was also conducted to examine the motivation of the volunteers (Starbird & Palen, 2011).

In this context, a novel form of organized effort in collaborative information gathering and community management, called Virtual Operations Support Teams (VOSTs), has been established. In order to have pre-established and functional links between formal agencies and digital volunteers, more and more response agencies initiate VOSTs (Fathi, Schulte, Schütte, Tondorf & Fiedrich,

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2018; Fiedrich & Fathi, 2018). In contrast to the more established digital volunteers, entry barriers for VOST memberships become higher and spontaneous participation is restricted to ensure better integration into available organizational structures. The team itself often works geographically dispersed at different locations and has a liaison officer, who works either directly in the emergency operation center (EOC) or close-by. The volunteers create actionable information for the disaster managers by detecting unusual events, creating Crisis Maps, filtering and aggregating eyewitness reports, or by analyzing images. However, it is still difficult to tap the full potential of information and findings contributed by digital volunteers in the decision-making process of emergency management agencies (EMAs). The integration of digital emergency teams such as VOSTs into the established structures of EMAs has a high potential to improve this situation. One benefit of a VOST is that its members can take up their work in a decentralized manner, remotely located from the actual emergency operations. This can be a great advantage in case of large-scale events like a power failure or flooding. In addition, the VOST members are familiar with the structures, hierarchies and formal communication channels of the agency they are embedded in. The operations carried out by a VOST are different compared to the work of digital volunteers, even if the virtual setup remains similar. Due to the real-time character of the operational work, the professionalized volunteers of a VOST have to synchronize their work in a time-critical environment. This poses a number of new tasks and challenges during an operation.

1.1. Tasks of a virtual operations support team

For this paper, we identify, and discuss scenario-dependent, high-priority tasks that are common during the deployment of a VOST. These tasks have been observed in the German VOST since its establishment in 2016 (Section 3). Their description is based on numerous working meetings with experts from various EMAs, decision-makers from authorities, and scientists. Both the operational experiences of the EMA staff and of the VOST members are considered in these descriptions. Based on the exchange of the various disciplines, the following stable, reoccurring tasks were identified:

- Monitoring social media and collecting social media data as well as conducting data processing, filtering, assessment, curation, and presentation to the operational staff of the EMAs (``Digital Deployment Investigation”).
- Verifying and geolocating information, identifying rumors and ``fake news”.
- Crowdsourcing and collaborations with other VOSTs and coordinating V&TCs.
- Sending and sharing useful information to/with the public and disseminating key messages (``social media crisis communications”).
- Creating and updating spatial analysis of digital maps (“Crisis Mapping”).
- Recognizing and analyzing trends and sentiment in social media.
- Executing ad-hoc tasks assigned by the operations team of EMAs.

This list can certainly be extended with additional tasks in the future, but it already depicts the possibilities and prospects of VOSTs. Some of the tasks are still in the (scientific) development phase, so that these operational options can only be used to a certain degree at the moment. Different scenarios require custom-tailored deployment structures in order to efficiently accomplish the specific goals. In addition, the realization of tasks is very heterogeneous at the international level. This is also due to the fact that VOSTs are organized differently, partly for historical reasons.

1.2. Research objectives and contribution

The main objective of the research presented in this paper is to gain insights into the new decision-making processes created by including Virtual Operations Support Teams into the workflow of emergency management agencies. The research is conducted as field research and as an explorative single case study, for which the *Grand Départ* of the Tour de France 2017 in Düsseldorf has served as the test bed. During our case study research, the following research objectives were addressed:

- Identification of structural and procedural requirements for a successful collaboration between a VOST and emergency management agencies **(R1).**
- Identification of technical requirements and evaluation of existing technical tools for real-time social media monitoring (**R2**).
- Analysis of the actual tasks performed by a VOST during the real- world deployment (**R3**).
- Organizational, structural and technical implications for future systems used in the decision-making process of the emergency operation center (EOC) (**R4**).

Previous research has primarily focused on technology usage in an experimental setting or on single aspects such as Twitter analysis. Although there are some multi-platform studies that also discuss field trials (e.g. Kaufhold, Rupp, Reuter & Habdank, 2019), none of them provide first-hand accounts about the EOC-integrated deployment of a specialized team like a VOST in a real-world setting. The motivation of our field research assumes that observing and understanding the inclusion of digital volunteerism into disaster operations of an actual VOST deployment can provide valuable insights and contributions for research and practice. As is typical for field study research, our research contributes less to detailed technical analysis of isolated aspects but rather to a deeper understanding of the complex decision-making processes in a real-world setting. Through the time-critical setting of the real-world deployment during this field study, results could be obtained that would not have been possible otherwise. This includes observations concerning the connection between the internal VOST structure and external links to the EOC via liaison officers as well as structured feedback of VOST members, which was collected through focus group discussion prior and after the deployment.

The paper is structured as follows: in Section 2, we provide a brief overview of the history and related literature of VOST and digital volunteers, the Digital Humanitarian Network (DHN) and the emergence of VOSTs. Because this paper focuses on decision-making for emergency management, relevant contributions from the Crisis Informatics domain are also included. Section 3 describes our case study on the *Grand Départ* of the Tour de France 2017 in Düsseldorf, including the organizational setup of the VOST, the collaborative tasks and used technologies. Further details about the organizational, procedural and technical requirements for the work of the VOST within our case study are described in Sections 4 and 5. Within these sections we provide further details on the actual tasks of the VOST (e.g. social media analysis, crisis mapping, etc.) and the technical support systems (e.g. ScatterBlogs, TweetDeck, HootSuite, etc.). Section 6 continues with the observations and analysis of the VOST operation during the *Grand Départ* by comparing the envisioned with the actual performance. Implications for current and future technical solutions in a VOST are discussed. Finally, we discuss the observations made (Section 7) and conclude our paper with an outlook (Section 8).

2. Background and literature review

In Section 2 below, the development and history of the phenomenon of ``VOST" is explained first (Section 2.1). The historical and global development from 2011 to the present is taken into account. The global networking of the individual national and superordinate continental teams is also highlighted. Subsequently, the topic will be analyzed in a wide-ranging literature overview (Section 2.2). In order to highlight the extensive background of the topic, research on digital volunteers, crisis informatics and the organizational implementation of virtual teams is examined.

2.1. VOST history and related work

The idea of Virtual Operations Support Teams originated from the aim of better integrating the work of digital volunteers into structures and processes of emergency organizations to get access to useful information from new sources. The term `Virtual Operations Support Team' was first coined in 2011 by Jeff Phillips, an emergency manager in the small town of Los Ranchos de Albuquerque in New Mexico, USA (St. Denis, Palen & Hughes, 2012). On March 14th, 2011 he expressed the wish on Twitter to found a VOST and asked who was interested (Fig. 1).

A key difference from traditional digital volunteer communities (Fig. 3) is that VOSTs are often officially tied to an established (volunteer) EMA or even to a governmental agency. The main difference between trusted agents (St. Denis et al., 2012) and digital volunteers is that trusted agents have already earned trust in emergency management agencies before an emergency occurs and that they can be reliably integrated into established structures. At a conference organized by the National Emergency Management Association (NEMA), the concept of a social media-assisting unit in emergency management was tested. The initial goals were defined as:

- Use of social media in real-world events without emergency character.
- Claiming trusted agents who work for the response organizations.

These goals are met by a VOST, whose activities include monitoring of social media activities and active participation in public communication through social media platforms. After the foundation of the first VOST, the Virtual Operations Support Group (VOSG) was established in 2012. In the meantime, it has become a superordinate group that forms the umbrella organization of Virtual Operations Support Teams worldwide. The VOSG has taken on an advisory role to guide new teams in their structuring. In addition, the advisory board can discuss VOST-related issues and act as a coordinator when different VOSTs work together. In order to better manage cooperation at a transnational level, VOST Europe, VOST Oceania and VOST Americas have created regional subdivisions (Fig. 2). These regional umbrella organizations also support the respective regional teams and help to establish new teams (Fathi et al., 2018).

One of the first extensive deployments of a VOST took place during the forest fire 2011 at Shadow Lake in Oregon, USA. In a

Fig. 1. "Want to set up a VOST…" tweet by Jeff Phillips in 2011.

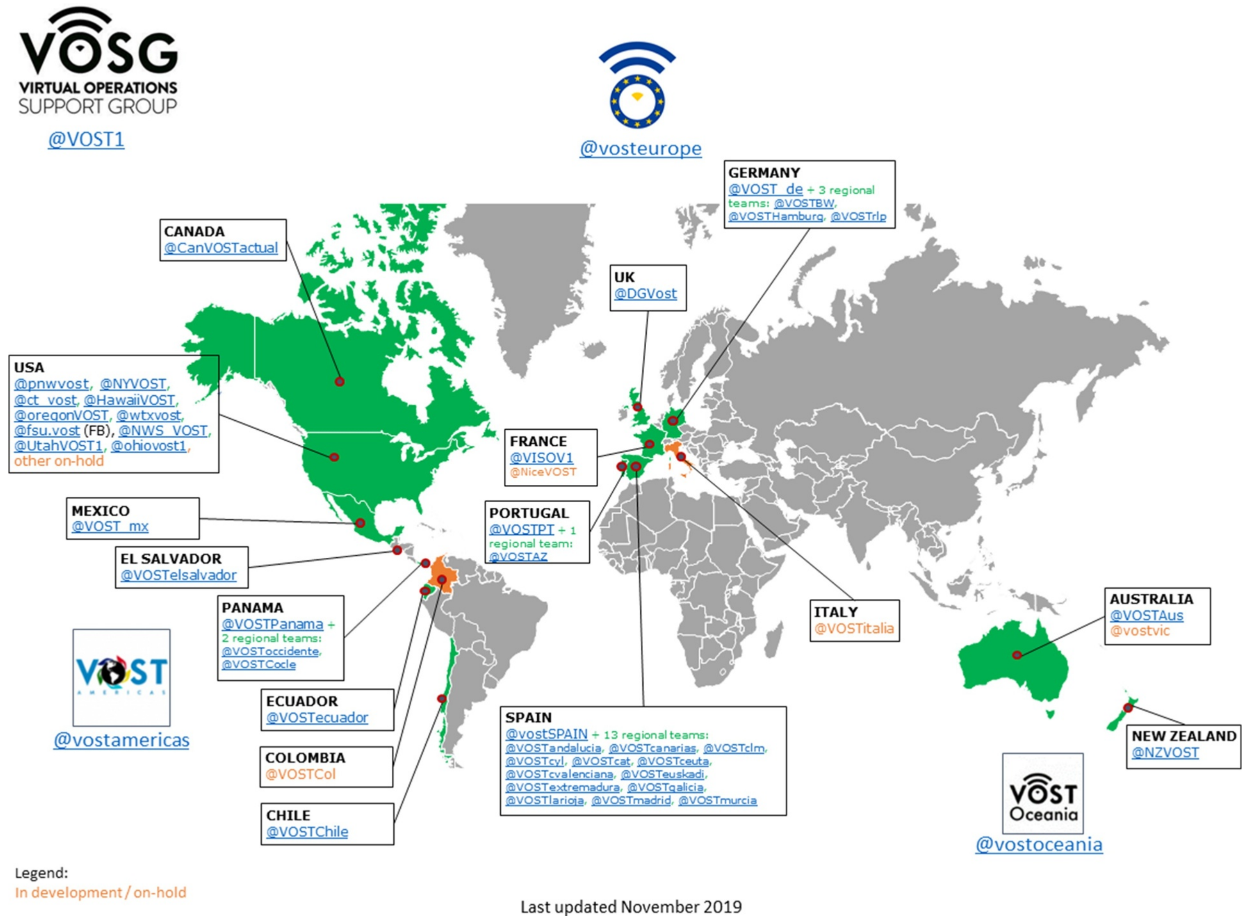

Fig. 2. Worldwide Virtual Operations Support Team, organized in VOSG. Reproduced with permission of VOST Europe.

scenario-dependent analysis, St. Denis et al. (2012) explain:

- The Virtual Operations Support Team members are placed independently of location and are geographically dispersed.
- Team leaders of a successful VOST have been able to effectively communicate information, assign tasks, roles and responsibilities within the team, and apply their authority in a way that is positively perceived by the team members.
- Smaller teams (4–9 members) work more effectively, can be better coordinated internally, and are more aware of common goals and assignments than larger teams (14–18 members).

The VOST working on the forest fire consisted of a combination of members with information technology skills and knowledge of social media as well as members with a public safety background. The communication within the team mainly took place via a team chat and Internet-based telephone conferences. Deployment documents were edited and documented in an shared cloud storage. This repository was accessible to all team members. Filed documents included, for example, a roster, the assignment of tasks to the individual team members, and contact lists.

2.2. Literature review

Early social media analysis studies in the field of crisis management analyzed how social media such as Twitter and Facebook were used during events to communicate timely information related to the incidents (Vieweg, Palen, Liu, Hughes & Sutton, 2008). The research field of crisis informatics emerged as a continuation of this initial investigation (Palen, Vieweg, Sutton, Liu & Hughes, 2007). Within the geographic research community, the spatial component of such Volunteered Geographic Information (VGI) data was of particular interest (Goodchild, 2007; Goodchild & Glennon, 2010; Sui & Zhao, 2015). In non-emergency domains, volunteer communities such as the OpenStreetMap group created VGI data in a more organized fashion (Scholz, Knight, Eckle, Marx & Zipf, 2018).

For the field of emergency management, Patrick Meier and his colleagues realized the potential of novel digital aids in crisis response efforts as well as the need for volunteers who are proficient in the use of web-based information technology. With the

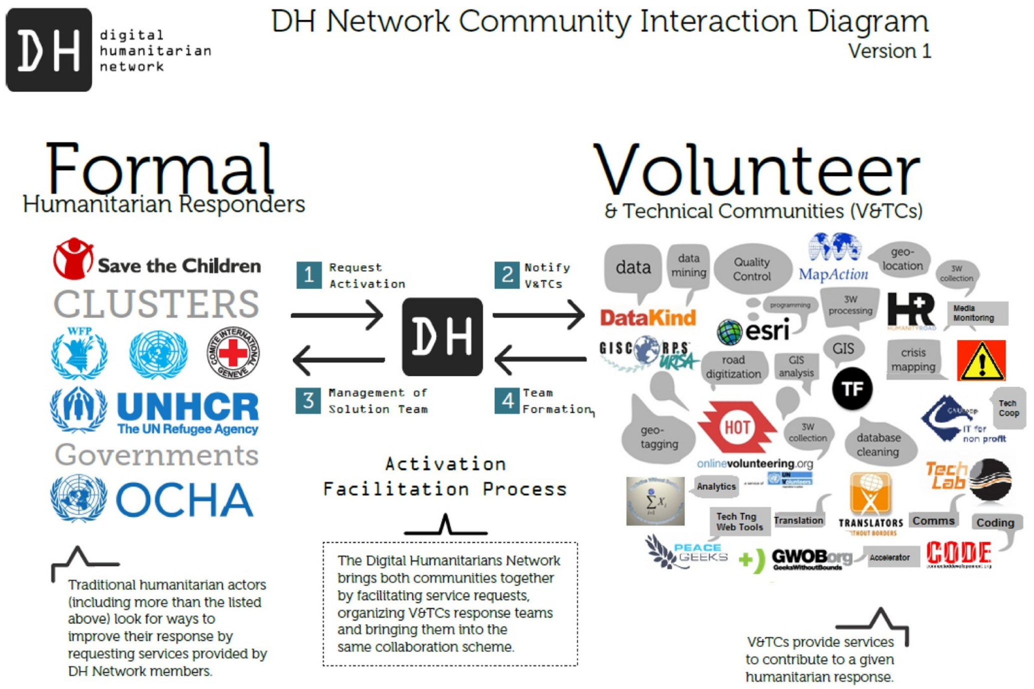

Fig. 3. Digital Humanitarian Network: interaction diagram. Reproduced with permission of the Digital Humanitarian Network.

creation of the CrisisMapper (Meier, 2015), their goal was to support relief activities with crowd-sourced geographic information, such as regional damage assessment or shelter locations, which would otherwise not be available to the responders or to the public. Following the success of this group, the Digital Humanitarian Network (DHN) was formed as a loose coalition of various V&TCs. A formal link to the United Nations Office for the Coordination of Humanitarian Affairs (UN OCHA) was established to improve collaboration with the institutional organizations (Meier, 2015). Which organizational, structural and through virtual work related challenges a V&TC like Humanity Road can have, for example, becomes clear with Starbird and Palen (2013). In this context, the difficulty of a purely virtual organizational form is also presented, such as how it is connected to EMAs and formal humanitarian responders.

Fig. 3 shows the cooperation between V&TCs and formal humanitarian responders. The established aid organizations are shown on the left and V&TCs on the right side. Within a few years, numerous communities of this kind have been formed, some of them with a high degree of professionalism.

In recent years, digital volunteer communities have had a large impact on disaster management practices. In humanitarian disaster response in particular, various volunteer communities such as the Standby Task Force (SBTF) or the Humanitarian OpenStreetMap Team (HOT) have created large amounts of VGI with the aim of improving disaster operations (Palen et al., 2015). Tasks included, for example, the validation of data and the creation of Crisis Maps. In general, four different types of V&TCs can be distinguished:

1 Communities that develop software platforms.
2 Collaborations in the area of mapping.
3 Networks of different experts, e.g. collaborative technology development.
4 Communities for data collection and analysis (van Gorp, 2014).

In order to improve the coordination of the efforts of different communities, the DHN was created as a mediator platform (Fathi, Polan & Fiedrich, 2017b). With the beginning of these initiatives, researchers investigated various options for the extraction of response-related data. Here, a focus has been on big data analysis of Twitter and other social media data, which were provided passively, e.g. without the primary goal of supporting organized response.

In addition, van Gorp describes numerous organizational and inter-organizational challenges in the integration of V&TCs (van Gorp, 2014). For example, she points out that the levels of engagement between V&TCs and formal aid organizations can vary. Van Gorp argues that the formalized organizations have a better overview of a deployment situation, while (digital) volunteers focus primarily on helping the affected people (van Gorp, 2014). She also discusses the differences in working methods: While emergency management organizations work in hierarchies, V&TCs tend to have a network structure with flat and decentralized structures. Due to the differences in structuring, it is also possible that the expertise of the individual digital volunteers remains unknown to the decision-makers. These findings illustrate the existing gap between decision-makers and digital volunteers. The professionalization of digital volunteer communities, such as VOSTs, can fill these gaps. The close integration of VOSTs, the professional qualification in an EMA and the experience of the members may make the expertise of the team more transparent for the decision makers.

Soden and Palen (2018) explain that innovative studies with participatory approaches have begun to explore new areas in the field of Crisis Informatics. This also includes situation reports or collaborative mapping as a method of information transfer into decision-making processes. Recently, Kaufhold et al. (2019) presented results from field trials of their Emergency Service Interface (ESI), a system for multi-platform social media monitoring that also supports automated alerting based on advanced algorithmic analysis. Their system was tested for longer periods of time by fire departments in Dortmund and Ljubljana. These field trials focused on the evaluation of the existing ESI design as well as their newly defined information quality metric in a real-world setting. To this end, it was used by fire department domain experts that also performed their regular functions while operating the system. They communicated with the researchers via Telegram messaging. The study presented in our paper differs from their work in three ways: First, the study presented here was conducted on-site and with immediate access to the analysts during the deployment. It can thus present an extensive, unobstructed account of their work, findings, and communication throughout the event. Second, in addition to technology use, the study observes the structures and processes of a team that is highly specialized as well as exclusively focused on virtual operation support tasks. In contrast to traditional emergency personnel, all of their operations are centered around and fully dependent on the availability of advanced analytical tools supporting functions like social media monitoring, crisis mapping, and information verification. Third, and most importantly, the study presented here is exploratory in nature. Although we discuss the ScatterBlogs system and various other tools that were used during the deployment, our primary goal is to gather requirements that are supposed to serve as a starting point for an iterative, open-ended development process.

Researchers furthermore looked into the question of how actionable VGI data actually is for the decision-makers and whether or how they use the information supplied. For example, approaches to improve the geographical identification of relevant flood information from social media data in combination with authoritative data were investigated. Albuquerque, Herfort, Brenning and Zipf (2015) conclude that natural hazards such as floods can provide valuable information for disaster management, but also for preventive monitoring. However, current research shows the challenges associated with the analysis of social media data (Alam, Ofli & Imran, 2018b). In addition to text-based analyses of the data, V&TCs also face challenges when it comes to social media image capture, processing and analysis. Current work includes the use of artificial intelligence and natural language processing (Alam, Ofli & Imran, 2019). Numerous factors can have a huge impact on the actual social media analysis, which consists of discovery, collection and preparation.

Stieglitz, Mirbabaie, Ross and Neuberger (2018) show in their study, that the volume of data is still the challenge cited most often. This and some additional aspects can also be observed in the context of emergency management agencies: the implementation of structures to integrate social media or V&TCs into the work seems to be difficult. Stieglitz, Mirbabaie, Fromm and Melzer (2018) identifying challenges in adopting social media analytics after a systematic literature review, make some propositions, and subdivide them into:

1 Propositions derived from technological challenges (e.g. ``Technical solutions should support crisis managers in the sense-making and information validation process for a high acceptance of social media analytics.")
2 Propositions derived from organizational challenges (e.g. ``A new role within EMAs should be defined in order to perform social media analytics on a daily basis.")
3 Propositions derived from environmental challenges (e.g. ``Governmental support might foster the adoption of social media analytics in EMAs.")

Several of these propositions can be found in the operating methods of a VOST. As already mentioned (and further expanded in Section 3), a VOST consists of deployment-experienced experts. Thus, technical approaches can be better communicated, which in turn can lead to higher acceptance among decision-makers. Due to the integrative approach of a VOST, the suggestion to the organizational challenge can be partially absorbed. In addition, a VOST is part of a governmental organization in which governmental support is directly provided. Some of these propositions have been included in the content of the elaboration of the conceptual implementation in the focus group discussion for the case study.

Hughes and Tapia indicate that, so far, there seems to be a significant gap between the data created by the communities and the actual requirements of the response organizations (Hughes & Tapia, 2015). Due to the lack of communication between officials and volunteers, there is also a high possibility of duplicate efforts. Therefore, it is necessary to improve the link between the decision-making requirements and digital volunteer efforts. Zade et al. (2018) also deal with this issue, specifically how to make information from social media ``actionable". However, the extraction and assessment of such information depend strongly on the individual responder and may vary. The function of an individual decision-maker can also influence perception. What is particularly important to one responder may be irrelevant to another.

When the crisis communication matrix developed by Reuter and Kaufhold (2018) is applied to the phenomenon of VOSTs, a process emerges: Virtual Operations Support Teams originated from a necessity. Citizens shared information with each other (Citizens to Citizens). The authorities recognized the need to also communicate with citizens via social media (Authorities to Citizens) in the sense of effective crisis communication. At the same time, V&TCs began to emerge and collaborate with authorities. These developments led to the principle of a VOST, which is in general linked to an emergency management agency, in our case consists of (digital) voluntary citizens. This is also because a VOST is in the ambivalent situation of being a governmental organization consisting of digital volunteers. However, as shown in Fig. 4, a VOST is to be classified as a virtual authority in the role typology matrix based on Reuter and Kaufhold (2018).

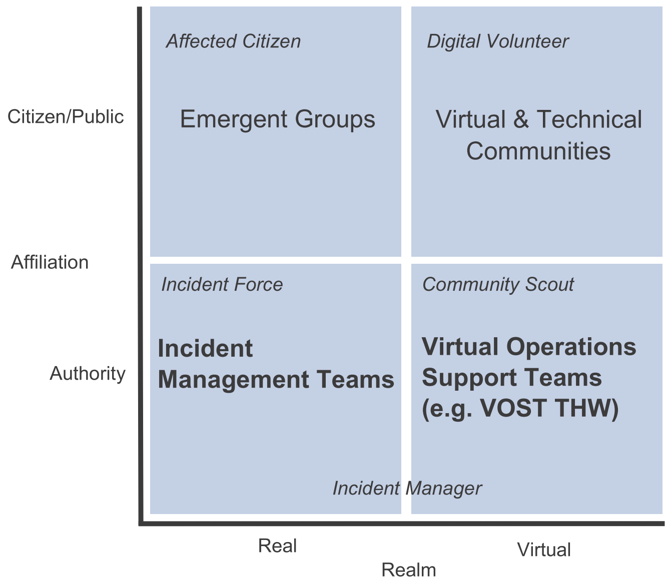

Fig. 4. Role typology matrix. Based on Reuter and Kaufhold (2018).

The role typology matrix shows a differentiated overview of the role patterns. A distinction is made between real/virtual and authority/citizen. As already mentioned, a VOST is to be classified as an institutional organization within the authorities. The unit collaborates on a horizontal inter-organizational level with the incident management teams, as further described in Section 3. In addition, a VOST also intends to cooperate with various other VOSTs and V&TCs in a joint deployment. Nevertheless, the requirements for effective collaboration between formal humanitarian response organizations and VGI communities are challenging (Fiedrich & Fathi, 2018). Collaboration between response organizations and digital volunteers seems to be easier in longer-term disaster risk reduction activities (Scholz et al., 2018). Further approaches examined the behavior of social media users during disasters (Kaufhold & Reuter, 2016). The use of data mining and machine learning concepts led to faster availability and evaluation of VGI and other response-related data (Imran, Castillo, Lucas, Meier & Vieweg, 2014). Imran, Castillo, Diaz and Vieweg (2015) have conducted a comprehensive literature review on the use of computational methods for analyzing social media (with a focus on Twitter messages) in the disaster management context. Imran also describes the difficulty of linking social media data to the users' information needs in general, because ``the information any individual, group, or organization finds useful and seeks out in a disaster will depend upon their goals" (Imran et al., 2015, p. 6).

