Sentiment Analysis of Twitter Users Over Time: The Case of the Boston Bombing Tragedy

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Abstract. Social Network Services (SNS), for example Twitter, play a significant role in the way people share their emotions about specific events. Emotions can spread via SNS and can spur people's future actions. Therefore, during extreme events, disaster response agencies need to manage emotions appropriately via SNS. In this research, we investigate the Twitter verse associated with an event - the Boston Bombing context. We focus on tweets in the context of hazard-describing keywords (Explosion, Bomb), important event timelines, and the related changes in emotions over time. We compare the results with a corpus of tweets collected at the same time that are not associated with the above hazard- describing keywords. A sentiment analysis shows anger was the most strongly expressed emotion in both groups. However, there were statistical differences in Anxiety and Sadness among the two groups over time.

Keywords: Social media · Big data · Emotion spread · Announcement · Disaster response

1 Introduction

The emergence of Social Network Services (SNS) has provided an additional option for people to share their personal emotions regarding specific events. Before the emergence of SNS, due to the restriction of communication channels, people could primarily share their emotions while they were physically close to people such as family members or friends via traditional media (phone, letter, or personal face to face meetings). These

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traditional communication channels limited the diffusion of emotions. The advent of SNS has provided new opportunities that enable people to express their emotions without any time or location restrictions and have allowed the spread of expressed emotions over a much larger footprint.

In the SNS platform, people's emotions can be expressed via SNS postings. These postings that include people's emotions have been found to be significant factors in various social actions. For instance, prior literature in this field has studied the impact of emotions on the public in the context of various disaster events. According to Pacherie [1], emotions are often portrayed as motivational forces of action or as the stimuli for action. Emotions that diffuse through SNS can also spur the future action of users. This is one of the main reasons why managing emotions in SNS is important and needs to be handled appropriately.

Especially, when people express negative emotions such as anger, sadness and anxiety, the mitigation of such emotions is important for disaster response authorities. This is because propagated negative emotions can spur unexpected negative actions. The motivation of this study is to understand the various characteristics of SNS messages during extreme events, such as emotion differences between different types of related tweets, the impact of announcements on emotions, the impact of announcements or news on expressed emotions. We are also interested in understanding the pervasive emotions during the extreme event, in order to provide valuable information to disaster response authorities. By using the results of this study, disaster response authorities can develop plans to mitigate public chaos and prepare for unexpected future behaviors by citizens.

The literature on emotion contagion in online communication [2, 3], has documented that the emotions of online communication users are influenced by online posts or messages of their online friends. Kramer [4] has addressed this emotion contagion in the context of SNS - when an SNS user posts a message, words used by him/her influence later word selection by their friends. That is, people's emotions could also be affected by the words used by SNS users. The literature on social information processing points out that in text based interaction, people may describe their thoughts, emotions, or attitudes by selecting their word and punctuation use [5].

Because of the characteristics of SNS, diffusion of emotions in the SNS environment is faster and broader than that of traditional communication channels [6]. The implication is that during extreme events, if related disaster response authorities such as police departments, and law enforcement agencies cannot deal with the spread of emotion in a timely manner, consequences of this diffusion can be much more difficult to manage. Therefore, investigating expressed negative emotions is an important issue [7]. Back et al. [8] studied emotion changes through the timeline of the World Trade Center terrorist attack. They explained that announcements and news about the incident impacted people's expressed emotions which were distributed by text pagers. Around a decade later, people are using SNS instead of text pagers. SNS increase accessibility and diversity of information about any event.

In this research, we explore negative emotions (anger, anxiety, and sadness) expressed in Twitter space during one extreme event - the Boston bombing tragedy of 2013. Our research questions are (1) Are there emotional differences between types of tweet that are specifically related to the incident and those that are not specifically related to the incident? (2) Do incident related announcements or news have an impact on people's emotions? (3) What type of negative emotions are presented more during terrorist attacks?

In order to answer our research questions, we focused on the Twitter messages that were created by Twitter users and captured during the incident. Many news media channels broadcasted the actual situation about the Boston tragedy in real time and people could obtain and share real time information via SNS. We assume that during the 5 days of the event period (from the time that the bombing happened to the time that the suspect was captured), announcements or news regarding the incident impacted people's expressed emotion on SNS.

