Exploring the Changes of Suicide Probability During COVID-19 Among Chinese Weibo Users

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Abstract. *Background:* Coronavirus disease 2019 (COVID-19) threatens people's physical and mental health, globally, and it may even trigger suicide ideation and suicidal behavior. *Aims:* We aimed to examine the impact of COVID-19 on suicide risk by sampling Chinese Weibo users and analyzing their social media messages. *Method:* We predicted the probability of suicide (including hopelessness, suicidal ideation, negative self-evaluation, and hostility) of Weibo users in order to assess the changes in suicide probability at different times. Repeated-measures ANOVA was performed to examine the differences in suicide probability in different regions during different periods. *Results:* There was no significant difference in suicide probability between profoundly infected areas (PIAs) and less infected areas (LIAs) before the outbreak of COVID-19. LIAs had an increase in hopelessness during the COVID-19 growth period, while hopelessness and hostility in PIA increased during the COVID-19 decline period, indicating potential suicide probability. *Limitations:* Results should be interpreted with caution, and cross-cultural research may be considered in the future. *Conclusion:* COVID-19 has a dynamic impact on suicide probability. Using data from online social networks may help to understand the impact pattern of COVID-19 on people's suicide probability.

Keywords: public health emergencies, online social networks, online ecological recognition, suicide probability, suicide prevention, COVID-19, Weibo

Public health emergencies (e.g., natural disasters, infectious diseases) threaten people's physical health and have an impact on their mental health, even triggering a severe psychological crisis like suicide (Norris et al., 2002). Coronavirus disease 2019 (COVID-19) may lead to negative emotions (e.g., hopelessness), negative cognitions (e.g., negative self-evaluation; Chesley & Loring-Mcnulty, 2003; Orbach et al., 2003), and even suicide (Chan et al., 2010; Xue et al., 2020). The occurrence of suicide not only causes grief to the family of the deceased but also has a substantial negative impact on society (Conejero et al., 2020), which may affect the implementation of epidemic prevention strategies and aggravate health problems during the epidemic.

Given the evolving situation of the pandemic, COVID-19 may have a dynamic impact on suicide probability. Previous studies have found that changes in suicide rate showed diverse patterns in different infected areas during the outbreak of an epidemic (Cheung et al., 2010; Yip et al., 2010). Therefore, it is essential to understand the patterns of the impact of COVID-19 on suicide probability, which can inform the development of more targeted and timely suicide prevention strategies.

The current assessment of suicide probability relies on self-report, mainly using the Scale for Suicide Ideation (Beck et al., 1979), Suicide Probability Scale (SPS; Cull & Gill, 1982), Multi-attitude Suicide Tendency Scale (Gutierrez et al., 2001), and the Semantic Differential Scale Attitudes Towards Suicidal behavior (Jenner & Niesing, 2010). However, we cannot predict the development of the epidemic, and there may be some recall bias by participants when recalling their psychological state 1 week or 1 month earlier (Bishop et al., 2000). Moreover, since the research period may be relatively long, filling out scales every day will undoubtedly increase the burden on participants who are already in an unstable mental state.

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Online social networks (OSNs; e.g., Weibo, Twitter) provide an opportunity to comprehensively understand the psychological state of participants in a noninvasive way (Young et al., 2014). Sina Weibo is a leading Chinese OSN with more than 550 million active daily users as of May 2020 (Weibo, 2020). These users are accustomed to sharing their daily life and interacting with each other through Weibo functions (e.g., publish, forward, reply, @function; Che & Ip, 2018), which provide rich data on user behavior. Online ecological recognition (OER; Liu et al., 2018) refers to the automatic recognition of a psychological profile by using predictive models based on ecological and behavioral data from Weibo. Previous studies have shown that social media data are useful for identifying suicidal ideation through OER (Guo & Zhu, 2019).

This study aimed to investigate the changes in suicide probability (*hopelessness, suicidal ideation, negative self-evaluation*, and *hostility*) during COVID-19 as indicated by Chinese Weibo messages between December 1, 2019 and April 18, 2020.

Method

Data Collection and Sample

The sample in this study was selected from the original Weibo data pool (Li et al., 2014), comprising more than 1.16 million active Weibo users. These users had recently published Weibo posts and had more than 500 posts after registering their account. The retrieved data included user profiles, network behaviors (e.g., forward, reply), and the content of the posts. They were all anonymous. Privacy was strictly protected during this process, referring to the ethical principles listed by Kosinski et al. (2015). The ethics code is H15009 and was approved by the Institutional Review Board at the Institute of Psychology, Chinese Academy of Sciences.

