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Mitigating information overload in social media during conflicts and crises: design and evaluation of a cross-platform alerting system

Marc-André Kaufhold ^{a,c}, Nicola Rupp^b, Christian Reuter^c and Matthias Habdank^b

^aInstitute for Information Systems, University of Siegen, Siegen, Germany; ^bComputer Application and Integration in Design and Planning (CIK), University of Paderborn, Paderborn, Germany; ^cScience and Technology for Peace and Security (PEASEC), Technische Universität Darmstadt, Darmstadt, Germany

ABSTRACT

The research field of crisis informatics examines, amongst others, the potentials and barriers of social media use during conflicts and crises. Social media allow emergency services to reach the public easily in the context of crisis communication and receive valuable information (e.g. pictures) from social media data. However, the vast amount of data generated during large-scale incidents can lead to issues of information overload and quality. To mitigate these issues, this paper proposes the semi-automatic creation of alerts including keyword, relevance and information quality filters based on cross-platform social media data. We conducted empirical studies and workshops with emergency services across Europe to raise requirements, then iteratively designed and implemented an approach to support emergency services, and performed multiple evaluations, including live demonstrations and field trials, to research the potentials of social media-based alerts. Finally, we present the findings and implications based on semi-structured interviews with emergency services, highlighting the need for usable configurability and white-box algorithm representation.

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Social media; emergency management; social media alerts; information overload; system evaluation

1 Introduction

As the work of professional bodies, volunteers, and others is increasingly mediated by computer technology, and more specifically by social media,¹ research on crisis management in HCI has become more common (Hiltz, Diaz, and Mark 2011; Palen and Hughes 2018; Reuter, Hughes, and Kaufhold 2018; Reuter 2018, 2019). The emerging research field of *crisis informatics* has revealed interesting and important real-world uses for social media (Soden and Palen 2018). Coined by Hagar (2007), crisis informatics is 'a multidisciplinary field combining computing and social science knowledge of disasters; its central tenet is that people use personal information and communication technology to respond to disasters in creative ways to cope with uncertainty' (Palen and Anderson 2016).

During conflicts and crises, it is necessary for emergency services to obtain a comprehensive situational overview for coordination efforts and decision making (Vieweg et al. 2010; Imran et al. 2015). In such situations, social media are increasingly used for the exchange of information (Hughes and Palen 2009) while emergency services encounter issues of information overload and quality (Mendoza, Poblete, and Castillo 2010; Hughes and Palen 2014; Plotnick and Hiltz 2016). Although

companies and researchers continuously develop systems to support social media analytics, including the discovery, tracking, preparation and analysis of social data (Stieglitz et al. 2014; Stieglitz, Mirbabaie, Ross, et al. 2018), research indicates that there is still a need for systems that support emergency services by providing manageable amounts of high-quality information (Moi et al. 2015). Furthermore, to overcome the issue of information overload, visual analytics strives for the automatic processing of data (Keim et al. 2008), but user interaction is required to filter and visualise data according to practitioners' requirements (Onorati, Díaz, and Carrion 2019). Indeed, research suggests that not only a customisation of filtering algorithms is required for an efficient response to specific crisis situations but also that social media analytics tools require a good usability during stressful crisis situations (Imran et al. 2015; Stieglitz, Mirbabaie, Fromm, et al. 2018). Based on a communication matrix (Reuter, Hughes, and Kaufhold 2018) and social media analytics framework (Stieglitz, Mirbabaie, Ross, et al. 2018), we designed and evaluated a system to support the two information flows of *crisis communication* and *integration of citizen-generated content* featuring social media. Thereby, we seek to answer the following research questions:

- How can social media alerts based on information gathering, mining, and quality filters help to mitigate the issue of information overload (RQ1)?
- How can the trade-off between automation and user interaction be designed to mitigate the issue of information overload (RQ2)?

To reflect the methodology used in our project, the paper is structured as follows: First, based on the analysis of related work and existing technical systems (section 2), we conducted interviews with emergency services followed by quantitative empirical studies and workshops with both emergency services and citizens (section 3). These results informed the design and development of a prototype including iterative evaluations in different phases (section 4). To evaluate the system, we conducted semi-structured interviews after demonstrations, field trials and a workshop exercise (section 5). Finally, we analysed (section 6) and discussed (section 7) the results to draw conclusions on how social media analysis might be improved during emergencies (section 8).

This paper contributes findings of how emergency services analyse and use social media with a three years study including empirical pre-studies, the design of a prototype and evaluation in practice. While the empirical pre-studies (Reuter et al. 2016, 2017) and a first round of evaluation with 12 distinct participants based on a preliminary version of the system (Reuter, Amelunxen, and Moi 2016) have already been published scientifically, the main contributions of this article are:

- Design of a novel multi-scenario and semi-automatic approach for generating and visualising social media alerts featuring information gathering, mining, and quality filters.
- Evaluation of the designed approach with emergency services using demonstrations, field trials and a workshop exercise to generate empirical insights on the functionality and usability of the approach.

Our results show that social media are more likely to be used in emergencies if alerts, defined as sets of grouped messages sharing a similar context, and information quality (IQ) indicators support the processing of big social data. The paper furthermore highlights the need for HCI research in terms of (1) usable configurability and (2) white-box algorithm representation.

2 Conceptual framing and related work

Based on natural and human-induced (large-scale) incidents, such as 2012 Hurricane Sandy (Hughes et al. 2014), the 2013 European Floods (Albris 2018), or the

2016 Brussels bombings (Stieglitz et al. 2018), a body of research has examined potentials and challenges of social media usage in conflicts and crises by both authorities and citizens (Reuter and Kaufhold 2018; Kaufhold and Reuter 2019). On the one hand, social media might enable crowdsourcing of specific tasks (Dittus, Quatrone, and Capra 2017; Ludwig et al. 2017), communication between authorities and citizens (Reuter et al. 2016; Reuter and Spielhofer 2017), coordination among citizens and mobilisation of unbound digital or real volunteers (Starbird and Palen 2011; Reuter, Heger, and Pipek 2013; White, Palen, and Anderson 2014; Kaufhold and Reuter 2016), (sub-)event detection (Sakaki, Okazaki, and Matsuo 2010; Pohl, Bouchachia, and Hellwagner 2015) or improved situational awareness (Vieweg et al. 2010; Imran et al. 2015).

Considering the challenges, according to a study with US public sector emergency services, the major barriers to social media use are organisational rather than technical (Hiltz, Kushma, and Plotnick 2014). Research suggests that human factors are crucial for effective emergency management, but also technology for conducting respective emergency tasks (Kim et al. 2012). However, once organisational guidelines, policies, and willingness are established (Kaufhold et al. 2019), technical systems are needed to make sense of the large amount of data. For instance, research has identified barriers and challenges in the authorities' use of social media, such as credibility, liability (Hughes and Palen 2014), reliability and overload of information (Mendoza, Poblete, and Castillo 2010), as well as lack of guidance, policy documents, resources, skills and staff within the organisation (Plotnick and Hiltz 2016).

In this paper, we present an approach for mitigating information overload, which includes the utilisation of a novel information quality algorithm. For the conceptual framing, we refer to the crisis communication matrix by Reuter, Hughes, and Kaufhold (2018) and the social media analytics framework by Stieglitz, Mirbaie, Ross et al. (2018). The crisis communication matrix distinguishes authorities (A) and citizens (C), both as sender and receiver, respectively, to derive four communication flows (Reuter, Hughes, and Kaufhold 2018):

- Crisis communication (A2C): Authorities include social media into their crisis communication to disseminate information on how to prevent or behave during emergencies as well as concrete emergency warnings.
- Self-help communities (C2C): Social media enable people, such as affected citizens, real and digital volunteers, to help each other and coordinate emergency response activities among themselves.

- Interorganisational crisis management (A2A): Authorities use social media for the awareness, distribution of information, communication, and networking among themselves.
- Integration of citizen-generated content (C2A): Authorities may enhance situational awareness based on citizen-generated content, such as eyewitness reports, pictures, and videos taken with mobile phones.

Since this paper presents an approach for managing the information overload of social media by authorities, we focus on the communication flow of C2A but also discuss aspects of A2C. Furthermore, the social media analytics framework comprises the steps of discovery, tracking, preparation and analysis of social data (Stieglitz, Mirbabaie, Ross, et al. 2018). In this paper, discovery of social data is driven by the research domain of crisis management and tracking involves a keyword-based use of multiple social media APIs. For pre-processing, heterogeneous data is stored according to a unified exchange format and the analysis comprises content- and metadata-related approaches (cf. Section 4).

2.1 Crisis communication perspective: the authorities' challenges of information overload, quality and communication in emergencies

To leverage social media information as a basis for authorities' decision-making, they are not only required to *integrate citizen-generated content* (C2A), i.e. monitoring social media, while managing the vast amount of data (Olshannikova et al. 2017). When tens of thousands of social media messages are generated during large-scale emergencies, authorities have to deal with the issue of information overload which is traditionally defined as '[too much] information presented at a rate too fast for a person to process' (Hiltz and Plotnick 2013, 823). Referring to the information overload problem from the field of visual analytics, Keim et al. (2008) highlight the danger of getting lost in data which may be irrelevant to the current task at hand as well as processed and presented in an inappropriate way. Considering the human capacity of information processing, Miller (1956) suggests 'organizing or grouping the input into familiar units or chunks' (p. 93) to overcome such limitations. Accordingly, functionalities such as filtering and grouping potentially assist in overcoming the issue of information overload (Tucker et al. 2012; Moi et al. 2015; Plotnick et al. 2015). This is supported by a survey of 477 U.S. county-level emergency managers which revealed that perceived information overload negatively influences the adaption of social media, while the 'chunking' or grouping of social media messages by specific tools positively influences the

intention to use social media during emergencies (Rao, Plotnick, and Hiltz 2017).