We separated the Boston bombing related Twitterverse into two spheres: one which focused on messages specifically related to the bombing and the explosion (Include the keywords "bomb" and "explosion"), while the second concentrated on messages not specifically focused on the incident but collected at the same time and which were related to Boston or the Boston marathon incident. In addition, by analyzing tweet messages collected hourly, we studied the impact of event-related announcements or news on expressed negative emotions (anger, anxiety, and sadness) as displayed on SNS.

The rest of this paper is organized as follows. First, we discuss the background and related literatures. Second, we explain the technique we used for sentiment analysis of emotions, Next, we introduce the data sets used in this research and describe the analysis and results. Finally, we conclude with a discussion of the potential implications and contributions of our research.

2 Research Background and Literature Review

2.1 Boston Marathon Bombing Tragedy

The Department of Homeland Security (DHS) reported that at 2:49 PM on April 15, 2013, two pressure cooker bombs (Improvised Explosive Device) placed near the 2013 Boston Marathon finish line exploded within seconds of each other, resulting in a death toll of three and injuries to more than two hundred people. On April 18th, the Federal Bureau of Investigation (FBI) identified Tamerlan Tsarnaev and Dzhokhar Tsarnaev as the primary suspects in this tragedy and released photographs and surveillance videos of them. One suspect, Tamerlan Tsarnaev, was shot during his encounter with the police and died shortly in Watertown, Massachusetts. The other suspect, Dzhokhar Tsarnaev, who ran away from the scene was caught the following day at 8:50 PM on April 19th [9].

When the explosions occurred near the finish line, around 5,700 runners were still in the race. Within 1 min, the event had been announced on SNS. During the period (April 15 – 19), many messages about the bombing incident were propagated via SNS, especially on Twitter. The messages created benefits as well as confusion among the public. There were a myriad of tweets that mentioned the incident itself, and gave actionable information that provided real time information to the public, information about tracking suspects providing useful clues. However, they also contributed to the apprehensions of law enforcement agencies because of the messages, which spread negative emotions such as anger, anxiety, and sadness to the public. Moreover, as these tweets were diffused the embedded emotions in the messages were also propagated.

2.2 Emotions

Many English language emotion analysis studies have applied Ekman's 6 basic emotion types [10–12] to classify people's sentiment from text based documents [13, 14]. The 6 basic emotions consist of Surprise, Happiness, Anger, Fear, Disgust, and Sadness. In this paper we focus on the three negative emotions, anger, fear and sadness: Anger is an emotion that includes an uncomfortable response to a perceived (or real) grievance [15].; Fear can be explained as being afraid of something and this is caused by being aware of danger [16]; sadness is the opposite emotion of happiness [17]. We suggest that the three negative emotions Anger, Fear (Anxiety), and Sadness help in understanding the tragedy better. We do not consider "disgust" among the list of emotions to study - "feelings of disgust are often immune to rationality" [18].

2.3 Emotional Contagion

"Emotional contagion" is described as "a process in which a person or group influences the emotion or behavior of another person or group through the conscious or unconscious induction of emotional states and behavioral attitudes [19]." Recently, Vijayalakshmi and Bhattacharyya [20] pointed out that emotions and emotional contagion are being increasingly considered as important factors which influence individual behavior. Burke et al. [21] mention that people's interactions within the SNS can mirror the manner in which people interact with others in their offline lives. Moreover, in the SNS, people need to pay more attention to emotions and emotional contagion than in the offline environment. As we mentioned earlier, development of SNS eliminates time and location restrictions and allows people to express their emotions across a much wider audience. The degree of negative emotion contagion via SNS is also uncontrollable if disaster response authorities cannot manage contagious emotions in a swift manner. Therefore, understanding the pattern of emotion changes and the impact of external factors such as announcements or news during the extreme event situation is essential.

2.4 Warning Sign Words

According to Ma et al. [22] signal words have a relationship to a person's emotional levels (perceived hazard level). When there is a human participant in the context of specific signal word, the emotion of the participant regarding an action-related target is different. For example, when participants played in a shooting game, emotions of the participants that were told about armed targets compared to unarmed targets were different [23]. In addition, when people were showed words which described risky environmental events, their psychological response was different [24]. This indicates that the use of keywords (directly related to incident) in the SNS messages can reflect on peoples' emotions and may show different levels of negative emotions regarding the specific event compared to when messages do not contain event related keywords.

