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Tracking and Analyzing Individual Distress Following Terrorist Attacks Using Social Media Streams

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Risk research has theorized a number of mechanisms that might trigger, prolong, or potentially alleviate individuals' distress following terrorist attacks. These mechanisms are difficult to examine in a single study, however, because the social conditions of terrorist attacks are difficult to simulate in laboratory experiments and appropriate pre-attack baselines are difficult to establish with surveys. To address this challenge we propose the use of *computational focus groups* and a novel analysis framework to analyze social media stream that archives user history and location. The approach uses timestamped behavior to quantify an individual's pre-attack behavior after an attack has occurred, enabling the assessment of time-specific changes in the *intensity* and *duration* of an individual's distress, as well as the assessment of individual and social level covariates. To exemplify the methodology we collected over 18 million tweets from 15,509 users located in Paris on November 13, 2015 and measured the degree to which they expressed anxiety, anger, and sadness after the attacks. The analysis resulted in findings that would be difficult to observe through other methods, such as that news media exposure had competing, time-dependent effects on anxiety, and that gender dynamics are complicated by baseline behavior. Opportunities for integrating computational focus group analysis with traditional methods are discussed.

KEY WORDS: risk communication, big data, emergency management, human behaviors; social media; disaster response; terrorism

1. INTRODUCTION

Terrorism provokes strong emotional responses, such as anxiety and anger, in large populations[(1)]. Though felt most intensely by those in the area of an attack in its immediate aftermath[(2)], the emotional impact of an attack can diffuse to those with personal or social connections to the area under attack[(3)], and linger for months afterward[(4)]. These impacts have short-term and longer-term effects on individuals' well-being, their perceptions of future risk, and their policy preferences for addressing these risks[(5,6)], such as avoiding modes of transportation associated with a prior attack[(7,8)].

Though potentially powerful and far-reaching, the longer-term negative effects of terrorist attacks are hardly consistent. Some individuals and communities show resilience in response to attacks[(9,10)], experiencing social bonding and communal support as the result of experiencing a shared threat. Others endure longer term negative consequences, such as chronic mental health problems[(11)], including PTSD[(12,13,14)]. Some use anger to target outsiders as the source of risk[(15)], others turn inwardly with grief[(10)].

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This diversity of responses raises the question of how and why individuals and communities take these different paths. For example, when first exposed to information about an attack, why do some people become fearful but others angry? Furthermore, how and why do some who are initially fearful become angry [3], while others find their fear dissipate?

As risk researchers have long argued, people's emotional reactions to shocking, threatening events have many complex causes [16]. Moreover, these complex causes operate *at multiple levels* [17]. For example, at the micro level, individual predispositions and characteristics play a role [18], but so do interpersonal social interactions [19]. Macro-social processes, such as reporting by news media, also have an influence [20]. Emotions are also subject to rapid change and fluctuation [21,22], making it critical to understand their temporal dynamics [5].

The dynamic, multi-level nature of these processes creates a methodological challenge. Traditional methods tend to excel in isolating the influence of processes at one level while obscuring the influence of others. For example, controlled experiments can track individuals' emotional dynamics and behaviors in response to simulated threats [23,24]. However, there are practical limitations on controlled experiments' ability to capture important aspects of the macro-social context in which real terrorist attacks are experienced, such as interactions within personal social networks [19,25] and news stories that "trend" or are shared over interpersonal connections [26,27].

Survey methods, such as those using long-term panels [6], can account for these broader influences, as individuals respond based on the total set of influences they have experienced in the world. However, since survey panels can only address the specifics of an attack after it has taken place, surveys tend to lack important prior information such as the respondent's baseline level of anxiety about terrorism [28]. In addition, surveys often cannot be deployed in the immediate aftermath of attacks, forcing respondents to recall how they felt after the immediate threat has subsided and their reaction has already been shaped by multiple influences.

These concerns have lead to the use of social media streams to track collective responses to terrorist attacks and natural disasters as they unfold [29,30,31,21,32,33]. However, to date, analyses of social media streams have relied on data from keyword searches that select all posts that are relevant to a topic, such as tweets that contain terms or hashtags referring to an attack site or communal

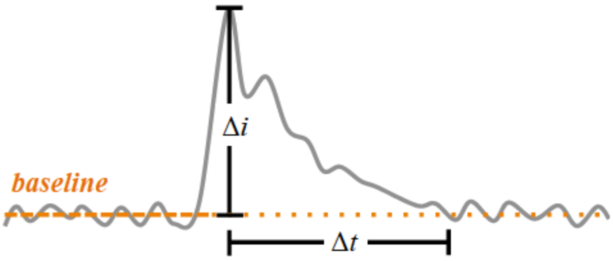

Fig. 1. Illustration of our analysis framework. We quantify the emotional outcome of individual users in two aspects, distress intensity increase (Δi) and recovery duration (Δt), both measured relative to a pre-event baseline.

response [34,31,35,36]. These approaches can be used to understand novel community phenomena [37], or to track novel messages, such as rumors, which are intended to be in relation to an event [35,38]. However, they are restricted to emotions expressed in reference to the event by individuals who are necessarily attending to it, rather than the effected community as a whole [39]. Furthermore, these keywords, which typically refer to the attack location [22], are only relevant after the attack or disaster has taken place. This makes it difficult to use this technique to evaluate *changes* in states or behavior, such as individual or communal distress, that require a meaningful prior baseline.

Currently there is little work exploring research designs capable of measuring and comparing the multi-level influences on reactions to terrorist attacks. In this paper we attempt to address this gap by proposing a new study design termed *computational focus groups* and an accompanying analysis framework focusing on the intensity and duration of distress expression.

1.1 Present work: Tracing distress dynamics at a fine-grained level

In this paper we create and analyze *computational focus groups* [40] to address the aforementioned limitations. Computational focus groups are comprised of social media users who are typically near to the site of an attack. Their pre-attack and post-attack social media behavior is then collected. This method integrates the advantages of mobile and social communication infrastructure by including precisely timestamped behavior drawn from multiple levels of observation of individuals with discoverable prior characteristics. These data enable us to evaluate the disparate effects of an attack in a more comprehensive model, allowing for inferences that are difficult to make with traditional designs. The technique can also be easily re-applied in new circumstances, enabling the study of responses to multiple attacks[24].

We construct these groups in the aftermath of the November, 2015 terrorist attacks on Paris and include observations from the attacks on Brussels several months later. Our analysis focuses on the expression of emotional distress, specifically, on the expression of the three primary negative emotions: anger, anxiety, and sadness[41]. Specifically, our analysis takes advantage of both an individual's baseline emotional expression and fine-grained timestamps of their emotions after the attacks to analyze two distinct dimensions of each distress emotion:

(1) The *intensity* of distress, that is, *how much* did the attacks increase the extent to which people expressed these emotions?
(2) The *duration* of distress, that is, *for how long* did individuals express heightened levels of distress?

These distinct theoretical concepts are illustrated in Fig. 1. In brief, the distress intensity increase (Δi) measures how a user's rate of expressing emotional distress increased from his/her own base rate immediately after the event, and the recovery duration (Δt) measures how long it took for a user's heightened rate to return to the pre-impact state. Using these time-dependent measures in comparison to their baseline levels will allow for the examination of novel dynamic relationships between terrorist attacks, individual and social characteristics, and distress.

1.2 Theoretical Motivations

Emotions. Emotions differ in both the circumstances that stimulate them and the kinds of judgments they subsequently induce. *Anxiety* or fear is triggered by a threat for which an individual lacks a clear response[42]. By contrast, *anger* is triggered by a threat for which an individual is confident in the appropriate response and frustrated by the failure to take action. The tendency for anger to direct blame outward at others[43] also distinguishes it from *sadness*. Sadness is an emotion that solicits cooperation and assistance[44], nurturing bonds between sympathetic others rather than straining the bonds between the estranged. There is also evidence that sadness is directed toward specific individuals, such as victims[45], whereas anger is often directed towards general others, such as out-groups[46].

Emotional expression is important for understanding responses to terrorism for a number of reasons. First, emotions underlie many aspects of risk perception[5,47]. For example, anxious individuals appear to rely more on anecdotal evidence when making decisions[48], or choose more certain, apparently less risky options than angry individuals[42,43]. Emotions expressed on social media also appear to influence the trustworthiness and usefulness of the messages[49]. The lingering nature of these emotions can also influence other judgments[50]. For example, there is evidence that anxiety about terrorism is associated with anxiety about disease outbreak[47] and that chronic anger at out-group members can lead to violence[15].

Second, the expression of emotion itself – the act of sharing a feeling – can further amplify it in a social group[51]. Furthermore, the expression of shared emotions has been associated with social bonding and collective efficacy[52]. This effect has been used to account for the pro-social and pro-communal behaviors often observed after terrorist attacks[53,9].

Thus, understanding the mechanisms that lead to the intensity and duration with which individuals express distress following attacks can help risk researchers address a number of important questions. However, isolating these effects and their antecedents with traditional methods is challenging. The problem is two-fold: these emotional dynamics are likely to be influenced by macro-social factors and thus hard to be realistically recreated with controlled experiments; yet, they are also temporally dynamic and reflexive and thus hard to be reliably recorded in surveys. Below we discuss four basic factors, drawn from the literature, that are difficult to address with these methods, and how these shortcomings are addressed with computational focus groups.

Proximity (to an attack). Individuals in close *proximity* to an attack will likely express more distress than those farther away[29,22]. The most apparent explanation is the immediate threat of physical danger[50,54]. However, many social factors can also have influence. In particular, individuals close to an attack are also likely to have friends and family close to the attacks[55,10], as well as to identify with victims as in-group members[56,3]. Proximity is also likely to have an impact on the duration of distress expression[6].

Studying the effect of proximity is more complicated than it would appear. In particular, while experimentally manipulating individual proximity to an attack can be achieved through immersive experimental methods (see Rosoff et al.[23]), it is generally not feasible to recreate the social conditions of the attack, such as calls from loved ones[57]. By contrast, because the observations from computational focus groups are drawn from real attacks that actually affect not only research subjects but their communities, they include the influence of subjects' social interactions.

Gender. Survey responses also include the influence of subjects' real social interactions. However, a weakness of surveys in the context of terrorist attacks is the difficulty of establishing a baseline. Survey questions probing the impact of a particular attack cannot be scheduled in advance. Thus, respondents must always answer *after* the attack has taken place. This distance in time already adds error to responses[58]. Furthermore, the extent to which an attack alters an individual's perception of the world[59] will also alter their memory of their emotional state and behaviors prior to the event.

