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Mining voices from self-expressed messages on social-media: Diagnostics of mental distress during COVID-19

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ABSTRACT

The COVID-19 pandemic has had a severe impact on mankind, causing physical suffering and deaths across the globe. Even those who have not contracted the virus have experienced its far-reaching impacts, particularly on their mental health. The increased incidences of psychological problems, anxiety associated with the infection, social restrictions, economic downturn, etc., are likely to aggravate with the virus spread and leave a longer impact on humankind. These reasons in aggregation have raised concerns on mental health and created a need to identify novel precursors of depression and suicidal tendencies during COVID-19. Identifying factors affecting mental health and causing suicidal ideation is of paramount importance for timely intervention and suicide prevention. This study, thus, bridges this gap by utilizing computational intelligence and Natural Language Processing (NLP) to unveil the factors underlying mental health issues. We observed that the pandemic and subsequent lockdown anxiety emerged as significant factors leading to poor mental health outcomes after the onset of COVID-19. Consistent with previous works, we found that psychological disorders have remained pre-eminent. Interestingly, financial burden was found to cause suicidal ideation before the pandemic, while it led to higher odds of depressive (non-suicidal) thoughts for individuals who lost their jobs. This study offers significant implications for health policy makers, governments, psychiatric practitioners, and psychologists.

1. Introduction

1.1. Background and motivation

The arrival of the novel Coronavirus has caused significant suffering all around the world. The spread of SARS-COV-2 (COVID-19), a new virus linked to the family of Severe Acute Respiratory Syndrome (SARS) viruses, has paralysed communities, restricted socialization, caused physical sufferings, created economic stress, and led to the loss of millions of lives [1–4]. Historical evidences suggest that pandemics have had an overbearing impact on mental well-being, which outlast the viruses themselves [5–7]. Such large-scale pandemics bring about immense psychosocial and economic implications, surpassing medical and physical ailments [8,9]. The increased incidence of psychological problems, fear and anxiety related to the infection, social restrictions, financial stress, etc., aggravate with the virus spread and leave a longer negative impact on humankind [7,10,11].

The above reasons, particularly during the current unprecedented crisis, have contributed to mental distress, triggering suicidal ideation [12]. The impact of such mental distress is not limited to the general population but has also affected frontline workers and healthcare providers [13,14]. An in-depth understanding of precipitants and arising symptoms is pivotal in early diagnosis and detection of distressed individuals. This also helps prevent further ideation of suicidal tendencies [15,16]. Accordingly, identifying factors that lead to a higher risk of suicide in the vulnerable population is critical for timely intervention and prevention [5,12,15]. The risk factors, particularly in such challenging times may not directly lead to suicide, but the ripple effect of mass panic would trigger a myriad of psychological, social, neuroscientific, and economic factors causing mental distress [5,7,10]. Although measures such as self-isolation, social distancing, and quarantines have helped to reduce the virus spread, these measures have

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exacerbated concerns over mental health [5–7,10,17]. Consequently, there is an urgent need to have an in-depth understanding of stressors of mental distress, arising after the COVID-19 outbreak.

Recent studies have highlighted the need to explore, investigate, and gauge the psychological, social, and neuro-scientific aspects of mental health [7]. In particular, the need to examine the precipitating factors influencing mental distress due to the pandemic have been outlined as current research priorities [7,17,18]. Furthermore, the COIVD-19 pandemic might aggravate the known and pre-established antecedents of mental distress and suicidal tendencies [7,10,17]. This study drew its motivation from the above premise and explored the factors underlying mental distress, particularly, during this COVID-19 pandemic. For a fair assessment of its influence on mental distress, we also observed other factors affecting mental health before the onset of the pandemic.

Even earlier, scholars had acknowledged the importance of identifying stressors causing depressive thoughts and suicidal ideation [19–21]. These works mainly argued that the role and in-depth investigation of precipitants of mental distress had been largely neglected mainly due to the credibility of primary data, lack of self-reports, biased testimony of friends and relatives, and veiled methodology [22,23]. Even scholarly research focusing on the antecedents of mental illness, had had a narrow scope, concentrating on specific contexts which relied on the opinions of a handful of domain experts, observers, non-representative samples or lab-based results [24–27]. None of these previous attempts offered a holistic view of the factors concerning mental health, particularly from the sufferers themselves. Previous studies had acknowledged that social media platforms provided an easy and important outlet for individuals to express themselves [28–30]. Based on this foundation and the concept established by [31], we endeavoured to capture thoughts related to the mental health concerns of individuals, by collation of their posts (messages) of self-expression and feelings across the social media platforms, both before and after the onset of the pandemic.

