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I feel you: Mixed-methods study of social support of loneliness on twitter

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ABSTRACT

Loneliness is considered an epidemic in the United States due to its widespread and harmful effects to psychological and physiological well-being. Twitter provides the option of anonymity, a large audience and a space where feelings of loneliness can be expressed, and feedback received. In this mixed-methods study, based on a sample of 4 million tweets containing expressions of loneliness, we examine factors associated with eliciting feedback and types of possible social support therein. We examine feedback both quantitatively in terms of number of likes, retweets, and replies, and qualitatively by annotating its content. We apply the categorization of social support and test the applicability of concepts of directedness, person-centeredness and invisible support to a sample of replies. Supporting previous literature, we show that Twitter users with larger social networks and those who use a more positive language are more likely to receive feedback, conversely swearing is associated with fewer responses. Most common social support provided is emotional, followed by esteem and information support, all of which often include the elements of invisible support including smileys, images, and text formatting. However, there is a fraction of replies which may be considered online bullying, pointing to avenues of possible needs for intervention.

1Introduction

Loneliness has been acknowledged to be an ongoing epidemic in the US (Cacioppo & Cacioppo, 2018). It has been linked to a myriad of health concerns, including high blood pressure, impaired cognitive performance, increased risk of Alzhimer's disease, as well as psychological effects on mood, personality, and increase suicidal ideation (Hawkley & Cacioppo, 2010; Valtorta et al., 2016). Loneliness is defined as the perceived discrepancy between one's desired and actual level of social connection (Paloutzian et al., 1982). Although loneliness is experienced commonly, it has often been stigmatized (Kerr & Stanley, 2021).

With the advent of social media and increased internet access, in recent years Social Networking Sites (SNS) became a new platform for the self-disclosure of feelings which may be otherwise stigmatized, and for the reception of social support and community affiliation (Zhang and Fox, 2019). The unique affordances of SNS, including anonymous profiles, ease of posting, and social feedback mechanisms may resolve the tension between revealing and concealing information about oneself to others (Petronio, 2002). Indeed, many internet users have shared their experiences around loneliness on SNS, including one of the largest such platforms, Twitter (Chen, 2011; Zhang & Fox, 2019). On Twitter, not only can one post a short message, but one could receive a variety of social feedback, including "likes", retweets, and replies.

Meanwhile, the unprecedented events surrounding COVID-19 pandemic prompted governments worldwide to resort to drastic measures by putting millions of people in a collective lockdown and enforcing strict physical social distancing rules. This change in socialization has pushed the working and socializing activities to the online realms, with a measurable increase in the use of SNS (Koh & Liew, 2020; Labrague et al., 2020), and potential qualitative change in their use (Nabity-Grover et al., 2020). During these lockdowns, online discourse increasingly mentioned mental health effects of lockdowns (Koh & Liew, 2020), and younger adults were shown to be especially more likely to experience loneliness (Lisitsa et al., 2020).

Supportive communication is key in establishing and maintaining human relationships and reducing stress. Furthermore, the buffer theory of social support suggests that individuals who receive social support are better at coping with stressful situations and illnesses (Cohen & Hoberman, 1983; Lo, 2019). People experience greater emotional improvement when they receive comforting messages (Priem & Solomon, 2018), whereas providing social support is associated with a

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stronger immune system and better health (Floyd et al., 2018). Akin to face-to-face support, receiving supportive communication online can also produce numerous positive outcomes (Lin & Bhattacherjee, 2009; Shaw & Gant, 2002). Although social support when done correctly has various positive effects (see Taylor, 2011 for review), attempts at supportive communication can fail to achieve their goal in numerous ways, such as being insensitive, overly optimistic or inadvertently blaming the recipient, resulting in unhelpful or even harmful consequences (Ingram et al., 1999). With online bullying and harassment being well-documented phenomena (Craig et al., 2020), it becomes imperative to examine what type of support those turning to SNS may receive during the times when social distancing is likely to contribute to increased experiences of loneliness.

A meta-analysis on social support on social networking sites has shown that SNS use can help with emotional and informational support, but not for tangible and esteem support (Liu et al., 2018). However, each social media website has a unique set of affordances (spanning composition and social response functionalities, privacy standards, etc.) and cultures (including sub-communities around particular topics). Therefore studies conducted on social support on Facebook (High & Buehler, 2017), or studies of general social support online in an experimental condition (Rains et al., 2017) might not be applicable to SNS like Twitter where potentially global and heterogeneous audience can interact with the sender of the message. Moreover, data available on Twitter allows for a large-scale observational study of in-situ social support directed to individuals expressing loneliness, during a unique point in history. Complementing standard approaches, such observational study captures social interactions at the time of their posting, without solicitation by a researcher, thus addressing several biases of surveys, including recall and conformity biases (The approach introduces a slew of its own biases, which we discuss at length below).