Thus while surveys can address the macro-social limitations of experiments, they present difficulties for accounting for the influence of simple individual characteristics which may be correlated with both emotional reactions to terrorist attacks and the influence of these reactions on memory. For example, there is some evidence that *gender* influences terrorism risk perceptions[18], but evidence is mixed[6,23]. Unfortunately, a survey that finds that women show more fear than men after an attack is problematic because it is difficult to know, first, whether the women surveyed are more fearful in general and, secondly, whether their higher level of fear is the result of a higher initial increase in fear or a slower recovery. Computational focus groups track fear as it is expressed, and include data from before the attacks as well as in their immediate aftermath when it is difficult to survey subjects.

Interpersonal communication. Conversations with others, even those not in danger or suspected to be in danger, can also amplify or attenuate the emotional response to an attack[19,60,20]. The understanding of risk is also constructed and made sense of via conversation within social communities about what is risky and worth worrying about[59,61]. Conversation within personal networks can thus lead individuals in one social group to dread an outcome that is accepted as normal in another[8,62]. At the same time, interpersonal interaction can also help to enhance social capital that can be leveraged to solve problems[63,64] or provide social support[3,65].

Unfortunately, neither experiments nor surveys are well-equipped to handle this variable. As described above, the capacity to allow individuals to interact with their natural array of social ties – friends, family, co-workers – within an experiment is cost prohibitive. At the same time, while survey responses include the effects that interpersonal interactions have had on individuals, accurately quantifying their extent as a time-dependent covariate is problematic due to people's difficulty in accurately recalling their social interaction frequency[58]. While computational focus groups cannot fully account for the range of interactions that take place outside of a particular social media platform, they can capture an individual's tendency and temporal variation to engage or withdraw socially in their interactions within the social media observed.

Media exposure. News media can have an important impact on the perception of risks of violence and terrorism, particularly at the societal level[66]. Individuals exposed to news media reports about terrorist attacks tend to be heightened in their perception that those in their society are at risk, which in turn can stimulate strong emotional reactions[56]. The heightened news media attention given to terrorist attacks is also likely to induce a stronger effect than media reports about less spectacular risks[20].

News media exposure can be experimentally controlled[23,24]; however, it is increasingly delivered through social channels[26]. Thus, the natural setting through which individuals receive news media is, like social interaction itself, increasingly difficult to simulate and also increasingly difficult for individuals to report in surveys. People are not likely, for example, to recall whether they read many news stories or simply saw friends sharing many new stories with them. As with social interactions, computational focus groups cannot capture all of an individual's attention to news media; however, they can allow for the measurement of engagement with news media through social media.

Dynamics of emotions. There is a growing literature on how emotions at one point in time give rise to different emotions at a later point in time. Though not yet a well-theorized area, two recent studies used Twitter to track changes in emotions over time in response to violent acts. For example, in a study of tweets sent after the shootings in Newtown, CT, Doré et al.[21] found that sadness was the initial emotion expressed, but that this eventually turned to anxiety. Lin and Margolin[3] found that communities that expressed more anger after the Boston Marathon Bombings later expressed more solidarity with the victims.

Assessing the relationship between and factors that influence short-term and long-term emotional responses is also challenging with traditional methods. Experiments can track short term shifts with fine-grained measures of emotional response. However, maintaining ecologically valid conditions within an experiment is difficult over days or even hours. Subjects must either be kept inside the experimental manipulation for an unnaturally long duration or be released to return later, during which time they have access to information and social resources that are not influenced by the experimental treatment. Meanwhile, surveys are generally administered at sparse time intervals, particularly after an event such as a terrorist attack. Thus, important changes that take place within the first day or two after an attack are unlikely to be captured by surveys. Computational focus groups use detailed time-stamped behavior that enable the measurement of fine-grained temporal dynamics.

2. METHODS

The study focuses on the emotional trajectories following terrorist attacks. We design a study based on all users identified to be relevant to the 2015 terrorist attacks on Paris, and subsequently track their activity following the attacks on Brussels several months later. This section details our study design and analysis method.

2.1 Data collection

To study the emotional response to the events we collected Twitter data for more than five consecutive months covering the two attack events. As discussed earlier, this study aims to examine the fine-grained, emotional trajectory of individual users during and after the events by observing social media streams. Unfortunately, the commonly used keyword based selection method is likely to have the issue of selection on outcome – meaning that users who are selected based on the use of specific keywords may be highly correlated with certain types of emotional response. To circumvent this problem, we adopt a novel quasi-experiment method called *computational focus group*[40,67]. We define "focus groups" as users of social media whose prior behavior shows them to be interested in information relevant to the study content but independent of the shocks. In this case, the relevant information we utilize is the location of users. Once group members have been identified, their individual features and communication history are extracted to compare their behaviors before and after the events of interest. Using this approach permits us to treat the attack as a quasi-natural experiment in which a large number of individuals with different observable background characteristics are subjected to a common, unexpected treatment[40].

User selection criteria and the creation of focus groups. Based on this design the data collection follows a multi-step process.

1) We first construct a panel of users based on the geo-locations of their tweets. In particular, with a time window of four weeks after the attacks, we obtained 16,950 users who posted geo-tagged tweets within the Paris area[4], through the Twitter API[68].
2) For every user in our candidate set, we collect his/her full historic tweets through the Twitter REST API. In total, we obtained 15,509 unique users whose first tweet in our collection was posted before October 1, 2015. In this way, we have their complete set of tweets since October 1, 2015.

Our final data collection includes over 18 million tweets, among which over 1.4 million tweets have geo-coordinates (about 7.7%). We further filtered out the users who did not post tweets with geo-coordinates in the Paris area prior to the attacks since Oct 1, 2015, which reduces the number of users to 6,514. The users considered in this study are extracted according to the aforementioned criteria and no further sampling step is applied.

It has been reported that social media users are not representative samples of the entire population in terms of age, gender, and socio-economic status. For example, Twitter is more popular among younger adults and within urban areas[69,70]. Nevertheless, the location demographics in our data collection covering Paris is relatively comprehensive. To estimate the location coverage of our data, we partition the whole Paris area into grid cells of equal size (1 km^2), and compare the fraction of our tweet data covering those grids with the hourly traffic occupancy rate in Paris[71]. The traffic occupancy rate, i.e., the fraction of time the road segment is occupied with traffic, is used as a proxy for dynamic population

[4]The region is defined within a rectangle boundary (48° 43' 21.5" N, 2° 04' 59.5" E, 48° 59' 4.8" N, 2° 36' 47.8" E) to cover the greater Paris area.

per small region. Our estimation indicates that over 77.2% space in Paris is covered by our data collection, with more populous grids having higher coverage rate – over 64.9% coverage for grids with 1% or higher traffic occupancy rate, and 83%–100% coverage for grids with 5% or greater traffic occupancy rate. The detailed estimation can be found in Appendix and Table A-I.

Fig. 2 shows a random sample of 2,000 tweets posted around the six attack sites within the first two days after the Paris attack event. Our dataset indicates there was a burst in the number of users and tweets on the day of the attacks. The average volume of tweets before, during and after the Paris attacks are 82,346 tweets/day, 161,188 tweets/day, and 100,388 tweets/day. The proportions of geo-tagged tweets do not exhibit significant difference across the event period (based on paired Wilcoxon signed rank test with continuity correction).

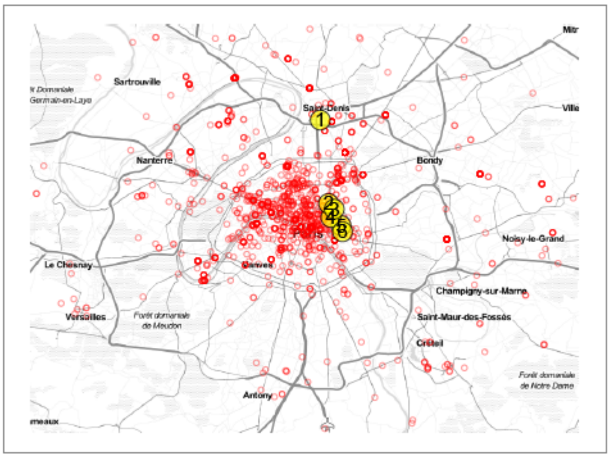

Fig. 2. A random sample of 2000 tweets posted around the 6 attack sites (yellow dots 1-6) within two days after the 2015 Paris attack event. Site markers indicate[72]: (1) Stade de France, (2) Le Petit Cambodge restaurant and Le Carillon bar, (3) Rue de la Fontaine au Roi, (4) Bataclan concert hall, (5) La Belle Équipe, and (5) Boulevard Voltaire.

2.2 Distress response

This research leverages the psycho-linguistic lexicon LIWC (Linguistic Inquiry and Word Count)[73,74] to determine the emotional expression of individual Twitter users. LIWC is one of the most widely adopted lexicon-based psycho-linguistic measures that rely on a predefined sentiment lexicon or affective word list to determine the sentiment categories of given texts. Such a lexicon-based approach has been widely adopted to analyze real-world data sets[3,40,75,76] because it can be easily scaled to large datasets, easily interpreted and does not depend on labeled data. In particular, LIWC has been used as linguistic markers of the psychological change surrounding September 11, 2001[77].

We utilize LIWC as it is one of the few lexicons that support a variety of languages, including French. This is particularly helpful in this work since a considerable portion of our data are in French (46% in French, 30% in English, 4% Spanish, 2% Portuguese, and others are undefined). In our analysis we focus on French and English written tweets and apply either English and French lexicons to obtain the measures.

The emotional states of users over time are determined as follows. For every user u, the *rate* of an emotional category c at a given time t, denoted as $r_u^{(c)}(t)$, is defined as:

$$r_u^{(c)}(t) = N_u^{(c)}(t)/N_u(t), \tag{1}$$

where $N_u(t)$ is the total number of tweets posted by user u within time t, and $N_u^{(c)}$ is the number of tweets from this set that contains at least one word from the category c in the lexicon. Based on LIWC, we identify rates of the positive and negative emotion categories, as well as three sub-categories of negative emotions: anger, anxiety, and sadness. In this work, we consider these three negative emotions as *distress* response. Fig. 3 shows the temporal variations of the three types of distress response in periods covering both Paris attacks on November 13, 2015 and Brussels attacks on March 22, 2016. All three distress measures, measured on a daily basis, exhibited a sudden increase immediately after the two events. The spikes during Paris attacks are 1.7–2.1 times stronger than those in the Brussels attacks, as the formal event was more intense to the Paris users.