In summary, the central objective of this research was to analyse social media messages from the sufferers of mental distress, both pre- and post-pandemic, to extract and identify the critical factors underlying mental health issues, specifically, depression and suicidal tendencies. We collected the self-reported thoughts and feelings of individuals through their posts on Twitter, a pre-eminent social media platform. Using computational intelligence and NLP, we uncovered the critically important but hidden factors which have significantly influenced depressive and suicidal tendencies in individuals. Furthermore, affective neuroscience suggests that depression or any related mental health concern is an outcome of mood or emotional disorder [32,33]. Moreover, the theory of emotional dysregulation suggests that people would tend to express extreme feelings when their emotions are more intense than the situations triggering them [34]. Prior research has also observed that emotional pain correlates with psychosocial aspects and overall pessimism, leading to suicidal ideation [13]. Thus, it becomes necessary to capture the antecedents of intense emotions in individuals. The literature has established that personal emotions are significant in the prediction of mental distress, especially chronic symptoms such as suicidal ideation [35,36]. In this regard, we postulated that various hidden factors would lead to the display of intense emotions, which in turn would impact the mental health of an individual.

From the groundwork of prior literature, we set out to measure the emotional intensity of self-expression. It has been previously shown that optimism and positive emotions such as humor in messages and posts on social media are negatively correlated with critical mental issues and suicidal ideation [37]. Based on the above premise, we captured both positive and negative emotions to create a composite score of the eight basic emotions. We called this measure an emotional valence and verified its role as a mediator between the identified factors and mental health issues. Specifically, this research posed the following questions:

1. What are the underlying factors affecting mental health during and post-COVID-19 situations?
2. What is the impact of the COVID-19 pandemic on the intensity of the known precipitants of mental health?
3. Does emotional valence mediate the relationship between the above-mentioned factors and mental health, both before and after COVID-19?

1.2. Research approach and contribution

Our work is distinct from the extant works due to our conceptualisation of a novel framework to understand the genesis of mental health concerns, particularly the impact of the Covid-19 pandemic on mental health. The in-depth understanding of stressors leading to mental health issues would give healthcare providers, medical practitioners, policy makers, and government agencies a more informed roadmap to take appropriate decisions and boost the morale of the masses. Moreover, on the known precipitants of mental health, we investigated the impact of factors using the pre-COVID-19 data from the literature [38–40]. Further, to investigate the precipitating factors before the onset of COVID-19, we resort to a secondary source hosting more than 2 million posts (2008–2021) pertaining to depression and suicidal ideation on the Reddit message board. Lastly, the additional postulation was to verify the mediating relationship of emotional valence.

This study adopted a rigorous research methodology. We identified the underlying factors and estimated their order of importance to explain depression and suicidal tendencies by a scientific approach. The model validation was based on more than 25,000 observations (including Twitter and Reddit posts), typically by those suffering from depression and having suicidal tendencies. The feature extraction models were based on various probabilistic distributions, such as the Latent Dirichlet Allocation (LDA) and Gaussian distribution. Note that “topic modelling” using Latent Dirichlet Allocation (LDA) is widely used to generate latent themes or underlying factors [28,41–43]. Moreover, in practice, most of the factors may be associated with each other. We thus relaxed the inherent assumptions of LDA and used more sophisticated models in our analysis [44]. As a consequence, both the Correlated Topic Model (CTM) and Structural Topic Model (STM) were adopted to help us extract both independent and correlated factors [45,46] in conjunction with LDA. Based on the principle of expectation-maximization, results using STM are deemed more generalisable and less prone to a narrow interpretation [44,47–49].

