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Quantifying Information Flow During Emergencies

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Recent advances on human dynamics have focused on the normal patterns of human activities, with the quantitative understanding of human behavior under extreme events remaining a crucial missing chapter. This has a wide array of potential applications, ranging from emergency response and detection to traffic control and management. Previous studies have shown that human communications are both temporally and spatially localized following the onset of emergencies, indicating that social propagation is a primary means to propagate situational awareness. We study real anomalous events using country-wide mobile phone data, finding that information flow during emergencies is dominated by repeated communications. We further demonstrate that the observed communication patterns cannot be explained by inherent reciprocity in social networks, and are universal across different demographics.

Much effort has been devoted to the study of human dynamics under regular and stationary situations[7,9–11,15,16,19,23,28,30–32,34,37,40,45]. Our quantitative understanding of human behavior under extreme conditions, such as violent conflicts[5], life-threatening epidemic outbreaks[3,9,10,25], and other large-scale emergencies, remains limited however. Yet, it is essential for a number of practical problems faced by emergency responders[29]. There is an extraordinary need, therefore, to quantitatively study human dynamics and social interactions under rapidly changing or unfamiliar conditions.

Previous studies[2,24] have suggested that mobile phones can act as *in situ* sensors for human behavior during anomalous events, finding that the occurrence of anomalous events triggers a large spike in the communication activity of those who witnessed the event. More specifically, they found that communication spikes following emergencies are temporally and spatially localized, indicating information flow through the social networks of affected individuals becomes an important means to spread situational awareness and information to the general population.

In this work, we quantify the propagation of real-world emergency information through the contact networks of mobile phone users. We denote the group of users directly affected by an emergency by population G_0, while users they contact during the timespan of the emergency that are not in G_0 form the population G_1. We focus here on how G_1 users change their communication patterns following an emergency. To be specific, we address three questions: First, to what magnitude do G_1 users change their communication behavior? Do they show the same volume spike as previously observed for G_0 users[2]? Second, what is the origin of the behavior changes of G_1 users? What is the dominant feature of these changes? Third, will a G_1 user prefer to *call back* the G_0 user, potentially offering comfort, support and seeking pertinent information? Or will they instead *call forward* to propagate their situational awareness to others. Intuitively we expect that G_1 users were chosen for contact by the G_0 users due to important relationship(s) between them, and they may communicate with each other more often than with other peers even during normal days. It is therefore important for future emergency detection and intervention to know whether or not there is abnormal reciprocal communication during emergencies, compared with ordinary activity levels.

Data and events. In this paper, we use a de-identified dataset from a large mobile phone company in a European country[1,4,8,14,16,20,21,27,28,33,36,37,39,42–44]. The data consist of approximately 10 million users and four years of cell phone activity, including both voice calls and text messages. Each data entry records the user initiating the call or text (caller) and the user receiving it (callee); the cellular tower that routed the call; and the date and time when it occurred. The locations (longitude and latitude) of cellular towers are also recorded, allowing us to infer the location of callers whenever they initiate a communication. Hence, given the spatiotemporal localization of an event, these data offers a unique opportunity to quantify the social response of the affected population.

To study real events covered by this mobile phone data, we need to determine their times and locations. We study the event set identified in previous studies[2], where the authors used Google local news (news.google.com) service to search for news stories covering the country and time period of the mobile phone dataset. Keywords such as 'emergency', 'disaster', 'concert', etc. were used to find potential news stories. Important events such as bombings, earthquakes and concerts are prominently covered in the social media. Study of these reports typically gave the precise time and the locations for these events[2].

