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This Is Not a Drill: Anxiety on Twitter Following the 2018 Hawaii False Missile Alert

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The accuracy of emergency management alerts about dangerous threats to public safety is key for the protection of life and property. When alerts of imminent threats are believed to be real, uncontrollable, and impossible to escape, people who receive them often experience fear and anxiety, especially as they await the threat's arrival (i.e., incubation of threat). However, what are the consequences when an alert turns out to be a false alarm? We explored psychological reactions (i.e., anxiety) to the 2018 Hawaii false ballistic missile alert using Twitter data from users across the state (1.2 million tweets, 14,830 users) 6 weeks before and 18 days after the event. We demonstrated that anxiety expressed on Twitter increased 4.6% on the day of the false alert and anxiety during the 38-min alert period increased 3.4% every 15 min. In addition, users who expressed either low, medium, or high prealert anxiety exhibited differential anxiety responses postalert, differential stabilization intervals (when anxiety stopped decreasing after the all-clear), and different postalert baselines relative to their prealert levels. Low prealert anxiety users expressed more anxiety at the onset of the alert and for longer relative to other groups. Moreover, anxiety remained elevated for at least 7 days postalert. Taken together, findings suggest that false alarms of inescapable and dangerous threats are anxiety-provoking and that this anxiety can persist for many people after the threat is dispelled. We offer several recommendations for how emergency management agencies should best communicate with the public after false alerts are transmitted.

Keywords: false alarm, Twitter, anxiety, collective trauma, social media

When danger in one's community is imminent, people often rely on local and state emergency management organizations for information to assess the severity of the threat and respond with appropriate measures to secure personal safety and protect property. Indeed, the success of emergency management personnel to effectively communicate risk information to at-risk populations plays an important role in saving lives (Rodríguez, Díaz, Santos, & Aguirre, 2007). However, when officials charged with disseminating information about impending threats falter, this might lead to a disaster (even if the threat becomes innocuous; Gilbert, 1998), and there may be a number of unintended consequences. For example, a lack of regular updates during an emergency can elicit distress and other negative psychological outcomes among individuals under threat (Jones, Thompson, Dunkel Schetter, & Silver, 2017).

False alarms are one example of how emergency management agencies might stumble. They occur when a transmitted warning of an impending threat is no longer relevant, such as when a hurricane changes course and no longer threatens a geographic area. False alarms also occur when an emergency organization broadly transmits a warning about an impending threat that does not actually exist, such as false active shooter reports. The implications of these types of false alarms have been studied by researchers across several disciplines. This body of work demonstrates how false alarms are related to loss of organizational credibility (Dow & Cutter, 1998; Ripberger et al., 2015), behavioral outcomes like diminished protective behavior among individuals under threat (Ripberger et al., 2015), and increased loss of life in tornado-prone areas with a high false alarm ratio (Simmons & Sutter, 2009). However, little work has directly examined the psychological impact of exposure to potentially life-threatening events that turn out to be false. Can a false alarm of an impending disaster itself be a form of collective trauma (i.e., a large-scale natural or anthropo-

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genic disaster that affects many people)? If so, how do people respond?

Research in psychology offers some clues about how individuals might respond to false alarms of an approaching catastrophe. Early experimental work on false alarms found that when the threat of a strong electric shock was perceived to be real, imminent, uncontrollable, and impossible to escape, individuals experienced a heightened physiological fear response (i.e., heightened heart rate) and subjective tension (Breznitz, 1984, 1985). During the moments in which participants anticipated the threat's arrival, subjective apprehension and worry increased over time (i.e., the incubation of threat; Breznitz, 1968, 1971, 1984). This work also demonstrated that when warnings of threat were cancelled, it took time for individuals to recover from their heightened state (Breznitz, 1984), suggesting that a cancellation of a threat warning does not immediately remedy the psychological consequences of having been warned.

Attention to fear and worry in this research is reminiscent of studies that highlight anxiety as a key psychological reaction to collective traumas such as terrorist attacks and natural disasters (Norris et al., 2002). For some individuals, lingering anxiety can cross clinical thresholds, developing into posttraumatic stress disorder (PTSD; Norris et al., 2002). Collective traumas often occur without warning and the threat they pose can sometimes be ambiguous. The inherent uncertainty in some disaster contexts (Gilbert, 1998) can elicit psychological distress depending on how it is appraised by those who experience it (Folkman, Lazarus, Dunkel-Schetter, DeLongis, & Gruen, 1986). For example, limited experience with a threat may increase situational ambiguity, thereby exacerbating anxiety (Lazarus, 1966). Thus, during dangerous or life-threatening situations in which information is lacking and ambiguity is high, uncertainty about the impending outcome may lead to anxiety (Taha, Matheson, & Anisman, 2014) and other negative psychological outcomes (Jones et al., 2017), especially among individuals for whom ambiguity is intolerable (Breznitz, 1984; Chen & Hong, 2010; Rosen, Knäuper, & Sammut, 2007).

