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All the lonely people: Effects of social isolation on self-disclosure of loneliness on Twitter

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Abstract

This study explores the effect of unprecedented mass isolation during COVID-19 lockdowns through the lens of self-disclosure of loneliness on Twitter. Using a dataset of 30 million public tweets, we use machine learning to identify tweets that contain self-disclosure of loneliness. We find that thousands more people turned to Twitter to express their loneliness during the lockdowns; however, this effect normalized within a month, demonstrating the "ordinization" effect on a collective level. Furthermore, lockdown brought a marked shift in the weekly timings of posting and a change in the accompanying emotions, which were more positive and other-focused. Finally, based on a qualitative analysis, we propose an updated typology of loneliness that captures the possibilities offered by the affordances of social media. Our findings illustrate the profound effect lockdowns had on the societal psychological state and emphasize the importance of mental health resources during extreme and isolating events.

Keywords

Computer-mediated communication, COVID-19, loneliness, self-disclosure, sentiment analysis, social media, Twitter

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Loneliness—or the perceived discrepancy between one's desired and actual level of social connection (Paloutzian and Ellison, 1982)—is fast becoming acknowledged as an epidemic (Cacioppo and Cacioppo, 2018). Loneliness can be detrimental to people's health as it is associated with increased aging, high blood pressure, personality disorders, suicide, impaired cognitive performance, increased risk of Alzheimer's disease, and increases in depressive symptoms (see Hawkley and Cacioppo, 2010; Valtorta et al., 2016). Furthermore, lonely people tend to view others more negatively (Tsai and Reis, 2009) and are more insensitive to partners' pro-relationship behaviors (Yamaguchi et al., 2017), which can result in interpersonal problems. Both objective and subjective social isolation are risk factors for mortality (Holt-Lunstad et al., 2015).

Self-disclosure of loneliness—or communicating information about the self to others—can contribute to emotional coping, getting social support, and, like other types of self-disclosures, can help people maintain relationships. Despite the positive effects of self-disclosure, there is a constant dialectical tension between the pressure to reveal and to conceal information about ourselves to others (Petronio, 2002). Past research suggests that disclosure of loneliness is social in nature and is particularly stigmatized, with lonely people being perceived as unattractive, self-absorbed, antisocial, and shy (Tsai and Reis, 2009). Due to this stigma, research suggests it may be easier for some people to disclose their feelings of loneliness through computer-mediated communication (CMC) channels (Zhang and Fox, 2019).

Social networking services (SNS), such as Twitter, can be a favorable platform for such disclosures, because Twitter users can remain somewhat anonymous unlike other platforms, such as Facebook, which requires a profile and real names (Chen, 2018). Past research connected to the hyperpersonal model (Walther, 2007) and on disinhibition effect (Suler, 2005) has demonstrated how self-disclosures are affected by anonymity and other affordances of online communication. As the users have the freedom to reveal only select aspects of their identity, the stigma experienced by marginalized groups may be alleviated. For instance, it was found that posts seeking support around sexual abuse receive more comments from "throwaway" (i.e., anonymous) accounts (Andalibi et al., 2018) on Reddit. Thus, the popularity and anonymity affordances of Twitter can provide a unique opportunity to study self-disclosure of loneliness.

The unprecedented lockdown and "social distancing" measures enacted during the COVID-19 pandemic presents a unique scenario wherein the intensity and pervasiveness of the feelings of loneliness may have changed dramatically (Koh and Liew, 2020; Labrague et al., 2020). Note that "social distancing" in this context is meant to be *physical*; the measures were not designed to prevent actual social interaction or communication between individuals; however, it resulted in a marked decrease in face-to-face socialization. In the United States, this national emergency not only increased usage of computer-mediated communication compensating for the lack of face-to-face contact, but also affected how Internet users self-disclose information on social media (Nabity-Grover et al., 2020). Although one may expect a mass expression of loneliness during such unprecedented times, it is possible that the size and ubiquity of the feeling may provoke new coping mechanisms that alter the experience of loneliness. Wilson et al. (2003) propose that in the process of dealing with drastic negative events, people strive to make sense of the new situation, thus normalizing, or "ordinizing" it. Some previous

studies have looked at manifestation of the ordinization on the individual level through self-reported data (Gilbert et al., 2004); this phenomenon has not yet been explored in large populations. The unique dataset of the expressions of loneliness before and during the COVID-related lockdowns that we introduce in this study provides an opportunity to test this theory on an unprecedented scale.

The examination of loneliness expression on social media provides not only an opportunity to verify established theories around the communication of emotions, and loneliness in particular, but it can also provide actionable insights for intervention design—both on and off the social media platforms under study. Already, efforts are ongoing to ameliorate the psychological and physiological side effects of loneliness, including community engagement, as well as suicide hotlines for those in crisis (Windle et al., 2011). Although numerous surveys have shown loneliness to be a problem during COVID-19—in the United Kingdom (Li and Wang, 2020), older adults (Savage et al., 2021) and cancer patients in Canada (Howden et al., 2021), and Chinese adults (Xu et al., 2021)—these fail to compare the levels of loneliness to pre-pandemic levels. Understanding the particular needs of people undergoing collective experience of loneliness is crucial in adjusting existing services to address the increasing need for support and intervention.

Below, we explore a large dataset of Twitter posts by users self-identifying to be the United States using a mixed-methods approach and provide a detailed thematic analysis of the context in which loneliness is expressed, as well as statistical analysis of the timing and social context of the posts. By measuring the change in self-disclosure of loneliness immediately before and during a worldwide pandemic, we provide a unique view on this concept and propose an expanded typology of loneliness that is more tailored to new media platforms.

Conceptual framework

This study extends the current framework of loneliness as a way to conceptualize the expression of loneliness on social media in a multidimensional way and implements the theoretical framework of region-beta paradox to explain the way physical isolation affects self-disclosure of loneliness online. Building on these concepts, we take an exploratory approach in looking at emergent categories of emotional context associated with self-disclosure of loneliness before and during the COVID-19 lockdown.

Self-disclosures of negative emotions, such as loneliness, were reported at higher levels at the start of the pandemic (Koh and Liew, 2020). However, in "The peculiar longevity of things not so bad," Gilbert et al. (2004) propose that there exists a critical threshold (call it *beta*) that triggers psychological processes that attenuate distress, resulting in a paradox: experiences of mild distress tend to last longer and feel worse than more distressing experiences—a paradox the authors dubbed the "*region-beta paradox*." These psychological processes were dubbed by Wilson et al. (2003) as *emotional evanescence*—the way human drive to reduce uncertainty and increase pleasure allows negative emotions to "wear off fairly quickly, more quickly than we think" (p. 209). The authors dub the process of making sense of events, or making them "ordinary" as "*ordinization*" (p. 211). Although initial research after the pandemic started predicted long-term negative effects, according to this theory, the "oridinization" would likely help

people normalize the effects of the pandemic in relation to loneliness fairly quickly; thus, we predict the following:

H1. The volume of self-disclosure of loneliness drastically increases after social distancing restrictions were put in place for the COVID-19 pandemic but normalizes even before the lockdown measures are lifted.