3 Methodology

3.1 Data Collection

On April 15th 2013, the race day turned deadly for Boston as two bombs went off near the finish line of the marathon, killing 2 spectators and injuring more than 260 people. Almost 4 h after the occurrence of this incident, we started collecting the data from Twitter using a custom tool developed for Twitter data collection. This tool uses the Twitter Streaming Application Program Interface (Twitter API) that helped us collect live feeds from Twitter. There were three keywords that were particularly of interest to us - "Boston", "BostonMarathon" and "BostonBombing". The search for Twitter feeds was based only on these three keywords. The data collection for the four-hour window that was missed out on initially (from 15th April 2013 18:52 GMT to 15th April 2013 21:53 GMT) was captured using a third party software called Topsy. Using Topsy, a hashtag-based search was performed using the same three keywords as mentioned above. This was to ensure uniformity in the data collection.

A total of 1,149,678 tweets were collected for this five-day period. The data was then separated into 2 major categories: one that included the keywords "explosion" and/or "bomb" (henceforth referred to as EB set), the other which did not include the keywords (henceforth referred to as non-EB set). For the simplification of the analysis of the data, we further divided the dataset in an hourly fashion (108 h which encompasses our 5 day dataset). Table 1 below indicates the details of the count of tweets by day:

Table 1. Message description

	4/15	4/16	4/17	4/18	4/19	Total number of tweets
(1) Number of tweets (with keywords EB)	146,601 (12.75%)	139,431 (12.13%)	48,278 (4.20%)	77,450 (6.74%)	43,239 (3.76%)	454,999 (39.58%)
(2) Number of tweets (without keyword - nonEB)	61,328 (5.33%)	391,169 (34.02%)	63,737 (5.54%)	109,154 (9.50%)	69,291 (6.03%)	694,679 (60.42%)
(1) + (2)	207,929 (18.09%)	530,600 (46.15%)	112,015 (9.74%)	186,604 (16.23%)	112,530 (9.79%)	1,149,678 (100%)

3 emotions were analyzed in the tweets – Sadness, Anger and Anxiety. We used Linguistic Inquiry and Word Count (LIWC) based sentiment analysis to chart out graphs for the three emotions mentioned and catalogued them separately for the EB and

non-EB datasets. The hourly transition of tweets for the 108 h period was the next step in data collection. For each emotion and every hour, we analyzed the transition of emotion and classified it either as peak (rise in value) or trough (decline in value). Peaks and troughs were based on the delta values (change in value of an emotion). This was carried out for the entire 108 h period, for the five day period and for all three emotions. Delta values of only 40 % and above were considered for the non-EB dataset and 50 % and above were considered for the EB dataset. Major events of every day during the 5-day period of the Boston Bombing incident were identified using these delta values. The content analysis was then performed taking into consideration the delta values and the time and event corresponding to these delta values.

3.2 Sentiment Analysis

In order to investigate the impact of keywords (use of Bomb or Explosion) directly related to the Boston bombing tragedy on people's expressed emotions, we conducted sentiment analysis using hourly collected tweet messages. The vital task carried out by sentiment analysis is to identify how sentiments are expressed in the texts or messages [25]. According to Stieglitz and Krüger [26], "this method is based on natural language processing, computational linguistics, and text analytics to identify and extract subjective information in different kinds of source materials."

In order to extract the sentiment of tweets automatically, we selected the LIWC 2007 software [27], because the LIWC based sentiment analysis has been previously conducted to analyze conversations that use instant messages, articles, or twitter messages [28–30]. LIWC is a text analysis software which has been developed to measure inherent emotions in the text using a psychometrically validated dictionary. This provides us with the rate of negative emotion word use in the messages by calculating their relative frequency based on the categorized dictionary.

For the three selected emotion types: anger, anxiety, and sadness, we captured the significant emotional changes in both EB and non-EB groups. In the process, we applied thresholds of more than 50 % of emotion change for EB and more than 40 % of emotional change for non-EB to analyze significant changes. Based on the results of sentiment analysis, we explored the expressed negative emotional differences between EB and non-EB groups in hourly time slices.

3.3 Content Analysis

Based on the published timelines of the Boston Bombing tragedy [31, 32], we performed content analysis. Two English speaking graduate students analyzed tweet data that was separated as EB and non-EB. We selected all announcements about the bombing itself as a major event on all days of EB and non-EB groups. For example, we decided on the following event as an announcement on day 2 for group of EB.