Besides dealing with information overload, authorities have to select the most accurate information (Shankaranarayanan and Blake 2017). The spread of misinformation and rumours can be understood as the result of a 'collective sense-making process whereby people come together and attempt to make sense of imperfect and incomplete information' (Arif et al. 2017; Krafft et al. 2017; Stieglitz et al. 2018). Although research highlights the capabilities of the so-called *self-correcting crowd*, Chauhan and Hughes (2017) suggest emergency services to monitor emerging event-based resources, such as Facebook pages that provided the highest percentage of relevant information, to ensure that the information they provide is accurate. Besides, local news media were observed to provide the timeliest information and highest number of relevant messages around the event. Thus, concepts of *information quality* may support the adaption and evaluation of information (Naumann and Rolker 2000; Shankaranarayanan and Blake 2017) and take into account the context-dependent and subjective characteristics of information quality (Ludwig, Reuter, and Pipek 2015; Reuter, Ludwig, Kaufhold, et al. 2015).

Furthermore, authorities integrate social media into their *crisis communication* (A2C) efforts to share official information with the public on how to avoid accidents or emergencies and how to behave during emergencies (Reuter et al. 2016), but also to 'shape social media conversation and mitigate misinformation and false rumour around a crisis event' (Andrews et al. 2016). A study highlights how authorities corrected mistakes caused by the 'emerging risks of the chaotic use of social media' (Chen, Carolina, and Ractham 2011). Emergency services may establish their trustworthiness by the three dimensions of ability, integrity, and benevolence (Hughes and Chauhan 2015), e.g. maintaining a public-including expressive communication approach (Denef, Bayerl, and Kaptein 2013). Research suggests that citizens share information across multiple platforms during crises (Hughes et al. 2016), indicating that both crisis communication and monitoring is required to encompass cross-platform interactions despite the observed lack of skills and staff by emergency services (Plotnick and Hiltz 2016).

2.2 Social media analytics perspective: suitability of existing systems for the authorities' use in emergencies

As public interfaces (APIs) enable the retrieval and processing of high volume data sets, 'systems, tools and algorithms performing social media analysis have been developed and implemented to automatize monitoring,

classification or aggregation tasks' (Pohl 2013). Here, *social media analytics* is defined as the process of social media data collection, analysis and interpretation in terms of actors, entities and relations (Stieglitz et al. 2014). Accordingly, Stieglitz, Mirbabaie, Ross, et al. (2018) differentiate between the steps of discovery, tracking, preparation, and analysis of social media data:

- **Discovery:** This first step entails the 'uncovering of latent structures and patterns' (p. 158). Even if – as often is the case in emergency situations – it is clear which topic is relevant, it may still be necessary to identify hashtags or keywords that are used frequently when referring to the emergency.
- **Tracking:** In this stage, decisions with respect to tracking approaches (keyword-, actor- or URL-related), sources (social platforms), methods (APIs or RSS/HTML parsing), and outputs (structured and unstructured data) are to be made.
- **Preparation:** This step requires data preprocessing, such as the elimination of stop words, stemming and lemmatisation. With respect to the veracity of data, it is advised to remove low-quality data by 'incorporating a filtering step in the preparation phase' (p. 164), ignore incomplete data or alternatively infer it.
- **Analysis:** In this step, based on the purpose of analysis (focusing on (1) a structural attribute or being either (2) opinion-/sentiment-related or (3) topic-/trend-related), one may correspondingly choose (1) statistical analysis, social network analysis, (2) sentiment analysis, or (3) content analysis, trend analysis.

Social media data, sometimes referred to as *big social data*, includes the characteristics of *high-volume* (large-scale), *high-velocity* (high speed of data generation), *high-variety* (heterogeneous data with a high degree of complexity due to the underlying social relations) and *highly semantic* (manually created and highly symbolic content with various, often subjective meanings) data (Olshannikova et al. 2017). Furthermore, with respect to the crisis management domain, Castillo (2016) introduces the notion of *big crisis data*, discussing its volume, vagueness, variety, virality, velocity, veracity, validity, visualisation, values, as well as the contribution of volunteers. These characteristics pose challenges for emergency services who need their own concepts of analysis.

Accordingly, specialised systems for social media analytics were developed. Pohl (2013) outlines that there are systems available for different online and offline applications, which consider one or multiple social media platforms for monitoring, are especially developed for crisis management and perform different kinds of

analysis. For instance, *Twitinfo* supports the analysis of Twitter feeds by visualising message frequency and popular links, showing geolocated Tweets on a map, and calculating event-relevant tweets and the overall sentiment (Marcus et al. 2011). *Public Sonar* (formerly *Twitcident*) proposes an architecture of (1) incident profiling and filtering as well as (2) faceted search and real-time analytics to explore social media, both including the aggregation and semantic enrichment of social media data (Abel, Hauff, and Stronkman 2012). Furthermore, the *Semantic Visualization Tool* combines Twitter searches and information categories with configurable visualisation techniques, such as a message list, timeline, tree map, word cloud, bubble chart and animated map, supporting the filtering and visualisation of social networks according to emergency managers' requirements (Onorati, Díaz, and Carrion 2019). Imran et al. (2014) created the *Artificial Intelligence for Disaster Response (AIDR)* platform, using artificial intelligence for classification of microblog communication in the context of crises, allowing users to search for emergencies located in a specific region and filter with respect to various topics like infrastructure damages or medical needs.

2.2.1 Social media analytics systems for event detection and alert generation

There is a variety of different tools for event detection or message grouping. To extract situational information in tweet streams, Rudra et al. (2015) present a classification-summarisation approach. This is achieved by developing a Support Vector Machine (SVM) classifier using low-level lexical and syntactic features while word coverage in the summarisation process, called COWTS (Content Word-based Tweet Summarization), is optimised by employing an Integer Linear Programming (ILP) framework (Rudra et al. 2015; Sen, Rudra, and Ghosh 2015; Rudra, Ganguly, et al. 2018). Furthermore, using the AIDR framework for classification, Rudra et al. (2018) proposed an approach based on simple algorithms identifying sub-events and creating summaries of a great amount of messages. Nguyen, Kitamoto, and Nguyen (2015) developed *TSum4act*, offering a summary through constructed event graphs for each topic, which are ranked and offer users a 'summary for recommendation' (p. 4) derived from top-ranked tweets. In detail, it comprises the components of (1) informative tweet identification using a classification algorithm, (2) topic identification using LDA and clustering, and (3) tweet summarisation using event extraction via NER, event graph construction via cosine similarity, ranking via PageRank and filtering via the Simpson equation.

Further works point out the necessity of alert generation. Adam et al. (2012) stress the importance of

customisation of alerts, including warning time, physical disabilities, socio-economic factors, location, connectivity and language as well as envisioning 'Full Disaster Lifecycle Alerts'. Their approach *SMART-C* includes an alert app service as well as an 'interface to other alerting systems' like IPAWS Open Platform for Emergency Networks, television, web or radio, encapsulating a given alert in a CAP message in the Standard EDXL-DE envelope (Adam et al. 2012). However, the focus of this approach lies in the customised generation of alerts for citizens, but not in the algorithmic generation of alerts for emergency services. Various scholars dedicate themselves to both event detection and alert generation (Avvenuti et al. 2014), yet, often solely referring to the incorporated email notification or early warning system without further elaboration on the parameters of alert generation. Cameron et al. (2012) developed an *Emergency Situation Awareness-Automated Web Text Mining (ESA-AWTM)* system which, in contrast to our factor-inclusive work, uses a burst detection method allowing authorities to distinguish between differently coloured and sized alerts words, both characteristics indicating the size of the burst. Yet, the alert monitor was accompanied by mapping of the tweets' geolocations, offering differentiation in this respect. The spatiotemporal model of earthquake detection by Sakaki, Okazaki, and Matsuo (2010) has already implemented this, similar to a lot of other event detection approaches (Veil, Buehner, and Palenchar 2011; Simon et al. 2014) and reaches users by notification (via email). Used by news agencies and emergency management services, *Dataminr* exemplifies an important alert service, offering real-time information (R. Miller 2017). Emphasising the need for trust and timely event response, Brynielsson et al. (2018) present the development process of a tool used to analyse social media content which serves as proof of concept and is integrated into the Alert4All environment (Párraga Niebla et al. 2011). The concept comprises an emotional classifier, including the classes 'positive', 'fear', 'anger', and 'other', as well as a variety of data filtering operations and interactive charts to visualise emotional content. However, the focus of this concept is not the creation of alerts but the monitoring of public reactions to warning messages. In order to facilitate the ranking of social media alerts, Purohit et al. (2018) propose a 'quantitative model for determining how many and how often should social media updates be generated, while also considering a given bound on the workload for an end user' (p. 212).

2.2.2 Comparison of existing social media analytics systems

A comparative review of social media analysis tools outlines tool- and data-related barriers, emphasising a lack of capacity to handle large amounts of information and

the lack of usability, amongst others (Trilateral Research 2015). A further market study compares existing systems regarding their management, analytics and visualisation functionalities focusing on their suitability for emergency services (Kaufhold et al. 2017). The study concludes that although some systems feature use cases of the public domain including emergency services, most systems are designed for the specifics of business contexts and none provides a framework for evaluating information quality of social media messages (Shankaranarayanan and Blake 2017). Furthermore, although these solutions support alarm notifications if specified indicators reach specific thresholds, research suggests to consider the qualitative context of individual messages, such as date, time, location, full text, identified event types or language (Reuter, Amelunxen, and Moi 2016); these might be important metadata for the grouping of messages and, consequently, for the mitigation of information overload (G. A. Miller 1956). An overview of intelligence, management and special systems (Table 1) reveals a lack of emphasis on the criterion of information quality regarding existing approaches, architectures, and implemented systems.

