Effective Use of Twitter Data in Crisis Management: The Challenge of Harnessing Geospatial Data

Completed Research

Dario Bonaretti
Louisiana State University
dbonar1@lsu.edu

Abstract

Could a Tweet save a life? The attention that public agencies and IS research have been dedicating to social media analysis in the last ten years seem to assume it could. Not only IS research in crisis-management is deeply oriented to harness the power of social media analysis, but public agencies are also following on this wave of enthusiasm for information extraction from social media (Twitter in particular). Our paper is an attempt to challenge some of the assumptions behind the ability to use crisis-related information on social media effectively, in particular, geospatial data. In particular, we suggest that current estimates about the volume of georeferenced data might be overoptimistic and ~35% of the georeferenced might not be precise enough to be used effectively in crises response initiatives such as localizing victims in the aftermath of an earthquake.

Keywords:
social media, emergency, crisis, disaster, representation theory

Introduction

In the last ten years, research in Emergency Management (EM) has repeatedly been advocating for harnessing crisis related data from social media (SM) to inform disaster response initiatives (Eismann et al. 2016; Herfort et al. 2014; Mukkamala and Beck 2016a; Tim et al. 2017), especially when urgent response is paramount (Valecha et al. 2013). Twitter, in particular, magnetizes scholarship's attention, and some government agencies are progressively institutionalizing SM analysis initiatives - for example, the American Red Cross has a dedicated Social Media Digital Operation Center for Humanitarian Relief. Anecdotic knowledge[1] suggests that SM streams might even help to locate victims during natural disasters. Moreover, the current literature is peppered with episodes of successful responses to help requests broadcasted through SM – particularly on Twitter (Acar and Muraki 2011). Thus, scholars advocate for overcoming the organizational barriers that still hinder information extraction from SM streams and to harness the georeferenced information to locate victims and gain situational information. For instance, a major barrier is the lack of dedicated personnel (Eismann et al. 2016; van Gorp et al. 2015; Shan et al. 2017) which hinders effective surveillance of SM streams.

SM is a very attractive data sources to gain situational information from in the aftermath of a disaster and are a perfect fit to develop frugal systems (Watson et al. 2013). Like frugal systems, SM embodies several features that are desirable in chaotic and emergent environments: Mobile, low-cost, easy-to-use, scalable, reliable, providing one-to-many communication, including spatial information, and connected to mainstream media and other organizations (Mills et al. 2009). There is a solid body of research in IS showing that SM analysis can successfully apply to monitor social crises, whether coming from man-made (e.g., riots, bombing) or natural disasters (Reuter et al. 2018). However, there is less enthusiasm for other IT solutions such as remote sensing, whether using satellite imaging (Lestari et al. 2016), and static sensors (Rodzi et al. 2017) or mobile physical sensors (e.g., UAVs) (for a study outside the IS field see Tuna et al. 2012).

---

[1] https://www.scribd.com/document/35737608/White-Paper-The-Case-for-Integrating-Crisis-Response-With-Social-Media

One of the reasons for the widespread optimism about the ability to extract crisis-related information from SM is probably due to the progress in investigating the research questions that drive SM analysis in EM. For instance, when the goal is rumor reduction, scholars identified promising patterns to improve the ability to extract first-hand information (Chen et al. 2008; Liu et al. 2014; Son et al. 2017). However, although reducing rumor in SM streams is intuitively understood as an enabler of effective use of SM information, the effective use of SM requires more truthful information.

To frame our investigation regarding the ability to use SM analysis effectively in EM we build on Representation Theory (Burton-Jones and Grange 2012). The adoption of a native-IS approach such as Representation Theory leads frame SM use in EM depending on their ability to faithfully represent the aftermath of a disaster. RT drives research towards understanding whether and how to use IT effectively in disaster response. Therefore, compared to other theoretical approaches, RT could offer a more comprehensive framework to comparatively evaluate SM analysis against other IT-driven initiatives.

Effective use implies that an SM-driven solution both works and does so efficiently compared to other alternative solutions. Our paper aims at contributing to the debate on the effective use of SM by adding to prior research on SM ability to effectively locate SM users. To review SM ability to inform EM we address the following questions:

- What triggered high interest for SM analysis in EM? To investigate this question, we frame SM adoption in EM from a historical perspective.
- How predominant is SM analysis in the IS scholarship? To address this aspect, we present some summary statistics about our literature review in IS.
- How has SM analysis been used to create information systems for EM and could those systems be effectively used to guide EM? To respond to this issue, we present an analysis of the accuracy of Twitter spatial data in the aftermath of the 2016 Central Italy Earthquake.

