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The Emotional Developments in Social Media Conversations Following a Terror Attack

PhD Dissertation

by

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Abstract

Emotions are an essential part of our communication. With the exceptions of guilt or shame, experiencing an emotion awakens a need to share it with others. The emergence of online social platforms during the recent decade has created new opportunities for such emotion sharing, and although research on expressions of emotion on social media has already yielded interesting insights, there are still gaps in our knowledge. Terror attacks are a particularly emotion-evoking type of event with heavy consequences on the emotional climate and well-being within a community. It is therefore a particularly interesting context in which to understand emotional mechanisms, and understanding them better can be used to inform actions that help members of the community overcome their trauma better. In addition, a better understanding of online communication dynamics will be helpful to emergency aid organizations in their attempt to filter relevant situational information in social media feeds during and after disasters. The research question posed and answered in this dissertation is *How are different emotions expressed on social media in the wake of a terror attack?*

This project started out by examining the existing wisdom on emotions on social media through a structured literature review. We found that theories are not extensively used or developed in the domain, that the most explored area of research is opinion mining, that the terms opinion and emotion are often used interchangeably, and that most studies study emotions through looking at polarity (positive vs. negative) rather than distinct emotion states.

One particularly interesting observation from the literature was that the findings regarding the role of emotions in information sharing are not always in agreement with each other. It is not clear whether these differences arise from contextual or cultural particularities, or differences in how emotions are analyzed. Because of these differences, and because information sharing has been found to be the primary use of social media in disaster situations, we decided to take a closer look at the relationship between emotions and information sharing. Our next step was therefore to examine the relationship between distinct state emotions and information sharing in an online conversation following a terror attack. We found that there were differences between negative emotions: fear and contempt were associated with lower retweeting rates, but anger and

sadness did not have a notable correlation with retweeting. Positive emotions had a small positive correlation with elevated retweeting.

It caught our attention that tweets from the affected area of the terror attack had a higher average of positive emotion and lower average of negative emotions than tweets from farther away: one would expect the opposite to be true for people who have recently been exposed to a traumatic event. Tweets from close by were also significantly more retweeted than other tweets. This prompted us to take a closer look into what people in different proximity areas are talking about, and how emotions are associated to different conversation streams. We analyzed the topics and emotions of three proximity regions over time following a terror event, and found that while some reactions are global, there are location specific collective emotions. As a result of this study, we propose a process model of the phases of post-terror online conversations, and outline how topics and emotions evolve during those phases.

The emotion expression on social media deviates from what literature says about emotions in two ways. Firstly, the theory on the social sharing of emotions states that the target of the sharing is a close person. However, emotion expression on social media is not targeted towards close people in specific, but to anyone who has access to the medium. Secondly, the overall duration of the post-terror discussion online is shorter than the phase of frequent discussions outlined by the social stage model of coping. Establishing causality requires future research, but it seems that social practices related to emotion expression online differ from those that occur offline.

This project contributes to our knowledge on how emotions are expressed on social media following a terror attack by finding that different emotions have different roles, that some of the collective emotional developments are specific to the proximity to the terror event location, and that emotional and topical trends are phase-specific, as well as proposes a model for the phases of post-terror online discussions.

Resume

Følelser er en essentiel del af menneskelig kommunikation. Med undtagelse af skyld og skam fremkalder følelser trangen til at dele dem med andre. Online sociale medier har over de sidste 10 år skabt nye muligheder for at dele følelser, men selvom forskning har givet os indsigt i hvordan følelser udtrykkes på sociale medier, er der stadig huller i vores viden. Terrorangreb er en type begivenhed, som fremkalder stærke følelser og kan have store konsekvenser for trivslen og det følelsesmæssige klima i et fællesskab. Derfor er det særligt interessant at undersøge følelsesmæssige mekanismer i denne kontekst, og hvis vi øger vores forståelse, kan den omsættes til handling, der hjælper mennesker i fællesskabet med at bearbejde deres traumer. Desuden kan en bedre forståelse af kommunikationsdynamikkerne i online fællesskaber hjælpe nødhjælpsorganisationer, så de kan filtrere relevant situationsbestemt information i feeds på sociale medier under og efter en katastrofe.

Problemformuleringen, som besvares i denne afhandling, er *Hvordan udtrykkes forskellige følelser på sociale medier i kølvandet på et terrorangreb?*

Projektet begyndte med en undersøgelse af den eksisterende viden om sociale medier via en struktureret litteraturgennemgang. Vi fandt ud af at teori ikke i udstrakt grad anvendes eller udvikles inden for dette fagområde, at det mest etablerede forskningsområde er opinion mining, og at ordene opinion og emotion ofte bruges i flæng. Desuden opdagede vi at de fleste studier studerer følelser ved at se på polaritet (positive versus negative) i stedet for at se på distinkte sindsstemninger.

En særligt interessant observation fra litteraturen var at studierne ikke altid er enige om hvilken rolle følelser spiller i forhold til informationsdeling. Det er uklart om disse forskelle skyldes særlige kontekstuelle eller kulturelle forhold, eller om det skyldes forskelle i hvordan følelser analyseres. På grund af disse forskelle, og fordi sociale medier i katastrofesituationer primært anvendes til informationsdeling, besluttede vi at se nærmere på forholdet mellem følelser og informationsdeling. Vores næste skridt var derfor at undersøge forholdet mellem distinkte sindsstemninger og informationsdeling i en online samtale efter et terrorangreb. Vi opdagede at der var forskelle mellem negative følelser: Frygt og foragt var associeret med lavere grad af retweeting, mens vrede og

tristhed ikke havde en bemærkelsesværdig korrelation med retweeting. Positive følelser havde en lille positiv korrelation med øget retweeting.

Det fangede vores opmærksomhed at tweets fra området, der var påvirket af terrorangrebet, gennemsnitligt havde en højere grad af positive følelser og en lavere grad af negative følelser end tweets fra områder længere væk. Man ville forvente det modsatte, når en gruppe mennesker for nylig er blevet udsat for en traumatisk oplevelse. Tweets fra området tæt på et angreb blev også markant mere retweetet end andre tweets. Dette motiverede os til at kigge nærmere på hvad folk i forskellige afstande fra terrorangreb taler om, og hvordan følelser er forbundet med forskellige samtalestrømme. Vi analyserede emnerne og følelserne i tiden efter et terrorangreb i tre områder, der lå i forskellig afstand til ulykken. Her kom det frem at nogle reaktioner er universelle, mens andre er lokationsspecifikke kollektive følelser. På baggrund af dette studie foreslår vi en procesmodel for de faser, som online samtaler går igennem efter et terrorangreb, og vi opridser hvordan emner og følelser udvikler sig gennem disse faser.

Måden hvorpå følelser udtrykkes på sociale medier afviger fra hvad litteraturen siger om følelser på to måder. For det første siger teorien om social deling af sindsstemninger at målet for delingen er en nærtstående person. Dog udtrykkes følelser på sociale medier ikke specifikt til nærtstående personer, men til enhver der har adgang til mediet. For det andet fortsætter den online diskussion efter et terrorangreb i kortere tid end fasen for hyppige diskussioner, som er beskrevet i den sociale fasemodel for coping. At fastslå en kausalitet vil kræve yderligere undersøgelser, men det ser ud til at social praksis omkring at udtrykke følelser online afviger fra den tilsvarende praksis offline.

Dette projekt bidrager til vores viden om hvordan følelser udtrykkes på sociale medier efter et terrorangreb ved at fastslå at forskellige følelser har forskellige roller, at den fysiske afstand til terrorangrebet har indflydelse på hvordan den kollektive følelsesmæssige udvikling ser ud, samt at følelsesmæssige og aktuelle tendenser er fasespecifikke. Derudover præsenterer projektet en model for faserne i online diskussioner efter terrorangreb.

Database abstract

Emotions are an essential part of our communication, and experiencing an emotion awakens a need to share it with others. The emergence of social media has created new opportunities for emotion sharing. Understanding how emotions are expressed in the wake of a terror attack helps emergency responders filter relevant information from online sources more efficiently. This dissertation examines how different emotions are expressed on social media in the wake of a terror attack. The work explores the research literature related to emotions on social media, investigates the correlation between distinct state emotions and information sharing in a terror attack context, and traces emotional and topical developments in post-terror online conversation. Positive emotions correlate positively, and fear and contempt negatively, with information sharing related to an act of terror. Some of the emotion expression online is specific to the proximity of the origin of the message to the area affected by the terror attack: people close by exhibit higher averages of positive and lower averages of negative emotions than people farther away. Although information sharing is the most common use of social media in a terror context, memorializing, support gestures, and opinion expression are more frequent in some phases of the online conversation.

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1 Introduction

This section provides an overview of the domain, research goals, findings, and contributions of the dissertation project, after which the structure of the remainder of the dissertation will be outlined.

Since its emergence, social media has created new opportunities for how we communicate: compared to traditional media, it enables information to travel faster, and reach a wider audience, including strangers we otherwise might not connect with. This creates new phenomena, ranging from positive, such as aiding the development of collective situation awareness in crisis situations (Mukkamala and Beck 2016), to negative including various types of rapidly escalating firestorms (Pfeffer et al. 2014). The main motivations for using social media are sharing and obtaining information, creating and maintaining connections with other users, and personal enjoyment (Dickinger et al. 2008; Ellison et al. 2007; Lin and Lu 2011).

Emotions play a central role in our communication: experiencing an emotion awakens the need to share it with others (Rimé 2009). Since its emergence, social media has provided a new platform for such emotion sharing, and there is evidence of the relevance of emotions in our communication. They play a role in information sharing decisions (Berger and Milkman 2012; Gruzd 2013; Hansen et al. 2011; Oh et al. 2013; Stieglitz and Dang-Xuan 2013) and in assessing the helpfulness of online reviews (Salehan and Kim 2016; Yin et al. 2014). Emotions are contagious (Fowler and Christakis 2008), which has also been found to apply in online environments (Gruzd et al. 2011; Kramer et al. 2014). Although much of our knowledge on emotion related behaviors of the physical world are applicable to online behavior, it is possible that not all of it translates directly. For instance, it may be that emotions in online conversations spread more rapidly, and possibly in a different way, than offline (Küster and Kappas 2013). Understanding the significance and role of emotions expressed on social media, and to what extent we can assume the dynamics of offline communication to apply online, is not only valuable through informing scholars on collective online behavioral patterns, but also has practical implications to both social media platform providers and any organization attempting to leverage that platform for both internal and external communication uses.

One of the challenges of social media research is that findings may be specific to context, culture, or type of online platform. One of the explanatory factors for context specific differences is that there are different types of conversations typical to online platforms (Ferrara and Yang 2015). In *anticipatory discussions* most of the discussion occurs before a peak that usually occurs during a real-world event. *Unexpected event discussions*, conversely, spark a sudden peak of conversation that fades away. The peak of the discussion is less distinct for *symmetric discussions* that typically unfold during a longer period of time, whereas *transient event conversations* tend to be short-lived with sharp, bursty peaks. Due to the context specificity of conversation dynamics, it is important to be aware of the scoping of research performed in this field, and the limitations in the generalizability of the findings. This dissertation work focuses on discussions revolving around terror attacks, a specific type of unexpected events, answering the following research question:

RQ: How are different emotions expressed on social media in the wake of a terror attack?

Terror attacks are emotion-eliciting events with significant consequences for the emotional climate and psychological well-being of a community (Boyle et al. 2004; Lerner et al. 2003; Morrison et al. 2001; Smith et al. 2001). That makes it a particularly interesting context for researching emotional reactions and mechanisms, the understanding of which is valuable in informing action aimed at helping the community members recover from the traumatic experiences. Understanding the dynamics of social media conversations is also informative to emergency responders and authorities attempting to access relevant situational information in online conversation streams without delay, which is essential, as social media is often the most up-to-date source of situational information in a crisis situation (Mukkamala and Beck 2016).

The first step in our quest to answer the research question above was to establish an overview of the current degree of knowledge regarding emotions expressed in online environments. We therefore conducted a structured literature review (Paper 1). The review found that theories are not extensively used to inform the research, that the terms *opinion* and *emotion* are occasionally used interchangeably, and that emotions are mostly analyzed in terms of polarity in spite of indications of the usefulness of considering distinct state emotions or several emotional dimensions.

The content analysis of the literature review revealed that the findings on how emotions are connected to information sharing on social media were divergent. While all studies agree that emotions play a role in sharing information online, the specifics differed: some found that positive emotions are related to increased information sharing (Gruzd 2013), while others found the presence of emotions to correlate with elevated information sharing regardless of the valence of the emotions (Burnap et al. 2014; Stieglitz and Dang-Xuan 2013). Yet others argued that the arousal level of the emotion, rather than the valence, is what determines the degree of information sharing (Berger 2011; Berger and Milkman 2012). There are several possible explanations for the divergence of the findings, ranging from cultural and contextual differences to the way emotions were analyzed in the studies.

Because information seeking and sharing is considered the most important social media use in crisis situations, and it was unclear to what extent previous findings are applicable to our research context, we decided to investigate how distinct state emotions are related to information sharing in terror attack situations (Paper 2). The analysis was performed on a large dataset containing tweets from the week following the Boston Marathon bombing, as well as a subset of the data containing the tweets that included geolocation information. We found differences between negative emotions: fear and contempt were associated with decreased information sharing, while anger and anxiety had a negligibly small positive correlation. Positive emotions were positively correlated with elevated information sharing in the whole dataset, but negatively correlated in the geolocation specific set, the potential reasons for which are detailed in the Discussion section. Proximity to the affected area was found to be strongly associated with increased information sharing.

One of the interesting observations from the Boston Marathon bombing dataset was that people near the terror attack location exhibited higher levels of positive and lower levels of negative emotions in their online communication than more remote conversation participants, which is counterintuitive given that they should be experiencing more severe stress and anxiety than people farther away (Morrison et al. 2001; Smith et al. 2001). This, along with the observation of proximity correlating with high information sharing, led us to be curious about what kinds of conversations are unfolding online at different proximity ranges, and how emotions are a part of them. Analyzing sentiment and topic developments over time for three proximity regions revealed that while some reactions to the terror attack are global, some of the collective emotions and behaviors are location specific (Paper 3). As an outcome of the study, we propose a process model for the phases of on online conversations following a terror attack, and outline the evolution of topics and emotions during the phases.

The findings of this dissertation project contribute to research by increasing our understanding of the relationship between distinct state emotions and online information sharing, as well as the collective emotional and topical developments of online conversations after a terror attack. In addition to the contributions to research, the findings from this project allow emergency responders and authorities to filter social media feeds more efficiently for relevant situational information in the wake of a terror attack.

The remainder of this introductory cover chapter for the dissertation is organized in the following manner. The next sections will review the theoretical background and relevant state-of-the art literature that informed this dissertation project. After reviewing the literature, I give an overview of the research design to outline the content of the project. The subsequent section lists the findings of the project, which will then be discussed along with the limitations and potential future avenues for research. The last section provides the concluding remarks for this dissertation project. In addition to the cover chapter, this dissertation contains three articles, each reporting in detail a part of the research that forms the contributions of this project.

2 Theoretical Background

2.1 Theoretical Background: Emotions

Emotions can be categorized in several ways. Some approaches define a number of distinct emotional states, such as *enjoyment, sadness, anger, fear,* and *disgust* (Ekman 1992). Typically, these states are top level categories, (often implicitly) containing finer-grained emotional categories. For instance, Ekman's definition of enjoyment includes amusement, relief, sensory pleasure, satisfaction and other types of positive emotions which would be difficult to distinguish between based on physiological signals (Ekman 1992). It is common that emotion categories list fewer positive than negative emotions due to negative emotions being more clearly distinct from each other (Fredrickson 1998). Other approaches conceptualize emotions as points in dimensions like *valence (*or *pleasure)* and *arousal* (or *activation*), expressing how pleasant and how intense an emotion is (Russell 2003). Some models include *dominance* as the third dimension (Mehrabian and Russell 1974).

There are also approaches that combine elements from both of the aforementioned ones, having distinct states but including dimensional thinking. Plutchik's wheel of emotions contains eight base emotions *joy, trust, fear, surprise, sadness, disgust, anger,* and *anticipation*, and a lower and higher intensity variant of each emotion (such as annoyance and rage for anger) (Plutchik 2001). Another combination approach to emotions is the hierarchical model of the affective domain where valence and activation serve as a basis for seven distinct states of emotion (Ekkekakis 2013). This work focuses on distinct state emotions, borrowing from Ekman and Ekkekakis whose categories have some overlap, the exact operationalization depending on the tools applied to the question at hand. In general, positive emotions are treated as a single category, while anger, fear (anxiety), sadness (depression), and in some cases contempt form the negative emotion categories.

According to the theory of *the social sharing of emotion,* experiencing an emotion elicits the need to share it to a listener (Rimé 2009). The urge to share an emotion applies to most emotions equally. However, shame and guilt seem to be exceptions to this – people were more reluctant to share experiences where shame or guilt played a role. The sharing behavior was found to occur independently of factors such as age, gender, education level, or cultural background.

The sharing of emotions tends to be a repetitive process, where the sharer seeks out several recipients, who often in their turn experience similar emotions and share them onwards. The number of repetitions and recipients correlates with the intensity of the emotional experience. Shortly after an emotional episode, the experiencer's working memory is actively processing the event, eliciting frequent sharing behaviour. Gradually, the emotional memory becomes more infrequent, decreasing the need to share it with others, until the emotional event becomes less active, and will only be recalled upon encountering a cue that activates the memory.

The target of the shared emotions is almost invariably a close person; a partner, family member, friend, or – in professional contexts – a colleague. In less than 5% of the cases is the target a professional person or stranger. This is particularly interesting from the point of view of researching emotions on (some types of) social media where a large part of the recipients of a message may be complete strangers. Although the initial development of the theory predates social media, the finding regarding targets being predominantly in the sharer's close social network is reiterated in more recent work by the original author (Rimé 2017).

Sentiment analysis is a means of analyzing emotions in text data or, more precisely, computational treatment of opinion, sentiment of subjectivity in text (Pang and Lee 2008). The two main approaches are *lexicon-based methods*, utilizing a dictionary containing emotion words and ranking texts based on the presence of those words (Esuli and Sebastiani 2007; Thelwall 2017), and *machine learning-based methods*, that classify texts into emotion categories based on examples in a training data set (Pang et al. 2002). It is also possible to combine the approaches by using lexicon scores as part of the input for a classifier (Meire et al. 2016). Sentiment analysis has typically focused on measuring polarity (valence) rather than distinct emotions, but there are some instances where more fine-grained approaches are used. Paper 1 contains examples of such cases and lists common application areas of sentiment analysis.

3 Literature Review

3.1 Emotions on Social Media

The first step in finding an answer to the main research question was to establish what we already know about how emotions are expressed on social media. We therefore started out by conducting a rigorous literature review (Paper 1), searching for relevant research in established scientific databases and the most relevant journals in information systems. In order to get an organized overview of what the state of the art is and what types of research streams exist within social media research, we asked the following research question:

RQ1: In which areas within social media research have expressions of emotion been studied?

A recent review on the usage of social media in disaster situations calls for more research to adapt and develop theory for social phenomena on social media (Eismann et al. 2016). In order to get a better understanding of what emotional phenomena previous research focuses on, we examine what kinds of theories on emotions are used in the studies:

RQ2: Which theories on emotions from reference fields does the research rely on?

Emotions can be conceptualized as points in dimensions (Mehrabian and Russell 1974; Russell 2003) or as distinct states (Ekman 1992; Plutchik 2001), and various categorizations have been suggested in the psychology literature on emotions. Although most sentiment analysis tools only measure one dimension, valence, some studies indicate that analyzing distinct emotions can provide additional insight. Online reviews containing indications of anxiety were considered more helpful than those containing indications of anger, having to do with the readers' beliefs on the reviewers' cognitive effort (Yin et al. 2014), and differential emotions were found more useful than polarity measurement in analyzing corporate social media accounts (Risius and Akolk 2015), as well as in predicting stock market developments (Risius et al. 2015). We were therefore interested in establishing how previous research conceptualizes and analyzes emotions:

RQ3: How are emotions categorized in the research?

As the literature relevant to this section is predominantly an outcome of the research effort answering the abovementioned questions, it will be elaborated on in the Empirical Results section of this cover chapter.

3.2 Emotions and Information Sharing on Social Media

The review gave us a good starting point for identifying where further research would be particularly valuable. Based on the findings of the literature review, we decided to take a closer look at emotions and information sharing. One of the reasons for choosing information sharing as a target of interest was that the previous results on the relationship between emotions and information sharing were not always in accordance with each other. Some state that positive emotions are shared more (Gruzd 2013), while others state that emotional content in general is shared more than unemotional regardless of the emotion (Stieglitz and Dang-Xuan 2013), while yet others conclude that instead of valence, the arousal level of the emotion is associated with elevated sharing (Berger and Milkman 2012), or that negative news are shared more often than non-negative ones but the opposite holds for other types of content (Hansen et al. 2011). These differences between previous findings may result from different types of discussions unfolding in different ways (Ferrara and Yang 2015), or perhaps from cultural differences, but it could also be that the online information sharing behaviors are specific to distinct emotions rather than a single dimension (valence or arousal). We therefore decided to investigate how different emotions are related to the degree of information sharing on social media by analyzing the sentiment in retweets.

Another reason to study information sharing behavior is that sharing and seeking information is the most common social media use in the context of terror attacks (Eismann et al. 2016; Heverin and Zach 2010; Huang et al. 2015), and is therefore central to understanding the emotional mechanisms of post-terror communication. Accessing and distributing information after a terror attack is seen as important and urgent – to the point where social media is preferred over traditional media in spite of the acknowledged risk regarding information accuracy – which implies the information sharing decisions may be affected by an individual's emotions (Huang et al. 2015; Kaufmann 2015). In spite of that, we do not yet know much regarding the role of emotions in information sharing in a terror attack context, aside from anxiety being connected to rumoring behavior (Oh et al. 2013).

RQ: How are different emotions related to the degree of information sharing on social media in the context of a terror attack?

Terror attacks elicit high levels of anxiety, sadness, and anger (Huang et al. 2015; Morrison et al. 2001; Pyszczynski et al. 2003; Smith et al. 2001). Not only do we expect to see the presence of these emotions in the data, but we hypothesize they are related to information sharing behavior. (For hypotheses, see Paper 2.)

Proximity to the location of the terror attack was included in the analysis as relevant to the investigation of the relationship between emotions and information sharing for two reasons. Firstly, people close by are likely to be more emotionally affected by the act of terror (Morrison et al. 2001; Smith et al. 2001), which might be reflected in the emotional levels of their online communication. Secondly, information originating from the proximity of the affected area is perceived as more credible (Starbird and Palen 2010; Thomson et al. 2012), which might be reflected in the rate at which it is shared. If information in general tends to be neutral in nature, but the best sources of information are experiencing particularly intense emotions, that may have interesting implications for the emotion levels of highly shared information.

3.3 Emotions and Topics in Online Conversations Following a Terror Attack

Upon studying emotions and information diffusion, we made some interesting observations. Firstly, it seemed that certain types of tweets contained specific types of emotions. Manual exploration of positive tweets showed trends of gratefulness towards authorities and various types of gestures of support and loyalty to Boston. The negative emotions, too, often seemed to revolve around particular topics. While previous literature has charted out different types of social media uses during disasters, it seemed that there was no research on what kinds of topics were prevalent in those discussions. Since understanding topical developments held potential to explain emotional processes, we decided to take a closer look at them through topic modeling, a machine learning-based approach to clustering text documents into categories with similar documents (Debortoli et al. 2016).

Secondly, the emotions and topics seemed to be specific to a point or period in time. Some of the tweets were clearly related to a specific turn of events such as arresting the suspect, but we wanted to find out whether there are also more general, collective level emotional trends that develop over time as a reaction to a terror attack, which led us to develop a process model of the emotions and topics in post-terror online conversations (see Paper 3). The two aforementioned observations led to the first research question in Paper 3:

RQ1: *How do emotions and topics of conversation manifest and change over time after a terror attack?*

According to the social stage model of coping, talking and thinking about a recent crisis event can be divided into three phases: *the emergency phase* where both thoughts and discussions about the event are frequent, *the inhibition phase* where thoughts are recurrent but conversations are infrequent, and *the adaptation phase* where levels of both thoughts and discussions are low (Pennebaker and Harber 1993). In this research, we focus on the emergency phase. According to the dual-process theory, reactions to terror events can be divided into *proximal* and *distal reactions*, which are responses to increased death-related thoughts and serve the purpose of controlling anxiety (Pyszczynski et al. 1999). Proximal reactions include shock, disbelief, safety concerns, and emotional reactions in general, whereas distal reactions include behaviors such as altruism, seeking value and meaning, information seeking and sharing, enforcing social connections, heightened patriotism and nationalism, and counter-bigotry advocacy (Yum and Schenck-Hamlin 2005). As both proximal and distal reactions include recurrent thoughts and discussions about the terror event, it is probable both of them are present during the emergency phase.

Thirdly, we found that the geographic origin of the tweet strongly affected retweeting rates. This led us to ask whether the emotions experienced and expressed might also be specific to the proximity from the terror event location. People in the directly affected area will have probably been hit with a stronger emotional impact to the event: after 9/11, people in or close to New York reported higher levels or stress and anxiety than people farther away (Smith et al. 2001). People in or near the location of a crisis event also have different ways of using social media than more remote conversation participants. In the crisis area, conversation focuses more on coordinating relief efforts, whereas people farther away engage more in memorializing (thoughts and prayers, and condolences) (Takahashi et al. 2015). Because of the differences in both experienced emotions and motives for social media usage, we decided to ask an additional question:

RQ2: *How proximity specific are the emotional and topical developments?*

4 Research Design

4.1 Methodology

The project commenced with a structured literature review (Paper 1), following established guidelines in the field (vom Brocke et al. 2015; Vom Brocke et al. 2009; Webster and Watson 2002). The first step of the process was deciding the scope of the review. The criteria for the search was determined to be that the articles be peer reviewed, in English, published in 2006 or later, and on the topic of how sentiment is expressed on social media. The second phase consisted of searching through the top journals in IS and, during that search, iterate through various search terms and search term combinations and compare the precision and recall to establish the optimal search term(s) for the subsequent searches. In the third phase, we searched through scientific databases. After determining the relevance of the articles found by the end of the third phase, we performed forward and backward search on the relevant papers, and iterated the process until reaching saturation point. Following the search phase, we analyzed the literature by means of manual content analysis (Krippendorff 1989).

Looking into the relationship between differential emotions and information sharing was done by deductively formulating hypotheses based on existing literature and testing them through quantitative, statistical analysis of the data. Because of the properties of the dataset, we chose to use a generalized linear mixed model for the analysis (see Paper 2 for details).