We adopted the categorisation and overview from Kaufhold et al. (2017), which distinguishes between intelligence, management and special systems, while expanding and updating each section, respectively. Thus, we replaced old system names, included architectures which were of academic importance but not implemented as systems, and introduced the criterion of event detection. We expanded the table accordingly in order to distinguish between systems intended to fulfil this task and systems not dedicated to detecting specific events (including those showing long-term trends). Thus, we were able to present systems focusing on event detection, thereby offering maps or visualised rankings of topics or events while not integrating an alert. Even though no specific notification based on contextual factors is sent, systems aiming at event detection use GPS data, event-detecting algorithms and allow for filtering with respect to e.g. location, language and issues. Both back- and forward literature review was conducted. Due to the vast body of social media analytics systems and the increasing number of respective papers, we naturally do not offer a complete overview (Brocke et al. 2015); yet, we tried to include the ones being used by (economically or socially) relevant actors. At the same time, we focused solely on systems and approaches of social media analytics, thereby excluding e.g. social networks aiming at the collection of information regarding emergencies, relying mainly on volunteers like *OpenCrisis*. We also assumed some systems to represent the work of a (group of) scholar(s), thereby not listing each single

Table 1. Overview of intelligence, management and special systems, adapted from Kaufhold et al. (2017).

Systems	Crossmedia	Communication	Monitoring	Alert	Event Detection	Collaboration	Influencer	Sentiment	Topic	Quality	Map	Filter	Diagrams
Intelligence Systems	<i>Adobe Social</i>	✓	X	X	X	✓	✓	✓	✓	X	✓	✓	✓
	<i>Mention</i>	✓	X	X	X	X	✓	✓	✓	X	X	✓	✓
	<i>BrandWatch</i>	✓	X	✓	✓	✓	✓	✓	✓	X	X	✓	✓
	<i>Cogia</i>	✓	✓	✓	✓	✓	✓	✓	✓	X	✓	✓	✓
	<i>Evolve24</i>	✓	X	✓	✓	✓	X	✓	✓	X	✓	✓	✓
	<i>GeoFeedia^a</i>	✓	X	✓	✓	✓	✓	✓	✓	X	✓	✓	✓
	<i>Meltwater</i>	✓	✓	✓	✓	✓	✓	✓	✓	X	✓	✓	✓
	<i>PublicSonar</i>	✓	X	✓	✓	X	✓	✓	✓	X	✓	✓	✓
	<i>Signals</i>	✓	✓	✓	X	X	✓	✓	✓	X	✓	✓	✓
	<i>Socialmention</i>	✓	X	X	X	X	X	✓	✓	X	X	✓	✓
	<i>Quintly</i>	✓	✓	✓	X	✓	X	X	X	X	X	✓	✓
	<i>Trackur</i>	✓	X	✓	X	X	✓	✓	✓	X	X	✓	X
	<i>TweetTracker</i>	X	X	X	✓	X	✓	X	✓	X	✓	✓	✓
	<i>ubermetrics</i>	✓	X	✓	✓	✓	✓	✓	✓	X	X	✓	✓
	<i>VicoAnalytics</i>	✓	✓	✓	X	✓	✓	✓	✓	X	X	✓	✓
Management Systems	<i>Dataminr</i>	✓	X	X	✓	X	X	X	✓	X	✓	✓	X
	<i>Coosto</i>	✓	✓	✓	X	X	✓	✓	✓	X	X	✓	✓
	<i>Crowdbooster</i>	✓	✓	X	X	✓	✓	X	X	X	X	✓	✓
	<i>Lithium</i>	✓	✓	X	X	✓	✓	✓	✓	X	X	✓	✓
	<i>HootSuite</i>	✓	✓	✓	X	✓	✓	✓	✓	X	X	✓	✓
	<i>Salesforce</i>	✓	✓	✓	X	✓	✓	✓	✓	X	X	✓	✓
	<i>Simplify360</i>	✓	✓	✓	X	✓	✓	✓	✓	X	X	✓	✓
	<i>Facelift</i>	✓	✓	X	✓	✓	✓	X	✓	X	X	✓	✓
	<i>SproutSocial</i>	✓	✓	✓	✓	✓	✓	X	✓	X	X	✓	✓
	<i>TweetDeck</i>	X	✓	✓	X	X	✓	X	X	X	X	✓	X
	<i>CrowdControlHQ</i>	✓	✓	✓	✓	✓	✓	✓	X	X	✓	✓	✓
	<i>Orlo</i>	✓	✓	✓	✓	✓	✓	✓	✓	X	X	✓	✓
	<i>MusterPoint</i>	✓	✓	✓	✓	✓	✓	✓	X	X	X	✓	✓
	<i>TalkWalker</i>	✓	✓	✓	✓	✓	✓	✓	✓	X	✓	✓	✓
Special Systems	<i>AIDR</i>	X	X	X	X	✓	X	X	✓	X	✓	✓	X
	<i>CircleCount^a</i>	X	X	X	X	X	X	X	X	X	X	X	✓
	<i>CrisisTracker^a</i>	X	X	X	X	✓	✓	X	✓	X	✓	✓	✓
	<i>SensePlace2</i>	X	X	X	X	✓	X	X	✓	X	✓	✓	X
	<i>Tweedr</i>	X	X	X	X	✓	X	X	✓	X	X	X	X
	<i>TwitInfo</i>	X	X	X	X	✓	X	✓	✓	X	✓	✓	✓
	<i>Twitris</i>	✓	X	X	X	X	✓	✓	✓	X	✓	✓	✓
	<i>Ushahidi</i>	✓	X	✓	✓	✓	✓	✓	X	X	✓	✓	✓
	<i>SMART-C^b</i>	✓	✓	X	✓	✓	X	X	✓	X	X	X	X
	<i>EARS^b</i>	X	✓	X	✓	✓	X	X	✓	X	✓	✓	✓
	<i>Leadline^b</i>	✓	X	X	X	✓	X	X	✓	X	✓	✓	✓
	<i>Alert4All^{a,b}</i>	X	✓	X	✓	✓	X	✓	X	X	✓	✓	✓
	<i>ESA-AWTM</i>	X	✓	✓	X	✓	X	X	✓	X	✓	✓	X
	<i>RSOE EDIS</i>	✓	✓	X	✓	✓	X	X	X	X	✓	✓	X
	<i>Vox Civitas^a</i>	X	X	X	X	✓	X	✓	✓	X	X	✓	✓
	<i>Visual Backchannel^b</i>	X	X	✓	X	X	X	X	X	X	X	✓	✓

^ade facto non-operating systems.^bArchitecture but no implemented system.

variant of their developed system. Conducting a thorough literature review (via Google Scholar, libraries) and online research of services' websites, our overview aims at representing the various strands of approaches (visual analytics, geo-mapping, earthquake-specific, etc.) to reflect dominant work. Review was conducted by searching for work related to e.g. 'alert generation', 'event detection', 'social media analytics'.

2.3 Research gap

Multiple studies examine barriers and potentials of social media use by authorities (Plotnick and Hiltz 2016) and technical solutions supporting the analysis of big social data (Olshannikova et al. 2017). Amongst others, they identified the issues of information overload (Hughes and Palen 2014; Plotnick and Hiltz 2016), credibility and reliability (Mendoza, Poblete, and Castillo 2010; Hughes and Palen 2014) as critical barriers of organisational social media use. Since the appropriation of social media analytics systems faces barriers in terms of data, tools, organisation and users (Plotnick and Hiltz 2016; Reuter et al. 2016), empirical evaluation studies may offer insights for developing mitigation strategies and improving the quality of supportive technological solutions (Trilateral Research 2015). Previous research highlights the relevance of designing with users to achieve useful and usable systems, especially in stressful situations, and the requirement of supporting the sense-making and information validation processes of emergency managers (Imran et al. 2015; Stieglitz, Mirbabaie, Fromm, et al. 2018). Furthermore, a recent study concludes that most previous research has focused on identifying information that contributes to situational awareness (Zade et al. 2018). Accordingly, the authors introduce and emphasise the concept of actionability, meaning that 'information relevance may vary across responder role, domain, and other factors' (p. 1) and that right information needs to reach the right person at the right time. Current studies on event detection and summarisation focus more on experimental evaluation designs (Nguyen, Kitamoto, and Nguyen 2015; Rudra et al. 2015; Rudra, Goyal, et al. 2018) but less on the user-based evaluation in deployed systems.

Based on the feature gaps of existing systems, especially the absence of comprehensive functionality for information quality assessment (Pohl 2013; Trilateral Research 2015; Kaufhold et al. 2017) as well as the need for actionability and usability (Imran et al. 2015; Zade et al. 2018), our aim is to contribute with the design, implementation and user-based evaluation of a novel approach and integrated system for overcoming information overload by (1) processing and analysing social

media data and transforming the high volume of noisy data into a low volume of rich content useful to emergency personnel (Moi et al. 2015) by grouping messages with regard to their qualitative context (Rao, Plotnick, and Roxanne Hiltz 2017). Furthermore, approach and system will (2) support authorities in the assessment of information quality (Shankaranarayanan and Blake 2017) and (3) enable communication among authorities and citizens.

3 Requirements analysis: methodology, pre-studies and workshops

One aim of the project was to show the positive impact of gathering, qualifying, mining and routing information from social media on the management of emergencies, i.e. the mitigation of the information overload problem (RQ1, RQ2), which is realised through requirements analysis, and the development and evaluation of artefacts for emergency services and citizens. Thus, Design Science Research (DSR) plays a significant role, which is considered a problem-solving paradigm that 'seeks to create innovations that define ideas, practices, technical capabilities, and products through which the analysis, design, implementation, management, and use of information systems can be effectively and efficiently accomplished' (Hevner et al. 2004). According to Hevner (2007), DSR features three cycles: The central process is the building and evaluation of design artefacts and processes (*design cycle*). That should be grounded in and contribute to the knowledge base (*rigour cycle*). Moreover, field testing is required to raise requirements for the development of technology (*relevance cycle*). Since insisting 'that all design research must be grounded on descriptive theories is unrealistic and even harmful to the field', as Hevner (2007) suggests, we integrated 'several different sources of ideas for the grounding of design science research', such as requirements based on literature findings, existing artefacts and the inquiry of domain experts.