Historical Perspective

Early attempts to harness crisis-related data from SM trace back to Hurricane Katrina (New Orleans, US, 2005), and the use of MySpace. Since then, the popularization of mobile devices made SM more pervasive, increasing the volume of users and data generated. That increased the expectations about the SM ability to monitor human behaviors, which becomes critical during crises. However, more than a decade later, some governments still struggle or are reluctant to incorporate real-time social media monitoring to inform EM initiatives – with some notable exceptions. For instance, both the American Red Cross and the Australian Emergency Management Agency uphold dedicated personnel to surveil crisis-related data streams on SM. Their goal is only to detect life-threatening situations, but to monitor rumormongering and the spread fake news. That is crucial to withstand the emotional disruption that might affect the public opinion in the aftermath of a disaster. The skepticism against SM use in EM rests on some salient episodes.

For example, during the Boston Marathon Bombing (Boston, US, 2013), the Police crowdsourced the investigations through a "Find Boston Bombers" subreddit. Unfortunately, the thread misidentified the suspect as a 22-year-old man after a Facebook picture was uploaded and compared with the footage of the bomber. Eventually, the thread turned into an online witch hunt for a student who had been reported missing 30 days before the attack. However, more recent episodes show that not only misinformation may be misleading, but also faithful information may unexpectedly backfire.

Figure 1 A tweet from the Belgian Federal Police asking to maintain "radio silence"

For instance, during the terrorist attack in Brussels (2015), the Belgian Federal Police inhibited citizens from using SM to share crisis-related information, since terrorist at large could use SM to collect data about the positions of police units (Figure 1). That episode shows that in some cases SM might not just be an ineffective source of crisis-related data, but should not even be used to either intentionally or unintentionally crowdsource crisis-related information.

Among different SM platforms, Twitter seems to magnetize scholars' attention the most because of its ability to fast and dynamically diffuse information around the globe (Oh et al. 2012). Moreover, citizens have developed reasonable expectations about the authorities' ability to monitor SM content, sometimes with detrimental side-effects. For instance, during Hurricane Harvey (Houston, US, 2017) the Houston Police needed to tweet to avoid using Twitter instead of emergency numbers for life-threatening rescue requests (Figure 2); that was somehow a foretold wayward.

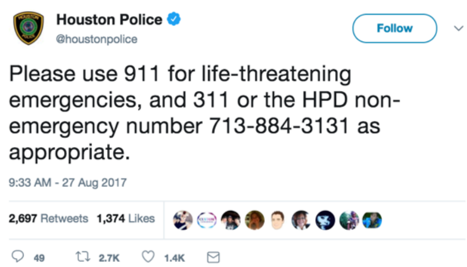

Figure 2 A tweet by the Houston Police during hurricane Harvey

In 2010, a survey of that 1 out of 3 US adults would privately or publicly message authorities on SM to seek help during emergencies[2]. Discerning what originated first, whether the citizens' expectation for authorities' responsiveness of SM or the authorities' interest for the latter, sounds like the old chicken-or-egg-first paradox. Although we cannot disentangle the *first cause* leading to the current scenario, we provide an overview of the relevance of SM analysis in current research in EM. Of course, our analysis focuses only on contributions to EM in IS, although SM analysis and EM draw from different disciplinary areas.

To measure the magnitude of IS publications focusing on SM analysis, we classify the relevant papers within the last ten years from the following outlets: The four major IS conferences (AMCIS, ECIS, ICIS, PACIS), the major conference in IS for crisis management (ISCRAM) and the journal papers from the Basket-of-Eight[3].

[2] Social Media Grows Up – Red Cross Emergency Social Data Summit. (n.d.). Retrieved February 28, 2018, from http://www.redcross.org/news/article/Social-Media-Grows-Up--Red-Cross-Emergency-Social-Data-Summit

[3] For reasons of space we cannot include all the references to the reviewed papers. The coding matrix for Figure 3 is available on request.