This methodology revealed that psychological disorder remained a predominant factor (across all models) for both pre- and post-COVID-19 contexts. Social rejection and social anxiety were found to be the antecedents before the onset of COVID-19. Notably, lockdown-related worries and anxiety associated with the spread of the virus, had caused significant mental distress. Post COVID-19, the model explanatory power was more than two-thirds, while it was observed to be less than 10% before the onset of COVID-19. This strongly indicates that this research successfully captured the underlying factors of mental illness in the context of COVID-19. We observed that specifically before the pandemic, emotional valence mediated the relationship between the underlying factors and mental health outcomes. Nevertheless, the mediating role of emotional valence was insignificant in the context of COVID-19. Accordingly, we concluded that external challenges and difficult situations would cause depression or suicidal ideation without the “intermediary role-play” of intense emotions. This conclusion opens new avenues of research for advocates of affective neuroscience and researchers on emotional dysregulation to verify their propositions throughout challenging times.

This research offers manifold contributions: First, the critical factors causing mental distress were identified from the self-expression of individuals, primarily by sufferers of mental illness. Using econometrics, the impact of various underlying factors and their order of importance were also ascertained. This would directly aid the decision-making process of practitioners, health workers, and social work professionals promoting mental well-being. This study also reflects on the most critical factors to be attended to for suicide prevention. Second, the use of emotional valence as a mediator confirms that psychological, social, and situational factors would lead to emotional distress, which in turn causes suicidal tendencies. Thus, it makes it possible to capture early warning signals of emotional distress by spotting individuals on social media platforms. This would aid health policy makers devise and eventually implement preventive strategies and provide assistance to sufferers, which is otherwise cumbersome through manual monitoring [31]. Third, focusing on the context of COVID-19, this work highlights factors pertaining to the natural consequences of the pandemic. Anxiety related to the virus spread and the stress caused by Lockdown measures were found to significantly and negatively impact mental health outcomes. Thus, governments and authorities of public administration should objectively account for such aspects while enforcing guidelines during lockdowns. The remainder of the paper explains the development of hypotheses, recent literature and detailed methodology. The major research findings are here reported with a discussion of the results. Finally, the paper concludes with implications of this study as well as outlines for the future research.

2. Development of hypotheses

The corona virus disease (COVID-19) has been associated with several mental health challenges. The disease has also raised concerns due to the psychological, social, and neurological impacts that it has brought to people [7]. A recent study on the residents of the UK & Ireland has found a moderate increase in the prevalence of mental health problems in the early stages of the pandemic [50,51]. In another study conducted in the US, it is found that depression symptoms are threefold higher during COVID-19 compared to pre-pandemic levels [52]. Likewise, in Turkey, it is found that the COVID-19 pandemic has psychologically affected women, individuals with previous psychiatric illness, individuals living in urban areas, and people living with chronic diseases [53]. In Hong Kong, it is also observed that one-fourth of respondents have complained of poorer mental health due to the pandemic spread [54].

Furthermore, it has been found that suicidal ideation and depression increased in the US and the UK due to the government-imposed lockdowns during the COVID-19 pandemic [11,55]. As a result, symptoms such as anxiety, depression, and stress have become very common and prominent during these challenging times [56]. This points towards an overall increase in the stress levels of individuals during the pandemic, leading to severe mental health disorders. Historically, strong evidence exists for the psychological disorder being a precursor to depression and suicidal ideation [57,58]. Thus, in order to answer the first research question investigating the factors underlying mental health, we propose the following hypothesis:

H1. *Psychological disorder leads to depression & suicidal ideation during COVID-19 pandemic.*

Mental health conditions have been found to deteriorate under the COVID-19 pandemic. Recent studies have also highlighted the role of emotional dysregulation in suicidal ideation in general [35,36]. Moreover, affective neuroscience suggests that depression or any related mental health concern is an outcome of a "mood or emotional" disorder [32,33]. The theories of emotional dysregulation have postulated and argued that intense emotions are a result of the underlying factors and may become severe, which can lead to self-harming tendencies [34–36]. Therefore, our second research question proposes that hidden factors can lead to the display of intense emotions, critically impacting mental health. To answer this research question, we correspondingly hypothesize that:

H1a. *Emotional valence mediates the relationship between psychological disorder and depression & suicidal ideation during the COVID-19 pandemic.*

In order to answer the second research question, i.e., gauge the impact of COVID-19 on the influence of psychological disorder on depressive versus suicidal thoughts, we also test the following:

H1b. *Psychological disorder leads to depression & suicidal ideation before the COVID-19 pandemic.*

H1c. *Emotional valence mediates the relationship between psychological disorder and depression & suicidal ideation before the COVID-19 pandemic.*