To identify requirements for a supportive approach, we employed a requirements analysis process: (1) scenarios and use cases from real-life operations were chosen to be illustrated and analysed; (2) these were presented in workshops to end users, development teams and experts to discuss different approaches, establish a common understanding and allow interaction with each other; (3) and to involve a broader community, we conducted online survey to collect data on the involved actors' views. All interventions (see Table 2) were supported by prior literature reviews to consider the state of the art and to inform the application of appropriate methodologies. The results of several empirical studies have already been published (Reuter et al. 2015; Reuter et al. 2016, 2017; Reuter and

Table 2. Empirical pre-studies and workshops.

Title and Focus	Year	Quantity
Interviews: Social media in emergencies	2014	11
Workshop I: End-user advisory board (ES)	2014	16
Survey I: Perception of emergency services	2015	761
Workshop II: End-user advisory board (ES)	2015	18
Survey II: Perception of citizens	2016	1,034
Evaluation I: First round of system evaluation	2016	12
Workshop III: End-user advisory board (ES)	2017	15
Survey III: Perception of emergency services	2017	473

Spielhofer 2017). For illustration, all elicited requirements were aggregated to high-level abstractions (Table 3).

Architecture implications were identified by reviewing guidelines, norms, laws (e.g. in terms of ethics, information security and usability), and literature on the technological state of the art (e.g. in terms of availability, stability and scalability). In summary, we decided to develop a web-based standalone solution that is easy to deploy and maintain in multiple system instances. Communication requirements were mainly identified by reviewing case studies on the use of social media during emergencies and thereafter validated in large-scale surveys (Reuter et al. 2016, 2017). Emergency services state that they currently most likely use social media to share information (A2C), but also consider monitoring to enhance situational awareness (C2A). To ensure wide use of social media, a facilitating organisational culture, trained personnel, appropriate knowledge and excellent communication skills are required. On the technical side, it demands an available and reliable internet infrastructure, including easy-to-use software artefacts that support users in dealing with multiple social networks. Our research, for instance, shows that around 45% of citizens use social media during an emergency and 46% expect to get a response to their social media post from emergency services within an hour.

Processing features were largely designed by reviewing the technological state of the art and existing solutions in terms of semantic data models, data gathering, data mining, information quality, and clustering algorithms.

Table 3. Abstraction of the system requirements.

Category	Description
Architecture	Easy-to-use, available, maintainable, privacy-respecting, secure, stable, and scalable web-based standalone solution.
Communication	Reception, publication, response and broadcast of messages with multimedia (audio, photo, video) between authorities and citizens.
Processing	Cross-platform gathering, enrichment, relevancy and quality assessment of social media activities and alert generation.
Tailorability	Filtering of results in terms of geolocation, keywords, relevancy (mining) and information quality.
Visualisation	Display of generated alerts on a list and map view and classification of alerts according to the Common Alerting Protocol.

The processing components were implemented considering the requirements of tailorability, which were refined iteratively based on feedback gathered from the workshops. Visualisation opportunities were designed and advanced by reviewing the state of the art and elicited user requirements from the workshops (top-down) and by analysing how the gathered data can be visualised in a meaningful manner (bottom-up). Finally, the visualisation was refined upon the feedback of the first round of scenario-based evaluation (Reuter, Ame-lunxen, and Moi 2016), which followed the structure of situated evaluation (Twidale, Randall, and Bentley 1994).

4 Development and architecture of a cross-platform social media based alerting system

This section presents the development and underlying architecture of the web-based Emergency Service Interface (ESI). The system is connected to a mobile application, which cannot be explained in detail within the scope of this paper but mentioned to define existing interfaces (see ‘app alerts’ in Figure 3). The system supports multiple information flows. First, authorities may use ESI to disseminate messages to multiple social media channels (A2C). Second, emergency services may monitor different social media, whose activities are grouped as social media alerts within the ESI (C2A). While A2C is a simple service forwarding messages to the respective APIs, C2A follows a complex path of processing information, which is described in the next section, before it is visualised in ESI.

4.1 The back-end: grouping messages to alerts

For the integration of citizen-generated content (C2A), a processing component (PC) manages the interplay of gathering, enrichment, mining, information quality, and alert generation components (Figure 1). If the user defines search keywords in the interface (section 4.2), these are sent to the processing component. It instructs the gathering component to collect and return the relevant data to the PC, which then serves as an input for the enrichment component. This process is repeated with all components until information is grouped and sent to the interface by the alert generator.

Since emergency services are likely to encounter a variety of different incident types, such as fire, floods, or traffic incidents, which can occur simultaneously, we implemented multi-scenario support. Accordingly, the user can instantiate this process multiple times, whereby we refer to each instance as a separate *pipeline*. The general idea is that each pipeline reflects a different scenario, e.g. a fire or a flood scenario (Table 4). A pipeline is then

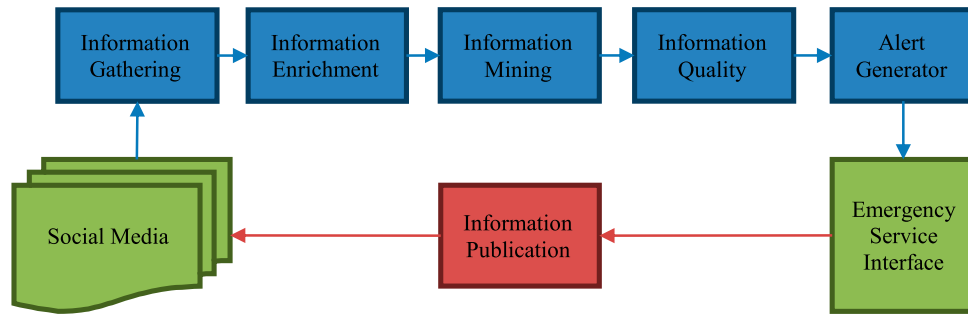


Figure 1. The back-end with C2A (blue) and A2C (red) information flows.

defined by the assignment of search keyword (e.g. ‘fire, bomb, explosion’ or ‘floods, thunderstorm, water level’) and a category (e.g. ‘Fire’ or ‘Meteorological’). The categories are derived from the Common Alerting Protocol (CAP), which is an exchange format for ‘all-hazard emergency alerts and public warnings over all kinds of networks’ (OASIS 2010). For different scenarios, varying characteristics and kinds of messages are relevant. Therefore, based on the defined category, differently trained Naïve Bayes classifiers (e.g. a classifier for fire and a classifier for floods) are used for determining relevant messages within the information mining component. All pipelines are directed to the same interface, but generated alerts are differentiated by respective category icons (section 4.2). Since, in contrast to fully automatic approaches, the user has to possibility to adapt the process by changing scenario details, i.e. keyword and category, we refer to this process as a semi-automatic approach.

To provide more detail, the process comprises the following steps: First, the *information gathering* (1) component allows the users to gather social media activities via keywords from Facebook, Google+, Twitter, and YouTube. The keywords are sent to and interpreted by the respective social media provider APIs. As these APIs return results in different exchange formats, we convert and store all messages according to the Activity

Streams 2.0 specification (World Wide Web Consortium 2016). Since we are interested in multiple metadata that are not provided by different social media APIs but required for the information quality component, the *information enrichment* (2) component computes additional metadata such as entropy, positive or negative sentiment, or the number of characters, punctuation signs, sentences and words.

Since we intend to reduce the large quantity of activities to a manageable amount of high-quality information, the *information mining* (IM) (3) component pre-processes the gathered activities and applies configurable geographic boundary and event type filters. This restricts the data to that generated in the incident specific area and regarding the identified incident only. As the last step, after some phases of pre-processing (basic normalisation, stop word removal, tokenisation, and URL extraction), a relevancy filter based on a trained Naïve Bayes classifier filters out activities whose contents are not related to an emergency. To support both the fire and flood scenario, we trained two respective classifiers based on data gathered from actual incidents, i.e. the 2016 BASF fire and 2013 European floods. The data sets were labelled by single and different labellers. For each data set, a scenario description was created, containing basic information about the incidents that were labelled. This approach aimed to enable the labellers to understand and immerse in the situation from an emergency service operative’s perspective. The labellers then were presented with the data and labelled it according to their understanding of the situation on a binary scale (relevant or irrelevant).² For the fire classifier, we manually labelled 3785 tweets, whereof 48% were labelled relevant and 52% irrelevant. Furthermore, 2000 tweets were manually labelled for the flood classifier and reached a relevant to irrelevant ratio of 66% to 34%. By comparing the manual labels with the automatically classified messages, the fire scenario classifier reached an accuracy of 73.3% and the flood scenario classifier an accuracy of 76.1%.

Thereafter, an *information quality* (IQ) (4) component evaluates the remaining social media messages with an

Table 4. Comparison of two exemplary pipelines and their characteristics based on simplified fire and flood scenarios.

Characteristics	Pipeline I	Pipeline II
Scenario	Analysis of fire-related messages	Analysis of flood-related messages
Keyword (1)	‘fire, bomb, explosion’	‘floods, thunderstorm, water level’
Category (1)	Fire	Meteorological
Enrichment (2)	Scenario-independent information enrichment	Scenario-independent information enrichment
Relevancy (3)	Use of a classifier trained for fire	Use of a classifier trained for floods
Quality (4)	Scenario-independent information quality assessment	Scenario-independent information quality assessment
Alert (5)	Grouping of pipeline I messages	Grouping of pipeline II messages
Routing (6)	Scenario-independent information routing	Scenario-independent information routing
Interface (7)	Alerts with fire icon	Alerts with flood icon

The affected component, if any, is indicated in parentheses within the first column.