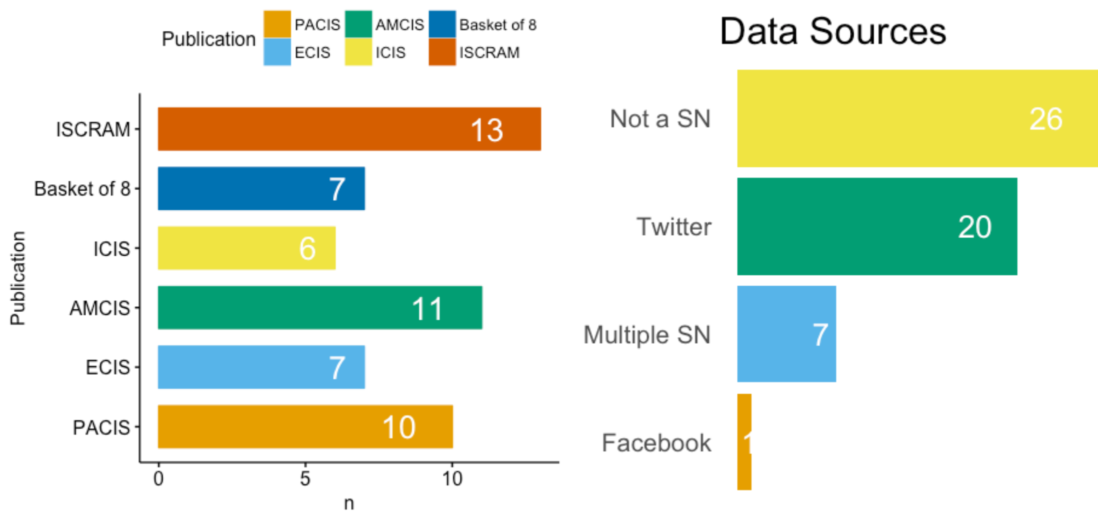

Figure 3. IS scholarship in social media for EM

To retrieve papers that are relevant to EM, we query the AIS e-library using the keywords: crisis, natural disaster, emergency management, disaster management, emergency. From the results, we exclude papers about business organizational crises and business resiliency during crises. Using these criteria, we retain 54 papers that we code depending on their data source or the social network under investigation. We classify each manuscript as referring to a specific SM name when possible, otherwise "multiple social networks" when the data come from different SM, or "not a social network" if the data or the research does not deal with using SM in EM. The results show a strong interest of the IS community towards analyzing Twitter data (20) and SM in general.
The infatuation of IS research for Twitter analysis seems to draw for research in *crisis informatics*, where higher accessibility of Twitter data (through a public API) and limitations in content dimension (140-280 characters) makes Twitter data easier to collect and analyze (Reuter et al. 2018). Twitters arguably constitutes a valuable repository of crisis-related information, which enables the exploration of methods for information extraction from unstructured content. The exploration of the technical aspects of SM analysis can inspire scholars to think about new ways of using crisis-related data. However, the IS community recommends caution against method-driven research (Hevner and Chatterjee 2010, p. 210). Our snapshot of the current literature suggests that this recommendation has to some extent gone unheeded.

Theoretical Framework

In the previous section, we outlined the elements that historically characterizes research in SM analysis to support EM initiatives. As we explain in the next session, the current body of research focuses on the potential for harnessing SM analysis (Figure 3) but downplays the evaluation of how information from SM can effectively inform EM initiatives. This section instead presents how the Representation Theory (Burton-Jones and Grange 2012) perspective focuses on *effective use* of IS and would offer a critical perspective on the current use of SM analysis in EM. For instance, studies building on Rumor Theory (Liu et al. 2014; Oh et al. 2013) view SM analysis as a rumor-reduction issue, aiming at uncovering "*unverified* proposition or belief that bears *topical relevance* for persons actively involved in its dissemination" (Oh et al. 2013 quoting (Rosnow and Kimmel 2000)). They severely question the ability of SM to faithfully represent the real world, focusing on rumor reduction and recognition in SM streams. Instead, for Representation Theory, a faithful digital representation of the real-world domain is only a precondition to enable effective use, but not the ultimate goal.

The notion of representational fidelity mirrors that of *accuracy* (Burton-Jones and Volkoff 2017), a three-dimensional construct representing the *truth*, the *whole truth*, and *nothing more* but the truth (Burton-Jones and Grange 2012). We stress that we distinguish between accuracy and what prior literature called *authenticity,* which is an attribute of the source, not of the content itself. For instance, scholars might consider as inauthentic the inherited geo-location of pictures shared on Twitter through Instagram, regardless of the accuracy of the inherited information (Kumar et al. 2017). We argue that such a distinction is secondary from a Representation Theory perspective since it does not affect the faithfulness of the digital representation of an event.

