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A study of self-disclosure during the Coronavirus pandemic

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Abstract
We study observed incidence of self-disclosure in a large set of tweets representing user-led English-language conversation about the Coronavirus pandemic. Using an unsupervised approach to detect voluntary disclosure of personal information, we provide early evidence that situational factors surrounding the Coronavirus pandemic may impact individuals' privacy calculus. Text analyses reveal topical shift toward supportiveness and support-seeking in self-disclosing conversation on Twitter. We run a comparable analysis of tweets from Hurricane Harvey to provide context for observed effects and suggest opportunities for further study.

Contents

1. Introduction

The last thirteen months have seen global restrictions on movement unprecedented in modern times. Curfews, quarantines, stay-at-home and shelter-in-place orders, shutdowns and lockdowns have been variably instituted as COVID-19 case counts rise and fall. At one point in early April 2020, 91 percent of the world's population was living under travel restrictions of some kind and nearly 50 percent under lockdown (Connor, 2020). Unsurprisingly, there has been an unprecedented surge in online activity during this period (James, 2020). Much of the increased traffic extends beyond typical Internet surfing and video streaming, as people find ways to leverage online resources to stay connected with one another, personally and professionally. Social media usage has seen a 61 percent increase as people turn to these platforms to support routine social activities (Holmes, 2020).

It is to be expected that the expanded breadth and depth of online activity will magnify privacy risks for individual users. Beyond simply spending more time online, the emergence of virtual play dates, happy hours and book clubs suggests that during this time of social distancing, people are looking for ways to stay close (*e.g.*, "apart but together" campaigns). This may be particularly the case for the many individuals facing heightened anxiety, stress and depression due to social isolation, grief, financial insecurity, and of course health-related fears of the virus itself (Pfefferbaum and North, 2020; Gao, *et al.*, 2020; Galea, *et al.*, 2020; Rajkumar, 2020; Cauberghe, *et al.*, 2021; Drouin, *et al.*, 2020).

The literature on social communication suggests that interpersonal connectedness and relationship development is fundamentally facilitated through iterative *self-disclosure* (Altman and Taylor, 1973), that is, intentionally revealing personal information such as feelings, thoughts, and experiences to others (Derlaga and Berg, 1987). In fact, there is a robust literature on (routine) self-disclosure in online social media outside the particular domain of crisis (Bak, *et al.*, 2014; Joinson and Paine, 2007; Nguyen, *et al.*, 2012; Houghton and Joinson, 2012; Attrill and Jalil, 2011; Willems, *et al.*, 2020; Luo and Hancock, 2020). Research indicates that as users engage in discussion online, they leverage self-disclosure as a way to enhance immediate social rewards (Hallam and Zanella, 2017), increase legitimacy and likeability (Bak, *et al.*, 2012), and derive social support (Tidwell and Walther, 2002). A majority of users report that these rewards are mediated by concerns about privacy (Smith, *et al.*, 2011). Individual privacy concerns typically evolve over time, tied to the day's events and the longer arc of shifting norms (Acquisti, *et al.*, 2015; Adjerid, *et al.*, 2018). Ultimately, decisions to self-disclose are inherently personal and contextual, influenced by platform affordances (Joinson and Paine, 2007), audience (Bazarova and Choi, 2014; Choi and Bazarova, 2015), discussion topic (Umar, *et al.*, 2019), and peer effects (Barak and Gluck-Ofri, 2007).

Less is known about the evolution of users' sharing practices during public health emergencies. The crisis informatics literature has highlighted the role of social media during acute events for crisis management, public participation, and backchannel communication (Palen, 2008; Goolsby, 2010; Alexander, 2014). We know that victims of Hurricane Harvey sought assistance through social media, in some cases revealing their full names and addresses online (Seetharaman and Wells, 2017). However, what we are witnessing in the case of the Coronavirus pandemic is distinct from previous crises in important ways. COVID-19 is a global, relatively protracted acute threat. Unlike natural disasters or military engagements, the pandemic has left communication infrastructure intact. Digital outlets have become lifelines.

Our work addresses the following research questions. (*RQ1*) We ask whether and to what extent we see an increase in self-disclosing behaviors on Twitter during this time, specifically in posts related to the COVID-19 pandemic. (*RQ2*) We ask whether any observed deviations in self-disclosing behaviors correspond with acute events during the pandemic. Furthermore, we seek (*RQ3*) to identify the primary set of topics associated with self-disclosure in pandemic-related conversations and explore the implications such disclosures may therefore have on user privacy. Finally, we question (*RQ4*) whether themes and sharing behavior changes are crisis-centric or exhibited consistently across crises.

We analyze instances of self-disclosure in a dataset of 53,557,975 tweets representing conversations on Coronavirus-related topics. We define self-disclosure as the voluntary behavior of sharing personal information online within self-authored posts. We operationalize this definition using an unsupervised method for identifying personal information shared by an author about themselves. The approach we take identifies both subjective and objective personal information, and our analyses do not distinguish between the two.

Our analysis reveals a steep increase in instances of self-disclosure, particularly related to users' emotional states and personal experiences of the crisis. We compare observed self-disclosure patterns during the Coronavirus pandemic to observed self-disclosure patterns during a different crisis, *i.e.*, Hurricane Harvey in late summer 2017. Although hurricanes are an annual expectation, the landfall duration and subsequent impact of Hurricane Harvey created a crisis throughout communities in the south central region of the United States. This overwhelmed traditional emergency response infrastructure and affected citizens took to social media to seek emergency assistance (Sebastian, *et al.*, 2017; Smith, *et al.*, 2018). The Harvey study provides some context for these unprecedented times, suggesting similarities and differences that better inform our observations during the current crisis and implications for the privacy community.

2. Related work

Our work is situated within the general literature on self-disclosure. Historically the purview of psychologists' early work focused on the role of verbal disclosure in interpersonal relationships and identifying factors that may facilitate or inhibit these behaviors (see Cozby [1973] for a review). Research in the space of online interactions has sought to understand the actualization of self-disclosure in digitally-mediated social communication. Studies suggest that disclosure behaviors in online environments may be meaningfully different than their off-line counterparts, *e.g.*, anonymity and lack of non-verbal cues afforded by social media may encourage greater disclosure of sensitive information (Forest and Wood, 2012; Joinson, 2001). Similar findings are reported in Ma, *et al.* (2018) where the authors explore the impact of content intimacy on self-disclosure. It is well established for face-to-face communication that people disclose less as content intimacy increases, but this effect seems to be weakened in online interactions.

Our study is motivated by recent work positioning online self-disclosure as strategic behavior targeting social connectedness, self-expression, relationship development, identity clarification and social control (Bazarova and Choi, 2014; Gibbs, *et al.*, 2006; Abramova, *et al.*, 2017; De Choudhury and De, 2014). Voluntary disclosure of personal information has been associated with improved well-being, meaningfully related to increased informational and emotional support (Huang, 2016). In tandem, insights from the privacy literature suggest that stress may dampen privacy concerns related to self-disclosure on social media (Zhang, 2017; Zhang and Fu, 2020), and that self-disclosure may moderate the relationship between stressful life events and mental health (Zhang, 2017; Johnshoy, *et al.*, 2020). In tandem, these findings suggest that users may be engaging in increased self-disclosure during this time and drive our primary research question. Our work is responsive to a recent call to further understanding of online self-disclosure during the COVID-19 crisis (Nabity-Grover, *et al.*, 2020), and builds on initial studies of self-disclosure in response to psychosocial effects of the pandemic (Saha, *et al.*, 2020; Zhen, *et al.*, 2021).