Table 5. The information quality framework with criteria and indicators.

IQ Criteria	IQ Indicators
Believability	Existence of URLs, locality, proximity, existence of media files
Impact	Number of comments, number of shares, involvement, number of likes, number of views
Reputation	Number of followers, number of statuses, verified account, trusted account
Completeness	Existence of URLs, number of characters, number of hashtags, type of information present, time of information present, location of information present
Relevancy	Existence of emergency words, relative frequency of emergency words, amount of contained crawl keywords, number of relevant entities, number of sentences with relevant entities, relative frequency of relevant entities
Timeliness	Closeness, first occurrence of an emergency word, post age
Understandability	Average length of words, readability, existence of media files, information noise, appropriate language

IQ framework (Table 5) estimating the criteria of believability (including the sub-criteria of impact and reputation), completeness, relevancy, timeliness, and understandability by different indicators (e.g. number of followers). The dependencies between criteria and indicators are modelled as nodes of a Directed Acyclic Graph (DAG). The output of each indicator node lies within [0,1] and criterion nodes collect and aggregate the output of indicator nodes dependent on them. They compute a weighted arithmetic mean and output a value within the interval [0,1]. The weights are attached to the edges of dependent nodes and express the importance of the dependent indicator or criterion. Thus, the higher the importance of a dependency, the bigger its influence of its output for the result of the criterion. Since the output of each node lies between 0 and 1, we compute the overall IQ in a single value. Although, in principle, it is possible that end-users manually set the weights according to their own preferences, for our evaluations, we trained the weights of the IQ graph using the Backpropagation Algorithm (BPA), which consists of two phases (Werbos 1994). Three experts used an IQ assignment tool to create a training set of 2.500 posts with assigned IQ values. In the first phase, the training data was propagated through the neuronal network and the IQ values were calculated automatically. The results were reported back, compared to the results the human evaluators provided, and the difference between automatically and manually rated IQ values was calculated. If both values differed, the second phase of the BPA was executed. In the second phase, the weights were adjusted to better fit the manually rated IQ value. These steps were repeated until the performance reached a satisfactory threshold.

Finally, the *alert generator* (5) component groups messages to provide meaningful and manageable bits of information for emergency services. We refer to an alert as a set of classified messages sharing a similar

Table 6. The contextual filters influencing the generation of alerts.

Factor	Description	BE	FE
Event Type	The algorithm only groups messages of the same event type (options: Fire, Meteorological, Transport, or Other).		x
Keywords	The algorithm includes keywords that match the defined Boolean search query (options: use of Boolean operators, such as AND, OR, NOT, etc.).		x
Language	The algorithm excludes messages that are not within the range of specified languages (options: allow a single, multiple and all languages).	x	
Location	The algorithm excludes messages that are disseminated outside of a specified bounding box (default: no bounding box, but for the field trials bounding boxes were created).		x
Platform	The algorithm includes the configured social media platforms (options: one or multiple platforms of Facebook, Google+, Instagram, YouTube, Twitter).	x	
Quality	The algorithm excludes messages based on information quality thresholds (options: include low, medium and high-quality messages).		x
Relevancy	The algorithm excludes irrelevant messages (Naïve Bayes classifier) and retweets (options: include also irrelevant or only relevant messages).		x
Time	The algorithm excludes messages that are older than a specified number of hours (default: two hours).	x	

Some factors are configurable in the back-end (BE) and some in the front-end (FE).

context, which is defined by event type, keywords, language, location, platform, quality, relevancy, and time. The relevant contextual filters are described in Table 6. Due to the project's time constraints, we were not able to integrate the configurability of all contextual factors in the front-end. Thus, some of them were pre-configured by experts in the back-end depending on the requirements of the respective exercise or field trial. After the contextual filters are applied, in a last step, a geographical database is used to group geo-located messages at the nearest geographical named entity of the database. Using the *information routing* (6) component, these alerts are sent to the *user interface* (7).

4.2 The front-end: visualisation of alerts

The web interface is split up into the four different pages (1) *Dashboard*, (2) *Social Media (SM) activity*, (3) *App activity* and (4) *Settings*. The dashboard is the default page featuring the display of alerts within the *map view* and *list of alerts* to provide a quick orientation (Figure 2). Following the CAP standard, alerts are categorised as either 'Fire', 'Meteorological', 'Transport' or 'Other', the latter comprising all other CAP categories. We chose to only integrate the most relevant subset of categories for our scenarios (cf. section 5.3) to keep the interface clear and simple. Each category has its own symbol, which is used on the map, list and alert counters above. Furthermore, using text input fields, the user can define a distinct set of complex Boolean keywords for

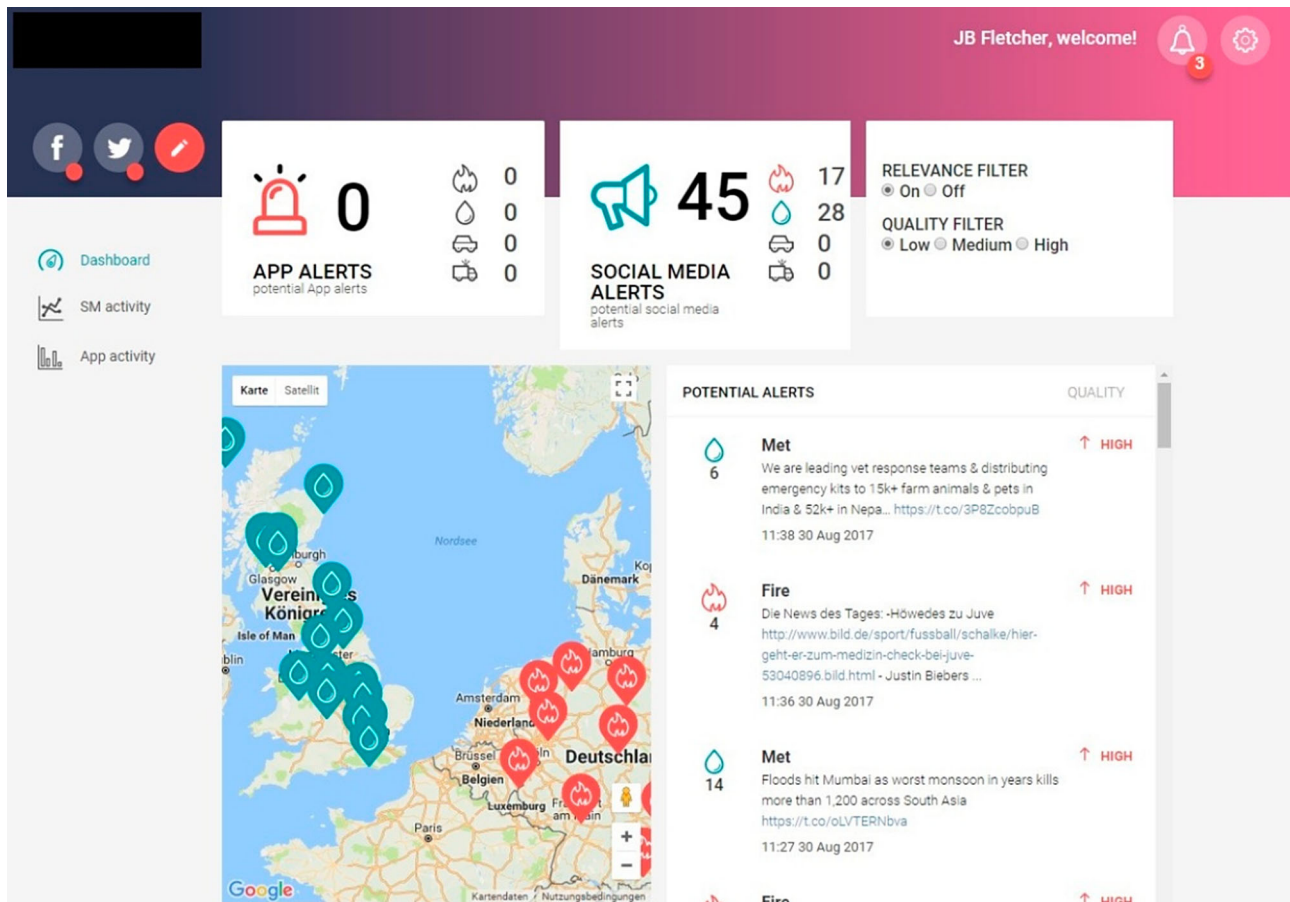


Figure 2. The Emergency Service Interface (ESI): dashboard view.

each category, such as 'Dortmund (fire, bomb)' for the fire category. In this example, the results are filtered by social media messages that contain the term 'Dortmund' as well as 'fire' and/or 'bomb'. At the top-right corner, the user may enter the settings page to define the sets of keywords (information gathering).

For each alert in the list view, the overall IQ score is indicated by the indicators 'high', 'middle' and 'low'. Since preliminary results suggested to keep the UI simple (Reuter, Amelunxen, and Moi 2016), we chose this approach instead of visualising the whole IQ graph of criteria for each alert. The user can filter the list of alerts by the relevance filter (IM) and an IQ threshold. If the user clicks on an alert, a window containing the list of individual social media messages are listed including their IQ value (Figure 3). Three icons at the top-left corner represent the information sharing functionality allowing the user to login to private social media accounts and to share information on Facebook and Twitter (A2C). Lastly, while the *SM activity* page lists individual, non-grouped social media activities using the same layout, the *App activity* page displays app alerts and allows emergency services to reply to them individually.