Truth	Is the information factual?	truthfulness
Nothing but the truth	Is the information rumor-free?	falsehood
Whole truth	Is the information complete?	completeness

Table 1 The dimensions of faithful representation

From a Representation Theory view, what matters is whether the extraction of crisis-related information from SM ultimately enables faithful representation of real-world crises and effective disaster response. When looking back at the "accuracy Trinity" (Table 1), IS research has so far been mostly focusing on two elements: Extracting the *truth* and *nothing but the truth*, but completeness (the *whole truth)* seems to be implicitly assumed because of the distributed nature of social networks. Perhaps this might build on the idea that humans are the most widely deployed sensors, and technological advancements (such as wearable devices) are increasing the ability to provide a digital representation of environmental changes (Yang et al. 2012). Their ubiquity and mobility can enhance coverage since remote sensors have inevitably blind spots (Li et al. 2017) to the point that some researchers consider human sensing superior to physical one; particularly during crises, when the intrinsic adaptability of human sensing is a priceless asset to deal with emergent environments (Jiang and Mcgill 2010). Included in the concept of representation *completeness*, is the precision of the representation. For instance, a first-hand Tweet by a victim seeking help although true and rumor-free might virtually provide no actionable knowledge unless it is tagged with geospatial information accurate enough. However, Representation Theory ignores the role that *timeliness* plays in chaotic context. When it comes to EM, information is actionable only if it is timely processed and delivered to represent the real world. Therefore, even accurate representations are perishable and eventually worthless when they come untimely.

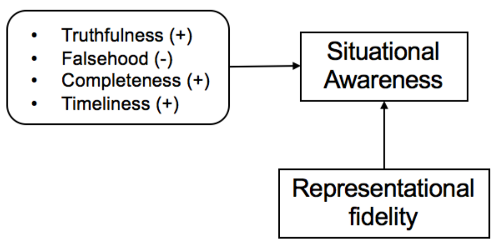

Figure 3 Proposed adaptation of Representation Theory to in EM. See Burton-Jones and Grange 2012 for the complete nomological network.

According to Representation Theory, representational fidelity enables informed action. However, because of the complexity of EM initiatives, we argue that action involves many more aspects that are beyond the scope of effective IS use. Thus, we propose that the goal of IS in EM should be to pursue *situational awareness*, that prior literature defines as the "perception of the elements in the environment within a volume of time and space, the comprehension of their meaning and the projection of their status in the near future" (Endsley 1995). Thus, we propose that to apply Representation Theory to EM we should redefine its nomological network as in Figure 3.

Digital Representation on Twitter

In the previous section, we outlined how the ultimate scope of integrating SM analysis in a system for EM is to provide faithful representations of the crisis. In this section, we comment on the use of Twitter streams in particular and review some major limitations of pursuing situational awareness through SM analysis from a Representation Theory.

The idea that enhancements in the Twitter analysis might lead to achieving higher situational awareness builds on the assumption that Twitter's users constitute a distributed network of human sensors. Any inference from the digital representation of a crisis through twitter stream is – similarly to representations from physical sensor data – an extrapolation from punctual observations; but with one important difference: Networks of physical sensors are designed, while human sensors frugally emerge in practice.

This difference has major epistemological implications, such as possible self-selection biases based on the digital divide, connectivity, and demographical characteristics. Biases such as self-selection do not necessarily decrease a system's ability to represent the truth and nothing but the truth, yet they pose serious limitations in pursuing a limitation of the whole truth. For example, more densely populated areas, more educated, or with better internet access, can increase the volume of tweets and inflate the perception about needs severity (Mulder et al. 2016). Unlike physical sensors, Twitter streams do not originate from a pre-designed network. Therefore, it is important to be aware of the socio-technical circumstances leading to the actualization of a network of human sensors. When decision makers can rely on a predesigned network, it may be desirable to obscure the underlying assumptions of the extrapolation process in order to provide a more stable representation of the reality (Almklov et al. 2014). This is less advisable in SM analysis, where the emergent nature of human sensing makes riskier to assume the extent to which the network is mapping the *whole truth* about our domain of interest.

Current scholarship on information extraction from Twitter roughly investigates three main content types: unstructured textual information, pictorial information, and geolocational information. Text analysis mainly looks at sentiment analysis (Joseph et al. 2014; Mukkamala and Beck 2016b; Oh et al. 2015), topic modeling (Son et al. 2017), word frequency analysis to isolate keywords bursts (Yin et al. 2012), or a combination of those techniques (Imran et al. 2015).

Image recognition of pictorial content has also been investigated, and the popularization of tools for pictorial analysis (e.g., Google Cloud Vision API) is likely to further encourage research on pictorial content. However, real-time image recognition of Twitter streams presents some criticalities, particularly concerning the retraining of the model with new data from an ongoing crisis (Nguyen et al. 2017). The classification of new images to feed the training set needs to be timely and accurate, two ambitious goals when working under severe time constraints.