This study utilizes a mixed-methods analysis. We employed both manual coding and automated filtering in order to curate a collection of 4 million tweets containing loneliness self-disclosures, spanning March 15, 2019–March 14, 2021, and thus capturing a year before and year during the COVID-19 pandemic. We examined the extent to which different forms of social feedback have been received by these posts, and what kinds of self-disclosures were more likely to attract feedback. We then focused on the replies to these self-disclosures, and manually coded them for the type of support provided by the Twitter community. Thus, we corroborate the existing social support theories, and extend them in the light of new possibilities afforded by SNS in the light of the physical isolation during the COVID-19 lockdowns.

2. Related work

In this work, we extend the latest theoretical work concerning SNS by producing quantitative and qualitative insights around supportive communication in the context of loneliness. In particular, we use the Dual Process Model (Bodie & Burleson, 2008) and extend the categorization of support proposed by Cutrona and Suhr (1992) to the online setting, incorporating the support made possible by the unique affordances of Twitter platform. To explore these affordances we test the usage of concepts of directedness (Bazarova & Choi, 2014), person-centered messages (Burleson, 1984; Jones, 2004) and invisible support (Bolger et al., 2000), all of which can hypothetically increase effectiveness of providing and receiving social support online.

2.1. Expression and support volume

Computer mediated communication (CMC), of which SNS is becoming a prominent part, complements our face-to-face interactions. SNS are becoming an outlet for emotional expression – an important part of building relationships (Feeney, 1999). From the beginning of Twitter's conception, researchers noted that "by using Twitter and its functions people gratify their need to connect with others … [which] fosters para-social gratification" (Chen, 2011, p. 757). During the physical isolation associated with the pandemic mediation efforts, the opportunities to communicate emotions in person were drastically limited. Simultaneously, an increase in SNS use has been recorded (Koh & Liew, 2020; Labrague et al., 2020). Thus, we hypothesize:

H1a. The volume of loneliness self-disclosure on Twitter increased during the periods of physical isolation, compared to before the start of the pandemic.

Further, the need for social feedback will also likely move to SNS because of limited face-to-face interactions. As the experience of social physical distancing is collective, this may produce added sympathy and increase in feedback to posts about loneliness. Thus:

H1b. The rate of feedback in terms of retweets, replies and likes to the loneliness disclosure tweets will increase during the periods of physical isolation.

2.2. Extent of support

Next, we turn to the attributes of the loneliness self-disclosure sender, receiver, and the message, which may be associated with increased rate of replies. Dual Process Model, a social cognitive theory rooted in constructivism, outlines a "helper" and a "recipient" of a potential supportive message (Bodie & Burleson, 2008). First, the chances for social interaction should be proportional to the potential audience for the message, which in the case of Twitter may be operationalized as the number of followers a recipient has. As the tweet is likely to be seen only by these accounts (although others may see it, if it is retweeted or searched for), the size of a user's on-line social network will likely be related to the number of potential "helpers". Outside SNS, it has been shown that those with larger off-line social networks perceive a greater amount of resources and even report better health (Bolger & Amarel, 2007). Our hypothesis, then, concerns whether this relationship is preserved on SNS:

H2a. The recipients with larger social networks are more likely to receive social support compared to those with smaller number of followers.

Second, we examine the "directedness" property of the message. One affordance that distinguishes social media from face to face interpersonal communication is the ability to communicate en masse to strangers. Twitter users are able to post public posts not directed to anyone in particular, which are visible by everyone. Alternatively, they can direct the message by tagging certain individuals (though the message is still visible to everyone, the tagged individuals will be specifically notified). The undirected communication on SNS has been linked to an audience representation that may span from close friends and followers to a "mass audience" (Schau & Gilly, 2003). Bazarova and Choi (2014) extend the functional model of self-disclosure of Derlega and Grzelak (1979) with the properties of directedness and visibility, which present affordances that change the posting behavior of SNS users when it comes to personal disclosure. Such targeting of self-disclosure may result in a difference in the social response rate and quality. Thus we hypothesize:

H2b. Recipient is more likely to receive social support when he/she directs the message to a specific helper than to the broad audience of Twitter.

Third, we consider the content of the message. While taking advantage of the SNS affordances of privacy and message directedness, the individuals posting there still consider their self-image and social norms (Zhang & Fox, 2019). There is a well-documented positive bias in

[1] The approach introduces a slew of its own biases, which we discuss at length below.

self-disclosure online, and it has been shown that people carefully craft their messages, which may contribute to greater intimacy (Walther, 2007). It is not immediately clear whether the loneliness self-disclosures with more drastic negative language would attract response due to the perceived emotional need, or whether more positive language would encourage engagement of other users. Thus, we ask:

RQ1. What words and sentiment are more common in self-disclosures which receive replies, compared to those that do not?

2.3. Content of support

Finally, we turn to the content of the supportive messages. According to Zhang and Fox (2019), disclosing loneliness online can facilitate social support and may alleviate the feelings of loneliness (Zhang & Fox, 2019). Burleson, MacGeorge, Knapp, & Daly (2002) define supportive communication as "verbal and nonverbal behavior produced with the intention of providing assistance to others perceived as needing that aid" (p. 374). Furthermore, according to Dual Process Theory of supportive communication: "simple, brief support messages may be just as effective (and perhaps, more effective) than longer, more complex messages when recipients are unlikely to think carefully about the content of the support messages" (Bodie & Jones, 2015, p. 2). Limited number of characters allowed by Twitter provide a perfect platform for brief supportive replies.