Despite the “upsides”, *i.e.*, socially adaptive motivations for disclosure, we know that self-disclosure can come at a cost; leaving users exposed to identity theft, cyber fraud and other crimes (Hasan, *et al.*, 2013), discrimination in job searches, credit and visa applications (McGregor, *et al.*, 2018), and harassment and bullying (Peluchette, *et al.*, 2015). Of course, not all shared personal information is of equal concern with respect to privacy risk. More sensitive (Liu and Terzi, 2010) or surprising (Chen, *et al.*, 2013) disclosures may more meaningfully affect privacy risks.

Early work by Acquisti and Gross (2006) suggested that social network users were neither fully aware nor responsive to privacy risks. Over time, studies have captured a shift toward increased privacy awareness (Johnson, *et al.*, 2012; Vitak and Kim, 2014), but there remains great variability in information sharing behaviors amongst individuals and across platforms (Zhao, *et al.*, 2016). It has been shown that culture plays a role in disclosure decisions (Zhao, *et al.*, 2012; Krasnova, *et al.*, 2012; Trepte, *et al.*, 2017), as does gender (Sun, *et al.*, 2015) and socioeconomic status (SES) (Marwick, *et al.*, 2017). Overarchingly, the cost-benefit analyses underlying an individual’s decision to share in the presence of privacy risk is postulated by social exchange theory (Emerson, 1976) and re-framed in the context of online social networks as the so-called privacy calculus (Krasnova, *et al.*, 2010; Dienlin and Metzger, 2016). Critically, work in a number of domains suggests that contextual and situational factors, *e.g.*, trust, anonymity, financial incentives, are embedded within the privacy calculus (Joinson and Paine, 2012; Hann, *et al.*, 2007; Li, *et al.*, 2010). Amongst these factors, emotion has also been suggested to play a meaningful role in privacy behaviors (Laufer and Wolfe, 1977; Berendt, *et al.*, 2005; Li, *et al.*, 2017). This finding is in keeping with the general theory of feeling-as-information (Petty, *et al.*, 2001), whereby emotions serve as information cues directly invoking adaptive behaviors (Lazarus, 1991). Few studies have tried to link emotions with self-disclosure in circumscribed settings (Zhang, 2017; Zhang and Fu, 2020).

This work is complementary to the body of research in crisis informatics, which typically focuses on the related but fundamentally distinct problem of mining self-disclosed information for the purposes of identifying and deploying assistance and relief to impacted individuals and communities (see Muniz-Rodriguez, *et al.* [2020] for review). Threads in this field include social network analysis for disaster management (Zelenkauskaite, *et al.*, 2012; Imran, *et al.*, 2013; Takahashi, *et al.*, 2015; Chew and Eysenbach, 2010) and perceptions of crisis, including pandemics, mined through social media (Szomszor, *et al.*, 2011; Valaskivi, *et al.*, 2019). A robust literature is also emerging on the spread of misinformation in crisis (Starbird, *et al.*, 2014; Huang, *et al.*, 2015; Bursztyn, *et al.*, 2020) and we note the critical relevance of this work in the COVID-19 crisis we study here.

Our work dovetails with the literature on detection and tagging of self-disclosure in text (*e.g.*, Bak, *et al.*, 2014; Caliskan, *et al.*, 2014; Wang, *et al.*, 2016; Vasalou, *et al.*, 2011; Chow, *et al.*, 2008; Choi, *et al.*, 2013). Chow, *et al.* (2008) developed an association rules-based inference model that identified sensitive keywords which could be used to infer a private topic. Similarly, multiple studies utilized pattern or rule based methods to detect specific types of disclosures (Umar, *et al.*, 2019; Vasalou, *et al.*, 2011). Choi, *et al.* (2013) detected exposures of sensitive information such as location by looking for specific sentence patterns with occurrences of words like fly to, live in ,etc. used in conjunction with place names. Likewise, a study by Vasalou, *et al.* (2011) developed a privacy dictionary that differentiated between private and non private text. The detection was based on occurrence frequency of specific utterances associated with private categories. A recent method (Akiti, *et al.*, 2020) considers semantic role labeling to identify the lexical units and their semantic roles that signal self-disclosure.

Past work has attempted to classify self-disclosure by levels, or degree of disclosure. Caliskan, *et al.* (2014) used AdaBoost with a Naive Bayes classifier to detect privacy scores for Twitter users’ timelines. Bak, *et al.* (2014) applied modified Latent Dirichlet Allocation (LDA) topic models for semi-supervised classification of Twitter conversations into three self-disclosure levels: general, medium and high. Wang, *et al.* (2016) used regression models with extensive feature sets to detect degree of self-disclosure. Because the notion of sensitive information is based on user perception and context, studies on detection of self-disclosure levels are often difficult to generalize beyond their original context.

3. Datasets

Our primary dataset is a repository of tweet IDs corresponding to content posted on Twitter related to the Coronavirus pandemic (Chen, *et al.*, 2020). We collect a secondary dataset representing tweets during Hurricane Harvey to support comparative analyses and discussion of crisis-specific vs. crisis-general observations (*RQ4*).

3.1. COVID-19

Our primary dataset contains 508,088,777 tweet IDs for the period of activity from 21 January 2020 through 28 August 2020. Chen, *et al.* (2020) compiled tweets utilizing a combination of Twitter's Search API (for activity 21 January through 28 January) and Twitter's Streaming API (for activity 28 January through 31 July). The repository represents topically relevant tweets across the platform, canvassed based on designated keywords, as well as the full activity of selected accounts (See Tables 1, 2). Around 6 June 2020, the repository collection infrastructure transitioned to Amazon Web Services which generated a significant increase in tweet ID volume. No search parameters were adjusted or data gaps presented because of the transition; therefore, we analyzed the entirety of the dataset in a consistent manner. In analyses that follow, we focus our scope to highlight an important transitional period in the pandemic for individuals living in the United States by considering two sub-periods — prior to and after 11 March, the date of the World Health Organization's pandemic declaration and just two days preceding U.S. President Trump's declared national emergency.

Table 1: Keywords followed, by start date.