According to the region-beta paradox, not only are the feelings normalized fairly quickly after negative events, but also the emotional responses are not as strong or as negative compared to less distressing events when measured over time. This is because, according to this theory, the psychological mechanisms that attenuate negative hedonic reactions are triggered only at critical levels of intensity (Gilbert et al., 2004). In the context of loneliness, when comparing the way loneliness was self-disclosed during holidays versus after a lockdown during a world pandemic, the region-beta paradox predicts that individuals would initially feel more distressed, but after taking attenuating action will feel better. However, the extent of attenuation of an emotional response to loneliness during a drastic event has not yet been tested on a collective level or longitudinally. In the current case, we predict the following:

H2a. Emotional valence associated with loneliness during the lockdown is at first more negative compared to the valence of loneliness self-disclosure before the lockdown.

H2b. After an initial negative period, the emotional valence normalizes and remains more positive than during holidays before the lockdown when people are likely to be lonely.

The changes to the experience of loneliness during a worldwide lockdown may not only be reflected in the overall emotional valence, but in the range, quality, and focus of emotions accompanying the experience. According to Weiss (1973), loneliness can be categorized into social loneliness and emotional loneliness. Social loneliness refers to the perceived lack of social connections with others and the discrepancy between the desired and actual social network, while emotional loneliness refers to feeling a lack of attachment or intimacy. This conceptualization of loneliness has been supported by a growing body of literature (Hyland et al., 2019; McWhirter, 1990), which includes research in the context of social media (Koh and Liew, 2020; Mahoney et al., 2019). Past research looking at what emotions are felt alongside loneliness point to three distinct types: (1) desperation (including panic, helplessness, and fear); (2) boredom; and (3) self-deprecation and depression (Rubinstein, 1986). Other research shows loneliness being correlated with anxiety, hostility, possessiveness, unhappiness, and other correlated variables (see review by McWhirter, 1990). Would the unprecedented situation in which everybody in the community (or country, or world) is feeling isolated change the nature of loneliness? We expect the emotional words used during COVID to reflect the collective experience of the loss of agency, isolation, and loneliness, possibly encompassing society at large. This leads us to an exploratory question:

RQ1. What emotions are associated with loneliness during the COVID-19 lockdowns compared to before?

RQ1a. How does the context of emotions associated with loneliness change after lockdown measures are implemented?

Besides understanding the qualitative aspects of the subjective experience of loneliness, in order to design and deploy effective interventions, it is imperative to determine the critical times when a remedial action can be taken. For instance, a suicide prevention hotline may be staffed more extensively during the high volume periods. Previous literature on loneliness in older adults showed that daily activities of individuals affect the state of loneliness and loneliness was associated with engaging in more activities alone than with others (Queen et al., 2014).

Past research on self-disclosure of loneliness on Twitter showed more disclosure of loneliness and negative valence at night compared to during the day and more such posting during the weekend compared to weekdays (Mahoney et al., 2019). The lockdown in the United States forced non-essential workers to work from home, changing how and who individuals interacted with during the day. As individuals interacted less with co-workers and friends face-to-face, simultaneously parents and co-habilitating partners spent more time with their children and partners at home. This leads to the question of how the lockdown affect self-disclosure of loneliness throughout the time of the day and day of the week, leading to the following:

RQ2. To what extent does the frequency and valence of loneliness self-disclosure posts sent at different hours of the day change, before and after COVID-19 lockdown?

Because of the working from home requirements which have affected many workers around the lockdowns and the lack of social interactions during the weekends, it is likely that the weekly variability in self-disclosure of loneliness that was detected earlier would be less pronounced during this time. Thus, we hypothesize the following:

H3. There will be less variability in the volume of loneliness tweets between days of the week during COVID-19, compared to prior to the lockdown measures.

Methods

Data were collected using Twitter Application Programming Interface (API) (Twitter, 2021c) via a Streaming query (Twitter, 2021a). The API provides a real-time sample of public tweets which pass a given keyword filter. In this study, "lonely" and "loneliness" were used as filters. The Streaming API provides the tweets as they are being posted in the form of a structured text object. A custom script was used to interface with the API using the python library tweepy (Roesslein, 2021). The information provided along with the tweet text includes the time it was posted, information about the user, and so on (for a full list of fields, see tweet object documentation [Twitter, 2021b]). We performed this collection from 17 September 2019 to 11 September 2020 such that we have 180 days

before and after 15 March 2020 (before and after major COVID-related restrictions come into force in the United States). We have chosen 15 March 2020 because on 13 March the United States declared COVID-19 a national emergency and 15 March is the start of the COVID-impacted period, as many states begin implementing distancing measures at around that time (Courtemanche et al., 2020). To heighten the probability that the tweets come from the United States, we geo-coded the Location field of each user using GeoNames and kept only those in the United States. Note that this process required manual examination of 1000 top matches, as users may write humorous or hyperbolic locations (such as "at home" or "up in Heaven") which may often match to small towns. Note also that users may be untruthful about their location. The above steps resulted in 29,694,370 tweets in total.

The collection of potential self-disclosures on social media provides several unique advantages: We capture the post at the very time it is posted, which is formulated freely by the user, without solicitation. Thus, the data capture potential real-time expressions of loneliness as the user felt ready to share them. This distinguishes this approach from interview and survey data, which are often retrospective, and may suffer from recall and desirability biases (Althubaiti, 2016). On the contrary, it does not capture those who do not choose to share their feelings on the platform. Therefore, we present social media analysis as a complementary tool to existing methodologies.

To ensure the tweets are indeed about self-disclosure of loneliness, the authors manually coded 1500 randomly selected tweets to verify that they were indeed self-disclosures of loneliness. Then, lyrics mentioning loneliness and other non-relevant keywords such as the guidebook series "Lonely Planet" were identified and filtered. Then, we built a machine learning model to classify the remaining tweets. After lower-casing and converting smileys to text equivalents, we computed the following features for each tweet: number of sequences of 1, 2, or 3 words; number of punctuation characters; number of capitalized letters; and an indicator variable that marked if the tweet began with a mention (which usually means the tweet was publicly directed to that user). We then used these tweets to train a Support Vector Machine (SVM) classifier (with an RBF kernel, balanced class weights, gamma of 0.0001, and C of 1000). The final classifier had a precision of 0.71 and a recall of 0.82 when tested using 10-fold cross-validation. (training on 9/10th of data, testing on the rest). We applied this classifier to the tweets remaining after the previous filter, resulting in 10,057,087 tweets that were likely to be self-disclosure of loneliness.