To identify the beginning and the end of an event, t_{start} and t_{stop}, we adopt the following procedure[2]. First, we scan all calls in the event region during the day covering the event, giving the event day call volume time series (number of calls per minute) $V_{\mathrm{event}}(t)$[2]. Then, we scan calls for a number of "normal" days, those modulo one week from the event day, exploiting the weekly periodicity of $V(t)$. These normal days' call volume time series are averaged to get $\langle V_{\mathrm{normal}}\rangle$. To smooth the time series, call volumes were binned into 10 minute intervals. The standard deviation $\sigma(V_{\mathrm{normal}})$ as a function of time is then used to compute $z(t) = \Delta V(t)/\sigma(V_{\mathrm{normal}})$, where $\Delta V(t) = V_{\mathrm{event}}(t) - \langle V_{\mathrm{normal}}\rangle$ is the call volume change during the event day. Finally, the interval $[t_{\mathrm{start}}, t_{\mathrm{stop}}]$ was the longest contiguous run of time intervals where $z(t) > z_{thr}$, for some fixed cutoff z_{thr}. To be consistent with pervious studies[2], we chose $z_{thr} = 1.5$ for all events.

Results

To extract the contact network between users during an event, we track all outgoing calls in order of occurrence during the event's time interval $[t_{\mathrm{start}}, t_{\mathrm{stop}}]$. We therefore identified the individuals located within the event region (G_0), as well as a G_1 group consisting of individuals outside the event region but who receive calls from the G_0 group during the event, a G_2 group that receive calls from G_1, and so on.

To determine how unusual the observed activities are, we compare the call volume during the event to the average call volumes of a number of "normal" days (Sec. Data and events). Since a temporal contact network can always be constructed from mobile phone dataset, even when no event occurs, it is necessary to design a proper control for normal days to make the call volumes between event day and normal days comparable.

To design a proper control, we study new "cascades" generated by the same eyewitness users G_0 during the same time interval $[t_{\mathrm{start}}, t_{\mathrm{stop}}]$ for each normal day, and create a different cascade $\{G_0, g_1, g_2, \ldots\}$ for each normal day. G_i are for event period whereas g_i are for normal period. G_i and g_i share the same G_0, that is by definition $G_0 = g_0$. e.g. g_1 users are the users who receive cell-phone communication directly from G_0 users, g_i users ($i > 1$) are the users who receive cell-phone communication directly from g_{i-1} users.

The number of G_i users will typically be larger than that of g_i users and G_i users may be more active than g_i users, so the normal day's call volume time series, $V(t|g_i)$, must be rescaled when compared to the event day's call volume time series, $V(t|G_i)$. For this purpose, we multiply $V(t|g_i)$ by a constant scaling factor a_i,

$$a_i = \int_{\delta t} V(\tau|G_i)d\tau \Big/ \int_{\delta t} V(\tau|g_i)d\tau, \qquad (1)$$

where both integrals run over the same "calibration interval" δt, and $\tau = 0$ is the start of the selection window. For most events, we integrate over a 24-hour period two days before the event window. The factor a_i was chosen such that the total number of calls during normal time periods for $V(t|G_i)$ is approximately equal to $a_i V(t|g_i)$, equalizing the normal-day time series and removing any biases due to $|G_i| \neq |g_i|$. This control procedure allows us to investigate call volume patterns of different user groups.

To explore the call volume patterns in different user groups, we measure the call volume change

$$\Delta V(t|G_i) = V(t|G_i) - \langle a_i V(t|g_i)\rangle \qquad (2)$$

for G_0 and G_1 groups as a function of time, where $V(t|G_i)$ is the call volume in the event day and $\langle a_i V(t|g_i)\rangle$ is the call volume averaged over selected "normal" days.