Our inclusion criteria were: (1) Weibo users who have published more than 50 original Weibo posts from December 31, 2019 to January 26, 2020. (2) The user account was non-institutional (e.g., individual user). (3) The geolocation in the profile description was identified as regions in China (e.g., not "overseas" or "other"), including Mainland China, Hong Kong, Macao, and Taiwan.

The initial screening yielded 23,033 active Weibo users from a user pool of 1.16 million. We then retrieved all their original posts published from December 1, 2019 to April 18, 2020. We classified these users into 34 categories based on their geolocation in China, and further categorized these locations into two groups according to the number of confirmed cases in each region (World Health Organization, 2020): profoundly infected area (PIA), for example, Wuhan (possessed approximately 75% of the total confirmed cases); (2) less infected areas (LIAs), that is, other areas. Their corresponding group labels did not change from December 1, 2019 to April 18, 2020.

Next, according to the number of newly confirmed daily cases released by the National Health Commission, the spread of COVID-19 in China can be divided into three periods:

1. Before COVID-19: Since the first official notification of COVID-19 was on December 31, 2019, we defined the period from December 1, 2019 to December 31, 2019 as the stage before the outbreak.
2. The COVID-19 growth period: The number of daily diagnoses had been on the rise from January 1, 2020 to February 12, 2020. It reached 15,152 on February 12, 2020, which was the highest peak during the epidemic period. Therefore, we classified the period from January 1, 2020 to February 12, 2020 as a growth period.

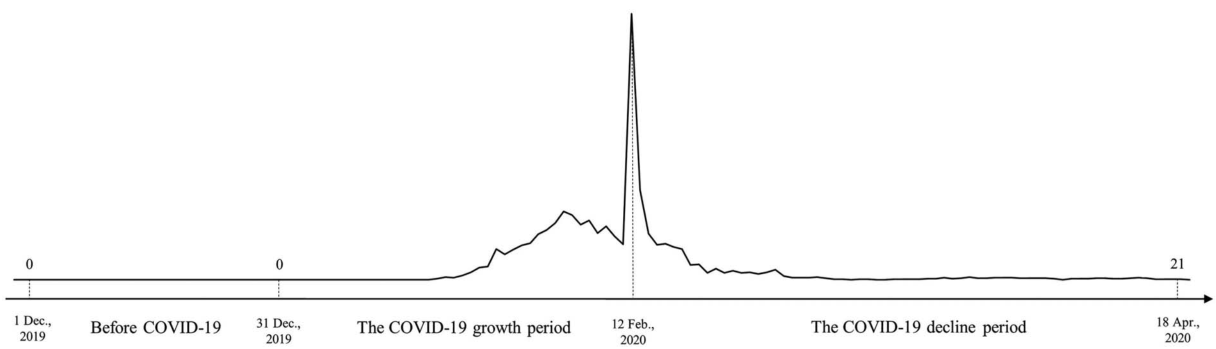

Figure 1. Timeline of the number of newly diagnosed cases per day.

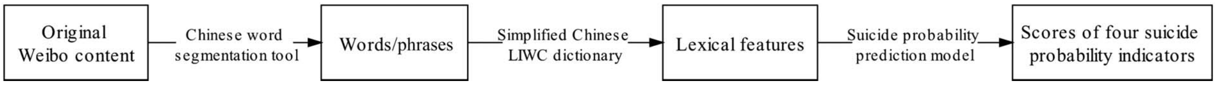

Figure 2. Procedures of feature extraction from online Weibo data and suicide probability predicted by lexical features.

3. The COVID-19 decline period: The number of confirmed cases gradually decreased after February 12, 2020. Therefore, the period from February 13, 2020 to April 18, 2020 was defined as a decline period.

Figure 1 portrays the trend of newly diagnosed cases per day and the classification of the epidemic period.

Measurement of Suicide Probability and Procedures

In this study, we employed OER (Liu et al., 2018) to obtain suicide probability based on Weibo data. The specific steps were as follows.