Following (Koh and Liew, 2020), we increased the chances of capturing individuals, as opposed to organizations, by identifying accounts that use human names. We used baby name listings from the US Social Security and the National Records of Scotland, as well as those extracted from Google+ in previous literature (see Magno and Weber, 2014; find the name of dictionaries and matching code at Mejova, 2021). After the name filter, 4,708,023 tweets remained. Finally, we filtered out tweets that are not original (retweets) and got 2,914,765.

Interrupted time series analysis

We began by examining the volume of loneliness-related tweets before and after the onset of COVID-19 lockdowns. To do this, we employed interrupted time series

analysis (Bernal et al., 2017), which aims to estimate the effect of an intervention that has a well-defined starting time. We employed the ordinary least squares (OLS) regression to model the volume of loneliness expression using two variables: T signifying time passage in days and X_t, an indicator variable indicating whether COVID-19 restrictions were in place (1 after 15 March 2020 and 0 otherwise). Specifically, in the following equation

$$y_t = \beta_0 + \beta_1 T + \beta_2 X_t + \beta_3 T X_t$$

y_t is the volume of loneliness expression at time t, β_0 is the baseline volume at the beginning of the time series, β_1 is the baseline change in volume over time before the intervention, β_2 is the effect of the intervention, and β_3 is the trend (slope) change following the intervention. Whereas it would be intuitive to model y_t as the number of loneliness-related tweets, such an approach would be vulnerable to users who post an inordinate number of tweets all at once, with a "vocal minority" potentially accounting for most of the volume (Mustafaraj et al., 2011). Therefore, we instead considered the number of distinct users who had posted at least one loneliness-related tweet in a day.

Temporal analysis

We analyzed the volume of sharing (in terms of unique users posting in a particular time window) across days of the week and hours of the day. The Twitter API provides time of posting in the GMT zone, which we adjust to the US Central Time, approximating the average posting by the US population. Thus, the hourly statistics have approximate accuracy within the United States.

Type of loneliness and sentiment

To understand the type of loneliness and the content of the tweets in the two time periods, we employed odds ratio with additive smoothing on individual words used before and after 15 March. We began by cleaning the text by removing special characters and URLs, lower-casing the remaining words, and removing the stop words (words most occurring in English language). We then de-duplicated tweets longer than 30 characters (as they are too long to be duplicates by chance and were likely copy/pasting of content instead of original). We then tokenized the text of all the tweets and counted the appearance of each token in the posts before and after 15 March, resulting in two distinct language models. We compared these language models by computing odds ratio (OR) and employing additive smoothing to compensate for rarely seen words with $\alpha = 100$. Finally, we considered words that appeared at least 10 times before and 10 times after 15 March to exclude niche words.

To enrich our dataset with information on sentiment, we used the SentiWordNet (Baccianella et al., 2010) lexicon to find words that are associated with strong emotions. SentiWordNet is an extension of WordNet (Fellbaum, 2012), a lexical database for English, which annotates common English words with scores for positive and negative emotional connotation. As the lexicon is over 100,000 entries, and most scores are weak

and potentially ambiguous in context, we considered only words with strong *polarity* (calculated as positive score−negative score). To do this, we chose words having polarity of under −0.5 or over 0.5 out of the possible range between −1 and 1. The final list of words contained 11,522 entries. We employed this lexicon to obtain a quantitative summary of the texts, as well as to perform qualitative exploration of the emotions mentioned. For the former, we found the emotional *valence* of the tweet by averaging the polarities of all words found in the text. For the latter, we examined words associated with emotions, chosen manually by the authors out of top 300 most used emotionally polarized words in the dataset, resulting in 77 words (which can be found at https://tinyurl.com/LonelyEmotionsTwitter).

To better understand which of these words is more likely to appear before versus during isolation periods, we again employed odds ratio. To visually explore the emotion words that are more likely to appear in one or the other period, we plotted two *co-occurrence word networks* wherein the size of the words (network nodes) is proportional to the odds ratio, and the weight of the connections (network edges) is proportional to the number of tweets in which the two words occur. We put a threshold on the edges to remove half of the weakest ones and to show the strongest relationships. Furthermore, we applied the Louvain algorithm (Blondel et al., 2008) to automatically detect communities and colored the nodes according to these communities. The network is then visualized using Gephi software (Bastian et al., 2009) via the Force Atlas 2 algorithm (Jacomy et al., 2014) such that most connected nodes are in the middle and less connected ones are on the periphery.

Finally, we selected a random sample of tweets for the top 5 most frequently occurring emotions before and during lockdown, 50 tweets for each emotion, totaling in 500 tweets. Using the network visualization of the data as the initial open coding, we proceeded to qualitatively analyze the random tweets from the top emotion tweet samples using a constant comparative method (see Charmaz, 2006). The data were first grouped into pre and post lockdown groups and then categorized into several major categories that later were collapsed into recurring themes: self-focused, other-focused, and situational tweets. Initial coding was open coding, followed by more deliberate comparison of content during the second and third rounds of coding. The emergent categories are not necessarily mutually exclusive and were further broken down into subcategories. To be transparent in the data analysis, the data are made available for cross-examination at https://tinyurl.com/LonelyEmotionsTwitter.

Results

Frequency over time

We predicted that the amount of tweets would drastically increase after lockdown followed by normalization before lockdown is lifted. Figure 1 (blue line) shows the daily number of distinct users who have posted at least one loneliness-related tweet. The vertical black line signifies 15 March 2020 when COVID-19 lockdowns begin in much of the United States. Visually, we see a marked elevation of the daily number of users expressing loneliness on Twitter after15 March 2020.

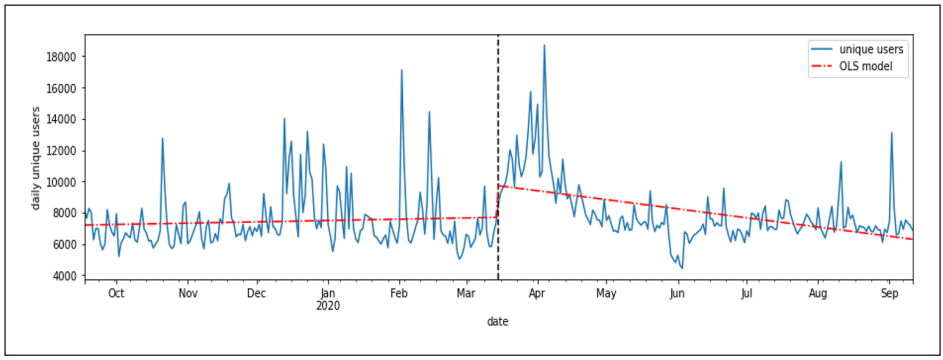

Figure 1. Daily number of distinct users posting at least one loneliness-related tweet in the period 17 September 2019 to 11 September 2020. Red line represents the interrupted time series analysis model's predicted trend.