Keywords followed	Start date
Coronavirus, Koronavirus, Corona, CDC, Wuhancoronavirus, Wuhanlockdown, Ncov, Wuhan, N95, Kungflu, Epidemic, outbreak, Sinophobia, China	28 January 2020
covid-19	16 February 2020
corona virus	2 March 2020
covid, covid19, sars-cov-2	6 March 2020
COVID-19	8 March 2020
COVD, pandemic	12 March 2020
coronapocalypse, canceleverything, Coronials, SocialDistancingNow, Social Distancing, SocialDistancing	13 March 2020
panicbuy, panic buy, panicbuying, panic buying, 14DayQuarantine, DuringMy14DayQuarantine, panic shop, panic shopping, panicshop, InMyQuarantineSurvivalKit, panic-buy, panic-shop	14 March 2020
coronakindness	15 March 2020

quarantinelife, chinese virus, chinesevirus, stayhomechallenge, stay home challenge, sflockdown, DontBeASpreader, lockdown, lock down	16 March 2020
shelteringinplace, sheltering in place, staysafestayhome, stay safe stay home, trumppandemic, trump pandemic, flattenthecurve, flatten the curve, china virus, chinavirus	18 March 2020
quarentinelife, PPEshortage, saferathome, stayathome, stay at home, stay home, stayhome	19 March 2020
GetMePPE	21 March 2020
covidiot	26 March 2020
epitwitter	28 March 2020
pandemie	31 March 2020
wear a mask, wearamas, kung flu, covididiot	28 June 2020
COVID__19	9 July 2020

Table 2: Accounts followed, by start date.

Accounts followed	Start date
PneumoniaWuhan, CoronaVirusInfo,V2019N, CDCemergency, CDCgov, WHO, HHSGov, NIAIDNews	28 January 2020
drtedros	15 March 2020

Text and metadata corresponding to these 508,088,777 tweet IDs were obtained through rehydration using the Twarc [1] Python library. Of the IDs passed for rehydration, 461,259,923 were successfully rehydrated. The 9.21 percent loss represents deleted content, therefore irretrievable through Twitter's API.

For the purpose of measuring and studying self-disclosure, we filtered the corpus to capture tweets that represent original content posted by individual users. Specifically, we removed quoted tweets, retweets [2], as well as all tweets associated with verified accounts and the specific organizational accounts listed in Table 2. We narrowed our analysis to English-language content in order to reduce situational heterogenity and maintain confidence in our labeling approach, which has been developed and validated on English-language text. The resulting corpus, which forms the basis of our analyses, consists of 53,557,975 unique tweets.

3.2. Hurricane Harvey

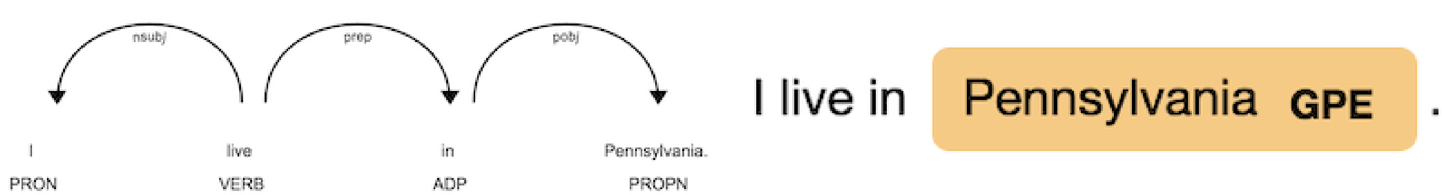
Our comparative dataset is a collection of 6,732,546 tweet IDs representing posted content inclusive of keywords “Hurricane Harvey”, “Harvey”, and/or “HurricaneHarvey” during a 12-day period after Harvey first made landfall, 25 August 2017, through 5 September 2017 (Alam, *et al.*, 2018). Similar to the COVID-19 dataset we hydrated the set of tweets using the Hydrator Tweet Retrieval Tool (v. 2.0) [3].

We experienced a 33 percent loss during data reconstitution (compare to 9.21 percent loss in the Coronavirus-related dataset), attributable to tweet and account deletion during the nearly three years which have passed since initial collection. We filter the resulting 4,379,462 tweets for original content in the same fashion as we handled the COVID-19 data — removing all quoted tweets, retweets, content from verified accounts, and non-English content as identified by Twitter. We pre-process the resulting 551,061 tweets and apply unsupervised labeling to detect instances of self-disclosure and topic analysis techniques as detailed in following Sections 4 and 5.

4. Automated detection of self-disclosure

4.1. Method

We use an unsupervised method (Umar, *et al.*, 2019) to detect instances of self-disclosure in our dataset. Consistent with the literature on detection of self-disclosure in text (see, *e.g.*, Bak, *et al.*, [2014]; Houghton and Joinson, [2012]; De Choudhury and De, [2014]; Wang, *et al.*, [2016]), we consider the presence of first-person pronouns. Specifically, we consider sentences containing self-reference as the subject, a category-related verb and associated named entity. Consider the example of location self-disclosure shown in Figure 1. A first person pronoun “I” is the self-referent subject of the sentence. It is used with a location-related verb “live” in the vicinity of the associated location entity “Pennsylvania”. Notably, subjective categories of self-disclosure such as interests and feelings do not have associated named entities. These are differentiated through rule-based schemas based on subject-verb pairs. The approach described is implemented in three phases: 1) subject, verb and object triplet extraction with awareness to voice (active or passive) in the sentence; 2) named entity recognition; 3) rule-based matching to established dictionaries. Our dictionaries are adopted from Umar, *et al.* (2019).



(a) Dependency tree

(b) Named entity recognition

Figure 1: Phases in self-disclosure categorization scheme [Umar, *et al.* (2019)].

As the proposed approach is based on sentence structure and syntactic resources (subject, verb, object and entities), it can be applied to any textual content. However, we acknowledge that tweets present unique characteristics. Due to character limits and consequent emerging norms of the platform, users more frequently engage acronyms and abbreviations (Han and Baldwin, 2011). Relatedly, sentence structure and syntax are noisier when compared to more verbose platforms (Boot, *et al.*, 2019). User mentions, hashtags, and graphic symbols are embedded within text. Considering these differences, we pre-process tweets as follows. All Unicode encoding errors are corrected. We remove markers associated with retweets (*e.g.*, “RT”) and filter user mentions and hashtags. Additionally, symbols like “&” and “$” are replaced with their respective word representations. E-mail addresses and phone numbers are replaced with placeholders “emailid” and “phonenumber”, while URLs are filtered. We also replace contractions in the tweets like “I’m” to “I am” and correct incorrect use of spacing between words. These pre-processing steps enable cleaner input to the detection algorithm.

4.2. Evaluation

While unsupervised classification is imperfect, our approach is both appropriate and effective for the task of labeling massive datasets like ours (see unsupervised approaches for similar tasks, *e.g.*, detecting offensive [Wiedemann, *et al.*, 2019], identifying ideology [Himelboim, *et al.*, 2013] and political party affiliation [Castro, *et al.*, 2017], and labeling stance on controversial topics [Darwish, *et al.*, 2020; Stefanov, *et al.*, 2020] on large Twitter datasets). Work developing supervised approaches for tagging self-disclosure in short text is ongoing, and all state of the art approaches still suffer from important limitations (see Related work).

To validate the unsupervised labeling approach in this context, we tested the method on a manually annotated subset of 5,000 tweets from our COVID-19 Twitter dataset. Each tweet was labelled by three raters on Amazon Mechanical Turk. Our labelling survey asked raters to evaluate different aspects of self-disclosure construct (Wang, *et al.*, 2016) on a scale from 1 (not at all) to 7 (completely). Specifically, raters were asked to rate the extent to which a tweet involved: 1) personal information; 2) personal thoughts; 3) personal feelings; 4) personal relationships; and, 5) the intimacy of the tweet (see Appendix A, Table A1). Intraclass correlation coefficient (ICC) showed fair to good (Cicchetti, 1994) agreement among raters for the first four labels (Good: Information (0.744), Feelings (0.665), Relations (0.672); Fair: Thoughts (0.446)). While, ICC for Intimacy was low, reflecting the particularly subjective nature of the label.

