Measuring daily-life fear perception change: a computational study in the context of COVID-19

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Abstract

Background: COVID-19, as a global health crisis, has triggered the fear emotion with unprecedented intensity. Besides the fear of getting infected, the outbreak of COVID-19 also created significant disruptions in people's daily life and thus evoked intensive psychological responses indirect to COVID-19 infections.

Objective: This study aims to develop novel digital trackers of public fear emotion during the COVID-19 pandemic, and to uncover meaningful topics that the citizens are concerned about to inform policy decision-making.

Methods: We construct an expressed fear database using 16 million social media posts generated by 536 thousand users in China between January 1st, 2019 and August 31st, 2020. We employ Bidirectional Encoder Representations from Transformers (BERT) to detect the fear emotion within each post and apply BERTopic to extract the central fear topics.

Results: We find that on average, 2.45% of posts per day having fear as the dominant emotion in 2019. This share spiked after the COVID-19 outbreak and peaked at 9.1% on the date that China's epi-center Wuhan city announced lockdown. Among the fear posts, topics related to health takes the largest share (39%). Specifically, we find that posts regarding sleep disorders (Nightmare and Insomnia) have the most significant increase during the pandemic. We also observe gender heterogeneity in fear topics, with females being more concerned with health while males being more concerned with job.

Conclusions: Our work leverages the social media data coupled with computational methods to track the emotional response on a large scale and with high temporal granularity. While we conduct this research in a tracing back mode, it is possible to use such a method to achieve real-time emotion monitoring, thus serving as a helpful tool to discern societal concerns and aid for policy decision-making.

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Original Manuscript

Original Paper

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Keywords: COVID-19; social media; fear; data-driven; health

Introduction

Fear is one of the six basic emotions [1], which is commonly considered to be a brief episode of response to a given threat, either physical or psychological [2,3]. Fear is not merely generated by the direct exposure to a threat to oneself [4]. It can also be transmitted indirectly through social transmission [5]. The perception of fear influences the decision-making process [4] and ultimately translates into behavioral change to help individuals avoid or confront the threat [6–8]. However, besides its benefits, fear could also lead to chaos in society. For instance, panic buying is a typical response to the uncertainty of crises, which depletes public resources rapidly and unnecessarily [9]. In other cases, the emotion of fear evoked by the social and political environment could lead to violence and protests [10].

Against this background, it is crucial for policy-makers to understand the causes and development of fear to solve the problems and calm down public anxiety [2]. With a good understanding of the sources and evolution of fear emotion, this seemingly negative emotion could even serve as a valuable tool for public agencies to promote socially desirable actions, such as conservation behaviors to mitigate climate change [11] and social distancing behaviors during epidemics [12].

Previous studies have found that disasters and crises could induce fear emotion [13]. COVID-19, as a global health crisis, has triggered fear vastly with unprecedented intensity [14,15]. Such fear is not merely driven by virus infection. As the pandemic is accompanied by the implementation of non-pharmaceutical policy interventions, the outbreak of COVID-19 has created enormous impacts on people’s daily life and evokes intensive psychological responses not directly related to COVID-19 infections [16,17].

Researchers and policy-makers mainly rely on surveys to measure fear perception [18]. However, surveys have their limitations, such as limited scalability, potential sample bias, high cost, and significant time delays [19]. These drawbacks are especially prominent in the context of COVID-19 when the public sentiment evolved rapidly, and timely interventions are critical for lives. When coupled with machine learning techniques, social media platforms could serve as a valuable tool, which enables the monitoring of public emotions with high temporal and spatial granularity. For example, using social media posts, Dodds et al. [20] explored the temporal pattern of emotions for 63 million users non-invasively; Mitchell et al. [21] estimated geographical happiness distribution using the geotagged Twitter. A recent study also shows the high correlation between social media expressed emotion measurement and traditional surveys [22], supporting the validity of such natural language processing (NLP) methods to measure emotion.