Table 1. Interrupted time series OLS model coefficients, confidence intervals, and *p*-values predicting (1) number of distinct users posting in a day and (2) average emotional valence of tweets in a day.

Variable	Coefficient	[0.025, 0.975]	*p*-value
Number of distinct users posting in a day			
Intercept	7211	[6689, 7733]	.0000
Time	2.7	[−2.3, 7.8]	.2861
COVID	5931	[4460, 7402]	.0000
Time: COVID	−21.7	[−28.8, −14.6]	.0000
Average emotional valence of tweets in a day			
Intercept	−0.0392	[−0.0537, −0/0246]	.0000
Time	0.0002	[0.0001, 0.0003]	.0068
COVID	0.0466	[0.0056, 0.0877]	.0259
Time: COVID	−0.0002	[−0.0004, 0.0000]	.0742

COVID: coronavirus disease; OLS: ordinary least squares.

The coefficients, 95% confidence intervals, and *p*-values of the resulting model are shown in Table 1. The intercept coefficient tells us that the loneliness expression was just above 7000 at the beginning of the time series, and this did not change substantially over time (the Time coefficient is not significant). A substantial and significant rise in posting volume is captured by the COVID-19 indicator variable, with an estimated increase of nearly 6000 additional users per day, with the trend slowly going down over time (negative Time: COVID-19 interaction). Indeed, the average number of daily users from the beginning of 2020 (1 January) to 14 March is 7354 (σ=2,020), and in the month following (15 March–14 April), it is at 11,298 (σ=2,252). The effect is largely gone after a month, however, with the average going to 7701 (σ=757) in the following month. The normalization began well before the first lifting of lockdown restriction around the

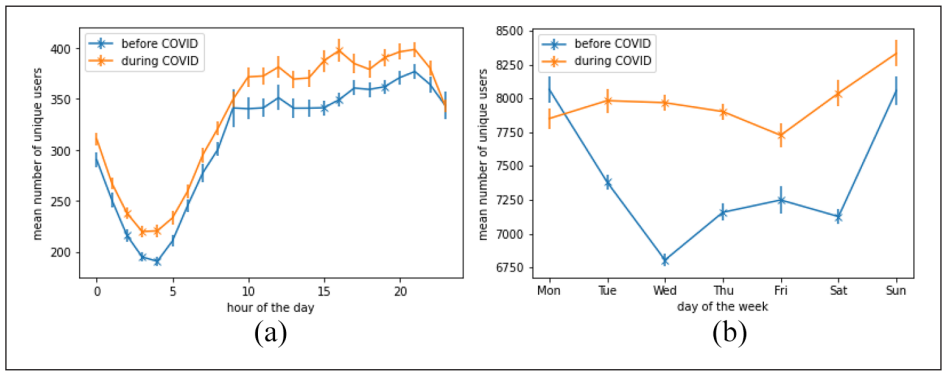

Figure 2. Average number of users posting (a) in an hour of the day and (b) in a day of the week. Vertical lines are standard errors. Points with crosses are significantly different before and during COVID at $p < .01$ using independent two-sided *t*-test.

United States, which happened in the span of late April through May (Wikipedia, 2021). These findings support *H1*.

Next, we examine the posting frequency in the span of a week and during the hours of the day. Figure 2(a) shows the average number of users posting on each day of the week (with vertical bars signifying standard errors). The points marked with crosses are significantly different between before and during COVID-19 at $p < .01$ using independent one-sided *t*-test. We find that before COVID-19 lockdowns, the highest posting rate is on Sunday and Monday, and it dips during the week, being lowest on Wednesday. The trend flattens out, however, during the COVID-19 period, with the highest point remaining on Sunday, but other days having similar volume, supporting *H3*. To answer *RQ2*, we similarly plot the average number of users posting on each hour of the day in Figure 2(b). We find a strong periodicity with nighttime hours being less popular. Overall, the trend during COVID-19 is greater than before, and especially during the night and afternoon hours.

Sentiment and valence

Figure 3 shows daily mean sentiment valence score of tweets in the duration of our dataset. We find that before the COVID-19 lockdown, we often observe days with very negative scores, such as one around mid-February (before and after Valentine's day) and semi-regular ones in 2019. However, we find no such downward peaks in the COVID-19 lockdown period, especially in the first 2 months. We then perform interrupted time series analysis, the results of which are visualized as a red dotted line in Figure 3. As we can see from Table 1, the change in valence detected by the method is positive, though small, with COVID-19 coefficient at 0.0466 with $p = .0259$. The change in distribution of emotional valence is also reflected in the standard deviation of the scores: pre-COVID period at $\sigma = 0.066$ and post-COVID period at $\sigma = 0.026$. Thus, the data do not support *H2a*, where we expected the valence to go down during the initial

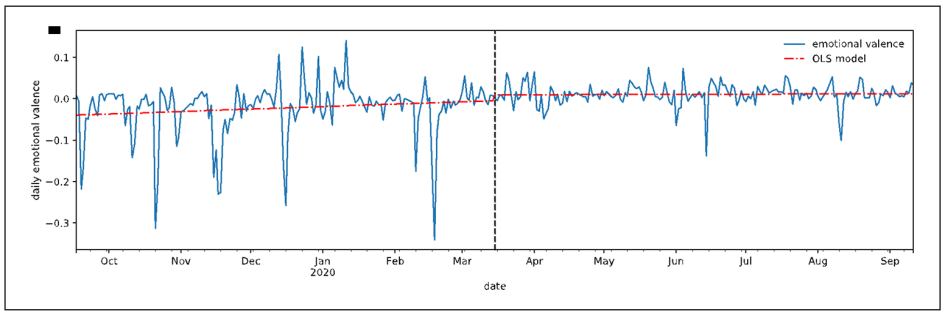

Figure 3. Average daily emotional valence of loneliness-related tweets in the period 17 September 2019 to 11 September 2020. Red line represents the interrupted time series analysis model's predicted trend.