Geo-location analysis also presents some major limitations regarding completeness. First, Twitter is a very limited source of locational information with as little as 1.2% (Dashti et al. 2014) and 3% (Herfort et al. 2014) of the tweets being geotagged. Thus, the use of geo-tagged information to build situational awareness relies on a restricted sample from the not necessarily representative population of Twitter users. Adding up to the scarcity of geospatial information, we need to account for rumor and noise on Twitter. Usually, approximately 75% of the tweets are retweets (Vaast et al. 2017) and thus constitute redundant information. On the top of redundant geolocation information, some of the gelocations might not be accurate enough to constitute valuable information, which reduces the base of usable information even further. To explore whether current estimations about the volume of usable locational data on Twitter may be overoptimistic, we analyze a Twitter stream that unfolds in the disruption that follows a natural disaster.

Data Collection

Our dataset[4] consists of tweets collected using the stream API with a 7mi. radius from Amatrice (42.695435, 13.294964), a small village in Central Italy affected by an earthquake on August 24th (6.2 M_w), causing 299 casualties and 388 injuries. The streaming started on August 25th, and the first week includes 2635 tweets, of which 1451 (55.1%) are retweets, and 660 (33.4%) are geotagged using a longitude-latitude value pair.

Results

To present our result, we plot the tweets on a map of the region of interest using their longitude-latitude coordinates (Figure 1). From a naïve look at geolocation data (Figure 1, b), geolocation data seem to reflect actual locations of Twitter users. However, in Figure 1a we plotted the same data tweaking the transparency of each dot to 1/10. This means that to make the hue of a dot from Figure 1b, we need to have 10 overlapping dots in Figure 1a. A closer look at Figure 1a, shows that geolocations rest on a virtual grid (we plotted few dashed-lines to highlight where the effect is more evident). This pattern is due to the different degree of precision of coordinates in tweets' metadata.

[4] Dataset available on GitHub:
https://github.com/DarioBoh/data/tree/master/earthquakeTweets_Italy2016

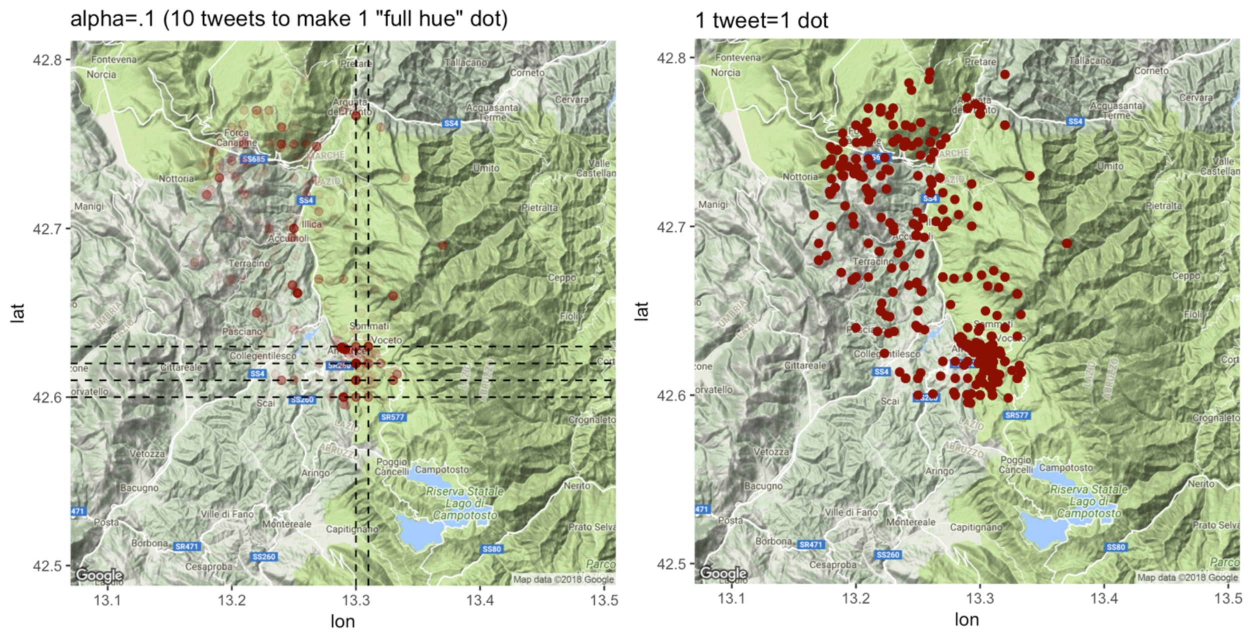

Figure 4 Geolocations of the Tweets of the Central Italy Earthquake

Decimals	Count	percent	Precision at the equator
2	47	7.10%	1.1132 km
3	231	35.00%	111.32 m
4	22	3.30%	11.132 m
5	158	23.90%	1.1132 m
6	3	0.50%	111.32 mm
7	2	0.30%	11.132 mm
8	12	1.80%	1.1132 mm
9	185	28.00%	11.132 µm

Table 1 represents the distribution of geo-location data by their degree of precision (column "Decimals"). First, we highlight that 35% of the tweets approximate their location to 3 decimals, ~100 m range. Another figure that stands out is the relatively high number of geo-locations representing an approximation that is below 1mm (28%). These values also rise a red flag, since 9 decimals would be enough to identify a speck of pollen, arguably smaller than the device which could have possibly have communicated the position. The reason why such an oddly high level of approximation shows app is still unclear to us. One explanation may be that the device communicates with a high level of precision (many decimals), but without much accuracy since the decimals are most likely erroneous.