We choose to measure individual users' distress response on a daily basis mainly for two reasons: (a) to eliminate the diurnal variation of user activity, and (b) to reduce the data sparseness (due to the lack of tweets for each user at each hour). We provide detailed hourly breakdowns for the number of tweets per hour in the Appendix (see Fig. A-I).

2.3 Individual covariates

We describe the theoretical variables, followed by the control variables that will be used in this study. Theoretical variables include *proximity*,

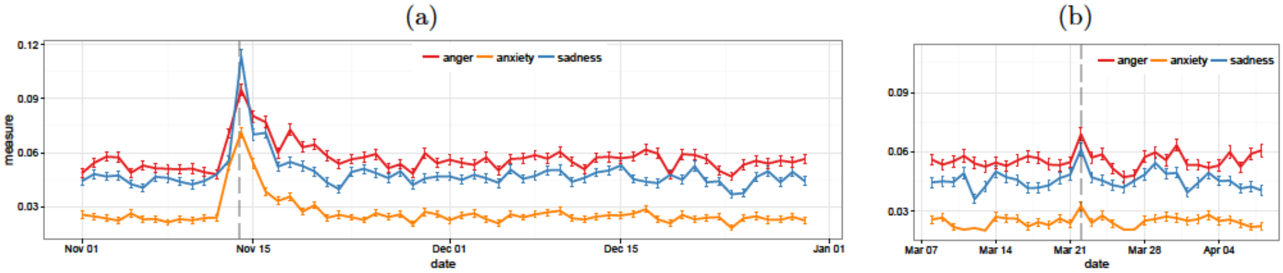

Fig. 3. The trend of distress response. Vertical dashed lines indicate the day of the events. Each data point shows the average affect measure of the same set of identified users with errorbars indicating standard errors. Two events are (a) Paris attacks on November 13, 2015, and (b) Brussels attacks on March 22, 2015.

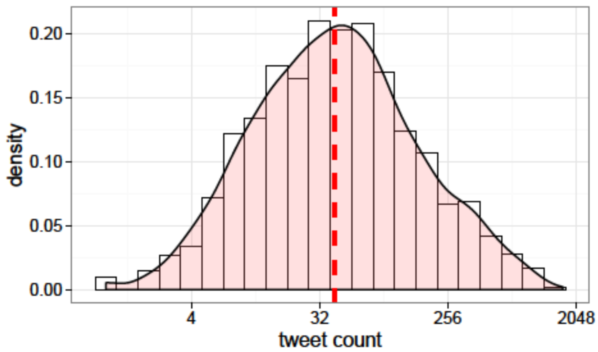

Fig. 4. The distribution of number of tweets posted within one month prior to the Paris attack event. The x-axis is on a base 2 logarithmic scale, and the red dashed line indicates the median count, indicating the distribution is skewed to the right (right-tailed).

gender, *interpersonal communication*, and *media exposure*.

Geographic proximity. Geographic proximity measures how close a user's current location is to the attack locations. There are six attack sites in the Paris attacks (as shown in Fig. 2). Geographic proximity is an inverse measure of the geographic distance from the attack sites. For every user, the distance is measured by computing the distance between the user's location at a given time t to the closest attack site, where the user's location at t is estimated based on the centroid of all geo-coordinates extracted from the user's geo-tagged tweets within the time t.

Gender. Users' gender information is not directly available from their Twitter profile. In this work we leverage the genderize API [78] to infer users' gender based on their first names. This method has been reported as one of the best name-based approaches, with accuracy above 0.8 for English names and 0.96 for French names [79]. Using this approach, we are able to infer the gender for 11,107 users, among which 47.8% of the users are female.

Interpersonal communication. Interpersonal communication measures how frequently a user directly interacts with others on social media. In this work we use the @-mention as a proxy for measuring the interpersonal communication. On social media, @-mention has been adopted by users as a convention to direct a public message to a particular user, or reply to another user's message. We construct a variable, *mention rate*, as a time-variant measure which estimates the extent to which a user's tweet messages contain @-mentions. It is quantified as the proportion of a user's tweets containing the expression "@username" relative to the total number of tweets posted by the user within a particular time.

Media exposure. Media exposure measures the extent to which a user engaged in sharing news information. It is quantified as the proportion of a user's tweets containing news URLs relative to the total number of tweets posted by the user within a particular time. We use tweets containing news URLs as a proxy for estimating media exposure, which is a parsimonious measure for "exposure" as users might be exposed to news media content without actively sharing the news links in their tweets. After the event, we further restrict the news tweets to be tweets that contain news URLs and have keywords "attack" or "terro*" (any word starting with the prefix "terro") to avoid the inclusion of news sharing irrelevant to the event.

Control variables include *activity level*, *positive rate*, and *social network size*.

Activity level. The activity level measures a user's expected tweet rate, i.e., number of tweets posted within a given period of time. This measure may be influential to the robustness of the distress measures as those rely on users' having a certain number of tweets within a given period of time. Hence, in our analysis, we further distinguish users into high and low activity groups using the median tweet rate. Fig. 4 shows the histogram of number of tweets per user within one month prior to the event. It can be observed that the distribution of users' tweet count is highly skewed, and the lower activity group of users on average posted less than 1.1 tweets per day.

Positive rate. The positive level measures a user's proportion of tweets containing positive words at a given time (i.e., $r_u^{(positive)}$ for user u). This is used as a control variable for comparing users' negative emotion with various levels of positive emotion.

Social network size. Social network size is measured as the number of social connections for each user. We measure a Twitter user's network connections based on his/her friend count and follower count, acquired through the Twitter API[68]. We assume a user's friend and follower counts are relatively stable and do not change over the analysis period. These variables enable a scrutiny on the effect of interpersonal communication within different sizes of social networks.

2.4 Analysis framework

In this work we seek an empirical understanding of users' immediate emotional response as well as the subsequent recovery process following the attack events. This approach is conceptually similar to that deployed in *event studies*, an econometric technique used to determine the impact of specific events, such as earnings announcements, on stock returns[28]. As with stock returns, our variable of interest, the expression of distress, follows a trajectory that is independent of the event itself. Isolating the impact of the event thus requires comparing the observed response (returns, distress) to that which would have been expected under normal circumstances.

As illustrated in Fig. 1, we quantify the emotional outcome of individual users in two aspects, distress *intensity increase* and *recovery duration*, both measured relative to a pre-event baseline. In this study, the time unit is one day.

Baseline. We measure a pre-event base rate of a user u's distress measure $b_u^{(c)}$ as:

$$b_u^{(c)} = \frac{1}{m} \sum\nolimits_{t_0 \leq t < t_e} r_u^{(c)}(t), \qquad (2)$$

where t_e denotes the time of the event, and m is the number of data points (of the measure) collected in the observation duration (between t_0 and t_e). $b_u^{(c)}$ captures the pre-event average rate $r_u^{(c)}(t)$, where in our study, the time t covers 28 days prior to the event. The measures $b_u^{(sadness)}$, $b_u^{(anger)}$, $b_u^{(anxiety)}$, with respect to the three distress categories, provide baseline estimates of each individual user's distress rate during normal time.

Distress intensity increase. As illustrated in Fig. 1, the distress intensity increase (Δi) measures how a user's distress increased from his/her own base rate immediately after the event. We quantify the distress increase as the difference between the immediate distress rate and base rate $b_u^{(c)}$, as:

$$\Delta i^{(c)} = \frac{1}{\delta} \sum\nolimits_{t_e \leq t < t_e+\delta} r_u^{(c)}(t) - b_u^{(c)}, \qquad (3)$$

where the first term, the immediate distress rate, is computed as the average rate $r_u^{(c)}(t)$ where in this study, the time t covers 4 days starting on the event day. We include the subsequent three days immediately after the event in order to cope with the data sparseness during a short period of time.

Distress recovery duration. As illustrated in Fig. 1, the recovery duration (Δt) measures how long it took for a user's distress to return to the pre-impact state. Similarly, to cope with the data sparseness during a short period of time, the distress rate on day t is computed as a rolling (smoothed) rate $\tilde{r}_u^{(c)}(t) = 1/\delta \sum_{t-\delta < t' \leq t} r_u^{(c)}(t')$ where in this study, we use $\delta = 4$. Then, the recovery duration for a distress category (sadness, anger, or anxiety) is quantified as the number of consecutive days after the event on which a user's distress rate is greater than his/her base rate for the respective category, which is given by:

$$\Delta t^{(c)} = min_{s \geq 0}\{s : \tilde{r}_u^{(c)}(t_e + s) - b_u^{(c)} \leq 0\}, \qquad (4)$$

where s is a non-negative integer indicating the post-event days on which a user's distress rate is no greater than the base rate.

Analysis of response intensity. We use multivariate regression analysis to identify important variables that can explain users' variation in distress intensity increase in response to the event. The analysis focuses on users whose distress intensity had positive increase compared with their individual base rate. The immediate response period – four days starting on the day of the event – is chosen as the majority of users returned to their baseline emotional state. The explanatory variables include aforementioned individual covariates such as geographic proximity, gender, social interaction (social network size and mention rate), and media exposure. Three variables, geographic proximity, mention rate, and media exposure, are measured both in the pre-event period (within 28 days prior to the event) and in the immediate response period (within four days starting at the event day). Because of their skewed distribution, the variables for friend count, follower count, and tweet rate are log-transformed, and the geographic distance is square-root transformed.

Analysis of recovery duration. We use survival analysis to identify important variables that can explain users' variation in distress recovery duration following the event. We consider Weibull distribution in the survival analysis, which is also a generalization of the exponential distribution without assuming constant hazard rates. When the shape parameter $\gamma > 1$, the hazard function is increasing; when $\gamma < 1$ it is decreasing, and the Weibull distribution reduces to the exponential distribution when $\gamma = 1$. Similar to the analysis of distress difference, the explanatory variables include aforementioned individual covariates. The three variables, geographic proximity, mention rate, and media exposure, are measured both in the pre-event 28-day period and on each day (the time-varying variables are calculated for each day t with a 4-day rolling sum covering $[t-3, t]$).

Analysis of response intensity in the new attacks. The analysis of Paris users' response in the Brussels attacks are similar to the analysis of Paris attacks. We use multivariate regression analysis to explain users' variation in distress intensity increase in the first four days immediately following the Brussels attack event. This analysis further focuses on users whose distress intensity had positive increase during the immediate response period compared with their individual base rate. The explanatory variables are similar to the analysis of the Paris event, except that the geo-proximity variable is removed as the Brussels attacks were distant from all the Paris users. The base rate variables are measured both in the pre-event period (within 28 days prior to the Brussels event). We also include users' distress intensity increase in response to the Paris attacks in order to examine potential emotional response correlation between the two events.