Previous work has studied several aspects of communication patterns, and found a spike in the volume of phone call activity during an emergency event[2]. Yet, by using the control mentioned above, we find the call volume change for different groups such as G_0 and G_1 exhibits different patterns in different events (Fig. 1). More specifically, we observe activity spikes in both G_0 and G_1 groups for three emergency events, referred to as "Jet Scare", "Plane Crash" and "Bombing" (Fig. 1a–c). Yet in all other events, there is no volume spike for the G_1 group, e.g. "Concert" (Fig. 1d). These results are consistent with previous findings[2], showing that the users in the G_1 group are triggered to a higher communication level, characterized by a sharp increase in call volumes, during the emergency events. Yet, it is somewhat puzzling that the call volume change of G_1 users have a spike, which is instantaneous and shows virtually no delay to the spike of G_0 users'. Note the spikes of G_0 and G_1 users are synchronous qualitatively, and sensitive to the time aggregation (see Supplementary Materials). As the activity spikes of G_0 users for emergency events are both temporally and spatially localized, the communication of G_1 users becomes the most important means of spreading situational awareness.

To quantify the reach of situational awareness, we focus on G_1 and study their communication patterns after receiving a phone call or message from G_0. As an example, we choose three G_0 users (diamonds) and their related G_1 users (circles) and G_2 users (triangles) in the Bombing event as a sample contact network (Fig. 2a). There are three types of communication behaviors for users in G_1: (1) call back to G_0 user(s), which are edges in orange, (2) call forward to G_2 users, edges in purple, and (3) calls to other G_1 user(s), edges in green. We denote these three kinds of communication behaviors with, C_{10}, C_{12}, and C_{11}, respectively. We measure the contributions of these three communication modes to the total activities of G_1 users, finding C_{11} constitutes no more than 5% of the total volume of G_1 users' communicating activities (Fig. 2b). The observed low volume of C_{11} among G_1 users during emergencies is somewhat unexpected, given the importance of triadic closure in social communications[6,17]. Hence, the spike observed in G_1 users in Fig. 1 is mainly determined by C_{10} and C_{12}.

The existence of different communication modes in G_1 (Fig. 2a) raises an important question: what is the temporal contribution of C_{10} and C_{12} to the observed spikes in G_1 users' activities? To this end, we decompose $\Delta V(t|G_1)$ into $V(C_{10})$ and $V(C_{12})$ by modifying the rescaling framework

$$V(C_{1i}) = V_{1i}(t|G_1) - \langle a_{1i} V_{1i}(t|g_1)\rangle \qquad (3)$$

for $i = \{0, 2\}$, where V_{1i} is the call volume from G_1 (g_1) users to G_i (g_i) users, and a_{1i} is a scaling factor modified from Eq. 1 as

$$a_{1i} = \int_{\delta t} V_{1i}(\tau|G_1)d\tau \Big/ \int_{\delta t} V_{1i}(\tau|g_1)d\tau. \qquad (4)$$

In Fig. 3, we show $V(C_{10})$ and $V(C_{12})$ as a function of time. We find that in all three emergency events, $V(C_{10})$ has evident volume spikes