In the past few years, there has also been an increase in the number of spontaneous volunteers arriving at the disaster site to support the professional responders (Sackmann, Lindner, Gerstmann & Betke, 2018). These spontaneous volunteers often organize themselves via social media networks, which leads to a collaboration between formal response agencies, spontaneous volunteers and digital volunteer communities (Fathi, Rummeny & Fiedrich, 2017c). In order to communicate with the various volunteer groups, the response agencies need to use social media channels in which specific communication rules can be developed for their official crisis communication (Fathi, Martini, Kleinebrahn & Voßschmidt, 2017a). However, after the initial phase, more professionalized and organized structures emerge (Fathi et al., 2017c). The new structures are often comparable to those of formal responders. This organizational shift seems to be a necessary requirement for the greater reliability and professionalization of digital and spontaneous volunteers.

3. Case study

In Section 3 below, we first describe the conditions in which a VOST was established. Subsequently, we will discuss the concrete data on which this work is based before we present the general conditions (Section 3.1) of the deployment. In Section 3.2 we finally introduce the focus group discussion.

In a recent pilot project, the German Federal Agency for Technical Relief (THW) established an official Virtual Operations Support Team to investigate functionality in real-world deployments as well as in integrated emergency response exercises (Fiedrich & Fathi, 2018). The THW is subordinate to the German Federal Ministry of the Interior, Building and Community. Although this makes it a governmental organization, the vast majority of members work as volunteers. In total, 99% of its 79,514 members were volunteers in 2016 (Bundesanstalt Technisches Hilfswerk, 2017). The main tasks of the THW are defined according to German law as:

- Civil protection and aid following natural disasters.
- Aid in foreign countries on behalf of the German government.
- Civil defense at the request of public offices responsible for disaster response coordination.

- Cooperation (Bundesanstalt Technisches Hilfswerk, 2017).

For the new VOST pilot project, 20 experts from disaster response, emergency management, social media analytics, and information technology were specifically appointed as THW members. When the unit is deployed, members no longer act as loosely assembled digital volunteers, but as team members in a governmental organization.

To enable the monitoring and analysis of social media data, the VOST has been equipped with ScatterBlogs, a prototypical social media analytics software that was developed at the University of Stuttgart (Bosch et al., 2013). ScatterBlogs is an analytical system that allows the collection, filtering, exploration, and semi-automated assessment of large volumes of user-generated messages from microblogging services. In the following we discuss the deployment of a VOST during the *Grand Départ* (GD) in Düsseldorf (Section 3.1), which was a unique event to observe and document the use of this kind of software under real-world conditions with an actual impact on the decision-making. We will also elaborate on the design of social media analytics software, its usefulness and applicability in context of the GD deployment, as well as on refined requirements and future prospects for technical VOST equipment. In addition to ScatterBlogs, various commercially available social media monitoring tools were used at the same time. They will be discussed in the later sections. Furthermore, the VOST made use of messaging and communication software that is freely available.

To evaluate the applicability and usefulness of a VOST as well as the structural, procedural, and technical requirements, we will explain our analyses of the first official deployment of the German VOST during the *Grand Départ* of the Tour de France 2017 in Düsseldorf (Germany). Since 1903, the Tour de France has been the largest and most important cycling race in the world, making its way through France and its neighboring countries in 20 stages. The location of the start of the Tour de France, the *Grand Départ*(``the great departure"), changes annually. This first VOST deployment serves as the case study for the field research presented in this paper. According to Yin (2003), a ``case study inquiry copes with the technically distinctive situation in which there will be many more variables of interest than data points, and as one result relies in multiple sources of evidence" (Yin, 2003, p. 13). Some of the key advantages of case study research are that the studied phenomenon is observed in its natural setting without experimental controls and that the complexity of the system in analyzed from various angles. Additionally, case studies typically include various data collection methods (Benbasat, Goldstein & Mead, 1987). Within our GD case study, various methods for data collection and analysis were used:

- Participant observation of the VOST deployment;
- Focus group discussion and informal interviews with VOST members and decision-makers before, during and after the deployment;
- Analysis of the transcripts and log files of the tasks performed by the VOST during the GD;
- Additional notes taken by the authors during the observation of the VOST deployment; and
- Further analysis of the organizational setup, technology usage and decision-making processes of the VOST.

3.1. Course of events

The *Grand Départ* in Düsseldorf included two stages. The first stage was an individual time trial on the streets of Düsseldorf over a 13-kilometer route. In the second stage, the athletes left the city in the direction of Belgium, passing through the German cities of Neuss, Mönchengladbach and Aachen. The VOST was primarily tasked with monitoring social media activity in and around Düsseldorf, where larger crowds had gathered along the route and co-located events took place. Secondarily, the VOST was also supposed to observe social media activity in other German cities along the second stage, where less activity was expected. In terms of analytical goals, the VOST had to identify messages, images and videos from social media users, which might indicate high density of crowds, violation of confined areas, vandalism, and potential safety hazards. Once detected, the VOST was furthermore responsible for assessing the validity and severity of such findings and for providing an estimate of the time and location at which the respective event or observation took place. To this end, it would have been necessary to compare images and videos with general context information and additional web sources, e.g. Google Street View, to identify places shown in user-provided images. In order to use the acquired information in the decision-making process, a liaison officer attended the hourly meetings of the emergency operation center. Two VOST members were on site during the deployment. In the briefings, which took place at regular intervals involving all actors, the VOST (represented by the liaison officer) was embedded as a component. When findings from social media were discussed, detailed information could be contributed through this integration. The VOST deployment ended after the cyclists left Germany and the crowds along the route dispersed.

3.2. Focus group discussion

Emergency management agencies are characterized in their diversity by a plurality of knowledge, values and working cultures. In an interdisciplinary deployment scenario such as the one at hand, information processes, communication, dialogue and cooperation gain in importance. As a result, dialogue and participation procedures play an increasingly important role in empirical research for civil security. Therefore, it was necessary to bring the various stakeholders together. The meetings were held in form of a focus group discussion. Focus group discussions are moderated discourse procedures, in which a group with common background discusses a concrete topic. The method has been widely established in numerous areas of empirical social sciences. It is used in many different ways as a test procedure, for the analysis of diversity of opinion or as an instrument of conflict resolution. In the recent past, the method has also been used to evaluate measures and work together on improvements with the help of a focus group (Schulz, 2012).

This approach was chosen because it is a resource-saving and effective method of working with different stakeholders on a particular issue. It is particularly suitable when different participants have to deal with a problem and conceptual improvements are expected to emerge from the results. As already described in Section 2, the perception of data from social media with information relevant to the deployment can vary depending on the responder and on the different pieces of information (Zade et al., 2018). The identification and definition of insights from social media, which are relevant for situational awareness and are ``actionable", is highly important for the work of the VOST. For this reason, it was particularly important to discuss key situations, scenarios and evaluation methods with the decision-makers from the emergency operation center. The focus group discussion was designed in such a way that all the key authorities and responders could participate. In preparation for the Tour de France 2017, the meetings took place three times before and once after the deployment. In this case, the responsible fire brigade, the organizer of the *Grand Départ* 2017, the German Federal Agency for Technical Relief, VOST members and the authors of this paper were involved. The results were documented in the minutes of the meetings.

The aim of the discussions was to develop a common understanding of the challenges and to derive approaches to solving them. Subsequently, scenario-dependent work tasks were defined in group discussions with the decision-makers. In order to determine these tasks, the requirements of the emergency management agencies for such a scenario and the possibilities of the VOST were investigated in more detail. The following working priorities were defined:

- Identification of critical crowd densities.
- Identification of critical crowd flows.
- Detecting unusual events.
- Social media image analysis.
- Creation of a digital situation map for spatial analysis.
- Identification of false information, rumors and ``fake news".
- Scenario-dependent tasks.

In order to successfully implement these tasks, effective and comprehensible structural and procedural requirements were discussed with the stakeholders, which are presented in more detail in Section 4. It was particularly important to consider the challenges associated with the virtual work of the VOST on the one hand, and the established structures of emergency management agencies on the other. Organizational requirements, such as a hierarchical organizational structure of the VOST, are included in the analysis (Section 4.1.2). Independent of the definition of working groups, it was decided that the internal hierarchical structure of the VOST should correspond to the usual structures in emergency management agencies. The VOST was thus aligned with established structures. This aimed to ensure consistent organizational structure for the collaboration with decision-makers. In addition, the technical requirements for the deployment leader and the liaison officer, both of whom worked in the emergency operation center, were defined. The most appropriate link to the decision-makers in the EOC was also determined. This was a room next to the emergency operation center, where all relevant decision-makers of the different EMA and local authorities came together. This ensured permanent spatial accessibility of the VOST for the EOC.

During the meetings, the conceptual elaborations were discussed with all stakeholders so that a framework of measures could be implemented. The final discussion three weeks after the deployment was particularly important. After this break, the impressions had been processed and all participants were able to discuss the deployment openly and to exchange observations and opinions. Common findings on the operational structure were also gathered, some of which directly led to organizational, structural and technical improvements. The findings and lessons learned are presented in Section 7.

4. Structural and procedural requirements for a VOST

As already mentioned, a VOST sets itself apart from other digital volunteer communities by its structural integration within emergency management agencies or public authorities. Such a closer structural integration requires adjustments to work and decision-making processes. Focus group discussions were held with the decision-makers (Section 3.2), to ensure closer cooperation, a synchronization of work processes, a common terminology and the definition of the main priorities of the work. Subsequently, conceptual work was carried out, which was then to be tested in close cooperation with the EOC.

4.1. Structural requirements for a VOST

The structuring of a virtual team in emergency management organizations is particularly challenging in many respects. For example, challenges that can arise through remote work alone were addressed. We have used an organization theory to create the necessary structural framework. This is necessary so that such a VOST, consisting of digital volunteers, can integrate into a time-critical and inter-organizational environment. For this reason, systematic and participatory integration approaches have been taken into account even before the deployment.

4.1.1. Theoretical background

The conceptual elaboration of organizational structures for the VOST in the scenario described above is based on the theory of structural dimensions according to Kieser and Walgenbach (2010). This approach is widely used and can be applied to the structure of established emergency management agencies. It brings together all the organizational challenges relevant for VOSTs. The approach is

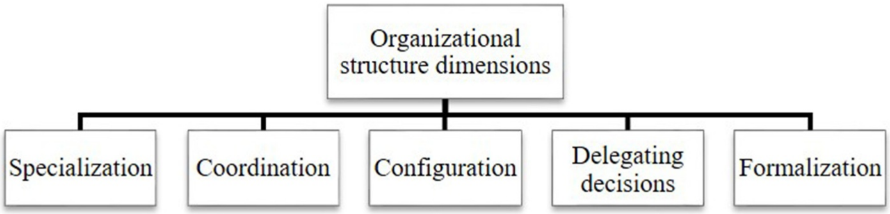

Fig. 5. The structural dimensions of the organization (based on Kieser & Walgenbach, 2010).

necessary to describe, analyze, and compare organizational structures (Bergmann & Garrecht, 2016). Fig. 5 illustrates the five structural dimensions specialization, coordination, configuration, delegating decisions and formalization:

The specialization of an organization requires the division of tasks and work, which allows adaptation to the abilities and skills of the employees. This division can be structured according to quantity, objects, functions, hybrids, or situation-specific (Kieser & Walgenbach, 2010). The division creates a need for coordinating the individual working groups to achieve the work objectives. The coordination can be differentiated into two approaches:

- Temporal coordination approaches: It is possible to differentiate between proactive coordination already defined in the planning phase and feedback coordination that develops during the deployment.
- Objective coordination approaches: It is possible to distinguish between person-oriented and technocratic coordination approaches. Person-oriented coordination tools include personal instruction and self-coordination. Technocratic coordination approaches imply coordination through programs and plans.

The configuration is defined as the structural construction, hierarchy and responsibilities of the organization. In particular, two systems, the one-line system and the multi-line system, are distinguished. The one-line system has a clear hierarchy, clear responsibilities, and fixed information management. By contrast, the multi-line system has a flat hierarchy that does not include clear responsibilities or fixed information management. The decisions within an organization can fundamentally be based on two different concepts:

- Centralization: All decisions are made in a central office.
- Decentralization: All decisions are made by local task forces.

The final structural dimension is the degree of formalization. This refers to, for example, written organizational rules, procedural instructions, written information, and communication. This theoretical background is used as a basis for the transfer to a virtual, interdisciplinary and collaborative unit such as a VOST as set out in the following section. The underlying scenario, namely the start of the Tour de France in Düsseldorf in 2017, is applied.

4.1.2. Application of the five structural dimensions of the organization

In order to realize the tasks defined in the focus group discussion (Section 3), internal organizational structures were created. The internal specialization of VOST members was guided by task definitions, which were aligned to the functions and the situation-specific conditions:

- Verification and geolocation.
- Crisis mapping.
- Digital deployment investigation.

This internal structuring of the VOST for the GD deployment can be illustrated as in Fig. 6.

A deployment leader manages the operation. She has received leadership training and coordinates the work of the working groups during an operation. She maintains close contact with the liaison office and distributes operational orders to the group leaders, with strategic goals in mind. In addition, she has overall responsibility for the deployment. A liaison officer has the task of connecting the VOST with the EOC and can be seen as an interface between the coordination units of the two (Fig. 7).

Hierarchically and structurally, the group leaders are at the next level of leadership. They are responsible for their respective working groups and pursue tactical goals. They coordinate their team members and maintain contact with the coordination unit and with the other group leaders in case there is a content overlap in the task fields. The team members make up the core of each working group. They carry out the work independently and in agreement with the respective group leader.

The coordination of such a deployment with three permanent working groups requires a control and coordination unit. This coordination unit consisted of the liaison officer, the heads of the individual working groups and a head of operations. For this, the methods of proactive coordination and feedback coordination are used. Proactive coordination is used, for example, to define the procedural steps that are to be followed during the deployment. However, adjustments were also necessary during deployment, so feedback coordination was also used. The VOST, which encountered established structures in this deployment, had to align itself with

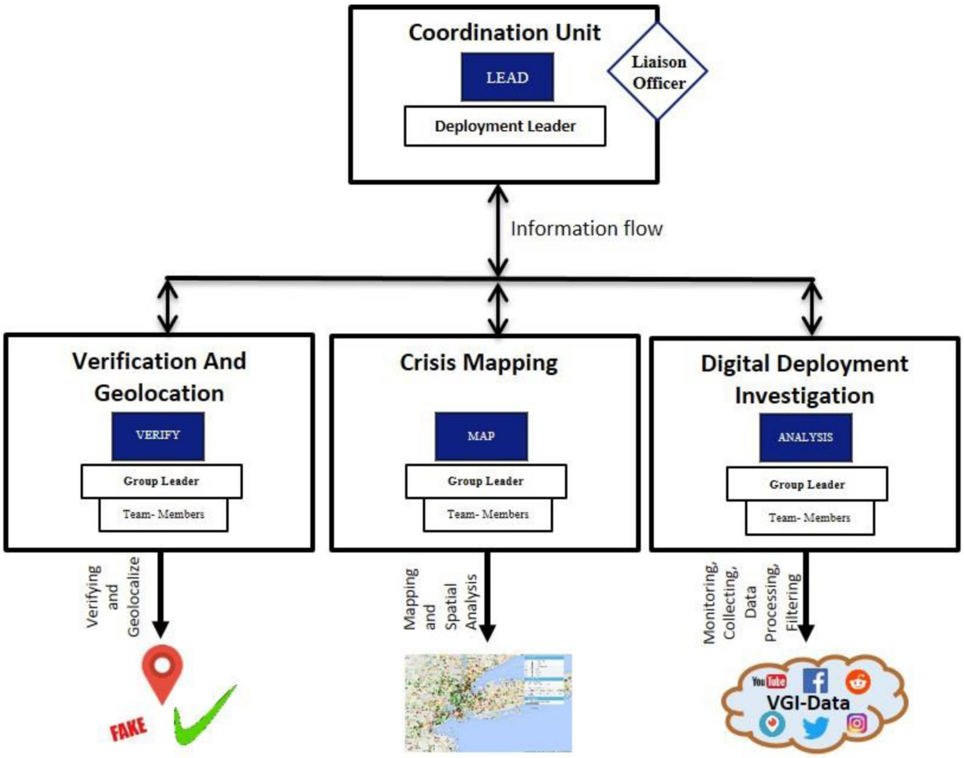

Fig. 6. Internal structure of the VOST during the *Grand Départ* 2017.

the structures specified by the deployment conditions. The result is an organizational structure that is hierarchical and in which responsibilities are defined. As seen in Fig. 6 central decisions are those made by the coordination unit, whereas decentralized decisions are those made by the individual group leaders for their working group. Central decisions also had a larger window of opportunity and were strategically located, whereas decentralized ones were shorter in time and tactical in nature. The last of the five organization dimensions refers to the formalization of an organization. For this scenario, certain formalization steps were introduced. Thus, communication processes and the hierarchical construct of the VOST were defined. The membership of all VOST volunteers in a governmental organization (THW), which is an emergency management agency, is also part of the formalization of this unit. A further characteristic is the tight integration into the decision-making process of the emergency operations center. However, the organizational requirements of a Virtual Operations Support Team must also be coordinated with procedural steps so that work goals can be achieved.

4.2. Procedural requirements for a VOST

Procedural requirements for the VOST must be divided into two areas. These include the internal processes on the one hand, while the procedural conditions of the requester on the other have to be taken into consideration. Some of the internal steps were described in Section 4.1. However, further additions have to be made here. The division of the VOST into task-related units leads to a need for coordination. Leadership concepts were developed in the preliminary phase of the deployment to be applied subsequently. Internal communication channels were defined within and between the working groups. External communication channels and the method of information presentation were also defined in advance.

It was determined that a briefing session would take place every hour during the operation in the form of a video conference. In this way, it was ensured that all VOST members had the same level of information. These briefings also made it possible to communicate changes to the work objectives. Due to the dynamic situation, permanent adjustments of the main tasks were necessary. In order to better communicate these changes to the VOST members, a so-called liaison officer was appointed. The liaison officer was required to gather information and summarize it in consultation for the VOST members. At the same time, this person was responsible for receiving situation-specific tasks from the EOC and providing technical advice. She held regular briefings with the coordinating staff and the decision-makers. The findings and work results of the VOST were summarized in situation reports and passed on by the liaison officer so that they could contribute to the decision-making process. During the deployment, specific tasks arose that were brought to the liaison officer via the decision-makers of EOC. Because the liaison officer was also on site, the task adjustments could be brought to the VOST Coordination Unit. The Coordination Unit decided on the adjustments and distributed the tasks to the responsible working group leader. When work results were achieved, the group leader communicated this to the Coordination Unit, which in turn created a situation report and forwarded it to the decision-makers via the liaison officer. These situation reports were

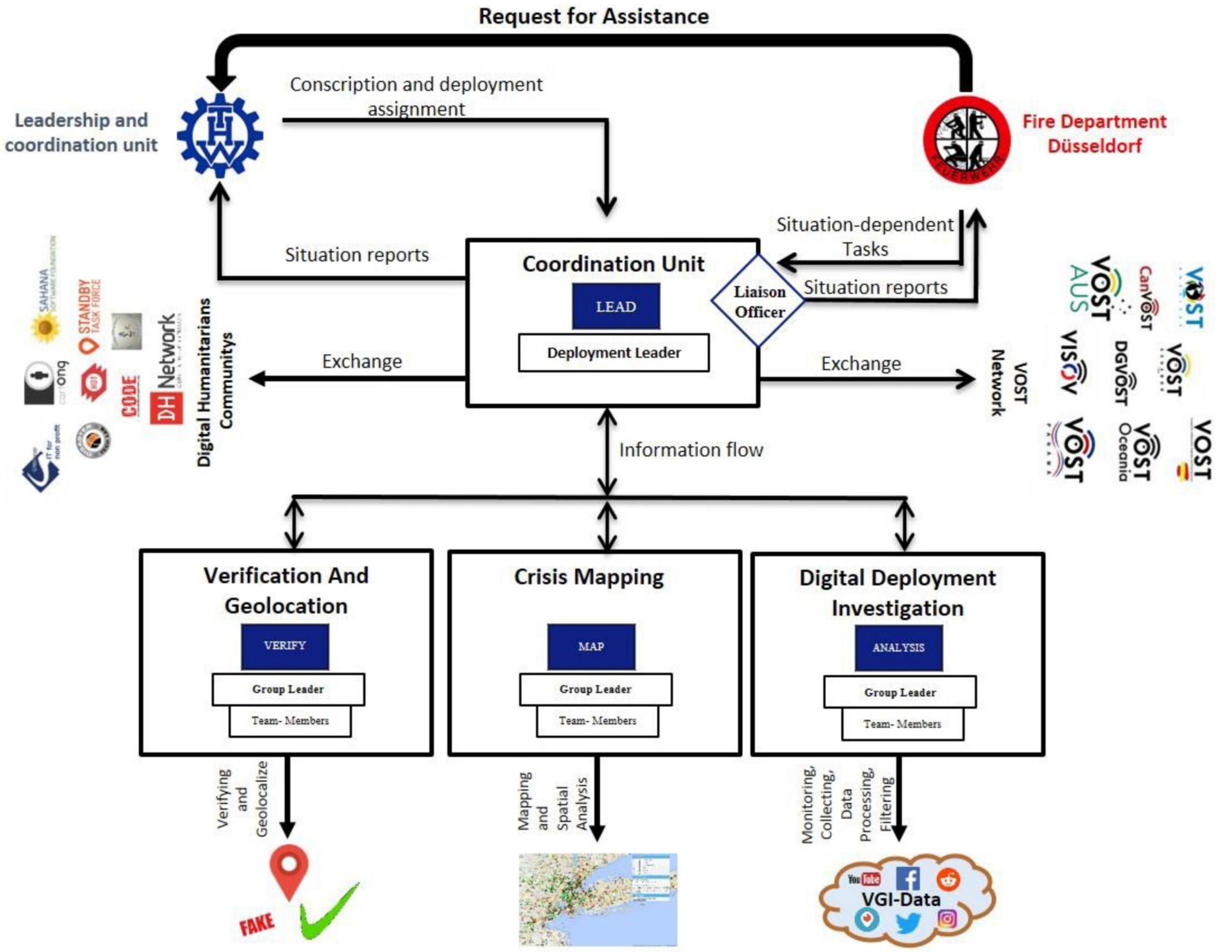

Fig. 7. Internal and external structure of the VOST during the *Grand Départ* 2017.

simultaneously sent to the Leadership and Coordination Unit of the German Federal Agency for Technical Relief. This ensured that all the decision-makers involved received the same information from the VOST. In addition, connections to other VOSTs were established in the planning phase of the deployment via the coordination unit (Fig. 6). While no further VOSTs were used during this operation, information was not exchanged until afterwards. Furthermore, the Coordination Unit has connections to digital volunteer communities. If large tasks had arisen during the operation, they could have been assigned very specific tasks. Fig. 7 shows the structure and procedural solutions for this case study of the *Grand Départ* 2017. The lower part shows the internal structure, for which the work areas of the individual working groups are symbolically illustrated. Above all, it should be clarified how information flows in an operation.

Identified findings relevant to the operation are collected, verified, geolocalized, and, if necessary, transferred to the Crisis Map. Subsequently, the Coordination Unit decides how the findings can be transferred into the decision-making process.

The first of these steps, the collection of findings - which involves large-scale extraction, aggregation, and filtering of information from various social media sources - needs to be strongly supported by advanced technical means. These means will be further detailed in the following section. Once the potentially relevant observations are identified, the subsequent steps, namely verification and possible geolocation, usually resemble more traditional information research patterns that should follow established procedures of information foraging and sensemaking (Pirolli & Card, 2005). Various researchers have discussed the challenge of validating the information contained in messages, photos, or video shared in social media (Brandtzaeg, Lüders, Spangenberg, Rath-Wiggins & Følstad, 2015; Hermida, 2012; Starbird, Maddock, Orand, Achterman & Mason, 2014; Zampoglou et al., 2015). Apart from the disaster management community, abundant research has also been conducted in the area of journalistic inquiry (Diakopoulos, Choudhury & Mor, 2012), as there is an increasing probability that breaking information or accurate insider accounts on a story are first discovered in social media. Generally, the verification procedures in VOSTs take inspirations from both of these communities and follow the general guidelines set forth by them in the recent past (Hiltz & Gonzalez, 2012; Silverman, 2014). Finally, the manual geolocation of information - necessary if this was not possible by automated means (Ajao, Hong & Liu, 2015) - as well as the curation into a Crisis Map (Shanley, Burns, Bastian & Robson, 2013) is often performed by meticulous analysis of details that can be found in individual messages, user profiles, or within a shared image.