The methodology used for generating theory by exploring a set of unstructured data in the final study (Paper 3) draws from *data-driven computationally-intensive theory development*, as it provides a feasible approach to exploratory computational research (Berente et al. 2018; Berente and Seidel 2015). The approach is based on the idea of combining elements from grounded theory methodology (GTM) and computational theory discovery (CTD) to develop theory from large sets of digital trace data. There are four main phases: *data sampling/collection*, *synchronic analysis* (categorizing data and looking for relationships between concepts), *lexical framing* (drawing upon and extending the vocabulary relevant to the research), and *diachronic analysis* (generating theory). These phases are not a chronological sequence, but rather iterated between during the exploratory process.

Our data collection was done in a single iteration, as is often the case with digital trace data used in research, whereas a typical GTM process would include iterations of resampling guided by new information revealed during the iterative process. The synchronic analysis phase was assisted by computational approaches such as descriptive statistics, sentiment analysis, and topic modeling, but also included axial coding of topics into higher-level categories. The core of our pre-theoretic lexicon was formed based on theories of emotion and concepts in literature in social media analytics and sentiment analysis, and iteratively expanded based on the needs for vocabulary for the emerging patterns in the data. One could argue that drawing from existing wisdom to inform theory building makes the process somewhat abductive, although data-driven theory building is often referred to as an inductive process. The sense making process eventually leading to the development of the process model occurred in the diachronic analysis phase(s).

4.2 Data and Empirical Analysis

4.2.1 Data

The data used in this dissertation project is a set of tweets related to the Boston Marathon bombing from 15th–23rd of April 2013 with non-relevant tweets (such as tweets not in English, or about Boston but not the bombing) removed during pre-processing. After counting the number of retweets for each original tweet in the data and storing the information for analytical purposes, retweets were removed from the dataset. The reasoning for this was twofold. Firstly, it was to avoid confounding the analysis with the retweet rates of retweets identical to the retweet rates of the original, which are likely to differ but the effect of which is unknown (for the purposes of the work outlined in Paper 2). Secondly, it was done to avoid confounding what kinds of topics and emotions are expressed in each of the proximity regions by including data where a topic or emotion originating in one region is passed on by a user in a different region without being able to understand their reasoning for sharing it and the extent to which they agree with the shared message. After the preprocessing, the dataset consisted of 4,4 million tweets, out of which 90 000 contained geolocation information.

4.2.2 Sentiment analysis

The emotions in the dataset were detected using sentiment analysis. As one of the goals of this dissertation was to gain a better understanding of how distinct state emotions might differ from each other, a tool differentiating between emotions was required. We decided to use customized emotion specific lexicons (Risius et al. 2015; Risius and Akolk 2015) developed to be used in conjunction with SentiStrength, a sentiment measuring tool designed in particular for short, informal texts (Thelwall et al. 2010). The operationalization of the emotions covered by the lexicons follow the seven distinct emotions in Ekkekakis' affective domain: affection, happiness, satisfaction, anger, fear, depression, and contempt. Upon discovering that the positive emotions have a strong correlation in our dataset, we eventually decided treat them as one emotional category in our analysis.

In spite of the lexicons having been evaluated previously, a reviewer expressed concerns on our usage of a sentiment analysis approach that was not widely used. In order to address these concerns, we eventually decided to use LIWC2015 (Linguistic Inquiry and Word Count) in further analyses (Pennebaker et al. 2015). The categories of the customized SentiStrength lexicons with positive emotions combined (positive, anger, fear, depression, contempt) were close to the emotional categories LIWC covers (positive, negative, anger, anxiety, sadness), the biggest difference being that LIWC does not account for contempt, which we deemed an acceptable trade-off to the tool being well established.

4.2.3 Topic Analysis

Topic analysis is a machine learning approach to clustering data entries into topical categories based on lexical similarity. This project used a Latent Dirichlet Allocation (LDA) based topic modeler provided by the cloud-based text analysis service MineMyText (http://www.minemytext.com), following the recommendations and advice given by the researchers who implemented the service (Debortoli et al. 2016; Müller et al. 2016). Although topic modeling enables clustering similar data entries into coherent groups, reasoning about those groups is left to the human reader. Furthermore, topic analysis requires the number of topical groups as input, and the optimal number of topics varies across data sets. We experimented – with an increment of ten at a time – from 20 topics up to 100, manually inspecting the output, before deciding on 70 topics, where the number of clusters containing several topic streams as well as the number of overlapping, minimally different clusters were simultaneously as low as possible.

The topics were labeled manually by the author of this dissertation. A subset of 20% of the topics were labeled by a second researcher, and was deemed a sufficient control measure due to high inter-coder agreement (slight terminological differences in five out of fourteen labels, agreement of the relevant content reached through short negotiation). The topics were then grouped into higher level categories manually by the two aforementioned researchers, independently from each other. The grouping was mostly identical, apart from four ambiguous cases, that were assigned into their appropriate categories through negotiation and reasoning between the researchers.

4.2.4 Regression Analysis

The inferential statistical analysis approach used in the analysis of the correlation between information sharing and emotions (Paper 2) was determined based on the properties of the data. The dependent variable values were non-negative integers and over-dispersed (i.e. the variance was greater than the mean), which supported the choice of a *generalized linear model* (GLM). After examining the data and assessing the fit of various models in the GLM family, we determined the *negative binomial model* to be the best fit for our data. Due to having to account for multiple tweets from the same user probably being more similar than two tweets between different users, a random variable had to be included, which is why the final choice was a *generalized linear mixed model with a negative binomial distribution*. The variables and formulae of the models for the full and geolocation specific datasets can be found in Paper 2.

5 Empirical Results

5.1 Paper 1: State of the Art Based on the Literature

The literature review gave us an overview of the existing knowledge regarding emotions on social media. The main findings were that sentiment analysis mostly focuses on polarity, theories are not commonly used, that the terms emotion and opinion are often used interchangeably, and that emotions have been researched in particular in the contexts of *electronic word of mouth/online customer reviews, collective sentiment, outcome prediction* (especially stock market prediction), and *emotional contagion*.

The categories in which emotions have been investigated in social media research are *collective sentiment, emotional contagion, CRM/eWOM/OCR (customer relationship management, electronic word-of-mouth, and online customer reviews), information diffusion, literature reviews, methods and tools, negative behavior, outcome prediction, predicting user engagement,* and *affect on social media in general.* Some of these categories were more prevalent in the data than others. Online reviews were a particularly common area of interest, looking into phenomena such as the perceived helpfulness of online reviews (Malik and Hussain 2017; Salehan and Kim 2016; Yin et al. 2014) and factors in reviewer decision making (Chen et al. 2017; Goes et al. 2014). The research on collective sentiment typically focused on either a collective mood within a community in general (Bollen, Mao, and Pepe 2011; Durahim and Coşkun 2015; Nguyen et al. 2014; Qi et al. 2015) or around a particular event (Gratch et al. 2015; Liu et al. 2014; Nguyen et al. 2013; Pang and Ng 2016; Thelwall et al. 2011). The studies on outcome research that were not about predicting stock market prices were either about predicting election results (O'Connor et al. 2010; Tumasjan et al. 2011) or Premier league football results (Schumaker et al. 2016).

Although IS scholars routinely draw from theories on related fields, it does not seem to be extremely common in the analysis of emotions on social media. The theory density seems to depend on the area of research: in spite of being the largest area of interest (20 out of 82 articles), opinion mining (CRM/eWOM/OCR) in general did not leverage theories in their research question or hypothesis building, whereas almost one third of the research in the emotional contagion category uses some emotions related theory. The theory usage includes *the affect heuristic theory* (Yu et al. 2015)*, the affect infusion model* (Nofer and Hinz 2015)*, affective response model* (Wakefield and Wakefield 2016)*,* and *positivity bias* (Ferrara and Yang 2015).

A large majority of the articles analyzed emotions on a positive vs. negative scale. Nevertheless, some papers argue that differentiated emotions give us more insight than mere polarity (Berger and Milkman 2012; Bollen, Mao, and Zeng 2011; Malik and Hussain 2017; Risius et al. 2015; Yin et al. 2014), and 19 out of 82 papers analyze differential or partially differential emotions.

5.2 Paper 2: Emotions and Information Sharing After a Terror Attack

In order to answer the research question on how emotions are related to the degree of information sharing on social media after a terror attack, we analyzed a large dataset of tweets related to the Boston Marathon bombing. For each tweet, the sentiment was analyzed using dictionaries for differential emotions, after which the correlations between each emotion and the number of retweets were determined using a generalized linear mixed model. To account for the possibility that the information sharing behavior may be related to the proximity of the origin of the tweet location to the terror attack location, we conducted additional analysis on the set of tweets containing geolocation information, adding a categorical proximity variable to the statistical model.

Examining the relationship between retweets and distinct emotions yielded some interesting insights. Firstly, fear and contempt have a negative correlation with retweeting (with a 4% and 7% decrease in the geolocation dataset, respectively, and a 2% and 5% decrease in the full dataset), whereas anger and anxiety had barely any influence (1% increase in the full dataset, findings not significant in the geolocation dataset).

Secondly, positive sentiment in tweets had a slight positive correlation with retweet rates in the whole dataset, but a rather strong negative one in the geolocation specific dataset. This could mean that the people who choose to disclose their location on Twitter (disclosing location is opt-in) may have a markedly different online communication culture, which may also impact what their followers choose to share as relevant. Another possible explanation would be related to the Boston and Massachusetts area tweets being more positive than tweets from farther away. Without the location information included in the model, it may look like the retweeting of tweets originating from the affected area is related to their positivity levels.

Thirdly, including proximity to the terror attack location in the analysis revealed that location is almost as important a predictor for retweet rates as follower count. Tweets from the Boston and Massachusetts areas were more than 1.5 times more likely to get retweeted than tweets originating from outside of the US, and tweets from the US were 1.3 times more likely to be retweeted than from abroad. To the best of our knowledge, previous research looking into online information sharing in a crisis context has not considered location as an explanatory variable.

Positive emotions were initially divided into three distinct categories: affection, happiness, and satisfaction. However, after noticing they strongly correlated with each other, we decided to merge them into one positive emotions category. This observation is in line with literature stating that positive emotions are less distinct from one another than negative emotions (Fredrickson 1998).

5.3 Paper 3: Emotions and Topics in Phases of Post-Terror Online Conversations

In the third paper, we looked at how emotions and topics developed over time on Twitter in the wake of the Boston Marathon Bombing. The dataset was divided into three proximity categories (Massachusetts, the rest of the US, and abroad) to enable establishing which developments are specific to proximity to the terror event.

Based on the social stage model of coping as well as the dual-process theory on proximal and distal reactions to terror attacks as well as patterns in the data, the paper suggests a process model for the online conversations following a terror attack, where the first phase is *shock*, followed by a *making sense* phase, followed by one or more optional custom *subsequent events*, leading to the final phase, the *aftermath*. We propose the shock, making sense, and aftermath phases are present in post-terror online discussions in general, while the subsequent event phase varies based on the specifics of the event. In the case of Boston Marathon Bombing, there were two subsequent events: the suspect chase, sparking a lot of situational information sharing, and closure upon the suspect's arrest, eliciting information sharing and gratitude towards authorities.

Positive sentiment was stronger in Massachusetts, the area directly affected by the terror event, throughout the whole emergency phase, whereas negative emotions were stronger farther away. Sadness spiked during the first two days everywhere, but quickly decreased, whereas anger and anxiety fluctuated within a narrower range. Positive emotions spiked globally around the time the suspect was caught after an extensive police operation. During the aftermath phase, when most of the conversation had died down, the remaining discussion contained elevated levels of anger and anxiety

The topic analysis resulted in 70 topics, which were manually classified into twelve higher level categories. Some of the topics (such as shock and upset, memorializing, support gestures) were strongly emotional, whereas others (such as sharing news, updates on suspect chase) were mostly neutral in tone. The top topics varied over time and by location. During the shock phase, memorialization was the most common topic. Gratitude and different kinds of support gestures were most prevalent within Massachusetts, whereas opinion expression was more commonplace farther away.

Throughout all of the phases, information sharing was among the top topics in all of the location categories. This is not surprising, as it is the primary use of social media in crisis situations (Eismann et al. 2016; Takahashi et al. 2015). However, our analysis shows that although information sharing is a common topical category throughout the event, there are situations and phases where other uses are more dominant. Information sharing spikes after something happens – in the shock and subsequent event phases – and gradually decreases to make way for other types of topics. For instance, collective support gestures and gratitude towards authorities were trending more strongly than information sharing in the affected area during all phases except the shock and the subsequent event.

6 Discussion

6.1 Contributions to Research

This section outlines how the empirical results explained above contribute to research pertaining to emotions expressed on social media.

6.1.1 Emotions on Social Media

The first step of this project was to form an overview of the state-of-the-art research in the field. We conducted a structured literature review following established guidelines in the field (Vom Brocke et al. 2009; Webster and Watson 2002). We focused in particular on what kinds of research domains are prevalent in the literature, what types of emotion theories were used to inform the studies, and how emotions have been categorized in the analyses.

The collection of articles included a database search phase, which means that it includes studies outside of information systems research, which may be an explanatory factor in the rarity of theory usage in the literature. Conventions on drawing from a theoretical base vary between different fields of research. Nevertheless, we argue the sparsity of theory driven argumentation is curious, given that availability should not be an issue – emotions are extensively covered in psychology literature. More extensive usage of those theories could help provide answers to why emotions are expressed in certain ways in certain situations on social media.

Emotions were typically analyzed in terms of polarity rather than distinct states or several dimensions, although findings support differential analysis of emotions being useful (Berger and Milkman 2012; Bollen, Mao, and Zeng 2011; Malik and Hussain 2017; Risius et al. 2015; Yin et al. 2014). There may be several explanatory factors to polarity analysis being prevalent in spite of the benefits of differential emotion analysis. It might be that the relevance of differentiating between emotions depends on the research question and interests: perhaps the type of emotion plays a central role in some fields, while in others, polarity analysis is adequate for the purposes of the study. Another possible explanation is that the possibility and relevance of analyzing distinct state emotions is not familiar to some researchers, or that access to tools capable of such analysis is limited. By pointing this out, we do not mean to imply that polarity analysis is always inferior to differential emotion analysis, or that analyzing distinct state emotions is always necessary. Rather, we aim to suggest that choosing between the approaches be an informed choice by the researcher rather than defaulting to polarity analysis merely because of its prevalence.

6.1.2 Emotions and Information Sharing on Social Media

The literature review revealed some inconsistencies between studies on the role of emotions in information sharing on social media. Since information sharing is one of the predominant uses of social media in crisis situations, it was relevant for us to know which previous findings might apply to our context of research. We therefore decided to examine the relationship between emotions and information sharing in the context of a terror attack. Aside from two exceptions (Berger and Milkman 2012; Oh et al. 2013), the information diffusion related research measured emotions through polarity rather than differentiating between emotions. Because of the possibility that different emotions have different types of relationships with information sharing, we chose to account for that by differentiating between emotions in our analysis. Our initial intention was to analyze positive emotions in three categories – affection, happiness, and satisfaction – but after finding that they correlate strongly, decided to combine them into one combined measure of positive emotion. The similarity between the positive emotions was not surprising, as the differences between positive emotions are less pronounced than between the negative ones (Fredrickson 1998). The negative emotions included in the study – anger, fear, depression, and contempt – were clearly distinct from each other in the correlation analysis.

Social media uses in a crisis context differ based on the proximity to the location of the crisis (Takahashi et al. 2015), and people in the proximity of a terror attack are more strongly hit by stress and anxiety than those more distant (Morrison et al. 2001; Smith et al. 2001), which is why we deemed it relevant to examine whether proximity also plays a role in online information sharing tendencies. We found this to be the case – tweets from the area affected by the terror attack were tweeted significantly more than tweets originating farther away from the location. This stands to reason, as people in the area have access to situational information, which is likely to be deemed as relevant by other social media users (Mukkamala and Beck 2016).

One of the more surprising location related observations was that the affected area exhibited higher averages of positive and lower averages of all of the negative emotions, although they will have been more emotionally affected by the trauma. While this is not one of the main findings of the study, it inspired questions relevant for future research. It is likely that several different conversations are unfolding on social media simultaneously, and understanding in what way the positive and negative posts are part of these conversations could help explain the differences.

The negative correlations for fear and contempt were somewhat surprising. While previous findings disagreed on the sharing of information containing negative emotions, in the cases where negative emotions were found to play a role in information diffusion they reported either an overall positive correlation between information sharing and emotions in general (Stieglitz and Dang-Xuan 2013), or that negative emotions had a context-specific positive correlation with information sharing (Hansen et al. 2011). Our results deviating from previous findings have a few possible explanations. Analyzing emotions separately might yield results where some of the negative emotions have a small negative correlation and others have a small positive correlation, and when analyzed without distinguishing between them, the average correlation does not reveal the emotion specific tendencies. Another possible explanation is that terror (or crisis) context specific factors – such as prioritizing situational awareness related information sharing – influence user preferences and behavior. Determining whether the explanation is related to context or emotion categories requires further research, but regardless of the nature of the explanation, the results indicate that findings regarding emotions in information sharing in one context may not generalize well into other contexts.

While the differences between the negative emotions are not massive, they are around the same magnitude level as coefficients in previous research on emotions and information diffusion (Stieglitz and Dang-Xuan 2013). Anger and anxiety had a barely notable positive coefficient with retweet rates in the full dataset (the results in the geolocation set being not significant). This confirms that there indeed are differences between distinct emotions, beyond what valence and arousal levels indicate, and that it also holds true in a terror attack conversation context.

Positive emotions had a small positive correlation with retweeting in the full dataset but a notably larger negative correlation in location dataset. The negative correlation is peculiar, as none of the previous studies report similar findings, but quite the contrary (Burnap et al. 2014; Gruzd 2013). One possible explanation for the discrepancy stems from the tweets in the affected area being more positive than other tweets in the dataset. Once location is included in the analysis, it could be that the elevated retweet rates for those positive messages are related to the location rather than the positivity, whereas in the model without location information, the positivity is the primary correlating variable. Another possibility is that the online conversation culture among people who actively choose to disclose their location (which is opt-in on Twitter) favors certain types of social media usage, and that is reflected in sharing behavior that deviates from a more mainstream conversation culture. The take-away from these results is that in a dataset of around four million data points, positive sentiment correlates with elevated retweeting, but because of the discrepancy between the geolocation model and the full model, positivity is not likely to be a satisfactory causal explanation for information sharing decisions. Further research on determining the reason for the discrepancy would help scholars make inform research design choices regarding whether to factor location information into their analysis, and what tradeoffs that decision might have.

These findings contribute to a deeper understanding of the relationship between emotions and information sharing on social media in a terror context. We found that there are differences between emotions in how they are related to information sharing, and that the degree of information sharing is related to the proximity to the terror attack site.

6.1.3 Emotions and Topics in Online Conversations Following a Terror Attack

Driven by the curiosity around the positivity of the tweets from the affected area, we mapped out predominant topics and emotions over time for three proximity regions (the affected area, the affected country, and abroad), based on which we proposed a process model for the phases of post-terror attack online conversations.

The phases of post-terror discussions are the shock phase, the making sense phase, the (optional) subsequent event phase(s), and the aftermath phase. The observations from the Boston Marathon bombing tweet data during the shock phase were in accordance with the description of the proximal phase of the dual-process theory (Pyszczynski et al. 1999): shock, disbelief, emotional reactions, and worrying about close ones' safety were all among the predominant topics during the shock phase. Regardless of the proximity to the terror attack location, sadness was at its highest level during this phase.

At the shift from the shock phase to the making sense phase there is a proportional increase in collective support gestures in the affected area, and in opinion expression and information sharing elsewhere. This matches with the description of the distal phase, which is characterized by behaviors such as altruism, enforcing social connections, seeking value and meaning, heightened nationalism and patriotism, counter-bigotry advocacy, and information seeking and sharing (Yum and Schenck-Hamlin 2005). The collective support gestures include expressions of love and support in general towards Boston, charity and blood donation initiatives, and pride towards Boston and its sports teams, thus containing elements of altruism and a certain sense of heightened group identity comparable to patriotism. The opinion expression topics contain commentaries ranging from attempting to make sense of what happened and detective work to identify suspects based on event footage to political opinions against Islam as well as political opinions against political opinions against Islam, displaying elements of seeking value and meaning, information seeking and sharing, and anti-bigotry advocacy.

Subsequent event phases are inevitably case specific: there is no one generally applicable formula to what happens in the days or weeks following a terror attack. In the case of the Boston Marathon bombing, there was a secondary event four days after the terror attack, when the police got on the trail of the suspects. A manhunt ensued, during which a police officer and one of the two suspects died. After a night of suspense, the surviving suspect was apprehended. During the suspect chase, information sharing was the dominant use of Twitter regardless of the proximity to the events.

After some deliberation, closure – the online reactions to the apprehension of the terrorist – was treated as its own phase, separate from the subsequent event. The reasoning for this is two-fold. Firstly, the emotional and topical activities of these two phases were quite distinct from each other. Upon moving to the closure phase, positive emotion averages spike to around twice as high as during the previous phases, anger levels increase, and the proportion of gratitude and support related topics increases. Secondly, the concept of closure is actually quite interesting in the terror context. The threat of terrorism fosters a sense of psychological insecurity, which leads to a need for cognitive closure (Orehek et al. 2010). The need for closure can be defined as the desire for a quick and firm answer to a question and the aversion toward ambiguity (Kruglanski et al. 2006), or as a state of psychological resolution that is achieved when people feel they can effectively move beyond the trauma they have experienced, and attend to other problems and concerns (Skitka et al. 2004). Striving towards closure in the wake of a terror attack is done through value affirmation, moral outrage, and outgroup derogation (Skitka et al. 2004). The overlap with the distal reactions in the dual-process model is noteworthy.

Upon transitioning to the aftermath phase, most of the discussion online died away. The remaining messages exhibited elevated levels of anger and anxiety, the amount of elevation depending on the proximity to the terror attack location. The topics of the conversation were similar to the making sense phase, with the difference that memorializing was mostly substituted by support gestures, and a large part of the information sharing was related to the events during the subsequent event and closure phases. It thus seems that there are some social media users for whom the distal reactions last longer than average.

Although information sharing is the most prevalent use for social media in overall volume, a fine-grained analysis of the dataset reveals it is not necessarily the most frequent one on a phase level. In the shock phase, the proportion of messages focusing on memorializing was bigger than messages sharing information. In the making sense and aftermath phases, gratitude and support gestures dominated the discussion in the affected area while opinions and comments were most discussed farther away, and information sharing ranked second in frequency. While information sharing is undeniably an important part of social media usage in a terror attack context, acknowledging the phase-specific prevalence of other uses for social media gives a more balanced view of what happens in post-terror conversations.

These findings contribute to our understanding of the temporal developments of emotions and topics in online discussions related to a terror attack, some of which are specific to the proximity from the terror attack location.

6.2 Implications for Practice

The practical relevance of the findings of this dissertation project pertain to obtaining situational information in the context of crisis events, and in particular, terror attacks. Accessing situational information in the wake of a crisis event is essential to organizations and authorities attempting to mitigate the damage and coordinate help (Mukkamala and Beck 2016). Understanding what kinds of discussions are unfolding on social media, and which features identify the conversation streams containing relevant information helps emergency actors access relevant information with a smaller delay, enabling swifter action.

When and where possible, organizations seeking situational information should focus on posts originating from close to the crisis event location. However, geolocation information is not always readily or sufficiently available. Based on the findings that posts from the affected area are shared more often, and that information sharing related topics are typically low in emotion content, focusing on messages with low emotion content and high sharing rates could serve as a useful approximation for high proximity relevant posts.

6.3 Limitations and Perspectives for Future Research

The work outlined in this dissertation is subject to some limitations. We discuss those limitations here, and outline promising future research avenues to address them.

The insight generated during this project is drawn from data concerning a terror attack. Although it is likely that some of the wisdom generalizes to other crisis event contexts, further research is required to determine to what extent that holds. For instance, it may be that natural disasters evoke different types of emotions due to there not being a personified evildoer, and due to the fact that the phase after a natural disaster would typically contain actions related to reconstruction as well as food and medical aid, which is likely to be reflected in the prevalent topics in online discussions. This line of thinking is supported by the findings of topical analysis on the tweets related to the Chennai floods confirming that requesting and offering help as well as organizing relief efforts are recurrent topics in online conversations (Mukkamala and Beck 2018). The phases of online conversation outlined in Paper 3 are based on insight on the psychological reactions to acts of terror. While the main phases in other types of crises may well be similar, it is worth noting that the underlying reasons will be likely to be different, and establishing those phases would require context specific understanding of psychological reactions to natural disasters, accidents, or whichever type of crisis is in question.

As was learned from the study on the emotional and topical phases of the online discussions, some topics are more strongly emotional than others. The information sharing study concluded that posts containing fear and contempt are shared less than other types of posts. Without having included topics in the analysis, it is unclear to what extent the sharing decisions are a result of the emotions in the post, and to what extent that sharing behavior might be better explained by the topic of the post instead. It is also entirely possible that information sharing behavior is not constant over the duration of the whole conversation. If prevalent topics are phase specific, perhaps the information shared as relevant varies phase by phase as well. Investigating the relationship between topics and information sharing could improve our understanding of what kinds of information is seen as relevant, and to what extent the decision is made based on content as opposed to emotions involved.

Discovering that social media users in the affected area exhibited higher levels of positivity than others was one of the more surprising findings during this project. Examining why that is was not possible within the scope of this work, but the observation offers a promising avenue for future research. It is unclear whether these users genuinely experience more positive emotions, or whether they choose to emphasize positive content in their online communication. In either case, understanding the reason behind the positivity could have practical implications for supporting collective coping in online environments after a traumatic event. One possible explanation for the higher positivity levels could be that people in the affected area feel they have a certain degree of agency – the ability to intentionally influence one's functioning and life circumstances (Bandura 2006). Self-efficacy, the subjective perception of one's agency –– decreases emotional arousal, and an individual's perceived coping self-efficacy contributes to post-traumatic recovery (Bandura 1982; Benight and Bandura 2004). This means that people with high perceived agency or self-efficacy are likely to experience fewer negative emotions and recover faster after a terror attack. One practical implication of this is that it might be possible to reduce negative emotions on a collective level in the wake of a terror attack by providing social media users with concrete opportunities for exercising agency, such as donating to reconstruction projects, advice on local blood banks, or simply providing advice on how to cope psychologically after a traumatic event.