We extracted content features using TextMind (Gao et al., 2013), which includes a Chinese word segmentation tool (Li et al., 2014) and a psychoanalytic dictionary (Zhao et al., 2016). The Chinese word segmentation tool could split the user's original Weibo content into independent words/phrases with linguistic annotations (e.g., verbs, nouns, adverbials, objects; Liu et al., 2011). The psychoanalytic dictionary extracted psychologically meaningful categories through the simplified Chinese Language Inquiry and Word Count dictionary based on these independent words/phrases (Zhao et al., 2016).

After extracting lexical features, we applied the suicide probability prediction model (Han et al., 2017), which had been trained by machine-learning algorithms to predict the *hopelessness*, *suicidal ideation*, *negative self-evaluation*, and *hostility* of the Weibo users. The suicide probability prediction model is a tool developed for the purpose of research through big data and deep-learning technology. It was established based on the SPS by using the pace regression method. A 10-fold cross-validation was used to take most advantage of data and lessen the effect of overfitting. Four dimensions of SPS (hopelessness, suicidal ideation, negative self-evaluation, and hostility) had reached a moderate correlation with questionnaire scores, with correlation coefficients from 0.33 to 0.44 (Zhang et al., 2015). The suicide probability prediction model could output scores for the four dimensions of SPS using the lexical features that were input. Figure 2 portrays the procedure from feature extraction to suicide probability prediction.

We predicted the scores of hopelessness, suicidal ideation, negative self-evaluation, and hostility of Weibo users. We then applied 2 (regions) × 3 (periods) repeated-measures ANOVA to test differences using SPSS version 22.

Results

Demographics

Among 23,033 active Weibo users, 27% were males, and 98% of them were in LIAs. According to the registered age in the users' profiles (n = 4,954, 21.52%), ages ranged from 2 to 99 years with a median age of 29. The demographic characteristics are presented in Table 1.

Suicide Probability

In this study, we calculated and compared scores of hopelessness, suicidal ideation, negative self-evaluation, and hostility of Weibo users in PIA and LIAs at different periods (shown in Table 2). *T-before* represents the period before COVID-19, *T-growth* represents the COVID-19

Table 1. Demographic characteristics of samples

Characteristics	*n* (%)
Gender	
Male	6,232 (27.06)
Female	16,801 (72.94)
Age (years)	
≤9	193 (0.84)
10–19	43 (0.19)
20–29	2,434 (10.57)
30–39	1,831 (7.95)
40+	453 (1.97)
Missing data	18,079 (78.49)
Regions	
PIA	399 (1.73)
LIA	22,642 (98.3)
Total	23,033 (100)

Note. LIA = less infected areas, i.e., others; PIA = profoundly infected area, e.g., Wuhan.

Table 2. Repeated-measures ANOVA of suicide probability

	$M \pm SD$					
Dimensions	T-before	T-growth	T-decline	F_{regin}	F_{period}	$F_{\text{region} \times \text{period}}$
Hopelessness						
PIA	14.80 ± 0.15	14.88 ± 0.25	15.00 ± 0.19	0.074	4.511[a]	17.608[b]
LIA	14.89 ± 0.11	15.00 ± 0.30	14.82 ± 0.10			
Suicidal ideation						
PIA	14.62 ± 0.30	14.33 ± 0.50	14.71 ± 0.42	0.750	7.991[b]	10.505[b]
LIA	14.73 ± 0.24	14.56 ± 0.49	14.50 ± 0.15			
Negative self-evaluation						
PIA	20.80 ± 0.35	20.56 ± 0.28	20.94 ± 0.45	28.154[b]	3.579[a]	25.424[b]
LIA	20.66 ± 0.18	20.61 ± 0.39	20.38 ± 0.16			
Hostility						
PIA	27.08 ± 0.38	27.10 ± 0.28	27.53 ± 0.47	23.841[b]	2.144	37.983[b]
LIA	27.05 ± 0.19	27.18 ± 0.46	26.83 ± 0.20			

Note. LIA = less infected areas, i.e., others; PIA = profoundly infected area, e.g., Wuhan.
[a]$p < .05$.
[b]$p < .001$.

growth period, and *T-decline* represents the COVID-19 decline period. The results showed that there were significant interactions between regions and periods regarding hopelessness, $F(2) = 17.608$, $p < .001$, $\eta^2 = .114$, suicidal ideation, $F(2) = 10.505$, $p < .001$, $\eta^2 = .071$, negative self-evaluation, $F(2) = 25.424$, $p < .001$, $\eta^2 = .157$, and hostility, $F(2) = 37.983$, $p < .001$, $\eta^2 = .217$. Simple effect analysis should be further conducted on these four indicators.