Analysis

Our results offer a compelling basis to comment on the effective use of Twitter geolocation data. First, we highlight that in those cases where high accuracy is required, the amount of geo-located data that is usable might be even lower than what prior research suggests (3-5%). More than 40% of the tweets with geo-locational information is rounded to maximum three decimals, identifying an area which is as large as a baseball field. That may question the ability to provide a faithful representation through location data. Moreover, in chaotic scenarios, faithfulness is not only a matter of accuracy but entails timeliness too. Delivering information timely, ultimately depends on the ability to process information, and to avoid unnecessary computation. In that regard, virtually 1/3 of the geolocations round to nine decimals, which is about the dimension of the head of a pin. Besides from accuracy concerns – it is unlikely for an observation to be precise *and* accurate to nine decimals – it is hard to make a case for when it is useful processing spatial data to such a high level of precision. Geolocations beyond six decimals offer little incremental utility in improving representation faithfulness and constitutes redundant information.

Limitations

To enhance our understanding of effective use of Twitter spatial data in EM we could extend the analysis in different ways. For instance, we could look at the type of account, to identify whether certain kinds of accounts systematically present a certain level of approximation. For example, commercial or media account might communicate with lower levels of precision. For now, our goal is only to highlight a possible overoptimism in the availability of twitter geospatial data in the current body of research; thus, we do not control for account types.

Conclusions

Scholarship on harnessing social media data has gained remarkable momentum. Prior research shows that the data available through social media such as Twitter enable a digital representation of the event and the geospatial information about the users involved in the crisis. However, the current body of research seems to underrate the side-effects of pursuing situational awareness through SM. Treating networks of human sensors similarly to physical networks leads to ignoring the fundamental challenges that human sensing poses in pursuing completeness. However, when approaching EM from a Representation Theory perspective, issues of completeness of the information become pivotal. The implication of

The ethical implications of an over-optimistic approach to SM analysis are worrisome, as well as their impact on users' behavior. Seeking help during a disaster is something that happens under severe time constraints, and the cost-opportunity for seeking help through suboptimal media might lead to dramatic consequences. Thus, it is crucial to investigate whether the use of SM for seeking help reflects their actual effectiveness. Interestingly, current scholarship in EM pushes for gathering unstructured information from SM, but not as much for enabling new ways of communicating with public authorities, by using emergency numbers to send text and visual content. The concern is that IS research in the field may suffer a method-driven bias, leading researchers to investigate social media analysis leveraging the large availability of methods for collecting and analyzing such data while ignoring other valuable data sources (e.g., public data). Of course, the access to government data (e.g., calls to emergency numbers) depends on the synergies between government agencies and researchers.

"Although we know a lot about the way college students behave in contrived laboratory settings, [...] we know considerably less about the way all other types of people think and behave in their real-world environments." (Reis and Judd 2000, p. 246) This well-known methodological concern in behavioral research might paraphrase to the current body of research in EM given the strong dominance of studies on Twitter data. However, the implication is not only epistemological – offering a narrower but still valuable bulk of knowledge on the topic – but ethical too. The risk is that government agencies develop aprioristic beliefs about the potential of SM analysis because of the growing interest of the scientific community to the topic and before strong evidence about its practical impact. Instead, from a Representation Theory perspective, IS research should strive to reorient the attention towards evaluating the effectiveness of SM analysis.

References

Acar, A., and Muraki, Y. 2011. "Twitter for Crisis Communication: Lessons Learned from Japan's Tsunami Disaster," *International Journal of Web Based Communities* (7:3), pp. 392–402.

Almklov, P. G., Østerlie, T., and Haavik, T. K. 2014. "Situated with Infrastructures: Interactivity and Entanglement in Sensor Data Interpretation," *Journal of the Association for Information Systems* (15), p. 263.

Burton-Jones, A., and Grange, C. 2012. "From Use to Effective Use: A Representation Theory Perspective," *Information Systems Research* (24:3), pp. 632–658.