In this paper, we study how COVID-19 triggered fear for different aspects of people’s daily life (the contents that people posted not directly mentioning the virus-related words). This is achieved by using the Bidirectional Encoder Representations from Transformers (BERT) model to detect fear contents and the BERTopic to extract fear-related topics on a self-constructed social media dataset.

Methods

Data Collection and Preprocessing

We collect the social media data from Sina-Weibo’s (the largest microblogging social media platform in China) application programming interface. The data contains 16 million original posts from a cohort of 536 thousand active users between January 1st, 2019, and August 31st, 2020.

Besides the raw content, we collect the exact posting time, number of likes, and re-posts for each post. To ensure data quality, we follow several rules when collecting data and constructing the research database: 1) We only collect posts from those users who registered before January 1st, 2019; 2) We exclude the posts generated by institutional accounts (e.g., companies and organizations) from our sample; 3) We drop users with post numbers within the top 10% to reduce the influence from extreme posters; 4) We randomly select and scrutinize 50 thousand posts to identify advertisements with a fixed format (For instance: I am the 3545th to celebrate the shopping festival, please join us!). We then apply regular expressions to remove advertisements in these formats for all posts; 5) We apply a series of functions to remove URLs, emojis, special characters, hash symbols from the posts to reduce the impacts of irrelevant information.

We retrieve the publicly accessible personal information from the profile page of each individual in our sample, including the birth date, gender, number of fans, number of followers, and the registration location. (Supplementary Table A.1) shows the summary statistics of our users. All people provide gender information, with 65.31% users reported to be a woman. 63.0% users provide birth date, with average age of 29.01 (SD = 5.85, Min = 10, Max = 80). Supplementary Figures A.2 and A.3 show the comparison of location and age distribution between Weibo users and Chinese 2010 census data.

Expressed Fear Emotion Classification Using Natural Language Processing

NLP is a computational method that translates unstructured large-scale text data into structured measures [23]. Sentiment analysis, a sub-area of NLP, is purposefully designed to evaluate the emotional status embedded in the text [24]. An increasing number of studies attempt to detect the change of perceptions or attitudes on social media either towards general or specific topics based on the measures generated from these methods [25].

In this study, we use BERT, a text classification model developed by Google [26], to classify each post into six categories of emotions (i.e., Anger, Fear, Happiness, Sadness, Surprise, and Others). Specifically, we finetune a pre-trained BERT model provided by [27] using our data and then impute the likelihood of expressing emotion in each post for each of the six emotions. The posts are tagged with the emotion of the highest possibility. Supplementary Section B.1 describes the construction of the training dataset according to Lyu et al. [28]; Supplementary Figure B.2 displays the performance of our trained model in classifying fear posts; Supplementary Figure B.3 shows the temporal trend of the six emotions, which depicts that the major emotional response during COVID-19 is the fear emotion.

To better understand how the fear in topics not directly related to COVID-19 developed, we construct a dictionary of COVID-19 related words (Supplementary Table B.4). The post that contains any word in the list will be treated as COVID-19 related posts. Supplementary Figure B.5 shows how fear posts classified as COVID-19 and non-COVID-19 related evolved on a daily basis.

Topic Modeling

To understand why people express fear emotion in social media, we implement the topic model to discover the abstract topics within the dataset. Such a method is widely used by researchers to understand the public attentions and opinions [29,30]. BERTopic is a state-of-the-art machine learning method that leverages BERT embeddings, uniform manifold approximation and projection (UMAP) dimensionality reduction, hierarchical density-based spatial clustering of applications with noise (HDBSCAN), and class-based term frequency-inverse document frequency (c-TF-IDF) [31] to identify interpretable topics. Using a pre-trained multi-lingual sentence embedding model to encode the text, we apply BERTopic on non-COVID-19 fear posts to identify the fear sources in people's daily life. We apply the model on COVID-19 posts as well to support the analysis. To decide the best topic size, we impute the coherence score by varying the number of clusters. As shown in Supplementary Figure C.1, topic sizes of 60 and 30 are chosen for the two groups respectively. We re-run the algorithm and display the most informative words of each topic (using c-TF-IDF) in Supplementary Table C.2.1 and C.2.2. For sample posts in topic clusters, please refer to