As our research questions center around incidence of self-disclosure, we consider four out of five dimensions (*i.e.*, excluding intimacy) of the self-disclosure construct that represent the categories of personal revelations. We binarized each of the self-disclosure categories namely, information, feelings, relations, and thoughts. A rating of “1” (Not at all) was taken as representative of no self-disclosure, while ratings greater than “1” represented presence of self-disclosure. Binary labels for each question were obtained for individual tweets through majority voting among three raters. A tweet was labelled self-disclosing if self-disclosure was noted for at least one of the four questions. Of 5,000 tweets, 4,297 were considered self-disclosing by this metric and the remaining 703 were not. We compared the performance of the automated approach to our manual labels. We obtained precision, recall and F1 scores of 93.3 percent, 62.9 percent, and 75.12 percent respectively. This performance provides support for the appropriation of the unsupervised labeling method in this work. We note that our research question centers around change over time rather than absolute quantification of self-disclosure, so that barring any temporal bias in the data and/or labelling approach, measures of change should be faithful.

5. Topic modeling

We consider topic modeling as a follow-up analysis to better understand topics of conversation in self-disclosing and non-self-disclosing tweets, and their evolution over time to address *RQ3*. We use Latent Dirichlet Allocation (LDA) (Blei, *et al.*, 2003), wherein each document (in our case, a single Tweet) in the corpus (set of tweets) is considered to be generated as a mixture of latent topics, where each topic is a distribution over words. For a document, each word is assigned topics according to a Dirichlet distribution. Iteratively cycling through each word in each document and all documents in the corpus, topic assignments are updated based on the prevalence of words across topics and the prevalence of topics in the document. Based on this process, topical coherence is assessed and final topic distributions for documents and word distributions for topics are generated.

In addition to the data cleaning steps described in Section 4, we pre-process tweets using tokenization, conversion to lower case, lemmatization and removal of punctuation and stopwords. Top six topics are generated from the resulting corpora using the LDA model within the Gensim Python library [4]. Gensim LDA is an unsupervised method to discover topical similarities within a corpus of text through analysis of semantic structure of the provided text.

We consider topic analyses over subsets of interest within the complete Coronavirus dataset. Namely, we explore unique topic models for tweets in two time windows pre- and post-March 11, 2020 (21 January — 11 March; 12 March — 15 May) and compare topical themes between tweets with presence or absence of detected instances of self-disclosure over the entirety of this subset. To better understand disclosure trends presented post-March 11, we also generate topic models over one-month windows for the remainder of the Coronavirus dataset: 16 May through 15 June, 16 June through 15 July, and 16 July through 15 August.

Through pyLDAvis (Sievert and Shirley, 2014) we generate intertopic distance maps (Appendix B) and top keywords for each generated topic. The intertopic distance maps visualize the topics in two-dimensional space with the area of the circles proportional to the amount of words belonging that topic across the dictionary. Overlapping topical circles show crossover in keywords identified, thus overlapping theme content. Distinct themes are evidenced by non-overlapping clusters spread out across the space. Key terms are classified through saliency and relevance. Saliency is a measure of how useful the term is for interpreting the topic while relevance is the measure at which a word belongs to a topic at the exclusion of being included in another topic. The relevance parameter lambda, λ, ranges from 0 to 1. A λ value closer to 0 identifies words more exclusive to the topic, while λ closer to 1 identifies terms more frequently presented in the topic, but also present in other topics. We use a λ value of 0.6, as this has been deemed optimal for interpreting topics (Sievert and Shirley, 2014).

6. Findings

Here we explore the frequency of self-disclosure tweets within the COVID-19 dataset, as well as topical themes for previously mentioned subsetted windows of time. We also present work on the Hurricane Harvey dataset for comparison analysis.

6.1. Analyzing COVID-19 disclosures

Of the 53,557,975 Coronavirus-related tweets analyzed, approximately 19.07 percent (10,215,752 tweets) contain elements of self-disclosure. Looking more closely at daily variance from January until June, we identify a significant transition point in activity around 11 March 2020, as shown in Figure 2. To fully answer *RQ1*, we confirm the significant behavioral change as a sustained pattern by overlaying 7-day and 30-day simple moving averages which smooth day-to-day variance by taking the average disclosure percentage value over the given time window.