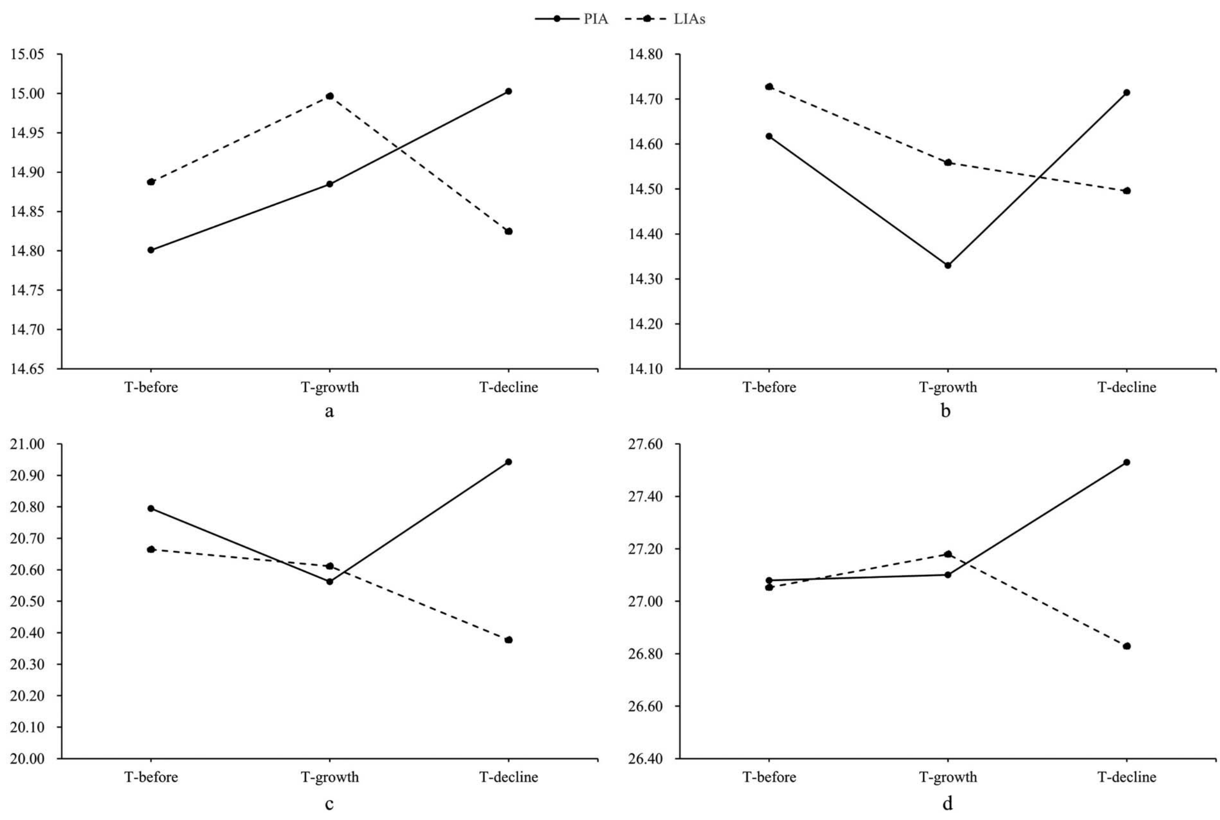

Figure 3. Region × period interaction of suicide probability in four dimensions.

The region × period interaction of suicide probability in four dimensions (hopelessness, suicidal ideation, negative self-evaluation, and hostility) is shown in Figure 3.

Hopelessness

Regarding regions, there was no significant difference between PIA and LIA before COVID-19, $F(1) = 2.999$, $p = .084$, $\eta^2 = .011$ (Figure 3a). The hopelessness in PIA was significantly lower than in LIA during T-growth, $F(1) = 7.071$, $p = .008$, $\eta^2 = .025$, but higher during T-decline, $F(1) = 26.609$, $p < .001$, $\eta^2 = .089$). There were significant differences in different periods regarding hopelessness in PIA, $F(2) = 12.101$, $p < .001$, $\eta^2 = .081$, and LIA, $F(2) = 10.018$, $p < .001$, $\eta^2 = .068$. Hopelessness in PIA during T-decline was significantly higher than that during T-before ($p < .001$) and during T-growth ($p = .007$). The hopelessness in LIA during T-growth was significantly higher than during T-decline ($p < .001$).