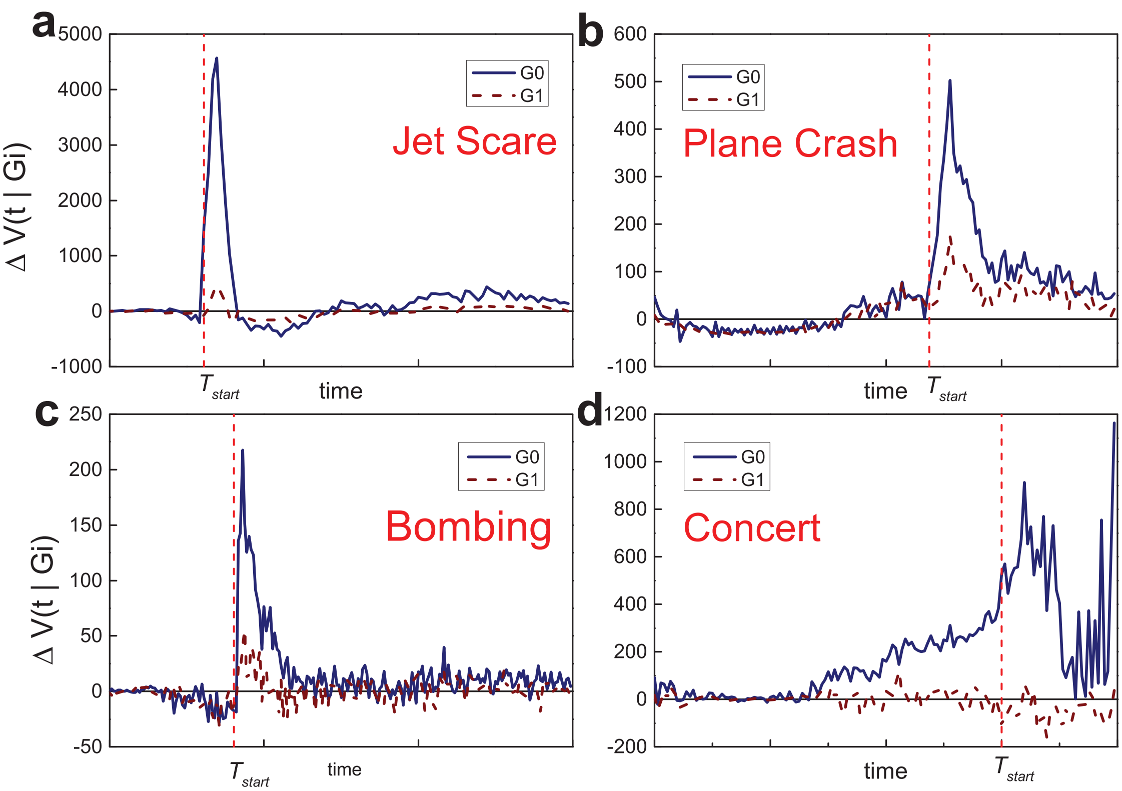

Figure 1 | The temporal behavior of the call volume change for three emergency events and one non-emergency event. (a), Jet Scare; (b), Plane Crash; (c), Bombing; (d), Concert. Call volume changes for the event are compared to the average rescaled call volume change of five corresponding normal days to compute $\Delta V(t|G_i)$. Dark blue line is for G_0 users, dark red line is for G_1 users. Vertical dashed line in red is the start time of the event.