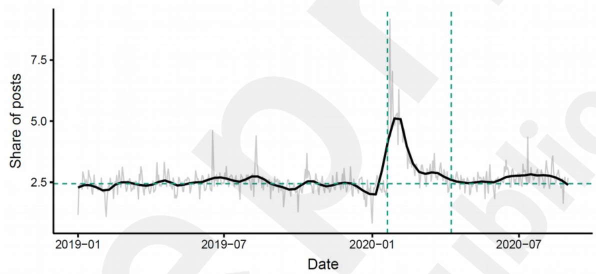
Supplementary Table C.3.

Results

Emotion classification

We find that fear emotion is relatively stable across 2019. There are 2.45% posts on average classified as fear posts (i.e., posts dominated by fear emotion) for each day, while the share reaches a peak of 9.1% on January 23rd (the date that epi-center Wuhan city announced lockdown). The share of fear posts drops afterward and remains 2.64% of total posts after April 8th, 2020, slightly higher than the 2019 baseline.

Figure 1. Line graph shows the daily trend of the share of fear posts among all posts. Light grey and the dark black line show the original and smoothed time series respectively. To better locate the peak COVID-19 period, we draw two vertical dashed lines in the plot showing the start of COVID-19 (left, January 20th) and the re-open date of Wuhan city (right, April 8th). The horizontal dashed line depicts the average share of posts during the year 2019.



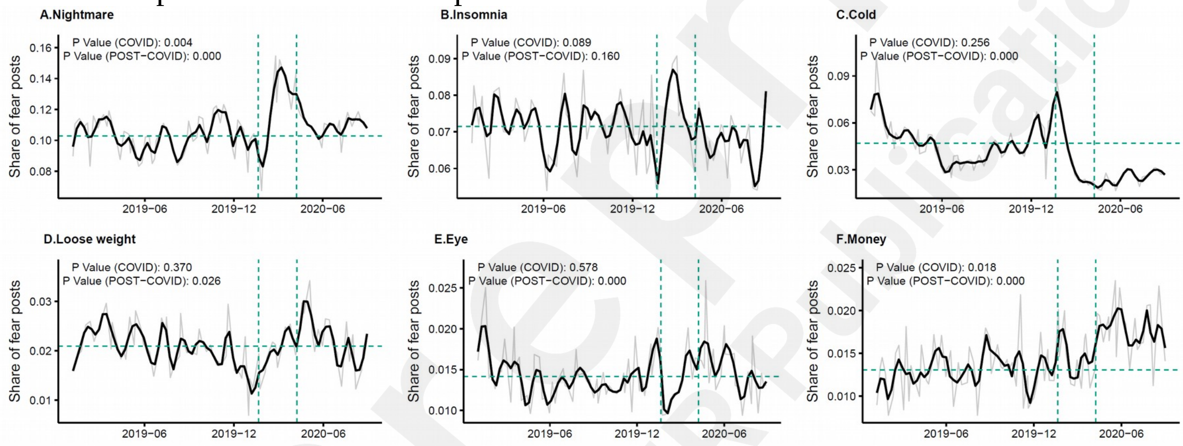
Evolution of non-COVID-19 related fear topics

BERTopic automatically splits the data into meaningful clusters. There are 60 fear topics unrelated to COVID-19, lying into six large categories (Supplementary Table C.2.2 and Figure D.1). Health-related fear topics take up the largest share among all the fear posts, followed by relationship, weather and catastrophe, transportation and work/ education. To identify the fear alterations, we conduct t-tests to compare the fear share by topics during and after the peak COVID-19 pandemic with the same period in 2019. Specifically, we define the pandemic periods in China as follows: (1) COVID-19 peak period started from January 20th, 2020 and ended on April 8th, 2020 (i.e., the date when Wuhan city, the epi-center of COVID-19 pandemic in China, re-opened); (2) post-COVID-19 period started from April 9th and ended at August 31st for 2020. Health and work-related topics had the largest change during the COVID-19.