Recent research suggests statistically solid associations between pandemic fears and suicidal thoughts [11]. There have also been rising concerns about people experiencing a higher level of psychological stress, while facing social distancing in their homes. All these would lead to increased self-harm and suicidal ideations [56]. This work further establishes that lockdown restrictions have stimulated stress levels and suicidal ideation with each passing month. Hence, based on our research questions exploring the underlying factors and the mediating role of emotional valence, we hypothesize:

H2. *Pandemic related anxiety leads to depression & suicidal ideation.*

H2a. *Emotional valence mediates the relationship between pandemic related anxiety and depression/suicidal ideation during the COVID-19 pandemic.*

H3. *Lockdown related anxiety leads to depression & suicidal ideation.*

H3a. *Emotional valence mediates the relationship between lockdown related anxiety and depression/suicidal ideation during the COVID-19 pandemic.*

Existing research confirms a strong relationship between "substance abuse" and suicide [59]. Recent studies have also reported that an increased substance abuse as a means to cope with stress related to COVID-19 [55]. Accordingly, we hypothesize that:

H4. *Substance abuse leads to depression & suicidal ideation during the COVID-19 pandemic.*

H4a. *Emotional valence mediates the relationship between substance abuse and depression & suicidal ideation during the COVID-19 pandemic.*

Self-deprecating humor is associated with suicidal ideation in adolescents. A lack of self-respect or self-esteem in an individual would trigger self-deprecation which can lead to self-harm and suicidal behaviors [60,61]. As we can see from previous pandemics, COVID-19 can exacerbate shameful experiences, and echo a lack of self-respect. As a result, devastating effects on individual's mental health may appear. Hence, we hypothesize:

H5. *Self-deprecation leads to depression & suicidal ideation during the COVID-19 pandemic.*

H5a. *Emotional valence mediates the relationship between self-deprecation and depression & suicidal ideation during the COVID-19 pandemic.*

Pessimism has been found to be a predictor of suicidal risk. Former studies have well validated the role of pessimism in predicting suicidal tendencies in, e.g., university students [62]. Studies have also found that stress due to the COVID-19 pandemic has significantly increased the pessimism of individuals [18]. Hence, we hypothesize the following:

H6. *Pessimism leads to depression & suicidal ideation during the COVID-19 pandemic.*

H6a. *Emotional valence mediates the relationship between pessimism and depression & suicidal ideation during the COVID-19 pandemic.*

Based on the hidden factors explored using the pre-pandemic social media messages and posts, we also test the following:

H6c. *Pessimism leads to depression & suicidal ideation before the COVID-*

19 pandemic.

H6d. *Emotional valence mediates the relationship between pessimism and depression & suicidal ideation before the COVID-19 pandemic.*

Furthermore, financial problems due to job losses and unemployment are crucial factors leading to anxiety and stress [63,64]. Many previous studies have found that financial constraints are an antecedent of suicide, particularly for working-class people. The financial burden due to lack of economic opportunities has led to severe mental disorders such as suicidal ideation [65,66]. Furthermore, a recent study in the USA posited that due to the ongoing COVID-19 pandemic, people facing economic instability are vulnerable to depression, anxiety, alcoholism, and exacerbation of pre-existing psychological conditions, eventually leading to suicide [67]. Hence, we hypothesize the following:

H7. *Financial issues lead to depression & suicidal ideation during the COVID-19 pandemic.*

H7a. *Emotional valence mediates the relationship between financial issues and depression & suicidal ideation during the COVID-19 pandemic.*

Most of the studies previously from the medical sciences have observed financial stress as a strong trigger for depressive thoughts and suicidal ideation [63,65,66,68]. *Consequently, to also answer our second research question, we test for the following hypothesis so as to evaluate the effect of pandemic on the influence of this stressor:*

H7b. *Financial issues lead to depression & suicidal ideation before the COVID-19 pandemic.*

H7c. *Emotional valence mediates the relationship between financial issues and depression & suicidal ideation before the COVID-19 pandemic.*

In prior studies, suicidal ideation is found to be significantly associated with "perceived authoritarian parenting", insufficient parental warmth, high maternal control, harmful, improper child-rearing practices, and a negative family climate [69,70]. The earliest impact of job loss during the COVID-19 pandemic should be felt by parents. This would lead to mental health deterioration due to the loss of childcare and food security [52].