2 PM – 8 PM: FBI bulletin states that bombs were made by packing explosives, shrapnel and nails into pressure cookers. They are still unaware as to who detonated them and why.

The Number of Keywords used in the 2nd day's group of EB tweet messages.

FBI – 3353, Shrapnel – 36861, Pressure cooker – 6665, Detonate – 248, Bomb – 140471

Subsequently, using content analysis results (from EB and non-EB), we analyzed hourly sentiment analysis results to investigate the impact of the announcement on expressed emotion change in SNS.

4 Analysis Result

In this section, we present analysis results to answer our 3 research questions:

First we investigate the first research question - "Are there emotional differences between two types of tweets specifically related to the incident and not specifically related to the event?" and the third research question "What type of negative emotions are presented more during the terrorist attack?"

In order to answer the above two research questions, we compared consolidated means of the three expressed emotions during the 5 days, for both EB and nonEB groups; we then ran Analysis of Variance (ANOVA). Table 2 shows ANOVA results between two groups (EB and non-EB) for three negative emotions and the percentage mean value of each expressed emotion. The mean value of each emotion calculated by considering all of each emotion's expressed sentiment score during the incident.

Table 2. Analysis of variance result by group

	Consolidated mean	Mean of EB	Mean of non-EB	Mean square	F	p
Anger	1.465	1.610	1.320	4.226	2.449	0.119
Anxiety	0.536	0.474	0.597	20.321	12.26	0.001
Sadness	0.652	0.335	0.969	0.759	134.97	0.000

The consolidated mean shows that anger was the most highly expressed emotion during the 5 days. Consolidated mean of Anger was 1.465 % and this was around 2.5 times higher than any other emotion. This indicates that during the Boston bombing tragedy people expressed anger via the SNS more than Anxiety and Sadness.

This can be compared with other extreme event study cases, studied in prior literature, such as natural disaster (Japan earthquakes) [33] and another terror event (911 tragedy) [8]. In the case of natural disaster events, people expressed fear and anxiety on SNS rather than unpleasantness and anger. In addition, emotion expression regarding the 911 terrorist attacks showed that anger was the most strongly expressed emotion during the event period on the text pagers network. Our result confirmed that expressed emotions reflect the characteristic of the extreme event. For instance, terrorist attacks mostly made people angry, but on the other hand, natural disaster incidents made people worry about others and these emotions are clearly expressed on SNS.

Moreover, Table 2 shows whether the mean difference between the EB group and the non-EB group was statistically significant for three negative emotions (Anger, Anxiety and Sadness). The result indicates that for Anxiety and Sadness there are statistically significant differences in the expressed emotion between EB and non-EB groups ($F = 12.26$, $p < 0.01$, $F = 134.97$, $p < 0.001$). In addition, both Anxiety and Sadness were expressed higher (0.597 % and 0.969 %) when people did not include E&B keywords, which were directly related to the Boston bombing event. This implies people might avoid expressing emotions like anxiety and sadness in direct relation to extreme event related keywords.

Results for anger show that there is no statistically significant difference between the EB group and the non-EB group ($F = 2.449$, $p > 0.05$). This indicates that the emotion, anger, might not be impacted by the people's use of keywords. We interpreted this result as being derived from the characteristics of the extreme event. Since the Boston Bombing tragedy had infuriated people, the enhanced level of this anger could not be controlled, and this is what the SNS users expressed on SNS. An implication is that, if the disaster response authorities wish to mitigate people's expressed emotion, coping strategies needs to be separated between Anger and the other 2 emotions.

Table 3. shows ANOVA results by the day for three negative emotions, as well as the percentage mean value of each expressed emotion. The result indicates that for all three emotions (Anger, Anxeity, Sadness), there are statistically significant expressed emotion differences during at least one of the five days ($F = 5.706$, $p < .001$, $F = 3.002$, $p < 0.05$, 11.698, $p < 0.001$).

Table 3. Analysis of variance result by days

	Consolidated mean	Mean of day1	Mean of day2	Mean of day3	Mean of day4	Mean of day5	Mean square	F	p
Anger	1.401	1.059	1.752	1.990	1.327	0.878	9.608	5.706	0.000
Anxiety	0.532	0.510	0.560	0.613	0.537	0.441	0.189	3.002	0.020
Sadness	0.655	0.665	0.947	0.714	0.628	0.320	2.420	11.698	0.000

In order to investigate the impact of announcements or news on expressed emotions on SNS, we performed content analysis using hourly data collected during the 5 days of the Boston marathon bombing related tweet messages. By mapping the important event related announcements or news to the expressed sentiment change we can perhaps answer the remaining two research questions - "Do incident related announcements or news have an impact on people's emotions?" and "How long does it take those announcements or news to impact actual expressed emotions?"