For health-related topics, we find that topics regarding sleep (i.e., nightmare and insomnia) have the largest share in fear posts during our sample period of two years. On average, 10% and 7% of fear posts are related to nightmares and insomnia, respectively. As shown in Figure 2, during the COVID-19 peak period, fear posts with contents of “nightmare” significantly increased, reaching a share of 16% of all fear posts. Though this share dropped after the COVID-19 peak period, it remains significantly higher than the same period in 2019 until the end of August, indicating a long-lasting impact. Since “nightmare” could be expressed not only as having an unpleasant dream but also as a way to describe a disastrous event, we further explore the posting time within a day to check whether the fear posts are likely to be sleep-related. We assume that if the “nightmare” is used to describe the awful dream, people are more likely to post in the morning right after having a bad sleep. The results in Supplementary Figure D.2 indeed show that posts about “nightmare” are concentrated in the early morning, and the posting times within a day are similar in 2019 and 2020, indicating that there is no significant change in word usage. “Insomnia”, i.e., unable to sleep, displays a similar spike during the COVID-19 peak period (Figure 2), suggesting that people were more likely to have difficulty falling asleep. However, the share of “insomnia” posts soon recovered to pre-pandemic status after April. Besides sleep disorders, among health topics, we also notice a significant drop in posts mentioning “cold and fever”, and a significant increase in posts mentioning “lose weight” and “eye” (Figure 2).

Besides health, work is one of the key areas for which the COVID-19 pandemic created significant impacts. Many researchers have identified the economic impacts of COVID-19 [14,32]. The lockdown policy could curb the infections but at the same time prevent people from going to work. The share of posts mentioning “money” increased significantly since the beginning of the COVID-19, suggesting the rises in financial concerns. After checking the content of posts, we find that people are paying more attention to the importance of having money imposed by the pandemic.

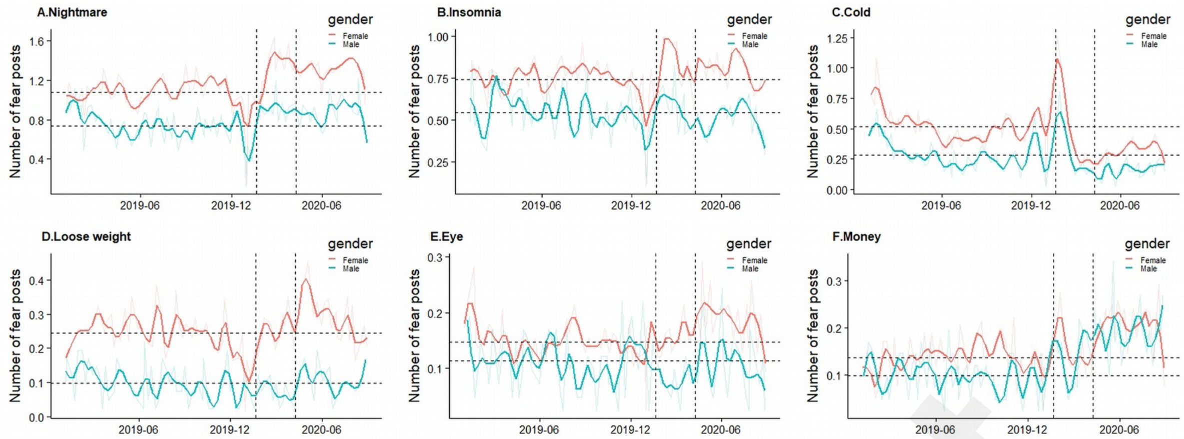
Figure 2. Line graphs show the number of posts for nine non-COVID-19 related topics by week. The name of each subplot is the most informative word for each topic. The dark solid lines in each subplot display the smoothed number of posts per day. *P*-value (COVID) and *P*-value (post-COVID) indicate the t-test results testing the differences of trend between 2020 peak COVID-19/ post-COVID-19 periods with the same period in 2019.