A known uncertainty in social media analytics is to what extent the behavior witnessed online reflects the users' internal processes in the physical world. We can therefore not say with certainty that the emergency phase characterized by frequent thinking and talking about the terror attack is genuinely over after the online conversation subsides. It is possible that people merely shift their conversations to a more closed or offline context. Combining social media data analysis with interviews and/or surveys of the social media users active in online conversations would establish whether the duration of the emergency phase is the same in both the virtual and physical word. If the emergency phase offline were to be found as short as online upon such a study, the follow-up questions would include whether social media as a platform enabling rapid information exchange and communication cycles might speed up proceeding through the phases of processing the traumatic event, and whether terror attacks differ from the crisis events used in outlining the stage model of coping.

It seems like the duration of the emergency phase is not constant between different terror attack related online discussions. The conversation following the Boston Marathon bombing lasting less than two weeks could be specific to the case, and related to closure in form of the arrest of the terrorist. While the Boston Marathon bombing discussion died away within a few days of the terrorist arrest, and conversation following a terror attack in Berlin had a similar duration of approximately one week (Fischer-Preßler et al. 2019), a study on the Woolwich terror attack found the online conversation around the event to last for 14 days (Burnap et al. 2014).

It is entirely possible that some of our findings are specific to a cultural context. For instance, the positivity of the messages in the affected area could be the result of a country or area specific culture. However, recent research on German Tweets after a terror attack in 2016 (Fischer-Preßler et al. 2019) confirms that the time span of the online discussions as well as the topical trends are similar to the Boston Marathon case, confirming that some of the phenomena is not particular to Boston or the US, but more general in nature. Whether the applicability of the information extends beyond the US and (at least parts of) Europe requires further research into terror attacks outside of these geographic regions.

7 Conclusion

The emergence of social media has provided new communication opportunities, reaching audiences wider and faster than was possible before. Emotions are an essential part of online communication, and there is still much to be learned regarding the role of emotions in online communication, in particular in the context of emotion-eliciting events such as terror attacks and other crises that impact the emotional climate of a community. Examining the emotional reactions related to the process of coping online yields valuable information on how a community leverages social media for collective coping after a traumatic experience, and provides practitioners with improved means to access relevant real-time information.

This dissertation project set out to answer the question of how different emotions are expressed on social media in the wake of a terror attack. The findings show that different emotions have different relationships with information sharing in a terror attack context: positive emotions are associated with elevated information sharing, whereas fear and contempt are shared less, and anger and anxiety play a negligible role in the levels of information sharing. Some of the emotional and topical expression online is connected to the proximity of a social media user to the area affected by the terror attack. High proximity posts are shared more, and they are on average higher in positive and lower in all the negative emotions. People close by focus more on topics related to safety concerns and support gestures, while people farther away express more opinions. The post-terror online discussion can be divided into phases (shock, making sense, possible event specific phase(s), and aftermath) based on the emotional and topical developments in the discussion.

These findings contribute to our understanding of how emotions are expressed in online environments, how emotions are related to online information sharing, and the emotional developments in online discussions following a terror attack. Improved knowledge on the emotional and topical features of posts likely to contain situational information has practical value to emergency responders extracting up-to-date information from social media feeds.

This cover chapter provided and overview of the dissertation project, synthesizing the findings and contributions of the research efforts undertaken during the project. These efforts are outlined in detail in the following articles.

8 References

Bandura, A. 1982. "Self-Efficacy Mechanism in Human Agency.," *American Psychologist* (37:2), p. 122.

Bandura, A. 2006. "Toward a Psychology of Human Agency," *Perspectives on Psychological Science* (1:2), pp. 164–180.

Benight, C. C., and Bandura, A. 2004. "Social Cognitive Theory of Posttraumatic Recovery: The Role of Perceived Self-Efficacy," *Behaviour Research and Therapy* (42:10), pp. 1129–1148.

Berente, N., and Seidel, S. 2015. "Don't Pretend to Test Hypotheses: Lexicon and the Legitimization of Empirically-Grounded Computational Theory Development," *University of Georgia, University of Liechtenstein*.

Berente, N., Seidel, S., and Safadi, H. 2018. "Research Commentary—Data-Driven Computationally Intensive Theory Development," *Information Systems Research,* 30(1), pp. 50-64.

Berger, J. 2011. "Arousal Increases Social Transmission of Information," *Psychological Science* (22:7), pp. 891–893.

Berger, J., and Milkman, K. L. 2012. "What Makes Online Content Viral?," *Journal of Marketing Research* (49:2), pp. 192–205.

Bollen, J., Mao, H., and Pepe, A. 2011. "Modeling Public Mood and Emotion: Twitter Sentiment and Socio-Economic Phenomena," in *Fifth International AAAI Conference on Weblogs and Social Media*.

Bollen, J., Mao, H., and Zeng, X. 2011. "Twitter Mood Predicts the Stock Market," *Journal of Computational Science* (2:1), pp. 1–8.

Boyle, M. P., Schmierbach, M., Armstrong, C. L., McLeod, D. M., Shah, D. V., and Pan, Z. 2004. "Information Seeking and Emotional Reactions to the September 11 Terrorist Attacks," *Journalism & Mass Communication Quarterly* (81:1), pp. 155–167.

Burnap, P., Williams, M. L., Sloan, L., Rana, O., Housley, W., Edwards, A., Knight, V., Procter, R., and Voss, A. 2014. "Tweeting the Terror: Modelling the Social Media Reaction to the Woolwich Terrorist Attack," *Social Network Analysis and Mining* (4:1), p. 206.

Chen, K., Luo, P., and Wang, H. 2017. "An Influence Framework on Product Word-of-Mouth (WoM) Measurement," *Information & Management* (54:2), pp. 228–240.

Debortoli, S., Müller, O., Junglas, I. A., and vom Brocke, J. 2016. “Text Mining for Information Systems Researchers: An Annotated Topic Modeling Tutorial.,” *Communications of the Association for Information Systems (CAIS)* (39), p. 7.

Dickinger, A., Arami, M., and Meyer, D. 2008. “The Role of Perceived Enjoyment and Social Norm in the Adoption of Technology with Network Externalities,” *European Journal of Information Systems* (17:1), pp. 4–11.

Durahim, A. O., and Coşkun, M. 2015. “# Iamhappybecause: Gross National Happiness through Twitter Analysis and Big Data,” *Technological Forecasting and Social Change* (99), pp. 92–105.

Eismann, K., Posegga, O., and Fischbach, K. 2016. “Collective Behaviour, Social Media, and Disasters: A Systematic Literature Review.,” in *Proceedings of the 24th European Conference on Information Systems (ECIS), Istanbul, Turkey*.

Ekkekakis, P. 2013. *The Measurement of Affect, Mood, and Emotion: A Guide for Health-Behavioral Research*, Cambridge University Press.

Ekman, P. 1992. “An Argument for Basic Emotions,” *Cognition & Emotion* (6:3–4), pp. 169–200.

Ellison, N. B., Steinfield, C., and Lampe, C. 2007. “The Benefits of Facebook ‘Friends:’ Social Capital and College Students’ Use of Online Social Network Sites,” *Journal of Computer-Mediated Communication* (12:4), pp. 1143–1168.

Esuli, A., and Sebastiani, F. 2007. “SentiWordNet: A High-Coverage Lexical Resource for Opinion Mining,” *Evaluation* (17:1), p. 26.

Ferrara, E., and Yang, Z. 2015. “Quantifying the Effect of Sentiment on Information Diffusion in Social Media,” *PeerJ Computer Science* (1), p. e26.

Fischer-Preßler, D., Schwemmer, C., and Fischbach, K. 2019. "Collective Sense-Making in Times of Crisis: Connecting Terror Management Theory with Twitter Reactions to the Berlin Terrorist Attack," *Computers in Human Behavior* (100), pp. 138-151.

Fowler, J. H., and Christakis, N. A. 2008. “Dynamic Spread of Happiness in a Large Social Network: Longitudinal Analysis over 20 Years in the Framingham Heart Study,” *Bmj* (337), p. a2338.

Fredrickson, B. L. 1998. “What Good Are Positive Emotions?,” *Review of General Psychology* (2:3), pp. 300–319.

Goes, P. B., Lin, M., and Au Yeung, C. 2014. “‘Popularity Effect’ in User-Generated Content: Evidence from Online Product Reviews,” *Information Systems Research* (25:2), pp. 222–238.

Gratch, J., Lucas, G., Malandrakis, N., Szablowski, E., Fessler, E., and Nichols, J. 2015. “GOAALLL!: Using Sentiment in the World Cup to Explore Theories of Emotion,” in *2015 International Conference on Affective Computing and Intelligent Interaction (ACII)*, IEEE, pp. 898–903.

Gruzd, A. 2013. "Emotions in the Twitterverse and Implications for User Interface Design," *AIS Transactions on Human-Computer Interaction* (5:1), pp. 42–56.

Gruzd, A., Doiron, S., and Mai, P. 2011. "Is Happiness Contagious Online? A Case of Twitter and the 2010 Winter Olympics," in *44th Hawaii International Conference On System Sciences (HICSS),* pp. 1–9.

Hansen, L. K., Arvidsson, A., Nielsen, F. \AArup, Colleoni, E., and Etter, M. 2011. "Good Friends, Bad News-Affect and Virality in Twitter," in *Future Information Technology*, Springer, pp. 34–43.

Heverin, T., and Zach, L. 2010. *Microblogging for Crisis Communication: Examination of Twitter Use in Response to a 2009 Violent Crisis in the Seattle-Tacoma, Washington, Area*, ISCRAM.

Huang, Y. L., Starbird, K., Orand, M., Stanek, S. A., and Pedersen, H. T. 2015. "Connected through Crisis: Emotional Proximity and the Spread of Misinformation Online," in *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ACM, pp. 969–980.

Kaufmann, M. 2015. "Resilience 2.0: Social Media Use and (Self-) Care during the 2011 Norway Attacks," *Media, Culture & Society* (37:7), pp. 972–987.

Kramer, A. D., Guillory, J. E., and Hancock, J. T. 2014. "Experimental Evidence of Massive-Scale Emotional Contagion through Social Networks," *Proceedings of the National Academy of Sciences*.

Krippendorff, K. 1989. *Content Analysis*, p. 8.

Kruglanski, A. W., Pierro, A., Mannetti, L., and De Grada, E. 2006. "Groups as Epistemic Providers: Need for Closure and the Unfolding of Group-Centrism.," *Psychological Review* (113:1), p. 84.

Küster, D., and Kappas, A. 2013. "Measuring Emotions in Individuals and Internet Communities," *Internet and Emotions* (22), pp. 48–64.

Lerner, J. S., Gonzalez, R. M., Small, D. A., and Fischhoff, B. 2003. "Effects of Fear and Anger on Perceived Risks of Terrorism: A National Field Experiment," *Psychological Science* (14:2), pp. 144–150.

Lin, K.-Y., and Lu, H.-P. 2011. "Why People Use Social Networking Sites: An Empirical Study Integrating Network Externalities and Motivation Theory," *Computers in Human Behavior* (27:3), pp. 1152–1161.

Liu, F., Burton-Jones, A., and Xu, D. 2014. “Rumors on Social Media in Disasters: Extending Transmission to Retransmission.,” in *Proceedings of the 18th Pacific Asia Conference on Information Systems (PACIS), Chengdu, China,* p. 49.

Malik, M. S. I., and Hussain, A. 2017. “Helpfulness of Product Reviews as a Function of Discrete Positive and Negative Emotions,” *Computers in Human Behavior* (73), pp. 290–302.

Mehrabian, A., and Russell, J. A. 1974. *An Approach to Environmental Psychology.*, the MIT Press.

Meire, M., Ballings, M., and Van den Poel, D. 2016. “The Added Value of Auxiliary Data in Sentiment Analysis of Facebook Posts,” *Decision Support Systems* (89), pp. 98–112.

Morrison, J. L., Sandra, and Berry, H. 2001. *A National Survey of Stress Reactions After the September 11, 2001, Terrorist Attacks.*

Mukkamala, A., and Beck, R. 2016. “Enhancing Disaster Management through Social Media Analytics to Develop Situation Awareness What Can Be Learned from Twitter Messages about Hurricane Sandy?,” in *Proceedings of the 20th Pacific Asia Conference on Information Systems (PACIS), Chiayi, Taiwan,* p. 165.

Mukkamala, A., and Beck, R. 2018. “The Role of Social Media for Collective Behavior Development in Response to Natural Disasters,” in *Proceedings of the 26th European Conference on Information Systems (ECIS), Portsmouth, UK.*

Müller, O., Junglas, I., Vom Brocke, J., and Debortoli, S. 2016. “Utilizing Big Data Analytics for Information Systems Research: Challenges, Promises and Guidelines,” *European Journal of Information Systems* (1), p. 14.

Nguyen, T., Phung, D., Adams, B., and Venkatesh, S. 2013. “Event Extraction Using Behaviors of Sentiment Signals and Burst Structure in Social Media,” *Knowledge and Information Systems* (37:2), pp. 279–304.

Nguyen, T., Phung, D., Adams, B., and Venkatesh, S. 2014. “Mood Sensing from Social Media Texts and Its Applications,” *Knowledge and Information Systems* (39:3), pp. 667–702.

Nofer, M., and Hinz, O. 2015. “Using Twitter to Predict the Stock Market,” *Business & Information Systems Engineering* (57:4), pp. 229–242.

O’Connor, B., Balasubramanyan, R., Routledge, B. R., and Smith, N. A. 2010. “From Tweets to Polls: Linking Text Sentiment to Public Opinion Time Series,” in *Fourth International AAAI Conference on Weblogs and Social Media.*

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).

Orehek, E., Fishman, S., Dechesne, M., Doosje, B., Kruglanski, A. W., Cole, A. P., Saddler, B., and Jackson, T. 2010. "Need for Closure and the Social Response to Terrorism," *Basic and Applied Social Psychology* (32:4), pp. 279–290.

Pang, B., and Lee, L. 2008. "Opinion Mining and Sentiment Analysis," *Foundations and Trends® in Information Retrieval* (2:1–2), pp. 1–135.

Pang, B., Lee, L., and Vaithyanathan, S. 2002. "Thumbs up?: Sentiment Classification Using Machine Learning Techniques," in *Proceedings of the ACL-02 Conference on Empirical Methods in Natural Language Processing-Volume 10*, Association for Computational Linguistics, pp. 79–86.

Pang, N., and Ng, J. 2016. "Twittering the Little India Riot: Audience Responses, Information Behavior and the Use of Emotive Cues," *Computers in Human Behavior* (54), pp. 607–619.

Pennebaker, J. W., Boyd, R. L., Jordan, K., and Blackburn, K. 2015. "The Development and Psychometric Properties of LIWC2015."

Pennebaker, J. W., and Harber, K. D. 1993. "A Social Stage Model of Collective Coping: The Loma Prieta Earthquake and the Persian Gulf War," *Journal of Social Issues* (49:4), pp. 125–145.

Pfeffer, J., Zorbach, T., and Carley, K. M. 2014. "Understanding Online Firestorms: Negative Word-of-Mouth Dynamics in Social Media Networks," *Journal of Marketing Communications* (20:1–2), pp. 117–128.

Plutchik, R. 2001. *The Nature of Emotions*.

Pyszczynski, T., Greenberg, J., and Solomon, S. 1999. "A Dual-Process Model of Defense against Conscious and Unconscious Death-Related Thoughts: An Extension of Terror Management Theory.," *Psychological Review* (106:4), p. 835.

Pyszczynski, T., Solomon, S., and Greenberg, J. 2003. *In the Wake of 9/11: The Psychology of Terror.*, American Psychological Association.

Qi, J., Fu, X., and Zhu, G. 2015. "Subjective Well-Being Measurement Based on Chinese Grassroots Blog Text Sentiment Analysis," *Information & Management* (52:7), pp. 859–869.

Rimé, B. 2009. "Emotion Elicits the Social Sharing of Emotion: Theory and Empirical Review," *Emotion Review* (1:1), pp. 60–85.

Rimé, B. 2017. "The Social Sharing of Emotion in Interpersonal and in Collective Situations," in *Cyberemotions*, Springer, pp. 53–69.

Risius, M., and Akolk, F. 2015. “Differentiated Sentiment Analysis of Corporate Social Media Accounts,” in *Proceedings of the Americas Conference on Information Systems (AMCIS), Puerto Rico*.

Risius, M., Akolk, F., and Beck, R. 2015. “Differential Emotions and the Stock Market-The Case of Company-Specific Trading,” in *Proceedings of the 23rd European Conference on Information Systems (ECIS), Münster, Germany*.

Russell, J. A. 2003. “Core Affect and the Psychological Construction of Emotion.,” *Psychological Review* (110:1), p. 145.

Salehan, M., and Kim, D. J. 2016. “Predicting the Performance of Online Consumer Reviews: A Sentiment Mining Approach to Big Data Analytics,” *Decision Support Systems* (81), pp. 30–40.

Schumaker, R. P., Jarmoszko, A. T., and Labedz Jr, C. S. 2016. “Predicting Wins and Spread in the Premier League Using a Sentiment Analysis of Twitter,” *Decision Support Systems* (88), pp. 76–84.

Skitka, L. J., Bauman, C. W., and Mullen, E. 2004. “Political Tolerance and Coming to Psychological Closure Following the September 11, 2001, Terrorist Attacks: An Integrative Approach,” *Personality and Social Psychology Bulletin* (30:6), pp. 743–756.

Smith, T. W., Rasinski, K. A., and Toce, M. 2001. “America Rebounds: A National Study of Public Response to the September 11th Terrorist Attacks,” *Chicago, IL: National Opinion Research Center at the University of Chicago*.

Starbird, K., and Palen, L. 2010. *Pass It on?: Retweeting in Mass Emergency*, International Community on Information Systems for Crisis Response and Management.

Stieglitz, S., and Dang-Xuan, L. 2013. “Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior,” *Journal of Management Information Systems* (29:4), pp. 217–248.

Takahashi, B., Tandoc, E. C., and Carmichael, C. 2015. “Communicating on Twitter during a Disaster: An Analysis of Tweets during Typhoon Haiyan in the Philippines,” *Computers in Human Behavior* (50), pp. 392–398.

Thelwall, M. 2017. “The Heart and Soul of the Web? Sentiment Strength Detection in the Social Web with SentiStrength,” in *Cyberemotions*, Springer, pp. 119–134.

Thelwall, M., Buckley, K., and Paltoglou, G. 2011. “Sentiment in Twitter Events,” *Journal of the American Society for Information Science and Technology* (62:2), pp. 406–418.

Thelwall, M., Buckley, K., Paltoglou, G., Cai, D., and Kappas, A. 2010. "Sentiment Strength Detection in Short Informal Text," *Journal of the American Society for Information Science and Technology* (61:12), pp. 2544–2558.

Thomson, R., Ito, N., Suda, H., Lin, F., Liu, Y., Hayasaka, R., Isochi, R., and Wang, Z. 2012. *Trusting Tweets: The Fukushima Disaster and Information Source Credibility on Twitter*, p. 10.

Tumasjan, A., Sprenger, T. O., Sandner, P. G., and Welpe, I. M. 2011. "Election Forecasts with Twitter: How 140 Characters Reflect the Political Landscape," *Social Science Computer Review* (29:4), pp. 402–418.

Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R., and Cleven, A. 2009. "Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process.," in *Proceedings of the 17th European Conference on Information Systems (ECIS), Verona, Italy,* pp. 2206–2217.

Vom Brocke, J., Simons, A., Riemer, K., Niehaves, B., Plattfaut, R., and Cleven, A. 2015. "Standing on the Shoulders of Giants: Challenges and Recommendations of Literature Search in Information Systems Research," *Communications of the Association for Information Systems (CAIS)*, 37(1), 9.

Wakefield, R., and Wakefield, K. 2016. "Social Media Network Behavior: A Study of User Passion and Affect," *The Journal of Strategic Information Systems* (25:2), pp. 140–156.

Webster, J., and Watson, R. T. 2002. "Analyzing the Past to Prepare for the Future: Writing a Literature Review," *MIS Quarterly*, xiii–xxiii.

Yin, D., Bond, S., and Zhang, H. 2014. "Anxious or Angry? Effects of Discrete Emotions on the Perceived Helpfulness of Online Reviews," *Mis Quarterly* (38:2), pp. 539–560.

Yu, J., Hu, P. J.-H., and Cheng, T.-H. 2015. "Role of Affect in Self-Disclosure on Social Network Websites: A Test of Two Competing Models," *Journal of Management Information Systems* (32:2), pp. 239–277.

Yum, Y., and Schenck-Hamlin, W. 2005. "Reactions to 9/11 as a Function of Terror Management and Perspective Taking," *The Journal of Social Psychology* (145:3), pp. 265–286.

9 Paper 1

Emotions Trump Facts: The Role of Emotions in on Social Media: A Literature Review

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Abstract

Emotions are an inseparable part of how people use social media. While a more cognitive view on social media has initially dominated the research looking into areas such as knowledge sharing, the topic of emotions and their role on social media is gaining increasing interest. As is typical to an emerging field, there is no synthesized view on what has been discovered so far and – more importantly – what has not been. This paper provides an overview of research regarding expressing emotions on social media and their impact, and makes recommendations for future research in the area. Considering differentiated emotion instead of measuring positive or negative sentiment, drawing from theories on emotion, and distinguishing between sentiment and opinion could provide valuable insights in the field.

Introduction

Social media has become an increasingly important part of our private and professional lives. It is used for various purposes, the main motivations being maintaining and creating connections with other users, sharing and obtaining information and enjoyment [20, 24, 52]. There has been a fair bit of research within Information Systems (IS) on the usage of social media in general [2, 9], focusing on aspects like knowledge exchange [4], knowledge acquisition [49], and organizational benefits [78]. Although some promising work regarding emotional drivers in online behavior exists, we still know little with respect to how feelings are communicated on social media.

Emotions are connected with various types of success both in our private and professional lives. Happy people are healthier and have better relationships [56]. The organizational climate is strongly related to employee happiness [15], and happy people are more productive [28] as well as creative [3] at work. Emotions are also a key factor in knowledge exchange [50].

As in all communication, emotions play an important role in how we interact with other people online, whether it be about excitement prior to an event [101], a retweeting decision [35, 90], or the perceived usefulness of an online review [82]. Emotions have been shown to be contagious [29], which also applies in an online environment [36, 47], and they are linked to rumor spreading behavior [68].

Understanding better how individuals express emotions on social media has relevance not only for the providers of leisurely social media such as Facebook or Twitter, but also for companies using social media platforms for internal communication as well as organizations using social media as a customer relationship management channel.

Although there is evidence of the relevance of emotions in online communication, many yet unanswered questions remain, and the field seems to not yet have established internal coherence. The results of our literature review show that not many studies draw from theories on emotions, and some concepts could use clarification. An additional challenge in researching social media is that it is a moving target: previous research indicates that the way people communicate online seems to have changed markedly during the last decade [54], although we know little about how and how much, exactly. This means that some of the previous findings in the field may no longer apply and should not be relied on blindly.

Research on expressing emotions on social media seems to be off to a promising start, but still somewhat scattered. This paper aims to consolidate extant research on the topic, charting out what kinds of topical domains have been represented in research so far and what kinds of emotional theories and categorizations have been used. Using a structured literature review approach, this work sets out to answer the following research questions:

1. In which areas within social media research have expressions of emotion been studied?
2. Which theories on emotions from reference fields does the research rely on?
3. How are emotions categorized in the research?

Based on our analysis of the literature, we identify three helpful guidelines for future research. To our knowledge, a review covering research on how users express emotions on social media has not been conducted before in spite of increasing interest in the topic.

The remainder of the paper is structured in the following manner. We begin by discussing existing knowledge about emotions. In the Methodology section, we describe our approach in conducting a structured literature review. We report what we learned in the

Findings section and reflect on it in the Discussion section, after which we present our concluding remarks and suggestions for future research.

Related Work in Other Disciplines

There has been extensive research in the field of psychology on whether emotions and moods are distinct concepts or different points on the same continuum [5, 6, 22]. Although some research has made a distinction between the concepts, they seem to be often used interchangeably.

In this manuscript, the affective vocabulary is used according to the following definitions. *Affect*, or *core affect*, is a constant, underlying state of emotion or feeling, and can be experienced as free-floating (*mood*) or related to a specific event or cause (*emotion*) [22, 81]. This review focuses on literature about expressed or enacted emotion in the context of social media. Emotion expressions online are typically researched using *sentiment analysis*. In the context of sentiment analysis, *sentiment* can refer to either a feeling or emotion, or an attitude or opinion.

Various categorizations for emotions have been proposed. Some of them include distinct states, like Ekman's five core emotions *enjoyment, sadness, anger, fear, and disgust* [23]. Others conceptualize emotions situated along dimensions like *pleasure* (also referred to as *valence*), *arousal* (also referred to as *activation*), and *dominance*, such as the Pleasure-Arousal-Dominance (PAD) emotional state model [60] or Russell's circumplex model of affect [75] (used e.g. in [101]). Yet others combine elements from both of the abovementioned approaches. Plutchik's wheel of emotions defines basic emotions as well as milder variants of them, and describes how they relate to each other [74] (used in e.g. [18, 57]), and Ekkekakis defined a hierarchical structure of the affective domain, combining the idea or core emotions and dimensions [22] (used in e.g. [79]).

Sentiment analysis is, as defined by Pang and Lee [71], "computational treatment of opinion, sentiment, and subjectivity in text". Traditionally, sentiment analysis has measured the positive and negative sentiment of a sentence or longer text, but there are recent examples of using more fine-grained approaches based on emotion categories such as the ones mentioned above (e.g. [57, 106]). There are two main methodological approaches. Lexicon based methods utilize a dictionary of words and their sentiment values – most often positive and negative – to assign a sentiment score to an input text [25, 96], whereas machine learning approaches classify documents into sentiment categories based on training data [72]. Some recent studies combine the two by using lexicon scores as input for a classifier [61].

Methodology

Our literature review process consisted of deciding the inclusion criteria, searching for relevant work, and finally analyzing the discovered articles. It was conducted following the recommendations of Webster and Watson [103] and vom Brocke et al. [100]. The structured literature analysis had five phases. The first step was to determine the scope of the review. The second phase was searching through the most important journals in IS, the *basket of eight* (http://aisnet.org/?SeniorScholarBasket), as well as collecting and testing potentially useful search phrases. The third step was to search through scientific databases, and the fourth to conduct backwards and forwards searches for the articles identified as relevant in the previous phases. As the final step, we analyzed the articles, categorizing them according to topic, theory usage, and emotional categorization.

Phase I: Deciding the Scope of the Literature Review

This literature review was conducted to map out the current knowledge regarding expressions of emotion in social media environments. The main focus is on IS, but other fields – such as computer science and social sciences – are taken into account as well. The criteria for including articles were that they be (1) peer reviewed, (2) in English, (3) published in 2006 or more recently, and (4) on the topic of how sentiment is expressed on social media. For both quality assurance and time management reasons this work focuses mainly on journal articles in the first two phases.