The proposed analysis framework has a unique contribution in terms of establishing baseline measures for response variables and creating time-sensitive co-variates, which are typically unobservable in traditional methods. Table I summarizes the strengths of the proposed analysis framework compared with the traditional study designs.

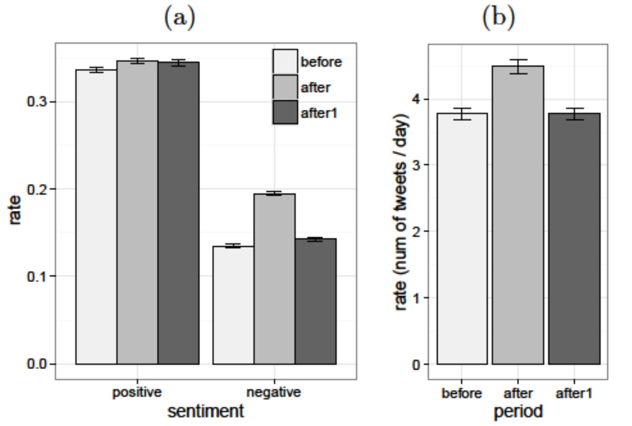

Fig. 5. User activity changes before and after the Paris attacks. The three bars show the corresponding average measures within one week before and in the first and second weeks after the event. The measures are (a) average rate of observing positive and negative tweets, and (b) average tweeting rate per day. The measures in the week immediately after the event are significantly higher than those in other periods, while the measures in the subsequent week did not show significant difference from those in the before-event week.

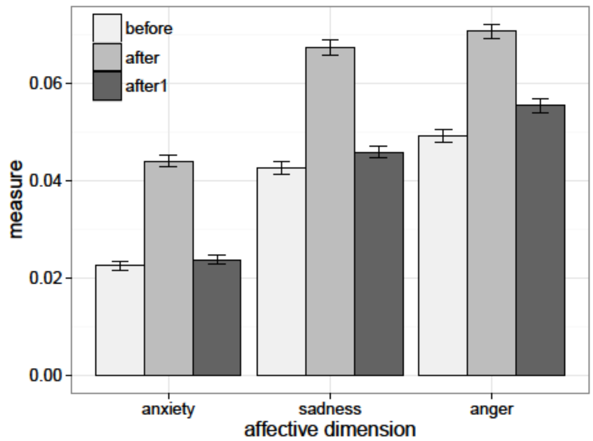

Fig. 6. The affect responses before and after the Paris attacks. The three bars show the corresponding average measures within one week before and in the first and second weeks after the event. All affect measures in the week immediately after the event are significantly higher than those in other periods, while the measures in the subsequent week did not show significant difference from those in the before-event week.

Table I . The advantages of the proposed analysis framework compared with traditional methods.

Variable	Temporal dimension	Prior methods and limitations*	Present work
Emotion	General / baseline	E [42]	Computed as time-dependent and continuous variables; both baseline and post-attack dynamics of emotions are measurable
	Post-attack	E [23,24], S [42,80,81], K [22,29,21]	
Gender	N/A	S [6]	Identifiable (inferred)
Proximity (to attack site)	General / baseline	E [23,82], S [54]	Identifiable – the geocode (exact latitude and longitude) allows for creating time-dependent and continuous variables; both baseline and post-attack locations are measurable
	Post-attack	E [82], S [80,50], K [22,29,21]	
Social interactions	General / baseline	S [83]	Identifiable – the observable social media interactions (@-mention) allows for creating time-dependent and continuous variables; both baseline and post-attack locations are measurable
	Post-attack	U	
Media exposure	General / baseline	E [43]	Identifiable – the observable social media traces (news sharing) allows for creating time-dependent and continuous variables; both baseline and post-attack locations are measurable
	Post-attack	E [23,24], S [80,54]	

***Abbrev. of methods and major limitations:**
(E) Measured by experiments that simulate events or threats
Issues: hard to simulate social interactions and concerns present in real events
(S) Measured by surveys
Issue: difficulty of obtaining accurate pre-event baselines for some variables due to subjects' recall bias
(K) Posts to social media selected by use of keywords
Issues: Keywords only relevant post-event; data only includes individuals & posts that explicitly address event topics
(U) Unmeasured or unobservable in prior work

3. RESULTS

3.1 Impact of attacks on emotional expression

To statistically evaluate the differences in the emotional states of users before, during and after the attack event we divide the users' tweets into three time periods: one week before the event ("before"), one week after the attacks ("after"), and the week subsequent to the after period ("after1"). Because the activity measured from repeated observations of the same individuals do not exhibit normal distribution (as shown in Fig. 4), we use paired Wilcoxon signed rank test to assess the statistical significances among the three periods.

Fig. 5 compares the average twitter behavior of our panel members for these periods. Error bars indicate 95% confidence intervals. Fig. 5 (a) shows that for the Paris attacks, the expression of negative emotion is significantly greater during the "after" period when compared with the other two periods (both with $p < 0.001$). This effect does not apply to emotion in general, however, as the change in the expression of positive emotion is substantially less pronounced, as shown in Fig. 5 (a), and statistically insignificant.

Fig. 6 provides the same analysis broken out

Table II . Correlation among tweet activity and distress measures: before (B) vs. immediate responses (I). Spearman's rank correlation coefficients are reported due to the skewed distribution in variables. All correlations are significant with $p < 0.001$.

	Baseline (28 days before the event)					Immediate (day 0-3)				
	tw. cnt. (B)	anx. (B)	ang. (B)	sad. (B)	pos. (B)	tw. cnt. (I)	anx. (I)	ang. (I)	sad. (I)	pos. (I)
tweet count (B)	1.000									
anxiety (B)	0.456	1.000								
anger (B)	0.449	0.439	1.000							
sadness (B)	0.410	0.377	0.389	1.000						
positive (B)	0.112	0.168	0.114	0.159	1.000					
tweet count (I)	0.746	0.426	0.434	0.396	0.089	1.000				
anxiety (I)	0.330	0.268	0.300	0.254	0.108	0.466	1.000			
anger (I)	0.337	0.288	0.349	0.276	0.072	0.474	0.402	1.000		
sadness (I)	0.295	0.265	0.248	0.262	0.161	0.410	0.285	0.308	1.000	
positive (I)	0.126	0.115	0.102	0.127	0.302	0.156	0.112	0.118	0.097	1.000

Table III . Regression results for immediate distress increase response. Time-variant variables include baseline (B) measured within 28 days before the event and immediate (I) measured within the immediate response period. Coefficients are standardized to facilitate comparison among variables.

	M1			M2		
	anxiety	anger	sadness	anxiety	anger	sadness
geo-proximity (B)	0.01**	0.01	0.01	0.01	0.01	−0.002
gender male	−0.0001	−0.004	−0.02**	−0.001	−0.004	−0.02**
mention rate (B)	−0.01	−0.03	−0.07**	−0.01	−0.02	−0.01
media exposure (B)	0.03	0.02	0.03	0.02	0.02	0.03
activity high	−0.12**	−0.27***	−0.18***	−0.10**	−0.27***	−0.20***
tweet rate	−0.04***	−0.10***	−0.10***	−0.04**	−0.10***	−0.11***
positive rate	−0.01	−0.01**	0.02***	−0.01	−0.01*	0.02***
friend count	−0.01	0.001	−0.01	−0.01	0.001	−0.01
follower count	0.002	−0.001	−0.002	0.002	−0.0004	−0.002
geo-proximity (I)				0.004	0.004	0.01*
mention rate (I)				−0.02	−0.02	−0.11***
media exposure (I)				0.28***	0.14	−0.03
activityHigh:tweetRate	0.01	0.07***	0.04***	0.01	0.07***	0.04***
Constant	0.42***	0.57***	0.58***	0.42***	0.57***	0.61***
Observations	785	807	846	785	807	846
R^2	0.36	0.36	0.34	0.37	0.36	0.35
Adjusted R^2	0.35	0.35	0.34	0.36	0.35	0.34

Note: *p<0.1; **p<0.05; ***p<0.01

by negative emotion categories. The attacks had a significant impact on the expression of each negative emotion. The differences between "before" and "after" for all three categories are statistically significant (all with $p < 0.001$). The differences between "before" and "after1," while much smaller, are also significant at the 0.05 significance level ($p = 0.021$ for anxiety, $p = 0.028$ for sadness, and $p < 0.001$), indicating the lingering effects of the attacks.

Analysis of tweet rates also indicates that measuring emotional expression as the proportion of tweets may understate the extent to which emotions are amplified through the Twitter network immediately after the attacks. This is because the rate of tweeting also increases in this period, as shown in Fig. 5 (b) ($p < 0.001$). Unlike the negative emotions, this higher rate is not sustained into the subsequent week, as the tweet rate difference between "before" and "after1" is non-significant ($p = 0.199$).

Table IV . Survival analysis for distress recovery duration. Time-variant variables include baseline (B) measured within 28 days before the event and time-dependent (T) measured on a daily basis. The shape parameter γ in the Weibull distribution is estimated as 1/scale. The estimated risk increases over time as $\gamma > 1$ in all cases. Coefficients are standardized.

	M3			M4		
	anxiety	anger	sadness	anxiety	anger	sadness
geo-proximity (B)	0.01	−0.02	−0.01	0.01	−0.03*	−0.03
gender male	−0.04	−0.03	−0.06*	−0.04	−0.03	−0.06*
mention rate (B)	0.01	−0.04**	−0.03	0.01	−0.05***	−0.03
media exposure (B)	−0.03*	0.03	0.003	−0.03*	0.03	−0.002
activity high	−0.06	0.11	0.09	−0.05	0.12	0.09
tweet rate	0.14	0.04	0.01	0.14	0.02	0.01
positive rate	0.004	0.04	0.01	−0.01	0.05	0.002
friend count	0.02	−0.02	0.02	0.02	−0.02	0.02
follower count	−0.02	0.004	−0.04*	−0.01	0.01	−0.03*
geo-proximity (T)				0.04**	0.05***	0.06***
mention rate (T)				−0.004	0.03	0.002
media exposure (T)				−0.02	0.08	−0.14**
activityHigh:tweetRate	−0.07	0.02	0.11*	−0.07	0.03	0.11*
Constant	1.70***	1.63***	1.60***	1.73***	1.67***	1.65***
Log(scale)	−0.77***	−0.79***	−0.77***	−0.77***	−0.80***	−0.79***
Observations	747	750	795	747	750	795
Log Likelihood	-1,577.83	-1,639.54	-1,721.71	-1,574.04	-1,632.93	-1,712.42
χ^2 (df)	35.77*** (10)	49.49*** (10)	35.34*** (10)	43.33*** (13)	62.70*** (13)	53.91*** (13)

Note: *p<0.1; **p<0.05; ***p<0.01

Table V . Regression results for immediate distress increase response (Paris users during Brussels attacks). Time-variant variables include baseline (B) measured within 28 days before the event and immediate (I) measured within the immediate response period. Measures of distress intensity increase in Paris attacks (PI) are also included. Coefficients are standardized.