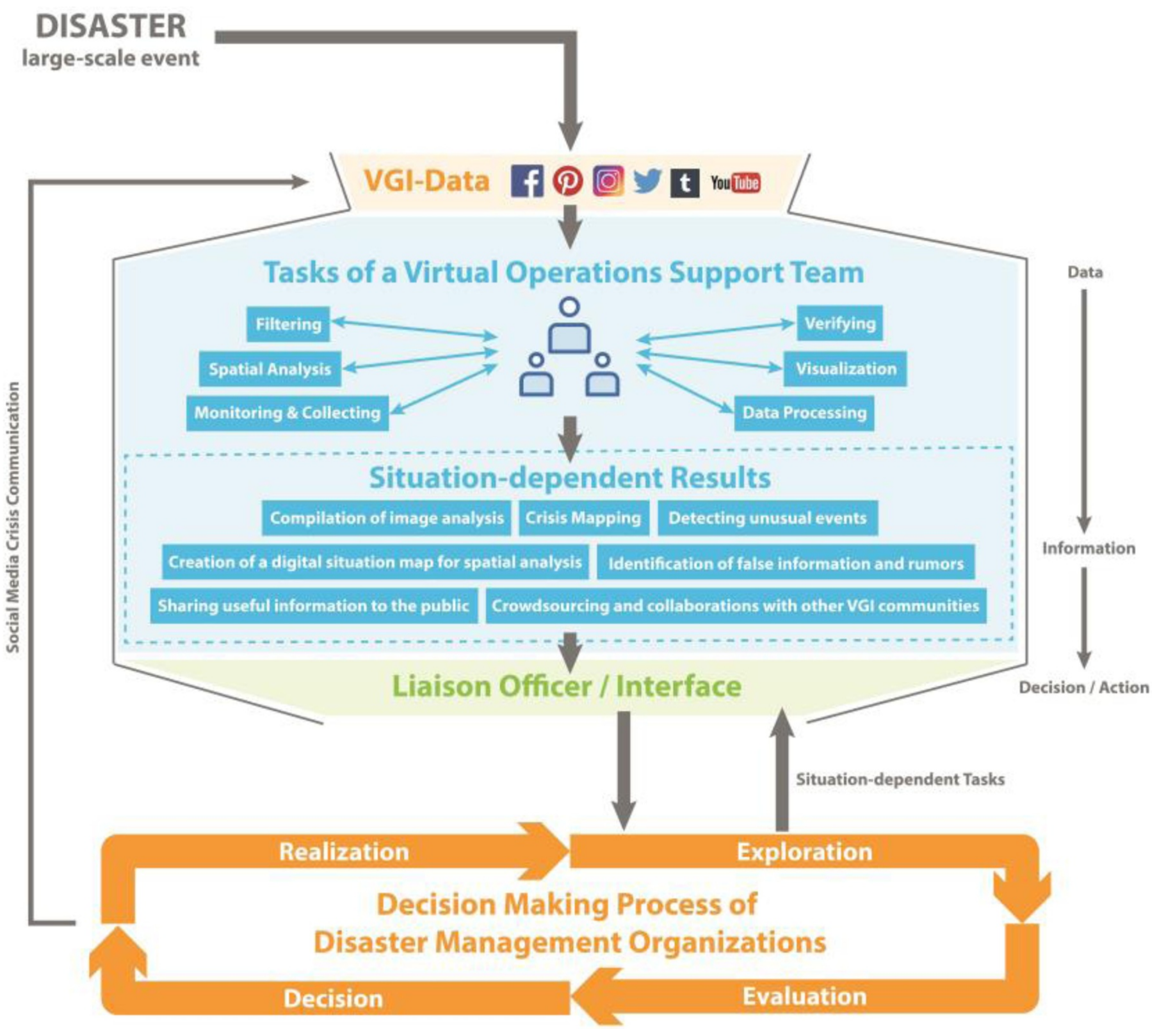

Fig. 8. Integration of a VOST into Disaster Management Organizations.

Both the structural and procedural considerations for a VOST in the context of decision-making in time-critical environments are illustrated in Fig. 8. The team uses a range of VGI data from Twitter, Facebook, Instagram and other data sources to conduct various tasks. These tasks typically include filtering, verification, spatial analysis or visualization. The team itself is often geographically dispersed across different locations and has a liaison officer who either works directly in the EOC or close by. The VOST creates actionable information for the disaster managers by detecting unusual events, creating Crisis Maps, aggregating image analysis, etc. To perform these tasks, the team may also collaborate with the more traditional, loosely linked VGI communities (SBTF, etc.) or other VOSTs.

5. Technical requirements for a VOST

Many social media sources[1] are potentially useful for gaining additional insights during conflicts, emergencies, and large event monitoring that are not available from traditional communication and information channels of involved organizations. In the scenarios presented in this work, Twitter, Facebook, and Instagram were identified as the most interesting sources. Such social media sources exhibit all the characteristics of big data including volume, velocity, variety, and veracity as it was characterized by Ming et al. (2014) and Wang et al. (2014). Due to these characteristics, it is nearly impossible to exploit information from social media sources during emergency and event monitoring in a timely, informed manner without using enhanced algorithmic tools and techniques. Subsequently, we describe and motivate the usage of interactive visualization tools during VOST operations, we reflect on

[1] Here we do not refer to social media platforms which were built particularly for being used during crisis response, but common social media platforms with a large number of users who might be visitors at a mass event or eyewitnesses of a disaster situation.

how the application of these tools can inform the organizational structure of VOSTs, and we identify remaining challenges and problems that can and should be addressed.

Volume of information in particular is a problem for most social media, where no clear distinction of posts about an event of interest, or only a weak one, is inherently available. As a consequence, filtering methods, automatic classification, and aggregation, e.g. through clustering, are inevitable steps to deal with these kinds of sources. Almost all social media platforms offer possibilities to let users restrict the number of contributions with respect to different characteristics. Unfortunately, such methods are often not optimal for supporting the collection of relevant information in the context of emergency and disaster management.

One reason for this is that many social network platforms are tailored to entertainment, propagation of newsworthy contributions, marketing purposes, etc. As a consequence, many of them are useful for getting overall trends or following certain users or groups of users. Unfortunately, it can be difficult to identify information which is relevant for crisis response. Such information can be of low frequency with respect to the number of postings on the same observation, it may report on rather small facts or aspects and it is therefore difficult to filter with search methods provided directly by the respective platforms. Some social media platforms allow to establish channels for specific events, such as hashtags. However, the contributions from such dedicated, topic-related channels can differ from what is required in emergency management. They are usually independently defined by the users of the platform and are frequently used in an incorrect or incomplete manner because their meaning is misunderstood, or they are even unknown to most users. A way to avoid this is using additional tools and systems with appropriate filtering and aggregation capabilities. For the described VOST deployment, the specifically developed ScatterBlogs system was used by VOST members, in addition to commercial tools for social media monitoring, such as TweetDeck[2] and HootSuite,[3] to extract information of potential interest. In this deployment, ScatterBlogs and TweetDeck were only used for Twitter. Instagram and Facebook were analyzed in a more manual search process that utilized the native query mechanisms of these platforms. Due to the restrictive data extraction policies as well as the limited public APIs of these services, it is currently doubtful when and how this challenge might be addressed with more powerful analytical tools.

5.1. The ScatterBlogs system

ScatterBlogs equips analysts with various interactive mechanisms including keyword-based, temporal, and spatial filtering as well as automated anomaly-detection techniques. In particular, mechanisms to understand spatio-temporal characteristics of reported observations are important for event monitoring (Reuter, Ludwig, Kaufhold & Pipek, 2015). ScatterBlogs is designed as a client-server system with a desktop client software used by each VOST member of the Digital Deployment Investigation working group individually and a server-based backend hosted at the University of Stuttgart. The design and development of ScatterBlogs have been extensively covered (Bosch et al., 2013) and evaluated (Thom et al., 2015) in previous works as well as in the works of other researchers (Bertone & Burghardt, 2017; Paul, Monica & Trishanka, 2017; Wanner et al., 2014; Wu, Cao, Gotz, Tan & Keim, 2016). This section only provides a brief summary of the features and capabilities of the system to help the reader understand how the tool supports VOST members in their work. ScatterBlogs provides a highly interactive user interface enabling real-time analysis of the data stream provided by the backend. It comprises six major areas organized in an integrated multi-view configuration, as can be seen in Fig. 9.

The views are interconnected by a brushing and linking scheme enabling a distinct range of capabilities:

1 Map View - ScatterBlogs puts a major focus on the spatial aspect of the data and specifically supports geo-centered analysis. The large map in the center consequently serves as the primary view and interaction canvas for the user. The map is based on OpenStreetMap and can be freely zoomed and moved by the user. Every time, a new social media message is posted, collected by the backend, and assigned with a geographic location, this location is immediately highlighted as red dot on the map. A brief ripple-like animation furthermore indicates the arrival of such new data to the user. The user can select sets of messages by drawing a bounding polygon directly on the map. These messages can then be specifically highlighted in the other views. The Map View can be switched to Anomaly Detection Mode, where potentially relevant events automatically detected by the system are shown as labels directly on the map. To this end, the ScatterBlogs backend automatically selects one or more representative words from each event, which are then visually placed at the detected event location. In lower zoom-levels, smaller events are automatically aggregated and one representative term for all events is selected.
2 Timeline View - An overview of message frequencies over time is shown in the Timeline View panel. This can also be restricted to sets of messages that had been selected in the map view. Additionally, the timeline view illustrates the relative share of messages with positive (green), negative (red) or neutral (blue) sentiment.
3 Content Table - If one or more messages are selected in the Map or Timeline View, the content table highlights the textual contents of these messages along with additional attributes such as timestamp or message author.
4 Control Panel - The control panel allows to enter keywords in order to select and show only the messages in other views that contain the keyword. It furthermore provides a range of controls to change the behavior of the various views, e.g. activating/deactivating the anomaly map mode or the Content Explorer.
5 Content Explorer & Content Lens - The user can activate a manual content exploration tool, which works as a magnification lens

[2] https://tweetdeck.twitter.com/.
[3] https://hootsuite.com/.

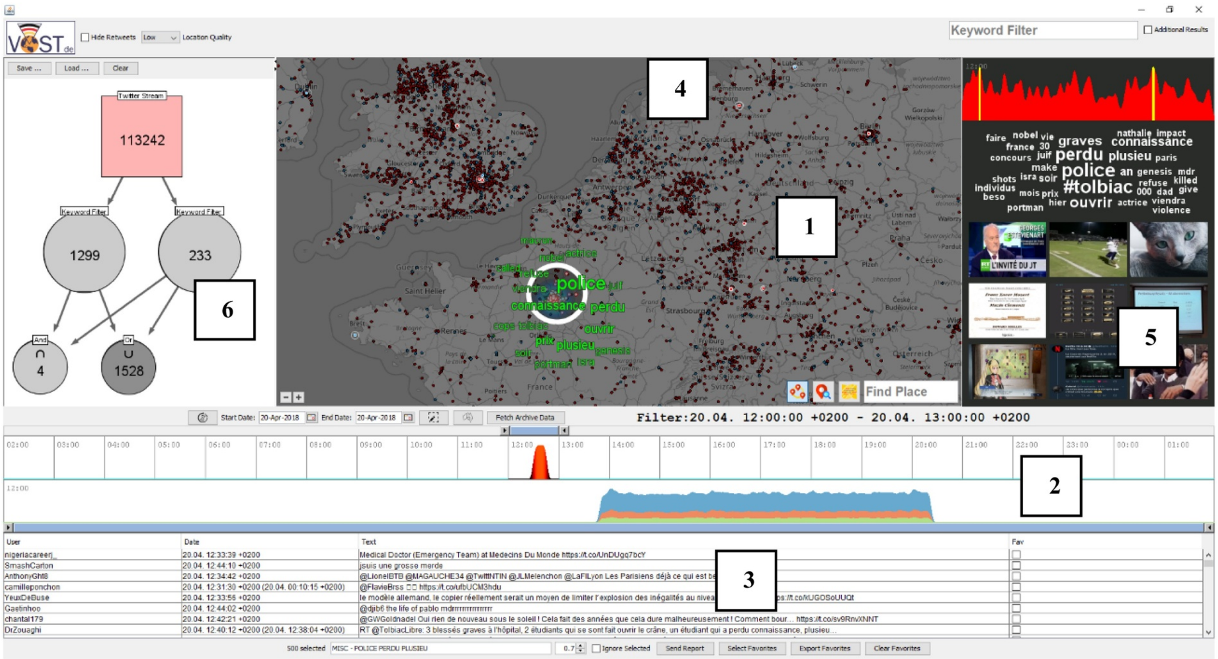

Fig. 9. The ScatterBlogs frontend.

metaphor on the Map View. When the user moves the lens with the mouse pointer, the messages under the lens are analyzed and the most frequent terms (excluding stop words) from these messages are shown as word cloud around the lens (Bosch et al., 2011). When the user clicks with the mouse pointer, the lens is permanently placed at the current location and adapts to real-time data updates in that area. Furthermore, the Content Explorer panel on the right shows an aggregated summary of messages from the area. In addition to a more detailed word cloud, it presents the user with a temporal signature of these messages and also selects the six most representative images that had been attached with these messages by the users.

6 Selection Management View - The selection mechanisms used in the other views, such as keywords, temporal ranges, or geospatial bounding polygons can be stored as visual nodes in the Selection Management View. The user can use these nodes to activate and deactivate these selections. Furthermore, the user can create Boolean combinations of the selections by connecting the nodes with each other and with specific operator nodes. For example, the user can create a Boolean ``AND” combination between a keyword selection and a geographic selection. The result of this combination can then again be connected with other nodes to create more specific filters.

ScatterBlogs primarily helps to manage and control the number of social media contributions effectively, without overloading VOST members with too much information at once. Of course, this observation has to be seen in the context of an event-monitoring situation in which no severe emergency has occurred (Thom et al., 2015).

6. Observations from the *Grand Départ* deployment

The following results are based on retrospective qualitative evaluations within the VOST and on group discussions (Section 3.2) with the focus group and the decision-makers in the operation.

6.1. Observations on situation monitoring

To prepare for the social media monitoring during the event, the VOST members had collected keywords, hashtags, and user-names of possible relevance in a Google Sheet in advance. The selection of keywords and hashtags mostly consisted of event-specific terms, such as *#Letour2017*, location-specific terms, such as *Rheinkniebrücke*, and more general crisis-related terms, such as *terrorists* or *(active) shooter*. The list of user names primarily contained the social media accounts of local authorities, local news media, and the event organizers. The monitoring strategy was to use these keywords as the basis for an initial search and to extend the list further on the basis of the observations and indications provided in the retrieved messages.

In the course of the *Grand Départ* event, various individual findings and ongoing trends had been detected using ScatterBlogs and the additional commercially available tools. In the initial phases of the event, the weather was rather clouded and rainy and so reports on social media mostly revolved around the low density of audience along the track (Figs. 10 and 11). That situation changed shortly before the beginning of the event (Fig. 12).

Fig. 10. Initial observations about crowd density collected from Twitter with ScatterBlogs.

Fig. 11. Initial observations about crowd density collected from Twitter with ScatterBlogs.

Such observations were usually made using keyword-based approaches and the selections defined during preparations for the event. Here, the team members experienced a major challenge in keeping the lists up-to-date as well as keeping in synchrony with contributions of others. Although the Google Sheets document allowed to share and see updates of others immediately, the updated keyword-lists still had to be manually copied repeatedly from the sheets into the different monitoring tools. To document and report possibly relevant findings, another Google Sheet was used. For the monitoring activity, the team followed the assumption that any finding and observation can be at least associated with a timestamp of discovery, as well as a URL identifying the corresponding resource, such as an individual website, tweet, image, blog post, etc. In addition to these two attributes, the prepared Google Sheet contained optional columns for the (geographic) location of origin, the type of content, the type of observation, and reasons for highlighting the finding. The type of observation was taken from predefined categories, such as CROD for crowd behavior or MEDI for media reports. Furthermore, each finding could be associated with a level of severity that was either green, yellow or red. This document was primarily used to share observations within the team and to allow a collaborative assessment of the relevance and severity of the findings. On this basis, the team leader selected information and compiled regular summaries to be given to the liaison

Fig. 12. Later observations about crowd density.

officer.

While sharing within Google Sheets worked well, the team was slowed down by the effort of manually copying information from the tools back to the document. During this process, which might take between 2–5 min per observation, the actual monitoring is paused and the analyst has to skim through the accumulated messages quickly once she returns, while keeping up with new information. This leaves some room for error if the analysts overlook relevant messages.

Overall, the *Grand Départ* passed without any major incidents, problems or other anomalies. Apart from the reports on the formation and dissipation of crowds before, during, and after the event, only minor acts of vandalism or opinions on the organization of the event were discovered by the social media monitoring group (Fig. 13).

The variety of social media sources is an issue that immediately arises if different social media platforms are monitored. This was the case with Facebook and Twitter during the described VOST operation. Here, solutions that integrate different social media channels are certainly beneficial for a number of reasons. Reuter et al. (2015) indicate that integrating postings from different social media channels in a single interface is beneficial during event monitoring.

With HootSuite and ScatterBlogs, two different approaches were used that integrate more than one social media source. Here, the existing familiarity of VOST members with different tools had to be taken into account and so different tools were used simultaneously. From our perspective, it is currently still unclear whether a harmonization or restriction to a single interface for social media monitoring has sufficient benefits to justify the costs of familiarization with a new interface.

As stated above, velocity and dynamicity can be an issue when dealing with social media. Dynamicity, which makes social media a relevant source for emergency management, makes a continuous adaptation of filters and other retrieval techniques necessary. Inadequate filters quickly lead to situations in which VOST analysts are flooded with postings that can no longer be inspected and assessed in a timely manner or situations where large amounts of potentially interesting information cannot be found at all. While the first problem becomes immediately visible, the second one is harder to detect and address. The ScatterBlogs *system helps to monitor numbers of posts with its options* to combine filters (Fig. 9) and additional animated charts to illustrate changes in numbers. This turned out to be very useful for the real-time monitoring of situations during the VOST operations.

6.2. Observations on crisis mapping and verification

A Crisis Map was established by the VOST using Google Maps. It provided an interactive illustration of where critical crowd densities or crowd flows arose or were expected to arise (Fig. 14). In part, predictions were made about the places that are particularly attractive to visitors and where to expect a high crowd density. This was realized with the help of image analysis, the analysis of frequencies in the posting behavior of visitors, and the calculation of crowd densities. If information from social media about a high crowd density were frequently found in one place, this would have been passed on to the decision-makers by the situation reports. In addition, the Crisis Map showed positions of webcams, accident rescue points, a mobile fire department, live open-air screening events, vehicle gateways, pedestrian bridges, and all relevant georeferenced and verified situational information from social media.

Fig. 13. Observation of event-related vandalism.

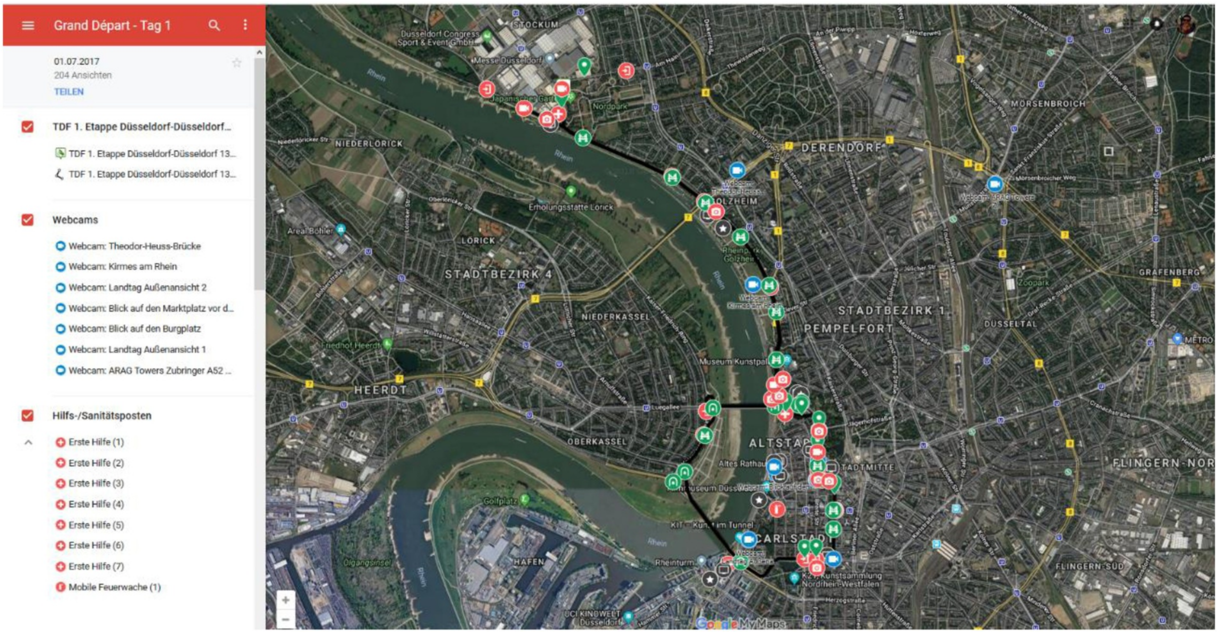

Fig. 14. Crisis Map for day 1 of the deployment. It shows the track that had to be followed by the athletes together with viewing spots and POIs along the route as well as some initial potentially relevant social media entries.

Fig. 15. Highly relevant post about police officers on a roof.

The insights from social media on the Crisis Map were accessible at any time for the liaison officer and could be correlated with the reports from other sources of information, e.g. a comparison using surveillance cameras. The Crisis Map was constantly updated during deployment by a subunit (Fig. 6).

The amount of online discussion among the VOST members on the entries and updates to the Crisis Map showed that this task generated a considerable workload. It seemed highly important to all members of the mapping group that communication channels and data preparation must be consistent so that information can be transmitted as precisely as possible. In this regard, one of the biggest challenges consisted in manual geo-parsing of media-based data, such as photos and videos provided in social media posts. Although automated solutions like ScatterBlogs sometimes provide indication where the post might have been created, manual assessment always had to follow before an entry could be added to the Crisis Map. To this end, the VOST members usually investigated the history of individual users and/or the contents of a given image to assign a most probable location. In most cases, only the latter approach yielded trustworthy results. Many pictures taken during the event contained landmarks that could be unambiguously identified using additional tools like Google Street Maps or by matching it with live footage from ongoing TV reports.

The key role of the Verification and Geolocation working group became particularly visible in the following example. It was possible to identify a picture showing people on a rooftop wearing ski masks (Fig. 15). The user, writing in Dutch, indicates that he feels safe because the event seems to be well guarded by the authorities. However, such a picture can be misused to cause trouble, particularly as it is not clear whether the persons depicted were actually police forces. The working group verified the picture and found out on which building roof the masked officers were located. By consultation with the decision-makers, it was possible to determine which police unit was being set up there. If this photo was to be used incorrectly, for example, in the context of rumors or fake news, the decision-makers would have been able to quickly publish a correction. Through this multi-faceted work, the image, which was detected by the Digital Deployment Investigation group, was transferred to the Crisis Map.

As described in Section 3.2, the identification of critical crowd densities and the identification of critical crowd flows were defined as working priorities, among other things. One of the many recorded verified and geolocalized posts can be seen in Fig. 16. In the image, one can observe spectators standing still in one place and watching the action. There is also an open space to be seen where participants can move around freely. A critical crowd density or critical crowd flow cannot be observed. After comparing this information with other sources, a critical situation could be ruled out. Event participants are standing still in one place and are watching the action. There is even an open space to be seen where participants can walk around. A critical crowd flow or density cannot be determined. After comparing this information with that from other sources, it could be established that these findings were identical.

6.3. Observations on structural and procedural integration

As explained in Section 3 and further expanded in Section 4, the VOST prepared in structural and procedural terms for the event. Various observations were made during the deployment, which are outlined below.

Fig. 16. Image that was used for identification of critical crowd densities.

6.3.1. Observations on structural integration

The high coordination effort required by digital communication is due to the distributed mode of operation of VOST and takes up much of the deployment leader's time. Due to the dynamic working environment, spontaneous coordination as a reaction to the situation was observed on both days. The liaison officer, who connected the emergency operation center and VOST, periodically reflected developments in operational procedures to the VOST members. This periodic mirroring was also realized in hourly held meetings and enabled situation-specific work assignments to be taken up and forwarded to VOST for processing. Although the VOST has a hierarchical structure, the distributed decision by the group leader resulted in spontaneous and special working groups. These groups received a specific individual assignment and worked through special tasks for a defined period of time. After completion of this assignment, the group was dissolved and the members were returned to their original structure. This method of dynamic group member structuring could also be observed in the work peaks of a single group. In several cases, this also occurred at the suggestion of individual group members.

It was also a time-consuming task for the group leaders to integrate members from the break into the work. This was partly done with the help of more experienced group members. Even when the temporary special groups were subsequently dissolved, these communication channels continued to exist. Thus, on the second day of operation, numerous members accumulated a number of communication channels.

6.3.2. Observations on procedural integration

The aim of the procedural steps was above all to integrate the findings of the situation monitoring seamlessly into the decision-making process (Fig. 8). For this purpose, concrete information flows were defined with the decision-makers (Section 4.2). These steps include the transmission of relevant information from VOST to EOC and the assignment of specific tasks from EOC to VOST. The VOST prepared regular situation reports in which all relevant results were visualized according to the defined main tasks. These reports helped decision-makers to use the information to assess developments and take action. Through numerous consultations with the EOC staff by the liaison officer during the GD, it was pointed out that this procedure is suitable for non-emergency situations. For actual emergencies, it was already agreed during preparation that no time should be lost by writing situation reports. For this reason, time-critical information was sent directly through the liaison officer to the responsible decision-makers. In such cases, there was no time-consuming preparation of the information, such as a visualization or an analysis in the usual situation report. In time-critical situations, when the information was not processed but communicated directly to the decision-maker, numerous inquiries followed. The questions frequently included:

- The exact date of publication of the information.
- Exact geolocalization of the information.
- Verification of the information.
- Findings in comparison with information from other information sources.
- Estimation of the trust of the user.

All these observations were made by us, were documented on site and were reviewed in the focus group discussion with the EOC staff after the GD deployment. The three requirement areas (structural, procedural, technical) were systematically discussed.

7. Lessons learned and discussion

In order to derive relevant lessons learned from the joint observations of the VOST and the EMAs and to address research question **R3** (see Section 1.2), the results were summarized in a focus group discussion. Overall, the results of the focus group show that the VOST deployment was seen as very useful and successful. The relevant findings were prepared in an effective way and then made available to the decision-makers on time. Through the defined working groups and the decentralization of the tactical decisions, situation-related findings could be forwarded quickly and appropriately to the decision-makers. The one-line system made the hierarchical structure comprehensible to the EMA and other organizations involved and improved over time. For example, on the first day, the situation reports of the working groups were evaluated and summarized every hour by the deployment leader and by the liaison officer. The results of these situation reports were subsequently submitted to the briefings with the EOC. After the first day, it was found that this procedure creates routine and summarizes work results adequately. Thus, it was continued on the second deployment day. The fast transfer of time-critical information via the direct path has also proven its worth despite of the communication overhead caused by subsequent queries. In addition, it was soon discovered that reconciling information from social media with that from conventional methods (e.g. field response, surveillance cameras) was insightful. This allowed differences to be identified and developments to be anticipated earlier than with conventional methods.