According to Cutrona and Suhr (1992), there are five distinct ways to communicate support to others: 1) Emotional Support - expressions of caring, concern, and empathy, 2) Esteem support - bolstering someone's esteem by making them feel capable, valued or admired, 3) Informational Support - giving specific advice, including facts and information that may help someone solve a problem, 4) Tangible support - providing physical assistance, goods, or services such as helping complete a task that needs to be done and 5) Network Support - directing someone to a person or group who can help them. Research suggests that emotional support is the most effective, as it can provide care and comfort to the recipient (High & Dillard, 2012). Thus, we ask:

RQ2a. What types of support is provided to people self-disclosing loneliness on Twitter before and during the periods of physical isolation?

Further, quality of person-centeredness captures the effectiveness of the supportive communication (Burleson, 1984; Jones, 2004): (1) highly person-centered messages help and comfort the person by validating the person's feeling and providing comfort, (2) moderately person-centered messages acknowledge the distress, but do not provide comfort, finally (3) low person-centered messages deny the legitimacy of the persons feeling invalidating their experience. Highly person-centered messages have been shown to be perceived most positively by the receiver as supportive (Jones & Guerrero, 2001) and help one reevaluate the event to seem less distressing (Jones, 2000). Thus,

RQ2b. What is the extent of person-centeredness of the support received in reply to loneliness self-disclosures before and during the periods of physical isolation?

Finally, the affordances of SNS and Twitter in particular allow for the expression of invisible support that is apparent through non-verbal elements. "Invisible support" was defined by Bolger et al. (2000) as non-verbal actions designed to provide social network interactions. This type of support is deemed most effective, as it is more subtle and does not focus on the source of the problem. Nonverbal messages present an important communication experience and are mainly the use of text formatting, smileys, and images. Smileys provide facial expression information, which trigger built-in face recognition circuits in our brains (Kanwisher et al., 1997), text formatting enriches our understanding of intonation and stress, and images and short videos provide a rich context and nuance (Jiang et al., 2017). How these affordances enrich the feedback on SNS is an open question. Thus, we ask:

RQ2c. What is the extent of use of invisible support received in reply to loneliness self-disclosures before and during the periods of physical isolation?

3. Methods

3.1. Data collection

The data was collected via the Application Programming Interface (API) provided by Twitter (Twitter 1, 2021). Using the API, we collected a real-time sample of tweets that contained the keywords "loneliness" and "lonely". The API provides a structured text object containing the following information about the posted tweet: text of the post itself, ID of its author, and other meta-data including time of posting, name of the user, and whether it was in reply to another tweet or a reposting (a "retweet") of another tweet. For a full list of fields see Twitter API documentation (Twitter 2, 2021). The collected posts span 1 year before and 1 year during COVID-19, with the latter period beginning on March 15, 2020, when most lockdowns began in the US (Courtemanche et al., 2020). To ensure the tweets come from the US, we geo-coded the Location field of each user using GeoNames (GeoNames Geographical Database, 2022), and selected only tweets from users listing their location within the US. Although lockdown measures were instituted unevenly throughout the U.S. and in the duration of that year, numerous restrictions on the size of gatherings and social interaction were largely instituted between the lockdowns, thus we refer to the latter period as generally having "physical distancing" measures. Also note that the API provides only publicly visible messages, and not private ones sent directly from one user to another.

Upon manual examination, we found that a substantial portion of the collected messages were conversations, music lyrics, advertisements, and other irrelevant content. To clean the dataset, we employed supervised machine learning: training an automated algorithm on a large coded sample of the data and applying it to the rest of the uncoded messages. For this purpose, we coded 1500 randomly selected tweets (both in the periods before and during COVID-19) as either loneliness self-disclosure or not. In the meanwhile, we compiled a list of songs, artists, and lyrics, as well as other undesirable content, for filtering (such as "Lonely Island", which can be found at (Keywords, 2022)). We used the coded tweets to train a text-based Support Vector Machine classifier using the Python sklearn library (Scikit-learn, 2021), which performed at the precision of 0.71 and recall of 0.82 on 10-fold cross-validation. To those tweets that passed the classifier, we applied the keyword filter of songs, artists, and lyrics. We also removed any tweets which were not original (that is, retweets of somebody else's tweet). Finally, in order to increase the chances of capturing individuals, instead of businesses or bots, we filtered the users by their display names using the extensive name lists provided by the US Social Security and the National Records of Scotland, as well as those extracted from Google+ in previous literature (see Magno & Weber, 2014; find the name dictionaries and matching code at https://www.yelenamejova.com/resources). After all of these filtering steps, the dataset consisted of 4,020,249 tweets (on average 5500 per day).