4.1 Day 1

According to the content analysis results from both Groups of EB tweet data set and non-EB tweet data set, the major event for day 1 was the announcement that there were explosions in front of the Boston marathon finish line. Boston.com reported this as "2: 49 pm: There is an explosion in front of Marathon Sports on Boylston Street, close to the Marathon finish line. Thirteen seconds later and a block away, there is a second explosion in front of the Forum restaurant. Three people are killed, 282 are injured."

EB sentiment analysis result for day 1 showed peaks for all three emotions: anger, anxiety and sadness 4–5 h after the event happened. The change in emotion for anger, anxiety and sadness increased by 500 %, 112 % and 330 % respectively around 4 h after the incident. This indicates that the news about the bombing tragedy affected the change in all three emotions 4 h after the actual event.

Non-EB results also showed similar result for all three emotions. These three emotions significantly changed compared to the emotions expressed in the previous hours. The level of anger, anxiety, and sadness increased by 45.57 %, 44 %, and 77.05 % respectively also around 4–5 h after the actual event. The result of day 1 for both groups indicates that around 4–5 h later people's emotions were expressed on SNS and the degree of emotion change on keyword usage was much larger than that of non-keyword use group.

4.2 Day 2

For both the EB group and the non-EB group, we selected the announcement that "bombs were made by packing explosives, shrapnel and nails into pressure cookers. They are still unaware as to who detonated them and why." as a major event. This announcement started from 6 pm (GMT) and one emotion, anger, showed significant emotion change during the time period between 6 pm (GMT) and 8 pm (GMT). EB results showed that emotion change for anger showed both peaks and troughs in succession. Right after the announcement, a delta value of anger increased by 89.75 % then suddenly plunged to –85.11 % in the next hour. We assumed that the announced unclear information such as "unawareness" of reason and "suspicion" impacted people's emotions. For the non-EB group around 5–6 h after the announcement, 10 pm (GMT), there was a rise in the emotions of anxiety (52.83 %) and sadness (74.31 %). We interpret that levels in anxiety change occurred as a result of the broadcast about unawareness of the reason and suspects. However, we do not have an appropriate reason to explain the change in sadness.

4.3 Day 3

On day 3 a major announcement about the incident was "Several media outlets, starting with the CNN, report that an arrest has been made; BPD and FBI deny the report". Although the level of expressed emotion for anxiety and sadness were very low, EB results showed continuous fluctuation in all three emotions. Moreover, the non-EB results also reveal similar patterns regarding fluctuation of anxiety and sadness during the 4 h time period from 6 pm (GMT). This indicates that the diffused unverified information impacted people's negative emotions. However, when people did not include directly related keywords (E&B) in the message, anger did not have large fluctuations like the other emotions.

4.4 Day 4

Around 9 pm (GMT), FBI published surveillance photos of the bombing suspects and media around the world started broadcasting this announcement to the public. From both EB and non-EB results, we observed decreased negative emotions. The EB result shows that 1–2 h after the announcement, the levels of anxiety (–79.17 %) and sadness (–86.36 %) dropped compared to the levels before the announcement. In addition, the non-EB result showed that within 2 h of the announcement all three negative emotions anger (–46.63 %), anxiety (–44.44 %), and sadness (–67.03 %) decreased compared to before the announcement. We surmised that by making the announcement, FBI had reduced the uncertainty about suspects.

4.5 Day 5

The early morning 7 am (GMT) announcement about the investigation situation and the alert “Boston, Watertown has issued a ‘shelter in place’ advisory asking residents to stay in their homes as police continue their search for Tsarnaev. All mass transit is shut down” was also selected as a major event on day 5. Our sentiment result from EB groups showed that right after the announcement, people’s anger, anxiety and sadness decreased –84.46 %, –87.75 % and –81.25 % but increased drastically in the following hour 86.96 %, 166.67 % and 600 % respectively. This indicates that when people heard about the situation, their level of negative emotions decreased but again increased because of the absence of any follow-up announcements. Moreover, the non-EB group presented opposite patterns compared with the EB group. Specifically, increased negative emotion were revealed within the first hour (anger 94.34 % and sadness 463.64 %) then people showed decreased levels of emotions in the following hours (anger –80.58 %, anxiety (–50 %), and sadness –6.45 % (1st hour) –65.52 % (2nd hour)). This implies that emotions among users who were including direct event related keywords and those who did not include keywords can be different. Therefore, when disaster response authorities deal with two different groups of SNS user, they need to consider heterogeneity between the two groups of users.