When communities experience collective traumas, there may be marked variation in how they respond, and this variation may depend on characteristics of the individuals who reside within them. For example, researchers found that after 9/11, older adults had a steeper decline in their posttraumatic stress symptoms relative to younger individuals (Holman, Silver, Mogle, & Scott, 2016). Other researchers have focused on participants' past negative experiences to understand postevent responses. For example, in a national sample of Americans surveyed across subsequent waves following 9/11, Seery, Holman, and Silver (2010) found that the experience of zero or many negative life events was associated with poorer psychological outcomes over time relative to individuals with some negative life events (i.e., the association was quadratic). Further evidence suggests that negative psychological states, measured before a collective trauma, may be relevant as well. Among both youth and adults, experiencing negative psychological states (e.g., anxiety) before a collective trauma was associated with an increased risk of developing PTSD in its aftermath (Asarnow et al., 1999; Nolen-Hoeksema & Morrow, 1991). Overall, these studies suggest that, when possible, community-based studies of the impact of collective traumas should disaggregate individuals by their preevent vulnerabilities (e.g., characteristics or psychological states) to assess whether postevent outcomes differ in a meaningful way.

Variation in psychological responses to collective trauma has been studied mostly using traditional research methodologies (e.g., surveys and interviews). However, rigorously studying the psychological impact of a collective trauma is often difficult because of a lack of preevent data and challenges entering the field in a timely manner (e.g., securing funding and ethics board approval), among other hurdles (Jones, Wojcik, Sweeting, & Silver, 2016; Silver, 2004). Some social scientists have circumvented these challenges by using social media data to explicate psychological responses to collective traumas. Researchers have shown that big data from social media platforms, usually Twitter (e.g., "tweets"), are particularly useful for evaluating community responses to school shootings (Doré, Ort, Braverman, & Ochsner, 2015; Jones et al., 2016, 2017), terrorist attacks (Gruebner et al., 2016; Lin, Margolin, & Wen, 2017), natural disasters (Gruebner et al., 2017; Murthy & Longwell, 2013), and other collective adversities (De Choudhury, Monroy-Hernandez, & Mark, 2014).

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Twitter data offer unprecedented opportunities for theoretical insight because analyses of tweets, which contain the thoughts and feelings of Twitter users, possess several strengths compared with traditionally collected data. First, access to Twitter data is free to anyone with some technical know-how. Second, these data are an ecologically valid observational data source and can circumvent some biases inherent in traditional data collection methods, like surveys (e.g., low participation rates) or interviews (e.g., demand characteristics). Third, because Twitter data are archival by design, this enables an examination of emotion expression before and after collective traumas across an extended time frame that can be aggregated with granularity not possible with traditionally collected data. Fourth, Twitter data can also be explicitly linked to a user's location via geocoordinates if a user opts in to making this information public, or a user's location can be inferred based on the accounts they follow (see Jones et al., 2016).

The methodological strengths of working with Twitter data may also be useful for studying how individuals respond to false alarms of potentially life-threatening events. To date, the theoretical insights from experimental studies of false alarms have not been validated against large-scale, observational data. Thus, Twitter data were harnessed to explore anxiety responses to the 2018 Hawaii false ballistic missile alert. At 8:07 a.m. on January 13, 2018, Hawaii residents and visitors received an emergency alert from the Hawaii Emergency Management Agency over the radio, television, and on their smartphones stating that a ballistic missile was inbound to Hawaii, that people should seek shelter, and that this alert was "NOT A DRILL" (caps in original). Media reports cited increased anxiety among residents during the ordeal (Silva, 2018), and some residents reached out to their loved ones to say goodbye (Pactol, 2018). Presumably, many individuals thought that death or destruction was inevitable. However, a second message was transmitted 38 min later stating that there was "no missile threat or danger" and indicating that the original message had been a "false alarm."

This study addresses three main hypotheses. Consistent with other Twitter studies of collective trauma, we hypothesized that anxiety would increase at the time of the alert and remain elevated in the immediate aftermath. Second, consistent with the incubation of threat phenomenon, we hypothesized that anxiety would increase incrementally during the time from the transmission of the missile alert to the "all clear" 38 min later. Finally, because prior research demonstrates the importance of preevent vulnerabilities, we hypothesized that individuals exhibiting either low or high prealert anxiety might be at greater risk for experiencing anxiety after the alert. Specifically, we hypothesized that individuals who exhibited low and high anxiety before the alert would exhibit the greatest increase in anxiety after the alert, stabilize later, and exhibit higher postalert anxiety relative to their prealert baseline.