Structural and procedural findings (**R1**) were derived from the observations through the post-processing of the deployment in the focus group discussion. Thus, the initial formation of three small working groups proved to be a suitable group size for this concrete GD deployment. This allowed the individual group leader to distribute tasks to the members in a better way. The possibility of forming specialized work subgroups during the deployment, depending on the situation, made it possible to react dynamically to unexpected developments. These findings correspond to those acquired during a forest fire in 2011 (St. Denis et al., 2012). Through the exchange of information at the level of group leaders, it was possible to divide VOST members between the groups during peak periods or when temporary special groups were formed. After the first day, the individual working groups held independent debriefings and were thus able to make initial adjustments for the second day. In this way, adjustments could be implemented better and more quickly. Due to the division, a layer system could be created. This ensured the usefulness of the VOST throughout the entire operation. The implementation of a liaison officer has proved to be the key to success for all decision-makers on the EOC side, but also for VOST. By being present in the EOC himself, she is much closer to what is happening and can inform the decision-makers directly and without any loss of time about relevant findings.

7.1. Challenges, obstacles and anomalies

Apart from the individual findings reported in the previous sections, there have been various recurring technical challenges, obstacles and anomalies that we observed throughout the VOST deployment (**R2**).

For example, it quickly became apparent that the general frequency of social media posts, especially from mobile devices, considerably increased during the event compared to the timeframe before and after. Naturally, this behavior can be explained by the fact that more people had gathered on the streets than usual to participate in the event and that there was something publicly happening to report, take photos of, and talk about. Nonetheless, this observation must be taken into account if the prediction of potential numbers and density of on-site information sources during a critical event is based on average volumes from past data.

Another interesting observation relates to the difficulties of gathering useful information from casual footage provided in the social media posts. As highlighted in Section 3.2, the analysis and tracking of the location, size, and density of crowds was one of the core tasks during this deployment. Usually, the monitoring team found multiple photos, or even live videos, made by citizens who were part of a larger crowd or standing in its vicinity. Naturally, however, it is rarely the intention of these casual photographers to provide objective data about the crowd, but to share their subjective experience. Thus, the images usually depict the athletes, the user's friends, or other attractions in front of the crowd and only a small fraction of it is actually visible in the frame. Such imagery therefore provided only a very limited perspective on the crowd as a whole and virtually no solid basis to estimate its actual size and density. However, the images still provided an early indication of the general presence and formation of larger crowds and their specific locations, which was already a useful insight for the decision-makers.

Finally, despite the more automated data mining tools used during the deployment, keyword-based filtering, investigation of individual posts, and continuous manual updates to the keyword lists still constituted a significant part of the workload of the VOST analysts. Although, in this deployment, they were confronted with a largely uncritical event, the situation was still constantly evolving and sometimes dynamically changing in terms of topics and themes observed in social media. During the larger event, there were many sideshows and smaller events that often led to the use and dissemination of completely new hashtags and keywords flagging potentially relevant observations. In particular for data mining models that were statistically trained on past data, it is often hard or even impossible to accommodate such sudden changes in the set of textual entities and to correctly assume their meaning and relevance to the main event.

7.2. Prospects for technical development

Our observations indicate that there are multiple aspects that should be considered in the future research and development of technical support for VOSTs (**R4**). Various authors have highlighted how automated data mining tools, such as AI-assisted data prefiltering, aggregation, and anomaly highlighting are an integral part of time-critical decision-making. However, the currently available tools, including ScatterBlogs, are often complicated to use and, due to their black-box nature, the results are not always considered trustworthy by the users. This observation further supports existing findings by Kaufhold et al. (2019), who suggest the use of white-box approaches. Also, if the usability barriers of a method are too high or if the results are difficult to understand, the users, in this case the VOST members, usually fall back on their more traditional, hands-on means of analyzing the available data. Due to the size of available data, manual analysis usually amounts to an incomplete sampling of information based on subjective preconceptions about the situation at hand. If messages are only retrieved using keywords and hashtags that happen to be known/considered by the VOST and if the results are manually investigated, only a very small subset of available data will actually be covered. Thus, the manual method poses a high danger of ignoring potentially relevant observations that could lead to better decisions.

From our observations about using ScatterBlogs and the other tools in the deployment, we learned that it might be helpful to follow a more bottom-up approach of designing the automated parts of visual analysis systems instead of the top-down method that has been often used so far, particularly in academic research. For the tools to be accepted, they should support and tightly integrate with the typical information research processes that we usually already find in a time-critical decision-support team like the VOST. This is in line with propositions of Stieglitz, Mirbabaie, Fromm, et al. (2018a) who argue that social media analytics tools need a high degree of usability and customizability to find acceptance by the users. From the case study we identified three areas of system design where further development seems to be promising:

1 **Support for collaborative research**: As highlighted before, keywords and hashtags to search for were collected and organized in lists prior to the deployment. During the deployment these lists were then constantly extended based on new information that became available and the updates have to be shared and communicated to all team members. An interactive system could support this process in various ways. First of all, based on the nature of the event, the system could offer to collect and automatically analyze data from prior spatio-temporal frames, where similar events have happened. Based on this analysis, the system could then compile lists of keywords and hashtags that have been more frequently used in these frames, which indicates that they might be of specific relevance to the type of event. In addition, the system might automatically detect events in archived data that bear similarity to the current event to further support the curation and adaptation of meaningful keyword lists. Finally, the system could be integrated with interaction and communication means that are specifically tailored to the collaborative management of keyword lists and investigation of results. This might include better means for role-based editing rights, change notifications, interactive task-oriented division of work, and ways to export and import the data to and from other tools.

2 **Support for visual information sharing**: Another highly time-consuming task for the VOST consisted in the manual transformation of analytical insights into elements of the Crisis Map as well as parts of oral or written reports provided to the authorities. Here, it might be useful to support the creation of maps and reports in a more automated manner. For example, it would be beneficial if individual posts found in ScatterBlogs could be marked to be transferred to a comprehensive report document or to be included as an entry into a predefined Google Map. Also, the analytical path that brought the investigator to some particular conclusion could be documented and possibly reported as well. This includes the individual keywords that have been used to find some messages, the incorporation of semi-automated techniques in her analysis, as well as the communication and consultation with other team members and group leaders.

3 **Support for image analysis**: During the deployment, the many photos and videos provided by on-site reporters proved to be one of the most valuable sources of information for the team. Compared to just textual information, a picture provides an immediate and often verifiable indication about the situation at some relevant location. However, especially the verification of the images up to some acceptable level of trustworthiness involved time-consuming tasks, such as cross-correlating multiple images from the same location or user, identifying possible landmarks in the picture, resolving geo-locations of these landmarks, and checking if the same picture has already been posted in other or earlier instances. We think that at least some of these tasks could be better solved by automation as well as integration with the existing tools. To this end, the works of Alam, Ofli and Imran (2018a) (see Section 2.2), who provided a multimodal dataset and crisis-related annotation called CrisisMMD, could be a good starting point.

4 **Interoperability vs. holistic systems**: Looking at the broad variety of tools used by the VOST, ranging from documentation in Google Maps, and Google Sheets, over media monitoring tools like ScatterBlogs and HootSuite, to communication tools like Slack and Skype, the creation of a jack-of-all-trades system would probably not be a promising option. Such a tool might at some point cover every aspect of VOST work, but it would quite probably be inferior in each individual aspect compared to the specialized solutions. It is thus likely that the VOST members might regress to using the specialized tools for certain tasks, which would again create the known incompatibility and integration issues. However, during the GD deployment, it became apparent that monitoring and filtering observations from social media often constitutes the very core and usually the onset of any subsequent VOST effort. What has been collected there usually serves as the input for verification and crisis mapping. We therefore think that the most promising approach would be a base system, which supports that aspect very well, while at the same time ensuring integration with existing commercial or open-source tools as well as powerful import and export functionalities that allow interoperation with specialized tools and future research prototypes.

7.3. Discussion

As already mentioned, the operational situation during the field study was not an emergency. Due to the nature of a large event, the structures of the EMAs were prepared for a major operational situation. For this reason, it was possible to develop concepts, methods, and requirements by means of long-term preliminary planning, which could be tested in a structured manner in practice. However, all structures had been designed to best respond to a disaster or large-scale situation. The VOST was able to use these conditions to test its structures, processes and technical tools. The organizational integration in the processes of information-gathering and decision-making could also be tested in this way. Nevertheless, it is challenging to transfer all findings directly to other scenarios and operational situations. This is especially true for critical situations, as they involve many other influencing factors, such as emergencies or life-threatening situations, which were not encountered in this deployment. Nevertheless, due to the special conditions and the operational integration, insights for such emergencies can be derived.

Most importantly, due to our participation in the GD deployment, we were allowed to acquire a first-hand account of the actual tasks and routines that are performed and that generate workload in a typical VOST deployment. Following our initial research questions, these insights can be summarized as follows:

- **Structures & procedures (R1)**: It is a core novelty of the VOST concept that the group is tightly integrated in terms of structure and communications with the established emergency operation center and city authorities. The operational involvement means that the volunteers have a closer integration into the processes than V&TCs do. The analysis in time-critical environments can be implemented faster and integrated more effectively into the decision-making processes. However, new challenges are developing as a result of remote work, also with regard to occupational health and safety. Working alone at home means that communication with colleagues and coordinators can take place only via technical communication devices. This may make the communication of potentially stressful situations arising from the operation more difficult. The monitoring of obligatory break times is also a new challenge arising from virtual and remote work.
- **Automated systems (R2):** As already highlighted in the previous sections, some tasks could be better supported with automated tools, while other tasks, especially comprehensive social media monitoring, are virtually impossible without such tools. We also found that a carefully designed and reliable user experience, custom-tailored to the typical and very special tasks of a VOST, is even more important than to provide novel and more powerful mining capabilities. The team members need to be able to trust the tool in stressful situations and know that it will not significantly increase their already high mental workload. Only then can it be an actual opportunity instead of an additional obstacle in their relief efforts. We thus encourage researchers and developers to seek out partnerships with the various VOSTs and similar digital crisis response initiatives that are currently emerging around the world. Making sure that system design is shaped early on in the process by the actual requirements of the responders and repeatedly putting it to the test in real-world deployments is the only way to ensure that the algorithmic innovations become beneficial in a meaningful way.
- **Task types and workload (R3)**: We learned that the collection, filtering and documentation of user-generated content in the various social media platforms constitutes one of the most time-consuming tasks for the VOST members. At the same time, this task often turned out to be mentally demanding in multiple ways. For one thing, due to the volume of data as well as the specific language used in social media, the analysis team can hardly ever be sure if they successfully identified all potentially relevant content and whether they acquired an adequate situation picture. While checking the correctness is part of the subsequent analysis done by the verification team, ensuring the completeness of information the most vital challenge for the monitoring team. As this task has to be performed in a stressful and time-critical environment, it can only be completed successfully if it is based on through preparation and supported by advanced data mining tools. For another thing, although challenging, the task of situation monitoring turned out to be highly repetitive and mostly involves the steps of adapting filters, manually reading content or checking derived statistics, as well as documenting possible findings in a continuous loop. Our observations showed that a single analyst can only perform this procedure for a very limited amount of time before a second shift has to take over. Also, during the phases of filter adaptation and result documentation, new social media content still accumulates without being immediately investigated. Sometimes that amount can even exceed the capability of the analyst to catch up in the given amount of time and she has to refrain to a broad sampling of the data, which again increases the chance of overlooking relevant information. Thus, as the situation monitoring has to be continuously maintained throughout the deployment, it turned out to be vital that the VOST planned the monitoring shifts ahead of time and made sure that at least two analysts are always available for monitoring at any given time.

The other tasks of the VOST members primarily revolved around crisis mapping, information verification, and communicating the social media based situation picture to the EMA. While being highly challenging, these tasks also involve a higher degree of mental autonomy and alternation. Especially the crisis mapping and verification work resembles the typical modus operandi of journalistic inquiry. For example, quite often, the analysts have to come up with clever ideas about which parts of a given image can be used to correlate it with additional information or geographic locations. Nonetheless, this type of analysis can be time-consuming, which also becomes stressful if it has to be performed in a time-critical environment. Our observations showed that this demand can, to some degree, be mitigated through close collaboration and a high degree of communication among the group members. This is somewhat different from the Digital Deployment Investigation group, which needs a certain team size to ensure redundancy and completeness, but also allows more isolated research efforts of its individual members. Since the group members of the crisis mapping and verification teams also work in remote locations, it was very important for the groups to have adequate and stable forms of communication.

8. Conclusion and outlook

Performing sophisticated social media analysis to inform the decision-making in emergency management is a highly challenging endeavor. Thus, this valuable information channel has rarely been utilized in a comprehensive fashion so far. At the same time, numerous emergencies and crises have demonstrated how the proper monitoring and analysis of social media can considerably improve situational awareness (Fathi, Brixy & Fiedrich, 2019; Starbird et al., 2014). With a novel form of structured and properly equipped digital voluntary effort, the Virtual Operations Support Teams have shown that this capability can successfully be established in real-world settings. Once the structures have been developed, they can even be activated in time-critical environments.

The goal of this paper was to give the reader a first-hand account and in-depth insights into the procedures and structures as well as the distinct challenges faced by these newly formed voluntary initiatives. While previous research was mostly focused on technical aspects of social media monitoring under lab-conditions, our field research allowed the practical observation and understanding of digital voluntarism during an actual deployment. It is due to the nature of this type of study that the scientific generalizability of our findings is limited compared to more controlled types of experiments. However, we think that our observations can help to achieve a clear view of the real-world decision-making process as well as deeper insights into the more nuanced aspects of time-critical situation analysis in social media. We think that neither a controlled laboratory study nor a post-analysis of deployment documentation could have yielded similar results. While the former could hardly represent the effects of time-critical urgency in an accurate fashion, the latter would always be based on summarizing reports and thus often omit exactly the nuances in procedures and challenges we wanted to represent. Based on the unique opportunity we were given by the German VOST, we hope to inform and inspire the scientific community and provide a solid basis for future research in digital voluntarism.

As mentioned before, this deployment was a planned event instead of an ad-hoc emergency and it did not turn into a critical situation at any point in time. It might be particularly challenging for the VOST to provide the same resources and level of thoroughness of their analyses in an ad-hoc emergency or even a large-scale disaster. Naturally, it would also be highly valuable to observe and document the VOST effort from a scientific viewpoint in such a situation. In the past, it turned out to be challenging to realize a similar kind of embedded field study in an ad-hoc situation as opposed to what is possible at a planned event. Nonetheless, we will continue our cooperation with the German VOST and look forward to obtaining more extensive insights while also covering more critical situation analysis in our future work.

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5.1.2 Study II

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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

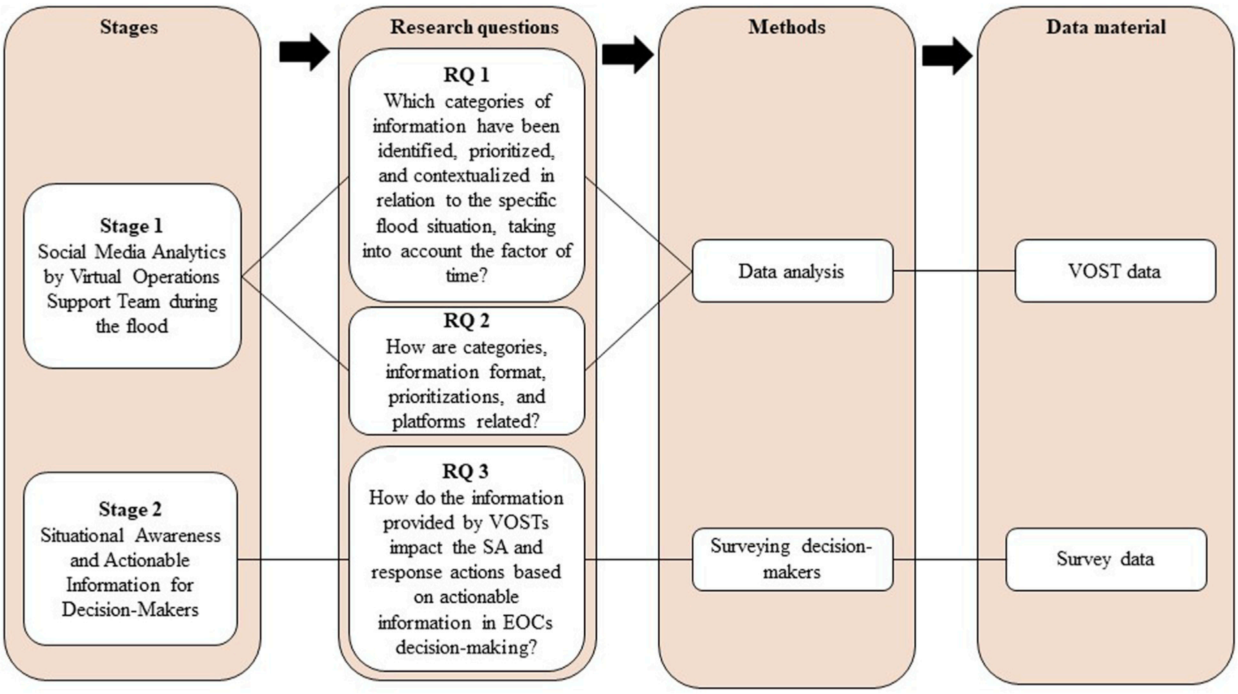

FIGURE 1
Research design.

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

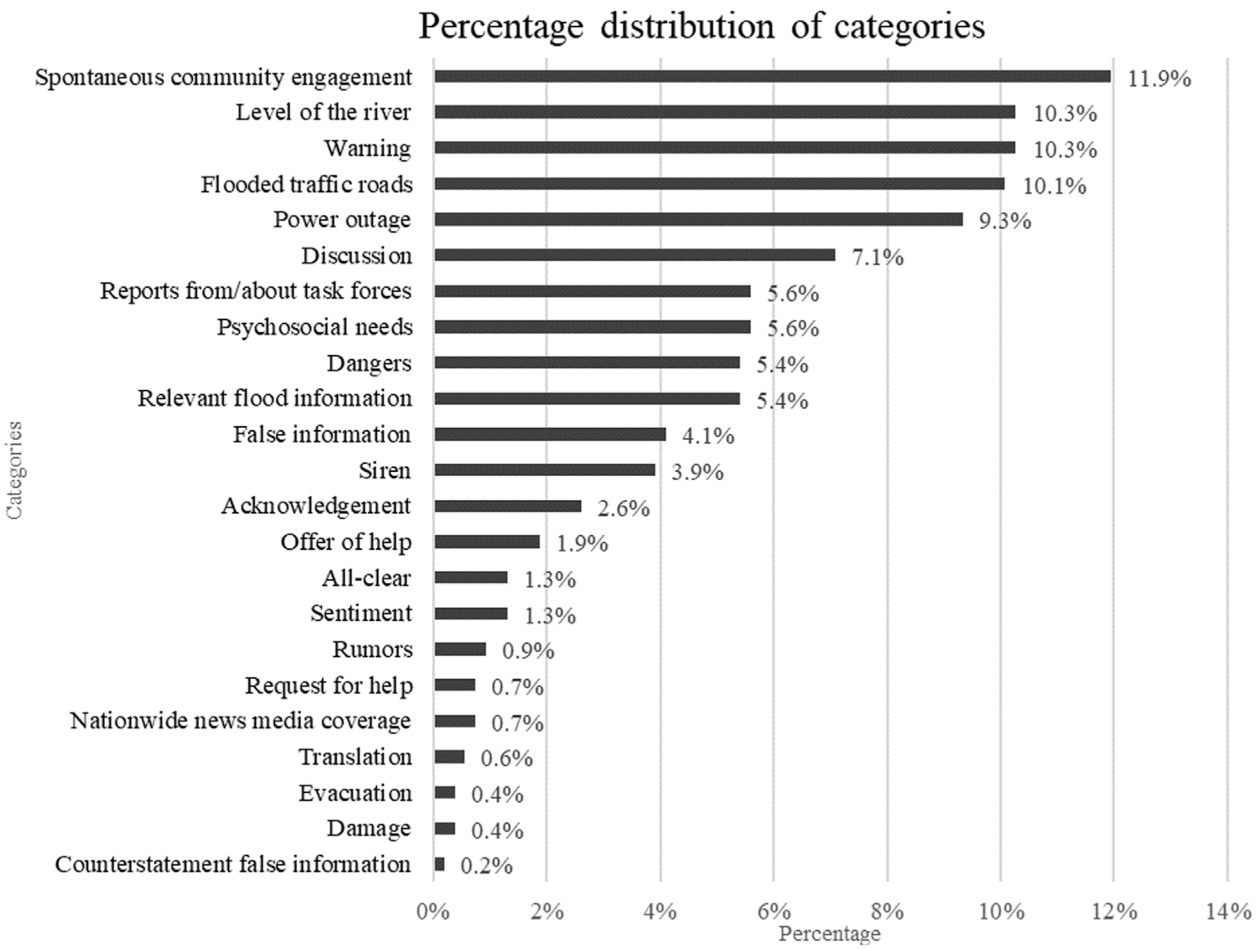

FIGURE 2
Percentage distribution of categories.

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.

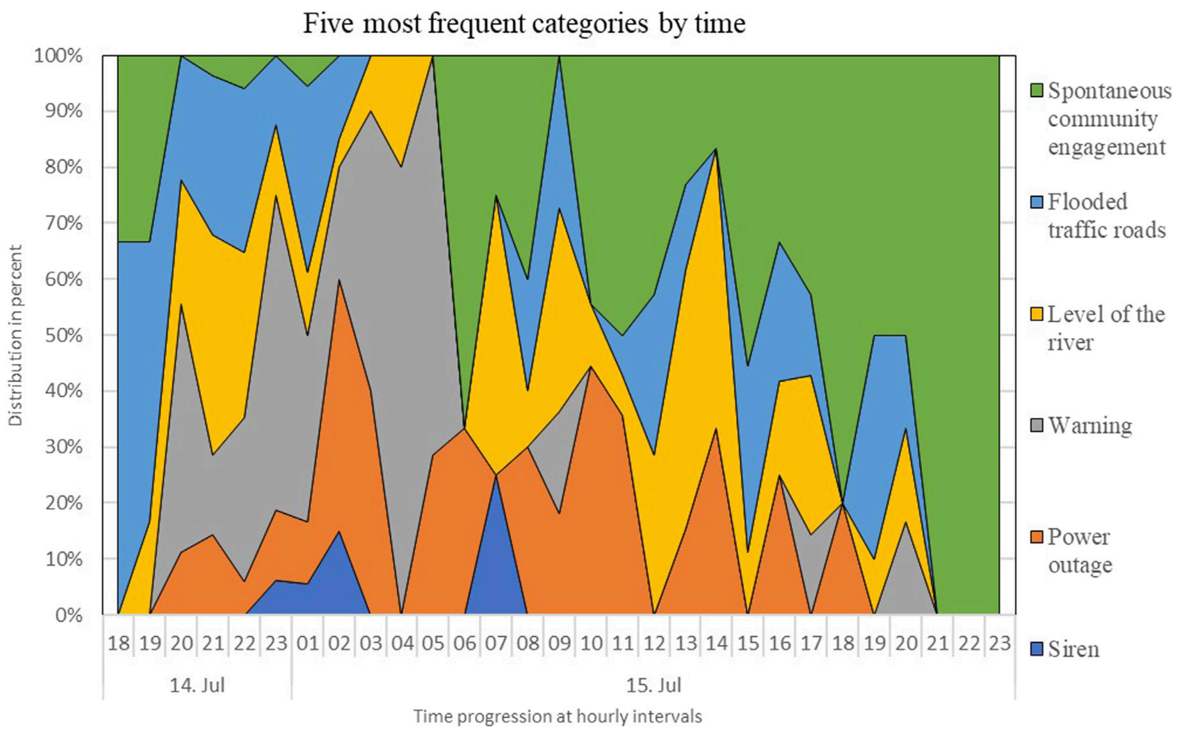

FIGURE 3
Five most frequent categories by time.

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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5.1.3 Study III

Paulus, D., **Fathi, R.**, Fiedrich, F., van de Walle, B., & Comes, T. (2022). On the Interplay of Data and Cognitive Bias in Crisis Information Management. An Exploratory Study on Epidemic Response. Information Systems Frontiers. DOI: doi.org/10.1007/s10796-022-10241-0

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On the Interplay of Data and Cognitive Bias in Crisis Information Management

An Exploratory Study on Epidemic Response

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Abstract
Humanitarian crises, such as the 2014 West Africa Ebola epidemic, challenge information management and thereby threaten the digital resilience of the responding organizations. Crisis information management (CIM) is characterised by the urgency to respond despite the uncertainty of the situation. Coupled with high stakes, limited resources and a high cognitive load, crises are prone to induce biases in the data and the cognitive processes of analysts and decision-makers. When biases remain undetected and untreated in CIM, they may lead to decisions based on biased information, increasing the risk of an inefficient response. Literature suggests that crisis response needs to address the initial uncertainty and possible biases by adapting to new and better information as it becomes available. However, we know little about whether adaptive approaches mitigate the interplay of data and cognitive biases. We investigated this question in an exploratory, three-stage experiment on epidemic response. Our participants were experienced practitioners in the fields of crisis decision-making and information analysis. We found that analysts fail to successfully debias data, even when biases are detected, and that this failure can be attributed to undervaluing debiasing efforts in favor of rapid results. This failure leads to the development of biased information products that are conveyed to decision-makers, who consequently make decisions based on biased information. Confirmation bias reinforces the reliance on conclusions reached with biased data, leading to a vicious cycle, in which biased assumptions remain uncorrected. We suggest mindful debiasing as a possible counter-strategy against these bias effects in CIM.