Figure 1 below shows an example of presented emotion change and the impact of the announcement for both EB and non-EB groups on Day 2. Graphs for all other days are in the appendix (Fig. 2).

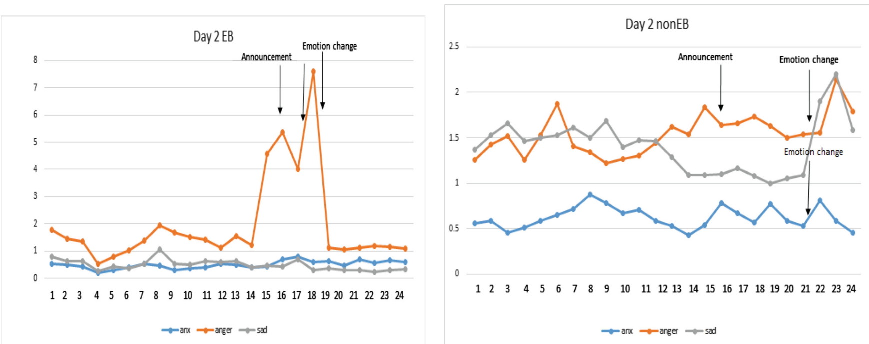

Fig. 1. Impact of announcement on emotion change

5 Discussion and Conclusion

In this research, we investigated three research questions "Are there emotion differences between two types of tweets", "what types of negative emotions are presented more during the terrorist attack", "what is the impact of an announcement on expressed emotion". Our analysis shows that for anxiety and sadness, differences in expressed emotion existed between the EB and non-EB group. In addition, anger was the most highly expressed emotion during the Boston bombing tragedy. By mapping our content analysis results into hourly-analyzed sentiment analysis results, we could see the impact of announcements on expressed emotion via SNS. Moreover, emotion change usually happened between 1 and 5 h from the announcement.

This study made the following theoretical and practical contributions. The study showed that expressed emotions were impacted by announcements/news, which had an effect on other user's emotions. In addition, based on the concept of warning signal keywords, we could separate the dataset into two groups called event related and non-event related groups and we could investigate the emotional differences among these two groups. The practical contribution of this study is that we can provide various information regarding expressed emotions during extreme events to disaster response authorities. Our analysis result indicates that in order to mitigate expressed negative emotion on SNS, disaster response agencies need to have specified strategies depending on the types of negative emotions and public keyword usage. In addition, depending on the extreme event context, mainly expressed type of negative emotion is varied. Therefore, developing mitigation strategies based on the characteristic of the extreme event is essential.

We also saw the impact of announcements from broadcasting system or government agencies on people's expressed emotions. For example, unverified announcements or lack of updates led to fluctuations of emotions. Finally, 1–5 h from announcement was the common interval between reactions and the actual announcement time. Therefore, if disaster response agencies want to mitigate the public's negative emotion, swiftness of action must also be considered.

There are however, some limitations to this study. First of all, we have only considered the Boston bombing tragedy as a case of extreme event. This may limit the generalizability of our findings. Second, we used a published timeline for content analysis and mapping. Although, the news in timelines described the major events during the Boston bombing incident, there is a possibility that we may have skipped other major announcements or news. Third, there are other widely used SNS channels such as Facebook, Instagram, or Google + but in this research; we focused on the Twitter SNS channel. Thus, as a future research, comparing the results of each popular SNS channel may be considered to improve our understanding regarding the characteristics of SNS channels.