The year 2006 was deemed a reasonable cut-off, as it was around that time social media started emerging as a result of Web 2.0. Most of the articles discovered during our search were published after 2010, which confirmed that limiting the review to after 2006 is a rather safe choice with regard to including important previous work.

In deciding what counts as social media, we followed Kaplan and Haenlein's [45] definition: "Social Media is 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". The term sentiment is used in a broad sense in this scoping – as is typical with sentiment analysis – and covers emotion, mood, and in some cases opinion.

Phase II: Searching the Top Journals and Identifying Search Terms

The first phase of the search was finding the relevant articles published in the basket journals. As they are of particular interest thanks to the overall high quality of the publications, we decided to search through them with particular care and use them as testing ground for various search phrases in order to avoid the failure to detect seminal works on the topic.

Several search words and search word combinations were tried out in order to ensure the discovery of as many relevant articles as possible and to get an overall idea of which search phrases work best. The search phrases tested include e.g. *"social media"* + *emotions*, *"social networking sites"* + *"sentiment analysis"*, and *"computer mediated communication"* + *sentiment*. Whenever a discovered article would contain a new potentially helpful key word or key word phrase, the list of search words was expanded. As a preparation for the next phase, search phrases were tested and compared to find a satisfactory balance between precision (i.e. how many of the articles in the search results were relevant) and recall (i.e. how many of the relevant articles we knew existed in the database the search would list).

The searches yielded some hundreds of results in all. Based on the titles and abstracts, 26 articles were chosen for closer inspection, out of which 13 were deemed relevant after reading.

Phase III: Database Literature Search

Based on the search phrase comparison in phase II, the database search was conducted using the search phrase "social media" + emotion + analytics. The databases searched were the AIS electronic library (AISeL), ScienceDirect and Springer. As previously, a reading list of 116 potentially relevant articles was assembled by reading through the titles and abstracts of the results. In all, 35 relevant documents were identified during this search phase, including a selection of relevant conference papers. The database search yielded a large number of papers focused on sentiment analysis from a purely methodological standpoint, and were excluded from this review unless they communicated empirical findings on the expression of emotions on social media.

Phase IV: Refining Literature Results

The final search phase consisted of forward and backward searching the articles identified as relevant in the two previous phases. The original inclusion criteria were applied for the articles examined, including the cut-off at 2006. As in the previous phase, some conference proceedings were included in the collection of relevant papers.

All in all, 82 articles were identified as relevant during the search phase, and were included in the analysis. (See Table 1.)

	Read through	Relevant
Basket (phase II)	26	13
Database (phase III)	116	35
Forward-backward (phase IV)	72	34
In all	**164**	**82**

Table 1: The number of articles identified for reading and deemed as relevant during the literature search

Phase V: Literature Analysis

After the completion of the search, the articles were read and analyzed. Notes were made for each article on what the area or topic of interest is (in order to answer research question 1), whether they draw from some emotion related theory (research question 2), and what kind of categories they use for emotions (research question 3). The topics were manually coded by one author and a random sample of 25 % papers was coded by another author in order to ensure the coding categories and decisions were sound. (See Table 2 for categories.)

There seems to be a steadily increasing interest in the topic recently. Most of the work published is from 2011 onwards, and 10 out of 13 basket papers have been published in 2013 or later. Nine of the papers are method or design focused, i.e. the research questions were formulated in a way that is related to the design or method rather than the empirical results. Three of the articles are reviews, and the rest of them are empirical.

Findings of the Literature Review

Table 2 lists the articles sorted by their topic and choice of categorizing emotion. Both the topic and emotion categories are a result of manually coding the literature.

The most typical way of looking at emotions was measuring positive or negative affect. The *Positive/negative* column also contains the papers that classified neutrality or polarity in addition to valence. *Emotion/no* is a simpler version of this, where only the presence or absence of emotions was considered. *Differentiated* contains all papers that look at differentiated emotions or focus on a specific emotion (e.g. anxiety), whereas articles using partially differentiated emotions in combination with valence (e.g. positive, negative, anger, anxiety and sadness) were classified in *Partial*, which also contains looking into only one dimension (e.g. high or low activation). *N/A* is where the papers using no emotional categorization – mainly literature reviews – were classified.

Collective sentiment contains articles on sentiment expression in a group of people, such as Twitter users, football spectators or Chinese bloggers. Changes in sentiment levels can be detected online in relation to cultural, social, political or economic events.

Contagion refers to emotional contagion between users, which the articles unanimously confirm occurs on social media. People tend to have similar well-being levels as their connections, although it is unclear whether this is due to contagion or other factors [10].

CRM/eWOM/OCR is a combination of *customer relationship management*, *electronic word of mouth* and *online customer reviews*. The three areas were merged into one category due to the topical overlap between them being very commonplace in the articles. Roughly one half of the papers focus on online reviews, and found sentiment to be connected to reviewer popularity and perceived helpfulness. Looking into differentiated emotions revealed that the perceived helpfulness of a review depends on which emotions the review contains [57, 106].

Information diffusion contains research looking into how emotions affect people's decisions to pass on information in their network. The papers focus on the virality of news and retweeting behavior. In spite of similar data sets and publication times between studies, there are some contradicting findings in this category. A study examining NY

Times articles found that the virality of a piece of news is connected to high arousal emotions, and that positive content is more likely to go viral than negative [8]. However, according to another paper, negative sentiment enhances virality in the context of news, but not in the context of tweets [38].

All the studies based on Twitter data seem to agree on emotions increasing the likelihood of retweeting, but there are differences regarding how, exactly. Some report that positive messages get more retweets [27, 35], others find no significant difference between the propagation of positive and negative tweets [90]. There were also some mixed results on whether negative tweets spread more rapidly than positive ones [27, 90].

Topics in the literature	**Categorization of emotions**					
	Differentiated	Partial	Positive/negative	Emotion /no	N/A	All
Affect on SM in general	[101]		[61][39][110][43] [59] [107][13][55] [102][34][70]			12
Collective sentiment	[11][76][53]	[64]	[97][44][33][63] [21]	[73][69]		11
Contagion	[18][62]	[48] [37]	[36][47][10] [105][26][58]			10
CRM/eWOM/OCR	[57][106]		[82][92][7][86] [32][85][17][14] [80][95][77][94] [87][108][31][99] [46]	[89]		20
Information diffusion	[68]	[8]	[90][35][38][27] [104]			7
Literature review					[9][2][83]	3
Methods and tools			[30][109][1]		[91]	4
Negative behavior	[42]		[40]			2
Outcome prediction	[79][12][65]	[98]	[84][51][67] [93][16][88] [66]			11
Predicting user engagement		[41]	[19]			2
In all	13	6	56	3	4	82

Table 2: The reviewed articles grouped by their topic and choice of emotional categorization

Outcome prediction papers predict some real-world effect based on social media data. Most of the articles address changes in the stock market based on social media sentiment. According to some, differentiated sentiment is necessary in order to obtain accurate results [12, 79]. Other work in this category found that measuring sentiment online can be a feasible substitute for or addition to political polls in predicting election results [66, 98].

The papers in *Predicting user engagement* found that the emotional content of a message affects how much users on social media engage with the message. In the case of political blog entries, elevated positive or negative sentiment led to a clearly increased the number of comments.

Affect on SM in general contains papers that investigate how affect is expressed on social media, but that do not fit into the other more specific categories. Findings include, among other things, that influential users online tend to use more affect in their messages [46, 50], that the levels of emotional expression are gender related [110] and that affect influences self-disclosure indirectly by adjusting the perceived benefits [107].

As social media research in general, the majority of the papers are rather data driven than theory driven [2]. Table 3 lists all the theories used in the analyzed literature. Even though most articles reference at least some psychological literature, it seldom goes beyond defining core emotions or phenomena on a general level. Out of all the reviewed work, 11 papers based their research questions or hypotheses on a theory about emotions, and no theory is mentioned twice. In contrast, some papers use multiple theories. Some of the largest topic groups, *CRM/eWOM/OCR* and *Outcome prediction*, contain no theories on emotion.

To synthesize, some domains are more extensively researched than others, and theories are not commonplace in any domain. Although there is evidence supporting the usefulness of analyzing emotions

Theories on emotion	Affect on SM in general	Collective Sentiment	Contagion	CRM/eWOM/OCR	Information diffusion	Literature review	Methods and tools	Negative behavior	Outcome prediction	Predicting user engagement
Affect heuristic theory	[107]									
Affect Infusion Model (AIM)										[65]
Affective events theory	[101]									
Affective response model	[101]									
Anthony's rumor theory		[69]								
Coping classification framework							[30]			
Direct causation theory	[107]									
Dissonance reduction theory	[102]									
Feedback process model	[102]									
Gross: 5 factors of emotion regulation			[58]							
Interpersonal theory of depression			[105]							
Mimicry			[48]							
Negativity bias					[90]					
Positivity bias					[27]					
Self-determination theory	[101]									
Social information processing theory			[105]							
Number of papers in topic category:	3	1	3	0	2	0	1	0	0	1

Table 3: Theories on emotion used in the literature grouped by topic

in a fine-grained manner, it is not a common approach thus far. In particular, domains like information diffusion, online customer reviews, and outcome prediction have focused primarily on bipolar sentiment.

Discussion of the Key Findings on Emotions in Social Media

During the past decade, social media has certainly claimed its place as a worthy area of interest, and the increasing amount of research regarding emotions in the domain is an indication of how essential they are in our online communication. The work done in the field so far has provided us with a lot of valuable insight, and now serves as a good basis for asking how we can do even better. Based on our literature analysis, we provide three concrete suggestions: using more theories on emotion to support the research, being more precise about the terminology, and considering whether looking at differentiated emotions provides better explanations than bipolar emotions.

Theories on Emotion in Social Media Research

One of the points of interest discovered in analyzing the literature was that although IS scholars are used to drawing from theories in other domains, it seems to not be a common practice when it comes to emotions in a social media context. The usage of theories explaining affect in the papers examined was sparse – little over 10% of the articles used a theory on emotion to guide their research questions or hypotheses – although emotions have been extensively researched within psychology for a long time.

It would be interesting to take a closer look at why such theories are not more commonly used. Could it be that most of the research on expressing emotions online so far has been focused on describing what happens instead of attempting to explain why it occurs? Theories on emotion serve as a good basis for explaining and reasoning about observed behavior, but might not be considered necessary for simply describing observations.

Distinguishing Sentiment, Emotion, and Opinion

The concepts of affect, emotion, and mood are not trivial to differentiate between, and even psychology scholars have varying views on how to define them [22], which makes it a challenge for social media researchers to be accurate with the terminology. Nevertheless, there is one particular case of unclear term usage that does not require extensive expertise in the psychology of emotions, and we would like to propose that it merits some attention.

There seems to be an implicit assumption about the concepts sentiment and opinion being interchangeable. However, sentiment can refer to either an emotion or an opinion. Both can be interesting and relevant topics for research, and sometimes the same tools may be good for measuring either of them. However, when we report findings, we should be clearer on which one is being discussed. Positive (or negative) opinion towards something does not necessarily equal positive (or negative) experienced emotion; in fact, they may even be opposite. For instance, imagine a hotel review saying *"I'm glad they're out of business!"*. The emotion – or sentiment – may be positive, but the opinion is most certainly not.

If we want to know how highly people value a service or product, opinion is of interest to us. If we want to know what drives people's behavior and communication, emotion is probably going to be of more interest. Applying what we know about opinions to emotions or vice versa is likely to not always be accurate. We would like to suggest that these two should be separated clearly when reporting findings, and treated as two distinct concepts.

From Bipolar to Differentiated Emotion

A further discovery from the literature is that analyzing sentiment has so far mainly happened on a bipolar scale. However, some recent papers indicate that differentiated emotions give us more insight than simply looking at valence [33, 35, 66, 100]. We know that the activation level of an emotion matters with respect to what kinds of behavior it triggers: anger – a high activation negative valence emotion – causes reactions very different from sadness, a low activation negative emotion [8]. Distinguishing between emotions in a more fine-grained way than before would be likely to increase our understanding of the phenomena we investigate. For instance, it would be interesting to investigate whether an analysis using differentiated emotions could explain the inconsistencies between the findings in the *Information diffusion* category regarding retweeting behavior and emotions.

Why are we, then, not looking at differentiated emotions more? It may well be that in some contexts a bipolar analysis approach is adequate for the purposes of the study. It is also possible that in spite of some findings pointing that way, the significance of differentiated emotion is not yet common knowledge in our field. Another possible contributing factor is that there is a much larger variety of tools readily available – or commonly known by researchers – for bipolar than differentiated sentiment analysis.

One useful thing to keep in mind regarding differentiated emotions is that the ways they are expressed may be context or culture dependent [23].

Conclusions and Avenues for Future Research

Emotions are an important part of how people communicate online, and there is much yet to be discovered in that realm. Looking at previous findings regarding emotions on social media helps us ask new questions and set new courses in our research. Based on the results of our literature analysis, theories on emotion are infrequently used to support the research, key terms – such as sentiment, emotion and opinion – are not always defined precisely, and sentiment analysis is mostly limited to measuring positivity and negativity instead of considering differentiated emotions. We argue that being better aware of the aforementioned observations will help scholars in the field make better informed choices regarding their research.

Possible future work avenues include looking into how differentiated emotion could bring further insight to e.g. how information diffusion works with respect to emotions, and what types of negative emotions cause certain types of antisocial behavior online. It would also be interesting to take a closer look at the studies where theories on emotion have been used; is there indeed a difference in what types of questions (e.g. what vs. why) are asked compared to the ones that do not draw from theories?

One limitation of this work is that although the literature search was structured and broad, and we used search term expansion as well as backward and forward searches in addition to covering the leading IS publication outlets, it is likely that some works will have evaded our attention in spite of our best efforts, since the nature of the topic is interdisciplinary and the publication outlets diverse.

References

[1] Abbasi, A. and Chen, H. CyberGate: a design framework and system for text analysis of computer-mediated communication. *MIS Quarterly*. 2008, pp. 811–837.

[2] Ahmed, A., Scheepers, H. and Stockdale, R. Social Media Research: A Review of Academic Research and Future Research Directions. *Pacific Asia Journal of the Association for Information Systems*. 6, 1, 2014.

[3] Amabile, T.M., Barsade, S.G., Mueller, J.S. and Staw,B.M. Affect and creativity at work. *Administrative science quarterly*. 50, 3 (2005), pp. 367–403.

[4] Beck, R., Pahlke, I. and Seebach, C. Knowledge exchange and symbolic action in social media-enabled electronic networks of practice: A multilevel perspective on knowledge seekers and contributors. *MIS Quarterly*. 38, 4, 2014, pp. 1245–1270.

[5] Beedie, C., Terry, P. and Lane, A. Distinctions between emotion and mood. *Cognition & Emotion*. 19, 6, 2005, pp. 847–878.

[6] Beedie, C.J., Terry, P.C., Lane, A.M. and Devonport, T.J. Differential assessment of emotions and moods: Development and validation of the Emotion and Mood Components of Anxiety Questionnaire. *Personality and Individual Differences*. 50, 2, 2011, pp. 228–233.

[7] Benthaus, J., Risius, M. and Beck, R. Social media management strategies for organizational impression management and their effect on public perception. *The Journal of Strategic Information Systems*. 25, 2, 2016, pp. 127–139.

[8] Berger, J. and Milkman, K.L. What makes online content viral? *Journal of marketing research*. 49, 2, 2012, pp. 192–205.

[9] Berger, K., Klier, J., Klier, M. and Probst, F. A review of information systems research on online social networks. *Communications of the Association for Information Systems*. 35, 1, 2014.

[10] Bollen, J., Gonçalves, B., Ruan, G. and Mao, H. Happiness is assortative in online social networks. *Artificial life*. 17, 3, 2011, pp. 237–251.

[11] Bollen, J., Mao, H. and Pepe, A. Modeling public mood and emotion: Twitter sentiment and socio-economic phenomena. *ICWSM*. 11, 2011, pp. 450–453.

[12] Bollen, J., Mao, H. and Zeng, X. Twitter mood predicts the stock market. *Journal of computational science*. 2, 1, 2011), pp. 1–8.

[13] Boutet, A., Kim, H. and Yoneki, E. What's in Twitter, I know what parties are popular and who you are supporting now! *Social Network Analysis and Mining*. 3, 4, 2013, pp. 1379–1391.

[14] Bygstad, B. and Presthus, W. Social media as CRM? how two airline companies used facebook during the "Ash crisis" in 2010. *Scandinavian Journal Of Information Systems*. 25, 1, 2012, pp. 51–72.

[15] Carr, J.Z., Schmidt, A.M., Ford, J.K. and DeShon, R.P.*Climate perceptions matter: a meta-analytic path analysis relating molar climate, cognitive and affective states, and individual level work outcomes*. American Psychological Association. 2003

[16] Checkley, M.S., Higón, D.A. and Alles, H. The hasty wisdom of the mob: How market sentiment predicts stock market behavior. *Expert Systems with Applications*. 77, 2017, pp. 256–263.

[17] Chen, K., Luo, P. and Wang, H. An influence framework on product word-of-mouth (WoM) measurement. *Information & Management*. 54, 2, 2017, pp. 228–240.

[18] Chung, W., He, S. and Zeng, D. eMood: Modeling Emotion for Social Media Analytics on Ebola Disease Outbreak. *International Conference on Information Systems (ICIS)*. 2015.

[19] Dang-Xuan, L. and Stieglitz, S. Impact and diffusion of sentiment in political communication–an empirical analysisof political weblogs. *6th International AAAI Conference on Weblogs and Social Media*. 2012.

[20] Dickinger, A., Arami, M. and Meyer, D. The role ofperceived enjoyment and social norm in the adoption of technology with network externalities. *European Journal of Information Systems*. 17, 1, 2008, pp. 4–11.

[21] Durahim, A.O. and Coşkun, M. # iamhappybecause: Gross National Happiness through Twitter analysis and big data. *Technological Forecasting and Social Change*. 99,2015, pp. 92–105.

[22] Ekkekakis, P. *The measurement of affect, mood, and emotion: A guide for health-behavioral research*. Cambridge University Press. 2013

[23] Ekman, P. An argument for basic emotions. *Cognition & emotion*. 6, 3–4, 1992, pp. 169–200.

[24] Ellison, N.B., Steinfield, C. and Lampe, C. The benefits of Facebook "friends:" Social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*. 12, 4, 2007, pp. 1143–1168.

[25] Esuli, A. and Sebastiani, F. SENTIWORDNET: A high-coverage lexical resource for opinion mining. *Evaluation*. 2007, pp. 1–26.

[26] Ferrara, E. and Yang, Z. Measuring emotional contagion in social media. *PloS one*. 10, 11, 2015.

[27] Ferrara, E. and Yang, Z. Quantifying the effect of sentiment on information diffusion in social media. *PeerJ Computer Science*. 1, 2015.

[28] Fisher, C.D. Happiness at work. *International journal of management reviews*. 12, 4, 2010, pp. 384–412.

[29] Fowler, J.H. and Christakis, N.A. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *Bmj*. 337, 2008.

[30] Gaspar, R., Pedro, C., Panagiotopoulos, P. and Seibt, B. Beyond positive or negative: Qualitative sentiment analysisof social media reactions to unexpected stressful events. *Computers in Human Behavior*. 56, 2016, pp. 179–191.

[31] Geetha, M., Singha, P. and Sinha, S. Relationship between customer sentiment and online customer ratings for hotels-An empirical analysis. *Tourism Management*. 61, 2017, pp. 43–54.

[32] Goes, P.B., Lin, M. and Au Yeung, C. "Popularity effect" in user-generated content: evidence from online product reviews. *Information Systems Research*. 25, 2, 2014, pp. 222–238.

[33] Gratch, J., Lucas, G., Malandrakis, N., Szablowski, E., Fessler, E. and Nichols, J. GOAALLL!: Using sentiment in the World Cup to explore theories of emotion. *Affective Computing and Intelligent Interaction (ACII), 2015 International Conference on* (2015), pp. 898–903.

[34] Grigore, M., Rosenkranz, C. and Sutanto, J. The Impact of Sentiment-driven Feedback on Knowledge Reuse in Online Communities. *AIS Transactions on Human-Computer Interaction*. 7, 4, 2015, pp. 212–232.

[35] Gruzd, A.. Emotions in the twitterverse and implications for user interface design. *AIS Transactions on Human-Computer Interaction*. 5, 1, 2013, pp. 42–56.

[36] Gruzd, A., Doiron, S. and Mai, P. Is happiness contagious online? A case of Twitter and the 2010 Winter Olympics. *44th Hawaii International Conference on System Sciences (HICSS)*. 2011, pp. 1–9.

[37] Hancock, J.T., Gee, K., Ciaccio, K. and Lin, J.M.-H. I'm sad you're sad: emotional contagion in CMC. *Proceedings of the 2008 ACM conference on Computer supported cooperative work*. 2008, pp. 295–298.

[38] Hansen, L.K., Arvidsson, A., Nielsen, F. Årup, Colleoni, E. and Etter, M. Good friends, bad news-affect and virality in twitter. *Future information technology*. 2011, pp. 34–43.

[39] Harris, R.B. and Paradice, D. An investigation of thecomputer-mediated communication of emotions. *Journal of Applied Sciences Research*. 3, 12, 2007, pp. 2081–2090.

[40] Ho, S.M., Hancock, J.T., Booth, C. and Liu, X. Computer-Mediated Deception: Strategies Revealed by Language-Action Cues in Spontaneous Communication. *Journal of Management Information Systems*. 33, 2, 2016, pp. 393–420.

[41] Hwong, Y.-L., Oliver, C., Van Kranendonk, M., Sammut, C. and Seroussi, Y. What makes you tick? The psychology of social media engagement in space science communication. *Computers in Human Behavior*. 68, 2017, pp. 480–492.

[42] Johnson, N.A., Cooper, R.B. and Chin, W.W. The effect of flaming on computer-mediated negotiations. *European Journal of Information Systems*. 17, 4, 2008, 417–434.

[43] Johnson, S.L., Safadi, H. and Faraj, S. The emergence of online community leadership. *Information Systems Research*. 26, 1, 2015, pp. 165–187.

[44] Jurek, A., Mulvenna, M.D. and Bi, Y. Improved lexicon-based sentiment analysis for social media analytics. *Security Informatics*. 4, 1, 2015.

[45] Kaplan, A.M. and Haenlein, M. Users of the world, unite! The challenges and opportunities of Social Media. *Business horizons*. 53, 1, 2010, pp. 59–68.

[46] Kim, K., Park, O., Yun, S. and Yun, H. What makes tourists feel negatively about tourism destinations? Application of hybrid text mining methodology to smart destination management. *Technological Forecasting and Social Change*. 2017.

[47] Kramer, A.D., Guillory, J.E. and Hancock, J.T. Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences*. 111, 24, 2014, pp. 8788–8790.

[48] Kwon, K.H. and Gruzd, A. Is Aggression Contagious Online? A Case of Swearing on Donald Trump's Campaign Videos on YouTube. *50th Hawaii International Conference on System Sciences (HICSS)* 2017.

[49] Leonardi, P.M. Ambient Awareness and Knowledge Acquisition: Using Social Media to Learn "Who Knows What" and" Who Knows Whom". *MIS Quarterly*. 39, 4, 2015, pp. 747–762.

[50] Levin, D.Z. and Cross, R. The strength of weak ties you can trust: The mediating role of trust in effective knowledge transfer. *Management science*. 50, 11, 2004, pp. 1477–1490.

[51] Li, Q., Wang, T., Li, P., Liu, L., Gong, Q. and Chen, Y. The effect of news and public mood on stock movements. *Information Sciences*. 278, 2014, pp. 826–840.

[52] Lin, K.-Y. and Lu, H.-P. Why people use social net-working sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior*. 27, 3, 2011, pp. 1152–1161.

[53] Liu, F., Burton-Jones, A. and Xu, D. Rumors on Social Media in disasters: Extending Transmission to Retransmission. *PACIS*. 2014.

[54] Liu, Y., Kliman-Silver, C. and Mislove, A. The Tweets They Are a-Changin: Evolution of Twitter Users and Behavior. *ICWSM*. 2014, pp. 5–314.

[55] Lorenzo-Dus, N. and Di Cristofaro, M. # Living/minimum wage: Influential citizen talk in twitter. *Discourse, Context & Media*. 13, 2016, pp. 40–50.

[56] Lyubomirsky, S., King, L. and Diener, E. *The benefits of frequent positive affect: Does happiness lead to success?*. American Psychological Association. 2005.

[57] Malik, M.S.I. and Hussain, A. Helpfulness of product reviews as a function of discrete positive and negative emotions. *Computers in Human Behavior*. 73, 2017, pp. 290–302.

[58] Mayshak, R., Sharman, S.J. and Zinkiewicz, L. The impact of negative online social network content on expressed sentiment, executive function, and working memory. *Computers in Human Behavior*. 65, 2016, pp. 402–408.

[59] Mayshak, R., Sharman, S.J., Zinkiewicz, L. and Hayley, A. The influence of empathy and self-presentation on engagement with social networking website posts. *Computers in Human Behavior*. 71, 2017, pp. 362–377.

[60] Mehrabian, A. and Russell, J.A. *An approach to environmental psychology*. 1974

[61] Meire, M., Ballings, M. and Van den Poel, D. The added value of auxiliary data in sentiment analysis of Facebook posts. *Decision Support Systems*. 89, 2016, pp. 98–112.

[62] Moreno, M.A., Jelenchick, L.A., Egan, K.G., Cox, E., Young, H., Gannon, K.E. and Becker, T. Feeling bad on Facebook: depression disclosures by college students on a social networking site. *Depression and anxiety*. 28, 6, 2011, pp. 447–455.

[63] Nguyen, T., Phung, D., Adams, B. and Venkatesh, S. Event extraction using behaviors of sentiment signals and burst structure in social media. *Knowledge and information systems*. 2013, pp. 1–26.

[64] Nguyen, T., Phung, D., Adams, B. and Venkatesh, S. Mood sensing from social media texts and its applications. *Knowledge and information systems*. 39, 3, 2014, pp. 667–702.

[65] Nofer, M. and Hinz, O. Using Twitter to Predict the Stock Market. *Business & Information Systems Engineering*. 57, 4, 2015, pp. 229–242.

[66] O'Connor, B., Balasubramanyan, R., Routledge, B.R. and Smith, N.A. From tweets to polls: Linking text sentiment to public opinion time series. *ICWSM*. 11, 2010, pp. 122–129.