5 Methodology of the systems' evaluation

This section deals with the second evaluation of the EmerGent ICT system using different surveys. The need for a second evaluation became apparent due to several reasons: Firstly, based on the first evaluation and new requirements, the ESI had been redesigned



Figure 3. ESI: details of an alert.

completely and the quality of the new interface was to be evaluated. Secondly, in the first version of ESI, most features were not fully implemented; therefore, the value of app alerts, potential alerts, keyword performance and information quality could not be tested thoroughly. Finally, due to the unfinished state of the first ESI version, we could only perform a constructed scenario-based evaluation. Thus, the evaluation based on a functional prototype and in real-world scenarios e.g. via field trials promised richer feedback from the users.

To evaluate and achieve productive feedback on the system's components, we decided to conduct semi-structured interviews. The interview guideline was derived from the first evaluation (Reuter, Amelunxen, and Moi 2016) but the questions were refined to get better feedback on individual functionalities. In terms of personal details, the guideline asks for the type of organisation, main role, command level, work years, age, gender, and country. Additionally, organisational details such as current and future role of social media as well as organisational barriers were asked. The survey consisted of six guiding questions, which were open-ended unless indicated differently by footnotes:

- Q1: What is your first impression?
- Q2: How would you evaluate the functions according to their importance in your job?³
- Q3: How do you evaluate 'social media alerts'?⁴
- Q4: How do you evaluate 'information quality'?²
- Q5: What functionality of the application do you find most useful or has potential?
- Q6: Is there any additional functionality you would like the application to have?

Overall, 21 interviews with emergency services were conducted during the second evaluation (Table 7). Interviews were audio-recorded and transcribed for further analysis. In our subsequent analysis, we employed open coding (Strauss and Corbin 1998), i.e. gathering data into approximate categories to reflect the issues raised by respondents based on repeated readings of the data, organising them into similar statements. As most of

the analysis was conducted in German, selected quotes were translated into English by the authors.

To allow for different degrees of emergency services involvement, considering their potentially limited time resources, we conducted different types of evaluation, which are presented in the following subsections.

5.1 Live & paper-based demonstrations (2017)

During a live system demonstration, based upon a short introduction of its functionalities, the participants could interact with the system, which was preconfigured with fire and flood scenario keywords (see Figure 3), before and during the guideline-based inquiry. In a paper-based demonstration, the interviewer introduced prepared screenshots of the system and explained its functionality as a foundation for the inquiry. One survey was conducted in 2017 in Warsaw, Poland, by the Scientific and Research Centre for Fire Protection – National Research Institute (CNBOP-PIB), and further two interviews with members of volunteer fire departments (FD) in Germany.

5.2 Workshop exercise (2017)

The integrated system was tested at a convention in Salzburg, Austria. During the live exercise, a video of an incident (a fire) was shown, and the audience was asked to participate by using their Facebook and Twitter accounts. The audience, representing the role of active citizens, used the video for taking pictures of the incident scene and sending them along other valuable information to a simulated command and control (C&C) room (Figure 4). The video started with a general introduction, but then visualised a fire which grew bigger and was followed by explosions as well as response efforts from emergency response teams. Furthermore, social media demo accounts were used to flood the system with prepared messages simulating a constant flow of false or irrelevant information, which are common in real-world scenarios. The C&C room, amongst others, was manned with an incident commander (gold level firefighter from FD Dortmund) and a social media manager (bronze level firefighter from FD Ljubljana) who used the ESI to get relevant incident information from social media and to broadcast relevant information to ESI users on Facebook and Twitter.

5.3 Field trials (2017)

For longer-lasting testing periods in real-world scenarios, three field trials were conducted. The field trial of FD Dortmund was in March/April 2017 (four

Table 7. Second evaluation: personal details of participants.

Category	Data
Roles	crew (10), head (1), incident commander (8), other (6), press (5), PSAP operator (1), PSAP supervisor (5), section leader (3)
Level	gold (3), silver (9), bronze (8), none (1)
Age	20–29 (2), 30–39 (10), 40–49 (6), 50–59 (3)
Gender	male (18), female (3)
Country	Germany (13), Poland (7), Slovenia (1)
Type	Field trial (10), live and paper-based demonstration (9), workshop exercise (2)



Figure 4. ESI in a simulated C&C room during the workshop.

interviews) and of FD Hamburg in April/May 2017 (three interviews), both lasting four weeks. Another one was conducted in July 2017 with FD Hamburg during the G20 event (three interviews). During these trials, the system was used by different functions of the organisation alongside their regular duties: The public relations (PR) department, the head of the dispatchers and the department of strategic planning. Dortmund decided to use the system with keywords for the topics ‘fire’, ‘rescue’ and ‘severe weather’ which remained the same over the whole field trial. Hamburg preferred the topics ‘fire/terror’, ‘CBRN’, ‘malfunction of subway/bus’ and warnings about ‘contamination’. During the first Hamburg field trial, the keywords were regularly discussed and adapted with the help of technical experts and using a *Telegram* messenger channel. For instance, after regular revisions, Hamburg used the following final keyword set for the ‘fire’ scenario, as translated from German: ‘(Hamburg, HH, hvv, TMC) (fire, flames, incident location, unsecured, chemical accident, police operation, incident, breaking news, bomb threat, blaze, bomb, injured, smell, gas leak, poisoning, weather alert, RTW, personal damage, rescue mission, protest, conflict)’. The second field trial in Hamburg was not planned from the beginning, but due to the fire department’s positive reception of the system, they encouraged the conduction of a field trial during the G20 event where extensive demonstrations and riots from left-wing groups were announced and expected.

6 Results of the systems’ evaluation

The main results of the first evaluation, which have already been published (Reuter, Amelunxen, and Moi 2016), include the potential of the system to identify risks and to filter using own criteria. It was mentioned

that precise information (alerts) is needed, especially in mass events. Approaches that allow both individual settings and automatic processing of data can help here. As for the threats, false information is available and negative consequences might occur. To summarise one key requirement: ‘Keep it simple on the UI and complex in the back-end’. In the following sections, we focus on the results of the second evaluation. In the following sections, we use the identifiers I1-I21 to reference statements by participants.

6.1 General attitudes and impressions (Q1)

6.1.1 Positive reception of the system

Overall, 13 of 21 participants expressed a positive attitude towards the system. While two considered it to be useful (I5, I21) and to provide important information (I2) in a general manner, others explicated more specific benefits: It can be used to support decision-making (I8) and the reporting of incidents (I6), inform the population (I1, I15), reduce reaction time to emergencies and thus improve overall safety (I1). Six participants highlight the simplicity of ESI, although one participant found the map handling to be difficult (I15) and one indicated that training is required, e.g. in terms of selecting suitable keywords to get the most out of the tool (I14). The workshop exercise was perceived as a proof of concept with limitations: ‘The demonstration during the final workshop was a good proof of concept, although it was not directly integrated into the whole [control room] system’ (I9). Some participants were sceptical about the interface’s aesthetic look (I12, I13).

6.1.2 Negative reception of the system

However, besides mentioning the system being supportive but not a telephone replacement (I7), two participants

have mediocre (I12, I13) and one participant a strong negative or sceptical attitude towards the system, listing several issues (I10): Some important events in Dortmund were not properly detected, the system often provided results from the same sources, information was often hours or days old and rather from ‘press offices than from normal users’. Another participant did not perceive the system to be not useful in the current state unless some minor changes were applied (I9).

6.1.3 Importance of keyword management

The way of dealing with social media keywords is likely to be the reason for some important events in Dortmund not being detected. While we pre-designed the keywords in Dortmund – the preparation of scenarios was perceived as important (I15) – to be used during the whole field trial, we developed and regularly changed the keywords during the Hamburg field trials. In Hamburg, I14 was responsible for keyword management and adapted the keywords on demand if new relevant hashtags or topics emerged. These were not only extracted from social media but also from other internal and external information sources at hand. Thus, five participants involved in field trials highlighted that the regular adaption of keywords is essential and required, with participants from Dortmund reporting negative (I10) and those from Hamburg reporting positive results (I14–I16). While in Hamburg, specific keywords were also used to increase the probability of location-specific results, one participant mentioned that a geographical restriction in terms of the towns’ administrative area was required (I16).

6.2 Social media alerts (Q3)

6.2.1 Situational overview and specific information

Evaluating ‘social media alerts’, eleven participants indicated a huge, six a medium, three a small and one no benefit of the functionality (Table 8). The respondent indicating no benefit said that ‘when there is not yet any direct threat, just a potential one, people will not take it seriously’ (I1). Besides the risk of false information and spread of panic (I6), other feedback was more positive. Social media alerts were considered useful (I17) and assessed as ‘one of the most relevant aspects of the system’ (I8). Five participants indicated that it was a good

opportunity to get a general situational overview of local events and developments (I10, I12, I15, I19), which was especially useful for press offices (I16), but also to get more specific information sometimes, e.g. ‘to recognise emerging situations [and] where something is brewing’ (I10). For instance, Hamburg was able to prepare for a train with thousands of protesters during G20 which they detected via social media alerts (I18). Although, according to two participants, most times the social media alerts did not deliver faster information than other media and control room systems, the information retrieval was perceived to be fast, and there were some occurrences, e.g. about road conditions and road closures which were delivered faster via social media alerts (I15, I16).

6.2.2 Access to unfiltered data

As already indicated, one key aspect regarding the performance of the system was the careful selection and adaption of relevant keywords: ‘The keywords and the algorithms were tuned properly. Now the messages are really goal-driven’ (I17). Although the filtering was perceived as good, one participant wished to access non-filtered data as well (I17). During G20, Hamburg also used Twitter and TweetDeck to search for individual and popular keywords, which was sometimes faster with respect to achieving specific information (I18, I19). However, both interviewees would appreciate a combination of all functions within an integrated tool such as ESI, e.g. to support documentation of activities (I18).