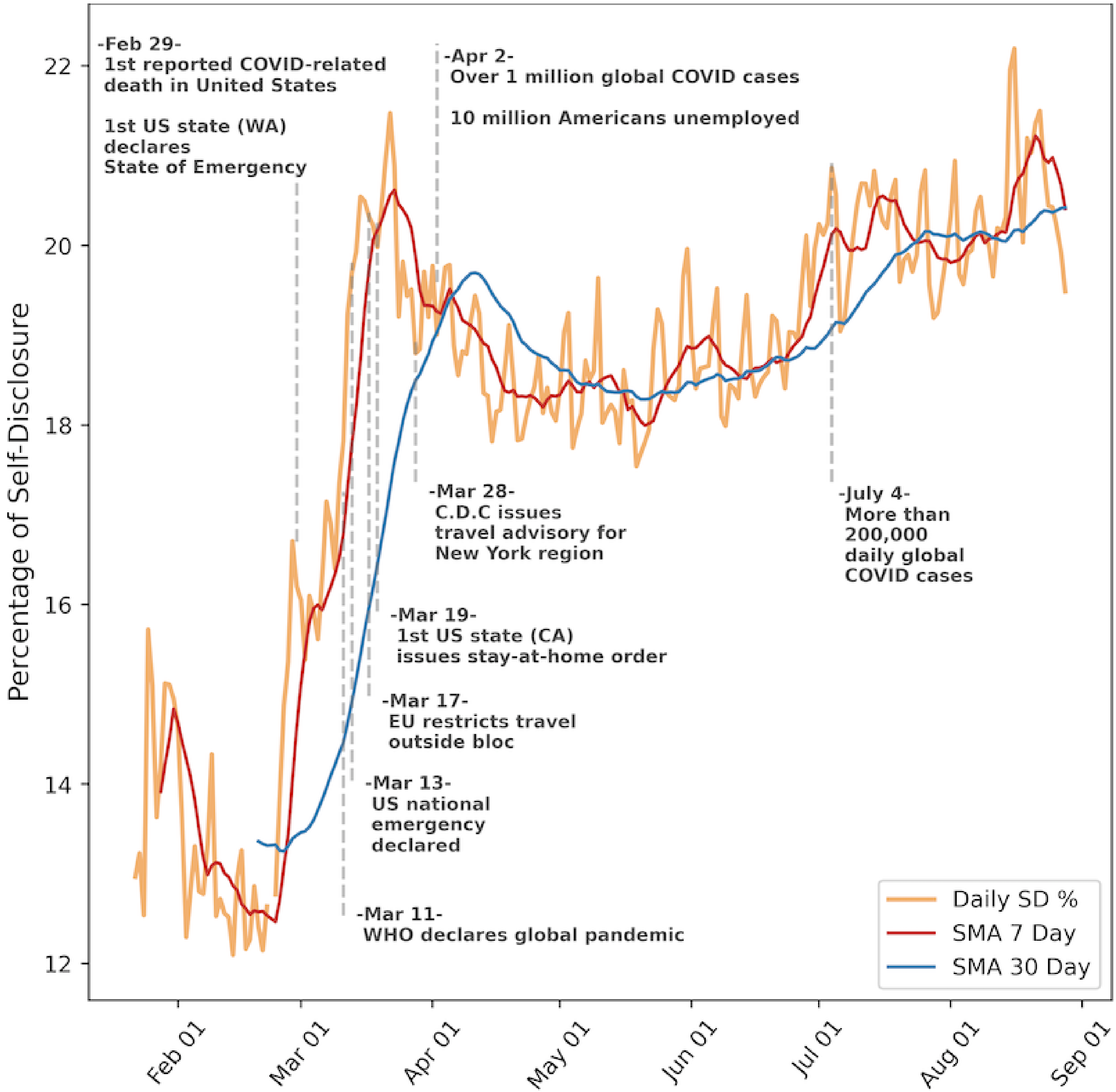


Figure 2: Percentage of tweets containing self-disclosure, assessed daily with 7- and 30-day simple moving averages.

We see disclosure change from the period 21 January through 11 March, where the average daily percentage of self-disclosing tweets is 14.63 peercent; compared to 12 March through 15 May, where the average daily percentage of self-disclosing tweets was 18.89 percent. Addressing *RQ2*, this change in activity coincides with an escalation in severity and increased global awareness of the crisis, with the World Health Organization (WHO) officially classifying Coronavirus as a pandemic (11 March). Current events coincident with observed changes in the rate of self-disclosure are noted on 13 March and 19 March when the United States officially declared a national state of emergency, and when the governor of California issued the first statewide 'stay-at-home' order, respectively. Self-disclosure activity remains high for the remainder of the dataset with an average daily percentage of 19.79 percent from 16 May through 28 August. As shown in Figure 2, additional inflection points are present coincident with acute events throughout the pandemic.

These observations suggest that situational context, in particular during crisis, may meaningfully influence short- and long-term disclosure behaviors.

We explore messaging around the Coronavirus pandemic through topic modeling, as outlined in Section 5. As discussed, self-disclosing behaviors increase steeply around 11 March, and interesting distinctions are noticeable in the topical breakdown comparing the periods just before (21 January 21 — 11 March) and after (12 March — 15 May) this date of interest, as reported in Table 3.

Table 3: Topical comparison of self-disclosing COVID-19 tweets before and after 11 March 2021.

Topic	Top six keywords
1	cdc,death,flu,test,number,report
2	get,like,fuck,shit,mask,die
3	trump,president,america,blame,economy,country
4	hand,buy,stock,wash,market,sell
5	hope,help,pray,god,epidemic,fight
6	travel,case,flight,quarantine,wuhan,confirm
(a) 21 January — 11 March 2020	
Topic	**Top six keywords**
1	distance,social,love,day,time,watch
2	corona,death,covid,virus,die,get
3	china,trump,country,virus,president,world
4	covid19,health,test,need,community,help
5	home,stay,mask,safe,order,wear
6	help,pay,sir,money,job,request
(b) 12 March — 15 May 2020	

Diving deeper to answer the presence of topical themes asked in *RQ3*, we examine that leading up to 11 March (Table 3a), self-disclosing conversation focused on general information (Topic 1) and sentimental impacts (Topic 2) representing 20 percent and 24 percent of all tweets, respectively. After 11 March (Table 3b), terms related to global and sentimental aspects of the crisis remain present (Topic 3, Topic 2) but prominent conversations also shift to managing the spread of the virus (Topic 5, Topic 1) and discussions about needs, help, thanks and support (Topic 4, Topic 6). In fact, Topics 4 and 6 together make up nearly half of the Tweets in that period, representing 23 percent and 24 percent of activity, respectively. This represents a shift from outward-looking to self-centric messaging as well as early evidence of emotional support and support seeking through disclosure.

Centered on the mid-March increase in disclosure behaviors, we also compare topical variance between disclosing and non-disclosing Coronavirus-related tweets for entirety of the aforementioned subsetted time window (21 January — 15 May; see Table 4). Generally, extracted topics reflect terminology pervasive in mainstream media at the onset of the crisis, including but not limited to expected impacts of COVID-19 (economy, market, lockdown, quarantine), recommendations (stay home, social distance, mask), and political impact (Trump, administration, democrat, government). Topic 1, the most prominent topic within the self-disclosing tweets, is represented by emotive terms (like, fuck, feel) not prominent in any non-self-disclosing themes.

Table 4: Topical comparison of self-disclosing and non-self-disclosing COVID-19 tweets through 15 May 2020.

Topic	Top six keywords
1	get,like,lockdown,day,fuck,feel
2	country,world,market,economy,chinese,government
3	test,case,death,flu,number,infect
4	mask,help,covid19,work,sir,support
5	trump,die,president,say,lie,know
6	home,stay,social,distance,safe,lockdown
(a) Self-disclosing tweets	
Topic	**Top six keywords**
1	virus,people,corona,like,time,spread
2	covid19,outbreak,health,help,pandemic,social
3	lockdown,home,stay,thank,safe,late
4	test,news,wuhan,patient,quarantine,hospital
5	case,new,death,report,confirm,update
6	trump,president,house,white,democrat,response
(b) Non-self-disclosing tweets	

We also analyze monthly subsets within the remaining timeline of our dataset, 15 May through 15 August, where the proportion of self-disclosing conversations remains elevated, and in fact, continues to gradually increase over time. The observed sustained higher rate of self-disclosure through the summer is particularly interesting. We speculate that users may have recalibrated their own sharing practices during the pandemic, and that this recalibration may represent a longer-term effect. Consistent with preceding time windows were themes of support seeking and political opinion. We observe the introduction of new themes related to social movements and education, while, discussions surrounding daily life (working/staying home) become the most prominent topic representing 38 percent and 41 percent of all self-disclosing tweets in the final two months of the collection. This again suggests a possible transition from discussions of anxiety and need to potentially coping with lifestyle changes and establishing a new normal. A listing of topics in this period is provided in Appendix A, Table A2.

6.2. Comparing COVID to Hurricane Harvey

To better understand RQ4 and the level of uniqueness attributable to the pandemic, we compare findings from the COVID and Hurricane Harvey datasets. Through analysis of the 551,061 tweets in the Hurricane Harvey dataset, we observe an average nine percent self-disclosure rate (49,595 tweets) over the 12-day collection period — substantially lower than the 19.07 percent observed in the Coronavirus-related dataset. Several factors might account for the difference. The current pandemic has been marked by efforts to maintain social distance and, we have proposed, increased levels of disclosure may be related to relationship-building with online cohorts. But what we may also be seeing is a reflection of a general trend toward greater self-disclosure in online social media over the course of nearly three years separating the two events.

Table 5: Example of self-disclosing tweets for selected topics from Table 3.