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Appendix

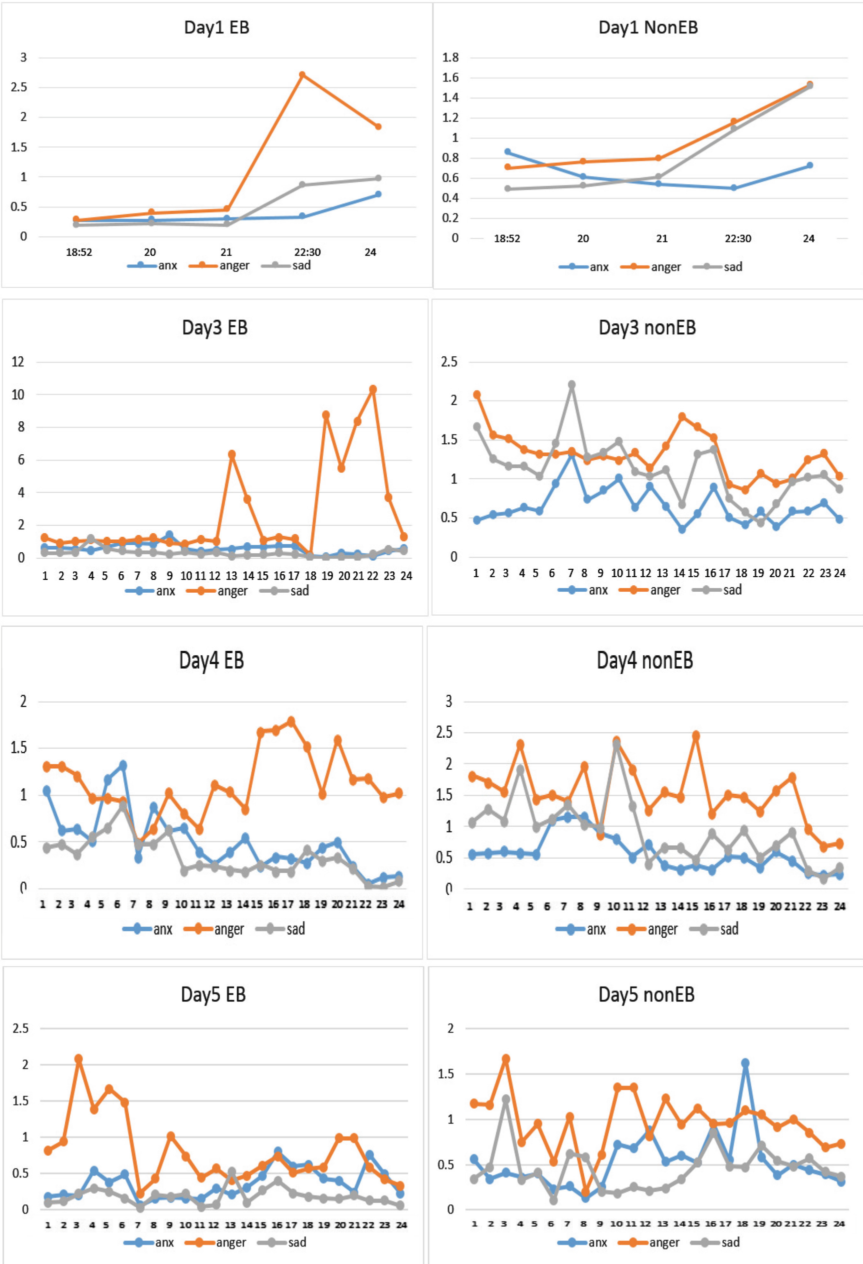

Fig. 2. Emotion changes for days 1, 3, 4 and 5

References

1. Pacherie, É.: Emotion and action. Eur. Rev. Philos. **5**, 55–90 (2002)
2. Hancock, J.T., et al.: I'm sad you're sad: emotional contagion in CMC. In: Proceedings of the 2008 ACM Conference on Computer Supported Cooperative Work, San Diego, CA, USA. ACM (2008)
3. Hancock, J.T., Landrigan, C., Silver, C.: Expressing emotion in text-based communication. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems. ACM (2007)
4. Kramer, A.D.: The spread of emotion via Facebook. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Austin, TX, USA. ACM (2012)
5. Walther, J.B.: Interpersonal effects in computer-mediated interaction a relational perspective. Commun. Res. **19**(1), 52–90 (1992)
6. Choudrie, J., et al.: Comparing the adopters and non-adopters of online social networks: a UK perspective. In: 46th Hawaii International Conference on System Sciences (HICSS), Hawaii, USA. IEEE (2013)
7. Rana, N.P., Dwivedi, Y.K., Williams, M.D.: A meta-analysis of existing research on citizen adoption of e-government. Inf. Syst. Front. **17**(3), 1–17 (2013)
8. Back, M.D., Küfner, A.C., Egloff, B.: The emotional timeline of September 11, 2001. Psychol. Sci. **21**(10), 1417–1419 (2010)
9. DHS, Unclassified Summary of Information Handling and Sharing Prior to the April 15, 2013 Boston Marathon Bombings (2014)
10. Ekman, P.: Facial expression and emotion. Am. Psychol. **48**(4), 384–392 (1993)
11. Ekman, P.: Argument basic emotions. Cogn. Emot. **6**(3–4), 169–200 (1992)
12. Ekman, P., Friesen, W.V., Ellsworth, P.: Emotion in the Human Face: Guidelines for Research and An Integration of Findings. Elsevier, Burlington (2013)
13. Alm, C.O., Roth, D., Sproat, R.: Emotions from text: machine learning for text-based emotion prediction. In: Conference on Human Language Technology and Empirical Methods in Natural Language Processing, Vancouver, BC, Canada. Association for Computational Linguistics (2005)
14. Strapparava, C., Mihalcea, R.: Learning to identify emotions in text. In: Proceedings of the 2008 ACM Symposium on Applied Computing, Fortaleza, Ceara, Brazil. ACM (2008)
15. Frisch, N.C., Frisch, L.E., Frisch, L.E.: Psychiatric Mental Health Nursing. Delmar/Thomson Learning, Clifton Park (2006)
16. Merriam-Webster, Fear, in Merriam-Webster, Merriam-Webster, Editor. Merriam-Webster (2015)
17. Merriam-Webster, Sadness, in Merriam-Webster. Merriam-Webster (2015)