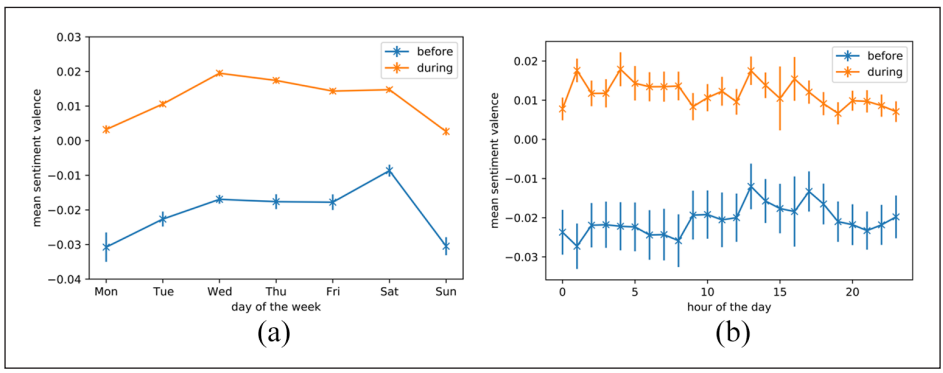

Figure 4. Mean sentiment valence per day of the week and per hour of the day. Vertical lines are standard errors. Points with crosses are significantly different between before and during COVID at $p < .01$ using independent two-sided *t*-test: (a) days of the week and (b) hours of the day.

stages of the lockdown, but the overall more positive trend does support *H2b*, where we expected the valence to normalize at a more positive level.

Figure 4(a) and (b) shows the mean daily sentiment valence posted on each day of the week and hour of the day. In both, we find that during COVID-19 the valence is higher. Considering days of the week, Monday and Sunday show the lowest valence. The change in valence is less pronounced during the hours of the day, but the slight periodicity (with lowest valence in the hours of the night) is not as pronounced during COVID-19, compared to before.

Classification of emotions

Furthermore, we consider the usage of words referring to emotions in particular to address the research question *RQ1*. Emotion words more likely to be posted before

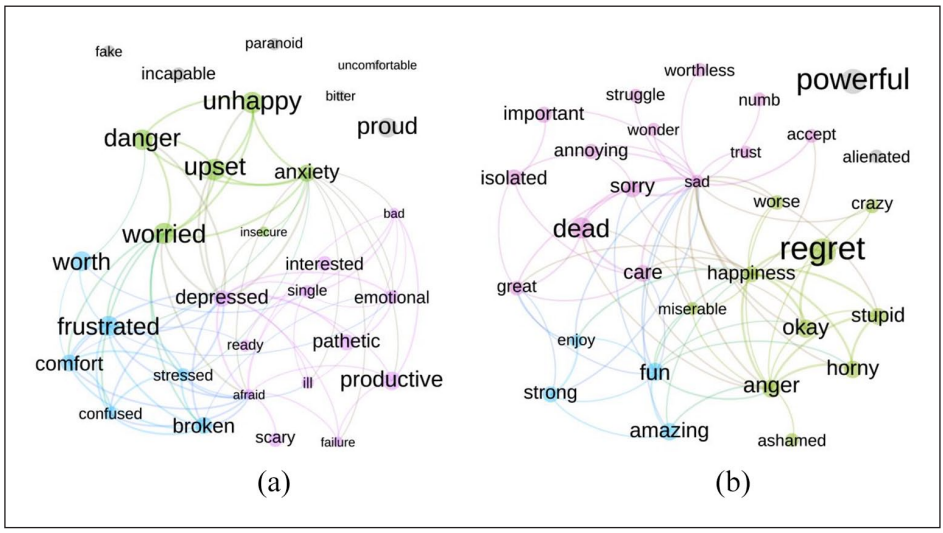

Figure 5. Top 30 emotion-related words more likely to be posted in the periods before (left) and during (right) lockdowns by odds ratio. Node size is proportional to the odds ratio, and edges represent co-occurrence strength (thresholded to reveal most connected words), colored according to automatically detected communities: (a) before lockdowns and (b) during lockdowns.

COVID-19 are shown in Figure 5 on the left, and those more likely to be posted during COVID-19 on the right, arranged in a co-occurrence network (as described in "Methods" section). We notice self-directed emotions to be more likely used before, including *pathetic, unhappy*, and *incapable*, whereas strong emotional terms that may be positive in nature used during COVID-19, including *amazing, powerful*, and *care*. The latter list also includes *dead* and *isolated*.

To examine the context around the emotions expressed in self-disclosure of loneliness and to address *RQ1a*, the authors manually examined the contexts of these emotions by reading and classifying a random sample of 500 tweets containing the most common emotional words, 50 tweets for each emotion. Three clear themes emerged when examining self-disclosure of loneliness on Twitter: self-focused, other-focused, and situation-focused (see Figure 6). Examples of tweets for each subcategory can be found in the supplemental materials available online (Hommadova Lu and Mejova, 2021).

Other-focused tweets

As can be seen from the figure, the largest category addresses the need for others, echoing Weiss' typology of loneliness wherein loneliness is categorized as either emotional or social. Indeed, we find numerous mentions of friendship, romantic and familial companionship. Some share their struggles with parents:

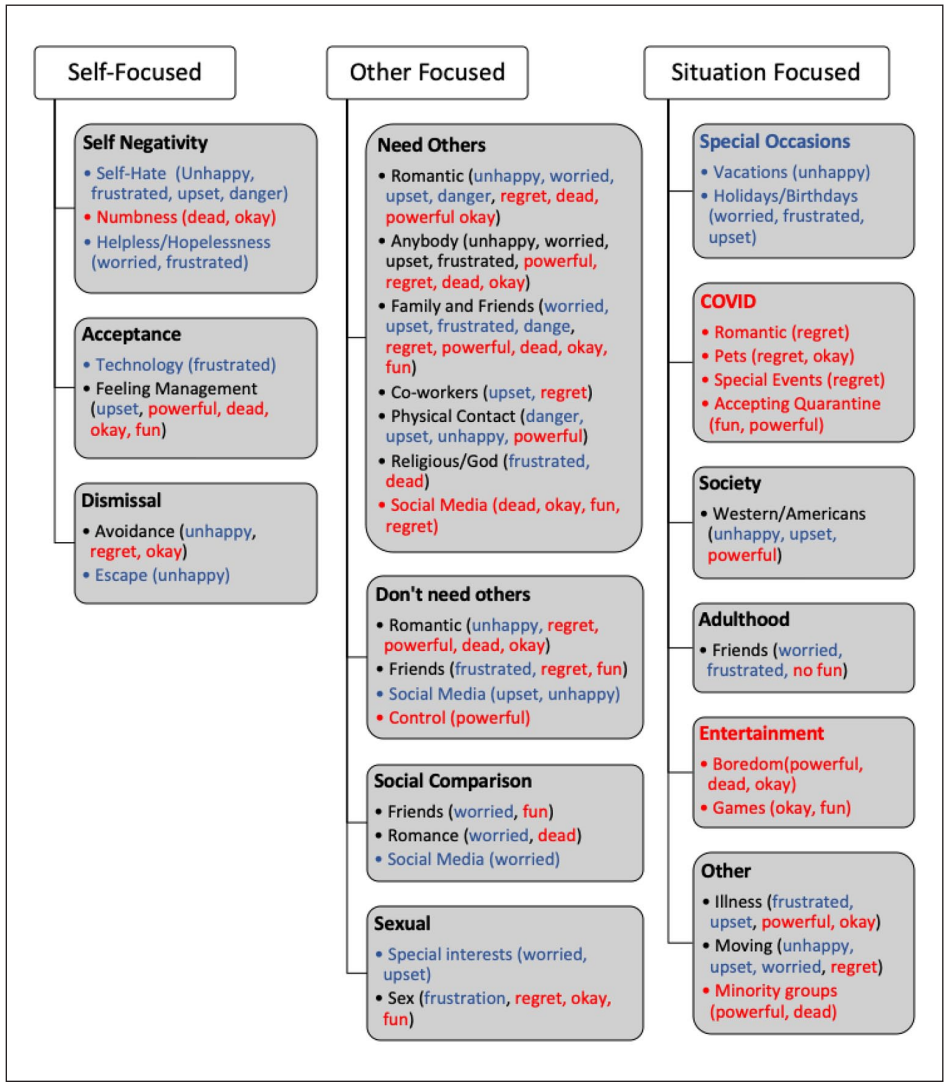

Figure 6. Categories and emotion in tweets before (in blue), during (in red) the lockdown, and in both time periods (in black).

> Upset at how lonely I have been so I told my mom and she shut me down saying it's my own problem, but saw on her phone history she googled how to make a 25 year old not feel lonely. I am 24.

Others contemplate their time away from friends: "I'm so confused about everything and I'm gonna cry about it because I'm frustrated. Everything always seems fine when I'm with my friends who I love, but I always feel so incredibly lonely when I'm by myself."

Yet others express their longing for a romantic connection: "I really am getting upset because I want a gf and ik I have so much to offer but I am lonely and completely overlooked. Its ur loss." However, the unique affordances of social media, and Twitter in particular, make possible categories not considered by Weiss. Emergent from the content is a frequent call to anybody, for any kind of social interaction: "Can anyone help me? I really am lonely and wanna die, there is no one here for me, I am too upset."

Furthermore, mentions of physical contact become frequent, ranging from hugging to sexual encounters: "I am lonely and sexually frustrated, thank you for coming to my ted talk." Thus, as morality around sex changes in our society, we find it necessary to update the understanding of loneliness of Weiss' era to include the open solicitude of casual relationships. Although Twitter is not a mobile dating app (Albury et al., 2017), its affordances seem to enable hook-up solicitations that are more common on dating apps. Interestingly, dating apps are less likely to have negative self-disclosures such as being lonely (Walther, 2007) and are more likely to have positive presentation of the social self in sexual solicitations (Smith, 2021).

Another new category that emerged was loneliness in relation to religion, God, or higher being, which we refer to as *spiritual loneliness*. In the recent literature on loneliness, the discrepancy between the wanted and perceived connection to God has not been mentioned, although Sadler (1978) referred to this as "cosmic loneliness" and defined it as perceived separation from God or nature. Both before and during the lockdown Twitter users self-disclosed spiritual loneliness, with posts such as "It wasn't until I found Jesus that I realized just how lonely I was before."

The free-form format of Twitter posts also allows for more complex expressions of loneliness not accounted for by other theories. Specifically, we find many instances of social comparison, especially in the period before COVID, for example: "Already too many happy couples bragging on Facebook. I am back on twitter where everyone is lonely and bitter and sexually frustrated. I like it here." This observation is in line with past research on social networking sites, connecting loneliness with social comparison (Yang, 2016). The lack of social comparison during COVID may reflect the imposed isolation felt uniformly, although remarks about quarantining with one's significant others were frequent, such as "[. . .] I'm INSANELY jealous of anyone quarantining with another human being. I cannot wait to go back into the office solely to get that interaction. And I still don't fucking regret my divorce." Also, focus turns to social media as a space for social interaction:

> Why is my account so silent and dead? I have +2000 followers, and a month ago this place was really firing with activity! Maybe it's me, and my lack of content. At this point, my loneliness and heartache make me not even want to keep my Twitter anymore.

In fact, the word "dead" was most used to reflect the lack of activity on the platform. Furthermore, we find a substantial number of tweets claiming that, despite being lonely, the user does not need others to be happy, including (potentially "toxic") romantic partners— again, such sentiments are more often expressed before, but not during COVID-19. Finally, many others discuss the difficulties of expressing feelings:

> I'm just so unhappy, lonely and empty lately. i hate talking about these types of emotions on social media but at this point i need help figuring myself out. im acting like im all good but i'm really not. i just need somebody who could just listen . i'm trying to let everything out.

Self-focused tweets

Past research suggests that "lonely people are highly self conscious or self-focused and dwell on their own actions to a greater extent than do non lonely people" (Peplau and Perlman, 1982: 11). However, our findings show that this tendency of self-focus diminished during COVID-19. More recent studies further confirm this as online posts were more self-focused before COVID and other-focused during COVID (Nabity et al., 2020). During the pre-lockdown period, we find that the emotions of unhappiness, frustration, being upset, worried, and fearful were often directed to oneself, and less so in the COVID period.

These people attribute their loneliness not to lack of connection, but to negative self-attributes, yet others are unable to identify why they were lonely: "I am so frustrated, I don't know what is wrong with me. I got everything I want in life, family, friends, success, and a good job, so why the fk am I so lonely?" Note that Weiss' typology of loneliness is categorized by connections to others and does not look at the expression of loneliness that is self-focused.

The quality of self-focused tweets changes substantially over time. Whereas mentions of self-hate, helplessness, and need to escape are common before COVID, mentions of numbness become prevalent during the lockdowns: "I'm okay, but anxiety gets unbearable and I start getting numb. Been better than when this started, but been pretty dang lonely and busy. [. . .]" However, we also see an emergence of positive emotions associated with loneliness during COVID reflecting hope, "being okay," acceptance of the feeling, and acknowledging loneliness to be "powerful."