Gender difference

Researchers have identified significant gender differences during the COVID-19 period in aspects such as risk perception, time use, and compliance to social distancing policies [33,34]. Here, we explore the difference between genders regarding fear perceptions and topics. Females in general have a higher tendency to express fear. On average, a female user generates 2.27 fear posts during our research period, while a male user only generates 1.89 fear posts. For each topic, we apply four t-tests to detect the gender differences in the COVID-19 peak period and the post-COVID-19 period between 2019 and 2020 (Supplementary Table D.4)

Figure 3. Line graphs show the average number of fear posts generated by every 1,000 users in each gender by week (Female: solid line above, Male: solid line below). Two horizontal dashed lines depict the baselines (the mean values of 2019) by gender. Two vertical dashed lines show the start date of COVID-19 (January 20th) and the re-open date of Wuhan (April 8th).



Regarding the fear related to “nightmare”, we find that both genders increase posting during the COVID-19 period, with females having a larger and more significant extent (coefficient = 0.251, *P*-value = .005) comparing to males (coefficient = 0.103, *P*-value = .193). After the COVID-19 peak period, both genders remain to have a significantly higher frequency of nightmare-related fear posts (with coefficients of 0.270 and 0.197 for females and males respectively). The insomnia topic also shows a similar pattern that the female had a significant increase in posting during the COVID-19 period (coefficient = 0.1, *P*-value = .057). The results from the two sleep-related topics suggest that females are more likely to have sleep disorders during the COVID-19. And such impact lasts for months.

We also detect the differential changes by gender in the “cold and fever” topic. Cold and fever are prevalent in winter seasons, as shown by the peaks at the beginning of 2019 and 2020. However, unexpectedly, the post number drops quickly during the COVID-19 period. Females reduce the posts related to the “cold and fever” topic for non-COVID-19 related posts more than males. The reason for such difference is that females have a higher tendency to associate cold and fever symptoms to COVID-19, which again, reflects potentially higher mental stress of females during the pandemic.

Another pattern we find is related to losing weight. Males post less during the COVID-19 period while females increase their posting after the COVID-19 peak period in this topic. This suggests that people in our sample were less concerned about body shape during the peak pandemic period yet soon start to pay more attention to it once they need to resume work and social activities. The increasing concerns for weight loss could also indicate a reduction in physical activity, as found in previous studies [34].

Regarding monetary topics, both males and females increase their posting behavior during the COVID-19 period, with males having a larger extent (coefficient = 0.042, *P*-value = .064) comparing to females (coefficient = 0.034, *P*-value = .051). Such a concern becomes more significant after the COVID-19 peak period (Male coefficient = 0.090, *P*-value = .000; Female coefficient = 0.062, *P*-value = .000). The work-related topic result shows that, in opposite to health-related topics, males pay more attention to the economic side, indicating a different type of stress. The result could serve as a potential explanation of why men are having a higher suicide rate during the COVID-19 period [35].

Discussion

In conclusion, our study shows that the COVID-19 has altered people’s fear perception towards daily life topics unrelated to virus infection, and the perception change can last for months after the peak pandemic period. We find that the daily-life fear topics in the COVID-19 period which has significant change can be best classified into three clusters: (1) symptoms of fear (such as “nightmare”, “insomnia”), (2) fear related to other health problems (such as “lose weight”, “eye”), (3) fear about socio-economic consequences (such as “money”).