Burton-Jones, A., and Volkoff, O. 2017. "How Can We Develop Contextualized Theories of Effective Use? A Demonstration in the Context of Community-Care Electronic Health Records," *Information Systems Research* (28:3), pp. 468–489. (https://doi.org/10.1287/isre.2017.0702).

Chen, R., Sharman, R., Rao, H. R., and Upadhyaya, S. J. 2008. "Information Theoretic Approach to Design of Emergency Response Systems," in *14th Americas Conference on Information Systems*, Toronto, Ontario, Canada, p. 32.

Dashti, S., Palen, L., Heris, M. P., Anderson, K. M., Anderson, S., and Anderson, S. 2014. "Supporting Disaster Reconnaissance with Social Media Data: A Design-Oriented Case Study of the 2013 Colorado Floods," in *Proceedings of the 11th International ISCRAM Conference*, pp. 18–21. (https://pdfs.semanticscholar.org/a9da/e9ec0829e052a82c61967eca92726cedeae2.pdf).

Eismann, K., Posegga, O., and Fischbach, K. 2016. "Collective Behaviour, Social Media, and Disasters: A Systematic Literature Review.," in *26th Conference on Information Systems*, Instabul, Turkey.

Endsley, M. R. 1995. "Toward a Theory of Situation Awareness in Dynamic Systems," *Human Factors* (37:1), pp. 32–64.

van Gorp, A. F., Pogrebnyakov, N., and Maldonado, E. A. 2015. "Just Keep Tweeting: Emergency Responder's Social Media Use Before and During Emergencies.," in *25th European Conference on Information Systems*, Münster, Germany.

Herfort, B., Schelhorn, S.-J., Albuquerque, J. P. de, Zipf, A., and others. 2014. "Does the Spatiotemporal Distribution of Tweets Match the Spatiotemporal Distribution of Flood Phenomena? A Study about the River Elbe Flood in June 2013," in *International Conference on Information Systems for Crisis Response and Management, 11*, The Pennsylvania State University. (http://www.producao.usp.br/handle/BDPI/46102).

Hevner, A., and Chatterjee, S. 2010. *Design Science Research in Information Systems*, Springer.

Imran, M., Castillo, C., Diaz, F., and Vieweg, S. 2015. "Processing Social Media Messages in Mass Emergency: A Survey," *ACM Computing Surveys (CSUR)* (47:4), p. 67.

Jiang, M., and Mcgill, W. L. 2010. "Human-Centered Sensing for Crisis Response and Management Analysis Campaigns," in *In Proceedings of the 7th International Conference on Information Systems for Crisis Response and Management*, Citeseer.

Joseph, K., Landwehr, P. M., and Carley, K. M. 2014. "An Approach to Selecting Keywords to Track on Twitter during a Disaster," in *11th International Conference on Information Systems for Crisis Response and Management*, State College, Pennsylvania, USA.

Kumar, A., Singh, J. P., and Rana, N. P. 2017. *Authenticity of Geo-Location and Place Name in Tweets*, presented at the Twenty Third Americas Conference on Information Systems (AMCIS), Boston, Massachusetts. (http://aisel.aisnet.org/amcis2017/eGovernment/Presentations/10/).

Lestari, A., Rumantir, G., and Tapper, N. 2016. "A Spatio-Temporal Analysis on the Forest Fire Occurrence in Central Kalimantan, Indonesia.," in *20th Pacific Asia Conference on Information Systems*, Chiayi, Taiwan, p. 90.

Li, Z., Wang, C., Emrich, C. T., and Guo, D. 2017. "A Novel Approach to Leveraging Social Media for Rapid Flood Mapping: A Case Study of the 2015 South Carolina Floods," *Cartography and Geographic Information Science*, pp. 1–14. (https://doi.org/10.1080/15230406.2016.1271356).

Liu, F., Burton-Jones, A., and Xu, D. 2014. "Rumors on Social Media in Disasters: Extending Transmission to Retransmission.," in *18th Pacific Asia Conference on Information Systems*, Chengdu, China, p. 49.

Mills, A., Chen, R., Lee, J., and Raghav Rao, H. 2009. "Web 2.0 Emergency Applications: How Useful Can Twitter Be for Emergency Response?," *Journal of Information Privacy and Security* (5:3), pp. 3–26.

Mukkamala, A., and Beck, R. 2016a. *Disaster Management and Social Media Use for Decision Making by Humanitarian Organizations*, IEEE, January, pp. 1379–1385. (https://doi.org/10.1109/HICSS.2016.174).

Mukkamala, A., and Beck, R. 2016b. *Enhancing Disaster Management through Social Media Analytics to Develop Situation Awareness What Can Be Learned from Twitter Messages about Hurricane Sandy?*, presented at the Twentieth Pacific Asia Conference on Information Systems (PACIS), Chiayi, Taiwan, p. 165. (https://pure.itu.dk/portal/files/81652037/2016_PACIS_Enhancing_Disaster_Management_Hurricane_Sandy.pdf).