Method

Twitter Data Collection and Measures

Using procedures developed in prior research (Jones et al., 2016), Twitter data generated by users likely to be Hawaii residents were obtained. First, Twitter accounts ($n = 46$) operated by local government and commercial organizations (e.g., city hall, local radio stations) that were likely to be followed by Hawaii residents were identified in the days following the alert. Next, the rtweet package (Kearney, 2017) for R Software (R Core Team, 2018) was used to interface with Twitter's Application Programming Interface (API) and scrape the most recent 5,000 followers of each local account. If an account had fewer than 5,000 followers, all followers were downloaded. After filtering out non-English-language user accounts, user accounts created after December 2017 (because they would not have 6-weeks of prealert data), and both "private" and "verified" accounts (likely belonging to businesses, celebrities, and other public figures), a list of 32,239 user accounts was retained. Next, 18 days after the false missile alert, this list was read into an R script that interfaced with the Twitter API and downloaded the most recent 800 tweets generated by each user to obtain enough tweets dating back to 6 weeks before the alert. It should be noted that this cost-free method for sourcing Twitter data offers advantages over other methods of obtaining tweets from Twitter (e.g., standard level search API). Specifically, it circumvents restricted access to all but a fraction of public tweets and the restriction of only being

able to download tweets generated in the past 7 days from a given search.

In all, 1.2 million tweets representing 14,830 users who tweeted within a 9-week window around the false alert (6 weeks before and 18 days after) were downloaded. Data collection procedures for this study were reviewed by the University of California, Irvine's Institutional Review Board and assessed not to constitute human subjects research.

Measures

Anxiety expression. A custom R script was used to compare the words in each tweet with a list of 114 anxiety words (e.g., *afraid*, *scared*, *worried*) available in the LIWC program (Pennebaker, Booth, Boyd, & Frances, 2015; Tausczik & Pennebaker, 2010). The words *threat* and *alarm* were removed from the dictionary because these words were specifically used by government and emergency management personnel to refer to the missile alert event. Each tweet was then coded dichotomously such that it was assigned a 1 if it contained at least one anxiety word; all other tweets were coded 0. This approach allowed for a proportion of tweets with anxiety to be calculated across analytic time frames, and it provided a measure of anxiety expression that compensated for differential counts of tweets generated at each time-unit of analysis (e.g., minutes, hours, days).

Prealert anxiety. Users with prealert tweets (n = 8,746) were grouped as low, medium, or high anxiety based on their average proportion of prealert anxiety tweets generated 7 days before the alert. These proportions were then standardized across all users and the z scores were used to group users based on where they fell along this standardized distribution. Users in the "low" group (n = 6,849) did not express *any* anxiety on Twitter before the alert. Users placed into the "medium" group (n = 1,394) expressed some anxiety, up to just below one standard deviation; users in the "high" anxiety group (n = 503) expressed anxiety greater than or equal to one standard deviation relative to all other users.

Analytic Strategy

Data were cleaned and organized in R using tidytext (Silge & Robinson, 2016), and descriptive visualizations were created in R using ggplot2 (Wickham, 2009) and employed the generalized additive model smoothing function to depict a nonlinear line-of-best-fit across time. Trajectories of anxiety before and after the alert were evaluated at several time scales. All statistical analyses were conducted in Stata 14.2 (College Station, TX) using procedures outlined by others (Jones et al., 2016; Mitchell, 2012).

9-week window. The proportion of daily anxiety was calculated across the 6 weeks preceding the alert and the 18 days that followed. Before attempting to model trajectories of anxiety across time, a change-point analysis was conducted in R using the *changepoint* package (Killick, Haynes, & Eckley, 2016) to determine the discrete time point at which anxiety decreased to a stable level after the missile alert. This method employs the pruned exact linear time algorithm (Killick & Eckley, 2014) to identify when the mean and variance of a variable deviate over time. In other words, the algorithm evaluates the mean and variance in a block at the start of time, and then evaluates whether they are significantly different from the mean and variance calculated in the next block of time. The package then displayed the time values where the algorithm identified significant changes in daily proportions of anxiety.

The change-point analysis indicated that anxiety increased on the day of the missile alert and stabilized 2 days later. To evaluate these nonlinear changes over time, a piecewise regression approach (Kim, Fay, Feuer, & Midthune, 2000) with a discontinuity analysis (Thistlethwaite & Campbell, 1960) was used. This approach is well suited for modeling nonlinear changes in time-series data because piecewise regressions allow for separate regression lines to be estimated for specified time intervals in a unified statistical model. Specifically, time is blocked into meaningful intervals by analytic knots, or dummy-coded markers. A knot was placed on the day of the alert (January 13, 2018, at ~8:07 a.m. HST) so that an estimate of what anxiety expression would have been (had the alert never happened) could be compared with actual anxiety expression at the alert's onset. A knot was also placed 2 days after the event, as the change-point analysis revealed this to be a meaningful interval at which anxiety levels stabilized across all users. Importantly, the piecewise regression analysis was clustered around each user to account for within-user propensity for anxiety expression on Twitter.