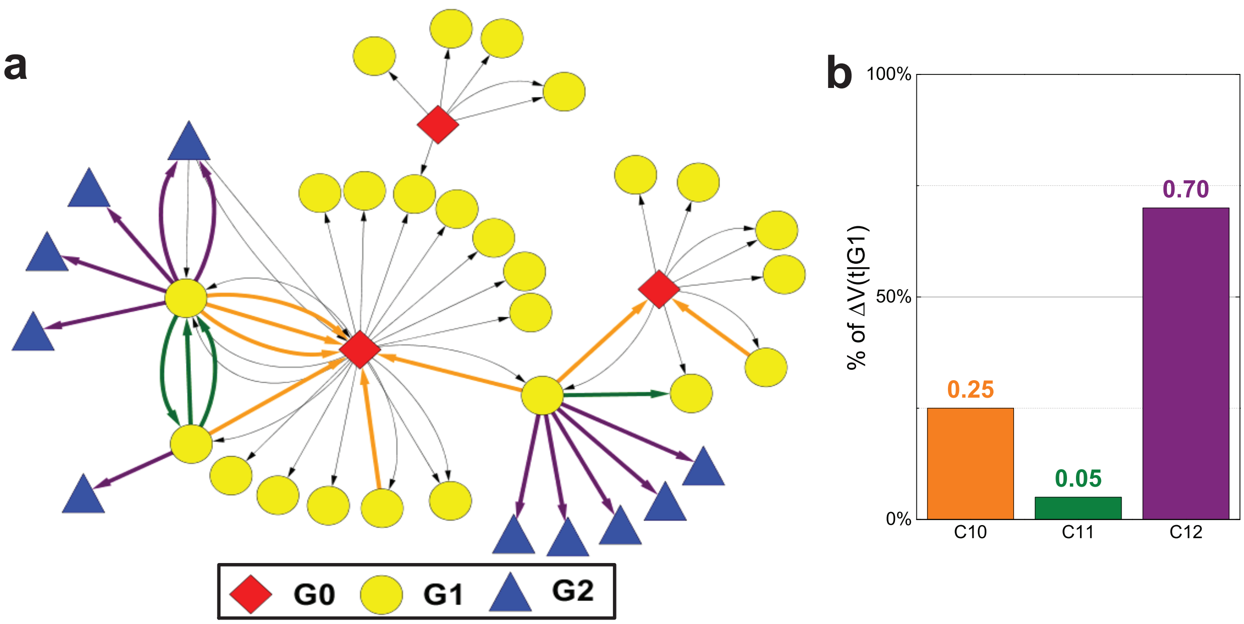

Figure 2 | There are three kinds of communicating behaviors for G_1 users. (a), A random sample contact network during the Bombing. The G_0, G_1, and G_2 users are in red (diamond), yellow (circle), and blue (triangle), respectively. Edges in orange, purple, and green represent call back (C_{10}), call forward (C_{12}), and calls to other G_1 users (C_{11}), respectively. (b), Histogram demonstrating how strongly each communication pattern contributes to the total communication activity. Only ≈ 5% of $V(G_1)_{event}$ is due to $V(C_{11})$ activity for example.