Mulder, F., Ferguson, J., Groenewegen, P., Boersma, K., and Wolbers, J. 2016. "Questioning Big Data: Crowdsourcing Crisis Data towards an Inclusive Humanitarian Response," *Big Data & Society* (3:2). (https://doi.org/10.1177/2053951716662054).

Nguyen, D. T., Alam, F., Ofli, F., and Imran, M. 2017. "Automatic Image Filtering on Social Networks Using Deep Learning and Perceptual Hashing during Crises," *ArXiv Preprint ArXiv:1704.02602*.

Oh, O., Agrawal, M., and Rao, H. R. 2013. "Community Intelligence and Social Media Services: A Rumor Theoretic Analysis of Tweets during Social Crises.," *Mis Quarterly* (37:2), pp. 407–426.

Oh, O., Eom, C., and Rao, H. R. 2015. "Role of Social Media in Social Change: An Analysis of Collective Sense Making During the 2011 Egypt Revolution," *Information Systems Research* (26:1), Research Note, pp. 210–223. (https://doi.org/10.1287/isre.2015.0565).

Oh, O., Tahmasbi, N., Rao, H. R., and de Vreede, G. J. 2012. "A Sociotechnical View of Information Diffusion and Social Changes: From Reprint to Retweet," in *International Conference on Information Systems, ICIS 2012*.

Reis, H. T., and Judd, C. M. 2000. *Handbook of Research Methods in Social and Personality Psychology*, Cambridge University Press.

Reuter, C., Hughes, A., Hiltz, S. R., Imran, M., and Plotnick, L. 2018. *Editorial of the Special Issue on Social Media in Crisis Management*.

Rodzi, M., Zuhaili, M., Nazir Ahmad, M., Zakaria, N. H., Ismail, M., and Ismawira, M. 2017. *Flood Sensor Development with Ontology-Based Knowledge Integration Using Design Science Research Methodology*.

Rosnow, R. L., and Kimmel, A. J. 2000. *Rumors. Encyclopedia of Psychology (Vol. 7, Pp. 122–123)*, Oxford University Press, Oxford.

Shan, Y., Plotnick, L., Hiltz, S. R., and Yang, L. 2017. "A Comparison of Emergency Management Social Media Use in the United States and England," in *23rd Americas Conference on Information Systems*, Boston, MA.

Son, J., Lee, H. K., Jin, S. S., and Woo, J. 2017. "How Do Multiple Topics in Terse Tweets Affect Retweeting? Evidence from the 2013 Colorado Floods.," in *23rd Americas Conference on Information Systems*, Boston, Massachusetts.

Tim, Y., Pan, S. L., Ractham, P., and Kaewkitipong, L. 2017. "Digitally Enabled Disaster Response: The Emergence of Social Media as Boundary Objects in a Flooding Disaster: Social Media for Disaster Response," *Information Systems Journal* (27:2), pp. 197–232. (https://doi.org/10.1111/isj.12114).

Tuna, G., Mumcu, T. V., Gulez, K., Gungor, V. C., and Erturk, H. 2012. "Unmanned Aerial Vehicle-Aided Wireless Sensor Network Deployment System for Post-Disaster Monitoring," in *International Conference on Intelligent Computing*, Springer, pp. 298–305.

Vaast, E., Safadi, H., Lapointe, L., and Negoita, B. 2017. "Social Media Affordances for Connective Action-an Examination of Microblogging Use during the Gulf of Mexico Oil Spill," *MIS Quarterly*.

Valecha, R., Oh, O., and Rao, R. 2013. "An Exploration of Collaboration over Time in Collective Crisis Response during the Haiti 2010 Earthquake," in *34th International Conference on Information Systems*, Milan, Italy. (http://aisel.aisnet.org/icis2013/proceedings/ResearchInProgress/96/).

Watson, R. T., Kunene, K. N., and Islam, M. S. 2013. "Frugal Information Systems (IS)," *Information Technology for Development* (19:2), pp. 176–187.

Yang, L., Su, G., and Yuan, H. 2012. "Design Principles of Integrated Information Platform for Emergency Responses: The Case of 2008 Beijing Olympic Games," *Information Systems Research* (23:3-part-1), pp. 761–786.

Yin, J., Lampert, A., Cameron, M., Robinson, B., and Power, R. 2012. "Using Social Media to Enhance Emergency Situation Awareness," *IEEE Intelligent Systems* (27:6), pp. 52–59.