Suicidal Ideation

There was no significant difference between PIA and LIA before COVID-19, $F(1) = 1.369$, $p = .243$, $\eta^2 = .005$ (Figure 3b). Suicidal ideation in PIA was significantly lower than in LIA during T-growth, $F(1) = 8.370$, $p = .004$, $\eta^2 = .030$, but higher during T-decline, $F(1) = 11.284$, $p = .001$, $\eta^2 = .040$. There were significant differences between suicidal ideation in PIA, $F(2) = 14.387$, $p < .001$, $\eta^2 = .095$, and LIA, $F(2) = 4.110$, $p = .017$, $\eta^2 = .029$, during the different periods. Suicidal ideation in PIA during T-growth was significantly lower than that during T-before ($p = .003$) and T-decline ($p < .001$). Suicidal ideation in LIA during T-decline was significantly lower than that during T-before ($p = .014$).

Negative Self-Evaluation

There was no significant difference between PIA and LIA during T-before, $F(1) = 2.487$, $p = .116$, $\eta^2 = .009$, and during T-growth, $F(1) = 0.493$, $p = .483$, $\eta^2 = .002$ (Figure 3c). Negative self-evaluation in PIA was significantly higher than in LIA during T-decline, $F(1) = 98.369$, $p < .001$, $\eta^2 = .264$. There were significant differences regarding negative self-evaluation in PIA, $F(2) = 17.949$, $p < .001$, $\eta^2 = .116$, and LIA, $F(2) = 11.054$, $p < .001$, $\eta^2 = .075$ during different periods. Negative self-evaluation in PIA during T-growth was significantly lower than that during T-before ($p = .008$) and T-decline ($p < .001$). Negative self-evaluation in LIA during T-decline was significantly lower than that during T-before ($p < .001$) and T-growth ($p = .001$).

Hostility

There was no significant difference between PIA and LIA during T-before, $F(1) = 0.087$, $p = .769$, $\eta^2 < .001$, and during T-growth, $F(1) = 1.081$, $p = .299$, $\eta^2 = .004$ (Figure 3d). The hostility in PIA was significantly higher than in LIA during T-decline, $F(1) = 127.241$, $p < .001$, $\eta^2 = .317$. There were significant differences regarding hostility in PIA, $F(2) = 26.654$, $p < .001$, $\eta^2 = .163$, and in LIA, $F(2) = 13.473$, $p < .001$, $\eta^2 = .090$, during different periods. Hostility in PIA during T-decline was significantly higher than that during T-before ($p < .001$) and T-growth ($p < .001$). The hostility in LIA during T-decline was significantly lower than during T-before ($p = .012$) and T-growth ($p < .001$).

These results clearly show that there were no significant differences between PIA and LIA in the four dimensions of the likelihood of suicide before the outbreak of COVID-19. There was no difference between PIA and LIA before the outbreak, and all dimensions were at the same baseline.

Discussion

In this study, we predicted suicide probability (hopelessness, suicidal ideation, negative self-evaluation, and hostility) among active Weibo users in PIA and LIA, from December 1, 2019 to April 18, 2020. Our results indicated that COVID-19 had an impact on the changes in suicide probability. The impact was diverse in different regions during different periods.

During the COVID-19 growth period, suicidal ideation and negative self-assessment significantly decreased in PIA while hopelessness increased in LIA. The results are consistent with previous studies, which found that people's negative emotions negatively correlate with the severity of the epidemic (Xie et al., 2011). The theory of cognitive dissonance might explain these results (Festinger, 1975); this theory claims that when people cannot change their environment, they change their cognition to reduce anxiety and discomfort caused by cognitive dissonance. People in PIA were unable to travel or relocate to LIA in China, and thus they transformed the cognition of "the epidemic caused many dangers" into "the epidemic can be controlled, and there is no need to worry" so as to avoid cognitive dissonance (Xu et al., 2020).

The influence of risk events increases through media publicity or other informal channels, affecting people in LIA (Kasperson et al., 1988). By contrast, people in PIA may automatically correct the "amplified" information due to their direct contact and experience of the COVID-19 pandemic. This results in people in these areas having a correct understanding of risk events that will not quickly generate excessive negative cognition (e.g., suicidal ideation, negative self-evaluation).