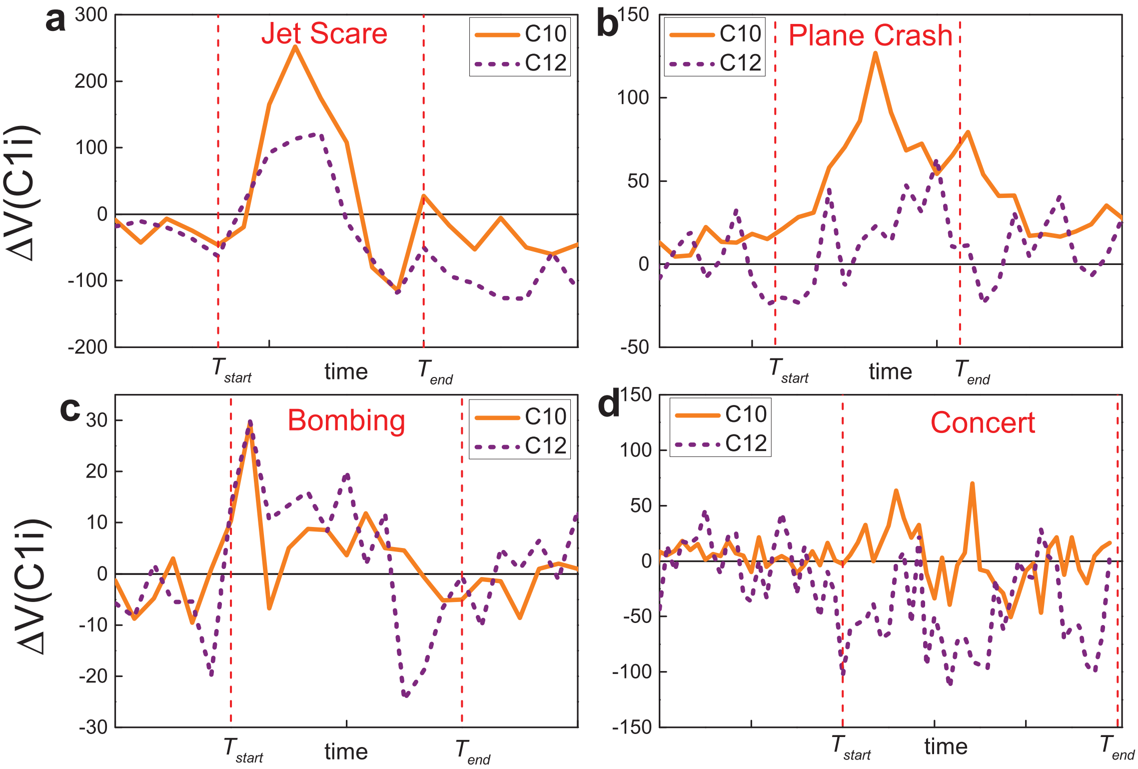

Figure 3 | The time dependence of call volume $V(C_{10})$ and $V(C_{12})$ for three emergency events and one non-emergency event. Solid (orange) line is call back volume $V(C_{10})$, dash (purple) line is call forward volume $V(C_{12})$. Vertical dash lines in red are the start and the end times of the event.

during the event period. And, by comparing Fig. 1 and Fig. 3, we find the peaks of $V(C_{10})$ are in close temporal vicinity to those of $\Delta V(t|G_1)$. Yet, for Concert (Fig. 3d), we observed no clear volume spikes. Overall, Fig. 3 demonstrates that C_{10}, as a major contribution to the observed spikes in G_1, indicating the call back actions (C_{10}) in emergencies contribute more to the spike of $\Delta V(t|G_1)$ than the call forward actions (C_{12}). That is, G_1 users prefer to interact back with G_0 users rather than contacting with new users (G_2), a phenomenon that limits the spreading of information. Indeed, C_{10} measures the reciprocal communications from G_1 to G_0, representing correspondence and coordination calls between social neighbors. C_{12}, on the other hand, measures the dissemination of situational awareness, corresponding to information cascades that penetrate the underlying social network. Hence, the results in Fig. 3 indicate that during emergencies both dissemination and call-back response of emergency information are important for information flow, and they together determine the magnitude of G_1 users' communication spikes (Fig. 1).

These preceding results indicate that reciprocal communications play a dominant role in social response during emergency, raising an important question: what is the origin of the observed reciprocal correspondence? There are two possible mechanisms likely at work here. First is the heterogeneous nature of reciprocities: Social ties are characterized by different reciprocities[18,22,26,35,38,41], corresponding to different likelihood of reciprocal communications upon receiving a call from others. Therefore, the large increase in reciprocal communications may represent a selection bias introduced by eyewitnesses by communicating with their social neighbors with high reciprocity. The second possible factor is a behavioral change of social neighbors after learning about the event, corresponding to coordination and providing additional information to eyewitnesses. To quantify the competition between these two factors, we measure the reciprocity of communications between any two individuals, during normal periods.

In an unweighted network, a general definition of link reciprocity R is to measure the tendency of two nodes to form mutual connections ($A \rightarrow B$ and $B \rightarrow A$)[12,26,46]. Hence, $R = 1$ for a purely bidirectional link, and $R = 0$ for a unidirectional one. Considering the weighted nature of contact networks[13,22,41], we define the reciprocity of communications between G_0 and G_1 users as

$$R = 1 - \left|1 - \frac{2V_{i\rightarrow j}}{V_{i\rightarrow j} + V_{j\rightarrow i}}\right|, \tag{5}$$

where $V_{x\rightarrow y}$ is the number of calls from user x to user y within a given period, and $|\cdot|$ is the absolute value. With this definition, two users have a reciprocity ranging from 0 to **1**, where $R = \mathbf{1}$ corresponds to reciprocal links, and $R = 0$ for non-reciprocal ones.

In Fig. 4, we show the reciprocity of communications averaged over all pairs of users in G_0 and G_1 for the four events during event periods. We find that, for Bombing, Plane Crash and Jet Scare, the average reciprocity for each emergency event shows a significant increase, deviating by approximately 1.8, 3 and 6 standard deviations from normal days, respectively. This result indicates that the observed increase in "call-back" actions from G_1 to G_0 during these emergency events correspond to behavioral changes in communications. If the increased call-back were entirely random, the distribution of reciprocity over the G_1 population would be sufficient to explain the resulting call-back, but we do not observe this. For Concert, we observe a decrease in reciprocity comparing to normal periods, with 4.7σ below the averaged reciprocity of normal days, indicating clear distinctions between emergency and non-emergency events.