Period	Topic keywords	Example of self-disclosing tweet

Before 11 March	travel, case, flight, quarantine, wuhan, confirm	Booking Number: [Removed] and [Removed] Guest Name: [Removed] Query/Concern: with the recent travel advisories and uplift in the no of cases of covid-19, I would like to request a refund of my flight to/fro bangkok.
	hand, buy, stock, wash, market, sell	I work in a hospital and I am around sick people daily. Am I worried about the coronavirus? Nope not really. I get more worried about hiv/aids when I go into Ryan White center. I still say I should buy stock in hand sanitizer lol
	cdc, death, flu, test, number, report	October 2019 — february 2020 CDC Flu Tracking: 18,000 46,000 estimated deaths with 310,000 to 560,000 hospitalizations. I caught the flu in November last year on a United/SFO trip to Oakland. Passed to my family in Indiana over Thanksgiving.
After 11 March	home, stay, mask, safe, order, wear	I started wearing a mask about a month ago. Been out about 5 times. No one really looks at me because others are wearing masks too. Was at Walmart yesterday and none of the workers had gloves OR masks on! I was shocked but I am in Las Vegas, NV where this is no stay at home order.
	covid 19, health, test, need, community, helpt	*I am 22 yrs old and I tested positive for COVID-19* Do not underestimate this virus. I have never been so sick in my life. I am lucky and grateful to be as healthy as I am, but not everyone else is. Thank you for helping me to get tested. Everyone, please be safe!
	distance, social, love, day, time, watch	I started social distancing to protect my patients on Saturday. Since then, approximately my entire town has come to my home to see me. I am loved. And also reverse social distanced.

With respect to topical focus, we see important parallels between the two crises. As illustrated in Table 6a, self-disclosing tweets reveal emotional messaging centered on seeking immediate spiritual, physical, and monetary support (Topics 1, 2, 4, 5, 6) with top terms including “red cross”, “raise money”, “donation”, “relief”, and “prayer”. While present, these themes are less prominent in the non-self-disclosing data. This finding across both datasets suggests that support-seeking during crisis might be a driver of self-disclosure and play a meaningful role in users’ sharing practices. Also mirroring the Coronavirus dataset, we observe one self-disclosing topic representing politically motivated conversation (Topic 3).

Table 6: Topical comparison of self-disclosing and non-self-disclosing tweets during Hurricane Harvey.

Topic	Top six keywords
1	affect,heart,prayer,thought,texas,safe
2	relief,donation,effort,fund,jake,paul
3	sign,day,trump,petition,hear,tornado
4	know,god,love,need,think,deal

5	money,raise,houston,add,click,playlist
6	red,cross,team,american,save,best

(a) Self-disclosing tweets

Topic	Top six keywords
1	think,know,get,bad,feel,good
2	relief,effort,donation,fund,day,gas
3	family,safe,stay,add,lose,save
4	people,prayer,affect,thought,team,texas
5	support,red,wake,cross,bring,american
6	money, sign, raise, click, jake, paul

(b) Non-self-disclosing tweets

While there is topical overlap between the two classes of Harvey-related tweets, non-disclosing tweets (Table 6b) present a focus on crisis-specific contextual information with relevant keywords “flood”, “Texas”, and “Houston” (Topic 4).

7. Discussion and conclusion

The most striking observation in the analyses we have described is evidence of heightened and sustained levels of self-disclosure during the ongoing Coronavirus pandemic, contextualized by observed disclosure during Hurricane Harvey. This global crisis is unprecedented in a number of ways, one being the scale and scope of human interaction through social media. Concerns about privacy have been at the center of discussion in popular press (see, *e.g.*, Servick [2020]; Cellan-Jones [2020]; Lin and Martin [2020]), but most of this conversation has been about privacy tradeoffs related to location surveillance and individual health monitoring in service to public health. Many appear willing to sacrifice some privacy in hopes of stemming the spread of the disease and helping to accelerate the return to normalcy; others are not. Scholarly work has begun to propose “privacy first” decentralized approaches for COVID-related tracking and notification (see, *e.g.*, PACT [2020]; COVID Watch [2020]; Dp^{3}t [2020]).

We aim, with this work, to engage the privacy community in the work of better understanding heightened self-disclosure behaviors emergent in the Coronavirus pandemic and in crisis more broadly. Through our topic analysis we know that, during Hurricane Harvey, individuals took to social media in search of immediate aid. Today, they are leaning on their online social communities for ongoing engagement and support. Our analyses suggest that the current pandemic and its effects may have a sustained impact self-disclosure behaviors. Exploratory topic analysis reveals increased self-disclosure around sensitive topics (*e.g.*, health, money, help, support). An increase in disclosures containing such sensitive information has meaningful implications for privacy risks, especially during a time when users are already vulnerable (Liu and Terzi, 2010; Chen, *et al.*, 2013).

Isolation, economic uncertainty, and health-related anxiety pose serious threat to mental health and well-being (Holmes, *et al.*, 2020; Academy of Medical Sciences U.K., 2020), but the potential manifestations of psychological impact in the domain of voluntary self-disclosure are unknown. The existing literature hints at the role of mood and emotion in the privacy calculus, but these relationships have not be well established.

An open question is whether this increase in sharing practices will become a new norm, or whether they fade over time and we will ultimately return to pre-COVID baselines. If the higher volume of self-disclosure sustains beyond this crisis, we might look to social theory for explanations. Threshold models of collective behavior (see, *e.g.*, Granovetter [1978]; Centola, *et al.* [2018]; Wiedermann, *et al.* [2020]) may offer insights. As the crisis continues to unfold, we suggest that additional work should aim to further develop, refine and test these hypotheses.

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Notes

1. https://github.com/DocNow/twarc.

2. Retweets are identified through the existence of the "retweeted_status" field in the tweet object returned by the Twitter API. Tweets beginning with the string 'RT @' were also treated as retweeted records.

3. https://github.com/DocNow/hydrator.

4. https://radimrehurek.com/gensim/models/ldamodel.html.

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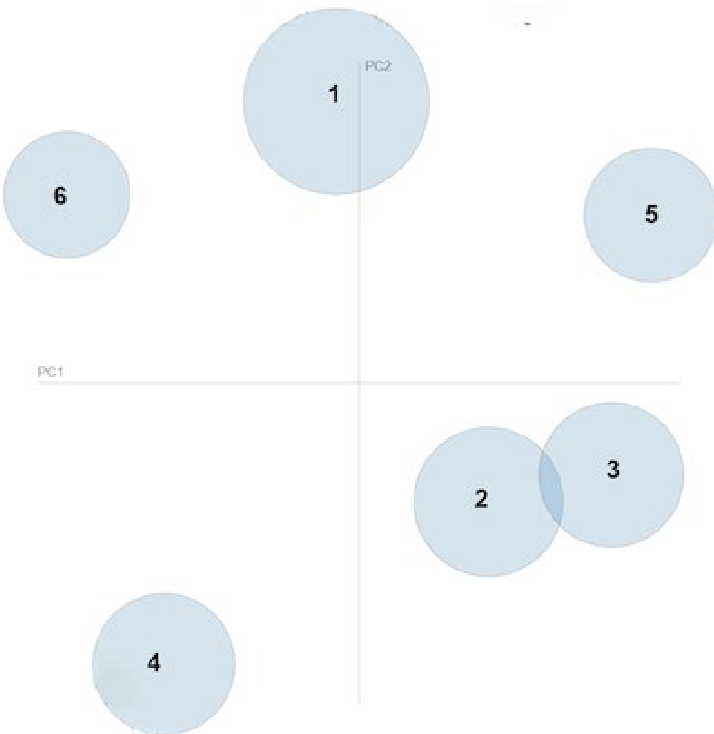
Appendix A

Table A1: Survey questions provided to MTurk workers for the labeling of each Tweet, adopted from Wang, *et al.* (2016).