12-hr window. Time across a period spanning 6 hr before and after the missile alert was parsed into 15-min intervals (cf. Jones et al., 2017), and the proportion of tweets with anxiety was calculated for each interval. A piecewise regression analysis was conducted on all tweets in this time frame to evaluate whether anxiety increased the moment the alert was transmitted and the extent to which anxiety continued to increase during the 38-min alert period. Thus, a knot was placed at the moment the alert was transmitted and 45 min later (roughly 7 min after the "all-clear" was transmitted). In addition to evaluating immediate changes in anxiety resulting from the missile alert, this approach also allowed for an analysis of the slope of anxiety expression during the 38-min alert period.

14-day window. Hourly proportions of tweets with anxiety generated in a 14-day window around the alert (7

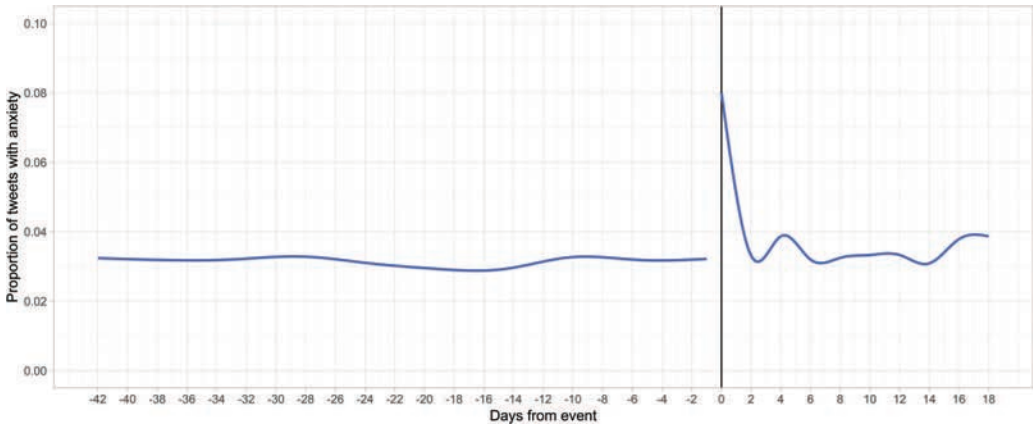

Figure 1. Daily anxiety among Hawaii Twitter users 6 weeks before and 18 days after the false missile alert (n_{tweets} = 1.2 million; n_{users} = 14,830). See the online article for the color version of this figure.

days before and after) were calculated for each prealert anxiety group (i.e., low, medium, high) to provide a more fine-grained analysis of the immediate impact of the alert and its sustained effect across the following week for each prealert anxiety group. To determine the discrete time point at which anxiety leveled off for each group, a change-point analysis was conducted for each group individually. Postalert change points were used to place a second knot in each piecewise regression to accurately model changes in anxiety over time for each group. Thus, a knot was placed at the moment the alert was transmitted and at the group-specific change point after the alert, when anxiety stabilized.

To evaluate whether the event had a lasting effect on each prealert anxiety group in the days that followed, we conducted three ordinary least squares regression analyses in which each group's prealert average proportion of anxiety expression (baseline anxiety) was compared with its postalert average (new baseline), after stabilization in anxiety occurred.