	M5			M6		
	anxiety	anger	sadness	anxiety	anger	sadness
gender male	−0.16	−0.09	−0.08	−0.10	−0.11	−0.08
mention rate (B)	0.55	0.18	−0.02	0.77	0.20	0.09
media exposure (B)	−0.13	0.31	−0.13	−0.04	0.35	−0.16
activity high	−2.42***	−0.80	−4.14***	−2.20***	−0.76	−4.40***
tweet rate	−0.88***	−0.45**	−1.37***	−0.73***	−0.45**	−1.46***
positive rate	0.03	0.14	0.004	−0.02	0.14	0.01
friend count	−0.03	−0.04	0.06	−0.07	−0.05	0.05
follower count	−0.03	−0.03	0.04	−0.02	−0.03	0.04
mention rate (I)	−0.49	0.04	−0.50	−0.58	0.09	−0.52
media exposure (I)	1.02	−2.84	−2.95	0.05	−2.70	−2.06
sadness (PI)				0.09	−0.003	0.05
anger (PI)				0.12	−0.07	0.01
anxiety (PI)				0.08	0.03	−0.19***
activityHigh:tweetRate	0.52***	0.06	1.04***	0.46**	0.06	1.12***
Constant	4.44***	2.26***	5.24***	4.09***	2.25***	5.58***
Observations	165	233	234	165	233	234
R^2	0.36	0.22	0.37	0.39	0.23	0.40
Adjusted R^2	0.31	0.18	0.34	0.33	0.18	0.36

Note: *p<0.1; **p<0.05; ***p<0.01

3.2 Predictors of immediate emotional expression

To evaluate the emotional states during normal and event periods we divide the tweets into two segments: the most recent 28 days before the attacks (B), and the 4 days immediately after the attacks (I). We focus on the first four days as the immediate response period since for about or above half of the users distress returned to the pre-impact state within four days – 55% for anxiety, 52% for anger, and 48% for sadness.

We then explore the correlates of these increases in sentiment. The correlation matrix shown in Table II indicates that, though the attacks are disruptive and cause an increase in aggregate twitter activity, the high correlation ($r = 0.746$, $p < 0.001$) between an individual's (B) and (I) tweet counts indicates that users of all baseline activity levels became increasingly active after the attacks to a similar extent.

The inclusion of individuals' baseline behavior is a feature of our approach. The level of individual users' baseline activity, i.e., tweet count (B), has a strong association with their base rate of expressing negative emotion ($r = 0.456$ for anxiety (B), $r = 0.449$ for anger (B), and $r = 0.410$ for sadness (B); all significant with $p < 0.001$). In other words, active tweeters tend to tweet with more negative emotion. This is not a general property of all emotional expression, as there is only a weak association with the base rate of expressing positive sentiment ($r = 0.112$ for positive rate (B)). After the attacks, the associations between users' tweet rate (in I) and the rates of expressing negative emotions (in I) slightly increase. During this time, the rate of expressing positive sentiment, i.e., positive (I), remains weakly associated with users' tweet activity (in I). This pattern suggests there is a risk of confounding when using the keyword approach to capture sentiment. More specifically, even neutral events that stimulate an increase in tweets from active users will increase the negative sentiment more than positive sentiment because of the tendency for active tweeters to express negative emotion. The weaker results for positive emotion also indicate that observed changes brought on by the attack are consistent with its meaning as a horrifying event and are not an artifact of a general increase in emotion.

The multivariate model reported in Table III allows a more comprehensive examination of these relationships. The dependent variable in these models is the *intensity increase* in the three types of emotion expressed during the immediate aftermath (I) as compared with the prior period (B). The first set of models (M1) predicts the change in each negative emotion expressed based on factors that precede the attacks, while the second set of models (M2) include variables that capture other aspects of the users' response.

Geographic proximity. The closer to the attack site an individual typically was, the more anxiety expression the attack induces. The effect of proximity before the attacks is significant (M1, geo-proximity (B) $\beta = 0.01$, $p < 0.05$). Similarly, the model without including geo-proximity (B) shows that geo-proximity (I) is not significant at the 0.05 level ($p = 0.052$) (see appendix Table A-II). However, neither is significant in M2, when both are included together. Inspection reveals that geo-proximity (B) and (I) are substantially correlated (Spearman's rank correlation $r = 0.470$, $p < 0.01$). Though the VIF test for collinearity shows that they are not collinear, this appears to explain the non-significance of each term.

Though the model suggests there is also a potential relationship between proximity in the aftermath and sadness expressed (M2, geo-proximity (I) $\beta = 0.01$, $p < 0.10$), inspection of confidence intervals shows this not statistically significant (see appendix Table A-IX).

Gender. Men show a significantly smaller increase in the expression of sadness than women do in both M1 and M2, gender male $\beta = -0.02$, $p < 0.05$). The coefficients for anger and anxiety are also negative but are not significant in these models. Examining the base rate of these emotions by gender is useful, however, because it provides some indications of how this difference (and these non-differences) are produced (see Fig. A-II and the description). Unsurprisingly, the within-subject differences between "before" and "after" the attacks, in the expression of all three emotion categories, are all significant for both genders. Sadness shows the expected dynamics: before the attack, men and women show no significant difference in sadness expression rate ($p = 0.16$); after the attack, both genders show a significant within-subject increase, and the increase for women is significantly larger ($p < 0.001$). Dynamics for anger follow a similar logic. Before the attack men and women show no significant difference in anger expression, after the attack both genders show a significant within-subject increase, both increases are of similar magnitude (not significantly different). Dynamics for anxiety are less intuitive, however. For anxiety, it is the pre-attack baseline that is significantly different, with men expressing less anxiety than women in this generic context. After the attacks, both genders express significantly more anxiety within-subjects, but the men's increase in anxiety is enough to reduce the gap with women's anxiety expression, leading them to no longer be statistically different.

Interpersonal communication. Social relationships and interaction appear to play a role in the expression of sadness but not the other emotions. M1 indicates that individuals who, in general, are more interpersonally interactive with specific others on Twitter show a smaller increase in the expression of sadness (mention rate (B) $\beta = -0.07, p < 0.05$). This effect is not significant in M2, however, when mention rate (I) is included. Rather, it is the tendency to interact with others during the aftermath period that is associated with a relatively reduced expression of sadness (mention rate (I) $\beta = -0.11$, $p < 0.01$)

Media exposure. General interaction with media, measured by the user's tendency to share news media URL's prior to the attacks, is not a significant predictor of increases in emotional expression (M1). However, interaction with media in the immediate aftermath of the attacks is associated with heightened anxiety expression (M2, $\beta = 0.280$, $p < 0.01$), though not the other emotions.

3.3 Short term dynamics

In this section we explore the correlates of individuals' recovery, that is, the duration for which they return to their baseline levels of emotional expression.

Table IV presents the results using survival analysis for heightened expression of each particular emotion. An individual is defined as being in the heightened expression state for an emotion if, since the attack, there has not yet been a day where their expression of that emotion is at or below their baseline level. We use a Weibull survival model, with a shape parameter γ indicating increasing or decreasing hazard. As shown in Table IV , the estimated risk increases over time as $\gamma = 1/\text{scale} > 1$ in all cases. Positive coefficients in the models indicate longer survival, that is, that the predictor is associated with the period of heightened expression for that emotion extending for more days. Negative coefficients thus indicate more resilience or faster recovery, that is, that expression of that emotion returns to normal more quickly.

Geographic proximity. Proximity to an attack site during the aftermath (T) shows a significant positive effect for each emotion (M4: $\beta = 0.060$, $p < 0.01$ for sadness; $\beta = 0.050$, $p < 0.01$ for anger, $\beta = 0.040$, $p < 0.05$ for anxiety). In other words, the closer to the site an individual tends to be after the attacks, the longer it takes for them to return to their normal levels of anxiety, anger, and sadness expression. Unlike with the intensity of distress expression, proximity prior to the attack (B) does not show a clear relationship to the duration of expression.

Gender. Though both M3 and M4 show that men's expression of sadness appears to last for a shorter period of time ($\beta = -0.060$, $p < 0.10$ in both M3 and M4), inspection of the confidence intervals for these models does not support a difference (see appendix Tables A-XII and A-XV).

Interpersonal communication. As described in the preceding section, interpersonal interactions via @-mentions had a significant effect on the intensity of sadness expressed in the aftermath. By contrast, there is no effect of interpersonal interaction on the duration of sadness. Conversely, while interpersonal communication had no effect on the increase in anger expressed, it is associated with a shorter duration of anger. Specifically, anger expression subsided more quickly for individuals who tend to use Twitter more in general (B) for interpersonal, directed messaging through the use of @-mentions ($\beta = -0.040, p < 0.05$ in M3, $\beta = -0.050$, $p < 0.01$ in M4). Engaging in more interaction on Twitter, captured by mention rate (T) after the attacks, was not associated with a difference in anger expression duration, however. As with intensity, mention rates did not show any significant association with the duration of anxiety expression.

Media exposure. As described in the previous section, sharing media stories in the aftermath was significantly associated with a more intense expression of anxiety. There is no significant relationship, however, between media exposure and the duration of anxiety expression. Instead, an individual's general, baseline rate of media exposure (B) is associated with a shorter duration of anxiety expression ($\beta = -0.003$, $p < 0.10$ in both M3 and M4).

Conversely, while sharing media stories in the aftermath showed no significant association with an increased intensity of sadness expression, it is associated with a shorter duration of sadness ($\beta = -0.140$, $p < 0.05$). Sharing media stories in general, or in the aftermath, showed no significant relationship to the duration of anger expression.

3.4 Responses to new attacks

Table V reports results of the same models reported in Table II but applied to individuals' responses to the Brussels attack five months later.

Consistency with Paris attacks response. The models do not show many significant relationships between the respondents characteristics prior to the attacks (B) or their activity during the attacks (I) on emotional expression. This is likely due to the prior finding that proximity to the attacks is an important predictor, and Paris respondents may be too far from Brussels to be impacted in the same way.