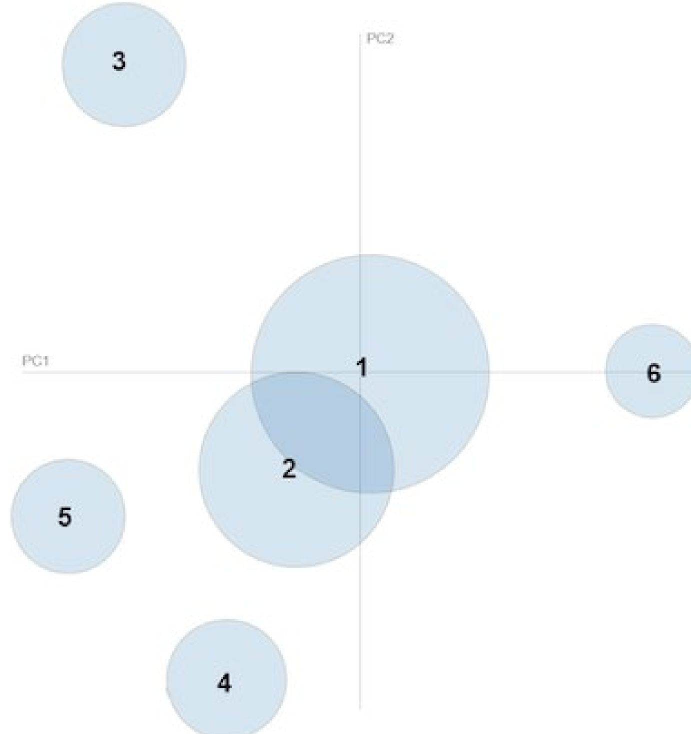
	To what extent does this post involve
A	personal information about the poster or people close to him/her, such as accomplishments, family, or problems the poster is having?
B	personal thoughts on past events, future plans, appearance, health, wishful ideas, etc.?
C	the poster's feelings and emotions, including concerns, frustrations, happiness, sadness, anger, and so on?
D	what is important to the poster in life?
E	the poster's close relationships with other people?

Table A2: Topical comparison of self-disclosing COVID-19 tweets between 16 May and 15 August 2020.	
Topic | Theme	**Top six keywords | Example**
1	get,day,love,time,year,feel
2	corona,death,covid,virus,die,get
3	china,trump,country,virus,president,world
4	covid19,health,test,need,community,help
5	home,stay,mask,safe,order,wear
6	pay,sir,money,june,help,exam
(a) 16 May — 15 June 2020	
Topic | Theme	**Top six keywords | Example**
1	home,get,like,stay,know,want
2	trump,american,president,vote,country
3	help,support,covid19,share,business,need
4	case,death,number,china,flu,virus
5	ear,distance,social,test,positive,school
6	play,student,cancel,exam,year,july
(b) 16 June — 15 July 2020	
Topic | Theme	**Top six keywords | Example**
1	get,like,home,want,stay,know
2	trump,distance,social,country,vote,american
3	lockdown,new,play,buy,game,watch
4	school,health,child,vaccine,risk,kid
5	money,pay,help,sir,sign,join
6	test,death,case,number,positive,flu
(b) 16 July — 15 August 2020	

Appendix B

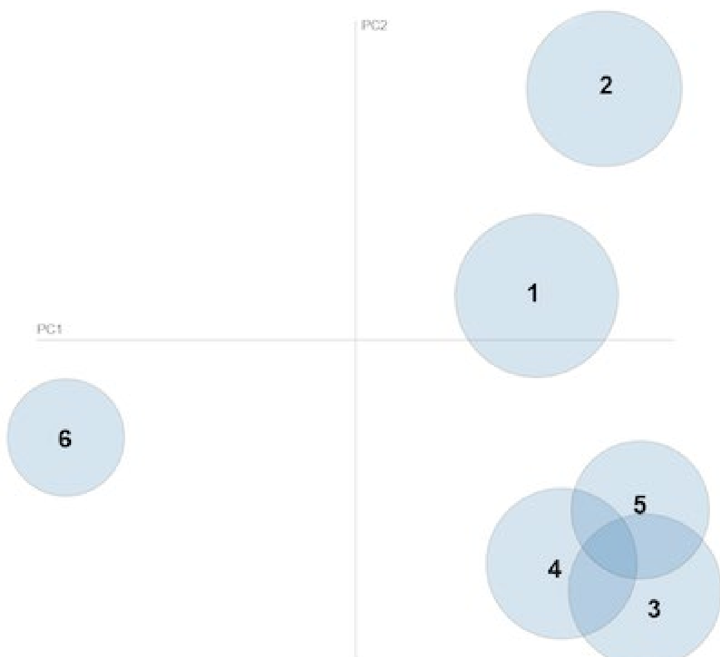


(a) Self-disclosing tweets

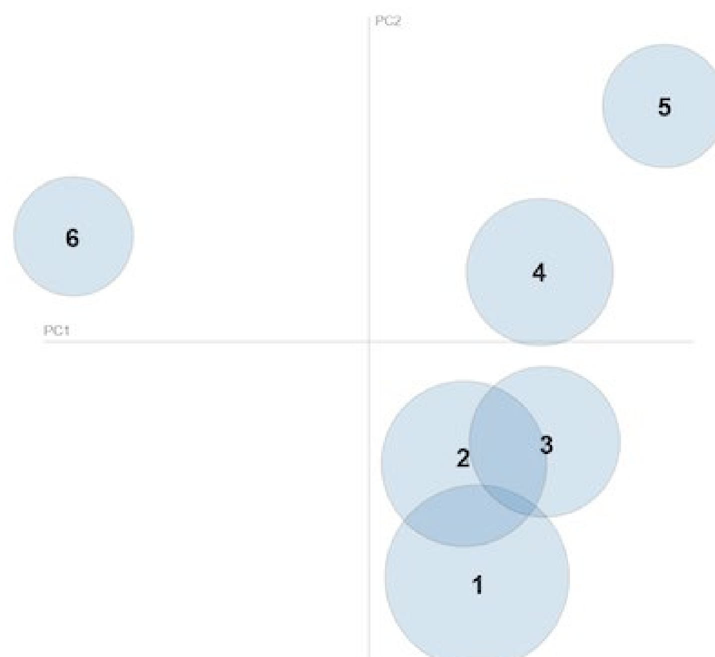


(b) Non-self-disclosing tweets

Figure B1: Intertopic distance maps for self-disclosing and non-self-disclosing COVID-19 tweets through 15 May 2020.