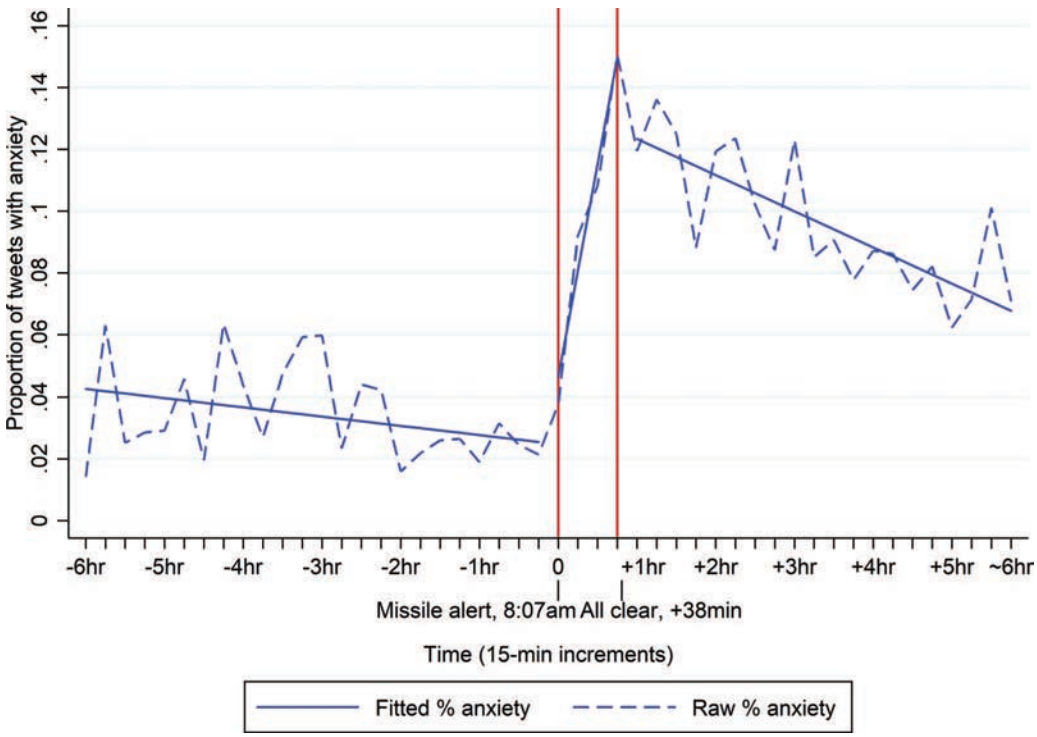

Figure 2. Anxiety on Twitter, 6 hr before and after the ballistic missile alert (n_{tweets} = 20,338; n_{users} = 4,415). See the online article for the color version of this figure.

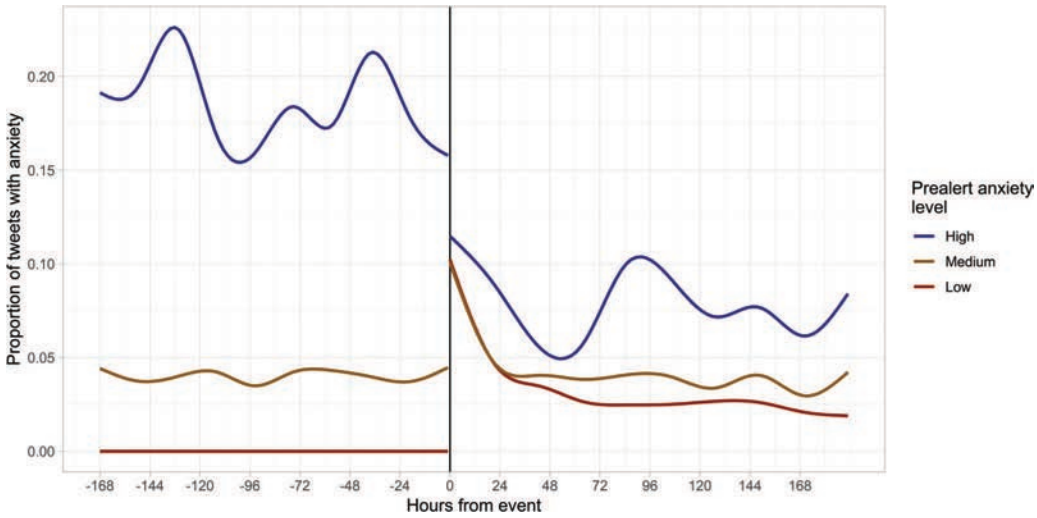

Figure 3. Hourly anxiety by Twitter users with low, medium, and high prealert anxiety, 7 days before and 7 days after the false missile alert (n_{tweets} = 324,010; n_{users} = 8,746). See the online article for the color version of this figure.

Results

First, daily proportions of anxiety across the full range of available data were examined. Consistent with the hypothesis that anxiety would increase on the day of the alert, across all users, anxiety increased 4.6% (standardized $b = .25$, standard error [*SE*] = .01, $t = 19.62$, $p < .001$; see Figure 1). In terms of percent change, this jump represents a 160% increase in anxiety expression.

Anxiety was also hypothesized to increase incrementally during the period from the release of the alert until the "all-clear" 38 min later, during which time users awaited the attack (i.e., incubation of threat; Breznitz, 1968, 1984). Consistent with this hypothesis, the results from 4,415 users (20,338 tweets) who tweeted in this time frame indicated that anxiety increased 3.4% in each 15-min block during the alert period (standardized $b = .12$, $SE = .02$, $t = 5.90$, $p < .001$; see Figure 2), until the all-clear was transmitted, at which point anxiety expression began to decline over time.

In a window 7 days before and after the missile alert (see Figure 3), the low prealert anxiety group's anxiety increased 9.5% at the onset of the alert period (standardized $b = .49$, $SE = .02$, $t = 22.87$, $p < .001$). The medium prealert anxiety group also increased in anxiety expression (5.8%; standardized $b = .30$, $SE = .03$, $t = 8.34$, $p < .001$). Although the high prealert anxiety group was hypothesized to exhibit an increase in anxiety expression, this group's anxiety decreased 8.8% (standardized $b = -.46$, $SE = .07$, $t = -5.93$, $p < .001$) at the onset of the alert.

Postevent stabilization rates also differed across groups (see Figure 4). As expected, the low prealert anxiety group took the longest to stabilize (~41 hr after the false missile alert). However, the high prealert anxiety group stabilized immediately after the alert was transmitted, the same point at which a significant drop in anxiety was observed for this group; the medium prealert anxiety group stabilized 23 hr postevent.