6.2.3 Issues of grouping and geolocation

Moreover, the grouping by geolocation was not perceived as a sufficient means of defining an actual alert (I12):

However, the grouping by geolocation is not enough, because it is not available in every message. Equally important are the content (text analysing, e.g. ‘smiles’, capitals), keywords, and psychological aspects: How many exclamation marks are used? Are there any emotions reflected in the message and if yes, which ones? What is the letter case? (I9).

Moreover, it was not clear how and if the geotagging worked properly: ‘Only geotagged information should be on the map’ (I14). Since geolocation data is either extracted directly from metadata (accurate GPS position), indirectly from metadata by using the attached bounding boxes of towns, or indirectly by analysing and extracting it from the actual message content (both inaccurate indications of positions), it should be indicated which method of location determination was

Table 8. Indicated benefits of social media alerts (Q3) and information quality (Q4).

Benefit	Huge (3)	Moderate (2)	Small (1)	None (0)	Ø
SM alerts	13	6	0	2	2.43
IQ	8	8	4	0	2.20

used, allowing the user to assess how accurate the displayed location of the alert is (I15).

6.3 Information quality (Q4)

6.3.1 Reliability and perceived preference for official accounts

Eight participants indicated a huge, further eight a moderate and four a small benefit from the IQ component (Table 8). On the positive side, on high settings, the component was perceived as a useful filter (I12), if the algorithm was trained correctly (I20), for the most crucial alerts (I2), worked reliably and allowed a focus on important results (I15). Thus, only a small amount of misclassification was observed (I15, I16). Three participants observed that, by tendency, authorities' and media messages were assigned a higher quality than citizens' messages which was viewed sceptically since potential eyewitness reports were rated lower than media reports from hours or days ago (I9, I10, I11). Moreover, two participants assumed that too many messages were filtered out (I21) and thus, a performance feedback (of the different layers of filters) was required (I16).

6.3.2 Issues of transparency and tailorability

Notably, seven participants criticised the lack of transparency concerning how the algorithm operates (I1, I9, I17): 'For users, it is unclear what happens when the filters are turned on' (I14). Moreover, they were sceptical about fixed quality criteria, e.g. the number of followers was not perceived as a crucial factor for IQ (I10). Thus, more delicate and visible criteria (I10) and the possibility to parametrise underlying quality criteria were wished for since 'the determination of quality criteria [is done internally] in the organisation' (I8, I11). On the one hand, the user's knowledge, e.g. about the credibility of specific authors, was recognised as an important resource (I8) that could contribute to an algorithm or a system that learns from user input (I10). On the other hand, one participant was sceptical whether the actual user was capable of parametrising quality criteria, suggesting that the job should be performed by the system's administrator (I9). Nevertheless, it was seen as an important option to define 'trusted users' whose quality level should be estimated as high: 'Expert groups, trusted people, THW relatives, potential app users, etc. – would be a high-quality group of users' (I10, I18).

6.3.3 Impossible to avoid misinformation

Besides the technical aspects, other participants stated that it was generally difficult to choose relevant information (I4), hard to determine true or false information (I5) and impossible to avoid 'fake' information (I6).

Table 9. Indicated importance of functionality (very important to not important at all).

Importance	max (4)	high (3)	low (2)	min (1)	Ø
C2A indirect	7	7	6	0	3.05
A2C indirect	9	8	3	1	3.19

Since a huge benefit was expected in cases of components working properly, but a lot of scepticism and potentials for improvement were mentioned, further research is required on this topic.

6.4 Importance and usefulness of functionality (Q2 + Q5)

6.4.1 Importance of functionality

Each functionality, representing a communication flow, was assigned high or maximum importance by at least two-thirds of the participants (Q2, Table 9). On average, A2C received a slightly higher value (3.19) than C2A (3.05). Although the average values are quite similar, there seems to be a small preference for A2C over C2A communication, which matches a qualitative snowball study indicating that emergency services are more likely to share information than to monitor or receive messages from social media (Reuter et al. 2016).

6.4.2 Usefulness of functionality

Most participants' answers could be assigned to a specific information flow. The C2A flow, represented by 'social media alerts', was the most recognised (by five participants; I9, I10, I15, I16, I19). One emphasised the importance of IQ to get only the most important messages during large-scale emergencies (I12). Three participants valued the C2A flow on a more general level: 'It's an additional way of contacting emergency services and in situations when lives are endangered, all ways are welcome and increase the possibility of helping a victim' (I5). It has the potential of an information advantage: 'Before the control room or personnel receives the information, it is on the ground. Information can be received which otherwise would have to be manually searched for' (I14). Thus, in everyday life, 'the information acquisition is most useful' (I17).

On the other hand, two participants highlight the relevance of A2C communication (e.g. sending a message or broadcast from ESI): 'Being in the "hot zone", I am receiving a proper message directly on my smartphone, at least I will consider that it is serious and I will follow the instructions' (I1). Thus, 'it may be helpful to tell people what to do in an emergency' and 'they may feel comforted as they know that they are not alone' (I6). Finally, three participants valued the way how

information is presented on the dashboard ‘to evaluate how the situation is at that moment’ (I14): ‘The graphical representation was great’ (I16). ‘The most useful feature is to get information presented this way in everyday life’ (I17, I18). Two participants highlighted the map to be the most useful function to get a first situational overview (I12) for the disposition of forces (I11).

6.5 Additional functionality (Q6)

6.5.1 Improving keyword management and visualisation

With only three people indicating that the application already includes the most important functions (I2, I4, I6), the participants offered broad feedback on additional functionality for ESI. Since participants emphasised the relevance of adequate keywords, keyword highlighting was desired to develop an idea regarding keywords producing certain results (I9). Also, an enhanced keyword management was wished for: ‘All dispatchers would use the same keywords; they should grow in number and be intact forever. It should be possible to add more keywords on UI level’ (I9). Since the keywords, IM and (potentially) IQ components filter the number of incoming messages, it was seen as important to get performance feedback ‘on the dashboard because it is important to know how many messages were mined and went through the system’ (I8, I15).

6.5.2 Enhancing the alert management

Further functionality was desired in terms of ‘app alerts’ and ‘social media alerts’. Four participants mentioned a sound notification if new alerts came in, with the option to turn it on or off, (I10, I11, I16) to ‘support the information advantage because the system can’t be watched the whole time’ (I14) or configurable mail or push notifications, e.g. based on keywords (I13, I18). To support further investigation of incoming alerts, two participants suggested to display the username, provide a link to the source platform of the message and add a symbol to indicate from which platform the message was received (I14, I17) since it is important to assess the quality of information (I10). Moreover, several management operations for the list of alerts were named: to mark alerts as read or done (I9), set custom priorities (I9) and custom categories for alerts (I19), modify the grouping of alerts manually (I11), manage favourites, pin important alerts or attach notes to alerts (I10).

6.5.3 Accessing and visualising historical data

Additionally, an alert archive with a search and filter functionality was demanded by five participants to allow post-processing of social media posts after an

incident. Two participants wished for a Telegram integration to forward all alerts to a private Telegram channel for use as an archive (I14) or to send messages to colleagues (I16). Besides a list-based archive, one interviewee emphasised the need for a chart-based analysis and filtering of past or current alerts, e.g. to show the volume of alerts during a specific timeframe (I11, I13, I19).

6.5.4 Adding collaborative features

Since in the current state, the interface shows the same view to all users and (private) information management features were suggested, the topics of collaborative work (I10, I18) and role management (I17) were also discussed, e.g. to provide different views for different functions such as press office and situation service (I12, I16). In contrast, another participant spoke against the need for additional collaboration: ‘As this is not an incident command system, it does not need additional collaboration features. If a colleague replies to an alert on another computer, he would know that because the message would be marked.’ (I9).

6.5.5 Enhancement of map functionality

The map view also received critical reception. First, considering the space it takes, the map was barely used, and the list of alerts regarded as more important: ‘We have our own maps on which we plot things. For that, we wouldn’t use ESI’ (I15). More accurate location information was requested, e.g. with the option to show the individual positions of the messages grouped in an alert or to indicate their distribution with a polygon (I11, I12, I15). The map, moreover, should only present alerts from the emergency services’ authoritative area, e.g. the bounds of Hamburg (I16). To improve the utility of the map, one participant wished for the integration of live stream (Facebook, Periscope), radio or webcam layers (I14). Another recommended connecting pictures and videos to geolocations and displaying them on the map as an additional layer (I8). Furthermore, he suggested implementing a multimedia view where only data such as pictures and videos are displayed. During large-scale events with plenty of alerts, such as G20, where up to 160 alerts were recognised by the system (I18), a solution is required if multiple markers overlap in a certain area (I11). Moreover, a better distinction of app alerts and social media alerts was requested (I19).

7 Discussion

We designed and evaluated a social media alerting system for emergency services to mitigate the potential information overload in social media during large-scale

Table 10. Outline of requested features in terms of display, alerts, filters, and map.

Class	Feature
Display	Custom information management and role-based views. Separate multimedia view (e.g. pictures, videos). Accessing, searching and filtering historical data. Chart-based filtering and visualisation of data.
Alerts	Improve the algorithmic message grouping into alerts. Further ways of notification (e.g. e-mail, push, sound). Management operations (e.g. read, done, notes, pinning, priority). Communication threads (e.g. response relations).
Filters	Improve and simplify the management of keywords. Allow keyword highlighting within the message texts. Show the performance of keyword, IM, and IQ filters. Allow tailoring of IQ graph to user or organisational preferences. Illustrate computation of IQ values on demand. Support the management of trusted and blocked users. Consider IM, IQ algorithms learning from user input.
Map	Allow the restriction of alerts by authoritative area. Indicate the precision of geolocation (e.g. GPS or city level). Show individual messages and comprising polygon for each alert. Allow display of further layers (e.g. radio, streams, webcams). Distinction of alert types and overlapping alerts.

conflicts and crises. Overall, most participants emphasised a positive attitude towards the system, including the statement that we delivered a good proof of concept. Several benefits for decision-making, reporting of incidents or informing the population were stressed, but participants also valued the simplicity of ESI and contributed potentials of enhancement (Table 10). In the following subsections, the main findings are presented and contextualised into existing literature, while recommendations of future research are discussed within the following sections.