3.2. Temporal volume analysis

In order to visualize the volume of loneliness self-disclosures, we plot the number of unique users posting every day across the 2 years of captured time frame. We opt to count users, instead of tweets, due to the fact that some users post many tweets at once, while most do not (a "vocal minority" and a "silent majority" as defined by (Mustafaraj et al., 2011)), and we did not want this abnormal behavior to skew the perception of the overall posting frequency. Further, to estimate the change in self-disclosure posting, we perform Interrupted Time Series analysis (Bernal et al., 2017), which consists of a linear regression, estimated using Ordinary Least Squares, capturing the initial posting rate (the intercept), change over time, change due to the "intervention" (here, beginning of the COVID-19 period), and subsequent change over time. The change in posting rate, then, can be both visualized as the model's trend line, and quantified via the coefficients of the model.

3.3. Reply analysis

Next, we turn to the focus of this study – the replies to the loneliness self-disclosures. Because the original data was gathered just as it was posted, it did not include the information about the eventual interactions with it, which may include people re-posting (retweeting) the tweet, clicking the "like" button, or replying to the tweet. In order to gather this information, we re-collect a sample of tweets. In particular, we sample 100 tweets from every day of the dataset, and re-query the Twitter API to collect information about the interactions. We found that some tweets or user accounts have been deleted in the meanwhile, but we were able to retrieve information for 12,788 tweets: 6071 before and 6717 during COVID-19 (note that the more recent time period has more tweets which have not yet been removed). Using the meta-data of this sample, we then compute the difference in the number of likes, retweets, and replies in the two time periods. Further, focusing on tweets which have or have not received a reply, we compare the user attributes (how many followers they have), as well as tweet attributes (whether tweet is directed to a specific user, and what kinds of words it uses). In order to compare the words used by loneliness self-disclosures which receive replies to those that do not, we first split the tweets into individual words, remove URLs and user mentions, and compute frequencies of their occurrence. After removing very popular words (such as "of" and "a", known as "stopwords"), we compute the Odds Ratio of one word appearing in a tweet with, versus a tweet without a reply. Note that these are not necessarily the most frequent terms in the tweet group (say, tweets with replies), but those that are more likely to appear in it, compared to the other group (tweets without replies).

3.4. Manual coding

Finally, two of the authors performed a manual coding of a selection of replies to the self-disclosure tweets by reading the replies to a random selection of 500 tweets from the period before and 500 during the periods of physical isolation. Once inter-coder reliability reached 95% the first-author coded the remaining tweets. The information provided to the coder consisted of the self-disclosure tweet, time of posting, interaction statistics (likes, retweets, and replies), and a link to the tweet. Using this link, the coder was able to view the replies to the self-disclosure tweet, copy/paste the content of the first reply into a spreadsheet, and annotate its contents. Content analysis was conducted on the original tweet and reply, coding for type of support message (emotional, esteem, information, tangible, network), level of person-centredness (low, moderately, highly), and if the message was verbal (text only), nonverbal (picture or emoji only), or had both. After the content analysis was completed, examples of tweets from each and cross-sectional categories were used in the paper.

4. Results

4.1. Expression and support volume

The volume of self-disclosure captured in the Twitter data in the year before and year during COVID-19 pandemic shows the highest peaks to be around Valentine's Day (February 14) in both years. Despite these fluctuations, we find a distinct increase in volume around the first period of physical isolation, as well as another wave during the winter 2020–2021. In Fig. 1, we plot the number of users posting per day (in blue) and the Interrupted Time Series (OLS) regression line (in red), which illustrates the difference in average posting frequency before and during physical isolation periods. The OLS analysis shows that at the beginning of the dataset on average 4282 users posted per day ($P < 0.0001$), this increased by 1770 in the physical isolation period ($P < 0.0001$). At the peak of the first wave, on March 27, 2020, 9148 unique users posted loneliness self-disclosures. Thus, we find a strong support for H1a concerning the increase in self-disclosures around lockdowns.

4.2. Extent of support

Next, we turn to the rate of feedback including likes, retweets, and replies. Based on the re-collected sample of the data, we estimate that 25.5% of tweets before physical isolation measures received at least one reply, and 30.1% of tweets during them did so, with the difference being statistically significant at $P < 0.0001$ (using two-sided difference in proportion z test). Interestingly, the number of retweets decreased from 14.3% having at least one retweet before isolation to 11.0% during ($P < 0.0001$). However, the number of likes does not significantly change. This can be attributed to the long-tail distribution of likes and retweets, with few tweets receiving inordinate attention. Thus, we find only a partial support for Hypothesis H1b, wherein feedback in terms of replies increases, retweets decreases, and likes does not change.

Next, we consider different attributes of messages that are more likely to receive replies. We begin by considering the potential social network of the user. We find that replies were sent to self-disclosures by users with a far larger number of followers at an average of 3798 followers before physical isolation and 3492 during, compared to self-disclosures that did not receive any replies (1618 and 1,359, respectively). The differences in the followers between messages with and without replies are statistically significant using the one-sided *t*-test at $P < 0.002$ before physical isolation and $P < 0.0001$ during. Thus, we find support for the Hypothesis H2a whereby users with a larger social network are more likely to receive a reply.