Each group's postalert baseline (after stabilization) was compared with its prealert baseline. The low prealert anxi-

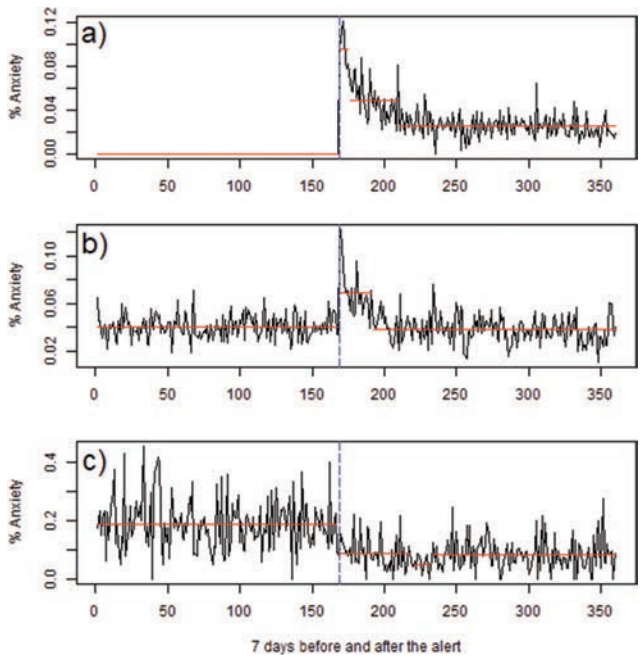

Figure 4. Change point analyses for each prealert anxiety group, in which Time 169 (vertical dashed line) is the moment the alert was transmitted: (a) group with low prealert anxiety (n = 6,849); (b) group with medium prealert anxiety (n = 1,394); (c) group with high prealert anxiety (n = 503). See the online article for the color version of this figure.

ety group, for whom anxiety expression before the alert was zero across a 7-day period, exhibited a new anxiety baseline that was 2.5% higher than its prealert baseline (standardized $b = .13$, $SE = .004$, $t = 28.15$, $p < .001$). The medium prealert anxiety group's new baseline was less than 1.0% lower than its prealert baseline (standardized $b = -.01$, $SE = .005$, $t = -2.11$, $p = .035$). The high prealert anxiety group exhibited a new baseline 10.5% lower than its prealert baseline (standardized $b = -.55$, $SE = .05$, $t = -10.76$, $p < .001$).

Discussion

For the first time, real-time psychological responses to a false alarm event have been captured using a big-data approach with large-scale observational Twitter data. Consistent with prior Twitter studies of collective trauma in which expressions of negative affect have been explored (De Choudhury et al., 2014; Doré et al., 2015; Gruebner et al., 2016, 2017; Jones et al., 2016, 2017; Lin et al., 2017; Murthy & Longwell, 2013), this study reveals a marked increase in anxiety among likely Hawaii residents that lingered well after the missile threat was dispelled. In the most fine-grained analysis, results were consistent with the incubation of threat hypothesis (Breznitz, 1968, 1971, 1984), which states that anxiety experienced in anticipation of a threat will increase in the moments during which one waits for the threat to arrive. Specifically, anxiety increased 3.4% every 15 min until the transmission of a message 38 min later reporting that the initial alert was a false alarm. Surprisingly, this trend was not thwarted by corrective tweets posted by the state's emergency management agency and by a local congressional representative shortly after the alert's transmission explaining that the missile alert was a mistake. Despite these corrections being retweeted by 35,000 users, the incubation of threat phenomenon persisted. This is likely the case because users either (a) did not see the messages dispelling the threat, or (b) saw them but did not believe them, as evidenced by a user who tweeted: "I'm still sheltering twenty minutes [later] who knows who's right?"

Alternatively, this "incubation of threat" trend could simply reflect the fact that unique users became aware of the missile alert at different points in time during the alert period. For example, if a large number of users woke up to the alert 35 min into the ordeal and generated tweets expressing anxiety, this would explain the observed increase in anxiety during the alert period. This alternative explanation was evaluated among 556 users who tweeted in at least two of the three 15-min intervals during the alert period. We found that anxiety increased incrementally across the alert period (at nearly the same rate) among these users as well. Overall, this suggests that evaluating tweets generated in the alert period, in aggregate, sufficiently captured the experience of the incubation of threat.