Paris response behavior as a predictor of Brussels response. Paris response behaviors were modest predictors of the response to the Brussels attacks. Model performance, captured by R^2, increases between 1–3% when these Paris expression variables are included. Surprisingly, this explained variation is not due to auto-correlation within emotions, as the extent to which an individual showed increased intensity in expressing anxiety (anger, sadness) after the Paris attacks was not associated with a tendency to increase anxiety (anger, sadness) expression after the Brussels attacks. Rather, the one significant relationship is between two distinct emotions. Individuals who expressed more intense anxiety after the Paris attacks expressed less sadness after the Brussels attacks (M6, $\beta = -0.190$, $p < 0.01$).

4. DISCUSSION

Below we summarize the results in two ways. For each independent variable, we first summarize the significant findings in our study. Next, we assess whether this finding would likely be detected using alternative methods. Finally, in the limitations sections, we discuss how traditional methods can be used to complement the limitations of computational focus groups in light of these findings.

Proximity. As expected, proximity to the attack sites had a significant relationship to the intensity with which users expressed anxiety after the attacks (though not the other emotions). Also, after the attacks, continued proximity to the sites was associated with a longer duration of heightened distress measured by each emotion.

While the findings for intensity are easy to anticipate, the findings for duration indicate a useful contribution of the computational focus group approach. This effect would be difficult to capture via experiments, surveys or keyword searches alone. While experiments can manipulate proximity to an attack at the moment it occurs (i.e. through a treatment that specifies whether an attack occurrs near or far from an individual), it is difficult to simulate the experience of spending several days near an attack site, observing damage, dealing with distraught neighbors and so forth. At the same time, while surveys and keyword searches can pick up the effects of these ecological influences, it is difficult for them to establish a prior baseline level of distress for each subject. This is because an unbiased measurement of a respondent's baseline distress would require measuring that distress prior to knowledge of the attack or its location.

Gender. Our results indicate that women increase their expression of sadness to a greater degree than men do. With a careful measure of individuals' base rate of expressing negative emotion, we showed that the result does not come from a higher initial level of sadness or a slower recovery for women (see the results of M3, M4, and Fig. A-II). Thus, surveys which show post-attack differences between men and women in terms of sadness expression are likely telling an accurate story: each gender starts in roughly the same place, women experience a greater intensity, and then they recover in a similar manner. Base rate inspection also shows, however, that surveys which show post-attack similarities across gender for anxiety may be misleading. In particular, men appear to begin with lower pre-attack levels of anxiety. This implies that there is the possibility that post-attack similarities across genders actually suppress a meaningful difference.

Social interaction. Results for social interaction indicate that individuals who tend to interact socially express both less intense sadness and express anger for a shorter time. Whether this effect is due to an individual's characteristic tendency to interact, or the extent to which they interact in the wake of a particular attack, is less clear. Anger amelioration appears to relate to an individual's general tendency for interaction. This is an encouraging result for experimenters who might struggle to simulate real-world interaction, as it suggests that concerns about the influence of post-attack conversations on anger may be somewhat limited. However, the fact that the intensity of anger is not related to interaction, but the duration of anger expression above normal levels is, suggests that surveys and keyword searches that do not capture individual baseline rates of emotional expression may be misleading.

Media exposure. Results for media exposure indicates a more complex, dynamic role for this variable than for the other variables. Engagement with media in the aftermath of the attacks is associated with a higher spike of one distress emotion (anxiety); however, it is also associated with a faster recovery to normal from another (sadness). Moreover, it appears that, unlike with social interaction, it is actual engagement with media in the aftermath, rather than an individual's tendency to engage with media in general, which has the effect. Taken together, these results indicate that media exposure is an important variable whose effects may be difficult to capture without access to both baseline data and fine-grained temporal measures.

4.1 Limitations and Further Research

The advantage of computational focus groups is that they capture fine-grained behavioral changes in multi-level, real-world social environments. Our goal in introducing this approach is not to suggest it replace traditional methods but that it complement them. Computational focus groups have a number of limitations. Below we discuss these and how traditional methods might be used to address them.

First, as with any methodology that relies on data from social media, there is the potential for selection bias [40]. In particular, active Twitter users may behave differently from the general population. For example, the regions of Paris that show the most anxiety or anger in our data may not be those where these emotions were most strongly felt. Thus, future research might explore the extent to which selection bias in Twitter users influences the measurement of these emotions by pairing computational focus group analysis with geographically targeted surveys. More specifically, surveys can be used to measure the overall level of emotion across different geographic areas. This measurement can then be compared to expressions of emotion on Twitter within comparable areas. If selection bias is minimal, the two measurements should be well correlated. Researchers can then rely on the more temporally fine-grained computational focus group data with more confidence.

Nonetheless, depending on the research question, the selection of over-active users may, in fact, be desirable. In computational focus groups, selection bias leads to an over-representation of the individuals in a theoretically important category – those who express themselves on social media. These individuals are likely to have more social influence in times of terror and thus are worthy of further study. Future research might focus more on the roles that these active members play in spreading information or emotion [84]. In particular, experimental designs might recruit pools drawn from active and inactive social media users to see if they respond differently to hypothetical stimuli.

Finally, in this study we also do not make a distinction between emotions expressed and emotions felt. Though LIWC has been validated in numerous studies [74], it cannot distinguish between norms of expression and sincere feelings. As mentioned above, geographically targeted survey research might look for correspondence between what people say and how they feel. More broadly, experimental designs might include mock Twitter interfaces in which individuals are encouraged to tweet in response to hypothetical disasters as well as respond to survey questions that probe their true feelings. Such studies may more precisely determine the relationship between what people feel and what they say when confronted with terrorism.

5. CONCLUSION

In this paper we introduce computational focus groups for analyzing social media responses to terrorist attacks. Results were largely consistent with prior theories, confirming in particular both the association between geographic proximity and distress and the emotion-attenuating effect of social support. The technique also afforded the detection of novel effects, such as the dual role of news media in relation to anxiety, as well as evidence for a dynamic relationship between anxiety and sadness. Future research may seek to further validate the approach as well as explore these new avenues.

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APPENDIX

Location representativeness

We partition the whole Paris area into grid cells, each 1 km^2 in grid size, and compare our tweet data coverage with the hourly traffic occupancy rate in Paris. The grid coverage, ρ, is defined as the fraction of grids with at least one geo-tagged user and his/her tweets in our collection at each hour. The traffic occupancy rate, TOR, is defined as the fraction of time the road segment is occupied with traffic, e.g., 10% occupancy rate indicates the road segment is occupied with traffic for six minutes. We use the traffic occupancy rate as a proxy for dynamic population per small region, as the existing census statistics are too coarse to reflect the fine-grained population distribution. The estimation is based on the data collection within one week prior to the Paris attacks, with a 4-hour moving average window for both ρ and TOR to avoid a boundary effect. The table indicates that our dataset has comprehensive location coverage, with higher coverage in grids with 5% or greater traffic occupancy rate.

Table A-I. Location coverage by traffic occupancy rate

TOR	ρ
< 1%	42.4%
1–5%	64.9%
5–10%	88.0%
10–15%	86.8%
15–20%	83.4%
20–25%	85.1%
≥25%	85.1%
Overall	77.2%

Choice of temporal resolution

In Fig. A-I we plot the hourly counts of tweets posted by all the Paris users within the two weeks centered on the Paris attack event. The event occurred at November 13 20:16 UTC, and the number of tweets per hour peaked two hours after the first attack. Specifically, the raw counts of hourly tweets, and tweets expressing anxiety/anger/sadness reached their highest points at 22:00–23:00 (see Fig. A-I (a–d) respectively). The extraction of the three different expressions are based on words contained in the LIWC lexicon, as described in 2.2. The hourly counts quickly dropped in the next two hours as the users' activity went down at midnight. The hourly counts (shown as black lines) exhibit a clear cyclic pattern reflecting the diurnal rhythms of user tweeting activity. To eliminate the cyclic pattern, we average the hourly counts through a 24-hour rolling window (shown as red lines). It can be seen that the heightened response, in terms of the average hourly counts, gradually declined in the next four days compared with the pre-event hourly counts.

Effect of Time-variant variables

The effect of time-variant variables measured in two time periods can be competing in the full models (M2, M4, and M6) due to their strong correlations. Here we provide additional models where only one set of variables is present. Table A-II shows the same specification as M2, except that the baseline (B) variables are excluded and only variables measured in the immediate response period (I) remain. Compared with Table III , the impact of geo-proximity (I)

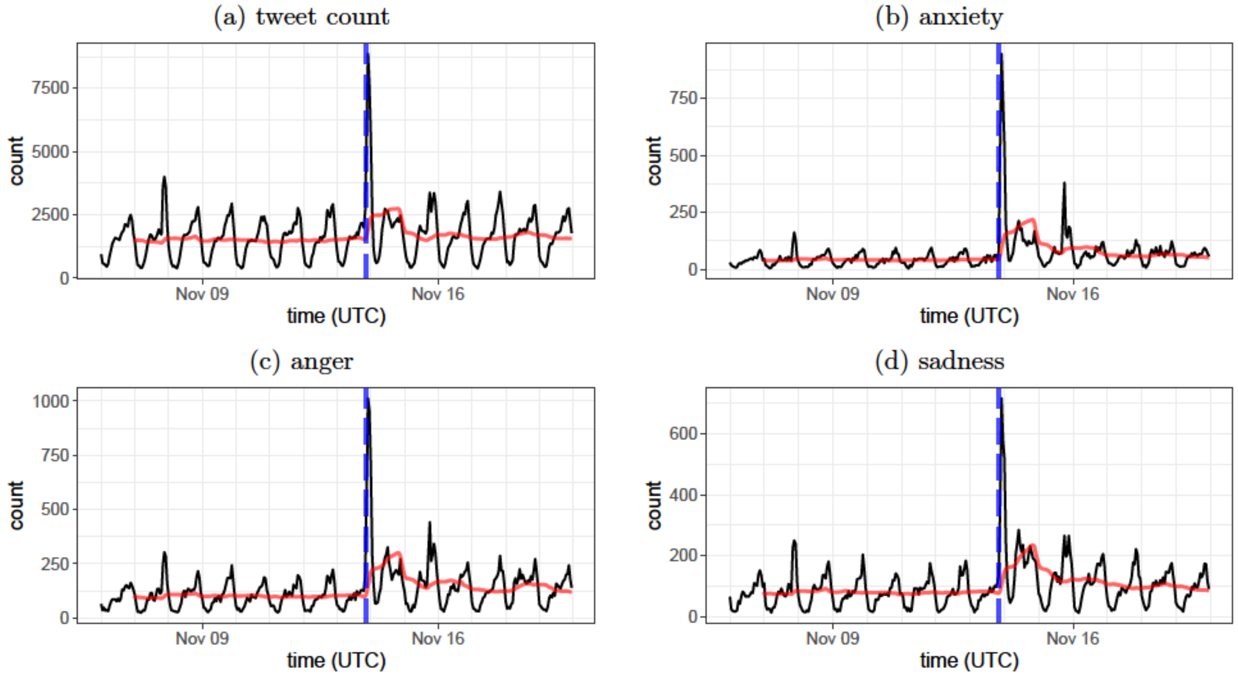

Fig. A-I. Hourly counts of tweets posted by the Paris users before and after the Paris attack event. The figure shows hourly counts of (a) tweets in total, (b) tweets expressing anxiety, (c) tweets expressing anger, and (d) tweets expressing sadness. Blue vertical dashed lines indicate the time of the event – November 13 20:16 UTC. Black lines show the raw counts of the tweets in each hour, and red lines are the rolling average of hourly tweets after removing the daily cyclic trend with a 24-hour rolling window.