When looking at probability of receiving a reply to a tweet self-

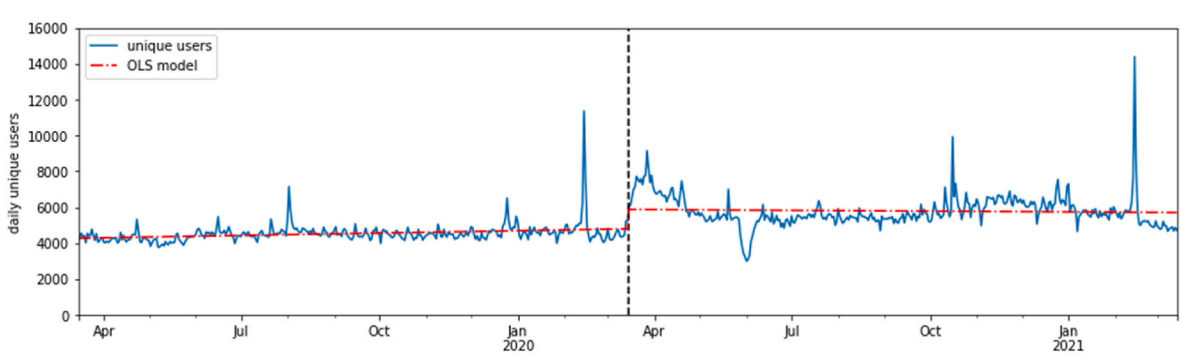

Fig. 1. Number of unique users posting loneliness self-disclosure per day (blue solid line). The Interrupted Time Series (OLS) model is shown as a red dotted line.

disclosing loneliness that directed to a particular account (by putting a user mention at the beginning of the tweet) compared to nobody in particular, we find that, both before and during the period of physical isolation, tweets were much more likely to receive a reply if they were directed at 38.1% before physical isolation and 39.8% during, compared to 22.9% and 27.0% without a directed mention, respectively (differences in proportion significant at $P < 0.0001$). These findings support Hypothesis H2b concerning the relationship between directedness of a message and the extent of the replies.

Finally, in RQ1 we examine the words more prevalent in the tweets receiving replies, versus those that have not. Fig. 2 shows the top 30 words in self-disclosure tweets which had a reply (left) and which did not (right) by Odds Ratio. We note that the tweets which receive replies contain more social and positive words such as “nice”, “kind”, “super”, and “hi”, whereas those that do not receive replies have swear words, talk more about loneliness, and are altogether more negative. This suggests that there is a positive bias in replies to loneliness self-disclosure, and a negative one against negativity and profanity.

4.3. Content of support

In answering RQ2 through manual coding, we qualitatively explore the different types of social support provided to users who disclose feeling lonely. The summary of category statistics is shown in Table 1, along with an example for each (tweets paraphrased for privacy).

First in answering RQ2a, the most common type of supportive communication is emotional support (around 50% in both time periods). Although Zhang and Fox (2019) hypothesized that lonely people would not be able to find much support they needed on SNSs, numerous types of emotional support was observed, including highly person-centered replies. For example:

Tweet #11 (before physical isolation): *I'm lonely*

Reply: *I know how you feel. I promise that if you're patient, the right person will come along. Don't settle for less than what you deserve. I know he's out there, but until then, take this time to grow. I love you!*

Another example of a highly person-centered support on Twitter that shows a clear validation of the persons feeling is as follows:

Tweet #124 (before physical isolation): *i just feel so lonely.*

Reply: *That's very relatable, many of us have the same experience. You can be sad, just remember* <smiley> *you matter we don't know each other but i appreciate you, and good things come your way.*

Moderately person-centered emotional support messages was the vast majority of the replies. The most common reply to someone who is lonely is “you are not alone”, “me too”, “mood”, “I know how that feels” or messages that offer companionship, either virtually or in “real life” such as “I here if you want to talk”, “call me”, “want me to come over?”

Concerning the mode of expression (RQ2c), many emotionally supportive messages used nonverbal elements, such as gifs (animated images) and emojis (small in-text images, often of faces), sometimes even

Table 1
Reply typology coding statistics and examples.