Keywords Data bias · Cognitive bias · Crisis information management · Digital resilience · Mindfulness · Epidemics

1 Introduction

Infectious disease outbreaks have been on the rise (Smith et al., 2014), with the COVID-19 pandemic being the prime example that epidemics, if not controlled, lead to severe humanitarian crises and exacerbate poverty and hunger in the Global South (United Nations, 2021). To respond to epidemic crises, information is central. Previous research has advocated for digital resilience via information systems, models, and algorithms that address the deluge of information and foster the stability of the digital ecosystem itself (Schemmer et al., 2021). Constantinides et al. (2020) define digital resilience as "[...] the phenomena of designing, deploying, and using information systems to quickly recover from or adjust to major disruptions from [...] shocks." Crises, however, put digital resilience to the test, especially the ability to rapidly adapt to a dynamic and highly volatile information environment.

The exceptional circumstances of crises put enormous pressure on crisis information management (CIM) as it needs to happen rapidly, despite tremendous uncertainty, and is often heavily resource-constrained (Schippers & Rus, 2020; Comes et al., 2020). These characteristics pose a double challenge: (a) data may not be available or is biased given limited access or data collection regimes, or it may be noisy, uncertain, and conflicting; and (b) the cognitive processes of crisis information managers and decision-makers may be under strain, given the urgency and high stakes of the situation.

Regarding (a), in crises, relevant data is often unavailable because of access constraints or destruction of infrastructure or because decisions have to be made quicker than it takes to collect and analyze data (Fast, 2017). This can lead to

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representational bias in data that potentially over- or under-represent issues, social groups, or geographic areas (Fast, 2017; Galaitsi et al., 2021). If such biases remain undetected and untreated in CIM, information products used to support decision-making will also become biased.

Regarding (b), crises pose significant challenges to the cognitive processes of information managers and decision-makers. Humans tend to be influenced by cognitive biases, especially in situations of urgency, uncertainty, risks, and high-stakes (Phillips-Wren et al., 2019). The concept of cognitive biases originates from the idea of bounded rationality that postulates, human thinking (within the complex world surrounding it) is limited, which prevents people from being purely rational (Simon, 1955). Confirmation bias is among the most prominent cognitive biases in crises (Brooks et al., 2020; Comes, 2016; Modgil et al., 2021). It leads people to search and select information that confirms their previous assumptions and decisions and neglect disconfirming information (Nickerson, 1998). Consequently, crisis responders might disregard valid and important information only because it conflicts with or does not confirm their initial assumptions.

We argue that the interplay of data bias and confirmation bias threatens the digital resilience of crisis response organizations. The consequences for crisis response can be particularly severe when data bias and cognitive bias reinforce each other in sequential decisions over time. When initial assumptions are made based on biased data, confirmation bias may lead people to further rely on information that confirms their initial biased assumptions. This might lead to a vicious cycle that hampers adaptation and prolongs initially wrong decisions rather than correcting them. Conventionally, the literature suggests that decisions in crises need to be adaptive to new information (Turoff et al., 2004). The principle of strengthening the adaptive capacity to manage uncertainty is underlying a broad range of literature on adaptive management in crises and (digital) resilience (Tim et al., 2021; Schiffling et al., 2020). However, we know little about the effectiveness of such adaptive approaches against the backdrop of combined data and confirmation bias.

A potential counter-strategy to mitigate the negative consequences of biases on CIM is mindful debiasing. Mindfulness means being more aware of the context and content of the information one is engaging with (Langer, 1992), thereby becoming less prone to confirmation bias (Croskerry et al., 2013). In a mindful state, information managers are more open to new and different information (Thatcher et al., 2018). In contrast, when being less mindful, people rely on previously constructed categories and neglect the potential novelty and difference within newly received information (Butler & Gray, 2006).

This exploratory study investigates the interplay of data and confirmation bias in a sequential setup. Through a three-stage experiment with experienced practitioners, we studied how our participants dealt with biased data, and in how far they were able to correct initial decisions, or whether path-dependencies to biased decisions emerged. Based on our findings, we outline how mindful debiasing can support the detection and mitigation of data and confirmation biases in crisis response.

The remainder of this paper is structured as follows: the next section reviews the relevant literature related to CIM, digital resilience and biases, and provides the research gap and research questions this paper is addressing. Section 3 describes the research design and methods, and Section 4 provides the results from our experiment. In Section 5, we discuss our contributions to literature and practice as well as future research avenues. In Section 6, we reflect on the limitations of this exploratory study, and Section 7 concludes the paper.

2 Background

2.1 Crisis Information Management

2.1.1 Approaches and Tools to Crisis Information Management

Crisis information management (CIM) entails the formulation of data needs, identification of data sources, data collection, cleaning and structuring, data analysis, and the design and development of information products (Currion et al., 2007). The objective of CIM is to support decision-making by providing trustworthy, accurate, and actionable information. With the rise of Big Data and Artificial Intelligence, larger humanitarian organizations have invested in analytics capacity (Akter & Wamba, 2019). While the potential for working with unstructured data for predictive analytics has been recognized, many humanitarian organizations active in the Global South do not possess the resources for large investments into information technology and statistical sophistication (Prasad et al., 2018; Baharmand et al., 2021). In these contexts, large parts of CIM are still supported through common office information systems such as Microsoft Excel and Google Spreadsheets (United Nations, 2020). These are used, amongst others, to store survey responses, conduct data integration, and develop information products, e.g., maps, tables, and infographics (Thom et al., 2015).

Especially in sudden-onset disasters, organizations frequently surge additional data analyst capacity to rapidly strengthen their CIM and digital resilience. Often, these are remotely working *digital volunteers*, that have been regarded as cost-effective, additional analyst capacities to support CIM (Poblet et al., 2018; Castillo, 2016). These external analysts contribute to CIM by supporting tasks such as data collection, analysis as well as the development of information products for decision support (Chaudhuri & Bose, 2020; Hughes & Tapia, 2015; Karlsrud & Mühlen-Schulte, 2017). External analysts have also contributed to epdiemics CIM, e.g., in the 2014 West Africa Ebola outbreak (Hellmann et al., 2016), or the Covid-19 response (Fathi & Hugenbusch, 2021).

Figure 1 shows on the left side an information product developed by external analysts during the 2014 Ebola outbreak. The product highlights the major challenges of access to data and shows that the mobile phone network corresponds to the areas of the officially reported cases (WHO map at the right-hand side of Fig. 1), clearly an indication of the widespread data biases, whereby access and phone coverage hampered reporting. Other information products created through such joint CIM processes include Excel and Google spreadsheets, graphs, and 1-pager summarizing results of social media data analyses (Hughes & Tapia, 2015).

Tasks and responsibilities frequently shift in crises (Nespeca et al., 2020), requiring information managers and decision-makers to interact with data in different ways. While external analysts are primarily turning raw data into information, decision-makers are concerned with interpreting the situation and putting received information into context by using experience, communicating with partners, acting, and reacting.

2.1.2 Sensemaking and Situational Awareness

While much work on decision-making in crises focuses on optimizing for isolated decisions, crises are typically characterized by nested and interdependent decisions, driven by cognition and experience. This process is recognized by the literature on *sensemaking*, whereby decisions are part of a broader collective process of meaning-making (Weick, 1995; Klein & Moon, 2006; Comes et al., 2020). Important components of sensemaking are information seeking, processing, creating, and using (Muhren et al., 2008). Data-driven approaches, e.g., predictive analytics, can support sensemaking by revealing internal and external cues. Sensemaking is also influenced by an organization's mandate, strategy and modes of operation (Zamani et al., 2021), and especially describes how people deal with 'gappy' information environments (Muhren et al., 2008).

Early studies on the work of external analysts emphasized the added value they bring to CIM by their remote and flexible structures (Meier, 2012; Ziemke, 2012; Bott & Young, 2012). It has been argued that their work contributes to the situational awareness of response organizations (Hughes & Tapia, 2015; Starbird & Palen, 2011). To achieve situational awareness successfully, however, it is important to switch between goal-driven and data-driven approaches (Endsley, 1995; Endsley et al., 2003; Fromm et al., 2021). While for goal-driven approaches, informational cues are intentionally considered in the pursuit of a set goal, data-driven approaches refer to open exploration of perceived cues that can lead to changes in priorities and readjustments. Situational awareness requires

(a) MapAction map showing mobile phone coverage

(b) WHO map of hot-spots of Ebola cases.

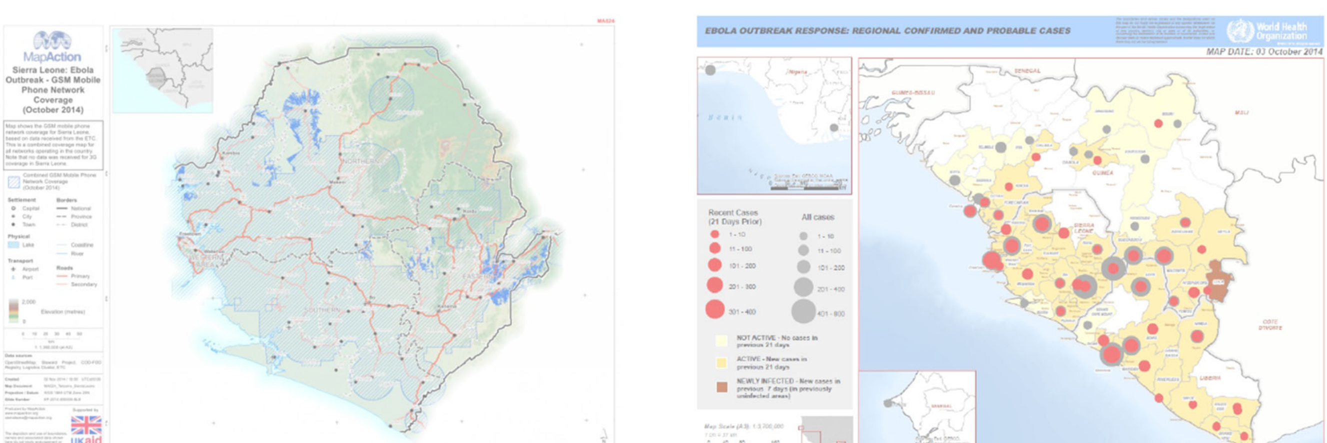

Fig. 1 Map comparison for Sierra Leone during the 2014-2016 Ebola outbreak

to alternate between these two forms because stringent goal-focus will lead to neglect of cues in the data, while stringent data-focus will be perceived as overly taxing (Fromm et al., 2021).

2.2 Digital Resilience and Crisis Information Management

2.2.1 Defining Digital Resilience

There are diverging perspectives on what constitutes digital resilience and whether it plays at the level of the physical infrastructure, the people or groups using the infrastructure, or the interplay among both. Some authors focus on the impact of digital technology on the user, stressing the importance of (access to) information in crises. For instance, according to Wright (2016), "digital resilience means that to the greatest extent possible, data and tools should be freely accessible, interchangeable, operational, of high quality, and up-to-date so that they can help give rise to the resilience of communities or other entities using them." Others focus on the resilience capabilities of individuals to process digital data and engage with virtual environments (UK Council for Internet Safety (UKCIS), 2019).

Here, we take an information systems perspective, understanding digital resilience as a phenomenon that emerges from the interaction of people with data through digital tools and infrastructure. We follow a crisis-related definition that describes digital resilience as a means to cope with disruptions: "[...] digital resilience [...] refer[s] to the phenomena of designing, deploying, and using information systems to quickly recover from or adjust to major disruptions from [...] shocks." (Constantinides et al., 2020). Crisis information management needs to foster digital resilience by supporting flexibility, agility, and adaptability (Turoff et al., 2004). Our definition also covers specific aspects of digital resilience during epidemics (Ma'rifat & Sesar, 2020), namely the collection and analysis of outbreak data, as well as the use of analysis results to inform crisis response. Since CIM incorporates data collection, analysis, and sharing to support crisis decisions, it is directly linked to digital resilience.

2.2.2 Challenges to Digital Resilience in Crisis Information Management

Previous literature identified several challenges to CIM that affect different functions (Van de Walle & Comes, 2015; Lauras et al., 2015) at different hierarchical levels (Bharosa et al., 2010). We argue that data and cognitive biases can emerge as consequences to these challenges and affect CIM by posing threats to digital resilience in terms of hampering the rapid recovery from crises. We use the challenges described below to design our experiments, described in Section 3.

Information has to feed into the fast crisis decision-making process (Warnier et al., 2020; Lauras et al., 2015; Turoff et al., 2004). The time pressure reinforces the tendency to focus only on information that is immediately available (Higgins & Freedman, 2013), which may induce a range of biases (Maule et al., 2000). Information needs also rapidly change during different crisis stages (Hagar, 2011; Gralla et al., 2015; Nespeca et al., 2020), posing challenges to the agility and flexibility of information management (Lauras et al., 2015).

As the destruction of infrastructure or lack of access may affect different regions to different degrees (Altay & Labonte, 2014), datasets are often geographically imbalanced or biased. Demographic biases can influence the data further. Especially in the Global South, the most vulnerable groups might not have access to mobile phones and therefore are not included in mobile phone data to track and trace population movements (IOM, 2021). Under-representation of geographic areas or social groups can lead to violations of the humanitarian imperative to '*leave no one behind*' (Van de Walle & Comes, 2015).

Relevant information about the crisis situation is often uncertain. Uncertainty is an umbrella term for information that is unavailable, incomplete, ambiguous, or conflicting (Comes et al., 2011; Tran et al., 2021). To reduce uncertainty, people likely use the tools and methods they are most familiar with. This behavior could lead to what is known as the law-of-the-instrument, which states that people tend to overly rely on a particular familiar tool (Johnson & Gutzwiller, 2020).

The high volume, velocity, and variety of irrelevant data can quickly lead to information overload, particularly when the veracity of data has to be evaluated as well (Schulz et al., 2012). This issue has become particularly prominent with the ubiquity of social media (Gupta et al., 2019), which makes it virtually impossible to filter and process all available data on time (Starbird & Palen, 2011; Van de Walle et al., 2016). Information overload has been shown to induce confirmation bias (Goette et al., 2020). Confronted with an overload of information, it is hard to identify any gaps in the available data, leading to exploiting what is known rather than exploring what could be known (Comes et al., 2020).

In the high stakes decision contexts of humanitarian crises, tremendous potential losses are combined with the irreversibility of decisions (Kunreuther et al., 2002). High stake situations have been shown to induce a large number of biases, ranging from a tendency to focus on short-term perspectives as well as an over-reliance on social norms and emotional cues (Kunreuther et al., 2002). For example, high-stakes decisions can lead decision-makers to exert group-think, which is manifested by overconfidence and a strive for in-group harmony, rather than critical self-reflection (Kouzmin, 2008).

2.3 Biases in Crisis Information Management

As we have shown, the characteristics of crises provide a breeding ground for data biases and cognitive biases (Comes, 2016). Here, we zoom into two of the most prominent biases that are relevant in the interplay of information and decision-making: data and confirmation bias.

2.3.1 Data Bias in Crisis Information Management

Data can become biased due to historical, social, political, technical, individual, and organizational reasons (Jo & Gebru, 2020). Representational data bias is among the most common forms and a broad category of data bias. It comes from the *"divergence between the true distribution and digitized input space"* (ibid.). In practice, that often means that a dataset systematically deviates from the real-world phenomenon the data is supposed to represent, for example, leading to the under-representation of geographic areas or social groups.

Data bias can be understood as a flaw of a dataset, negatively affecting the quality of the data and potentially causing damages and losses in organizational processes (Storey et al., 2012). Especially in sensitive contexts, data bias has been shown to replicate and reinforce existing inequalities (Jacobsen & Fast, 2019; Bender et al., 2020). Urgency and overload combined with uncertainty are common causes for data bias in crises (Fast, 2017).

In epidemic response, the misrepresentation of infection rates has been documented during the 2014-2016 Ebola outbreak in West Africa (Fast, 2017). Similarly, during the COVID-19 pandemic, different testing, tracing, or counting strategies have resulted in incomplete datasets and incomparable statistics (Fenton et al., 2020).

We look at representational bias in two key variables for epidemic response: numbers of infections and treatment capacity. Representational bias in those two variables can lead to a flawed understanding of the outbreak's severity and the available capacity, leading to misallocations and delayed or ineffective response.

One of the hopes in using additional analytic capacity is that this additional capacity identifies additional information and thereby helps overcome data bias. To test if additional external capacity actually helps in overcoming data bias, we draw inspiration from traditional hidden profile experiments (Stasser & Titus, 1985; Lightle et al., 2009). These experiments evaluated groups' decision-making performance. Group members received two sets of information, one set that contains the same information for all group members and another set that is different between group members. Only by joining the different, individual information sets together groups can identify the hidden profile, which is crucial to make the optimal decision. Hidden profile experiments have shown that generally groups overly discuss common information and neglect individual information so that the hidden profile remains hidden and the groups make an inferior decision (Stasser & Titus, 1985; Lightle et al., 2009). This behavior was also found in experiments on crisis decision-making (Muhren et al., 2010). However, previous experiments did not specifically look at representational bias in crises and whether adaptive approaches to surge additional analyst capacities help to improve the identification and mitigation of biases.

2.3.2 Confirmation Bias in Crisis Information Management

A cognitive bias that hampers adequate adaptation to new information is *confirmation bias*. Research on confirmation bias has shown that people tend to limit their information retrieval efforts to information that is more likely to confirm their assumptions (Nickerson, 1998). Because information that opposes preliminary assumptions increases discomfort (Hart et al., 2009), it may be discarded, and wrong assumptions remain undetected, leading to flawed decision-making (National Research Council, 2015). Confirmation bias, like cognitive biases in general, are often characterized as a byproduct of information processing limitations: because of urgency and overload, people use biases as mental shortcuts to judge and decide quickly.

The urgency of crises likely fosters confirmation bias because relying on already formed assumptions accelerates decision-making. Domain experts, however, can show the opposite behavior and deliberately seek disconfirming information (Klein & Moon, 2006). Counterfactual mindsets have been shown to be an effective debiasing strategy (Kray & Galinsky, 2003). However, we know little about the potential influence of confirmation bias on the information search and selection behavior of experienced crisis responders.

In this study, we investigate if crisis decision-makers and analysts are susceptible to confirmation bias and if they search for non-confirmatory data as a debiasing strategy. It could be possible that the deliberations between experts induce counterfactual mindsets, which, in turn, lead to a more critical assessment of prior decisions. However, path-dependencies may arise, whereby confirmation bias leads decision-makers and analysts to confirm assumptions in subsequent decisions, even though they were made based on biased data.

Previous research measured confirmation bias through tasks with two parts (Jonas et al., 2001; Fischer et al., 2011). First, participants made a preliminary decision between two options on a certain matter. Then, they were presented a set of information, which often are summaries of articles on the matter participants just made their preliminary decision on. For example, ten summaries of articles are presented, five supporting participants' preliminary choice, and five opposing it. Participants are then asked to select the articles they would like to receive in full. The experiment finishes, and participants are told there will be no full articles because it is unnecessary for the experiment. The researcher later counts the numbers of selected supporting and opposing article summaries and conducts a significant test for the difference. If significantly more supporting summaries were selected, we speak of confirmation bias.

2.4 Research Gap and Research Questions

In dynamic situations such as crises, information on the best course of action continuously changes. Therefore, the literature advocates for agile and adaptive management in epidemics (Merl et al., 2009; Janssen & van der Voort, 2020) or, more generally, in crises (Charles et al., 2010; Anson et al., 2017; Schiffling et al., 2020; Turoff et al., 2004).

Response organizations often lack sufficient capacities to respond. Therefore, remotely working external analysts are added as surge capacity. There is some hope that via this additional capacity, exploratory search strategies may be favored that help overcome the responsive and exploitative strategies of decision-makers. At the same time, the remote nature of the work of analysts may add to the biases they are subject to (Comes, 2016) and may make especially data interpretation harder (Comes & Van de Walle, 2016). Therefore, it is not yet known how and in how far the interplay of analysts and decision-makers in sequential decisions reduces or amplifies biases. In this paper, we investigate whether the surge of additional analyst capacity is effective to mitigate bias effects.

In sequential decisions, initial biases might limit the ability to effectively adapt, even though adaptation is widely described in the crisis management literature as key to managing the uncertainties and data biases that often prevail at the onset of a crisis (Mendonca et al., 2001; Quarantelli, 1988). Potentially, representational data bias and confirmation bias reinforce each other, leading to amplified biases. This is especially harmful if path-dependencies arise whereby the initial data bias does not only influence initial decisions but leads to flawed decision trajectories through confirmation bias.

Figure 2 depicts the interaction of the identified main challenges within the external analyst-supported CIM process. The response organizations activate external analysts in the first step (1). In steps (2) and (3) external analysts and decision-makers conduct information management and decision-making under the influence of the crisis, which can lead to biases. Information management and decision-making need to identify and mitigate biases to lead to unbiased results (4). Finally, the resulting information and decision are either influenced by biases, or bias mitigation was successful (5).

We are interested in (RQ 1) whether the surge of external analysts leads to unbiased information products for decision support, (RQ 2) if the joint CIM process between analysts and decision-makers facilitates debiasing, and (RQ 3) if data bias and confirmation bias reinforce each other leading to path dependencies in sequential decisions. We address the following research questions:

RQ 1: Is surging external analysis capacity effective in identifying and mitigating data bias?

RQ 2: How do external analysts and decision-makers jointly handle data bias in the decision process?

RQ 3: Does confirmation bias create path dependencies whereby biased assumptions persist in sequential decisions?

We used an exploratory, three-stage experiment to examine these research questions, which is described in detail in the next section.

3 Research Design & Methods

We conducted an exploratory study with three stages to address the three research questions (Fig. 3). RQ 1 and RQ 2 were addressed through a scenario-based workshop with experienced practitioners in the fields of crisis decision-making and external analysis for CIM support. RQ 3 was addressed through an online survey with the same participants. Figure 3 depicts the research questions together with the corresponding experiment stages, data collection, and analysis methods.

The experiment was designed to observe the crisis information management and decision-making process in a controlled environment. The controlled environment enables observation without interfering with the real response and allows us to conduct the experiment with three different groups. Yet, by designing realistic information flows, creating time pressure and providing the typical tools, the scenario is sufficiently realistic enough to inspire the same ways of thinking that external analysts or decision-makers also show in real epidemics. Through this setting, it was possible to observe the practices, communication and interactions within and between the participant groups. The experiment took place at the TU Delft Campus in The Hague in January 2020.

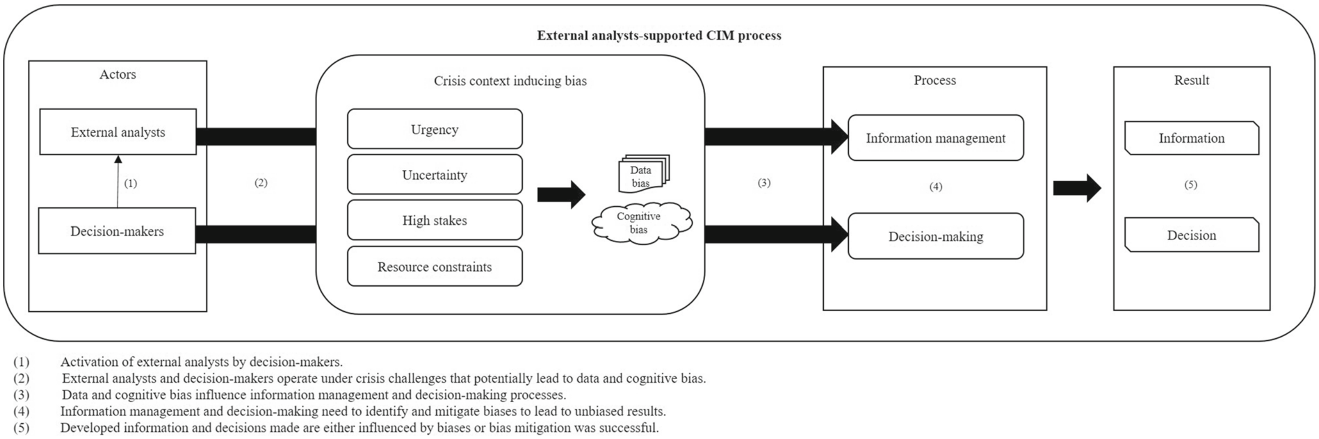

Fig. 2 External analyst-supported crisis information management process. Source: authors

3.1 Participants

3.1.1 Recruitment

Participants had to have work experience as external analysts or decision-makers in crises to be eligible for participation. The recruitment was done based on the competencies required to fulfill the tasks of our experiment. These competencies included technical skills such as merging tabular data in MS Excel or a similar tool and developing and interpreting crisis information products such as maps and graphs. In addition, participants needed to be affiliated to an established crisis response organization, data analytics organization, or research institute on crisis or epidemic management. The authors had contacts to a network of potential candidates through previous research. This enabled us to recruit participants who had the required skills and experience. The participants were recruited internationally from various countries. Table 1 lists the descriptive information of our participants.