To test the consistency of our results, we also study reciprocity for other emergency and non-emergency events. As shown in Supplementary Materials Fig. S1, the reciprocities for Blackout and Earthquake are characterized by only modest increase, well within the range of one standard deviation, reassuring the preceding results on correlations between activity spikes in G_1 (Fig. 3a in Ref. 2) and their increase in reciprocity.

Finally, to better understand the origin of the observed increase of reciprocity, we measure the contributions to G_1 users' behavioral

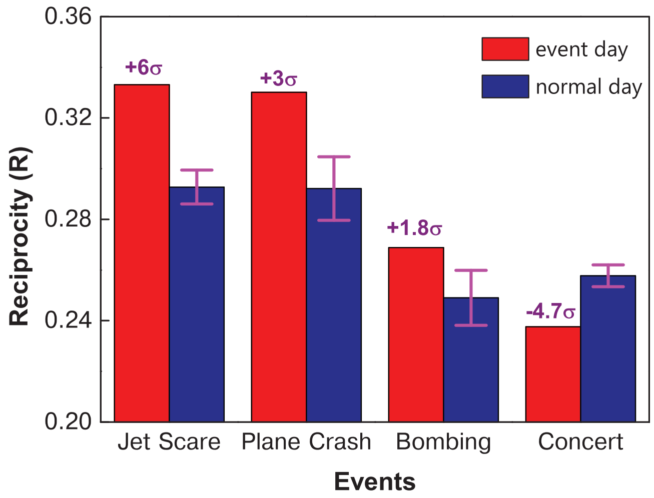

Figure 4 | Histogram for the average reciprocity (Eq.5) of communications during event period for three emergency events and one non-emergency event. The reciprocities of communications are averaged over all observed links between G_0 and G_1 users for the event day and each normal day. Event day's value is in red. The final averaged value for normal day is in blue, and averaged over five normal days' averaged reciprocities. The standard deviation of five normal days' averaged reciprocities are also shown as a error bar for each event.

change for different demographics. More specifically, we obtained self-reported gender information, available for 88% of users, and consider all communications in which gender information is available for both parties. There are four kinds of coupled pairs between G_0 and G_1 users: male-male (MM), male-female (MF), female-male (FM) and female-female (FF). For each event, we compute the reciprocities for the four different kinds of pairs separately. We also average the reciprocities of the MF and FM pairs as cross-gender pairs (CG), and the MM and FF pairs as same-gender pairs (SG). Interestingly, we find the collective response from different demographics is almost universal (Fig. 5). That is, for emergency events with significant increases in reciprocity (Jet Scare and Plane Crash), the reciprocities across different gender pairs are all several standard deviations larger than normal periods (Fig. 4 (a) and (b)).

Discussion

Taken together, we have studied cell phone communications during anomalous events, and find volume spikes in G_1's communication compared to normal days in three emergencies. To uncover the possible origin of the volume spikes, we decomposed G_1's communications into call-back (C_{10}) and call-forward (C_{12}) actions. Comparing to non-emergency events, we found that the dominant component of volume spikes is C_{10} for all three emergency events, indicating the need for correspondence with eyewitnesses is more critical than the dissemination of situational awareness during emergencies. We further demonstrated such communication patterns correspond to a behavioral change in G_1 users that cannot be explained by reciprocity or demographics. We believe the empirical findings reported in this paper present relevant information that can be used to benchmark potential models, and will play an increasingly important role as large-scale data flourish and our quantitative understanding human behavior deepens.