		Before COVID n = 279	During COVID n = 232	Example
Type of Support	Emotional	149 (53%)	114 (49%)	i love u ! im always here for you! <gif of a hug>
	Esteem	14 (5%)	12 (5%)	Hey you're not trash! let's talk! Don't be lonely. Show me your art and I'll show you mine)
	Information	5 (2%)	10 (4%)	I don't know you, but I saw your tweet and I feel you. Keep going, you can text: (number provided) It's TEXT, not a phone call. Easier sometimes. You have value and are loved. <Red heart>
	Network	3 (1%)	0 (0%)	way back I found this obscure website made by a mum in the US, and she had collected all this information, petitioning for proper medical attention. She was my hero. Just found her site, it's much bigger now <URL>
	Tangible	3 (1%)	4 (2%)	<Crying face > Tell me what games you want to play and I'll buy them so we can play together. Ff14 is already on that list. <Thumbs up>
Non-verbal Support	Verbal	165 (59%)	122 (53%)	I am an introvert and even that doesn't dave me from the pains of being isolated. I want this to be over soon so I can go back to campus and meet my professors in person.
	Nonverbal	25 (9%)	23 (10%)	<gif “sending virtual hug">
	Both	83 (30%)	83 (36%)	<smiley with hearts> Join your nice Canadian relative
Person Centered Support	Highly	24 (9%)	12 (5%)	Wanting a mutual loving relationship while ashamed of your own appearance, fearing rejection and loneliness contributes to abuse. You must love yourself first.
	Moderate	172 (62%)	160 (69%)	same here if you need someone to talk to
	Low	72 (26%)	58 (25%)	Said every person on Twitter

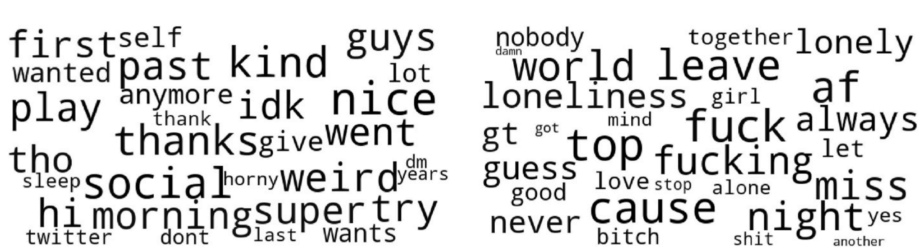

Fig. 2. Top 30 words by Odds Ratio in tweets having a reply (left) and not having one (right).

without text. For example:

> Tweet #184 (before physical isolation): *This weekend has been so strange and lonely I felt like going back home.*
>
> Reply: <gif "have a hug in case you need one">

Gifs of virtual hugs in response to self-disclosure of loneliness were also one of the most common emotional support messages that were observed. There was a high variety of gifs and emojis expressing nonverbal immediacy and support, including short videos, photos, and animations such as in Fig. 3.

Content that was labeled as low person-centered messages varied in the degree of appropriate responses. Some were ignoring or invalidating a person's feelings, however on the more extreme end, some of these might not fit the definition of supportive communication, as there is no way to know if the sender of the message realized that the lonely person might have been seeking support. Low-centered messages that criticize, insult or invalidate the feelings of the sender, do not fit the definition of supportive communication or, perhaps due to the affordances of Twitter, become malicious support borderlining bullying. For example:

> Tweet #203 (during physical isolation period): *Being broke and Lonely is a very bad combination.!* <smileys>
>
> Reply: *If you are unable to find someone for yourself why don't you find a job or start up something, don't be a loser two way round* < Rolling on the floor laughing>

Looking at other categories of support, the next most common after emotional support was esteem support. Esteem support messages complimented the person on various aspects, in the attempt to increase the person's self esteem. For example:

> Tweet #111 (before physical isolation period): *really?:(i feel so lonely right nowand like i'm not here for the people that mean the most to me. Being beautiful would be nice - but to feel valued would be s better. sorry to unload this all on the first tweet i saw!*
>
> Reply: *You are BEAUTIFUL and interesting and funny. Never forget that.*

Informational support varied in different types of advice. For example a person was told to get off Twitter and try other sites like Facebook if they needed support:

Fig. 3. Screenshot of an animated image (gif) of hugging cartoon characters (courtesy of chibird.com).

> Tweet #121 (before physical isolation): *hey can I be honest and say that I feel super lonely and ignored here? everyone else here has lots of friends and are super close and I have like no one.*
>
> Reply: *Well to be faireverything on twitter isbased on outward perception and isn't madeto create and maintain friendships like other apps (snap, insta, discord, even facebook) do. If you want to be involved with more people, I recommend replying to posts?*

Network support and tangible support were the least common types of support, but were still observed. For instance, we found a pointer to a phone help line (see Table 1).

Overall, as can be seen from the percentages of various categories in Table 1, we do not see a drastic change in their share between the before and during physical isolation periods, suggesting that the norms around the responses to loneliness self-disclosure did not substantially change during the lockdowns, at least in terms of this categorization, person-centeredness, and non-verbal expression. However, we do observe several explicit mentions of loneliness associated directly with the lockdowns, with responses showing commiseration about the situation and suggestions of TV shows to watch as a distraction.