3.1.2 Sample

Twenty-four participants participated in the experiment, of which twenty-one were experienced in crisis management (eleven external analysts and ten decision-makers),

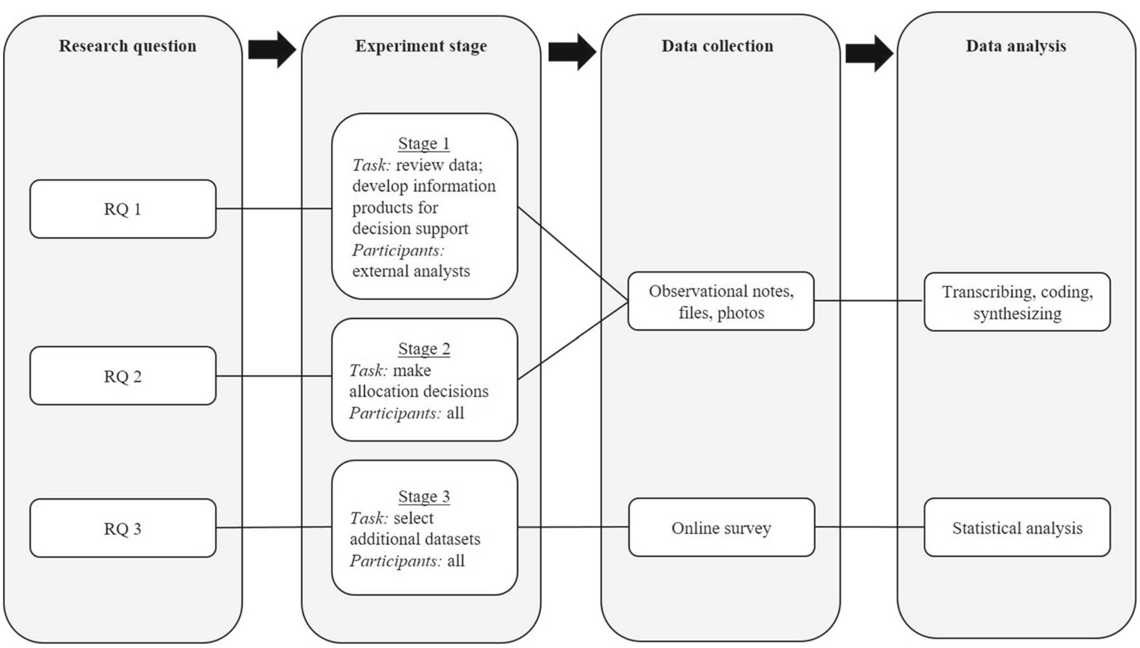

Fig. 3 Research design

Table 1 Descriptive information of all participants during the experiment. EA = External analyst, DM = Decision-maker

Group	Role	Organization	Competencies
Reloupe	EA	Humanitarian Openstreetmap Team	Mapping and open data for humanitarian action
	EA	MapAction	Mapping and open data for humanitarian action
	EA	Mark Labs	Data analytics for environmental and social transformation
	EA	510 (Red Cross)	Emergency data support, predictive impact analysis and digital risk assessment
	DM	TU Delft	Student with no prior experience
	DM	Red Cross	Emergency response, volunteer assistance, emergency training
	DM	Dorcas	Poverty reduction and crisis response
	DM	US Department of State	Senior humanitarian analyst
	DM	Municipal Health Service	Doctor of infectious disease control
Republic	EA	Standby Taskforce	Mapping and open data for humanitarian action
	EA	Virtual Operations Support Team	Social media data analyis in crisis response
	EA	Standby Taskforce	Mapping and open data for humanitarian action
	EA	TU Delft	Student with no prior experience
	DM	ZOA	Emergency relief and reconstruction of regions struck by disasters or conflicts
	DM	Red Cross	Emergency Relief Coordinator
	DM	World Vision	Disaster management, economic development, education, faith and development, health and nutrition and water.
Noruwi	EA	510 (Red Cross)	Emergency data support, predictive impact analysis and digital risk assessment
	EA	MapAction	Mapping and open data for humanitarian action
	EA	Leiden University	Development of data-driven decision support tools for humanitarian organizations
	EA	TU Delft	Student with no prior experience
	EA	Humanity Road	Social media data analyis in crisis response
	DM	TU Delft / European Commission Humanitarian Aid Office	Emergency and crisis management
	DM	Maastricht University Faculty of Health, Medicine and Life Sciences	Public health expert
	DM	Ministry of Foreign Affairs (NL)	Senior humanitarian advisor

and three were students. We added three students to create an element of reality to the group compositions as staff turnover is high in crisis response teams, with new and inexperienced staff needing to be integrated (St. Denis et al., 2012; Fathi et al., 2020). Based on the background and experience of the participants, they were given either the role as an external analyst or as a decision-maker. Participants within the group of external analysts were part of professional disaster relief organizations as well as organizations representing different fields of expertise such as digital mapping, social media analysis, and data analytics. The group of decision-makers consisted of representatives from different governmental and non-governmental crisis response organizations from numerous countries, including The Netherlands, Germany, the United Kingdom, and the United States. Table 1 gives an overview of all participants, their corresponding organizations, and competencies.

Recruiting experienced professionals for a scientific experiment leads to a smaller pool and thereby also lower participant numbers as compared to experiments with students or the general public. As the objective of this exploratory experiment was to gain insights into information management and decision-making approaches by actual practitioners, relying on samples drawn from student populations or the general public would have been inadequate.

Our sample size is in a similar range as comparable exploratory studies on information systems and information management (Antunes et al., 2020). Such exploratory studies provide a valid approach to build theory and identify metrics, mechanisms, processes, and concepts that can be investigated further in subsequent empirical research (Antunes et al., 2020).

3.1.3 Group Compositions

We divided the participants into three groups of seven to nine members. The group sizes match real-world work team sizes of external analyst-supported CIM processes (St. Denis et al., 2012). Further, members of geographically distributed teams of up to nine members have been shown to participate more actively and are more committed to and more aware of the team's goals than in larger teams (Bradner et al., 2003). Our groups were purposefully mixed with participants having complementary skills and expertise so that each group included experts on mapping and data analytics on a similar level. Therefore, the number of participants and the group compositions are a good representation of real-world teams.

3.2 Scenario Design

The fictional scenario of our experiment was an epidemic outbreak happening simultaneously in three countries. The experiment was inspired by the 2014-2016 Ebola outbreak in Guinea, Liberia, and Sierra Leone. The three country groups had to assess the situation in their respective country by analyzing the data provided during the experiment with the goal to support decisions on where (in which districts) to place treatment centers. The experiment resembled the main challenges of crisis information management, as mentioned in Sections 2.2 and 2.3, by putting participants under time-pressure (urgency), providing incomplete and low-quality data (uncertainty), requiring participants to make high stakes sequential decisions on treatment center placements and having to do so with a shortage of resources.

Before each stage of the experiment, we gave a brief introduction about the scenario and the participants' tasks. Each stage was concluded with a reflection moderated by the researchers.

3.3 Materials and Introduction of Representational Data Bias

As our participants were experienced practitioners, the data used in the experiment had to resemble reality closely. We used original data from the 2014-2016 Ebola epidemic. The datasets selected for inclusion were on infection rates, infrastructure capacities, demographics, and geography. We adjusted the original data for three reasons. First, some of the participants had been involved in the 2014-2016 Ebola response and should not have a head-start by already being familiar with the data. Second, our experiment required us to introduce a controlled representational bias into the data. Third, the original datasets were too large for the time frame of the experiment. The original data was downloaded from the Humanitarian Data Exchange platform[1] and we adjusted it as described in the following.

The **infection rate** is the key variable in epidemic response. We adjusted the original data so that infection rates were higher and more cases occurred in a shorter time. We retained columns from the original datasets and removed auxiliary columns to avoid information overload in the participants (Table 2). We included infection data for the first four months of the fictional outbreak (Table 3). Inspired by hidden profile experiments, in our experiment, one district per country was created with substantially more total cases than the other districts in the country. The data of this district was split among group members' datasets (Table 4). This implies that only by joining their datasets participants were able to identify the district with the most cases. If the bias remained undetected and untreated, the resulting information products would also become biased.

Infrastructure and capacity data During the 2014-2016 Ebola outbreak, mapping healthcare facilities and their capacities became a crucial task for crisis information management. However, up to 60 % of values in the original data on health infrastructure and capacities were missing, highlighting once more the high uncertainty analysts are confronted with. In addition, values had unclear and ambiguous meanings, making interpretation difficult. We adjusted the original datasets to include a reduced number of key variables. In the original datasets, detailed capacity data, i.e., numbers of beds per treatment center, was incomplete for 58 % of entries. We mimicked this representational bias in our adjusted datasets. Only one participant per group received capacity data on the number of beds per facility. The other group members received the same dataset but with an empty column for capacities.

Demographic and geographic data Demographic data are part of the common operational datasets in crisis response (Van de Walle, 2010). They are used to understand the overall population distribution in terms of age, gender, and geographic location. By providing a sense of population density and bordering regions, they become very important in predicting trends in epidemic outbreaks. We collected the original data, replaced country and district names with randomly generated names, and slightly adjusted the demographic numbers. We further included randomly generated maps corresponding to the three randomly generated

[1] https://data.humdata.org/ebola. Last accessed: October 12, 2021.

Table 2 Step 1: Retrieving original data from the West-Africa Ebola outbreak. Here truncated to show reported cases of infections. One row is one reported case

Country	Location	Epi week	Case definition	Ebola data source	...
Liberia	GRAND BASSA	25 to 31 August 2014 (2014-W35)	Confirmed	Patient database	...
Liberia	GRAND BASSA	08 to 14 September 2014 (2014-W37)	Probable	Patient database	...
Liberia	GRAND BASSA	15 to 21 September 2014 (2014-W38)	Probable	Patient database	...
Liberia	GRAND BASSA	22 to 28 September 2014 (2014-W39)	Probable	Patient database	...
Liberia	GRAND BASSA	13 to 19 October 2014 (2014-W42)	Confirmed	Patient database	...
Liberia	GRAND BASSA	20 to 26 October 2014 (2014-W43)	Confirmed	Patient database	...
Liberia	GRAND BASSA	20 to 26 January 2014 (2014-W04)	Probable	Situation report	...
Liberia	GRAND BASSA	27 January to 02 February 2014 (2014-W05)	Confirmed	Situation report	...
Liberia	GRAND BASSA	27 January to 02 February 2014 (2014-W05)	Probable	Situation report	...
Liberia	GRAND BASSA	03 to 09 February 2014 (2014-W06)	Confirmed	Situation report	...
Liberia	GRAND BASSA	17 to 23 March 2014 (2014-W12)	Probable	Situation report	...
...	...	...	...	...	...

Table 3 Step 2: Adjusted dataset based on the original data to resemble the infection rate and adapt the data to our fictional country and outbreak

Country	District	Month	Case definition	Ebola data source
Noruwi	Aameri	1	Confirmed	Situation report
Noruwi	Aameri	1	Probable	Situation report
Noruwi	Aameri	1	Probable	Patient database
Noruwi	Aameri	2	Probable	Situation report
...	...	...	...	...
Noruwi	Aameri	3	Confirmed	Patient database
Noruwi	Aameri	4	Probable	Patient database
Noruwi	Aameri	4	Probable	Situation report
Noruwi	Aameri	4	Probable	Situation report

Table 4 Step 3: Introduction of representational bias. We created biased versions of the adjusted datasets from step 2. The biased versions were distributed among participants

	Unbiased					Biased				
Districts	M1	M2	M3	M4	Total	M1	M2	M3	M4	Total
Aameri	4	12	44	140	200	4	12	44	140	200
Baldives Saintman	3	21	27	147	198	3	21	27	147	198
Bana Cadi	1	2	24	54	81	1	2	24	54	81
Grethernquetokong	1	8	12	52	73	1	8	12	52	73
Janmantho	1	6	19	39	65	1	6	19	39	65
Lemau	4	4	92	140	240	4	4	92	140	240
Mau Cari	1	4	20	49	74	1	4	20	49	74
Menia	1	1	20	32	54	1	1	20	32	54
Niprusxem	*5*	*20*	*125*	*160*	*310*	*5*	*0*	*0*	*0*	*5*
Samac Iali	1	3	17	62	83	1	3	17	62	83
Southdos Dinia	3	12	66	129	210	3	12	66	129	210
Thesey	1	3	24	37	65	1	3	24	37	65
Usda Nilia	1	4	14	29	48	1	4	14	29	48
Walof	1	2	12	42	57	1	2	12	42	57
Total	28	102	516	1112	1758	28	82	391	952	1453

The bias is here introduced in the district of *Niprusxem*. The district has the most cases in the unbiased dataset, but the least cases in the biased datasets. One group member only receives data for month 1 (displayed). Each other group member also only receives data for one month (not displayed). Only by joining the datasets, the unbiased case numbers could be received countries and districts. The maps were distributed to the participants in digital and printout versions.

Data volume Data volume differed slightly between the groups, with no large differences that could have significantly eased or complicated one group's data review and analysis process (Table 5).

Participants' access to the data We created Google accounts for each participant, and the created datasets were uploaded into the Google Drive folders of each participant. This allowed us to distribute the created datasets to the members of each group while making sure the introduced bias was identifiable. A print-out sheet with login information for the Google folder was created for each participant. Each participant received a laptop to access the files. The laptops had MS Office pre-installed for the information management work on the data. Further tools also used by our participants in their professional work, including RStudio Online and Google Spreadsheets, were also available.

3.4 Experimental Setup and Procedure

To address the first two research questions (*Is surging external analysis capacity effective in identifying and mitigating data bias?* and *How do external analysts and decision-makers jointly handle data bias in the decision process?*), we set up the first two stages of the experiment. To address research question three (*Does confirmation bias create path dependencies whereby biased assumptions persist in sequential decisions?*), we conducted an online survey with the same participants.

3.4.1 Experiment Stage 1

Stage 1 was conducted only with the group of external analysts. They were divided into the three groups we had defined in the planning of the experiment (Table 1). Each group was responsible for the information management for one country affected by the fictional outbreak.

Participants were told their group's objective was to review the available data and develop information products that could be used in stage 2 of the experiment for the prioritisation of districts that needed most urgent assistance. As all participants were used to preparing information products for crises, they were free to decide which information products to create (e.g. maps, tables, graphs, etc.). Participants were briefed they could use the MS Office Suite installed on the laptops provided to them, or any other online tools they would use in their professional work. Because of participants' experience, the importance of developing accurate information was clear to them. This includes the checking of data issues, gaps and comparing information quality among group members. We gave them no indication that they could expect the data they received was perfect, accurate and unbiased. Rather, we briefed them that the experiment should be seen as a simulation of a real case, with challenges that can be expected from real epidemic crises. Participants were briefed they had 2.5 hours for their task.

After the introduction, the three groups formed in three rooms, equipped with laptops and information sheets that contained user-login information for each participant to access the available data. The groups were asked to present the developed information products and suggestions for response decisions at the end of experiment stage 1.

Table 5 Dimensions of datasets handed to groups. Dimensions given in rows x columns

Group	Dataset	Dimensions
Noruwi	Infection cases	1759×4
Noruwi	Demographics	15×22
Noruwi	Capacity	58×19
Reloupe	Infection cases	1724×4
Reloupe	Demographics	14×5
Reloupe	Capacity	64×19
Republic	Infection cases	3142×4
Republic	Demographics	36×22
Republic	Capacity	87×19

3.4.2 Experiment Stage 2

In stage 2, decision-makers joined each of the three groups. Participants were briefed they had to make resource allocation decisions by placing treatment centers in priority districts of their respective countries. External analysts had to brief the decision-makers on the outbreak situation, priority issues, and districts using the information products developed by them in stage 1. Each group received a limited amount of treatment centers (in the form of small building blocks) that could be placed in districts of the fictional countries on printout maps. Participants were told that each treatment center, i.e., building block, had a fixed capacity of ten beds. We implemented resource constraints by limiting the number of available treatment centers and beds. Thus, not all districts could be fully equipped to respond to the rising infections and prioritization decisions had to be made. Participants were briefed that all decisions had to be made within 60 minutes.

After the introduction, the three groups formed in three rooms, equipped with laptops and the information products developed in stage 1. The groups were asked to present their final decisions at the end of the experiment.

3.4.3 Experiment Stage 3

To address the third research question after stage 2 was completed, all participants were asked to fill out an online survey on site. The research objective was to assess whether confirmation bias would lead to path-dependencies toward decisions that were made based on biased information. A significant confirmation bias result would mean that participants preferred to seek information that confirmed their previously formed assumptions, even when they were influenced by biased datasets.

The survey referred to participants' previous decision from stage 2, where they selected a priority district to which most treatment centers were allocated. In stage 3, participants were briefed that new information was available after they had made prioritization and allocation decisions. Their task was to select from a list of datasets those ones that they found most important to support further information management and decision-making. The survey item and confirmation bias measure is described in Section 3.5.2.

3.5 Data Collection and Analysis

3.5.1 Experiment Stage 1 and 2

In stages 1 and 2, one observer per group took notes of the information management processes, communication, and interaction within the groups. Photos were taken to document intermediate results and processes, for example of post-its on the printout maps. After the session, the group members' files of the information products created on the laptops were saved and analyzed by the researchers.

We conducted structured observations of the first two stages of the experiment that included the use of protocol sheets with guiding questions. Data collection through researcher observation is highly suitable in interactive experimental settings with dynamic group discussions. The goal was to capture verbal data, i.e., what is discussed, how by whom and when, as well as interactions among group members (Steffen & Doppler, 2019). Since an observer must select which person and interaction is the object of observation (selection problem), a result bias can occur (Steffen & Doppler, 2019). We addressed this potential issue by briefing observers beforehand on the observation protocol and guiding questions. Thus, before beginning an observation, researchers numbered participants in a common format to protocol activities in a standardized way, quickly and effectively. The protocol guideline included example observation items and was divided into three different sections: (1) description of workshop site, (2) communication and interaction description, (3) general impressions. The complete observation protocol is provided in the Appendix. The collected data was evaluated through qualitative content analysis (Döring & Bortz, 2016). The main activity was to summarize the collected observational data and reveal content related to our research questions. We further evaluated the information products developed by the participants in addition to conducting the qualitative document analysis. We proceeded in three steps:

1. **Paraphrasing:** To reduce the volume and complexity of the observational data and of the created information products, the first step was to identify passages that carry content relating to our research questions and delete passages that did not. In this process, the different data forms (text passages of the sheets and information products, e.g. maps) were analyzed separately.
2. **Coding:** In the second step, all paraphrases representing the main content were summarized in a single document. The separate paraphrases were coded and structured to answer our research questions and find explanations for these answers. We conducted two coding iterations to develop a set of coded categories of the observed discussions and activities.
3. **Analyzing:** In the final step, we analyzed the structured content with regard to our research questions. Through this content analysis, we were able to systematically evaluate and analyze all observation sheets and information products and present key results.

The first author coded the data in the first iteration. The resulting codes and corresponding observational notes were discussed with the second author. Adjustments were made to some of the coded categories, followed by the second iteration of coding by the first author. After review by the whole author team, the final categories of codes were agreed on. Table 6 presents example observation notes and coded categories.

3.5.2 Experiment Stage 3

In stage 3, participants were asked to complete the online survey on site. The survey was implemented in a Google Form and distributed to each participant. The survey prompted the participants with the following text: "Below are the summaries of 10 new datasets that are available. You can request the full version of those datasets but you only have limited time and resources to evaluate them all in detail. Select as many datasets as you want. District X is the district you have identified in the last session as the most critical district."

In stage 2, participants had to allocate treatment centers to the districts with the highest priority (referred to as *"District X"* in the survey). In the survey, ten summaries of ten fictional datasets were given in one-sentence statements.

Table 6 Example observation notes taken during the experiments and respective coded categories

Example observation notes	Coded category
Express need for information: transportation network	Requirements for additional data
Discussing data gaps: more background data on the country, transmission data, spread on daily basis needed	Requirements for additional data
Should we merge our data?	Debias behavior
Questioning why they have different datasets. Trying to understand the cause of the data bias	Debias behavior
One person uploaded their files into a shared folder, all others used the data from there	Data sharing
Receiving data from other groups	Data sharing
Deliberation of format of final information product for decision support	Discussion on decision recommendations
Information product proposal: curve by day, what is happening, did people die or not	Discussion on decision recommendations
Using familiar tool to create digital, layered map	Data work
Creation of (biased) aggregates for numbers of cases	Data work
Not sure what the most important dataset is	Interpretation of data
Need to know: where is the death rate the highest?	Interpretation of data
the data is not very clean; possibly underreporting	Communicating data limitations
we had different datasets between group members	Communicating data limitations
Decision-makers studying the developed map	Interpretation of situation
Discussion of possible causes for the outbreak	Interpretation of situation
Need to make a decision; what do we have and what is missing	Allocation strategy
where NOT to put centres?	Allocation strategy
Communication of available recources/capacities	Discussing capacities
Clarification of center capacities	Discussing capacities

Five dataset summaries supported that District X was indeed a priority district, whereas the other five dataset summaries opposed this. An example of a summary of a supporting dataset is *"Dataset 9: District X has a high amount of health care workers infected."* An example of a summary of an opposing dataset is *"Dataset 10: District X has a low amount of heath care workers infected."*

Participants did not receive any data to review besides those summaries, and after the survey was completed, they did not receive the datasets they selected, as it was not necessary to measure confirmation bias (Jonas et al., 2001; Fischer et al., 2011). The complete confirmation bias measure can be found in the Appendix.

The response data from the survey was imported into SPSS for statistical analysis. Following the measures of confirmation bias in previous studies, we first counted the selected supporting and opposing datasets per participant. Then, we used a paired samples test to identify whether the mean counts of selected confirming and opposing datasets were significantly different.

4 Results

In the following, we present the results for our three research questions.

4.1 Impact of External Analysis Capacity on Data Biases

In the first stage of the experiment, all three groups of external analysts identified differences between group members' datasets and discovered that the data providing the numbers of infections were biased.

Example observation *EA8 is looking up the data for Niprusxem. He says he only has month 2 for this and that this is strange. Asks to see EA12's data. EA9 says she only has month 3. EA12 has month 4. EA9: We have different datasets!*

However, the bias within the capacity data remained undetected in all three groups (see Table 7). This led to the development of information products that were overly focused on the outbreak situation and overlooked existing capacities.

Figure 4 shows the results of the coding and categorization process of our qualitative content analysis. The figure

Table 7 Overview of identified data biases per group

Group	Bias in infection data	Bias in capacity data
Noruwi	Identified	Not identified
Reloupe	Identified	Not identified
Republic	Identified	Not identified

provides a summary of the sensemaking process within the groups. It shows the share of each coded category (in percent) within the overall activities of the groups during five time intervals of 30 minutes each.

In the initial phase, participants rushed into downloading the datasets stored in their individual Google accounts and started the data analysis by importing the data into their preferred information systems (e.g., Excel, RStudio). Participants familiarized themselves with their own data and identified differences in the data of their group members. Figure 4 shows the share of *data work* remained constant during the first two time intervals (i.e. first 60 minutes). It became the dominant category during the third interval and then lost importance by making room for an increased focus on *decision-making recommendations*. Figure 4 also shows the groups started with attempts to integrate datasets as *debiasing behavior* in the first interval.

Example observation *EA10 suggests to the group to upload the data into Google Drive so he can easily merge them.*

These attempts were, however, not efficiently followed-up upon, and the share of *debiasing behavior* was reduced in the second time interval.

After an initial familiarization with the data, a collective sensemaking process started to emerge, characterized by intensive socializing, working, and experimenting with the data. The groups discussed how to define priority districts and what should be the key variables. This led to *debiasing behavior* gaining significance slightly and reaching its peak at the second last interval when groups recognized that datasets remained biased. The sensemaking process did not lead to due attention to biases. When differences between the group members' datasets were recognized, measures taken by the groups were insufficient to debias the data. One reaction was that one group member would upload their biased dataset into a shared folder, and the other group members would from then on use this data folder as the single-point-of-truth. From that time on, all group members accessed the same biased data. This behavior might be explained by groupthink, as the individual members of the groups strived to establish harmonic relationships, characterized by conformity and the minimization of conflict rather than openly articulating the disconfirming information they held.

Participants struggled with the non-availability of data they wished to have and perceived the data quality of some datasets to be too low to build accurate situational awareness and determine priorities. With the end of the experiment stage approaching and time pressure increasing, groups tasked individual members with creating information products, i.e., maps, graphs, and tables.

Example observation *EA11: Data quality is questionable, it is not meaningful to go into data analysis in the last 20 minutes, must be quick... I need to think of the report, we should still name projects or tasks that our organizations would work on.*

At this point, it became increasingly difficult for the groups to mitigate any data biases because individuals would turn their own data into information for decision support, and no critical data assessments were done. Figure 4 shows *Interpretation of data* and *decision-making*

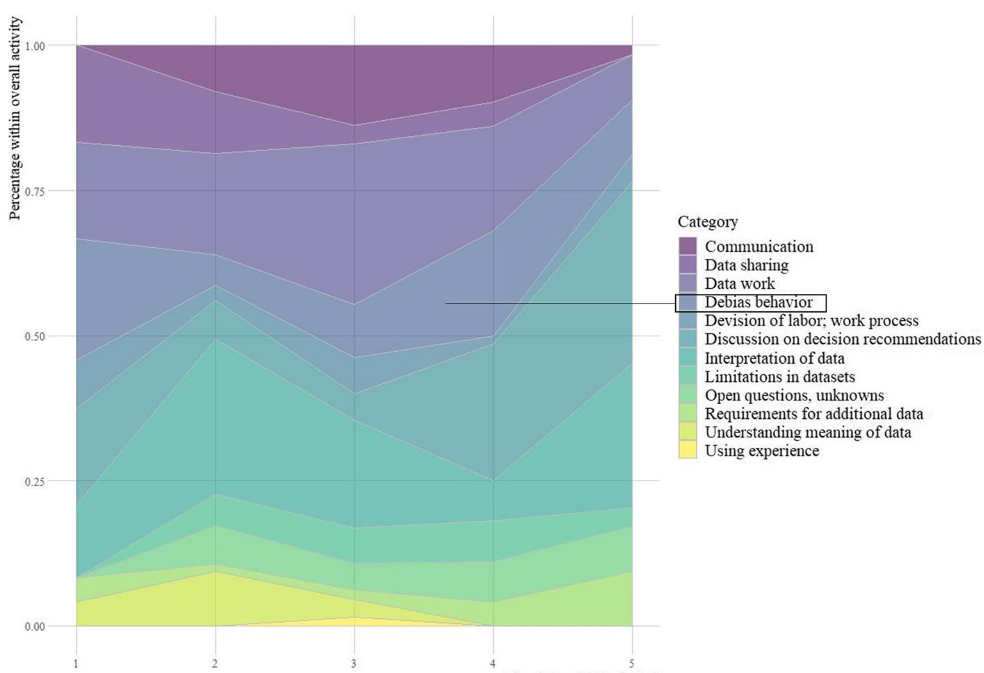

Fig. 4 Experiment stage 1 results of the coding and analysis process. The figure shows the share (in percentage over time) of the coded categories within the overall activities of the groups. Debiasing efforts were not sufficiently followed up upon and, towards the end of the experiment, largely replaced by discussions on decision-making recommendations

recommendations dominated the last time interval and *debiasing behavior* was again neglected.