Situation focused tweets

According to Cacioppo and Patric (2009), about half of the feelings of loneliness can be attributed to either one's genetic predisposition, whereas the other half to environmental factors. Indeed, Young (1982) conceptualized loneliness through temporal lens and Walter Mischel et al. (2004) added temporal and situational context to their conceptualization of loneliness in line with past research by Peplau and Perlman (1982). We find that in pre-COVID tweets, users mention holidays and special occasions, while during COVID the focus falls squarely on the quarantine situation. Some share traumatic experiences:

> "I feel very isolated. And lonely. Most days I am okay but this week is hard. A person I've loved and who loved me since I was 26 but our timing has been off, died unexpectedly last week and we had not been in touch during the pandemic bc of being down I am sad and full of regret.

Yet others share their acceptance of the situation:

> Now that I have accepted the quarantine and how life has changed as a whole, I've found solace. I'm actually starting to like this solitude. It just gets lonely. But I also enjoy my own company, I laugh at my own jokes and I think I'm pretty fun lol.

Other life events, such as growing up, moving, or being sick, also contributed to various emotions associated with loneliness before and during the lockdown. Finally, two other categories emerged during the lockdown: attempts to find entertainment such as video games, and posts by various minority group members such as LGBTQ+ (lesbian, gay, bisexual, transgender, queer [or sometimes questioning], and others). We leave a thorough examination of the latter for future work, as it deserves concentrated attention.

Summary of qualitative results

Based on the analysis of qualitative data, we propose to expand the typology of loneliness beyond emotional and social loneliness (Weiss, 1973), or loneliness based on genetics or environmental factors (Mischel et al., 2004), to a more comprehensive model based on self-disclosure of loneliness instead of examining loneliness using self-reported UCLA (University of California, Los Angeles) scale of loneliness. Our data show that there are three general themes that emerged from our field observations of self-disclosure of loneliness: *self-focus or intrapersonal loneliness, other-focused or interpersonal loneliness, and situational loneliness*. Intrapersonal loneliness is based on an internal dialogue with self, possibly about negativity, acceptance, or dismissal of one's loneliness. This type of loneliness stems from within the self and is related to what Sadler (1978) referred to as a dimension of psychological loneliness, which he defined as the feeling of not being in touch with parts of one's self.

Interpersonal loneliness focuses on (1) needing or (2) not needing a social connection with others (romantic partners, family, friends, online strangers, co-workers, or even God), (3) social comparisons, or (4) sexual loneliness. Weiss' typology of the various types of emotional loneliness related to romantic partner, family members, nurturing or being nurtured by others fits completely under the category of interpersonal loneliness, but we expand it even further. In loneliness that is associated with a lack of a perceived connection with others, Weiss (1973) defines loneliness as "Loneliness appears always to be a response to the absence of some particular type of relationship or, more accurately, a response to the absence of some particular relational provision" (p. 17). As the qualitative data indicate, the particular type of relationship is not limited to an interpersonal relationship with other people, but can also include the relationship with God (spiritual loneliness), physical relationship (physical loneliness), and an intrapersonal relationship.

Finally, situational loneliness focuses on a variety of situations including special occasions, major life events, social isolation (COVID), illness, or experiences associated with being a part of a minority group. Theoretical framework of loneliness suggested by Peplau and Perlman (1982) suggested that loneliness is caused by distinct two classes: precipitating events and predisposing/maintaining factors. They also mention situational loneliness and loneliness caused by precipitating events such as life-cycle changes best fit under the emergent category of situational loneliness which has a temporal

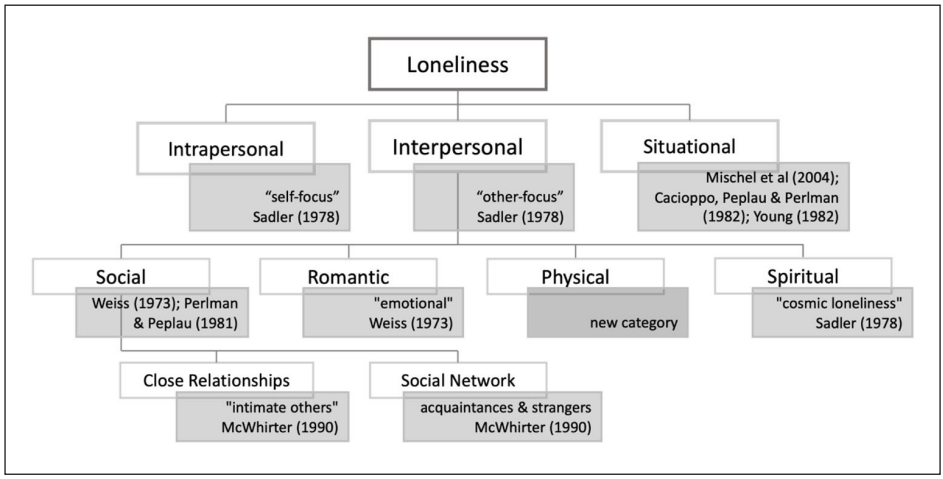

Figure 7. Overview of the proposed typology of loneliness incorporating Weiss' emotional and social loneliness, among other theories.

component of being transient or situational (Mischel et al., 2004; Peplau and Perlman, 1982; Young, 1982).

Our results show that the affordances of technology allow people to express complex understanding and contextualization of loneliness, necessitating the expansion of the existing typologies of loneliness. To better contextualize our findings, we draw from the emergent data and past literature to propose a more comprehensive model of loneliness as observed in the data both before and during COVID-19 and summarize the results in Figure 7. By far, the largest category of self-disclosure of loneliness is in relation to others, followed by situational loneliness and intrapersonal loneliness. The category of situational loneliness, as expected, has more disclosures of loneliness in regard to the lockdown situation, compared to prior to COVID. We find it interesting how dimensions of loneliness proposed in 1978 by Sadler—intrapersonal (self-focused), interpersonal (other-focused), and spiritual ("cosmic loneliness")—which have not been popularly used in the past 40 years, were observed in our dataset of self-disclosure of loneliness on Twitter.

Discussion

In this study, we examine the effect of physical social isolation on the self-disclosure of loneliness in the environment of a SNS. Uniquely, we corroborate the existing theories around loneliness utilizing big data methods applied to a large dataset of "natural" expressions of loneliness, as opposed to small-scale surveys that have been prevalent in the literature thus far.