5. Discussion

In this study, we illustrate the extent to which Twitter is used as a platform for self-disclosure around loneliness, and a source of social support. Especially during COVID-19, it has been shown that social media has become a venue for venting feelings of loneliness (Cauberghe et al., 2021; Mahoney et al., 2019), and discussing the impact of social distancing measures on one's mental health and community in general (Koh & Liew, 2020). Indeed, we find a marked increase in loneliness expression from March 15, 2020, which swells especially during the periods with physical distancing measures. These findings support findings by Hesse et al. (2021) who find that affection deprivation during this period is positively associated with loneliness. However, in our sample even before these events, on average just over 4000 people expressed their feelings of loneliness per day on the platform. These expressions spiked especially around Valentine's Day (February 14), amounting to over 10,000 users, both in 2020 and 2021, indicating external social events and expectations spur such activity. These figures lead us to conclude that, at least for a substantial number of individuals, it is perceived as socially acceptable to disclose feelings of loneliness on Twitter.

The quantitative results of this study provide insights on the circumstances that increase the chances of feedback. First, those users with a larger number of followers (virtual social network) are more likely to receive replies to their loneliness self-disclosures. Note that on Twitter, although one has control over who one follows, there is no such control over others following one's account. Users which post content interesting to others, perhaps to whole other communities, are more likely to gain followers, who can be considered "social capital" (Hofer & Aubert, 2013). This insight may be operationalized in two ways: as an individual, it is advisable to post such content that results in the increase of one's social capital on the platform; and as an intervening party, additional focus should be given to individuals lacking such capital. For instance, if a loneliness intervention (such as community engagement, mental health services, etc.) is to be advertised, it may be most beneficial to target those SNS users who lack in social capital – both because they receive less emotional support from it, and because they are less likely to receive this information through it. Overall, these results support previous work showing that those with larger social networks perceive more support, which may be associated with better health (Bolger & Amarel, 2007). In addition, our findings concerning directed messages support the approach of growing one's social network ahead of time, so that it becomes possible to directly message SNS users who are familiar and would be more likely to engage in a conversation.

Further, our findings suggest that communicating self-disclosures in a positive fashion and abstaining from profanity may result in a higher chance of receiving a reply. It has been shown that relationships which involved name calling, criticism and swearing were more likely to result in disengagement (Clements et al., 1997). Still, vulgarity is a constant feature of unrestricted social media platforms, often used as an intensifier of the sentiment present in the writing (Cachola et al., 2018). Using vulgarity during emotional self-disclosure, though, may prove to be counter-productive, if one is aiming to receive social support in reply to the messages.

According to the dual-process theory of social support, the most important type of support is "being there", unfortunately the vast majority of tweets self disclosing loneliness did not receive any type of a response. Only 25–30% of the sample tweets elicited a reply. During the qualitative analysis, we find the vast majority of these replies to be supportive, or at least neutral, indicating that, for the most part, the platform does not display a social stigma toward loneliness. Recently, a survey of a diverse sample of U.S. population showed little evidence of stigmatization around loneliness when not reclusive (Kerr & Stanley, 2021), unlike the earlier studies limited to college students (Lau & Gruen, 1992). We find this positive attitude to loneliness both before and during the physical isolation periods, illustrating that such acceptance is not purely a result of a mass social distancing measure. Further, we find an increased rate of replies during COVID-19, which remained positive throughout the period.

Both before and during the physical isolation measures came into effect, emotional support was the most common type of reply to self-disclosure of loneliness. The reply was more likely (over 60% chance) of being moderately person-centric, meaning at the very least the helper was acknowledging the feelings of the sender. Sadly, 25–26% of the replies were low person-centered – they invalidate the feelings of the lonely individual and can cause more harm than support. These low person-centered messages in some cases can reach cyber-bullying level (such as the reply to Tweet #406 (during physical isolation period): "You are an idiot") and may potentially negatively affect any person who made themselves vulnerable by disclosing that they are lonely online. Fortunately, we find only 8 occurrences of such behavior in our data (4 in each period).

On the other hand, the second most common category of support we found dealt with the boosting of the recipient's esteem by compliments and praise. Previously (Liu et al., 2018), found that SNS use in general was not associated with esteem support, theorizing that upward social comparison may prevent positive effects of online interactions. Given the evidence of explicit esteem boosting in the analyzed replies, future research must address whether such interactions indeed result in an improvement in self-perception for the recipient.

Whereas person-centeredness is a way of showing verbal immediacy, invisible support through nonverbal immediacy has been commonly seen as a way of showing emotional support. In particular we observe many gifs and emojis of hugging, love and other ways of showing caring and empathy through CMC. In particular, we note a remark on the platform's affordances in one of the replies (to tweet #458 (before physical isolation)): "I pressed like but I didn't mean "I like this"", indicating the inadequacy of the simple feedback mechanisms to convey complex human emotions. There have been instances of platforms acknowledging and addressing this need, however, such as the introduction of the care reaction button (smiley hugging a red heart) by Facebook in April 2020 in reaction to COVID-19 (Hutchinson, 2020). It is up to the platforms to evaluate the trade-off between the expressiveness and the simplicity of their systems, while keeping in mind the constraints such decisions put on the self-disclosure of their users.