Even though all groups identified the bias within the infection data, the groups failed to successfully debias the data. Successful debiasing would have required that members of each group merge their datasets for infection rates and infrastructure capacity. However, even though the bias was recognized, each group relied on the data of only one of its members in the design of information products. Remarkably, one group identified early during the experiment that its members had received biased data and shared their finding with the other groups, but still all groups presented results based on biased data at the end of the experiment.

The resulting information products of each group showed numbers of infections in the most affected districts that were lower than the complete and unbiased information they could have acquired by merging their datasets. Figure 5 shows one example of a developed information product. It depicts that the district with the most cases in the unbiased dataset was presented with biased numbers based on only one of the participants' datasets.

Overall, an explanation for the unsuccessful debiasing is the strong perception of time pressure and the experienced urgency by participants to deliver an information product in time that is presentable and actionable for decision-makers. Even though the additional analyst capacity is meant to alleviate the time pressure, they are subject to the same biases of exploiting, rather than exploring data (Comes et al., 2020). Analysts were not able to develop unbiased information products for decision support, since the data was accepted with its flaws, and information products needed to be developed anyway based on the low-quality data.

4.2 Data Bias in the Decision Process

In experiment stage 2, all three groups relied on the biased datasets and resulting biased information products from stage 1 in their discussions on treatment center placement decisions. External analysts briefed decision-makers using the biased numbers of infections.

Example observation *They decide to place treatment centers based on the case numbers, and also want to place them along the border. EA12 shows the map of the confirmed cases to the DMs.*

As described Section 4.1, no group was able to identify the data bias on existing bed capacities during information product development (see Table 7). Consequently, no detailed capacity data was communicated to decision-makers, and allocation decisions were made in the absence of detailed data on existing capacities. If the capacity data bias had been discovered, it potentially could have facilitated the groups' allocation decisions.

Decision-makers took the role of *advocatus diaboli* by critically questioning the underlying data of the developed information products. In their role as decision-makers, they pressured external analysts on the data gaps and data quality issues very early in the experiment.

Example obervation *DM3: why are some areas empty? EA5: the data is not very clean; possibly underreporting. DM1: is the data trustworthy? EA5: we had different datasets between group members.*

Analysts briefed decision-makers on data limitations. This led to the joint understanding that the available data was unreliable to some degree. However, when

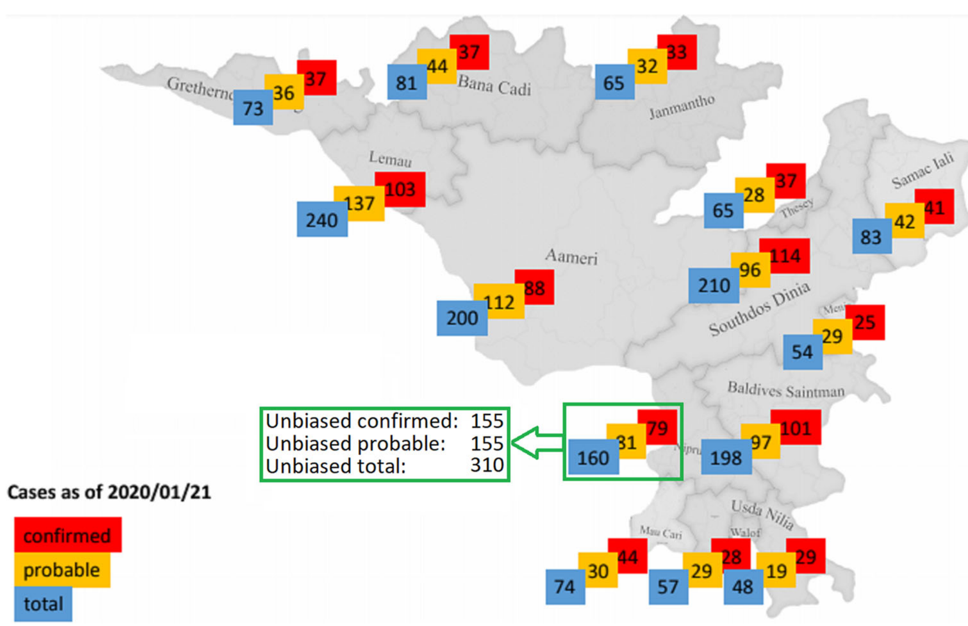

Fig. 5 Example information product resulting from stage 1. Country map shows the numbers of cases per district (colored by the participants in red, yellow, and blue). The green box (added by us) shows that the unbiased numbers of cases for the most affected district were much higher than those reported in the information product developed by the participants

data limitations were mentioned, decision-makers did not pressure enough. When analysts explained data gaps, other group members, who had access to that missing data, would not step in to clarify. Decision-makers would not press the group sufficiently to mitigate the data bias. Instead, they would pressure to make prioritization decisions for treatment center allocation.

Example observation *DM5: Based on my experience, you have to make decisions on very little data. Indecision kills.*

Figure 6 shows the results of the coding and categorization process of our qualitative content analysis of experiment stage 2. It shows the share of the coded categories (in percent) within the overall activities of the groups during four time intervals which are 15 minutes each. Deliberations on *allocation strategies* dominated discussions from the second interval onward till the end of the experiment. It reached its peak during the second last interval, where 35 % of discussions were on *allocation strategies*.

Groups showed stronger debiasing behavior at the beginning of the session, where *data limitations* were communicated and discussed. However, this focus was reduced over time, only increasing slightly in the last time interval. This pattern of debias neglect was already observed in stage 1.

Requirements for additional data mainly were articulated in the beginning and were then constant throughout the later intervals even though it was communicated to the participants that there would be no additional data provided during the experiment. This behavior shows a heavy dependency on *more* data and the conviction that more data will help the decision process, even if the quality of the future data is unknown and can be questioned if the currently available data is already of low quality.

Interpretation of the situation out-weighted the *interpretation of the data* throughout all intervals, showing the influence of the decision-makers who relied more on their previous experience to assess the situation than basing their assumptions on the available data that was known to have limitations.

Overall, the joint information management and decision-making process between analysts and decision-makers did not result in sufficient debiasing, and allocation decisions were made based on biased information.

4.3 Persistence of Bias in Sequential Decisions

In the final phase, participants were asked to select additional information that supported or conflicted with their allocation decisions. Our analysis of the survey responses shows that the mean count of selected supporting datasets was higher ($M = 2.94$, $SD = 1.56$) than the mean count of selected opposing datasets ($M = 1.82$, $SD = 1.88$), indicating that participants selected more supporting than opposing datasets. Wilcoxon signed-rank test was used to test if the discrepancy between means

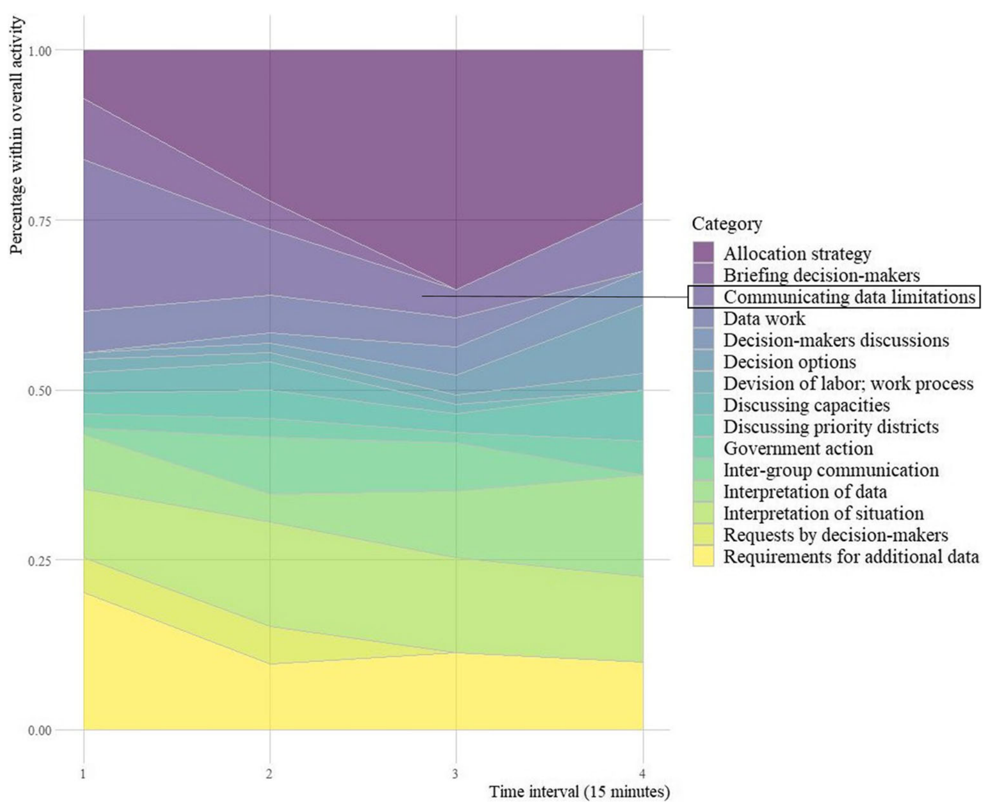

Fig. 6 Experiment stage 2 results of the coding and categorization process. The graph shows the share (in percentage over time) of the coded categories within the overall activities of the groups. Initial discussions on data limitations were not sufficiently followed-up upon and discussions on allocation strategy dominated the group discussions from the second interval onward

was statistically significant. The result reveals significant confirmation bias in the participants' selection of additional datasets (n = 17, z = -2.537, p = .011). We, therefore, find that our participants showed significant confirmation bias and that the bias drives their information selection decisions.

This is particularly concerning as the participants' preliminary decisions were flawed and based on biased information. In stage 3, participants tried to substantiate further their previously biased decisions instead of using the opportunity to counter-check their assumptions. Confirmation bias reinforced their biased assumptions and strengthened their reliance on potentially further biased data.

A significant confirmation bias at this stage is in line with our observations in the earlier stages of the experiment, where participants followed an exploitative and satisficing strategy given the time pressure, rather than an exploratory strategy. Although much of the literature on crisis and disaster management suggests an adaptive approach to manage the uncertainties that typically exist at the onset of a crisis (Comes et al., 2020; Quarantelli, 1988), we found that over time the initial mental models and decisions became deeply ingrained and persistent. As such, it became increasingly difficult for participants to implement a debiasing strategy that allowed them to correct their decision because the initial data biases were never effectively discussed and mitigated, even though new information became available that could have facilitated corrections. Even though they knew that their information had been incomplete and possibly flawed, the participants' debiasing behaviour was diminished, and they were overconfident in their decisions. If participants would have laid more focus on discussions on data limitations, they might have been more mindful and showed a more balanced or even disconfirming information selection behavior to correct previously flawed decisions.

5 Discussion

5.1 Contribution to Literature

Our experimental evidence adds to the theoretical understanding of the role of biases and debiasing strategies in crisis information management (Mirbabaie et al., 2020; Ogie et al., 2018; Comes, 2016). Our experiments show that a reason for the lack of debiasing efforts is the urgent context of crisis information management and the strong group cohesion that lead to a neglect of critical data assessments within the initial exploratory step of the analysts. Debiasing behavior is particularly strong during the onset of workgroup collaborations. However, these debiasing efforts are increasingly neglected as time pressure builds and mental models are formed. This implies that rather than using additional capacity to broadly scan the available information, the process follows a satisficing strategy, whereby one dataset is 'good enough' to develop information products quickly that are directly actionable and support decision-making. Because biases remain untreated, information products and decisions become affected by them.

Even though conventionally there is hope that additional data analysts will mitigate the impact of data bias, our findings show that even though biases are detected, they are not mitigated. Hughes and Tapia (2015) emphasized the expertise of external analysts with specialized software. We find that the preference to start data analysis quickly in participants' preferred tools moves the focus away from debiasing efforts. The law-of-the-instrument was clearly present in our groups, especially in the initial phase of the experiment. This indicates that our participants had strong preferences for their preferred information systems. In an effort to understand their own data, participants approached data analysis with tools they were familiar with and knew best. Datasets from other group members, and their potential differences, were not receiving due attention.

Our findings show the interplay of data and cognitive bias in crisis response. We find that confirmation bias can exacerbate the reliance on biased assumptions and that data biases and cognitive biases can reinforce each other, leading to amplified bias effects. As proposed by Comes (2016), and experimentally confirmed in our study, crisis information managers and decision-makers are prone to significant confirmation bias. Our participants significantly more often selected new information that confirmed their previous assumption about priority districts, which was influenced by biased data. This holds true even considering the broad level of experience of our participants, and although they did know the initial data was biased. We therefore show that awareness of bias does not automatically lead to bias mitigation. The urgent, uncertain, and resource-constraint contexts of crisis response have led to calls for adaptive management (Merl et al., 2009; Janssen & van der Voort, 2020; Charles et al., 2010; Anson et al., 2017; Schiffling et al., 2020; Turoff et al., 2004). Our findings indicate that such adaptive approaches can fail due to the interplay of data and cognitive bias.

5.2 Mindful Debiasing and Future Research

Future CIM theory needs to further explain the interplay of data bias and cognitive bias, looking into reinforcing and mitigating mechanisms. Crisis situations are known to cause stress in responders, and this stress is known to increase the susceptibility to cognitive biases such as confirmation bias. Especially in data-critical environments like CIM, where responders have to handle various information systems, techno-stress can further increase stress and susceptibility to biases. Mindfulness has been found to alleviate some of this stress (Ioannou & Papazafeiropoulou, 2017) and therefore is a promising strategy to reduce the susceptibility to cognitive bias in CIM. Mindfulness means being more aware of the context and content of the information one is engaging with (Langer, 1992). When crisis information managers are mindful about the context and content of the information they are engaging with, falling into the trap of ever-confirming information-seeking behavior becomes less likely. In a mindful state, information managers would be more open to new and different information, and able to develop new categories for information that is received. In contrast, in a less mindful state, people rely on previously constructed categories and neglect and ignore the potential novelty and difference within newly received information. Being mindful means to increase one's metacognition, i.e., being aware and having a focus on one's own thought processes (Croskerry et al., 2013). Boosted metacognition might be effective in mitigating confirmation bias (Rollwage & Fleming, 2021). Future research should investigate the effectiveness of such debiasing efforts empirically.

Like Ogie et al. (2018), we argue that data created in crises, especially from the affected population, can be subject to a multitude of biases, which have to be taken into account if systems and algorithms are designed that are supposed to turn those data into objective, neutral decision recommendations. In a similar vein as Weidinger et al. (2018), who called for more research on users' perception of novel information systems and technologies for crisis response, we argue, crisis information management literature needs to account for data biases that systematically over- or under-represent issues, social groups, or geographic areas in the form of representational biases. If information management does not account for biases, resulting information products can become flawed and negatively influence decision-making, with detrimental effects for crisis-affected people.

Previous research proposed new forms of information systems, models, and algorithms to support resource allocation decisions in crises (Avvenuti et al., 2018; Kamyabniya et al., 2018; Schemmer et al., 2021). We argue that such systems need to consider the abilities and limitations of information managers and decision-makers to identify and mitigate biases in the usage of such systems. This includes data biases as well as cognitive biases. We emphasize previously proposed debiasing efforts, e.g., nudging (Mirbabaie et al., 2020), that can be implemented into information systems for crisis response with the objective to mitigate cognitive biases.

Previous research provided examples on effective debias interventions. Interventions can range from fast and frugal options to intensive training sessions (Sellier et al., 2019). Information managers and decision-makers can be trained to counter-check their assumptions by actively seeking disconfirming information and considering the opposite of their preliminary hypothesis (Satya-Murti & Lockhart, 2015; Lidén et al., 2019). Future research needs to test the effectiveness of such interventions in crisis settings.

We reiterate calls for sensemaking support in crisis response (Muhren et al., 2010; Comes et al., 2020). We add to that with our finding that decision-makers can act as advocatus diaboli to their external analyst partners. By trying to make sense of the unfolding situation and posing confrontational questions to external analysts regarding the quality and shortcomings of the data that underpinned developed information products, decision-makers uncovered important data gaps quickly. However, these also have to be effectively followed-up upon to lead to successful debiasing.

5.3 Implications for Practice

It can be observed that the response organizations are building up stronger internal crisis information management structures. Where once there were large skill gaps in data analysis and mapping, digital response concepts are now being observed within established organizations (Fiedrich & Fathi, 2021). External analysts are being integrated into permanent structures.

However, our findings suggest that crisis information management needs to invest in detecting, and most importantly, mitigating biases. Even if complete debiasing is not feasible, we give some concrete implications of our findings on crisis information management practice.

First, bias-awareness trainings can highlight the potential influence of biases in information management and decision-making, and provide guidelines for debiasing. We found that work groups initiated debiasing efforts and became aware of biases. Debiasing then however lost its significance in favor of quick analysis results and decision-making. More awareness of the pitfalls of biases might shift the focus to debiasing first, before final information products are developed and decisions are made. Post-mortem analysis of information management and decision-making processes after crisis response can be implemented in lesson learnt and debriefing sessions. Further, large-scale crisis response trainings, which are organized annually by major response organizations to train together for real crisis event (e.g., SIMEX, TRIPLEX), should incorporate debias interventions in training agendas.

Second, the development of models, algorithms and information systems to support information management and decision-making in crisis response, should implement functions that help identify and mitigate biases in (a) the datasets used by these systems, and (b) the cognitive processes of system users.

6 Limitations

In our paper, we present an initial exploratory study on the interplay of data and confirmation bias in time-critical sequential decisions. Because of the exploratory nature of our study, there are several limitations that can be addressed in future research.

First, and to the best of our knowledge, while our study is the first of its kind that brings external analysts together with decision-makers to study their joint CIM process in a realistic scenario-based experiment, and our participants were all experienced in their roles, the number of participants is a limiting factor in our study. Similar studies have reported larger participant groups, mostly of inexperienced students and other laypersons who are easy to recruit. We suggest to expand on our findings in additional larger-scale experiments and surveys across diverse groups and different professional experiences.

Our experimental design was inspired by hidden profile experiments. In traditional hidden profile experiments (Stasser & Titus, 1985; Lightle et al., 2009), participants are asked to study their received information before joining the group conversation. In contrast, we allowed for discussions from the start because crisis information management is characterized by fast, agile communication. Our approach decreased the chances that participants constructed a rigid mental model of what data they received initially. Two characteristics of our research design counter this shortcoming. First, we allowed for perfect recall, i.e., participants kept all materials during the workshop experiment. Second, participants needed to continuously engage with the data by aggregating, analyzing, and visualizing it, so they had to build a deep understanding of the data during the experiment.

It is a major challenge to simulate a realistic crisis environment in an experimental setting. This includes a realistic but still unknown scenario, decision-making under urgency, uncertainty, high stakes, and constraint resources, allowing for interactive collaboration with multiple actors, and providing equipment that resembles experts' real work environment. Simplifications have to be made to make the experiments controllable. In addition, we had to consider that some organizations might implement and pursue different approaches to information management and decision support than required by the tasks we set. In real-world scenarios, external analysts work with a larger group of colleagues. Because of the framework required by our experiment, for example, the discussions on the creation of the information products had to be objectively observed on site, it was not possible to include further external analysts from those remotely working communities. Here, we suggest to complement our findings with more ethnographic and field studies in real disasters to observe real-world debiasing and decision-making behaviour.

7 Conclusion

Crisis response organizations integrate external analysts into the CIM process to strengthen their digital resilience. In this capacity, external analysts collect and analyze data and develop information products (e.g., maps, tables, infographics) for decision support. While this extended capacity is meant to improve the evidence base for decisions, the CIM process remains challenged by circumstances of urgency, uncertainty, high stakes, and constraint resources. Consequently, crises are prone to induce biases into the data as well as the cognitive processes of external analysts and decision-makers. We investigated how biases influence the CIM process between experienced external analysts and decision-makers through a three-stage experiment.

Our findings show that data biases, even if detected, influence the development of information products for crisis decision support. We show that effective debiasing does not happen because crisis information managers have a strong commitment and urgency to deliver a presentable information product that is actionable enough for decision-makers to make decisions directly. Efforts for creating information products are prioritized, and debiasing is neglected. In subsequent deliberations and decision-making discussions, decision-makers are influenced by biased information products in their allocation decisions of scarce resources. Confirmation bias amplifies the reliance on problematic assumptions that were formed based on biased data. This implies that the biased, misleading information that shapes initial decisions is perpetuated by a vicious cycle of biased information search that influences future decisions. Our findings indicate that decisions in crisis response can only be effective if initial data and confirmation bias are identified and mitigated. Mindful debiasing could be a successful strategy to improve broad information search and tackle both biases.

Appendix

A: Observation Protocol

A. General description on site	B. Communication and interaction description	C. General impressions
How does the workspace you are observing look? (Seating arrangement, communication devices, support materials, additional characteristics, etc.)	Describe the sequence of events over time (e.g., information search, prioritization, processing, request, sharing, group discussion, decision-making,)	Tone of the discussion (rational, empathic, humorous, etc.)
Participant coding	Which information is shared among the participating V&TCs?	Speedy vs. lengthy discussions?
Was communication rather face-to-face or mediated via technology?	Are additional information sources used? How is the need for information expressed and communicated? Which decisions are anticipated to be supported by the V&TCs? Describe how and why specific types of information products are selected and created for the decision-makers. Which information is included and why? Which technology and other decision aid materials are utilized and how?	Attitude of individual participants (engaging, negative, overwhelmed,) To what extent was available information not shared / retained? Additional comments

B: Confirmation Bias Measure

"Below are the summaries of 10 new datasets that are available. You can re-quest the full version of those datasets but you only have limited time and re-sources to evaluate them all in detail. Select as many datasets as you want. District X is the district you have identified in the last session as the most critical district."

- Dataset 1: District X has less treatment capacity than infection cases.
- Dataset 2: In district X the infection rate is likely to increase.
- Dataset 3: District X has high infrastructural damage.
- Dataset 4: District X has a low percentage of people reached.
- Dataset 5: District X has more treatment capacity than infection cases.
- Dataset 6: In district X the infection rate is likely to decrease.
- Dataset 7: District X has low infrastructural damage.
- Dataset 8: District X has a high percentage of people reached.
- Dataset 9: District X has a high amount of health care workers infected.
- Dataset 10: District X has a low amount of heath care workers infected.

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Declarations

Conflict of Interests The authors have no conflicts of interests to declare.

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5.1.4 Study IV

Löchner, M., **Fathi, R.**, Schmid, D., Dunkel, A., Burghardt, D., Fiedrich, F. & Koch, S. (2020). Case Study on Privacy-aware Social Media Data Processing in Disaster Management. International Journal of Geo-Information. DOI: doi.org/10.3390/ijgi9120709

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Case Study on Privacy-aware Social Media Data Processing in Disaster Management

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Abstract: Social media data is heavily used to analyze and evaluate situations in times of disasters, and derive decisions for action from it. In these critical situations, it is not surprising that privacy is often considered a secondary problem. In order to prevent subsequent abuse, theft or public exposure of collected datasets, however, protecting the privacy of social media users is crucial. Avoiding unnecessary data retention is an important question that is currently largely unsolved. There are a number of technical approaches available, but their deployment in disaster management is either impractical or requires special adaption, limiting its utility. In this case study, we explore the deployment of a cardinality estimation algorithm called HyperLogLog into disaster management processes. It is particularly suited for this field, because it allows to stream data in a format that cannot be used for purposes other than the originally intended. We develop and conduct a focus group discussion with teams of social media analysts. We identify challenges and opportunities of working with such a privacy-enhanced social media data format and compare the process with conventional techniques. Our findings show that, with the exception of training scenarios, deploying HyperLogLog in the data acquisition process will not distract the data analysis process. Instead, several benefits, such as improved working with huge datasets, may contribute to a more widespread use and adoption of the presented technique, which provides a basis for a better integration of privacy considerations in disaster management.

Keywords: disaster management; virtual operations support teams; privacy; data retention; hyperloglog; focus group discussion

1. Introduction

Social media services are almost always available, so that in times of crises people can access them as established and interactive communication resources. The Corona pandemic has even strengthened their special role: through measures such as social distancing, the use of social media services for communication and information dissemination is growing fast [1]. Numerous disasters in the past have demonstrated how important the role of social media is for crisis communication as well as for information gathering [2]. Both the people affected by a disaster and those indirectly affected use online services to obtain information about their relatives, the extent of any damage, possible further dangers or offers of help.

Those affected by a disaster are a vulnerable group. Some are dependent on receiving or sharing credible information or seeking help only through social media services like Facebook or Twitter. For example, in case of missing relatives, real names, addresses or even pictures of people could be published publicly. Personal data can also arise when affected people communicate publicly with authorities on social media platforms, view content or participate in self-help groups [3].

At the same time, large amounts of data are created on social media services during disasters, that are available to the public and can include important and relevant information for decision-makers. With the aim of processing and visualizing information from social media for decision-makers, so-called Virtual Operations Support Teams (VOST) are established. Consisting of volunteers, VOSTs analyze social media systematically and in a coordinated manner, and evaluate operation-relevant information.

Some of the VOSTs use social media analysis programs that store and analyze data from various social networks automatically. Such analysis software retrieves data from social media services e.g., through their application programming interfaces (API) and stores them in their own databases. This is usually necessary for the application to be able to access the actual data in a reasonable amount of time, not only since data analysis during a disaster is usually very time-critical.

Due to the usually time-critical nature of these operations, privacy aspects are prioritized rather low in disaster management. This is especially devastating because of the aforementioned very personal character of the collected data. In particular, we have determined *data retention* to be the problem with the highest urgency in this specific case.

Data retention "is the continued storage of an organization's data for compliance or business reasons" [4]. While storing the data is necessary for the analytics software to work properly, it is dangerous for its operator for multiple reasons. Constantly changing terms of services of social media services may evoke legal issues of their business [5]. Furthermore, storing large amounts of data opens the risk of possible abuse, theft or accidental public exposure [6].