[67] Oh, C. and Sheng, O. Investigating predictive power of stock micro blog sentiment in forecasting future stock price directional movement. *International Conference on Information Systems (ICIS)*. 2011.

[68] Oh, O., Agrawal, M. and Rao, H.R. Community intelligence and social media services: A rumor theoretic analysis of tweets during social crises. *MIS Quarterly*. 37, 2, 2013, pp. 407–426.

[69] Oh, O., Kwon, K.H. and Rao, H.R. An Exploration of Social Media in Extreme Events: Rumor Theory and Twitter during the Haiti Earthquake 2010. *International Conference on Information Systems (ICIS)*. 2010.

[70] O'Leary, D.E. On the relationship between number of votes and sentiment in crowdsourcing ideas and comments for innovation: A case study of Canada's digital compass. *Decision Support Systems*. 88, 2016, pp. 28–37.

[71] Pang, B. and Lee, L. Opinion mining and sentiment analysis. *Foundations and Trends® in Information Retrieval*. 2, 1–2, 2008, pp. 1–135.

[72] Pang, B., Lee, L. and Vaithyanathan, S. Thumbs up?: sentiment classification using machine learning techniques. *Proceedings of the ACL-02 conference on Empirical methods in natural language processing-Volume 10*. 2002, pp. 79–86.

[73] Pang, N. and Ng, J. Twittering the Little India Riot: Audience responses, information behavior and the use of emotive cues. *Computers in Human Behavior*. 54, 2016, pp. 607–619.

[74] Plutchik, R. The Nature of Emotions. *American Scientist*. 2001.

[75] Posner, J., Russell, J.A. and Peterson, B.S. The circumplex model of affect: An integrative approach to affective neuroscience, cognitive development, and psychopathology. *Development and psychopathology*. 17, 3, 2005, pp. 715–734.

[76] Qi, J., Fu, X. and Zhu, G. Subjective well-being measurement based on Chinese grassroots blog text sentiment analysis. *Information & Management*. 52, 7, 2015, pp. 859–869.

[77] Relling, M., Schnittka, O., Sattler, H. and Johnen, M. Each can help or hurt: Negative and positive word of mouth in social network brand communities. *International Journal of Research in Marketing*. 33, 1, 2016, pp. 42–58.

[78] Riemer, K., Richter, A. and Seltsikas, P. Enterprise Microblogging: Procrastination or productive use? *AMCIS*. 2010.

[79] Risius, M., Akolk, F. and Beck, R. Differential Emotions and the Stock Market-The Case of Company-specific Trading. *European Conference on Information Systems (ECIS)*. 2015.

[80] Risius, M. and Beck, R. Effectiveness of corporate social media activities in increasing relational outcomes. *Information & Management*. 52, 7, 2015, pp. 824–839.

[81] Russell, J.A. Core affect and the psychological construction of emotion. *Psychological review*. 110, 1, 2003.

[82] Salehan, M. and Kim, D.J. Predicting the performance of online consumer reviews: A sentiment mining approach to big data analytics. *Decision Support Systems*. 81, 2016, pp. 30–40.

[83] Sapountzi, A. and Psannis, K.E. Social networking data analysis tools & challenges. *Future Generation Computer Systems*. 2016.

[84] Schumaker, R.P., Jarmoszko, A.T. and Labedz, C.S. Predicting wins and spread in the Premier League using a sentiment analysis of twitter. *Decision Support Systems*. 88, 2016, pp. 76–84.

[85] Seebach, C., Beck, R. and Denisova, O. Sensing Social Media for Corporate Reputation Management: a Business Agility Perspective. *European Conference on Information Systems (ECIS)*. 2012.

[86] Shen, W., Hu, Y.J. and Ulmer, J.R. Competing for Attention: An Empirical Study of Online Reviewers' Strategic Behavior. *MIS Quarterly*. 39, 3, 2015, pp. 683–696.

[87] Shen, Y., Chan, H.C. and Heng, C.S. The Medium Matters: Effects on What Consumers Talk about Regarding Movie Trailers. *International Conference on Information Systems (ICIS)*. 2016.

[88] Smailović, J., Grčar, M., Lavrač, N. and Žnidaršič, M. Stream-based active learning for sentiment analysis in the financial domain. *Information Sciences*. 285, 2014, pp. 181–203.

[89] Standing, C., Holzweber, M. and Mattsson, J. Exploring emotional expressions in e-word-of-mouth from online communities. *Information Processing & Management*. 52, 5, 2016, 721–732.

[90] Stieglitz, S. and Dang-Xuan, L. Emotions and information diffusion in social media—sentiment of microblogs and sharing behavior. *Journal of Management Information Systems*. 29, 4, 2013, pp. 217–248.

[91] Stieglitz, S. and Dang-Xuan, L. Social media and political communication: a social media analytics framework. *Social Network Analysis and Mining*. 3, 4, 2013, pp. 1277–1291.

[92] Stieglitz, S. and Krüger, N. Analysis of sentiments in corporate Twitter communication–A case study on an issue of Toyota. *Analysis*. 1, 2011.

[93] Sul, H.K., Dennis, A.R. and Yuan, L.I. Trading on twitter: The financial information content of emotion in social media. *47th Hawaii International Conference on System Sciences (HICSS)*. 2014, pp. 806–815.

[94] Tang, C. and Guo, L. Digging for gold with a simple tool: Validating text mining in studying electronic word-of-mouth (eWOM) communication. *Marketing Letters*. 26, 1, 2015, pp. 67–80.

[95] Tang, C., Mehl, M.R., Eastlick, M.A., He, W. and Card, N.A. A longitudinal exploration of the relations between electronic word-of-mouth indicators and firms' profitability: Findings from the banking industry. *International Journal of Information Management*. 36, 6, 2016, pp. 1124–1132.

[96] Thelwall, M. Heart and soul: Sentiment strength detection in the social web with sentistrength. *Proceedings of the CyberEmotions*. 5, 2013, pp. 1–14.

[97] Thelwall, M., Buckley, K. and Paltoglou, G. Sentiment in Twitter events. *Journal of the American Society for Information Science and Technology*. 62, 2, 2011, pp. 406–418.

[98] Tumasjan, A., Sprenger, T.O., Sandner, P.G. and Welpe, I.M. Election forecasts with Twitter: How 140 characters reflect the political landscape. *Social science computer review*. 29, 4, 2011, pp. 402–418.

[99] Ullah, R., Amblee, N., Kim, W. and Lee, H. From valence to emotions: Exploring the distribution of emotions in online product reviews. *Decision Support Systems*. 81, 2016, pp. 41–53.

[100] Vom Brocke, J., Simons, A., Niehaves, B., Riemer, K.,Plattfaut, R., Cleven, A. and others. Reconstructing the giant: On the importance of rigour in documenting the literature search process. *European Conference on Information Systems (ECIS)*. 2009, pp. 2206–2217.

[101] Wakefield, R. and Wakefield, K. Social media network behavior: A study of user passion and affect. *The Journal of Strategic Information Systems*. 25, 2, 2016, pp. 140–156.

[102] Wang, W., Zhao, Y., Qiu, L. and Zhu, Y. Effects of emoticons on the acceptance of negative feedback in computer-mediated communication. *Journal of the Association for Information Systems*. 15, 8, 2014.

[103] Webster, J. and Watson, R.T. Analyzing the past to prepare for the future: Writing a literature review. *MIS Quarterly*. 2002, pp. xiii–xxiii.

[104] Wu, B., Jiang, S. and Chen, H. The impact of individual attributes on knowledge diffusion in web forums. *Quality & Quantity*. 49, 6, 2015, pp. 2221–2236.

[105] Xu, H., Phan, T.Q. and Tan, B. How Does Online Social Network Change My Mood? An Empirical Study of Depression Contagion On Social Network Sites Using Text-mining. *International Conference on Information Systems (ICIS)*. 2013.

[106] Yin, D., Bond, S. and Zhang, H. Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS Quarterly*. 2014.

[107] Yu, J., Hu, P.J.-H. and Cheng, T.-H. Role of affect in self-disclosure on social network websites: A test of two competing models. *Journal of Management Information Systems*. 32, 2, 2015, pp. 239–277.

[108] Zavattaro, S.M., French, P.E. and Mohanty, S.D. A sentiment analysis of US local government tweets: The connection between tone and citizen involvement. *Government Information Quarterly*. 32, 3,2015, pp. 333–341.

[109] Zhang, K., Bhattacharyya, S. and Ram, S. Large-Scale Network Analysis for Online Social Brand Advertising. *MIS Quarterly*. 40, 4 2016, pp. 849–868.

[110] Zhang, Y., Dang, Y. and Chen, H. Research note: Examining gender emotional differences in Web forum communication. *Decision Support Systems*. 55, 3, 2013, pp. 851–860.

10 Paper 2

Fear and Loathing in Boston: The Role of Different Emotions in Information Sharing on Social Media Following a Terror Attack

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Abstract

Emotions are essential to how we communicate, and online discussions are no exception. As most of the analysis on emotion so far has looked at polarity rather than specific emotions, we do not yet have a full understanding of how different emotions spark different behaviours. This study examines how five different emotions are associated with information sharing in the context of a terror attack both on a large scale and when including geolocation information in the analysis. Contrary to what previous findings suggest, increased fear and contempt levels have a negative relation with increased levels of retweeting. Positive emotion in tweets meant a decrease in retweet rates in the geolocation specific data, but an increase when all tweets were considered.

Keywords: social media, emotion, sentiment analysis, terror attacks.

Introduction

Social media has since its emergence quite drastically changed the way we communicate, not only affecting how and how easily it can be done, but also altering with whom we can connect. Some of the most common user reported motivations for using social media platforms are creating and maintaining connections with other users, sharing and obtaining information, and personal enjoyment (Dickinger et al., 2008; Ellison et al., 2007; Lin and Lu, 2011). Compared to traditional media, social media enables information to travel faster and reach a wider audience, resulting to phenomena such as allowing the development of collective situation awareness in crisis (Mukkamala and Beck, 2016), or – on the darker side of things – various types of rapidly escalating firestorms (Pfeffer et al., 2014).

Some social media messages go viral, but we do not yet fully understand what compels people to share them. Emotions certainly play a role in the decision to share information or opinions, but the findings regarding how, exactly, vary from one case to another (Gruzd et al., 2011; Hansen et al., 2011; Stieglitz and Dang-Xuan, 2013). The context of the discussion may be part of the explanation: different types of events spark very different types of online conversation (Ferrara and Yang, 2015). In *anticipatory discussions*, most of the discussion happens before the peak, which typically occurs around some real-world event. The converse is true for *unexpected events*, which quickly spark a peak of conversation that fades away. *Symmetric discussions* have a less distinct peak, and the discussion goes on for a longer period of time, whereas in the case of *transient events*, the peaks in conversation activity are sharp and bursty, and the activity fades quickly.

Emotions are contagious within a social network (Fowler and Christakis, 2008), and it has been shown to also apply to online environments (Hancock et al., 2008; Kramer et al., 2014; Kwon and Gruzd, 2017). It is therefore no wonder that emotions affect our information sharing behaviour (Gruzd, 2013; Hansen et al., 2011; Oh et al., 2013; Stieglitz and Dang-Xuan, 2013); when a social media user sees something emotional on social media, sometimes the emotion is passed on to the user, which makes the user more likely to share the emotion-evoking message onwards. We hypothesize that this also applies to the conversations occurring during and after a crisis event such as a terrorist attack.

In addition to context affecting the impact of emotions on information sharing, a potential explanation to the differences between previous findings is that some emotions may drive sharing behaviour more strongly than others: for example, anger is more likely to spark the action of sharing news than sadness in a one-to-one communication relation (Berger and Milkman, 2012). While previous research has yielded plenty of valuable information about the relationship of emotions and information sharing online, it seems that most of the analysis so far has focused on measuring the positivity and negativity levels without looking at specific emotions separately. Therefore, to expand our understanding of the role of specific emotions, the main goal of this study is to investigate *how different emotions are related to the degree of information sharing on social media in the context of a terror attack*.

In addition to hypothesising that context and the type of emotion are connected to how information is shared, we consider whether geographic location is related to how and whose information is shared online. Research on the after-effects of 9/11 found that in the aftermath of a terror attack, people in the affected regions suffer from more elevated stress and anxiety than people farther away. This may mean the emotional intensity of online communication may depend on the location of the actor. Proximity to the attack location might also enable an actor to provide timely, relevant information, which might compel others to share the information onwards more actively.

Geolocation data can be a valuable tool for investigating local phenomena, not the least in crisis situations such as natural disasters (Mukkamala and Beck, 2016). However, disclosing location information is typically voluntary on social media platforms, which means that the proportion of users who actively decide to do so may be small enough to noticeably limit the size of analysable data, and potentially introduce an unknown degree of self-selection bias in the dataset. To examine the effect of the location, we analyse a geotagged subset of the data used for this research and report the results for both the full dataset and the location specific subset side by side to examine the impact of including location information into the analysis of online information sharing.

The remainder of the paper is organised in the following way: First, we lay out the basis of our study by going through existing research on the topic and formulating our hypotheses. In the section Methods and Data, we explain our data collection and processing, the reasoning behind our approach, and the methodology applied in this study. In the subsequent section, we report our results, after which we discuss our findings in the context of existing knowledge. The last section reports our conclusions, limitations, and suggestions for future research in the area.

Theoretical Background

The Role of Emotions in Information Sharing Online

Where there is conversation, there is also emotion. Sentiment analysis enables analysing the presence and extent of emotions in an automated fashion, and has been used for purposes such as customer relation management (Risius and Beck, 2015), mining for electronic word-of-mouth (Chen et al., 2017; Kim et al., 2017; Relling et al., 2016), and predicting changes in the stock market (Risius and Beck, 2015) as well as outcomes of sports matches (Schumaker et al., 2016). There are two main approaches to sentiment analysis: lexicon-based approaches utilise dictionaries containing information about the emotional loadings of words, and machine learning based approaches use training data sets and/or features to build classifiers to sort text into emotion categories (Pang and Lee, 2008). Most sentiment analysis looks at the polarity (positive and negative sentiment) of the text analysed, but there are some studies that adopt a more fine-grained approach (Hyvärinen and Beck, 2018).

Over the last decade, Twitter has become a massively popular social media platform with celebrities and laymen alike expressing their views, and often retweeting messages authored by other people. Retweeting was a convention that organically emerged among the users during the early years, after which it has steadily become more and more commonplace (Liu et al., 2014). By 2014, around 25–30% of all messages posted on Twitter were retweets, which makes it clear that sharing information and opinions is an integral part of the conversation culture (Liu et al., 2014).

It seems the tone varies from one conversation to another. A study on tweets about the 2010 Winter Olympics found that there are more positive than negative tweets, and that positive tweets were three times more likely to be retweeted (Gruzd et al., 2011). On the other hand, a study on German political tweets found that emotional tweets are more likely to get retweeted regardless of whether they are positive or negative (Stieglitz and Dang-Xuan, 2013). A third study posits that news related content propagates better when the sentiment is negative, whereas the opposite holds for non-news content (Hansen et al., 2011). The studies agree on elevated emotions being related to increased information sharing, but the descriptions of the exact nature of that relationship vary. One explanation for the differences between the findings could be the type of the event examined, as that has been found to influence the emotion levels of online conversations (Ferrara and Yang, 2015). Another possible contributing factor could be how emotional contagion works. Emotions have been shown to be contagious online (Hancock et al., 2008; Kramer et al., 2014; Kwon and Gruzd, 2017), but how contagion works may depend on the type of conversation, the relationship between participants, and the type of emotion in question.

A study examining the role of emotions in forwarding information via email finds that high activation emotions (such as anger or fear, sometimes also referred to as high arousal emotions) are associated with an increased tendency to share information, which means that valence (positivity or negativity) alone is not sufficient in explaining information sharing behaviour (Berger and Milkman, 2012). Although the study focused on a dyadic context, it is possible that the finding also applies to social media sharing, which is more of a broadcasting, one-to-many type of communication setting. We were therefore interested in looking at different emotions beyond polarity analysis in order to find out whether they have unique effects on information sharing on social media, which is a question the previous studies in the area have not yet covered, to the best of our knowledge.

Psychology literature contains various categorisations and definitions for emotions; some divide emotions into distinct states such as enjoyment, sadness, anger, fear, and disgust (Ekman, 1992), others define them as points in the dimensions of valence (or pleasure) and arousal (or activation) (Russell, 2003). The hierarchical domain of emotions developed by Ekkekakis (Ekkekakis, 2013) combines the distinct state and dimension approaches into a comprehensive framework while drawing from the previously existing wisdom (see Table 3). This study uses a sentiment analysis approach developed based on that framework, developed for the purpose of analysing differential emotions on social media (Risius et al., 2015). The positive emotion categories are *affection, happiness*, and *satisfaction*, and the negative ones are *anger, fear, depression*, and *contempt*. Our initial plan was to treat each emotion separately, but – upon finding correlations between the positive emotions in the analysis phase notable enough to potentially cause trouble – decided to merge the three positive emotion categories into a single one. Our observation regarding the proximity of the positive emotions could be due to negative emotions being more distinct from each other than positive ones (Fredrickson, 1998).

Negative emotions have been associated with elevated levels of information sharing in several past studies (Berger and Milkman, 2012; Hansen et al., 2011; Stieglitz and Dang-Xuan, 2013). We expect that effect to be particularly pronounced in our dataset, given the context of a terror attack evoking several types of negative emotions. This assumption is further supported by a study on information propagation on Twitter following the Woolwich terrorist attack in 2013 concluding that the presence of (any) emotion in tweets is related to a higher level of retweeting (Burnap et al., 2014), which is in accordance with the findings concluding that sentiment increases information diffusion on social media in other contexts (Gruzd et al., 2011; Hansen et al., 2011; Stieglitz and Dang-Xuan, 2013).

Information Sharing Online in the Context of a Terror Attack

The primary function of using social media in a disaster situation is sharing and obtaining information, which also allows actors to make sense of the events (Eismann et al., 2016). In the context of human caused disasters – such as terror attacks – social media are used for expressing emotions and memorialising victims, establishing connections between geographically distant members of the community, and coordinating response and recovery efforts (Huang et al., 2010; Kaufmann, 2015; Mazer et al., 2015; Neubaum et al., 2014). Twitter is used across disaster categories by all types of social units to share warnings and situational updates, but also in a more interactional fashion, such as confirmations on others' wellbeing and conversations on events and their consequences (Eismann et al., 2016). In crisis situations such as natural disasters, anxiety has been linked to the behaviour of spreading rumours (Oh et al., 2013), which means anxiety may correlate with an increased urge to share information also in the context of an act of terror.

In the wake of a terrorist attack, people are driven to seek information, but also talk about the attacks on social media in order to defend their cultural world views and maintain their self-esteem (Fischer et al., 2016). An act of terrorism will increase the levels of fear, uncertainty, and anger in people's minds, which affects their behaviour also online (Boyle et al., 2004). People close to areas where terror attacks occur report stress and anxiety after the incident, which leads us to include geographic proximity as a variable in our analysis (Morrison et al., 2001).

Anger was the dominant reaction to the 9/11 attacks, and was particularly intense in the New York area where the levels of negative emotions in general were higher than in the rest of the country (Smith et al., 2001). We therefore expect the levels of anger to be high, and be likely to be actively passed on due to emotional contagion in the aftermath of the Boston Marathon bombing.

Hypothesis 1a: The higher the level of anger in a terror-related tweet, the more it is retweeted

The second most prevalent emotion following a terrorist attack is fear, which is typically related to questions such as how the crisis affects one's own life or whether anyone is safe

(Smith et al., 2001). Like anger, fear is a high activation emotion, and is therefore likely to be associated to increased information sharing (Berger, 2011).

Hypothesis 1b: The higher the level of fear in a terror-related tweet, the more it is retweeted

The level of depression was also found to be elevated following an act of terror (Lerner et al., 2003; Smith et al., 2001). Crying was reported as one of the most common physical and emotional symptoms following the 9/11 attack (Smith et al., 2001). Due to sadness – for which this study uses the term depression – being a low activation emotion, we expect the rate of sharing to be lower than in the case of anger and fear. However, we still expect the relation to be positive. People tend to feel the need to find a shared space for mourning a crisis event, leading to online convergence (Hughes et al., 2008). Consequently, we hypothesize that feeling sadness, and feeling the need to share that will also mean users are more likely to relate to content matching their emotions and thus more likely to share it.

Hypothesis 1c: The higher the level of depression in terror-related a tweet, the more it is retweeted

In this context of usage, contempt is defined as a negative emotion related to socially offensive or inappropriate actions (e.g. “deceitful”, “despicable”), and personal reactions to them (e.g. “shame”, “guilt”, “condemn”). This is perhaps the most unpredictable of the negative emotions with respect to information sharing. In general, we know that experiencing an emotion will make people want to share it with people around them; however, guilt and shame seem to be exceptions to this rule (Rimé, 2009). A study comparing emotional reactions to the shooting of John F. Kennedy and to the 9/11 attack found that the shooting evoked more shame related emotions than 9/11, and that people were less willing to discuss the event with others than after 9/11 (Smith et al., 2001). Although the study does not establish causality, the findings are in line with shame in general being associated with lower willingness to share emotions. We therefore hypothesize that contempt is the only negative emotion associated with decreased retweeting.

Hypothesis 1d: The higher the level of contempt in a terror-related tweet, the less it is retweeted

Hypothesising how positive emotions are related to information sharing in the context of a terror attack is less straight-forward as with negative ones. It may be that in a context abundant with negative emotions sparked by immediate negative events, positive messages would feel less relevant and thus be shared less. On the other hand, in the case of non-news content, positive emotion is associated with increased information sharing; perhaps gratitude towards helpers, sharing experiences and thoughts, or relief might prompt retweeting under such circumstances. Based on previous findings, positive emotion tends to rather increase than decrease retweeting, which leads us to formulate the hypothesis:

Hypothesis 1e: The higher the level of positive emotions in a terror-related tweet, the more it is retweeted

As one might expect, proximity to the affected area of a terror attack increases the intensity of the emotions people experience during the aftermath (Smith et al., 2001). Initial inspection of the tweets in our data set containing location information showed that – contrary to what one might expect – tweets in the directly affected area (Boston and Massachusetts) are less emotional than tweets originating farther away. It could be that Bostonians are focusing on sharing valuable situational information rather than expressing how they feel (Mukkamala and Beck, 2016). Although in general lower emotion content is associated to lower information sharing (see previous section), we suspect that in the case of situationally relevant information, location plays a role equal of or bigger than emotions, leading us to formulate an additional hypothesis:

Hypothesis 2: Tweets from the affected area retweeted more than other tweets

Methods and Data

Data

The data in this study consists of Boston Marathon Bombing related tweets from during and after the event 15th – 23rd of April 2013. Non-English and other non-relevant tweets (e.g. related to Boston but not the bombing) were removed during the pre-processing.

After careful consideration, we decided to exclude retweets from the data. Initial analysis revealed that retweets get significantly fewer – if any – retweets compared to the original post even when the original one has high retweet rates and the content is identical. This has the potential to severely confound the analysis of the relationship between the emotional content of a message and its probability of being shared onwards. Without a further look into the reasoning of users sharing retweets versus the originals upon encountering a retweet (which is out of scope here, but perhaps worthy of its own study), including the retweets' retweet rates in the data set might introduce a bias in the results, which is why we decided it to be prudent to exclude them from the analysis.

Our final data set thus consists of 4.4 million original tweets for which we extracted relevant metadata and counted the number of retweets. That dataset contained 93 000 tweets with geolocation information, which is around 2% of the full dataset. For those tweets, we extracted the coordinates, based on which we grouped them into four location categories:

(1) *"within the same city"* (within 30 km of the location of the bombing, which covers Boston as well as nearby areas such as Cambridge and Brookline), N=5 525

(2) *"not within the same city but within the same state"* (any coordinates outside of the first category but inside the state of Massachusetts), N=1 968

(3) *"not within the same state but within the same country"* (any coordinates outside of Massachusetts within the US), N=55 265

(4) *"abroad"* (everything outside of the US), N=30 338

We started out by getting an intuition of what our data set contains by examining it: the levels of each emotion it contains, how the retweet rates – our main interest – vary, and what kinds of messages are high in emotional intensity in general. In addition to statistical analysis, manual inspection of subsets was frequently used to confirm the observations. Tables 1, 2a, and 2b contain basic information of and emotion levels in the data. As could be expected, some of the high outliers in retweet numbers in the full data are not included in the geolocation set, which is also reflected in the variance of the retweets.

The overall tweeting density related to the bombing was markedly higher within the Boston and Massachusetts area with proportion to the 2013 population counts (0.11 tweets per citizen for Massachusetts including Boston, 0.02 tweets per citizen elsewhere in the US).

	Full set	**Geo set**
The number of retweets, mean	1,34	0,72
The number of retweets, variance	3 308	1 106
The number of retweets, maximum	65 294	8 762
Data set size	4 442 261	93 096

Table 1. The mean, variance, and maximum value for the number of retweets in each data set.

	Anger			**Fear**			**Depression**			**Contempt**		
	none	low	high	none	low	high	none	low	high	none	low	high
Boston	61.83	36.71	1.47	89.00	7.73	3.28	83.96	13.35	2.68	88.72	10.70	0.58
MA	60.42	37.35	2.24	90.50	6.66	2.84	83.11	15.15	2.74	89.74	9.56	0.71
US	50.75	47.02	2.23	88.26	7.97	3.77	80.20	15.91	3.89	86.03	12.93	1.04
Abroad	47.84	49.54	2.62	82.10	12.33	5.57	79.47	16.24	4.30	85.94	12.02	2.03
Full set	44.84	53.24	1.92	86.78	9.73	3.49	81.01	15.86	3.13	85.17	13.84	0.99

Table 2a. The percentages of levels of negative emotion in the full dataset of 4,4M tweets, and in the geolocation dataset of 93 000 tweets for each of the four location categories. SentiStrength scores 4-5 are combined in "high", scores 2-3 are combined in low, and score 1 is "none". Each tweet in the dataset is scored separately for each sentiment, which means it can simultaneously have a higher than 1 score on more than one emotion.

	Positive		
	none	low	high
Boston	81.92	18.06	0.02
MA	79.37	20.63	0.00
US	82.91	17.09	0.00
Abroad	84.72	15.28	0.00
Full set	87.42	12.57	0.00

Table 2b. The percentages of levels of positive emotion in the full dataset and the geolocation.