5.1. Limitations & privacy

Despite being one of the most popular SNS in the world, Twitter's user base is not representative of the U.S. population – it tends to be a bit younger and wealthier, but it is distributed quite evenly between race and urbanization (Auxier & Anderson, 2021). Further, we are able to study only those who have chosen to share their feelings of loneliness on the platform, and it is not easy to ascertain just how many struggle with the feelings without sharing it (a survey may be able to answer this question better). The study is also limited by time, despite spanning 2 years: the social norms surrounding SNS use are constantly evolving, and will require continuous research effort to monitor. Further, the automated tools used in this study are not perfectly accurate, and it is possible that some portion of the captured posts is not meant as loneliness self-disclosure. Conversely, some tweets that included self-disclosure of loneliness could have been missed if they did not contain keywords "lonely" or "loneliness" (including those in other languages). More technical work needs to be done to create accurate machine learning tools that recognize emotional expression in text. Similarly, the name matching used to filter out organizational and bot accounts likely also discarded those in which users did not use their names, filtering out those who may be more sensitive to privacy issues. Further, although the tweets were collected from users who indicated they were located within the US, the geolocation may have false matches (note that we manually verified the top 500 most popular matched locations to ensure quality). Beyond this, the physical distancing measures were implemented across the country often at the state or even finer geographic level, making the experience of lockdowns different across the country. This focus on the US also limits the generalizability of the results to other countries, and more work needs to be done to assess the mental impact of socially-disruptive public health interventions in other countries. Despite 23% of US adults using the platform, the user base of Twitter is not representative of the US population, being younger, more affluent, and college educated (Pew Research Center, 2021), thus this methodology should be used in combination with other survey methods.

Finally, despite the fact that all of the posts the Twitter API provides are public, it is possible that the users posting these tweets are intending for the message to reach only their followers or particular individuals (there are privacy settings to change this visibility). Further, some of the tweets and accounts posting them may be deleted over time. Thus, when manually coding the replies, we only code those which remain on Twitter website, and exclude deleted content from consideration. Because of this privacy concern, and due to the Twitter Terms of Service (https://twitter.com/en/tos), we will not be posting the original dataset on the public Internet, but will make it available only upon request by other researchers. This work has been approved by the IRB of a major university in the U.S.

5.2. Implications: practical and theoretical

In February 2021, a survey found that "36% of all Americans—including 61% of young adults and 51% of mothers with young children—feel 'serious loneliness'" (Cashin, 2021). Considering possible psychological and physiological correlates of loneliness, it is imperative that the issue is not ignored by the public health authorities.

Practical implications of this study are twofold: firstly, we provide advice to lonely SNS users who are seeking social support on Twitter, and secondly to actors interested in providing support for people who are lonely. For individuals who disclose loneliness online in hopes of receiving a response, our data suggests tweets that: a) are directed at certain users instead of general Twitter public, b) posted by users with a large number of followers, c) are more positive and do not have swear words will be most effective in eliciting a response. For actors interested in providing social support, it is important to stress that the majority of tweets disclosing loneliness do not receive a reply, therefore it would be beneficial to encourage users to disclose their loneliness to other people in other channels of communication or have agencies post replies and offer help or guidance, because in the current data, we found no instances of official help being suggested to those disclosing the feelings of loneliness, with mostly only emotional support provided by other users.

Furthermore, our data shows that users with fewer contacts on Twitter are less likely to receive social support from others – these users might benefit from extra attention from services interested in providing help online.

Finally, special attention needs to be paid to the potential cyberbullying that those expressing feelings on SNS may provoke. Recent studies show that cyberbullying victimization is correlated with depression and anxiety, especially in men (Schodt et al., 2021), and such experiences may only worsen the situation. Yet more research needs to be done to reveal the self-disclosure of loneliness of potentially vulnerable groups, including those with diagnosed mental illness, as well as marginalized communities. For instance, quite a few tweets in our data were posted by or about the LGBTQ + community, suggesting that it is possible to conduct further research concerning the unique expressions, needs, and interactions around the emotional self-disclosure on SNSs by such community members.

Theoretical implications of this study include the expansion of the dual-process theory to the SNS context and providing evidence of supportive messages in the form of invisible support online. As dual-process theory suggests, just being there and being present is an effective form of social support (Bodie & Jones, 2015); we observed a copious amount of positive nonverbal and verbal supportive messages showing users presence through images or messages like “I am here for you”. In addition, in accordance with the theory, we have observed a variety of quality of supportive communication, with the vast majority being emotional support. Further, we illustrate the applicability of Cutrona and Suhr’s (1992) five types of support to SNS, showing that, despite it being a networked medium, network support is one of least observed in the data. On the other hand, it contains a rich variety of verbal and nonverbal emotional support, which maiky benefit from a closer examination.

Credit author statement

Dr. Mejova collected the data, cleaned, geocoded, and filtered the data, implemented the machine learning classifier, gathered additional reply data, computed statistics and produced visualizations. Dr. Hommadova Lu wrote the theoretical grounding and qualitative interpretation of the results. Both authors engaged in the conceptualization of the work, performed manual labeling of data, and wrote the manuscript.

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