The necessity arises for a method to store large amounts of social media data in a way that is technically reasonable on the one hand and privacy-aware on the other. Dunkel et al. [7] have developed a method to store and process data from any social media service in a privacy-aware fashion, using an algorithm called HyperLogLog. With this method, data queried from a social media service API can be stored in a local database, without the possibility to leak information about single entities afterwards. The resulting visual output of an analytics application will not differ significantly from what was created from conventionally stored data.

While in the past numerous studies have dealt with the topic of data analysis in crises [8] or the integration of VOST into the working environment of decision-makers [9], questions about privacy and VOST are not considered, yet. In this paper, we therefore develop approaches to answer the following central research question: what opportunities and challenges can be identified for VOSTs to work with privacy-enhanced data and what potential implementation barriers can be detected? Figure 1 outlines the concept in a graph, including stakeholders and the data flow.

To approach the research questions, we prepared and carried out a focus group discussion with voluntary VOST members, in which they were confronted with the topic and some sample dataset, which we extracted from social media services. We found, that VOST members are generally worried about losing important data, when it comes to privacy regulations. From the technical point of view they were rather indefinite, but since storing social media data using HyperLogLog both reduces storage space and increases processing speed significantly, they turned out to be quite open to a privacy-aware storage implementation.

In Section 2 we discover the fundamentals of our interdisciplinary research. Following, we describe the methods implemented in the data acquisition and the preparation and provision of the focus group discussion (Section 3). Afterwards, we discuss the results of the discussion and our findings (Section 4), concluding with an outlook of our further research plans on that topic (Section 5).

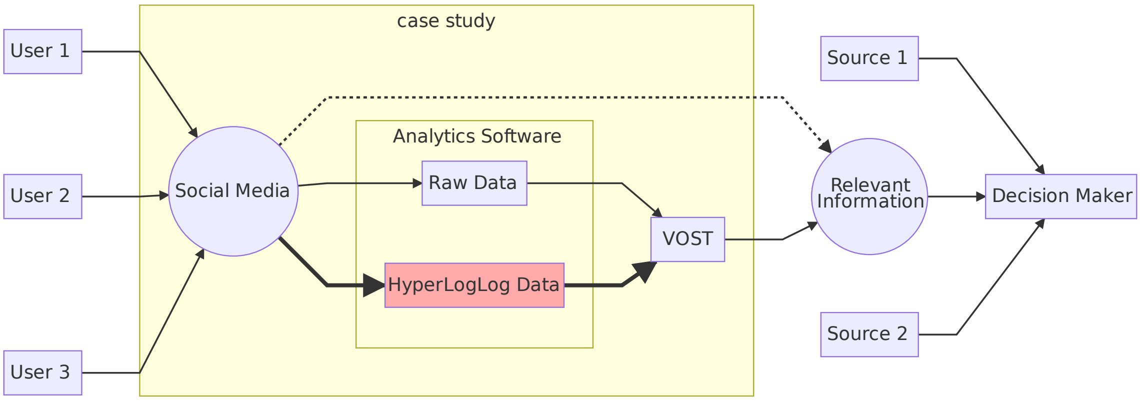

Figure 1. Users of social media services supply data, that is then parsed by analytics software, before the VOST evaluates it. Relevant information from social media is then passed to decision-makers, who found their decisions on it among other sources. The case study wraps up the part that involves social media, the analytics software and the VOST. We propose to base the analytics software on privacy-enhanced HyperLogLog data as a substitute to conventional raw data.

2. Fundamentals

In this section we explain the fundamentals and present relevant research results in the following subsection. First, we will present research that primarily addresses social media and disaster management. We examine both historical and current aspects, such as the use of online media during the Corona pandemic. Afterwards we will introduce the novel VOSTs and their tasks during a disaster. An introduction to the privacy aspect of data retention and its challenges follows. Finally, we introduce a method to store social media data in a privacy-preserving way, which we based this case study on.

2.1. Social Media and Disaster Management

As communication and collaboration platforms, social media services play an important role in disaster management, not only since the Corona pandemic. Numerous major incidents in the past have made clear that those affected, eyewitnesses or spontaneous volunteers actively use digital tools for information and communication [10]. However, there are various possible uses and behaviors, even within the different population groups. In a recent survey by Statista, 60% of the 2087 respondents (age group 18–64) state that they regularly use social networks such as Facebook, while 52% use so-called media-sharing platforms such as Instagram. In addition, 74% said they regularly use instant-messengers such as WhatsApp [11].

During crises and disasters, it can be observed that the need for information is very high, not only among the affected population but also among relatives and among other indirectly affected persons. This increased need is also reflected in the social media: In a representative survey commissioned by "Digitalverband Bitkom", 75% of users of social media services in Germany stated that they had been increasingly active in social networks during the Corona pandemic and used them more intensively. According to the survey, almost all age groups spent more time on platforms such as Facebook, Twitter, TikTok, Instagram, etc. than usual. Among the 16 to 29 year olds, the figure was as high as 86%, among the 30 to 49 year olds 82%, among the 50 to 64 year olds 74% and among the over 65 year olds 32%. At the same time, a total of 82% increasingly communicated via instant-messengers [12].

In past major incidents, such as the earthquake in Haiti in 2010, the Elbe flood in 2013 or the urban flashflood in Münster in 2014, social media helped thousands of volunteers to spontaneously network with each other and to actively participate in disaster management [13]: In Münster, hundreds of spontaneous volunteers who networked and organized themselves via social media founded their own temporary aid organization. They participated in disaster relief in sub-groups structured parallel to the governmental emergency aid mechanisms. They carried out tasks such as easier clearing work or filling sandbags [14].

Experiences of past disasters also show that fake news can spread online within minutes, which in turn can have serious effects on psychosocial needs and government crisis management [15]. In a previous study, for example, it was possible to identify patterns and differences of false information during crisis that could be used for an automated identification of disinformation [16]. Current work such as that of Kirchner et al. examines the acceptance of social media users for approaches such as warning of misinformation [17].

A similar phenomenon is also emerging in the context of the Corona pandemic. According to Situation Report 13 of the World Health Organization [18], the outbreak and the reactions to the pandemic are accompanied by a massive "infodemic", an abundance of true and false information.

Already in 2008, Vieweg et al. [19] analyzed the use of social media in disaster relief. As a result, a new and distinct field of research developed: crisis informatics. Since then, numerous scientists from different academic perspectives have been working in this field [20–23]. Parallel to this, due to the importance of geographic data, the research area that places the use of Volunteered Geographic Information (VGI) at the forefront of scientific debate, has developed [24,25].

Since the beginning of crisis informatics research, information-technology research questions have dominated the scientific discourse. One focus has been the analysis of large amounts of data (Big Data) generated by social media [10]. Innovative research is investigating the use of artificial intelligence and methods for the machine processing during crisis [26].

Further research addresses the question of whether decision makers can actually use VGI data and whether or how they use the information provided [21]. Some studies indicate that there seems to be a significant discrepancy between the data produced by digital volunteers and the requirements of organizations involved in disaster relief [27]. Successful cooperation requires stable structures, reliable data quality and consistent forms of organization that outlast individual disaster relief operations [27].

Nevertheless, the authorities are also facing major technological challenges, especially in the area of information management. Field studies after Typhoon Haiyan in the Philippines and during the Ebola crisis (2014/2015) suggest that executives need a better understanding of their decision-making processes. It is particularly important that the needs for mission-relevant information, such as spatial data or VGI, be clearly communicated to digital volunteers [28].

In a systematic review, Reuter and Kaufhold [2] analyze 15 years of research into the use of social media in disasters, starting in 2001, the year of the attack on the New York World Trade Center. They focus on the collection of patterns of use, perception and roles that have been identified by studies in different disaster situations. Reuter and Kaufhold [29] also present derived role typologies in a matrix that differentiates between authority and citizen/public on the one hand and between real and virtual on the other. They describe that these roles and role types take either the perspective of a citizen (public) or an authority (organizational) and refer either to the real or virtual realm.

A new form of authority digital operational support are *Virtual Operations Support Teams* (VOST). They work as part of a public organization with digital volunteers in an entirely virtual environment.

2.2. Virtual Operations Support Teams

In the initial phase of crises and disasters, one of the key factors in the management of these situations is that emergency forces with the necessary skills, such as the analysis of social media for a situational awareness, are a limited resource. With the aim of processing and visualizing social media information for decision-makers, the first so-called Virtual Operations Support Team (VOST) was formed in 2011 [30]. It pursued the goal of integrating data from social media more effectively into decision-making processes. Divided into working groups, VOSTs carry out various tasks during operations:

- Social media monitoring as well as conducting data processing, filtering and assessment
- Creating and updating spatial analysis of digital maps
- Recognizing and analyzing trends and sentiment in social media
- Identifying rumors and false information
- Verifying and geolocating social media posts
- Crowdsourcing and collaborations with other VOST
- Presentation to the operational staff of the EMAs [31].

The Federal Agency for Technical Relief (Technisches Hilfswerk, THW) has been operating the first German VOST on federal level since 2017. 25 digital volunteers are deployed using innovative organizational strategies and innovative analysis tools to master the challenge of the data flood and to process situation information for decision makers. In September 2018, the Ministry of the Interior, Digitization and Migration of Baden-Württemberg established its own Virtual Operations Support Team on state level. With the time further teams followed, e.g., at the fire department Hamburg.

In a study, participating observations were used to identify organizational, procedural and technical requirements for the successful integration of VOSTs in emergency operation center structures [31]. In addition, process analyses were able to document for the first time the working methods of the VOST, such as the way information is provided to decision makers. It became clear that in many cases real-time information from publicly accessible sources contributed to an awareness of the situation and was used in time-critical decisions of the crisis management team.

The concept of these teams is also based on the fact that the helpers can work in working groups at different locations and times. Based on this high flexibility, VOST THW has already been able to manage over 25 operations. A further study shows that the public also appreciates this work. In this study, the authors show that 67% of the German population expect authorities to monitor social media. In addition, 20% of those questioned say that they use social media to search for and share information during crises and disasters [32].

2.3. The Privacy Aspect of Data Retention

Users of social media services tend to lack the awareness for the data they provide to the particular network is subject to being analyzed by third parties [33]. The daily work of VOSTs is based on data analytics software that does assemble, store and analyze data from various social networks. Storing the data in a local database is necessary for the software to be able to access it quickly, but it basically means copying of sets of data to a different place. This can as well be interpreted as *data retention*. Data retention has been defined as "the continued storage of an organization's data for compliance or business reasons" by Rouse [4].

Blanchette and Johnson [34] already addressed the disappearance of social forgetfulness as a side-effect of data retention. In terms of social networks this means that a social media user may delete their post on a network, but the post still remains existing as a copy in any dataset downloaded and stored by a third party, and the user has no chance to even take notice of this. This is especially relevant with social media data associated with crises and disasters. In certain situations, users are dependent on social networks as their only way to communicate, seek help or share credible information e.g., with public authorities [3]. Fearing their personal data being subject to theft, exposure or other abuse like mass surveillance e.g., by authorities, users may retreat from posting publicly on social media services like e.g., Twitter or Mastodon, and move to closed messaging groups in other messengers like e.g., Telegram or Matrix [35]. Miller [6] has pointed out recent incidents, where data retention has lead to theft or accidental public exposure. This underlines the significance to respect users the right to informational self-determination [36].

This would be destructive for a wide range of beneficiaries. Especially humanitarian actions rely on public availability of social media data [37]. Therefore the gradual retreat of the user base must be prevented.

2.4. Privacy-Aware Storage

Recent publications try to raise awareness for privacy aspects in humanitarian action [**?**]. They outline the necessity for suitable methods yet to be developed. VOSTs usually prioritize privacy considerations rather low due to their work being very time-critical.

A wide range of techniques to address privacy issues in big data analytics have been published, e.g., *k-Anonymity* [39] or *Differential Privacy* [40]. None of these are suitable to process huge amounts of data in a constantly updating stream, as it is the case with social media data.

A rather new technique to approach the problem of processing large datasets are *Probabilistic Data Structures* [41]. A specific example is a cardinality estimation algorithm called *HyperLogLog* [42]. Its fundamental strength is the ability to *estimate* the distinct count of a multiset (*cardinality*), stored in a data structure, that does not allow the extraction of single elements (see sample data in Figure 2). Regarding privacy protection, it is notable that without further external knowledge, it is impossible to retrieve single items out of the stored dataset [43].

Furthermore, processing data using HLL is very efficient in terms of processing time and storage space. The characteristic distinct count estimation of HLL increases the speed of processing significantly, but the result has a potential offset of about 2% [42]. When dealing with huge datasets, such as social media data, an offset of this size is negligible, because in visualizations the difference to the actual raw data is not visible.

A dataset is built upon one specific query to the original social media source, e.g., the application programming interface (API) of a social media service. Depending on the configuration of the algorithm, the dataset can only answer a certain amount of questions, that can usually be broken down to counting its elements. So HLL data can be seen as *disposable* data, since it is impossible to draw other information out of it, than originally intended. These characteristics make HLL a suitable algorithm to process social media data in a privacy-aware fashion [44].

Krumpe et al. [45] have defined a general structure to handle social media data across any social media service. Based on that structure and the HLL storage algorithm, Dunkel et al. [7] developed a method to store and process location-based social media data in a privacy-aware fashion. In this case study, we aim to investigate, whether VOSTs are able to work with data, that has been processed with this privacy-aware storage method.

3. Methods

In this section we outline the methods applied to the case study. We explain the structure of the focus group discussion and the reasoning for applied concepts. In addition, we describe how we acquired the dataset utilized as sample data in the discussion.

3.1. Focus Group Discussion

In this case study, we address the questions, what opportunities and challenges we can identify for VOSTs to work with data sets processed with the cardinality estimator HLL, and what potential implementation barriers we can detect. This issue has so far received little attention. Privacy and data protection are generally an open topic in the humanitarian aid community. Therefore, we designed a group discussion with VOST members to examine the feasibility of implementing HLL data in the VOST workflow and their sensitivity for the privacy aspect.

Participants in the discussion were members of two different VOSTs (THW and Baden-Württemberg), along with the authors of this paper, and one independent recording clerk.

Our concept intended a guideline-based discussion in order to develop approaches to answer the research questions by analyzing the discussion protocol after the discussion. The overall goal of the discussion was to document the expertise of the participants being volunteers with experience in the field.

We chose the focus group discussion method [46] because, as described in Section 2, the members of the VOSTs are very heterogeneous. They differ, for example, in their level of knowledge, working methods and working culture. As a result, there is an increased need for communication within the teams in case of operations in order to establish structures and discuss working methods. The purely virtual working method is an additional complicating factor. In focus group discussions, guideline-based and moderated sessions are encouraged so that a concrete topic can be dealt with together. The method is used in many different ways, e.g., to achieve conflict management. Nevertheless, the focus group discusson is also suitable for representing diversity of opinion and for jointly developing improvements and solutions. Because we used the established communication structures of the VOSTs, we were able to work on the specific topic using this resource-saving method.

A video conference was chosen as the venue for the discussion, using an instance of Jitsi Meet. VOST members ought to feel confortable in this environment, since they live spread across the country and virtual communication environments are their familiar place to work in the VOST (see Section 2.2).

The schedule of the discussion included a brief introduction to privacy as a concept in general and a very basic outline of the HLL data structure. The content of a sample dataset with raw and HLL-processed data was introduced along. Since the VOST members are not at all technically proficient, the introduction did not include any mathematical or computational details, but rather demonstrated the differences of raw and HLL-processed data in a tabular view (see Section 3.2).

After the introduction the VOST members were confronted with the three hypothetical scenarios and were asked to discuss their respective approach in each of them one after the other. The scenario catalog, which generally serves as a guideline for focus group discussions, was intended to establish a discussion structure and to examine the research questions. All three scenarios had the pandemic spread of the Corona virus as their basic operational situation, and only differed in the location level of operation: national, regional and local. The aim of these distinctions was the hypothesis, that different privacy challenges may occur at different levels of operation in the analysis of social media by VOST. For example, we expected that different requirements would arise at the local level than for the analysis of social media data at the federal level. Since the members of the two participating VOSTs were involved in managing such operational situations before, no detailed explanation of the scenarios was necessary.

During the discussion, however, the sample dataset only received minor attention in favor of discussing more fundamental aspects, so that the prepared scenarios did not come into action. Nevertheless, they were utilized as a guideline in which, for example, discussion questions were derived from.

The end of the discussion marked a short summary by the authors and acknowledgements to the participants.

3.2. Data Acquisition

To explain the advantages of HLL during the focus group discussion, we chose to present a sample dataset that could potentially serve as real data for a VOST operation and its members feel familiar with. So we created a dataset, that covers all German posts on Twitter containing the hashtag `#corona` from January through May 2020. Thusly, we collected `72.743.465` posts from `6.038.577` distinct users via the Twitter API. For this particular scenario, we relied on Twitter's language tagging and collected only German posts. Posts that were tagged as containing other or undefined languages were discarded. We chose to limit the collected data to only contain German posts for two reasons: (1) a German VOST team would predominantly concern with German tweets, and (2) limiting the data to contain only German posts shortened the time we spent pre-processing the data significantly. Still, pre-processing and creating the databases took about two weeks of mostly unattended computation.

We utilized the data conversion tool `lbsntransform` [47] to read the dataset into two PostgreSQL databases: one for HLL-processed data and one for the plain data, to compare against. The table in Figure 2 shows an example query to the dataset, including the structure of the HLL-processed data, as it is stored in the database. It makes clear, that no original data can be revealed from that storage format. It further illustrates the slight difference between the actual number of posts and the *estimated* number counted by HLL (see Section 2.4).

hashtag	actual_count	hll_count	hll_data
corona	755797	763316	\x148b7f52d4d4b0c93a9696a16a4c14c42549531484a52852d083294b5456
coronavirus	614201	609185	\x148b7f4392c525a83b9886a9294a9296356b3a9473a5487a1a85ad485214
afd	391075	378847	\x148b7f521273a9074ad273a96842d08425884a5084a907629466290c3290
covid19	341884	339737	\x148b7f5252c524e639ce56a92752d4941d494a14941d283a107528c83a52
hanau	289371	277753	\x148b7f5a947320e94accb329065a108420e53a4e84a8ec521694290d5990
coronakrise	212108	215994	\x148b7f32cec4a10749cc7321075ad26424e75994631d064212d320ef31ce7
merkel	203142	201882	\x148b7f39ce74198531d0a6a4c73a94542148318c83a8e83a9273214759d6
cdu	194358	199547	\x148b7f4acc731cab4a96d518e739ca84212739cc85214841d2b69ccc72cea
berlin	183407	192788	\x148b7f425cb394e829cc9524f14210631987625694992832109 3bd264190
polizei	185625	185865	\x148b7f42d26521265a50641cec438e74a14861927499076a8c739d062a50

Figure 2. Most frequent descriptive metadata terms (hashtags) of posts in the sample dataset for the focus group discussion are shown in column one. The next two columns show the number of posts that contain these hashtags. Column two shows the corresponding raw count, the actual number of posts in the dataset. The equivalent HLL count, the value estimated by the HLL algorithm, is shown in column tree. The last column shows the HLL-processed data structure and emphasizes the impossibility to read original data from it.

4. Evaluation

In this section we evaluate our case study applied as a focus group discussion. First, we enumerate and explain details of the results of the discussion. A subsequent analysis of the results constitutes scientific insights, implementation examples as well as proposals for approaches and alternatives to negative results.

4.1. Findings of the Discussion

The focus group discussion examined the requirements of VOSTs in operations. Especially when VOST members get in contact with personal data of social media users, a focus on privacy aspects is crucial.

Once the participants were introduced to the privacy preserving measures, they initially were under the false assumption that more privacy would lead to less data. This would lead to them not being able to fulfill their tasks. The brief introduction into the technical features of HLL (see Section 3.1) cleared up these misunderstandings. Afterwards, participants opened up to the concept of privacy preserving aggregations, rather than using the raw data. The misconception was probable, since the VOST members were only used to working with big data. Privacy measures usually do mean that there will be less (or no more) data to work with.

However, findings of the focus group discussion encompass the disproof of our assumption that the VOSTs work is mostly based on big data analytics. In fact, the majority of efforts done by VOST members is inspecting single entities of social media data, e.g., posts, images, videos etc. As a participant already pointed out at the beginning of the discussion, an intuitive interface of the applied analysis software applied, is the far most important requirement in a time-critical work environment.

Not uncommon would be an open end investigation, where initially it is unclear to the VOST members, what they are searching for. A participant explained, it was possible that all relevant posts of a minor emergency situation, in which the VOST is activated, are first identified and then evaluated for relevance to decision-makers afterwards.

Participants of both VOSTs agreed, that one of their most important tasks is the verification of the information, that a post encompasses. This happens based on experience of each individual VOST member, and the consult of further information, usually by analyzing the meta-data of a post (e.g., time, location) and other details. It would be crucial to determine whether information in a social media post is trustworthy. Important indicators were claimed to be e.g., how long the user account actually exists, what language(s) the account usually uses, time ranges of postings (e.g., does the user sleep sometimes) and the number of followers, likes and retweets of its postings. Another method of verifying social media posts would be to compare them with alike user names and avatars of accounts on other networks.

The participants also highlighted the fact that the scale of a disaster and the level at which an operation takes place would not have a major impact on standard work processes. They furthermore pointed out that in addition to quantitative analysis, qualitative analysis would also have to be performed manually, e.g., when assessing the relevance of a high range social media post for decision-makers. Here again, the meta-data of an account could play an important role.

An entirely different aspect, that came up during the discussion, is training of the VOST members. For exercises and practice, it is possible for VOST members to be confronted with archived datasets. This contradicts with the characteristic of HLL-processed data being *disposable*, meaning that it is not possible to draw other information than originally intended from it.

In turn, it came to light that a frequently occuring problem would be to deal with the immense size of social media data and the time to process it, accordingly. Here, using HLL-processed data can help very much, because of its characteristics to be very lightweight in storage size and fast in processing.

4.2. Analysis of the Findings

The introduction to the subject area of privacy theory and the outline of the HLL algorithm have been designed to be brief and superficial, due to the audience consisting of civil protection experts and not of information scientists. The superficiality of this introduction can be a reason, why the discussion participants showed a certain amount of skepticism about our research and a general debate about privacy issues. The discrepancy between guiding into the topic and avoiding too much technical details is apparent.

The participants expressed concerns about alleged loss or inaccessibility to important information for their work, e.g., because of privacy regulations. The volunteers explained that in disaster relief, the information content of a social media post is always more important than the personal data of a user. They are aware of the topic of privacy, but see potential challenges in its application in everyday work, specifically during a crisis. This would certainly be a problem, especially in situations where human life is in danger. In those situations, the sentiment in the team usually gets tense, and time gets critical. Other situations, e.g., tracing fake news on pandemics, do not require time-critical decisions, and allow more time to do research work.

However, according to the results of the discussion, we can indicate our key finding is that none of the findings of the discussion are opposing the proposition, the VOST could work with HLL-processed data. This can be stated, because most of the VOSTs work happens *after* any potential processing of HLL data.

Usually the VOST work starts with a search for a term, hashtag or place. The analytics software then queries the APIs of the social media services and, for technical convenience, stores the answers in a local database. Right here HLL will come into play, because it can store only the data that is really needed to answer the query.

An example query could be for the number of posts per user on a certain hashtag. The answer is a list of user IDs and the according number of posts. No further information is required, so any information on each post is unnecessary to be stored in clear text, so it can be stored in HLL. The list can then be sorted by number to identify the user having the highest number of posts. Having its' user ID, the analytics software can then query the API of the social network to get all the details about that user ID. No information about the user has been stored to the local database, and no data retention has happened.

Regarding the exercise scenario described in Section 4.1, our proposition to apply HLL data can not be applied at all. Following the mental image of disposable data, it can not be used for any other purpose. Consequently, an exercise can only lead to only one solution. Using archived HLL data from a past situation could miss the exercise objectives. We propose the usage of publicly available example datasets with licenses that allow their utilization for purposes free of choice, like e.g., listed on the Awesome Public Datasets list [48].

As a side finding, we can declare that splitting the scenarios into three separate parts was not necessary. The size of the situation is irrelevant, since the VOST members are spread across the country and interacting mostly virtually with each other anyways.

5. Conclusions and Outlook

Privacy is an important aspect, when dealing with social media data, especially in times of crises and disaster scenarios. With HyperLogLog we proposed an appropriate technology to approach this issue and process social media data in a privacy-aware fashion. We raised the question of what opportunities and challenges can be identified for VOSTs to work with this privacy-enhanced data as a substitute for conventional datasets, and what potential implementation barriers can be detected.

In a conducted focus group discussion, we found that the underlying technology is fewer of importance to VOST members, because they hardly get in contact with it. Good interface usability and processing speed is of much larger importance, as well as comprehensive data availability. Inaccessibility or loss of data is dramatic, especially in life-depending situations. In turn, VOST members declared that dealing with social media data can be stressful due to the plain size, resulting in large storage requirements and slow processing speed. This may sound like a contradiction. However, the results of our research presented in this paper show that with using appropriate technology it is certainly possible to implement a method to provide privacy-aware infrastructure for social media data processing. But we also have to take into account that by selecting representatives from only two (German) VOSTs, other constellations of participants might produce other findings. The goal of our case study was to develop first approaches to answer our research question, we did not pursue the goal of a representativeness of the results.

These findings encourage further research on that topic. Our first subsequent step is to develop a qualitative survey featuring an interview-style experiment with VOST members. This should feature an experimental setup based on HLL-processed data, that will be presented to the participants in their familiar working environment. Following a mix of established survey methods *behavior coding* and *think aloud protocol* [46], they should explain their working steps in a supervised surrounding and express their user experience regarding limitations or barriers. We are confident, that such an experiment will confirm our findings of this work and lead to an actual implementation in common social media analytics software.

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