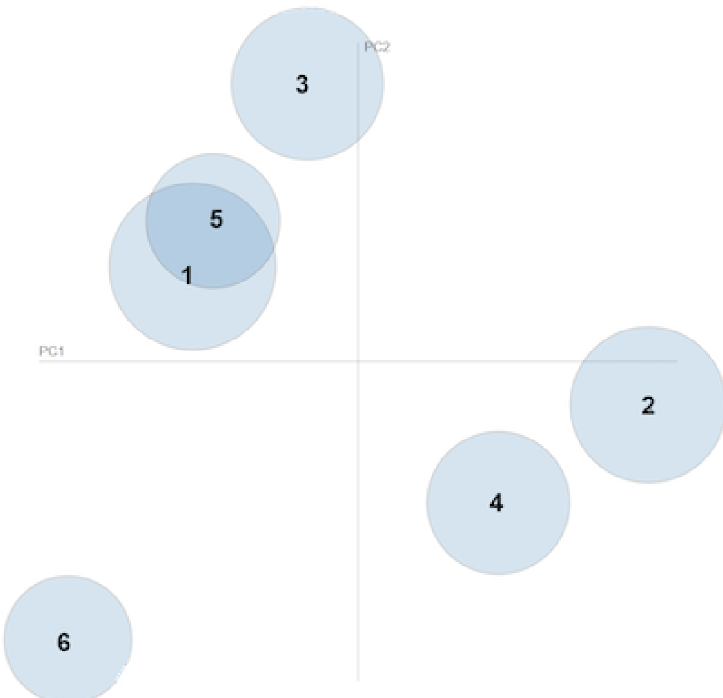


(a) Self-disclosing tweets

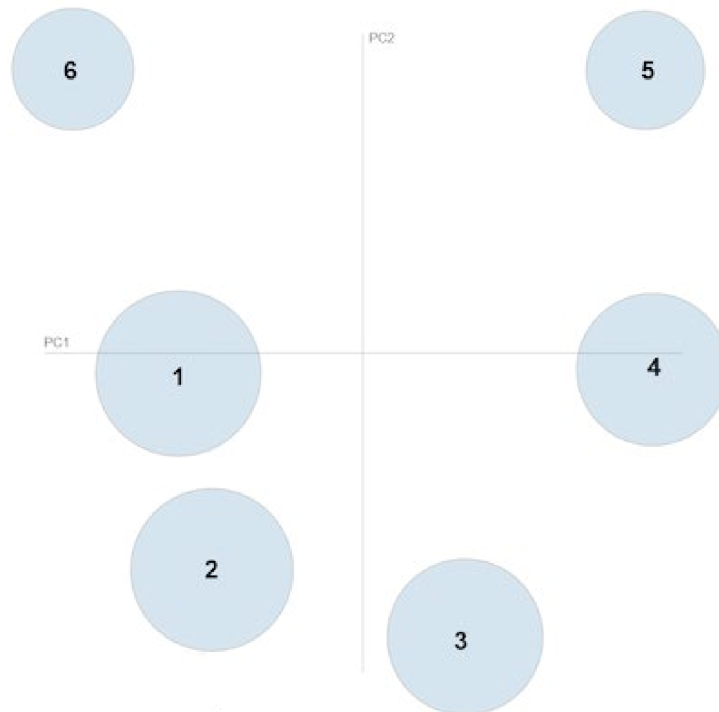


(b) Non-self-disclosing tweets

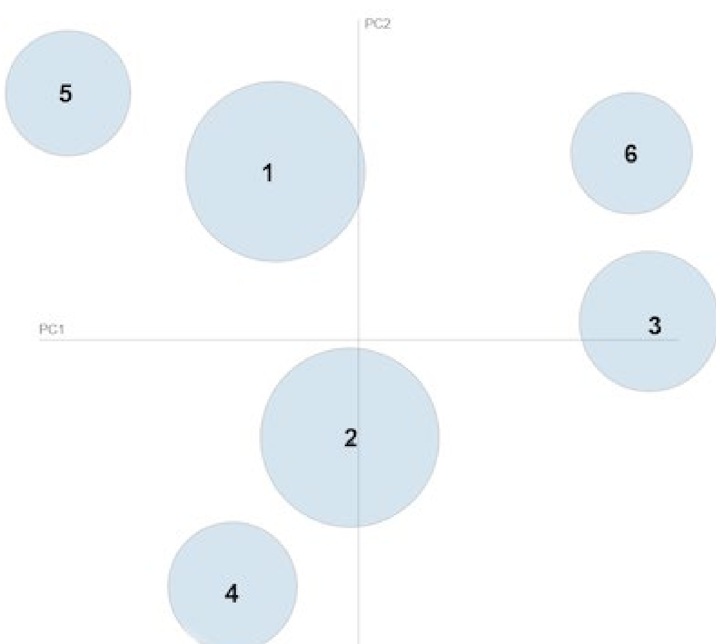
Figure B2: Intertopic distance maps for self-disclosing and non-self-disclosing tweets during Hurricane Harvey.



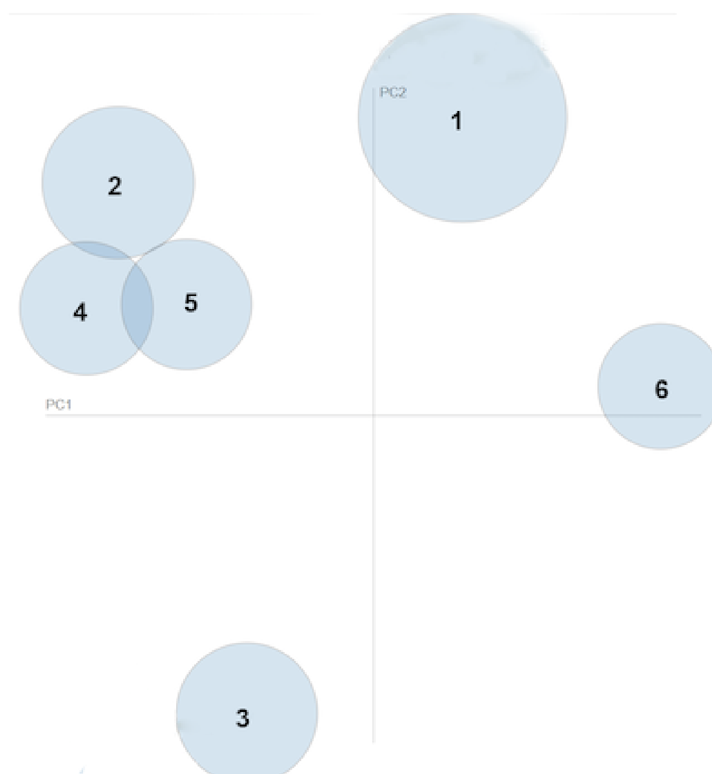
(a) 21 January — 15 March 2020



(b) 12 March — 15 May 2020



(c) 16 May — 15 June 2020



(d) 16 June — 15 July 2020

(e) 16 July — 15 August 2020

Figure B3: Intertopic distance maps for self-disclosing tweets in COVID-19 dataset.

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