Our results have important implications. First, the significant increases in fear towards these topics indicate an increase in the mental distress and anxiety caused by the COVID-19. Our result shows that fear posts related to “nightmare”, the largest non-COVID-19 related fear source, take up a significantly higher proportion of fear posts even months after the peak pandemic. Deteriorated sleep quality brought by mental distress during the COVID-19 could contribute to latent risks for the population's physical and psychological health, which should receive added attention. Second, our results suggest that COVID-19 and related policies induced health and financial concerns. Staying at home was accompanied by a reduction in physical activities and an increase in screen time, thus inducing more fear posts for weight and eye problems. The increased attention to “money” indicates that people were also faced with higher economic burdens during the pandemic. These results reveal the importance of paying attention to the broader social consequences of the COVID-19 on people’s daily life, instead of solely focusing on the COVID-19 related posts when analyzing the fear response. Finally, our findings indicate that females are more affected by the COVID-19 in general while males are more concerned with work-related issues points out the importance to explore further the reasons that underlie the sub-group differences in fear responses. Such investigations can assist the designs of tailored policies for the vulnerable population.

Our work leverages the large-scale social media data coupled with computational methods to track the emotional response on a larger scale and with higher temporal granularity than the traditional surveys. Although we conduct this research in a tracing back mode, it is possible to use such a method to achieve real-time emotion monitoring, thus serving as a helpful tool to discern societal concerns and aid for policy decision-making. Our method also has several limitations. First, users of social media platforms might not be able to represent the whole population. Research has found that social media users are younger and are more concentrated in big cities [36] which we also observe in our sample. Second, we use the expressed fear within posts to proxy the fear emotion. Whether the expressed emotion could accurately represent the inner emotional state is still a nascent research area and thus without a clear conclusion. Third, even if the expressed fear can represent the actual feeling of users, we only observe changes in the number of posts with fear as the dominant emotion. Our algorithm does not directly measure the fear intensity of each post at the current stage. Fourth, comparing to a delicately designed survey, using the data-driven method to automatically extract information from unstructured social media posts has unavoidable measurement errors, since the neural network can only capture the general knowledge from training samples and neglects the varying outliers. We hope that our work can motivate more future studies to explore the value of computational methods to understand human emotions and behaviors.

Authors’ Contributions

YC, SZ and JP conceptualized the study. JW and YC were responsible for data collection, and YC performed formal analysis. JW took care of methodology optimization. YC, JP and YF contributed to writing (original draft). All authors contributed to the design of analysis and writing (review and editing)

Conflicts of Interest

None declared.

Abbreviations

BERT: Bidirectional Encoder Representations from Transformers
c-TF-IDF: class-based term frequency-inverse document frequency
NLP: natural language processing

SD: standard deviation

References

1. Sauter DA, Eisner F, Ekman P, Scott SK. Cross-cultural recognition of basic emotions through nonverbal emotional vocalizations. Proc Natl Acad Sci U S A [Internet] 2010 Feb 9;107(6):2408–2412. PMID:20133790

2. Scherer KR. Emotion as a multicomponent process: A model and some cross-cultural data. Pers Soc Psychol Rev [Internet] 1984;5:37–63. Available from: https://psycnet.apa.org/fulltext/1986-17269-001.pdf

3. Adolphs R. The biology of fear. Curr Biol [Internet] 2013 Jan 21;23(2):R79-93. PMID:23347946

4. Lindström B, Golkar A, Jangard S, Tobler PN, Olsson A. Social threat learning transfers to decision making in humans. Proc Natl Acad Sci U S A [Internet] 2019 Mar 5;116(10):4732–4737. PMID:30760585

5. Haaker J, Golkar A, Selbing I, Olsson A. Assessment of social transmission of threats in humans using observational fear conditioning. Nat Protoc [Internet] 2017 Jul;12(7):1378–1386. PMID:28617449

6. Olsson A, Phelps EA. Social learning of fear. Nat Neurosci [Internet] 2007 Sep;10(9):1095–1102. PMID:17726475

7. Greist JH, Marks IM, Berlin F, Gournay K, Noshirvani H. Avoidance versus confrontation of fear. Behav Ther [Internet] Elsevier; 1980 Jan 1;11(1):1–14. [doi: 10.1016/S0005-7894(80)80031-1]

8. Eder SJ, Steyrl D, Stefanczyk MM, Pieniak M, Martínez Molina J, Pešout O, Binter J, Smela P, Scharnowski F, Nicholson AA. Predicting fear and perceived health during the COVID-19 pandemic using machine learning: A cross-national longitudinal study. PLoS One [Internet] 2021 Mar 11;16(3):e0247997. PMID:33705439