H8. *Parenting problems lead to depression & suicidal ideation during the COVID-19 pandemic.*

H8a. *Emotional valence mediates the relationship between parenting problems and depression & suicidal ideation during the COVID-19 pandemic.*

As mentioned above, parenting concerns have been one of the major precipitants of even in usual times. In order to gauge the impact of the pandemic outbreak on the influence of this underlying factor on mental health needs investigation. Accordingly, we test the following hypothesis:

H8b. *Parenting problems lead to depression & suicidal ideation before the COVID-19 pandemic.*

H8c. *Emotional valence mediates the relationship between Parenting problems and depression & suicidal ideation before the COVID-19 pandemic.*

Mental health issues have strong links to depression and suicidal ideation, which also remain a concern for children [69]. After the enforcement of lockdown policies, daycare, childcare facilities, schools, colleges, and similar institutions have remained closed and teaching have gone online via Zoom, MS Teams, etc. This has seriously impacted the socialization of the younger population [71]. Hence, we hypothesize that children rearing must have been more difficult during the COVID-19 pandemic. We hence postulate the following:

H9. *Family chores lead to depression & suicidal ideation during the COVID-19 pandemic.*

H9a. *Emotional valence mediates the relationship between family chores and depression & suicidal ideation the COVID-19 pandemic.*

To summarize, this work assimilates the variety of precipitating factors causing mental health problems. Most of the identified factors are specific to the COVID-19 pandemic context. Factors such as lockdown worries, pandemic anxiety, family responsibility, parenting concerns and financial burdens are observed in addition to the historically dominant causes of suicidal ideation. The exploratory nature of this work across the entire spectrum of pre and post COVID-19 has resulted in a significant number of factors underlying mental health. Such vast expression of inner thoughts and feelings would thus reflect the importance of social media in people's lives and well-being in general. We summarize in below some of the major contributions of machine learning based techniques in the study of the COVID-19 pandemic. (See Table 1).

Table 1
Table summarizing contribution of recent ML based studies on COVID-19.

Title	Author	Contribution
"Twitter Discussions and Emotions about Covid-19 Pandemic"	Xue et al. (2020)	This study uncovered unigrams and bigrams in text for multiple theme detection related to COVID-19
"Machine Learning to Detect Self – Reporting of Symptoms, Testing Access, and Recovery Associated with COVID 19 on Twitter: Retrospective Big Data Infoveillance Study"	Mackey et al. (2021)	This study used unsupervised machine learning for exploring the features of self-reporting of symptoms, experiences with testing, and mentions of recovery related to COVID-19 using relevant topic structures.
"Whether the Weather will Help us Weather the COVID-19 Pandemic"	Gupta et al. (2021)	This paper used topic modelling to identify perception of people on weather's effect on the pandemic
"CoAID-DEEP: An Optimized Intelligent Framework for Automated Detecting COVID-19 Misleading Information on Twitter"	Abdelminaam et al. (2021)	This study used multiple supervised learning algorithms to help classify fake and non-fake news about COVID-19 pandemic and proposed a framework for the same
"Machine Learning for COVID-19- Asking the Right Questions"	Bachtiger et al. (2020)	This study commented on the approach to apply machine learning in the diagnosis of COVID-19.
"Artificial Intelligence (AI) Applications for COVID-19 Pandemic"	Vaishya et al. (2020)	This study identified 7 significant areas of AI applications in COVID-19, including methods to detect cluster of cases and to forecast where the virus could affect in future.
"COVID-19 Pandemic Prediction for Hungary; A Hybrid Machine Learning Approach"	Pinter et al. (2020)	The paper proposed a hybrid machine learning model utilizing an "adaptive fuzzy inference system and a multi-layered perceptron model to help forecast the mortality rate during the pandemic
"COVID-19 Epidemic Analysis using machine learning and deep learning algorithms"	Punn et al. (2020)	The paper used an advanced machine learning approach as well as deep learning algorithms to predict the spread of the pandemic.
"Artificial Intelligence and Machine Learning to fight COVID-19"	Alimadadi et al. (2020)	The paper reported a machine learning analysis of the genetic variants in human genome to help identify and classify "asymptomatic, mild or severe" COVID-19 patients
"COVID-19 Coronavirus Vaccine Design Using reverse vaccinology and machine learning"	Ong et al. (2020)	The paper utilized machine learning based reverse tools to help predict COVID-19 vaccine choices