Comparing the Twitter posts mentioning self-disclosures of loneliness during the six months before and after the start of lockdowns, we find striking differences not only in the general volume of disclosure, but also in the timing during the week and day,

emotional valence of the words used, emotions mentioned, and the context of tweets. As postulated by Chen (2011), Twitter indeed attracts users who seem to seek to "gratify their need to connect with others." Our results in response to H1 showed the disclosure increased significantly in mid-March, suggesting the social and emotional connection needed was most acute at the onset of the lockdowns. However, this volume normalized almost to pre-lockdown levels after just over a month, despite the federal regulations on social distancing being in effect until 30 April 2020 (Foster and Mundell, 2020). The wave of new loneliness disclosures and its eventual decrease may be a sign of increased psychological stress, increased social media use overall, or lessening of the societal stigma around expressing the emotions online.

These findings stress the importance of proper timing of any intervention, such that the resources must be available at the onset of the potentially vulnerable time period to address the psychological and physiological needs, before the situation is "ordinized." Additional research is necessary to reveal whether the cessation of loneliness self-disclosure is due to a desirable development (e.g., adopting remedial strategies) or an undesirable one (abandoning attempts at social interaction). It is possible the ordinization process is heterogeneous in different populations, and policy-makers may need to study vulnerable groups separately, such as the elderly, those diagnosed with mental issues, and disadvantaged minorities, in order to design an effective and timely intervention. More research needs to be done to reveal both larger societal changes and individual experiences that the self-disclosures captured in this study suggest. For instance, in future research, we suggest empirically testing the beta paradox by considering the loneliness expression in locales under varying strictness of lockdown rules, possibly capturing the collective sense-making and emotional adjustment around events of different intensity.

The rate of self-disclosure of loneliness also changes throughout the week. Whereas we see a weekly periodicity with most loneliness-related tweets posted on Sunday and Monday, this periodicity flattens significantly during the COVID-19 lockdowns (although Sunday remains the weekday with most posts). We could be seeing this as an indication of a change in daily schedule around work. Knowing this change is important for providing timely mental health and suicide prevention resources, for instance during office hours, which may be spent alone by those working from home. However, the daily periodicity does not change much during the lockdowns, with the only major increase in posting around the middle of the night (2–5 a.m.).

The content analysis of the emotion words before COVID-19 confirmed the prevalence of negative feelings (*unhappy, worried, upset*, etc.), supporting previous literature (Cacioppo et al., 2006). Surprisingly, during COVID-19 more positive emotions emerged, as well as more other-centered (*fun, care, missed*, etc.). It is possible that during this time people who are normally satisfied with their social lives start expressing the feelings of loneliness in the context of their existing offline connections. A qualitative coding of a sample of tweets mentioning these emotions has shown that the affordances of Twitter as a social media platform allow for a broader range of expressions, including social comparison, addressing platform in aggregate instead of particular individuals, and self-directed views of loneliness. We further found social needs unaccounted for by Weiss's classification of loneliness, such as open solicitations of casual sexual relationships,

which may be more vocalized in a society that has changed since Weiss' initial formulation of his theory. Thus, our classification describes both the expression of loneliness in pre-pandemic times and during the COVID-19 era, allowing us to capture the change in feelings shared online at that time.

Limitations

The present study suffers from several limitations. First, the analysis of this study is limited to one (albeit quite popular) social media website, and the behavior captured on it may not generalize to other platforms. In future studies, it might be of great interest to do a comparison of self-disclosure of loneliness in cross-platform communication (Smith, 2021) which have different affordances, such as in terms of privacy, post visibility, and editorial oversight. Second, although we attempted to capture ample time before and during the COVID-19 onset, the data are limited to the peculiarities of these time selections, for instance, in the fact that there are more winter holidays in the before period. Furthermore, despite increased adoption of social media, its users still have a younger, more tech-savvy profile, which is, again, not generalizable to the whole population of the United States. The latest Pew survey has found that about a quarter of the US adult population use Twitter, and that they tend to be a bit younger and wealthier, but are distributed quite evenly between race and urbanization (Auxier and Anderson, 2021). Finally, we are limited to the tools at our disposal, and even after manual annotation and classifier tuning, the identification of loneliness self-disclosure is not perfect, allowing instances of strange phrasing or quotes of song lyrics to be included in the dataset. Nonetheless, the dataset collected here captures thousands of people at a unique point in world history, and we believe it can be a useful tool to examine the self-disclosure of loneliness. It is likely that this study captures only a fraction of people experiencing loneliness, as "explicit disclosures of loneliness only represent a fraction of masked loneliness disclosures on SNS and only a sliver of instances when individuals actually are experiencing loneliness" (Zhang and Fox, 2019: 101). In the future studies, we will also explore the diversity of the experiences users shared during COVID as we find both positive and negative emotions expressed during that time, indicating a variety which needs to be explored in more detail.

One final limitation of this work is the sensitivity of the material gathered. Even though it was collected using the Twitter API, which makes available only publicly visible posts, and even though the authors of these posts wrote them likely knowing these will be public, the sensitivity of the topic makes this population a potentially vulnerable one. Thus, in this article, we paraphrased all quoted tweets, except one cited in the news coverage. During the content analysis, only the text of the tweets was considered, and during the computation of statistics, the user IDs were anonymized. Finally, the project was approved by the Internal Review Board of a major US university.

Impact on policy

This study's findings have a significant implication for public health policy. As loneliness presents well-documented adverse effects on mental and physical well-being, it is

imperative to prepare a contingency plan to address loneliness during extreme events. Already, social support, increased opportunities for social interaction and courses on emotional regulation and stress reduction have been implemented to address loneliness, especially for the elderly (Helfand et al., 2020). During large-scale lockdowns, virtual help, sessions with social workers or other ways to connect community members to each other may be able to scale enough to reach large numbers of people. As we illustrate in this study, social media may be one of these channels, since at least some of its users are comfortable with self-disclosure on such public forums. Timely interventions may be even more needed due to potential risk of mental distress resulting in suicidal ideation (Sher, 2020). During our content analysis, we found some very alarming tweets both before and during COVID. In particular, some tweets mention death or suicide, for example, during COVID: "I don't have friends. I don't have a relationship. no one loves me. I'm so lonely. I have nothing. I may as well be dead." Another Twitter user tweeted before the lockdown about suicide:

> This time of year I get frustrated, lonely and depressed I wonder if I asked for forgiveness b4 committing suicide will God forgive me and still take me to heaven. I hate this holiday season more and more every year.

Care must be taken to strengthen existing suicide helplines and other mental health services especially during holidays and at the onset of highly distressing and alienating events.

Another exciting angle for future research is to focus on particular groups, such as the LGBTQ+. By searching for several LGBT-related keywords, we found 1,347,442 tweets in the period before COVID and 1,519,658 during COVID in our dataset (before name filtering). This data would allow a large-scale mixed-methods insight into the loneliness expressions for those mentioning alternative sexual and gender identities.

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