Sentiment Analysis

The sentiment was analysed using SentiStrength (Thelwall et al., 2010), a lexicon-based tool especially suited for short, informal texts. It assigns each unit of text – in this case tweet – a positivity (from 1 to 5) and negativity (from –1 to –5). Because we wanted to focus on differentiated emotions rather than polarity, we applied customized lexicons to detect affection, happiness, satisfaction, anger, fear, depression and contempt, each on a five-point scale. These lexicons were developed specifically to analyse different emotions in social media posts, and have been used and evaluated in previous research (Risius et al., 2015; Risius and Akolk, 2015). The emotional categories are based on Ekkekakis' hierarchical structure of the affective domain (Ekkekakis, 2013) (see Table 3).

We chose to use the custom lexicons rather than a more established approach because they cover differentiated emotions on an intensity scale in a way the existing and available sentiment analysis tools could not. However, just to be cautious, we decided to sanity check the quality against an established tool to the degree that is possible. Out of the established sentiment analysis tools, LIWC offers most insight beyond polarity, detecting positive sentiment, anger, anxiety, and sadness. We ran our geolocation data set through both LIWC and the custom lexicons to establish how often the two approaches agree on the presence of those four emotions.

For positive sentiment, the agreement rate is 84%, anger is at 61%, fear/anxiety at 93%, and depression/sadness at 87%. As agreement on anger is clearly lower than the others, we looked at the cases where the anger lexicon and LIWC disagree. In 30 698 out of those 34 584 cases, our anger lexicon detected the mildest level of anger while LIWC detected none. A manual inspection of these "false positives" showed that some of them were false negatives for LIWC (*"They finally got the Boston Bomber! Now Execute Him!!!"*), and some of them false positives for the anger lexicon (*"After watching hours of CNN they caught the second bomber in the Boston Marathon #success #caughtinaboat"*). The anger lexicon is clearly more sensitive in detecting anger than LIWC, which is likely due to the fact that the anger lexicon is bigger than the other emotion lexicons (Risius et al., 2015). This is good to remember when interpreting the results, but all in all the tool comparison does not give us reason to suspect the custom lexicons are unsuitable for our purpose.

Ekkekakis	Risius et al.	Description
Joy	Happiness	Amplified enthusiasm and excitement about attaining something desired or desirable
Love	Affection	Genuine fondness and liking attributed to a person or object
Pride	Satisfaction	Proud acknowledgement of and contentment with reaching a predetermined goal
Sadness	Depression	Impeding sadness evoked by an aversive event that may hinder activity
Anger	Anger	Animated animosity towards malice that can motivate rectification
Fear	Fear	Anticipatory horror or anxiety in unpredictable or potentially harmful situations
Shame	Contempt	Revulsion to something considered socially offensive or unpleasant

Table 3. Emotions in the hierarchical affective domain, their adaptation, and explanations for each emotion.

Preliminary examination of the data revealed that the levels of each of the negative emotions were lower in the proximity of the location of the terror attack than farther away, which is interesting considering that previous findings establish that after a terror attack, people living in the area exhibit stress and anxiety on a higher level than people with greater distance (see Table 2a).

Regression Analysis

We used regression analysis in order to examine the relationship between emotions and retweeting. The dependent variable is the *number of retweets* for each tweet in the data. Upon inspecting the correlation matrix, we established that the *positive emotions* were all highly correlated with each other, which lead us to decide to represent them using their mean as one variable instead of including them separately. No significant correlation was found between the negative emotions, so *anger, fear, depression*, and *sadness* were included in the model as separate variables. For the geolocation data set, the *location* is represented by a categorical variable denoting whether the tweet originated from Boston, elsewhere in Massachusetts, elsewhere in the US, or abroad. To account for other known effects in the data set, we use four control variables chosen based on their relevance in previous research: the *number of followers* of the author of the message, the activity of the author represented by the *number of messages* the author has previously posted, the number of *hashtags* in the tweet, and a binary variable for whether the tweet contains a *URL* (Stieglitz and Dang-Xuan, 2013).

The dependent variable – the number of retweets – in our dataset is count data consisting of non-negative integers, and is over-dispersed (the mean being significantly smaller than the variance for both the full and location specific datasets), which *generalized linear models* tend to be able to handle better than simpler models would. After examining model fits for different types of models (including quasi-Poisson estimation and negative binomial models), we determined the *negative binomial model* to be the most accurate model for our data set. In addition to the fixed independent variables, our final model contains a random variable to account for multiple tweets from the same user probably being more similar than tweets between users. Comparative tests including and excluding the random variable confirmed its inclusion to be a clear improvement to the model. The inclusion of a random variable meant using a mixed model, so our final choice was to go with a *generalized linear mixed model with a negative binomial distribution* with the following equation:

$$log(E(rt|*)) = \beta_0 + \beta_1 positive + \beta_2 anger + \beta_3 fear + \beta_4 depression + \beta_5 contempt + \beta_6 \, log(followers) + \beta_7 log(posts) + \beta_8 hashtags + \beta_9 url + \beta_{10}(1|userid)$$

The equation for the geodata subset is the same except for the addition of a categorical variable for location information:

$$log(E(rt|*)) = \beta_0 + \beta_1 positive + \beta_2 anger + \beta_3 fear + \beta_4 depression + \beta_5 contempt + \beta_6 location + \beta_7 \, log(followers) + \beta_8 log(posts) + \beta_9 hashtags + \beta_{10} url + \beta_{11}(1|userid)$$

where E(rt|*) is the expectation of the number of retweets given the right-hand side variables, location is a categorical variable for geolocation, and (1|userid) a random variable based on user ID numbers. The analysis of the model was run using the R package glmmTMB.

Results

The correlation matrices of the datasets confirm that correlation between independent variables is not an issue (see Tables 4 and 5). In both datasets, the highest correlation is <0.25 between the URL binary variable and posting history. The correlations between the variables of primary interest, the emotions, are all on a very low level.

The results of the regression analyses are reported in Table 6. As is the case typically with regression on large datasets, the standard errors and p-values for the full data are all very small, and the results should not be overinterpreted. Column *exp(b)* in Table 6 lists the exponentiated versions of the coefficients (*b*) for the sake of legibility, as coefficients from a negative binomial model are in relation to the logarithm or the

	positive	anger	fear	depression	contempt	followers	posts	hashtags	url
positive	1								
anger	-0.04***	1							
fear	0.01***	0.04***	1						
depression	0.02***	-0.02***	0.04***	1					
contempt	0.00***	0.08***	0.03***	0.03***	1				
followers	-0.01***	0.00	0.00***	0.00***	0.00	1			
posts	-0.07***	0.04***	-0.01***	-0.04***	0.02***	0.06***	1		
hashtags	0.01***	-0.10***	-0.02***	-0.01***	-0.02***	0.00***	-0.01***	1	
url	-0.16***	0.09***	-0.05***	-0.06***	0.00**	0.03***	0.22***	-0.03***	1

Table 4. Correlation matrix for the independent variables when analysing the full dataset. '*' < 0.001, '**' < 0.01, '*' < 0.05, '.' < 0.1**

	positive	anger	fear	depression	contempt	followers	posts	hashtags	url
positive	1								
anger	-0.03***	1							
fear	0.00	0.06***	1						
depression	-0.01*	0.02***	0.04***	1					
contempt	0.01*	0.06***	0.04***	0.04***	1				
followers	-0.01.	0.00	0.01**	0.00	0.00	1			
posts	-0.06***	0.06***	0.00	-0.01***	0.01***	0.04***	1		
hashtags	0.00	-0.13***	-0.03***	-0.03***	-0.03***	0.00	-0.10***	1	
url	-0.09***	0.02***	-0.05***	-0.04***	-0.01***	0.02***	0.24***	0.06***	1

Table 5. Correlation matrix for the independent variables when analysing the geolocation dataset. '*' < 0.001, '**' < 0.01, '*' < 0.05, '.' < 0.1**

dependent variable rather than the actual values. This means that, for instance, for a one unit increase in positive emotions for the full dataset, the number of retweets is expected to increase by 1.03 times, i.e. 3% (b=0.03, exp(b)=1.03), assuming all other variables remain constant.

For each model, the table discloses two types of pseudo R^2 measures: the marginal pseudo R^2 describing the proportion of variance explained by the fixed effects, and the conditional pseudo R^2 describing the proportion of variance explained by both the fixed and random effects.

There are some differences in the levels of control variables, but the tendencies are similar. The impact of a user's follower count on the expected retweet rate is large and significant in both data sets. This stands to reason, as the number of followers directly impacts how many people are likely to see the tweet, which is a necessary precondition for sharing it onwards. The largest difference in the control variables between the datasets concerns the URL variable (0.84 in the geolocation data, 0.55 in the full data), which – against expectations based on previous literature – has a negative correlation with retweet rates.

The correlations for fear and contempt were significant and negative in both datasets, although the effect was stronger in the geolocation dataset. The negativity of the correlation leads us to reject hypothesis H1b for fear as it suggested a positive relation, and confirm H1d suggesting a negative relation. For the other negative emotions, anger and depression, the results were significant only in the full data set. The coefficients are rather small, suggesting that with the presence of anger or depression in a tweet, the number of retweets is expected to increase by 1%.

The effect of the geolocation variable is almost as large as the effect of the number of followers. The strong positive relation confirms H2. The regression analysis uses the fourth category *abroad* as a baseline, and the exponentiated coefficients report how much higher we expect the number of retweets to be if the tweet originates from another category.

Results of the regression analysis for each dataset						
	Geo			**Full**		
Independent Variables	**b**	**SE**	**exp(b)**	**b**	**SE**	**exp(b)**
positive	-0.12***	0.03	0.87	0.03***	0.00	1.03
anger	0.02	0.01	1.02	0.01***	0.00	1.01
fear	-0.04**	0.01	0.96	-0.02***	0.00	0.98
depression	0.02	0.01	1.02	0.01**	0.00	1.01
contempt	-0.07***	0.02	0.93	-0.05***	0.00	0.95
log(followers)	0.68***	0.01	1.98	0.76***	0.00	2.14
log(posts)	-0.10***	0.01	0.99	-0.17***	0.00	0.84
hashtags	0.07***	0.01	1.07	0.11***	0.00	1.12
url	-0.18***	0.03	0.84	-0.59***	0.00	0.55
Constant	-4.85***	0.07		-4.82***	0.01	
Geo: Boston	0.45***	0.05	1.57			
Geo: MA	0.47***	0.07	1.60			
Geo: US	0.26***	0.02	1.30			
Pseudo R^2: marginal		0.18			0.26	
Pseudo R^2: conditional		0.42			0.53	
Number of observations		93 096			4 442 261	
p-values: '***' < 0.001, '**' < 0.01, '*' < 0.05, '.' < 0.1						

Table 6. The regression results for both the full dataset and the geolocation dataset. "b" is the coefficient resulting from the negative binomial model, "SE" is the standard error, "exp(b)" is the exponentiated coefficient allowing for easier interpretation

Hypotheses	Full data	Geodata
H1a: The higher the level of anger in a terror-related tweet, the more it is retweeted	confirmed	inconclusive
H1b: The higher the level of fear in a terror-related tweet, the more it is retweeted	rejected	rejected
H1c: The higher the level of depression in terror-related a tweet, the more it is retweeted	confirmed	inconclusive
H1d: The higher the level of contempt in a terror-related tweet, the less it is retweeted	confirmed	confirmed
H1e: The higher the level of positive emotions in a terror-related tweet, the more it is retweeted	confirmed	rejected
H2: Tweets from the affected area retweeted more than other tweets	N/A	confirmed

Table 7. The list of hypotheses outlined in the Theoretical Background section. Cases where the results did not have sufficient statistical significance are marked as inconclusive.

Tweeting from the Boston and Massachusetts area increase the expected retweet rate by a factor of 1.57 and 1.60 times respectively compared to tweets from abroad, and tweets from the US are also more likely to get retweeted than from outside the US.

Perhaps the most surprising result is that in the geolocation data, positive emotions are negatively correlated with retweet rates, while in the full dataset there is a small positive correlation. The negative relation in the geo set is the strongest correlation detected for any emotions in both datasets.

Discussion

Increasing our understanding on emotional drivers in user behaviour online is not only relevant from an academic standpoint, but also has some practical implications. In particular in the aftermath of a traumatic event, people seek out other people to exchange information, receive support, and make sense of what has happened. However, there are other motivations for using social media in a crisis context; several types of conversations unfold simultaneously on the same platform with different goals. Some aim to feel connected, others search for information and news either out of general curiosity or out of the need to ensure the wellbeing of others, and yet other actors monitor social media feeds to make sure they are updated on information relevant to their efforts. A better understanding of these conversations would enable more efficient real-time filtering for instance for emergency services or various authorities, but it would also allow organising the communication on social media to be better tailored for the users who are primarily seeking for connection and support.

Based on previous literature, we assumed that anger, fear, and depression would increase the number of retweets. Analyses on both datasets proved our assumptions wrong regarding fear, leading us to reject hypothesis H1b. For anger and depression, the correlations were either inconclusive (in the case of the geolocation dataset) or – in the case of the full dataset – very slightly positive, meaning that for the full data, hypotheses H1a and H1c are confirmed. Contempt was confirmed to be connected to retweeting, confirming hypothesis H1d. This allows us to conclude that analysing different emotions separately gives us better insight than treating all negative emotions as one feature.

One of the interesting questions arising from these unexpected results is why the positive relationship between elevated negative emotions and retweeting is not present in this case. It would seem reasonable to assume that when people are experiencing negative emotions, they also share them online, relate to other users' messages, and pass along what likeminded users have commented. On the other hand, if messages in the affected area were lower in emotion intensity and were shared more, it might suggest that retweeting is associated to passing on situational information and facts rather than engaging in conversations, making elevated negative emotions a distraction. Examples from the data illustrate that the informational value is relatively low in tweets with high levels of fear:

> *"Glued to the news. I honestly hope everyone I know in Boston is safe. This is absolutely horrific...."*
>
> *"Absolutely horrendous scenes in Boston! Dunno how people can be so evil! High alerts in London now Hope England not next crist! #Pray4Boston"*
>
> *"Watching this Boston explosions coverage. So fucking scary. Hope nothing happens at the London marathon"*
>
> Tweets containing high levels of contempt are also typically expressions of personal feelings:
>
> *".@NateBell4AR Using the tragedy in Boston to deliver tasteless commentary on guns is horrible and very cruel to the victims. Shame on you!"*
>
> *"Our first thoughts (are) with the victims... This was a heinous and cowardly act. FBI investigating as "act of terrorism" - Obama #Boston"*
>
> *"Please pray for the people of Boston, we MUST protect our homeland, and FIND THOSE GUILTY!!!! Terror will NOT stand!"*

Conveying and obtaining factual information is a known motivational factor for people using social media in a crisis context; after 9/11 people attempted to reduce feelings of uncertainty by seeking information through various media (Boyle et al., 2004). If there is an increased interest in obtaining information, it could lead to increased information sharing behaviour, which might contribute to explaining why the results of this study differ from what has been reported previously. It would be interesting to establish whether increased information seeking and sharing is a general property of the unexpected conversation type, characterized by spiking rapidly after a real-world event, containing negative emotions, and quieting down quickly afterwards (Ferrara and Yang, 2015).

Geolocation has quite a strong impact on retweet rates; Boston and Massachusetts get way more retweets in spite of their on average lower emotion levels, and US gets more retweets than posts originating elsewhere. It could be that retweeting messages from users close to the location of the bombings is motivated by an urge to share and obtain timely information on events, casualties, and the possible arrest of the bomber. Tweeters close to the events may be considered to have more important things to say than people farther away. It is also noteworthy that the people most affected by the bombing are the ones exhibiting the least extreme levels of emotion, which is surprising considering that they should be experiencing emotion levels higher than those with more distance. This means we cannot draw a direct parallel between the intensity of emotion an individual's experiences and the degree of emotion in their online communication. Perhaps the strongest emotional reactions remain outside of social media but manifest in offline personal communications, or perhaps proximity to a crisis event means there is less time or opportunity to focus on one's own emotions soon after the event.

The area specific differences suggest that when researching online user behaviour, there is a benefit in considering a smaller dataset in order to include more detailed information of user behaviour based on location, especially when dealing with a real-life event where proximity to the event location may have a large influence on people's emotions, behaviour and interests.

Positive emotions provide the biggest source of surprise in the findings of this study. The results for the two data sets differed from each other rather essentially: with only the geotagged data included, positive emotions were associated with a decrease in the retweet rates against our hypothesis H1e, while in the full dataset positive emotions meant more retweets, which is in favour of H1e. This could mean that there is some degree of self-selection bias among the Twitter users who choose to disclose their location. Are the location disclosers somehow different from other users? Are their average followers expecting specific types of tweets? Is there a reason for their positive tweets to be considered less important to retweet on average? It could be that disclosing location is a tendency specific to certain areas more strongly than others, which could mean there is a specific cultural emphasis in the geotagged data compared to the full dataset.

In order to examine the relationship between positive emotion and retweeting more closely, perhaps further research should be conducted on a dataset richer in positive expression. Due to the topic in the dataset, even the tweets scoring high on positivity are typically lined with worry:

> *"Sending love to the victims of the Boston Marathon bombing"*
>
> *"Showing respect for my daddy's hometown. Thoughts and prayers go out to everyone in Boston."*
>
> *"Hope everyone in Boston is all good and safe now."*

This is, in part, a limitation of the lexical sentiment analysis tools used in this study; as long as positive words, such as love or respect are detected, the sentence gets a higher positive score regardless of the larger topical context.

These questions may have implications for researchers with respect to choosing between the completeness of a dataset versus narrowing it down in order to be able to include potentially relevant factors such as geolocation. This means scholars should be mindful of how to choose their data based on what compromises they are willing to make, and what their primary interest is.

Conclusions, Limitations, and Future Work

Previous work unanimously states that emotions play an important role in what we say and share online, and our study extends the understanding of how by examining the emotional content of retweets in the wake of a terrorist attack, focusing on five categories of emotions: positive emotions, anger, fear, depression, and contempt.

We found that different emotions are associated with behaviour in different ways; elevated levels of fear and contempt in a tweet make it less likely to be retweeted, while other negative emotions have a small positive correlation. When focusing the analysis only on tweets of users who disclose geolocation information, positive emotions in the tweet are associated with a decrease in the retweet rates, but when examined on a larger level, the effect is opposite – positive messages get more retweets. Considering geolocation data in analysing social media content has the potential to provide interesting additional insight, but there is a chance it may mean compromising some of the generalizability of the results. We also found that tweets originating in the affected area of a terror attack are clearly more retweeted than tweets from farther away.

Our theoretical contributions are adding to the understanding of the role of emotions in online information sharing in the context of a terror attack, and discovering that proximity to the location of a terror attack influences online behaviour both on the part of the person providing information online and the people assessing the relevance of said information. Findings from previous research may not generalise well in all contexts, and it seems like sometimes a neutral message carries farther than an emotional one.

Our findings also have more practical implications. Including geolocation information in social media analysis is potentially useful, but as narrowing down the dataset may impact the results, we recommend exploring and comparing the datasets in order to be able to make an informed decision while aware of the trade-offs.

Better understanding of what types of conversations unfold online in the wake of crises allows for more efficient filtering and searching real-time social media streams, which is helpful from a crisis management point of view. Considering that the tweets from the Boston and Massachusetts area were low on emotion and highly retweeted, it might be a feasible approach to access timely local information by filtering out high emotion messages which may be less likely to be passed on as useful by others, and more likely to be written by someone far from the location.

The results from the geotagged dataset should be interpreted carefully, keeping in mind that it is a 2% subset of the complete data. The dataset could be biased due to user self-selection in disclosing location, as it is voluntary, and it is likely that specific types of users go through that explicit effort.

The geographic categories in this study are used for examining the relationship between Twitter users' geographic proximity to a terror attack and their emotional expression. In particular the category "abroad" covers a heterogenous group of users around the world and it is fairly likely to contain a wide range of cultural diversity which may have an essential impact on emotional self-expression online. We decided that accounting for that falls outside of the scope of this study, but it would be interesting to look into in the future on a more fine-grained level.

The results of this study, as usual, raise further questions relevant for future research. The motivations for using social media vary depending on the context, and several types of motivations are likely to exist in any given context. Different motivations lead to different information sharing behaviour, and being able to account for more than one of them at a time when analysing online discussions would enable a deeper understanding of them. Potential future avenues of research could include investigating the levels of different emotions over time, and looking more closely into dominant topics of discussion in order to better understand the collective online dynamics that follow a traumatic event.

References

Berger, J. (2011) 'Arousal Increases Social Transmission of Information', *Psychological Science* 22(7): 891–893.

Berger, J. and K.L. Milkman (2012) 'What Makes Online Content Viral?', *Journal of Marketing Research* 49(2): 192–205.

Boyle, M.P., M. Schmierbach, C.L. Armstrong, D.M. McLeod, D.V. Shah, and Z. Pan (2004) 'Information Seeking and Emotional Reactions to the September 11 Terrorist Attacks', *Journalism & Mass Communication Quarterly* 81(1): 155–67.

Burnap, P. et al. (2014) 'Tweeting the Terror: Modelling the Social Media Reaction to the Woolwich Terrorist Attack', *Social Network Analysis and Mining* 4(1): 206.

Chen, K., P. Luo, and H. Wang (2017) 'An Influence Framework on Product Word-of-Mouth (WoM) Measurement', *Information & Management* 54(2): 228–240.

Dickinger, A., M. Arami, and D. Meyer (2008) 'The Role of Perceived Enjoyment and Social Norm in the Adoption of Technology with Network Externalities', *European Journal of Information Systems* 17(1): 4–11.

Eismann, K., O. Posegga, and K. Fischbach (2016) 'Collective Behaviour, Social Media, and Disasters: A Systematic Literature Review', *ECIS*.

Ekkekakis, P. (2013) *The Measurement of Affect, Mood, and Emotion: A Guide for Health-Behavioral Research*. Cambridge University Press.

Ekman, P. (1992) ‘An Argument for Basic Emotions’, *Cognition & Emotion* 6(3–4): 169–200.

Ellison, N.B., C. Steinfield, and C. Lampe (2007) ‘The Benefits of Facebook “Friends:” Social Capital and College Students’ Use of Online Social Network Sites’, *Journal of Computer-Mediated Communication* 12(4): 1143–1168.

Ferrara, E. and Z. Yang (2015) ‘Quantifying the Effect of Sentiment on Information Diffusion in Social Media’, *PeerJ Computer Science* 1: e26.

Fischer, D., K. Eismann, and K. Fischbach (2016) ‘Usage Behavior of Social Network Sites in the Aftermath of Terrorist Attacks’.

Fowler, J.H. and N.A. Christakis (2008) ‘Dynamic Spread of Happiness in a Large Social Network: Longitudinal Analysis over 20 Years in the Framingham Heart Study’, *Bmj* 337: a2338.

Fredrickson, B.L. (1998) ‘What Good Are Positive Emotions?’, *Review of General Psychology* 2(3): 300–319.

Gruzd, A. (2013) ‘Emotions in the Twitterverse and Implications for User Interface Design’, *AIS Transactions on Human-Computer Interaction* 5(1): 42–56.

Gruzd, A., S. Doiron, and P. Mai (2011) ‘Is Happiness Contagious Online? A Case of Twitter and the 2010 Winter Olympics’, *System Sciences (HICSS), 2011 44th Hawaii International Conference On*. IEEE.

Hancock, J.T., K. Gee, K. Ciaccio, and J.M.-H. Lin (2008) ‘I’m Sad You’re Sad: Emotional Contagion in CMC’, *Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work*. ACM.

Hansen, L.K., A. Arvidsson, F. \AArup Nielsen, E. Colleoni, and M. Etter (2011) ‘Good Friends, Bad News-Affect and Virality in Twitter’, *Future Information Technology*, pp. 34–43. Springer.

Huang, C.-M., E. Chan, and A.A. Hyder (2010) ‘Web 20 and Internet Social Networking: A New Tool for Disaster Management?-Lessons from Taiwan’, *BMC Medical Informatics and Decision Making* 10(1): 57.

Hughes, A.L., L. Palen, J. Sutton, S.B. Liu, and S. Vieweg (2008) ‘Site-Seeing in Disaster: An Examination of on-Line Social Convergence’, *Proceedings of the 5th International ISCRAM Conference*. Citeseer.

Hyvärinen, H. and R. Beck (2018) ‘Emotions Trump Facts: The Role of Emotions in on Social Media: A Literature Review’, *Proceedings of the 51st Hawaii International Conference on System Sciences*.

Kaufmann, M. (2015) ‘Resilience 20: Social Media Use and (Self-) Care during the 2011 Norway Attacks’, *Media, Culture & Society* 37(7): 972–987.

Kim, K., O. Park, S. Yun, and H. Yun (2017) 'What Makes Tourists Feel Negatively about Tourism Destinations? Application of Hybrid Text Mining Methodology to Smart Destination Management', *Technological Forecasting and Social Change* 123: 362–369.

Kramer, A.D., J.E. Guillory, and J.T. Hancock (2014) 'Experimental Evidence of Massive-Scale Emotional Contagion through Social Networks', *Proceedings of the National Academy of Sciences*: 201320040.

Kwon, K.H. and A. Gruzd (2017) 'Is Aggression Contagious Online? A Case of Swearing on Donald Trump's Campaign Videos on Youtube'.

Lerner, J.S., R.M. Gonzalez, D.A. Small, and B. Fischhoff (2003) 'Effects of Fear and Anger on Perceived Risks of Terrorism: A National Field Experiment', *Psychological Science* 14(2): 144–150.

Lin, K.-Y. and H.-P. Lu (2011) 'Why People Use Social Networking Sites: An Empirical Study Integrating Network Externalities and Motivation Theory', *Computers in Human Behavior* 27(3): 1152–1161.

Liu, Y., C. Kliman-Silver, and A. Mislove (2014) 'The Tweets They Are A-Changin: Evolution of Twitter Users and Behavior', *ICWSM* 30: 5–314.

Mazer, J.P., B. Thompson, J. Cherry, M. Russell, H.J. Payne, E.G. Kirby, and W. Pfohl (2015) 'Communication in the Face of a School Crisis: Examining the Volume and Content of Social Media Mentions during Active Shooter Incidents', *Computers in Human Behavior* 53: 238–248.

Morrison, J.L., Sandra, and H. Berry (2001) *A National Survey of Stress Reactions After the September 11, 2001, Terrorist Attacks*.

Mukkamala, A. and R. Beck (2016) 'Enhancing Disaster Management through Social Media Analytics to Develop Situation Awareness What Can Be Learned from Twitter Messages about Hurricane Sandy?', *PACIS*.

Neubaum, G., L. Rösner, A.M. Rosenthal-von der Pütten, and N.C. Krämer (2014) 'Psychosocial Functions of Social Media Usage in a Disaster Situation: A Multi-Methodological Approach', *Computers in Human Behavior* 34: 28–38.