Consistent with early work suggesting that the cancellation of a threat does not immediately remedy reactions to a threatening situation (Breznitz, 1984), our results suggest that the experience of a false alarm may have a lingering impact on some individuals well after the threat is dispelled. The analysis of the entire sample across a 9-week window revealed that anxiety remained elevated for at least 2 days following the alert. When disaggregating users by their preevent propensity for expressing anxiety words, disparate patterns of postalert anxiety expression were uncovered. For example, for the group of users in this sample who did not express any anxiety before the event (i.e., the low prealert anxiety group), anxiety increased the most and lingered the longest, relative to other groups, before stabilizing to a new baseline level 2.5% higher than what it was before the missile alert. Insofar as anxiety expression on Twitter can be assumed to be reflective of a user's life experience (Jones et al., 2016), this pattern is consistent with evidence demonstrating that people who are likely to have had lives devoid of psychologically impactful negative experiences are at increased risk of negative psychological outcomes following a traumatic event (Seery et al., 2010). Moreover, the lingering presence of anxiety well after the threat was dispelled may be driven by some users in this group engaging in perseverative cognition, defined as the chronic activation of the cognitive representation of a psychological stressor (Brosschot, Gerin, & Thayer, 2006).

Research also suggests that individuals with pretrauma vulnerabilities (e.g., negative psychological states; Asarnow et al., 1999; Nolen-Hoeksema & Morrow, 1991) may be at increased risk for negative psychological outcomes after a traumatic event. However, our results show a different pattern. The high prealert anxiety group exhibited a *decrease* in anxiety following alert period, declining to a new baseline level 10.5% lower than the group's prealert baseline. It should be noted that this pattern is unlikely to be the result of regression to the mean because several prealert observations were available with which to accurately account for natural variations in anxiety expression and identify the "high" prealert anxiety group. However, diminished anxiety after the alert is consistent with downward counterfactual thinking (Byrne, 2016), such that users in the high prealert anxiety group may have recognized how much worse things could have been had the missile threat been real. It could also be indicative of near-miss relief (Sweeny & Vohs, 2012), a phenomenon observed when an aversive event is avoided.

Alternatively, we offer a few potential explanations that may be particularly relevant to this group. For example, a pattern of generalized worry about future negative events, characteristic of anxious individuals, may have buffered those in the high prealert anxiety group from experiencing even greater anxiety as a result of the alert (for a review of such "upsides" of worry, see Sweeny & Dooley, 2017). It

could also be the case that lower anxiety expression in this group reflects a process by which the threat of death via a ballistic missile put disruptive daily stressors into perspective. This supposition is consistent with the notion of a leveling theory of human adaptation to life events in which people react differently to positive and negative experiences, and how one responds depends on the totality of a person's life. For example, hedonic leveling (Lucas, Clark, Georgellis, & Diener, 2003) posits that happy individuals have less to gain when they experience positive life events (e.g., marriage), whereas unhappy people have more to gain from positive life events. The pattern for this group is also reminiscent of adaptation level theory (Brickman, Coates, & Janoff-Bulman, 1978), which highlights the importance of the contrast between what life is like after a significant event compared with what life was like beforehand. Insofar as these theories operate similarly with respect to negative life events (e.g., the false missile alert), anxious individuals may have more to appreciate when they experience a near-miss and thus express less anxiety on social media after having "survived" what would have undoubtedly been construed as a deadly situation.

Although our results mirror those in other studies of Twitter data that reveal increased negative emotion after a collective trauma, we acknowledge several limitations. First, Twitter users are not necessarily representative of the general population, as they tend to be younger (aged 18–29 years) and from urban locations (Pew Research Center, 2018). Second, we recognize that counting anxiety words embedded in tweets may not be a perfect measure of actual felt anxiety. Nonetheless, there are myriad face-valid examples of expressions of anxiety in the data we collected (e.g., "I'm scared guys"; "This is some scary [expletive]"). There is also a tradition in psychology of relying on the words people use to provide a window into their psychological state (for a review, see Pennebaker, Mehl, & Niederhoffer, 2003; Tausczik & Pennebaker, 2010). For example, researchers have linked depression to the use of first-person pronouns and negative emotion words (Rude, Gortner, & Pennebaker, 2004) and linked word usage to motivation (Pennebaker & King, 1999) and to traditional personality constructs (i.e., the Big 5; Schwartz et al., 2013), respectively. On balance, we believe that capturing anxiety words in this false alarm context reflects an important psychological signal despite the potential error inherent in a dictionary word count approach, and we maintain a person's prealert word usage pattern to be an acceptable proxy when other information is unavailable.

We also acknowledge that the method we used to source Twitter users precluded our ability to distinguish psychological responses of temporary visitors to the state compared with permanent residents. Moreover, the data we had available to us limited our ability to examine nuanced responses to the alert based on individual characteristics that we could not assess. Thus, the tweets we collected, although informative, are not linked directly to any person-level psychological data (e.g., personality, history of negative life events). In addition, it is possible that individuals with military connections, or Native Hawaiians versus those who recently relocated, may have experienced differential levels of anxiety in response to the false alert that our methodology could not capture. Other methods (e.g., survey research) might supplement the kinds of data we examine here to further explore these other factors (see Jones et al., 2017, for an example of this technique).