on the anxiety intensity is clearly shown, and the model M2a (with immediate response variables) slightly outperforms M1 (with baseline variables) in terms of adjusted R^2. Table A-III shows the same specification as M4, without the baseline (B) variables and only time-dependent variables (T) measured on a daily basis remain. This model, M4a, also has better prediction performance than M3. Table A-XXII shows the same specification as M6, with either the baseline (B) variables or the immediate response variables (I). Compared with Table V and III , we see a similar impact of mention rate (I) on the sadness intensity in the second event as in the Paris attacks.

Table A-II. Regression results for immediate distress increase response, using only the variables measured in the immediate response period (I)

	M2a		
	anxiety	anger	sadness
gender male	−0.002	−0.004	−0.02**
activity high	−0.10**	−0.26***	−0.20***
tweet rate	−0.04**	−0.10***	−0.11***
positive rate	−0.01	−0.01*	0.02***
friend count	−0.01	0.001	−0.01
follower count	0.002	−0.0001	−0.002
geo-proximity (I)	0.01*	0.01	0.01**
mention rate (I)	−0.03	−0.03	−0.11***
media exposure (I)	0.29***	0.15	−0.03
activityHigh:tweetRate	0.01	0.07***	0.04***
Constant	0.42***	0.56***	0.62***
Observations	785	807	846
R^2	0.37	0.36	0.35
Adjusted R^2	0.36	0.35	0.34
Note:	*p<0.1; **p<0.05; ***p<0.01		

Distress responses by gender

Fig A-II shows a gender breakdown of the distress responses before and after the Paris attacks. For both men and women, the attacks had a significant impact on the expression of all three emotion categories, as the within-subject differences between "before" and "after" are all significant (all with $p < 10^{-4}$ based on a paired Wilcoxon signed rank test). However, the differences between the two groups vary across emotion categories. Before

Table A-III. Survival analysis for distress recovery duration, using only the time-dependent variables measured daily (T)

	M4a		
	anxiety	anger	sadness
gender male	−0.03	−0.02	-0.06^{*}
activity high	−0.04	0.11	0.10
tweet rate	0.14	0.03	−0.01
positive rate	−0.01	0.04	0.004
friend count	0.02	−0.02	0.02
follower count	−0.01	−0.003	-0.04^{*}
geo-proximity (T)	0.04^{***}	0.05^{***}	0.06^{***}
mention rate (T)	0.0004	0.01	−0.005
media exposure (T)	−0.02	0.16	-0.13^{**}
activityHigh:tweetRate	−0.06	0.001	0.12^{*}
Constant	1.72^{***}	1.68^{***}	1.63^{***}
Log(scale)	-0.77^{***}	-0.79^{***}	-0.78^{***}
Observations	747	750	795
Log Likelihood	-1,575.62	-1,638.40	-1,714.91
χ^2 (df = 10)	40.17^{***}	51.76^{***}	48.93^{***}
Note:			*p<0.1; **p<0.05; ***p<0.01

the attacks, women's rate of anxiety expression was significantly higher than men's ($p = 0.01$ based on a Wilcoxon signed rank test); after the attacks, the rate increase was significant at the individual level, but the difference between two groups was insignificant ($p = 0.08$). For sadness, there was no significant difference in the sadness expression rate between men and women before the attack ($p = 0.16$); however, after the attack, not only was the within-subject rate increase significant, but the difference between two groups was also significant ($p < 10^{-3}$). In terms of anger expression rate, there were no significant differences between men and women both before and after the attacks ($p = 0.60$ and $p = 0.15$, respectively), and only the individual-level rate increase was significant.

Model estimation details

In section 3, we summarize the analysis results based on models M1–M6 (Table III , IV , and V). Here we provide the model estimation details for each of the models, including the estimates of the models' theoretical variables and effect size. The interpretation of significant effect, if found in theoretical variables, are also summarized. Table A-IV, A-V, and A-VI include the details of M1 with respect to anxiety, anger, and sadness, respectively. Similarly, Tables A-VII–A-XXI supplement the details for M2–M6.

Table A-IV. M1-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.044	(0.0003,0.02)
gender male	-0.0001	0.986	(-0.02,0.02)
mention rate (B)	-0.01	0.650	(-0.08,0.05)
media exposure (B)	0.03	0.178	(-0.01,0.08)

Multiple R^2: 0.36; Adjusted R^2: 0.35; Cohen's f^2: 0.53
F-statistic: 42.94 on 10 and 774 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
geo-proximity (B): 1% decrese in distance from attack sites is associated with a 0.01% unit increase in anxiety rate on average, all else constant.

Table A-V. M1-anger: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.110	(-0.002,0.02)
gender male	-0.004	0.658	(-0.02,0.01)
mention rate (B)	-0.03	0.380	(-0.10,0.04)
media exposure (B)	0.02	0.392	(-0.03,0.07)

Multiple R^2: 0.36; Adjusted R^2: 0.35; Cohen's f^2: 0.55
F-statistic: 45.18 on 10 and 796 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-VI. M1-sadness: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.356	(-0.01,0.02)
gender male	-0.02	0.014	(-0.04,-0.004)
mention rate (B)	-0.07	0.048	(-0.14,-0.001)
media exposure (B)	0.03	0.190	(-0.01,0.08)

Multiple R^2: 0.34; Adjusted R^2: 0.34; Cohen's f^2: 0.50
F-statistic: 43.59 on 10 and 835 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
gender male: Users with gender female are associated with a 0.02 unit increase in sadness rate on average, all else constant.
mention rate (B): Each unit increase in mention (proportion of tweets containing @-mention) prior to the event is associated with a 0.07 unit decrease in sadness rate on average, all else constant.

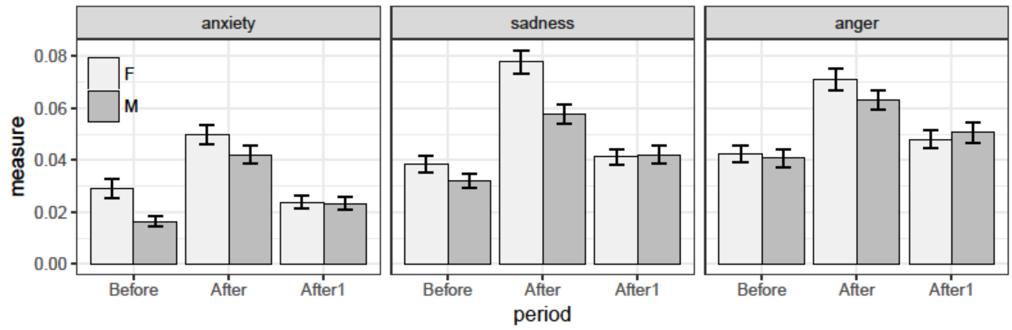

Fig. A-II. The affect responses before and after the Paris attacks, by gender group.

Table A-VII. M2-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.179	(-0.004,0.02)
gender male	-0.001	0.892	(-0.02,0.01)
mention rate (B)	-0.01	0.716	(-0.09,0.06)
media exposure (B)	0.02	0.460	(-0.03,0.07)
geo-proximity (I)	0.004	0.507	(-0.01,0.02)
mention rate (I)	-0.02	0.517	(-0.08,0.04)
media exposure (I)	0.28	0.0005	(0.13,0.44)

Multiple R^2: 0.37; Adjusted R^2: 0.36; Cohen's f^2: 0.55
F-statistic: 34.46 on 13 and 771 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
media exposure (I): Each unit increase in media exposure (proportion of tweets containing media URLs) immediately after the event is associated with a 0.28 unit increase in anxiety rate on average, all else constant.

Table A-VIII. M2-anger: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.265	(-0.01,0.02)
gender male	-0.004	0.668	(-0.02,0.01)
mention rate (B)	-0.02	0.644	(-0.10,0.06)
media exposure (B)	0.02	0.463	(-0.03,0.07)
geo-proximity (I)	0.004	0.571	(-0.01,0.02)
mention rate (I)	-0.02	0.526	(-0.09,0.05)
media exposure (I)	0.14	0.193	(-0.07,0.36)

Multiple R^2: 0.36; Adjusted R^2: 0.35; Cohen's f^2: 0.55
F-statistic: 34.9 on 13 and 793 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-IX. M2-sadness: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	-0.002	0.853	(-0.02,0.01)
gender male	-0.02	0.012	(-0.04,-0.01)
mention rate (B)	-0.01	0.725	(-0.10,0.07)
media exposure (B)	0.03	0.255	(-0.02,0.07)
geo-proximity (I)	0.01	0.085	(-0.002,0.03)
mention rate (I)	-0.11	0.007	(-0.18,-0.03)
media exposure (I)	-0.03	0.860	(-0.33,0.28)

Multiple R^2: 0.35; Adjusted R^2: 0.34; Cohen's f^2: 0.52
F-statistic: 34.65 on 13 and 832 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
gender male: Users with gender female are associated with a 0.02 unit increase in sadness rate on average, all else constant.
mention rate (I): Each unit increase in media exposure (proportion of tweets containing media URLs) immediately after the attacks is associated with a 0.11 unit decrease in sadness rate on average, all else constant.