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

Pang, B. and L. Lee (2008) 'Opinion Mining and Sentiment Analysis', *Foundations and Trends® in Information Retrieval* 2(1–2): 1–135.

Pfeffer, J., T. Zorbach, and K.M. Carley (2014) 'Understanding Online Firestorms: Negative Word-of-Mouth Dynamics in Social Media Networks', *Journal of Marketing Communications* 20(1–2): 117–128.

Relling, M., O. Schnittka, H. Sattler, and M. Johnen (2016) 'Each Can Help or Hurt: Negative and Positive Word of Mouth in Social Network Brand Communities', *International Journal of Research in Marketing* 33(1): 42–58.

Rimé, B. (2009) 'Emotion Elicits the Social Sharing of Emotion: Theory and Empirical Review', *Emotion Review* 1(1): 60–85.

Risius, M. and F. Akolk (2015) 'Differentiated Sentiment Analysis of Corporate Social Media Accounts', *AMCIS*.

Risius, M., F. Akolk, and R. Beck (2015) 'Differential Emotions and the Stock Market-The Case of Company-Specific Trading', *ECIS*.

Risius, M. and R. Beck (2015) 'Effectiveness of Corporate Social Media Activities in Increasing Relational Outcomes', *Information & Management* 52(7): 824–839.

Russell, J.A. (2003) 'Core Affect and the Psychological Construction of Emotion', *Psychological Review* 110(1): 145.

Schumaker, R.P., A.T. Jarmoszko, and C.S. Labedz Jr (2016) 'Predicting Wins and Spread in the Premier League Using a Sentiment Analysis of Twitter', *Decision Support Systems* 88: 76–84.

Smith, T.W., K.A. Rasinski, and M. Toce (2001) 'America Rebounds: A National Study of Public Response to the September 11th Terrorist Attacks', *Chicago, IL: National Opinion Research Center at the University of Chicago*.

Stieglitz, S. and L. Dang-Xuan (2013) 'Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior', *Journal of Management Information Systems* 29(4): 217–248.

Thelwall, M., K. Buckley, G. Paltoglou, D. Cai, and A. Kappas (2010) 'Sentiment Strength Detection in Short Informal Text', *Journal of the American Society for Information Science and Technology* 61(12): 2544–2558.

11 Paper 3

How Emotions Unfold in Online Discussions After a Terror Attack

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Abstract

In the wake of a terror attack, social media is used for sharing thoughts and emotions, accessing and distributing information, and memorializing victims. Emotions are a big part of this, but there is a gap in our understanding on how those emotions evolve and what kinds of social media uses they are related to. Accounting for regional differences, we charted out what types of conversations unfolded online after the Boston Marathon Bombing and what kinds of emotions were associated with them, and present a process model covering the general trends of such conversations. Although the phases apply to reactions to terror attacks on a general level, there are proximity-based differences to the location of the terror attack: people in the affected area express more positive emotions and are more concerned about practical matters and safety than people farther away, who express more negative emotions and discuss more opinions.

Introduction

Social media has become an important means of relaying real time information in different types of crisis situations, often surpassing the more traditional media in the speed of providing the latest news (Eismann et al. 2016; Huang et al. 2015). However, information sharing is not the only motivation for social media use during and after crises – memorializing victims and sending well-wishes to the affected, confirming the well-being of loved ones, coordinating relief efforts, and expressing thoughts and emotions related to the crisis event are commonplace as well (Huang et al. 2010; Kaufmann 2015; Neubaum et al. 2014; Takahashi et al. 2015).

Expressions of emotions in the wake of a disaster are not merely a process of venting, they serve a purpose. Talking about personal traumas is linked to better physical and psychological health in the months and years following the trauma (Pennebaker and Harber 1993). In addition, collective emotions are associated with higher solidarity, improving the resilience of the affected community (Garcia and Rimé 2019). It is therefore no surprise that emotions are found to be contagious, online environments being no exception to this (Fowler and Christakis 2008; Hancock et al. 2008; Kramer et al. 2014; Kwon and Gruzd 2017). Emotions also play a role in how people share information online (Gruzd 2013; Hansen et al. 2011; Oh et al. 2013; Stieglitz and Dang-Xuan 2013), some emotions more strongly than others (Berger 2011; Berger and Milkman 2012). We decided to focus on terror attacks in particular because they are often temporally clearly defined (as opposed to an ongoing situation of undefined length such as natural disasters or wars) to ensure a clear view on how emotional processes develop as a result of a crisis event as opposed to an ongoing sequence of related events.

Given the contagiousness of emotions, and their relevance regarding a community's well-being through developing resilience, better understanding of collective emotional processes could not only improve our understanding of how emotions act as indicators of a community's ability to cope with the incident, but could also point us towards ways of improving coping in situations where it is most direly needed. In spite of steadily improving understanding on emotional reactions to crisis events, we still lack a nuanced view on how different emotions develop as people are processing the crisis, and what kinds of topics and concerns are related to those emotions. We therefore set out to answer the following research question:

RQ1: *How do emotions and topics of conversation manifest and change over time after a terror attack?*

How people use social media in the wake of a crisis varies by their proximity to the event. People close by focus more than others on relief coordination, while people farther away engage in greater levels of memorializing (thoughts and prayers, condolences) (Takahashi et al. 2015). People in the directly affected area are in a key position to provide situational information contributing to the collective awareness and support, whereas people far away are in a more passive spectator position (Mukkamala and Beck 2018). It is possible the differences in actions enabled by proximity affect the emotions experienced throughout the post-crisis discussion, which is why we ask an additional question:

RQ2: *How proximity specific are the emotional and topical developments?*

This study uses Twitter data related to the Boston Marathon Bombing in April 2013. The bombing was widely discussed both locally and internationally, most of the conversation being in English, enabling the comparison of local and global phenomena.

The main events following the bombing are listed in Table 1 to provide an overview as context for the online conversations discussed in this paper. Approximately 4 hours after the start of the marathon, two bombs went off near the finish line, killing three people and injuring hundreds of people. Three days later, the police published surveillance footage of the suspects based on witness accounts. At that point the identity of the suspects was not yet known. Five hours after the footage was released, the suspects shot an MIT police officer, the assumed motive being seizing his gun. Half an hour later, the suspects seized a car and took the car's owner as hostage. When they pulled over to fill the tank, the hostage managed to escape to another nearby gas station to call 911. He had left his cell phone in the car, allowing the police to track down the suspects. At 12:53 a.m. on the night of the 19^{th} of April, the police identified the suspects, and a gun fight ensued. One of the suspects got injured and was being wrestled down by the police, when the second suspect drove a car at the police and the injured suspect, and managed to escape. The injured suspect died about an hour later in a hospital, and his fingerprints helped identify the suspects as Tamerlan and Dzhokhar Tsarnaev. At 7 a.m., the police released the picture and name of the surviving suspect, Dzhokhar, commenced a door-to-door search in the Watertown area, and ordered residents to stay indoors. About 12 hours later, when the shelter in place order had been briefly lifted, a Watertown resident went into their yard to check on their boat, and found a man in it. By 8:30 p.m. the police had surrounded the boat, and 15 minutes later the suspect surrendered. (FBI archives 2013; O'Neill 2015; Wikipedia n.d.).

This work contributes to existing knowledge by increasing the understanding of emotional and topical developments and phases in online discussion following a terror attack, and by developing a process model for phases in post-terror conversations. The theoretical background for the phase model is outlined in the next section. Following that, we describe the data used in this study and outline our methodology. We then report our findings and discuss them, after which we present our conclusions as well as suggestions for future research.

Table 1. The Timeline of Events		
15th April	2:49 p.m.	Two bombs go off near the finish line of the marathon
18th April	5:20 p.m.	Police publishes photos of the suspects (no names yet)
	10:25 p.m.	Suspects shoot an MIT police officer on campus
	11:00 p.m.	Suspects seize a car and take a hostage at gunpoint
19th April	12:15 a.m.	Hostage escapes and calls 911
	12:43 a.m.	A gunfight breaks out between the suspects and the police in Watertown
	12:50 a.m.	One of the suspects drives a car at the policemen and the other suspect, and escapes
	1:35 a.m.	The suspect apprehended at the scene is pronounced dead. His fingerprints lead to identifying both suspects.
	7 a.m.	Photo and name of the remaining suspect published. The police start a door-to-door search in Watertown, residents are ordered to "shelter in place"
	6-7 p.m.	Shelter in place order briefly lifted. A Watertown resident goes into his yard to check on his boat, and finds a man under the tarp.
	8:30 p.m.	The police have surrounded the boat the suspect is hiding in
	8:45 p.m.	The suspect surrenders

Table 1. The events following the Boston Marathon Bombing

Theoretical Background

The *social stage model of coping* (Pennebaker and Harber 1993) outlines three stages of coping in the context of a crisis event. The model was developed based on data on the Loma Prieta Earthquake, and further tested on data on the Gulf War. During the initial *emergency phase*, people both talk and think about the traumatic event frequently. Rumination is common, and is frequently accompanied by elevated anxiety, depression, and trouble sleeping. At this phase, talking about the event may help resolve some of the distress. The emergency phase is followed by an *inhibition phase*, where thoughts about the event are still recurrent, but conversation around the topic decreases significantly. People reported still feeling the need to share thoughts around the event, but being tired of being the receiver of others' emotions and thoughts, leading to a collective inhibition reaction. Suppressing post-traumatic thoughts was found to increase health issues an inter-personal conflict during the inhibition phase. In the final phase, *adaptation*, thoughts around the event become less recurrent, and the social and health indicators of people affected by the crisis will mostly have returned to normal levels.

This study focuses on the emergency phase of the coping model, where people affected by the crisis actively discuss their thoughts and emotions related to the event, and identifies distinct sub-phases based on topical and emotional shifts in the conversation. The reactions to a terror attack can be divided into immediate, *proximal*, reactions, and *distal* reactions that follow after the initial reaction phase (Pyszczynski et al. 1999; Yum and Schenck-Hamlin 2005). The predominant proximal reactions to an act of terror were found to be shock and disbelief (Yum and Schenck-Hamlin 2005). Emotional reactions were found common, as well as concerns for close ones and their safety. The *distal reaction* phase contains behaviors such as altruism, seeking value and meaning, information seeking and sharing, enforcing social connections, heightened patriotism or nationalism, and counter-bigotry advocacy (Yum and Schenck-Hamlin 2005). The proximal and distal reactions are responses to an increase in death-related thoughts, and are an attempt to control ensuing anxiety (Pyszczynski et al. 1999). Particularly in the proximal phase, we expect to see high levels of expression of emotions in online conversations – according to the theory of the social sharing of emotions, experiencing an emotion will create a need to share that emotion (Rimé 2009). In specific, we expect to find high levels of anxiety, anger, and sadness, as those are the emotions people report experiencing elevated levels of following an act of terror (Lerner et al. 2003; Morrison et al. 2001; Pennebaker and Harber 1993; Smith et al. 2001). The proximal and distal reactions and the emotions and topics related to them are outlined in detail in the Findings section phase by phase.

It is likely that not all of the conversations around the thoughts and emotions elicited by a terror attack are expressed online. However, better understanding the dynamics in online conversations can offer valuable information on the emotional atmosphere in the community processing the crisis.

Methods and Data

Data

The data set used in this study consists of tweets related to the Boston Marathon Bombing, collected during and after the event 15th–23rd of April 2013. We focused exclusively on tweets containing geolocation information in order to be able to analyze geographically specific phenomena. After pre-processing and filtering out out-of-scope (e.g. non-English and off-topic) tweets, the data set consists of 89 688 tweets. Using the coordinates in the tweet metadata, we divided the data into three region categories; Massachusetts including Boston (7 910 tweets), the United States, excluding Massachusetts (57 783 tweets), and outside of the US (23 995 tweets), see Table 2 for details.

Table 2. Dataset Size

	Massachusetts	The US	Abroad
15th April	1930	23123	11102
16th April	1121	9647	5380
17th April	591	3083	1034
18th April	301	2484	706
19th April	1717	9935	2721
20th April	1183	6638	1900
21st April	268	941	554
22nd April	327	1191	383
23rd April	176	741	215
In total:	7910	57783	23995

Table 2. The number of tweets in each region category for each day in the dataset

Sentiment Analysis

Because we wanted to analyze the sentiment in the data set in more detail than polarity only, we chose to use LIWC2015 (Linguistic Inquiry and Word Count) (Pennebaker et al. 2015). In addition to positive and negative sentiment, it provides analysis of the three negative emotions that are frequently mentioned in research on terror events: anger, anxiety, and sadness. This allows for a deeper understanding on the emotional processes that develop over time. Each tweet in the dataset was given a rating of the presence of positive sentiment, anger, anxiety, and sadness. For examples of tweets containing high levels of emotions, see Table 3, and for the varying intensity of each emotion over time, see Figure 1.

Topic Modeling

Topic modeling is a way of clustering data entries into topical categories using machine learning approaches like Latent Dirichlet Allocation, LDA (Debortoli et al. 2016). This study uses MineMyText (http://www.minemytext.com/) for LDA-based topic modeling. Although topic modeling is a good way of getting an overview of the topics in the data, there are some steps in the process that are up to the user to take care of. Topic modeling does not utilize predefined categories nor does it label the clusters it creates; the task of making sense of the clusters is left for the researcher. The user also decides the number of topic clusters, and the suitable number of topics is found through iteratively testing numbers and manually inspecting the clusters. After testing numbers in the range of 20-90, increasing by ten at each iteration, we settled on 70 categories. Fewer than that would have yielded categories where several topics were clearly conflated into the same cluster, whereas more than that would have led to several near identical categories.

The topics were given labels based on manually inspecting the top 50 tweets and most frequent words for each topic. The appropriateness of the labels was verified by a second person, who labeled 33% (21 out of 70) of the topics. The labels differed in two cases, which led to slight alterations in the topic labels. Clustering the topics into higher level categories was done by two people independently of each other. The coders agreed on 66 out of 70 topics, and the remaining four edge cases were assigned categories through discussing and reasoning together. The resulting topical categories are listed in Table 4.

Table 3. Examples of Emotions in the Dataset	
Positive	*“love you Boston hope everyone's safe”* *“Thank you FBI. Thank you Boston Police. Thank you first responders. #heroes”*
Anxiety	*“Terrorist attacks on Boston??? #scare”* *“Boston bombing :"(horrible”*
Anger	*"Fucking shocking scenes in Boston fucking terrorist bastards"* *"Boston kill that asshole so we can all rage safely tomorrow @cosmic_revenge"*
Sadness	*"Pray for Boston #tragic #sad"* *"So sad and heartbreaking #Boston #bostonmarathon"*

Table 3. Examples of positive emotion, anxiety, anger, and sadness in the tweets analyzed

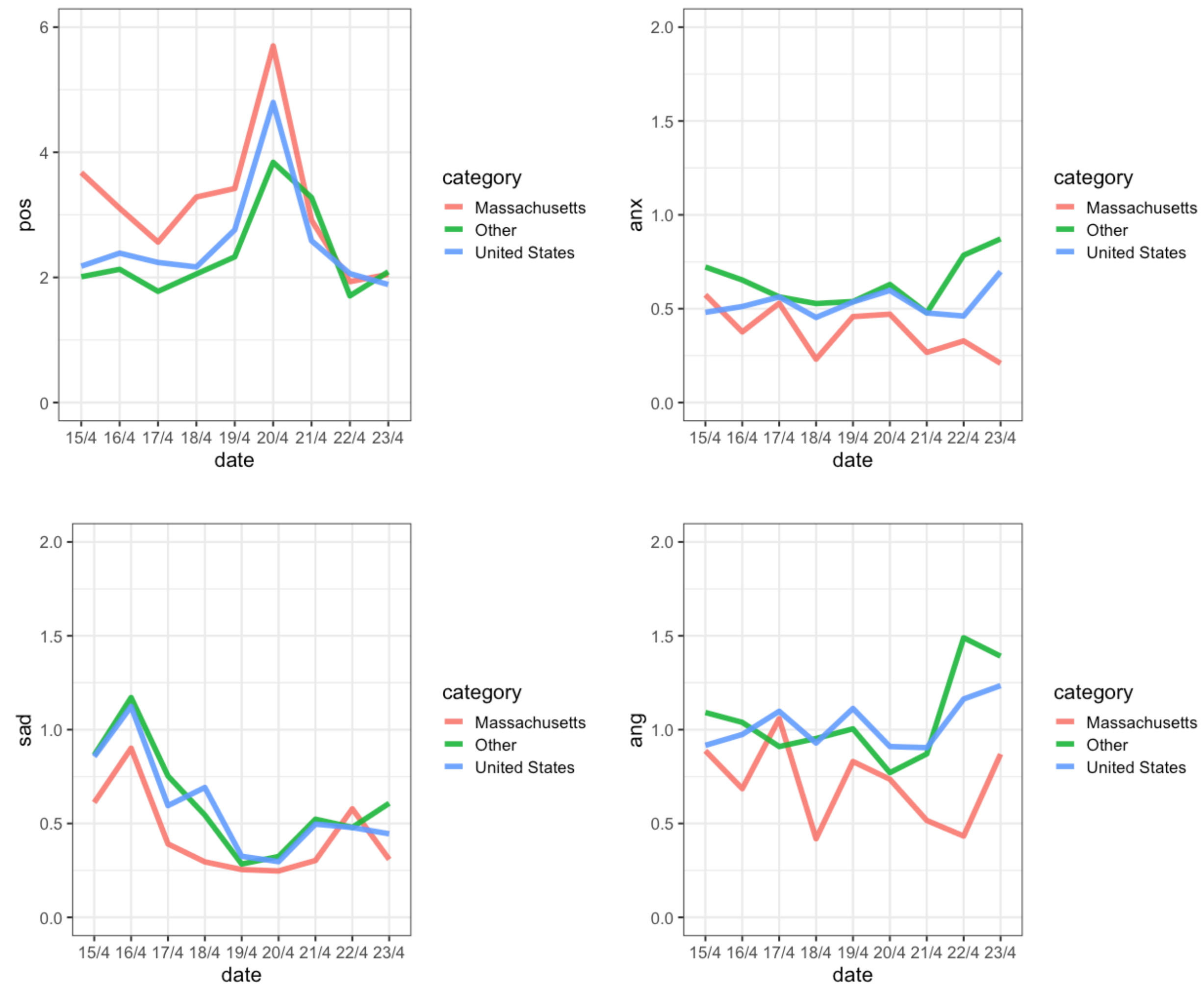

Figure 1. The levels of positive emotion, sadness, anxiety, and anger in tweets from each geographic region during the week after the terror event.

Table 4. Topic Categories		
	Examples of topics	Example tweets in topic category
Shock and upset (10 topics)	Shock and disbelief, Shocked at the news, Upset at bomber, Footage and initial reactions	*Who the hell thinks it was funny to put bomb @ the Boston marathon ! Like wtf is wrong with people .. People piss me off. #prayforboston*
Memorializing (8 topics)	Thoughts and prayers, Casualties, Prayers and God	*Thoughts and prayers going out to the families and victims of the bombings at the Boston marathon #bostonmarathon #explosion #atrocious #usa*
Safety (5 topics)	Safety concerns (be safe), Relief x is safe, Safety and practical in Boston	*I can breathe a sigh of relief: Friends and Family are safe. Hope and Best wishes for all who have Friends and Family in #Boston too.*
Support gestures (11 topics)	Gratitude at police, Runners' support gestures, Love and support to Boston	*So proud of the amazing men and women of the Boston Police Department!!! My respect for them is incredible! #BOSTONSTRONG #BostonPolice*
Comments on politics and terrorism (5 topics)	Political comments and Islam, Comments on Terrorism, Conspiracy speculations	*Fox News' guy said "we should kill all Muslims" that's like 1,600,000,000 people in the world in response to the Boston bombing, ok mate. :*
Comparison to other events (2 topics)	Comparison to elsewhere, Crazy world	*15 people die on a car bombing in Iraq and nobody gives a fuck, at the same time 2 people die in Boston and the world goes crazy...smh*
Media and reliability (5 topics)	Commenting on footage, Doubts on reliability of news	*@jilevin: CNN, the AP, and Fox News Get Boston Marathon Bombing Arrest Story Wrong http://t.co/tfTDToQcKM What happened to real reporting?*
Miscellaneous comments (6 topics)	Miscellaneous personal views and feelings, Justice, Anger at other people	*People moaning about tweets about the bombings in Boston. We are aware it won't change anything, show a little respect and consideration.*
Sharing news (7 topics)	Initial reports, Suspects and their family, Sharing witness accounts	*2 bombs blew up at the end of the Boston marathon a few minutes ago. A lot of people injured. God I hope everyone will be alright!*
Updates on suspect chase (5 topics)	Police action during Watertown manhunt, MIT shootout, Casualties during suspect chase	*State Police, MIT Police, Watertown Police, #BPD, Boston University Police among agencies at the scene in #Watertown. Comm. a struggle.*
Suspect caught (2 topics)	Suspect in custody: police announcement, Suspect in custody news	*Suspect mit shooting and boston marathon bombing in custody. Its over. Cnn live boston police tweet confirmation*
Communication from authorities (4 topics)	Reports related to security, Following police updates, Notifications and instructions from the police	*FBI releases new images showing full faces of 2 #BostonMarathon bomb suspects http://t.co/k5Xpk47moT & PICTURE http://t.co/FBSyhxXLKL*

Table 4. The topic categories for the topics found in the data, example topics, and example tweets from the topic category in question

Some topics are clearly more emotional than others; for instance, sharing news articles is often fairly neutral, whereas the different types of shock or condolence themed categories contain high average levels of negative emotions. Certain topics are continuously present in the discussion throughout the week, while others are transient, and specific to either a phase in the emotional aftermath or a concrete event.

The topic categories *comments on politics and terrorism, comparison to other events, media and reliability,* and *miscellaneous comments* mostly contain people expressing their opinions, and commenting and interpreting information related to the terror attack. For the analysis in the following section, these topical categories are collectively referred to as *opinions and comments*. The four categories referred to in the analysis as *information sharing* are *sharing news, updates on suspect chase, suspect caught,* and *communication from authorities*.

Findings

The Phases of Online Conversation Following an Act of Terror

This section reports the insight we gained from the literature and the data on how emotions and topics evolve in online conversations in the aftermath of a terror attack. We discuss both general and regionally specific phenomena. We identify five phases for the post-terror attack conversation: *shock, making sense, subsequent event, closure,* and *aftermath*. For each phase, we outline the relevant findings from previous research regarding emotional and behavioral processes, after which we report whether and how those findings are confirmed by our data. Figure x gives an overview of the process and its phases, and the changes in topics and emotions for each region.

Shock

The first, *proximal* reactions to a terror attack include shock, disbelief, elevated emotions, and safety concerns (Yum and Schenck-Hamlin 2005). The emotions reported frequently as a consequence of a terror event are most commonly anxiety, anger, and sadness (Lerner et al. 2003; Morrison et al. 2001; Pennebaker and Harber 1993; Smith et al. 2001). Sharing and obtaining information is also a common way of reacting, and the primary motivation for using social media in a crisis situation (Eismann et al. 2016). Another typical way of reacting to a disaster event, whether man-made or a natural disaster or accident, is to come together to memorialize the victims and pass condolences to their close ones – a behavior that in particular people farther away from the event site engage in as a way of participating (Hughes et al. 2008; Takahashi et al. 2015).

Following the Boston Marathon Bombing, the shock phase seemed to take around 1-2 days, with the peak number of social media messages within 24 hours of the event. The predominant topics regardless of location were expressing shock and upset, sharing information of the terror attack, and memorializing –condolences to the casualties and their families (see Table 5). Within the nation, and in particular in the affected area, safety related topics (being concerned of or relieved for close ones' safety) were also prominent. Abroad, the most prominent topic after shock, information sharing, and memorializing was opinions and comments related to the event and terrorism in general.

Based on previous findings, we initially assumed that people close to the affected area would express more and stronger negative emotions associated with the event (Morrison et al. 2001). However, the opposite was found – people in the Boston and Massachusetts area exhibited higher averages of positive and lower averages of negative emotions in their online communication than people farther away.

Social media users abroad started out with a fairly high baseline of anxiety and anger, whereas those emotions seemed to develop more slowly for the users within the affected region and nation. Sadness levels were at their highest everywhere one day after the terror attack, after which the expression of sadness rapidly decreased.

Table 5. Shock Phase		
Massachusetts	*US*	*Abroad*
Memorializing	Memorializing	Memorializing
Information sharing: Sharing news	Shock and upset	Shock and upset
Shock and upset	Information sharing: Sharing news	Information sharing: Sharing news

Table 5. The most prevalent topic categories during the shock phase for each region

Making Sense

After the initial shock reaction to a terror attack, people enter the *distal reaction* phase, characterized by behaviors such as altruism, seeking value and meaning, information seeking and sharing, enforcing social connections, heightened patriotism or nationalism, and counter-bigotry advocacy (Yum and Schenck-Hamlin 2005). People affected by the crisis attempt to process their feelings, make sense of what has happened, and rationalize about it in an attempt to reconstruct a sense of normality (Kaufmann 2015). They will often try to find answers to questions such as why the event occurred, who is responsible, and how to prevent it from occurring again (Houston et al. 2015). This sensemaking process is often challenging due to incomplete information, which often leads to the spread of misinformation (Huang et al. 2015). Based on the previous findings, we expected to see information sharing, expressions of opinions with heightened emotion, speculation on the identity of the perpetrator(s), and false news in the messages following the bombing. On the other hand, we also expected to see some part of the users expressing altruism and positive sentiments such as gratitude, love, and support, as is typical for people with high resilience in the aftermath of crises (Fredrickson et al. 2003). What we did not expect was how region specific the aforementioned behaviors were in the sense making phase.

After the shock had settled, sadness levels started to decrease and social media users started trying to make sense of what had happened. Many shared information, sometimes more avidly than is productive; at this point false news started circulating to the extent where they made the list of top ten most discussed topics. The users expressed malcontent with traditional media being too slow to report new information, and rumors started spreading. Several innocent people were painted as the bomber based on online information while the real culprits were not identified until later on.

Discussions about politics, terrorism, and religion started to emerge, as well as comparisons of the bombing to recent bombings in Iraq by the US forces (see Table 6 for top topics in the making sense phase). Some of the topics in this category were laced with negative emotions, anger in particular. This fits the urge to defend one's world view and seek for values and meaning described in previous research. One of the political commentary topics also contained several counter-bigotry advocacy themed tweets

Table 6. Making Sense Phase		
Massachusetts	*US*	*Abroad*
Support gestures	Opinions and comments: political comments and Islam, comments on news, comparison to other events	Opinions and comments: political comments and Islam, comments on news, comparison to other events
Information sharing: sharing news and communication from authorities	Information sharing: sharing news and communication from authorities	Information sharing: sharing news and communication from authorities
Opinions and comments: political comments and Islam, comments on news	Memorializing	Memorializing

Table 6. The most prevalent topic categories during the making sense phase for each region

reminding people to not jump to conclusions or prematurely accuse a religious or ethnic group.