In addition, the mere exposure effect claims that repetitive presentation of stimuli leads to a decreased sensitivity to the stimuli (Zajonc, 2001). People in PIA had been exposed to risk stimuli for a long time, and their adaptability to risks had increased over time, leading to a relatively stable mental state (Li et al., 2010). Therefore, compared with the mental state of those in PIA, people in LIA are more likely to show higher negative emotions (e.g., hopelessness), which may become an intolerable psychological pain. When the pain reaches a peak, and future changes cannot be predicted, some individuals may seek to free themselves from pain by ending their lives (Shneidman, 1993).

During the COVID-19 decline period, hopelessness and hostility increased significantly in PIA while suicidal ideation, negative self-assessment, and hostility decreased in LIA. The spread of COVID-19 in LIA was successfully under control during the decline period. The loss in LIA was relatively small, and there was no severe catastrophic trauma. Hence people in LIA were less aware of negative emotions, since they were in healthy mental states. According to the data released by the National Health Commission, the mortality rate was only approximately 2% before February 13, 2020, while it grew to 5.51% on April 18, 2020. This means that people in PIA had more traumatic experiences and loss, such as the pain of physical diseases or the death of loved ones. They were under severe psychological distress, causing negative changes in their ego (Bolger, 1999) with negative cognitive schemas of the future (Beck et al., 1974). These would trigger an increase in negative psychological indicators such as hopelessness and hostility, which may result in suicide.

Brende (1998) proposed that people in PIA usually traverse through five psychological and emotional phases after the occurrence of a public health emergency. In the period of early adaptation, people in PIA might doubt and deny the criticality of the situation, referring to a relatively low-risk perception of the epidemic and less negative emotions (Zheng et al., 2015). However, during the period of late-phase adaptation (usually 1–2 months after an outbreak), people in PIA are likely to develop hostile reactions, and even suicide (Chou et al., 2003), since the actual losses caused by the epidemic are gradually exposed over time. Moreover, the prevalence of mental disorders (e.g., posttraumatic stress disorder) might aggravate suicide probability in PIA (Kessler et al., 1999).

Our findings suggest that suicide prevention should be designed by targeting different regions during different periods of the epidemic. People in PIA are relatively calm during the growth period of the outbreak due to changes in cognition and a relatively comprehensive understanding of the information related to the epidemic. They may need supplies and measures against the epidemic rather than psychological counseling. By contrast, people in LIA tend to misjudge the development of the event due to cognitive bias, resulting in a strong sense of hopelessness. Therefore, psychological crisis consultation and the release of accurate information are needed in time to prevent severe consequences such as suicide. During the decline period, people in PIA experience severe trauma, such as the death of loved ones. They are more prone to stress disorders and even suicide. At this point, psychological assistance should be provided in time for suicide prevention. Social support can be provided (Ahern et al., 2004), and positive policy and messages can be released through mass media to offer encouragement to these groups (Vasterman et al., 2005). In addition, since the overall mental state of people in LIA has gradually returned to normal, showing a relatively low probability of suicide, some designated psychological counseling hotlines can provide enough help. These findings show the changing patterns in people's suicide possibility after public health emergencies, which can help to choose a reasonable time for intervention and identify the areas that need assistance.

Limitations

These findings must be considered in light of some important limitations. First, Weibo users are mostly young people and females, and results have limitations in generalizability. However, previous studies have shown that social media data are useful for examining people's mental health (Liu et al., 2018). Hence, these results are reliable to a certain extent but should be used with caution. Second, previous studies indicate that there are specific differences in various cultures when people experience traumatic events (Zheng et al., 2020). Since the current study only explores changes in China, cross-cultural research should be considered in the future.

Conclusion

In this study, we compared the suicide probability (hopelessness, suicidal ideation, negative self-evaluation, and hostility) between PIA and LIA in China at various stages of the epidemic. The results showed that LIA had an increase in hopelessness during the COVID-19 growth period, while hopelessness and hostility in PIA increased during the COVID-19 decline period, suggesting suicide probability. Using OSN data can help to understand the impact pattern of COVID-19 on people's suicide probability to some extent. It may assist in identifying high-risk areas with psychological crises and provide guidance for preventing severe consequences such as suicide.

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