Finally, there is no guarantee that all users in our sample were residents of Hawaii (although ~50% of users mentioned a Hawaii locale in their Twitter profile); we did not rely on geolocation data because less than 1% (.07%) of tweets in our data were geocoded. However, the method we used to source locally generated Twitter data has performed well in other studies of collective traumas (see Jones et al., 2016, 2017). In addition, the presence of heightened anxiety, despite the error inherent this method, suggests that the effects we demonstrated would likely have been even greater had we captured tweets generated by residents exclusively.

Despite these limitations, our results lead to several recommendations for mitigating the psychological impact of impending threats, false or otherwise. Early theorizing on false alarms posited the *false alarm* or "*cry wolf*" effect in which individuals may not believe the next threat warning because they lose faith in the credibility of systems or agencies responsible for disseminating them (Breznitz, 1984). Empirical work supports this. For example, residents of tornado-prone areas who perceive their local false alarm ratio to be high are less trusting of the National Weather Service (Ripberger et al., 2015). Other work indirectly shows that such perceptions can be deadly (Simmons & Sutter, 2009). Credibility loss is particularly important to combat in risk-prone locales like Hawaii, where residents remain in targeting range of a ballistic missile from North Korea, live near active volcanoes, and sometimes experience destructive weather events. In such a locale, it is critical to maintain the public's *continued* reliance on and trust in emergency management systems for information about impending danger.

When emergency systems falter, research shows that credibility loss can be mitigated by a clear explanation of why the false alarm occurred in the first place (Breznitz, 1984; Fischhoff, 2011). In the days and weeks following the Hawaii false missile alert, the media reported that the alert was sent in error by an employee with whom the agency had several past issues. This reporting likely raised questions about the agency's disciplinary procedures but may have assured the public that the entire affair was a fluke. Further reporting assured the public that new safeguards were in place to prevent one person from having the authority to

transmit any message on the statewide emergency system (Wamsley, 2018).

During a crisis, social media can be an important channel through which critical updates are transmitted. Indeed, the value of using social media accounts to transmit critical updates, in tandem with outlined procedures, has been acknowledged by the Department of Homeland Security for almost a decade (Silver & Fischhoff, 2011). Agencies should also increase public outreach efforts to ensure that community members are connected to critical information channels during a crisis. Such measures would serve to bolster the public's trust in reporting agencies. We also believe it is good advice for the public to seek out and follow verified social media accounts belonging to their local emergency management agencies as soon as possible so that they will have access to the most up-to-date information about any potential threat during a real emergency.

In addition to revealing new information channels to follow, false alarms may also raise awareness of potential threats. For example, some individuals in our sample expressed the realization of not being prepared: "Definitely scary. I live in a small studio a few blocks from the beach I was like take shelter where? I'm definitely not prepared." In the months before the false alert, aggressive rhetoric between government leaders heightened fears that a military conflict might be imminent. As a result, in December 2017, Hawaii began performing emergency drills and siren testing to prepare for such an eventuality, although what to do during an attack was not clear to all residents (Kelkar, 2018). In our sample, many users expressed confusion about what actions to take and were unsure where to seek shelter when instructed to do so. It is prudent for members of the public to educate themselves about emergency preparations and for emergency management agencies to use all available channels to transmit concrete recommendations for protective action (Fischhoff, 2011).

Insights from our data also highlight the importance of the interface between emergency management agencies and the news media. Users in our sample searched for information on traditional media channels to no avail, evidenced by tweets like "missile alert in Hawaii but no news coverage" and "nothing on the news. looked it up on twitter and people are as confused as we are." These tweets highlight the crucial importance of information dissemination via the news media during a crisis as the public relies on the media for critical updates (Jones et al., 2017).

Although the missile alert was an unusual event, false alarms of impending threats are not uncommon. For example, near the end of 2018, a false active-shooter alert was transmitted to the Walter Reed National Military Medical Center. The alert was transmitted widely without the words "exercise" or "drill" and was accordingly believed to be a legitimate warning. This false alert precipitated an hour-long lockdown of the hospital and was ultimately characterized as an "improper use of a mass notification system" (Martinez, 2018). As mass-communications technologies are developed to warn people of life-threatening events at both the local (e.g., schools) and national (e.g., presidential alerts) levels, such occurrences may increase if systems operate without clear procedures and proper oversight.

Free and open access to public Twitter data, coupled with Hawaii's false missile alert, provided an opportunity to study, for the first time, how several thousand people responded psychologically to the threat of an inescapable, impending tragedy. Although it is fortunate we were able to study this phenomenon without loss of life, we show that for many users, the anxiety elicited by this false alarm lingered well beyond the assurance that the threat was not real, which may have health consequences over time for some individuals (Holman et al., 2008). Thus, our results reveal how potently frightening a crisis period can be and highlight how intense experiences like this may have lasting effects that become even clearer after disaggregating users by their preevent psychological state. This event serves as an example of how accidental crisis communication can become a disaster (Gilbert, 1998) and should inform emergency management agencies how they can better serve the communities they are charged with protecting.

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