18. Konnikova, M.: Problems Too Disgusting to Solve, in The New Yorker. Condé Nast: Condé Nast, New York (2015)
19. Schoenewolf, G.: Emotional contagion: behavioral induction in individuals and groups. Modern Psychoanal. **15**(1), 49–61 (1990)
20. Vijayalakshmi, V., Bhattacharyya, S.: Emotional contagion and its relevance to individual behavior and organizational processes: a position paper. J. Bus. Psychol. **27**(3), 363–374 (2012)
21. Burke, M., Marlow, C., Lento, T.: Social network activity and social well-being. In: Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Atlanta, GA, USA. ACM (2010)

22. Ma, Q., Jin, J., Wang, L.: The neural process of hazard perception and evaluation for warning signal words: evidence from event-related potentials. Neurosci. Lett. **483**(3), 206–210 (2010)
23. Correll, J., Urland, G.R., Ito, T.A.: Event-related potentials and the decision to shoot: the role of threat perception and cognitive control. J. Exp. Soc. Psychol. **42**(1), 120–128 (2006)
24. Qin, J., Han, S.: Neurocognitive mechanisms underlying identification of environmental risks. Neuropsychologia **47**(2), 397–405 (2009)
25. Nasukawa, T., Yi, J.: Sentiment analysis: capturing favorability using natural language processing. In: Proceedings of the 2nd International Conference on Knowledge Capture, Sanibel Island, FL, USA. ACM (2003)
26. Stieglitz, S., Krüger, N.: Analysis of sentiments in corporate Twitter communication–a case study on an issue of Toyota. Analysis **1**, 1–2011 (2011)
27. Pennebaker, J.W., et al.: The development and psychometric properties of LIWC 2007 (2007)
28. Tausczik, Y.R., Pennebaker, J.W.: The psychological meaning of words: LIWC and computerized text analysis methods. J. Lang. Soc. Psychol. **29**(1), 24–54 (2010)
29. Tumasjan, A., et al.: Election forecasts with Twitter: how 140 characters reflect the political landscape. Soc. Sci. Comput. Rev. **29**(4), 402–418 (2010)
30. Yu, B., Kaufmann, S., Diermeier, D.: Exploring the characteristics of opinion expressions for political opinion classification. In: Proceedings of the 2008 International Conference on Digital Government Research. Digital Government Society of North America (2008)
31. O'Neill, A.: Tsarnaev trial. In: Timeline of the bombings, manhunt and aftermath. CNN: CNN (2015)
32. Morrison, S., O'Leary, E.: Timeline of Boston marathon bombing events. In: Boston.com., Boston.com: Boston.com (2015)
33. Vo, B., Collier, N.: Twitter emotion analysis in earthquake situations. Int. J. Comput. Linguist. Appl. **4**(1), 159–173 (2013)