In the Massachusetts area, the sense making phase was where collective and supportive topics started dominating the conversation, such as gratitude towards authorities and about loved ones being safe, different types of concrete and verbal support gestures towards Boston, the trending of the hashtag #bostonstrong as one of the many examples. Positive emotions were increasingly present in their messages. It seems like the directly affected area quickly started building collective support and resilience, while people farther away expressed more anxious and angry opinions. Anger and anxiety were also present in the messages from the affected area, initially increasing but shortly thereafter decreasing rapidly.

Outside of the affected area, both within the nation and abroad, most tweets were comments and opinions on the events or news. Information sharing – whether factual or not – as well as memorializing were also frequent, and the levels of anger and anxiety remained high.

Subsequent Event Leading to Closure

The fundamental aim and effect of terrorism is to cause fear and uncertainty. The threat of terror creates a sense of psychological insecurity that leads to a need for closure (Orehek et al. 2010). A high need for closure increases group-centrist behavior such as pressure towards opinion uniformity, endorsement of autocratic leadership, ingroup favoritism, conservatism, and perpetuation of group norms (Kruglanski et al. 2006). The anger and fear in some of the more political topics during the sense making phase could be outcomes of such a need for closure. It is possible that events leading to concrete closure regarding a terror attack, such as apprehending the terrorist, provide people with a sense of closure that allows them to let go of the anxiety stemming from uncertainty and a sense of threat, and start distancing themselves from the traumatic event, which would manifest as a reduced need to talk about the event and the emotions that it provoked. It could also help increase positive emotions that help foster resilience that helps people recover from the psychological trauma (Fredrickson et al. 2003).

The chase after the bombers formed a secondary event in the timeline following the terror attack, which can be seen as a sharp increase in the tweet volume. A little past midnight on the 19th of April, the authorities got on the trail of the Tsarnaev brothers, commencing a 21 hour long suspect chase followed closely by the online community. Information circulated on Twitter faster than news agencies could keep up with, and many tweeted live updates heard on the Boston area police scanner. The local levels of anxiety and anger increased, as safety concerns related to the manhunt worried people. However, by far the most discussed topics regardless of location were predominantly related to sharing timely information regarding the suspect chase (see Table 7). Gratitude towards authorities was also expressed in all regions. Outside of Massachusetts, opinions and comments were frequent.

Once the suspect was finally apprehended, there was a strong surge of positivity in the online conversation, including strong gratitude towards the police, decreasing in intensity with distance to Boston (see Table 8). In the Massachusetts area, sharing the news quickly gave way for a strong collective supportive sentiment. Farther away, the information sharing lasted slightly longer, perhaps partly due to information propagation taking some time, as well as the time differences between continents in the case of users outside of the

US. After the information regarding the suspect chase had spread, the conversation turned back to expressing opinions and commenting on news articles and events. The increase in anxiety in the US and abroad during the closure phase is curious. It could be a delayed reaction to the manhunt, or people returning to thoughts of overall anxiety about terrorism once the excitement is over.

Aftermath

Finding answers to the questions of who and why, as well as apprehending the person responsible for the act of terror likely served to give people a concrete sense of closure.

Table 7. Subsequent Event Phase		
Massachusetts	*US*	*Abroad*
Information sharing: updates on suspect chase	Information sharing: updates on suspect chase and communication from authorities	Information sharing: several topics
Safety	Opinions and comments: comments on news	Opinions and comments: comments on news
Support gestures: gratitude at police	Support gestures: gratitude at police	Support gestures: gratitude at police

Table 7. The most prevalent topic categories during the subsequent event phase for each region

Table 8. Closure Phase		
Massachusetts	*US*	*Abroad*
Support gestures	Information sharing: suspect in custody and updates on suspect chase	Information sharing: several topics
Information sharing: suspect in custody and updates on suspect chase	Support gestures	Opinions and comments: comments on news
Opinions and comments: comments on news	Opinions and comments: comments on news	Support gestures: gratitude at police

Table 8. The most prevalent topic categories during the closure phase for each region

Getting closure enables people exposed to a crisis situation to move beyond the trauma and get on with their lives (Skitka et al. 2004). It is also possible that since the terror attack was a transient event with a human causing it, the emergency phase of the social stages of coping is passed through more quickly than in the case of an earthquake (with extensive practical consequences) or war situation (which lasts longer than a single day event), and the community transitions into the inhibition phase sooner than the two weeks predicted by the model.

After the reactions to the news of the suspect being caught, the number of tweets dropped to a fraction of the volume of the previous days. The excitement was over, there was no longer an urgent need for timely information. The few posts that were made from the 21st of April onwards contain elevated levels of anxiety, anger, and sadness. This might mean that the users lingering after the closure phase are slower than the majority of the community at processing their emotions related to the event. This could be due to low resilience, as that has been found to negatively correlate with the frequency of negative emotions after terror attacks (Fredrickson et al. 2003). In the affected area, most of the messages at this point were expressions of gratitude and support, and information sharing, while on the national level and abroad, most of the discussion consisted of opinions and comments (see Table 9).

Table 9. Aftermath Phase		
Massachusetts	*US*	*Abroad*
Support gestures	Opinions and comments: several topics	Opinions and comments: several topics
Information sharing: sharing news and updates on suspect chase	Information sharing: several topics	Information sharing: several topics
Opinions and comments: comments on news and miscellaneous comments	Support gestures	Support gestures

Table 9. The most prevalent topic categories during the aftermath phase for each region

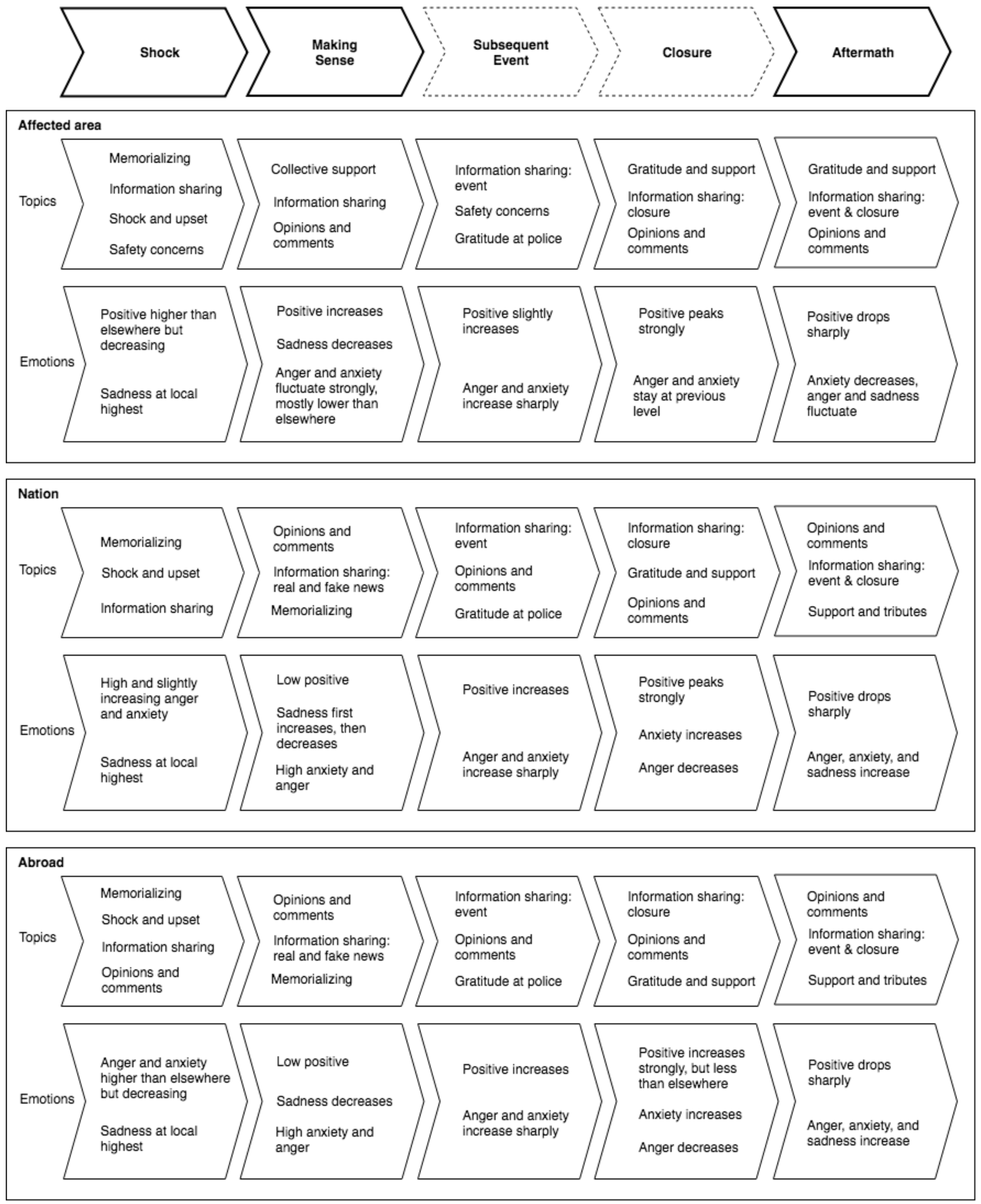

Figure 2. The topical and emotional phases of online conversation in each geographic region after a terror event followed by a subsequent event leading to closure.

A Model of Online Conversations After a Terror Attack

Based on the findings from the literature and data, we constructed a process for how conversations unfold after a terror event that is soon followed by an event that leads to closure (see Figure 2). The model contains topical and emotional trends for three levels of geographic proximity to the event site; the directly affected area, the affected country, and outside of the affected country.

Some of the phenomena are specific to geographic proximity. In particular collective, supportive gestures and emotions are predominant in the affected area, and stronger than farther away throughout the whole process. Information sharing cycles for specific news topics are shorter close to the event site, which could mean people distribute and access information with a smaller time lag than in more remote locations.

Locals also talk about safety more than others, both in terms of concern and relief for close ones. Farther away, topics such as memorializing (e.g. different types of "thoughts and prayers" messages), and expressing political opinions, often containing high levels of anger and anxiety. The levels of negative emotions are higher throughout the whole process farther away than in the affected area. Conversely, positive emotions are consistently higher in the affected area than elsewhere, and was the only region with a notable increase in positive emotions during the sense making phase: gratitude towards authorities as well as support and love towards Boston are prevalent themes through the whole period.

The subsequent event increases anxiety locally, where the consequences are most tangible. Once the subsequent event leads to closure, positive emotions spike strongly in all regions, and topics such as information confirming the closure and gratitude towards authorities are strongly represented. This is quickly followed by a decrease in all elevated emotions as well as the overall volume of the conversation.

After the subsequent event and closure, the volume of messages drops rapidly to a fraction of the previous phase. The people who remain express higher average levels of each of the negative emotions than at the end of the closure phase, mostly sharing the news preceding the closure and expressing opinions (with the exception of the directly affected area, where supports and gratitude are still strong themes).

The phases of the process are applicable to all geographic regions although the predominant topics and emotions vary at different proximities. Shock and upset were the primary reactions regardless of region during the first phase, and the transition to the making sense phase was simultaneous. In line with previous research, people using social media for information distribution is strongly present throughout the process.

Discussion

The first reactions to the bombing are unsurprisingly shock, upset, and disbelief. People send thoughts and prayers, worry about whether their close ones are safe, and try to figure out what happened.

After the shock wears out, people start collectively making sense of the event. Negative emotions in comments and opinions are probably an attempt at working towards closure, as value affirmation, moral outrage, and outgroup derogation have been found to facilitate psychological closure after a terror event (Skitka et al. 2004). The primary distal reactions to terrorism – searching for meaning and value, increased bigotry and patriotic sentiment, counter-bigotry activism, increased altruism, and greater appreciation of heroes (Pyszczynski et al. 2003) – are all present in the conversation after the shock phase. False news start circulating as people feel the urge to share and obtain information faster than media sources can verify news, and even some conspiracy theories are presented.

The making sense phase is where we start seeing regional differences in dealing with the trauma. Contrary to what one might expect, the highest anxiety levels in online conversations are not in the affected area, but abroad, whereas people close to the event site communicate more positive emotions than farther away. Why are they being positive rather than upset? Could it be that local people feel a stronger sense of agency or self-efficacy due to being able to access and share situational information and help out with practical matters locally? High levels of self-efficacy correlate with high performance accomplishments and low emotional arousal (Bandura 1982), which could mean that from an emotional standpoint, the Bostonians are faring better than remote mourners. Another explanatory factor for the prevalence of positive emotions in local tweets is that there was a strong trend of spreading grateful, supportive, loving messages. Being able to focus on something positive may help people build resilience, embrace positive emotions, and find meaning in connecting with others who share the experience.

It is not always the case that a terror attack is soon followed by an event that leads to closure, for instance in form of apprehending the terrorist. In some cases, the culprit is never caught, or the attack involves a planned suicide, or the terrorist is caught long after the attack. There might be other types of events that follow the initial attack, and they may not give people closure, without which people are often left with a lingering sensation of anxiety and insecurity from which they gradually return to a normal state. In the case of the Boston Marathon Bombing, the rapid drop of social media activity after the closure phase could mean that once the threat is removed, the levels of emotional arousal decrease to a level where people no longer feel a pressing urge to frequently share their emotions regarding the event, and are ready to move on to the inhibition phase of coping. Due to there being many alternatives for the consequences of a terror attack, it is difficult to describe the events in detail without compromising generalizability. Nevertheless, based on the literature on emotional processes, we posit that the shock, making sense, and aftermath phases are present in terror attacks regardless of the details, and potential additional events that might affect the pace of closure occur before the aftermath phase, leading to a general model with the three universal phases and an additional, optional phase for one or more case specific events (see Figure 3).

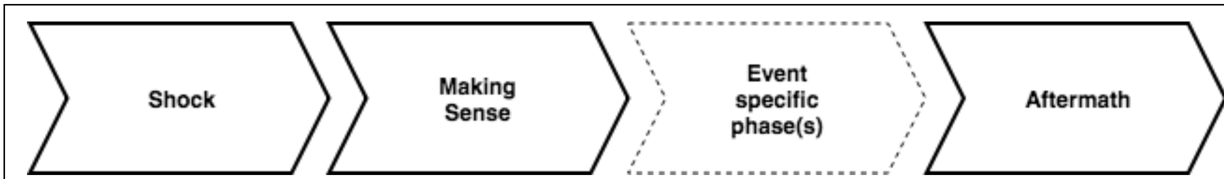

Figure 3. The process model for online discussions following terror attacks

Some people linger online during the aftermath phase, either sharing news from the closure phase, commenting events, and expressing opinions. Negative emotions, in particular outside of the affected area, are elevated. It could be that some people are more vulnerable to the anxiety caused by a terror attack, and that low resilience causes them to need a longer time to recover from the trauma. Perhaps they were not ready for the inhibition phase when the majority transitioned into it, leaving them to seek peer support from individuals experiencing the same. Understanding the lingerers better could perhaps help us devise strategies for helping people who are particularly strongly affected by crisis events.

The social stage model of coping posits that the emergency phase – where both thoughts and discussion sparked by a crisis are recurrent – lasts around two weeks. However, if the aftermath phase marks the shift from emergency stage to inhibition stage, the development found in our data is more rapid than suggested by the stage model. There are a few possible explanations for this. Firstly, the type of crisis event in question will undoubtedly determine some of its dynamics. The model is originally based on studies on a natural disaster (the Loma Prieta earthquake) and the Gulf War. It could be that the progression from the emergency stage to the inhibition stage is more rapid in context of an event with a short time span, an identifiable hostile actor, and a concrete conclusion to the events in the form of apprehending the person responsible and thus removing the remaining threat and allowing people to put their fears at rest. Determining which factors play a role in determining the duration of the emergency phase requires further research, but it seems plausible that there is some variation between different types of crises.

Secondly, the model was developed during a time when social media did not exist, and all of the information propagation happened through traditional media. Social media has enabled a faster information cycle than was possible before, granting people faster access to the information based on which they make sense of the events. Online communication also enables emotion sharing towards recipients that used to impractically far away (geographic distance) or implausible (strangers). Perhaps the online environment enables people to iteratively express their emotions at a more rapid rate than in offline conversations, speeding up the process of dealing with those emotions, and thus speeding up the process of transitioning from emergency to inhibition phase sooner than would have been the case before social media changed our communication dynamics. This means that some of the theories and models developed before the emergence of social media, while remaining valid, should be applied with awareness of the potential changes in communication styles and paces introduced by new technological possibilities.

Conclusions and Future Work

This study investigated how topics and emotions evolve in online discussion in the wake of a terror attack, accounting for the geographic proximity of the tweet location to the event site. Based on literature and analysis of tweets related to the Boston Marathon Bombing, a process model was developed for the phases of online conversation after a terror attack, outlining topical and emotional developments for different geographic proximities. The phases of the model are shock, making sense of the event, potential event specific phase(s), and aftermath. The potential events in the case of the Boston Marathon Bombing are a subsequent event and closure. One of the relevant limitations of such a model is that it is impossible for the it to be both generalizable and specific enough to accurately describe all the phases of the post-terror coping. We therefore proposed a general model with an optional, case-specific additional phase to allow for variation in how post-terror events unfold.

People in the affected area express higher levels of positive emotions and lower levels of negative emotions. A large part of the positive emotions expressed by locals were related to collective gestures of support and love, and gratitude towards authorities. People farther away were more preoccupied by commenting on the events, expressing opinions in messages containing elevated levels of anger and anxiety.

We contribute to the existing knowledge in the following ways: Firstly, we propose a process model for the collective emotional phases following a terror attack. Secondly, our study increases the overall understanding of how emotions develop after a terror attack, and how they are related to specific topics and locations. A fine-grained analysis of location, topics, and emotions enables better access to the social and psychological processes that unfold in online conversations. Thirdly, a practical contribution of this study is relevant to the emergency aid actors filtering real time crisis information from social media feeds; understanding which topics, characterized by which emotions, are more likely to primarily contain self-expression instead of situationally relevant information allows for more efficient filtering.

In future research, it would be interesting to examine terror attacks where the terrorist either eliminates themselves as a planned part of the attack, or attacks where the terrorist is not caught in the immediate aftermath of the event. It is likely that the topical and emotional trends of those types of events differ due to the lack of sense of closure, which may prolong anxiety and uncertainty. It would also be interesting to look into what role agency plays in recovering from a terror event, both on a collective and individual level. As the sense of agency is related to reduced levels of emotional arousal, it might be possible to devise ways of helping people recover from a traumatic event more quickly by increasing their agency over both their own psychological processes and the concrete consequences of the event.

References

Bandura, A. 1982. "Self-Efficacy Mechanism in Human Agency.," *American Psychologist* (37:2), p. 122.

Berger, J. 2011. "Arousal Increases Social Transmission of Information," *Psychological Science* (22:7), pp. 891–893.

Berger, J., and Milkman, K. L. 2012. "What Makes Online Content Viral?," *Journal of Marketing Research* (49:2), pp. 192–205.

Debortoli, S., Müller, O., Junglas, I. A., and vom Brocke, J. 2016. "Text Mining for Information Systems Researchers: An Annotated Topic Modeling Tutorial.," *CAIS* (39), p. 7.

Eismann, K., Posegga, O., and Fischbach, K. 2016. "Collective Behaviour, Social Media, and Disasters: A Systematic Literature Review.," in *ECIS*.

FBI archives. 2013. *Updates on Investigation Into Multiple Explosions in Boston*. (https://archives.fbi.gov/archives/news/updates-on-investigation-into-multiple-explosions-in-boston/updates-on-investigation-into-multiple-explosions-in-boston). Accessed 29/04/2019.

Fowler, J. H., and Christakis, N. A. 2008. "Dynamic Spread of Happiness in a Large Social Network: Longitudinal Analysis over 20 Years in the Framingham Heart Study," *Bmj* (337), p. a2338.

Fredrickson, B. L., Tugade, M. M., Waugh, C. E., and Larkin, G. R. 2003. "What Good Are Positive Emotions in Crisis? A Prospective Study of Resilience and Emotions Following the Terrorist Attacks on the United States on September 11th, 2001.," *Journal of Personality and Social Psychology* (84:2), pp. 365–376.

Garcia, D., and Rimé, B. 2019. "Collective Emotions and Social Resilience in the Digital Traces after a Terrorist Attack," *Psychological Science*.

Gruzd, A. 2013. “Emotions in the Twitterverse and Implications for User Interface Design,” *AIS Transactions on Human-Computer Interaction* (5:1), pp. 42–56.

Hancock, J. T., Gee, K., Ciaccio, K., and Lin, J. M.-H. 2008. “I’m Sad You’re Sad: Emotional Contagion in CMC,” in *Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work*, ACM, pp. 295–298.

Hansen, L. K., Arvidsson, A., Nielsen, F. \AArup, Colleoni, E., and Etter, M. 2011. “Good Friends, Bad News-Affect and Virality in Twitter,” in *Future Information Technology*, Springer, pp. 34–43.

Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Goldstein Hode, M., Halliwell, M. R., Turner McGowen, S. E., Davis, R., Vaid, S., and McElderry, J. A. 2015. “Social Media and Disasters: A Functional Framework for Social Media Use in Disaster Planning, Response, and Research,” *Disasters* (39:1), pp. 1–22.

Huang, C.-M., Chan, E., and Hyder, A. A. 2010. “Web 2.0 and Internet Social Networking: A New Tool for Disaster Management?-Lessons from Taiwan,” *BMC Medical Informatics and Decision Making* (10:1), p. 57.

Huang, Y. L., Starbird, K., Orand, M., Stanek, S. A., and Pedersen, H. T. 2015. “Connected through Crisis: Emotional Proximity and the Spread of Misinformation Online,” in *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work & Social Computing*, ACM, pp. 969–980.

Hughes, A. L., Palen, L., Sutton, J., Liu, S. B., and Vieweg, S. 2008. “Site-Seeing in Disaster: An Examination of on-Line Social Convergence,” in *Proceedings of the 5th International ISCRAM Conference*, pp. 44–54.

Kaufmann, M. 2015. “Resilience 2.0: Social Media Use and (Self-) Care during the 2011 Norway Attacks,” *Media, Culture & Society* (37:7), pp. 972–987.

Kramer, A. D., Guillory, J. E., and Hancock, J. T. 2014. “Experimental Evidence of Massive-Scale Emotional Contagion through Social Networks,” *Proceedings of the National Academy of Sciences*.

Kruglanski, A. W., Pierro, A., Mannetti, L., and De Grada, E. 2006. “Groups as Epistemic Providers: Need for Closure and the Unfolding of Group-Centrism.,” *Psychological Review* (113:1), p. 84.

Kwon, K. H., and Gruzd, A. 2017. “Is Aggression Contagious Online? A Case of Swearing on Donald Trump’s Campaign Videos on Youtube,” *Proceedings of the 50th Hawaii International Conference on System Sciences*.

Lerner, J. S., Gonzalez, R. M., Small, D. A., and Fischhoff, B. 2003. “Effects of Fear and Anger on Perceived Risks of Terrorism: A National Field Experiment,” *Psychological Science* (14:2), pp. 144–150.

Morrison, J. L., Sandra, and Berry, H. 2001. *A National Survey of Stress Reactions After the September 11, 2001, Terrorist Attacks*.

Mukkamala, A., and Beck, R. 2018. "The Role of Social Media for Collective Behavior Development in Response to Natural Disasters," in *ECIS*.

Neubaum, G., Rösner, L., Rosenthal-von der Pütten, A. M., and Krämer, N. C. 2014. "Psychosocial Functions of Social Media Usage in a Disaster Situation: A Multi-Methodological Approach," *Computers in Human Behavior* (34), pp. 28–38.

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).

O'Neill, A. 2015. *Tsarnaev Trial: Timeline of the Bombings, Manhunt and Aftermath*. (https://edition.cnn.com/2015/03/04/us/tsarnaev-trial-timeline/index.html). Accessed 29/04/2019.

Orehek, E., Fishman, S., Dechesne, M., Doosje, B., Kruglanski, A. W., Cole, A. P., Saddler, B., and Jackson, T. 2010. "Need for Closure and the Social Response to Terrorism," *Basic and Applied Social Psychology* (32:4), pp. 279–290.

Pennebaker, J. W., Boyd, R. L., Jordan, K., and Blackburn, K. 2015. "The Development and Psychometric Properties of LIWC2015."

Pennebaker, J. W., and Harber, K. D. 1993. "A Social Stage Model of Collective Coping: The Loma Prieta Earthquake and the Persian Gulf War," *Journal of Social Issues* (49:4), pp. 125–145.

Pyszczynski, T., Greenberg, J., and Solomon, S. 1999. "A Dual-Process Model of Defense against Conscious and Unconscious Death-Related Thoughts: An Extension of Terror Management Theory.," *Psychological Review* (106:4), p. 835.

Pyszczynski, T., Solomon, S., and Greenberg, J. 2003. *In the Wake of 9/11: The Psychology of Terror*., American Psychological Association.

Rimé, B. 2009. "Emotion Elicits the Social Sharing of Emotion: Theory and Empirical Review," *Emotion Review* (1:1), pp. 60–85.

Skitka, L. J., Bauman, C. W., and Mullen, E. 2004. "Political Tolerance and Coming to Psychological Closure Following the September 11, 2001, Terrorist Attacks: An Integrative Approach," *Personality and Social Psychology Bulletin* (30:6), pp. 743–756.

Smith, T. W., Rasinski, K. A., and Toce, M. 2001. "America Rebounds: A National Study of Public Response to the September 11th Terrorist Attacks," *Chicago, IL: National Opinion Research Center at the University of Chicago*.

Stieglitz, S., and Dang-Xuan, L. 2013. "Emotions and Information Diffusion in Social Media—Sentiment of Microblogs and Sharing Behavior," *Journal of Management Information Systems* (29:4), pp. 217–248.

Takahashi, B., Tandoc, E. C., and Carmichael, C. 2015. "Communicating on Twitter during a Disaster: An Analysis of Tweets during Typhoon Haiyan in the Philippines," *Computers in Human Behavior* (50), pp. 392–398.

Wikipedia. (n.d.). *Boston Marathon Bombing*. (https://en.wikipedia.org/wiki/Boston_Marathon_bombing). Accessed 29/04/2019.

Yum, Y., and Schenck-Hamlin, W. 2005. "Reactions to 9/11 as a Function of Terror Management and Perspective Taking," *The Journal of Social Psychology* (145:3), pp. 265–286.