7.1 Information quality and white-box algorithm representation: supporting the subjectivity, tailorability and transparency of filtering

The combination of social media, mobile and wireless technologies have significantly reduced the time lag between the capture and dissemination of data, and the analysis of big social data is likely to impact decision-making in the future (Imran et al. 2015; Shankaranarayanan and Blake 2017). Besides timeliness, information quality is defined by a variety of dimensions that only become visible in practice which is why we evaluated an information quality framework for social media with practitioners in this paper.

On high settings, the IQ component was perceived as a filter for the most crucial alerts, worked reliable and allowed a focus on important results. However, the performance of IQ should be compared to other ML algorithms, for instance, which learn from user input continuously. Furthermore, fake news, online rumours (Starbird et al. 2016; Arif et al. 2017) and the propagation of social bots (Ferrara et al. 2016) increasingly affect the

landscape of big social data and thus should be examined in the light of IQ. Notably, many participants mentioned that more transparency on how the overall IQ score is estimated by the system would increase the comprehensibility. Furthermore, participants demanded more delicate and visible criteria that could be parametrised by the organisation, as already indicated by Reuter et al. (2015), and stressed the importance of qualified or trusted users. In accordance with literature (Hilligoss and Rieh 2008; Ludwig, Reuter, and Pipek 2015), it was emphasised that quality has a subjective component. Thus, future versions of ESI should present more detailed IQ scores on demand and allow manually weighting IQ indicators to evaluate the appropriation, assessment, and performance of the IQ component.

The findings highlight the importance of an accurate representation of the system's state and its sub-processes as well as the adaptability of systems (McKinney 2011). The current 'black box' of algorithms does not allow the users to understand and 'fix the system so that its behaviour becomes more useful to their needs' (Burnett et al. 2017, 235). In accordance with the desired feedback on keyword and mining performance (cf. Section 7.2), a 'white-box' representation of algorithms – indicators and filters, which make the procedures transparent for the user – seems worth examining in future research to support the assessment of gathering, mining and quality performance as well as their adaption to situational demands. Since research in the education domain highlights the potential of white-box approaches for increasing the users' acceptance of algorithms (Delibaši et al. 2013; Romero, Olmo, and Ventura 2013), it seems a promising area for HCI to research the requirements, challenges and potentials of white-box algorithms and their visualisation across different types of algorithms, domains and users.

7.2 Information overload and usable configurability: improving the algorithmic performance and configurability of social media alerts by users

The increasing use of social media and thus the creation of big social data during emergencies raises the risk of information overload (Mendoza, Poblete, and Castillo 2010; Olshannikova et al. 2017). Since emergency services encounter a scarcity of personnel and time resources (Plotnick and Hiltz 2016), technological solutions might assist in the filtering of relevant data (Imran et al. 2015; Moi et al. 2015). Although there are existing architectures and systems that enable the filtering of big social data, e.g. Public Sonar (Abel, Hauff, and Stronkman 2012), only few of them integrated a

social media alert generation feature, which is why we introduced the concept of social media alerts.

Social media alerts were perceived as a good opportunity to get a general situational overview of local events and developments in social media, but also to get specific information, e.g. to prepare for or predict emergencies. However, amongst others, participants wished for an improved social media alert grouping, e.g. a more sophisticated grouping algorithm, more user metadata and more detailed location information of included messages. Thus, the implementation of more advanced classification (Habdank, Rodehutsors, and Koch 2017), clustering and role-based summarisation algorithms (Rudra et al. 2015; Nguyen, Kitamoto, and Nguyen 2015; Rudra, Goyal, et al. 2018), incorporating similarity measures, for event or sub-event detection are likely to increase the algorithmic performance of our approach (Imran et al. 2015; Pohl, Bouchachia, and Hellwagner 2015). Comparing the field trials in Dortmund (using pre-defined keywords) and Hamburg (regularly adapting pre-defined keywords), it became apparent that the definition and maintenance of suitable keywords is one key success factor for the system. Thus, an enhanced and more usable keyword management and a performance feedback, e.g. regarding the performance of keywords (in social media) and different filters, would improve the overall handling of the system and allow to adapt more quickly to changing situations. Moreover, several alert management functions were demanded such as: Mark alerts as read, prioritise alerts manually, pin alerts or manage favourites and provide an archive of past alerts, e.g. for the post-processing of deployments.

HCI should further research the issue of 'usable configurability' which demands, on the one hand, easy-to-use and integrated systems and, on the other hand, a configurability of (complex) components regarding the users' and organisations' use cases to achieve, in this case, the goal of a low volume of rich and useful content for emergency services. Based on the 'white-box' representation of algorithms (Section 7.1), concepts of end-user development, which comprise 'methods, techniques, and tools that allow users of software systems, who are acting as non-professional software developers, at some point to create, modify or extend a software artefact' (Lieberman et al. 2006) and usability engineering (Nielsen 1993) may be applied to achieve usable configurability.

8 Conclusion

In this paper, we analysed emergency services' potentials and barriers of using social media during emergencies as well as existing social media analytics systems identifying

a need to support emergency services regarding the assessment and the prevention of information overload (section 2). Based on empirical pre-studies, workshops and requirements analyses (section 3), we presented the development of the system (ESI) which supports the monitoring of social media via alerts, enables interactions between authorities and citizens, and supports the assessment of IQ (section 4). Using semi-structured interviews in different settings such as exercises, live demonstrations, and field trials (section 5), we conducted two iterations of evaluation whose results are presented (section 6) and discussed (section 7) in this paper in order to answer the following research questions:

How can social media alerts based on information gathering, mining, and quality filters help to mitigate the issue of information overload (RQ1)? With the Emergency Service Interface (ESI), we developed a novel approach for generating social media alerts, which transforms the high volume of big social data into a low volume of rich content that is useful to emergency personnel and aims to mitigate the issue of information overload. In comparison to existing social media analytics systems (Pohl 2013; Trilateral Research 2015; Kaufhold et al. 2017), ESI utilises an alert generation feature that considers the qualitative context of individual social media messages and integrates a filter layer based upon an information quality framework. During the evaluations, the approach was valued especially during large-scale incidents since it facilitates the adjustment of social media alerts by keyword (information gathering), relevance (information mining) and quality (information gathering) filters. The results suggest that a 'white-box' representation of algorithms would help emergency managers to better understand their computational behaviour, allowing to improve the users' utilisation of these filters and thus the mitigation of information overload.

How can the trade-off between automation and user interaction be designed to mitigate the issue of information overload (RQ2)? Besides user input in terms of setting or changing keywords as well as activating or deactivating the relevancy and quality filters, after an initial developer- and expert-based configuration, the back-end algorithms work automatically. While the evaluation outlines the need for improving the algorithmic performance, such as a more sophisticated grouping algorithm, end-users required the configuration of algorithms according to personal or organisational preferences and requirements, i.e. to adapt the weight of different information quality criteria and indicators. Thus, end-users required a 'usable configurability' combining easy-to-use and integrated systems with a sufficient configurability of complex algorithms or

components, that could be further improved by the application of end-user development concepts (Paternò and Wulf 2017) which we aim to realise with our application. Furthermore, real-time feedback and historic information is required for the end-user to assess the performance of the filter configurations and facilitate the gradual improvement of social media alert generation with regard to the dynamic and partially unforeseeable character of conflicts and crises.

After implementing a revised version of the system with proper alignment to related concepts of the knowledge base, an additional round of evaluation could contribute to these research areas. However, some limitations of the study must be considered. Firstly, the evaluation was mainly conducted with fire services, limiting the applicability of results to other types of organisations. After implementing the gathered user feedback, further evaluations could examine requirements and specifics of danger prediction and prevention by the police using social media via ESI. Secondly, while focusing on communication flows between authorities and citizens (A2C, C2A), inter- and intra-organisational crisis management (A2A) and self-help communities (C2C) were not in the direct scope of this evaluation. Although there are concepts of inter-organisational crisis management (C. White et al. 2009; Convertino et al. 2011; Ley et al. 2014; Reuter, Ludwig, and Pipek 2014), research should examine opportunities of social media collaboration including instant messengers like Telegram or WhatsApp. Moreover, while self-help communities at times act autonomously, authorities' and citizens' mutual awareness and cooperation, e.g. via Virtual Operations Support Teams (VOST) (St. Denis, Palen, and Anderson 2014), could be mediated via ICT such as ESI.

Notes

1. We follow the definition of social media as a 'group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content' (Kaplan and Haenlein 2010).
2. We recognise the weaknesses of this approach, especially concerning the manual labelling process, using a single labeller, resulting in heavily biased data. Since the focus of the project was on the development of an overall system and not on the optimisation of the classifier, this weakness was accepted. Further research in generally classifying data from emergencies should be done, placing more resources in the classification process, especially the labelling of a broad range of different incidents with sufficient labellers.
3. Participants had to indicate the importance of the C2A and A2C functions on a 4-point scale of max (4), high (3), moderate (2) and min (1).

4. Participants had to indicate the benefit on a 4-point scale of high (3), medium (2), low (1) and none (0) and were asked for further open-ended feedback.

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ORCID

Marc-André Kaufhold  <http://orcid.org/0000-0002-0387-9597>

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