Table A-X. M3-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	0.01	0.473	(-0.02,0.05)
gender male	-0.04	0.290	(-0.11,0.03)
mention rate (B)	0.01	0.563	(-0.02,0.04)
media exposure (B)	-0.03	0.081	(-0.07,0.004)

Weibull distribution; Scale= 0.465
Loglik(model)= -1577.8; Loglik(intercept only)= -1595.7
χ^2= 35.77 on 10 DF, p= 9.2×10^{-5}

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XI. M3-anger: theoretical variables and model estimation details.

Covariate	Coef.	*p*-value	95% CI
geo-proximity (B)	-0.02	0.262	(-0.05,0.01)
gender male	-0.03	0.385	(-0.10,0.04)
mention rate (B)	-0.04	0.031	(-0.07,-0.004)
media exposure (B)	0.03	0.117	(-0.01,0.06)

Weibull distribution; Scale= 0.453
Loglik(model)= -1639.5; Loglik(intercept only)= -1664.3
χ^2= 49.49 on 10 DF, p= 3.3×10^{-7}

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
mention rate (B): Each unit increase in mention (proportion of tweets containing @-mention) prior to the event is associated with a faster recovery in anger rate by a factor of 0.96.

Table A-XII. M3-sadness: theoretical variables and model estimation details.

Covariate	Coef.	*p*-value	95% CI
geo-proximity (B)	-0.01	0.396	(-0.05,0.02)
gender male	-0.06	0.057	(-0.13,0.002)
mention rate (B)	-0.03	0.120	(-0.06,0.01)
media exposure (B)	0.003	0.838	(-0.03,0.04)

Weibull distribution; Scale= 0.461
Loglik(model)= -1721.7; Loglik(intercept only)= -1739.4
χ^2= 35.34 on 10 DF, p= 0.00011

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XIII. M4-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	*p*-value	95% CI
geo-proximity (B)	0.01	0.732	(-0.03,0.04)
gender male	-0.04	0.318	(-0.11,0.03)
mention rate (B)	0.01	0.713	(-0.03,0.05)
media exposure (B)	-0.03	0.076	(-0.07,0.003)
geo-proximity (T)	0.04	0.011	(0.01,0.07)
mention rate (T)	-0.004	0.824	(-0.04,0.03)
media exposure (T)	-0.02	0.307	(-0.06,0.02)

Weibull distribution; Scale= 0.461
Loglik(model)= -1574; Loglik(intercept only)= -1595.7
χ^2= 43.33 on 13 DF, p= 4×10^{-5}

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
geo-proximity (T): 1% decrease in distance from attack sites is associated with a slower recovery in sadness rate by a factor of 1.04 on average, all else constant.

Table A-XIV. M4-anger: theoretical variables and model estimation details.

Covariate	Coef.	*p*-value	95% CI
geo-proximity (B)	-0.03	0.072	(-0.06,0.003)
gender male	-0.03	0.377	(-0.09,0.04)
mention rate (B)	-0.05	0.007	(-0.09,-0.01)
media exposure (B)	0.03	0.135	(-0.01,0.06)
geo-proximity (T)	0.05	0.001	(0.02,0.08)
mention rate (T)	0.03	0.010	(-0.01,0.06)
media exposure (T)	0.08	0.758	(-0.45,0.61)

Weibull distribution; Scale= 0.449
Loglik(model)= -1632.9; Loglik(intercept only)= -1664.3
χ^2= 62.7 on 13 DF, p= 1.7×10^{-8}

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
mention rate (B): Each unit increase in mention (proportion of tweets containing @-mention) prior to the event is associated with a faster recovery in anger rate by a factor of 0.95.
geo-proximity (T): 1% decrease in distance from attack sites is associated with a slower recovery in sadness rate by a factor of 1.05 on average, all else constant.

Table A-XV. M4-sadness: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
geo-proximity (B)	-0.03	0.118	(-0.06,0.01)
gender male	-0.06	0.079	(-0.12,0.01)
mention rate (B)	-0.03	0.145	(-0.06,0.01)
media exposure (B)	-0.002	0.924	(-0.03,0.03)
geo-proximity (T)	0.06	< 0.0001	(0.03,0.09)
mention rate (T)	0.002	0.911	(-0.03,0.04)
media exposure (T)	-0.14	0.041	(-0.27,-0.01)

Weibull distribution; Scale= 0.454
Loglik(model)= -1712.4; Loglik(intercept only)= -1739.4
χ^2= 53.91 on 13 DF, p= 6.3×10^{-7}

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
geo-proximity (T): 1% decrease in distance from attack sites is associated with a slower recovery in sadness rate by a factor of 1.06 on average, all else constant.
media exposure (T): Each unit increase in media exposure (proportion of tweets containing media URLs) each day is associated with a faster recovery in sadness by a factor of 0.86 on average, all else constant.

Table A-XVI. M5-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.16	0.245	(-0.42,0.11)
mention rate (B)	0.55	0.310	(-0.51,1.61)
media exposure (B)	-0.13	0.681	(-0.73,0.48)
mention rate (I)	-0.49	0.220	(-1.28,0.29)
media exposure (I)	1.02	0.659	(-3.52,5.56)

Multiple R^2: 0.36; Adjusted R^2: 0.31; Cohen's f^2: 0.45
F-statistic: 7.687 on 11 and 153 DF, p-value: $< 1.7 \times 10^{-10}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XVII. M5-anger: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.09	0.493	(-0.33,0.16)
mention rate (B)	0.18	0.738	(-0.86,1.21)
media exposure (B)	0.31	0.291	(-0.26,0.87)
mention rate (I)	0.04	0.911	(-0.72,0.81)
media exposure (I)	-2.84	0.254	(-7.69,2.02)

Multiple R^2: 0.22; Adjusted R^2: 0.18; Cohen's f^2: 0.22
F-statistic: 5.711 on 11 and 221 DF, p-value: $< 4.3 \times 10^{-8}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XVIII. M5-sadness: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.08	0.493	(-0.29,0.14)
mention rate (B)	-0.02	0.967	(-0.87,0.84)
media exposure (B)	-0.13	0.611	(-0.63,0.37)
mention rate (I)	-0.50	0.165	(-1.19,0.20)
media exposure (I)	-2.95	0.157	(-7.03,1.12)

Multiple R^2: 0.37; Adjusted R^2: 0.34; Cohen's f^2: 0.51
F-statistic: 11.75 on 11 and 222 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XIX. M6-anxiety: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.10	0.477	(-0.36,0.17)
mention rate (B)	0.77	0.160	(-0.30,1.83)
media exposure (B)	-0.04	0.885	(-0.65,0.56)
mention rate (I)	-0.58	0.150	(-1.38,0.21)
media exposure (I)	0.05	0.983	(-4.52,4.62)
sadness (PI)	0.09	0.205	(-0.05,0.22)
anger (PI)	0.12	0.103	(-0.02,0.26)
anxiety (PI)	0.08	0.303	(-0.07,0.22)

Multiple R^2: 0.39; Adjusted R^2: 0.33; Cohen's f^2: 0.49
F-statistic: 6.735 on 14 and 150 DF, p-value: $< 1.6 \times 10^{-10}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XX. M6-anger: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.11	0.415	(-0.36,0.15)
mention rate (B)	0.20	0.702	(-0.84,1.25)
media exposure (B)	0.35	0.237	(-0.23,0.92)
mention rate (I)	0.09	0.818	(-0.68,0.86)
media exposure (I)	-2.70	0.288	(-7.67,2.27)
sadness (PI)	-0.003	0.962	(-0.13,0.12)
anger (PI)	-0.07	0.301	(-0.19,0.06)
anxiety (PI)	0.03	0.591	(-0.09,0.15)

Multiple R^2: 0.23; Adjusted R^2: 0.18; Cohen's f^2: 0.21
F-statistic: 4.553 on 14 and 218 DF, p-value: $< 3.3 \times 10^{-7}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation: N/A.

Table A-XXI. M6-sadness: theoretical variables and model estimation details.

Covariate	Coef.	p-value	95% CI
gender male	-0.08	0.474	(-0.30,0.14)
mention rate (B)	0.09	0.835	(-0.76,0.94)
media exposure (B)	-0.16	0.515	(-0.65,0.33)
mention rate (I)	-0.52	0.136	(-1.21,0.16)
media exposure (I)	-2.06	0.330	(-6.19,2.07)
sadness (PI)	0.05	0.341	(-0.06,0.16)
anger (PI)	0.01	0.866	(-0.10,0.12)
anxiety (PI)	-0.19	0.001	(-0.29,-0.08)

Multiple R^2: 0.40; Adjusted R^2: 0.36; Cohen's f^2: 0.57
F-statistic: 10.53 on 14 and 219 DF, p-value: $< 2.2 \times 10^{-16}$

Control variables: tweet rate × activity high, positive rate, friend count, follower count
Main effect interpretation:
anxiety (PI): Each unit increase in anxiety rate following Paris attacks compared to the individual's pre-impact state is associated with a 0.19 unite decrease in sadness rate following Brussels attacks on average, all else constant.

Table A-XXII. Regression results for immediate distress increase response (Paris users during Brussels attacks). M6a uses only the variables measured prior to the event (B), and M6b only the variables measured in the immediate response period (I).

	M6a			M6b		
	anxiety	anger	sadness	anxiety	anger	sadness
gender male	−0.08	−0.12	−0.09	−0.09	−0.09	−0.08
mention rate (B)	0.24	0.34	−0.30			
media exposure (B)	−0.07	0.32	−0.18			
activity high	−2.06***	−0.67	−4.46***	−2.16***	−0.70	−4.39***
tweet rate	−0.73***	−0.44**	−1.48***	−0.77***	−0.45**	−1.46***
positive rate	0.02	0.14	0.01	0.04	0.12	0.02
friend count	−0.07	−0.07	0.05	−0.07	−0.02	0.05
follower count	−0.03	−0.01	0.04	−0.03	−0.02	0.03
mention rate (I)				−0.17	0.09	−0.42*
media exposure (I)				−0.36	−2.53	−2.35
sadness (PI)	0.07	0.005	0.04	0.08	0.004	0.05
anger (PI)	0.10	−0.07	−0.002	0.11	−0.06	0.01
anxiety (PI)	0.09	0.03	−0.19***	0.07	0.03	−0.18***
activityHigh:tweetRate	0.42**	0.04	1.14***	0.45**	0.04	1.12***
Constant	4.01***	2.22***	5.61***	4.15***	2.36***	5.49***
Observations	165	233	234	165	233	234
R^2	0.38	0.22	0.39	0.38	0.22	0.40
Adjusted R^2	0.33	0.18	0.36	0.33	0.18	0.37

Note: *p<0.1; **p<0.05; ***p<0.01