9. Bentall RP, Lloyd A, Bennett K, McKay R, Mason L, Murphy J, McBride O, Hartman TK, Gibson-Miller J, Levita L, Martinez AP, Stocks TVA, Butter S, Vallières F, Hyland P, Karatzias T, Shevlin M. Pandemic buying: Testing a psychological model of over-purchasing and panic buying using data from the United Kingdom and the Republic of Ireland during the early phase of the COVID-19 pandemic. PLoS One [Internet] 2021 Jan 27;16(1):e0246339. PMID:33503049

10. van Troost D, van Stekelenburg J, Klandermans B. Emotions of Protest. In: Demertzis N, editor. Emotions in Politics: The Affect Dimension in Political Tension [Internet] London: Palgrave Macmillan UK; 2013. p. 186–203. [doi: 10.1057/9781137025661_10]

11. Stern PC. Fear and hope in climate messages. Nat Clim Chang [Internet] Nature Publishing Group; 2012 Jun 17 [cited 2021 May 10];2(8):572–573. [doi: 10.1038/nclimate1610]

12. Yan Y, Malik AA, Bayham J, Fenichel EP, Couzens C, Omer SB. Measuring voluntary and policy-induced social distancing behavior during the COVID-19 pandemic. Proc Natl Acad Sci

U S A [Internet] 2021 Apr 20;118(16). PMID:33820846

13. Cvetković VM, Öcal A, Ivanov A. Young adults' fear of disasters: A case study of residents from Turkey, Serbia and Macedonia. Int J Disaster Risk Reduct [Internet] Elsevier BV; 2019 Apr;35(101095):101095. [doi: 10.1016/j.ijdrr.2019.101095]

14. Witteveen D, Velthorst E. Economic hardship and mental health complaints during COVID-19. Proc Natl Acad Sci U S A [Internet] 2020 Nov 3;117(44):27277–27284. PMID:33046648

15. Presti G, Mchugh L, Gloster A, Karekla M, Hayes SC. The dynamics of fear at the time of covid-19: a contextual behavioral science perspective. Clinical Neuropsychiatry [Internet] 2020;17(2).

16. Pérez-Fuentes MDC, Molero Jurado MDM, Martos Martínez Á, Gázquez Linares JJ. Threat of COVID-19 and emotional state during quarantine: Positive and negative affect as mediators in a cross-sectional study of the Spanish population. PLoS One [Internet] 2020 Jun 25;15(6):e0235305. PMID:32584897

17. Mahmud MS, Talukder MU, Rahman SM. Does "Fear of COVID-19" trigger future career anxiety? An empirical investigation considering depression from COVID-19 as a mediator. Int J Soc Psychiatry [Internet] 2020 Jul 2;20764020935488. PMID:32615833

18. Ahorsu DK, Lin C-Y, Imani V, Saffari M, Griffiths MD, Pakpour AH. The Fear of COVID-19 Scale: Development and Initial Validation. Int J Ment Health Addict [Internet] Springer; 2020 Mar 27;1–9. PMID:32226353

19. Nayak M, Narayan KA. Strengths and weakness of online surveys. IOSR Journal of Humanities and Social Science [Internet] 2019;24(5):31–38.

20. Dodds PS, Harris KD, Kloumann IM, Bliss CA, Danforth CM. Temporal patterns of happiness and information in a global social network: hedonometrics and Twitter. PLoS One [Internet] 2011 Dec 7;6(12):e26752. PMID:22163266

21. Mitchell L, Frank MR, Harris KD, Dodds PS, Danforth CM. The geography of happiness: connecting twitter sentiment and expression, demographics, and objective characteristics of place. PLoS One [Internet] 2013 May 29;8(5):e64417. PMID:23734200