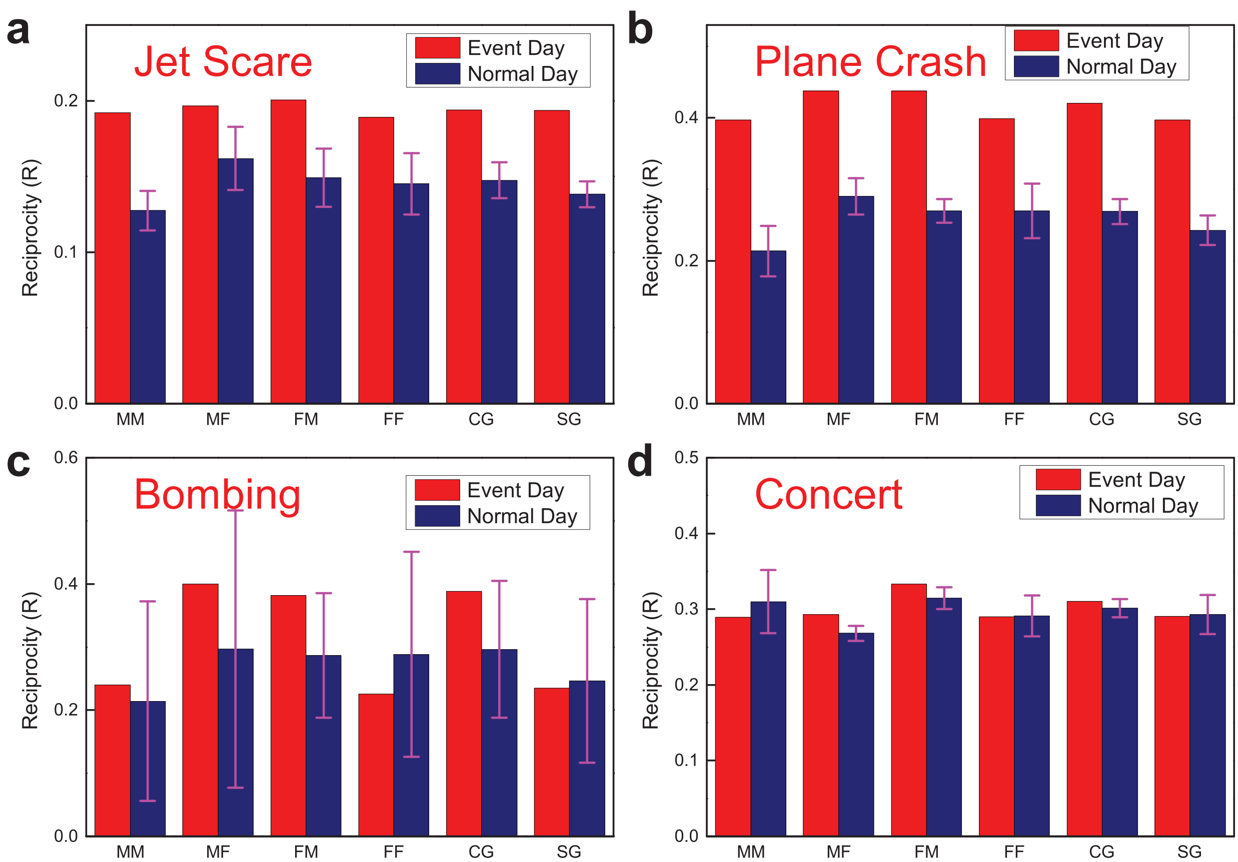

Figure 5 | Gender influence on reciprocity. Histogram for the average reciprocity of communications during three emergency events [(a) Jet Scare, (b) Plane Crash, (c) Bombing] and one non-emergency event [(d) Concert]. In (a) and (b), there is a strong change in R which is unaffected by gender. In (c) and (d), however, reciprocity does not generally change in a significant manner. Error bars denote the standard deviation.

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Author contributions

L.G., C.S. and D.W. designed research; L.G. and D.W. performed research; L.G., J.B. and D.W. analyzed data; L.G., Z.G., A.B., J.B. and D.W. wrote the paper.

Additional information

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