22. Jaidka K, Giorgi S, Schwartz HA, Kern ML, Ungar LH, Eichstaedt JC. Estimating geographic subjective well-being from Twitter: A comparison of dictionary and data-driven language methods. Proc Natl Acad Sci U S A [Internet] 2020 May 12;117(19):10165–10171. PMID:32341156

23. Gentzkow M, Kelly B, Taddy M. Text as Data. J Econ Lit [Internet] 2019 Sep [cited 2021 May 24];57(3):535–574. [doi: 10.1257/jel.20181020]

24. Zhang L, Wang S, Liu B. Deep learning for sentiment analysis: A survey. Wiley Interdiscip Rev Data Min Knowl Discov [Internet] Wiley; 2018 Jul;8(4):e1253. [doi: 10.1002/widm.1253]

25. Zheng S, Wang J, Sun C, Zhang X, Kahn ME. Air pollution lowers Chinese urbanites' expressed happiness on social media. Nat Hum Behav [Internet] Springer Science and Business Media LLC; 2019 Mar;3(3):237–243. PMID:30953012

26. Devlin J, Chang M-W, Lee K, Toutanova K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding [Internet]. arXiv [csCL]. 2018. Available from: http://arxiv.org/abs/1810.04805

27. Liu Y, Ott M, Goyal N, Du J, Joshi M, Chen D, Levy O, Lewis M, Zettlemoyer L, Stoyanov V. RoBERTa: A Robustly Optimized BERT Pretraining Approach [Internet]. arXiv [csCL]. 2019. Available from: http://arxiv.org/abs/1907.11692

28. Lyu X, Chen Z, Wu D, Wang W. Sentiment Analysis on Chinese Weibo Regarding COVID-19. Natural Language Processing and Chinese Computing [Internet] Springer International Publishing; 2020. p. 710–721. [doi: 10.1007/978-3-030-60450-9_56]

29. Han X, Wang J, Zhang M, Wang X. Using Social Media to Mine and Analyze Public Opinion Related to COVID-19 in China. Int J Environ Res Public Health [Internet] 2020 Apr 17;17(8). PMID:32316647

30. Boon-Itt S, Skunkan Y. Public Perception of the COVID-19 Pandemic on Twitter: Sentiment Analysis and Topic Modeling Study. JMIR Public Health Surveill [Internet] 2020 Nov 11;6(4):e21978. PMID:33108310

31. Bhuiyan AKMI, Sakib N, Pakpour AH, Griffiths MD, Mamun MA. COVID-19-Related Suicides in Bangladesh Due to Lockdown and Economic Factors: Case Study Evidence from Media Reports. Int J Ment Health Addict [Internet] 2020 May 15;1–6. PMID:32427168

32. Giurge LM, Whillans AV, Yemiscigil A. A multicountry perspective on gender differences in time use during COVID-19. Proc Natl Acad Sci U S A [Internet] National Academy of Sciences; 2021 Mar 23 [cited 2021 Mar 27];118(12). [doi: 10.1073/pnas.2018494118]

33. Galasso V, Pons V, Profeta P, Becher M, Brouard S, Foucault M. Gender differences in COVID-19 attitudes and behavior: Panel evidence from eight countries. Proc Natl Acad Sci U S A [Internet] 2020 Nov 3;117(44):27285–27291. PMID:33060298

34. Giuntella O, Hyde K, Saccardo S, Sadoff S. Lifestyle and mental health disruptions during COVID-19. Proc Natl Acad Sci U S A [Internet] 2021 Mar 2;118(9). PMID:33571107

35. Khan AR, Ratele K, Arendse N. Men, Suicide, and Covid-19: Critical Masculinity Analyses and Interventions. Postdigital Science and Education [Internet] 2020 Oct 1;2(3):651–656. [doi: 10.1007/s42438-020-00152-1]

36. Perrin A. Social media usage. Pew research center [Internet] secretintelligenceservice.org; 2015;125:52–68.

Supplementary Files

Multimedia Appendixes

Extended details on methods and data analysis.
URL: http://asset.jmir.pub/assets/7867c9bba875c5d390cb1e8ea1c14cf1.docx