3. Methodology

3.1. Data collection and processing

It is a challenge for researchers to collect self-reported, personal experiences of mental health conditions. Individuals are reluctant to share their inner thoughts and feelings due to the concern of being judged and objectified by research collectors and society at large. However, with the increase in social media exposure and use, these platforms are becoming an easy outlet for individuals to express themselves [28,35]. In this regard, netizens utilize these platforms to voice their thoughts and share inner feelings [72]. It is observed that past studies have also analyzed messages of self-expression on Twitter and other platforms to understand their experience of mental health conditions [31,35]. Accordingly, data is collected through the open-source API platform created by Twitter. In order to collect tweets related to the expression of feelings and inner thoughts, keywords are chosen following the past related studies [72,73]. Field experts are then consulted for their inputs to ensure validity. Finally, we choose to use the following keywords:

#mentalhealth; #mentalwellbeing; #stress; #anxiety; #depression; #suicide; #insomnia; #addiction; #loneliness; #stresspain; #stressedout.

Retweets (i.e., the sharing of Tweets written by someone else) are deleted by removing duplicated messages. In the end, we have retrieved 8440 unique tweets. These tweets are manually labeled for the presence of suicidal intention by psychologists and students. The labeling is done in a binary manner, i.e., indicating the possibility of suicidal intentions or self-harm tendency viz-a-viz baseline depressive symptoms. To add to the above corpus, we have also filtered messages expressing mental concerns on the Reddit message board. Only those messages, which have mentioned COVID-19 outbreak, are retrieved. Keywords such as COVID, pandemic, lockdown, virus and vaccine are used to gather an additional 1440 messages. Adding to the above 8440 tweets, the corpus now comprises of a total of 9880 posts. Mining the underlying patterns and tenets of feelings related to mental health, after the onset of COVID would be more generalizable for a large corpus (approximately 10,000 messages). For this objective, we have followed the general protocol of text pre-processing [48,74,75]. We have removed the functions words, numbers, punctuation, special characters to come up with the limited number of content words that have a semantic reference. Next, we describe the approach to explore the underlying factors in the above-processed text.

3.2. Feature extraction

The central focus of this study is to extract the factors underlying the concerns of negative mental health outcomes. To pursue this objective, we have used the generative models based on various probability distributions. The most popular and widely used generative model is LDA, a technique that assumes that words are generated from independent probability distributions [47,76]. Underlying or latent distributions are inferred as "factors" or "a theme" comprising of a set of the most coherent words. The list of words with a higher likelihood of occurrence in the corresponding distribution are matched with the words of the message to assign the orientation of that message with each of the underlying distributions. Each message of self-expression then corresponds to all the factors to a different degree. This is analogous to the concept of exploratory factor analysis in common statistics, one of the quantitative techniques for dimensionality reduction [77–79]. Documents as messages represent respondents, while words act as the items corresponding to the latent factors [80]. Likewise, the generative procedure explores hidden factors from this document-term matrix. Based on the catalog of words within each factor, subjective assessment of those words helps assign a context or identity to each factor. This task is similar to assigning item variables to the corresponding latent factors [48].

As an initial input, the number of factors is treated as the hyperparameter for the model. However, we objectively derive the number of unique and distinct factors. Fig. A1 in Appendix represents the perplexity score which denotes the randomness associated with the number of distributions. This randomness is mathematically captured as the entropy corresponding to a varying number of distributions [41]. Lower perplexity scores indicate a lower entropy and, correspondingly, the most optimal number of factors [81]. The two-factor model has minimal randomness; however, a marginal increase in perplexity helps capture a more significant number of factors. We observe a kink after 7 themes and thus consider factors more than 7. Later, a physical check for 8 and above factors has indicated an overlapping of terms leading to a lack of exclusivity. Thus, we end up with seven factors.

To summarize, it is well-known in the literature that there are two steps under the generative models, including LDA. For each tweet, say 'd', in the entire corpus of messages say 'D', a probability of $\theta_{d,\,k}$ denotes orientation of the corresponding tweet 'd' to the kth factor document, where θ_d follows a Dirichlet distribution [47,82,83], with the parameter α: $\theta d \sim Dir(\alpha)$, $\alpha = (\alpha 1, \alpha 2, \ldots\ldots, \alpha k)$. Next, the list of words is observed describing each factor. For a factor $z_{d,n}$ with nth word of dth document, the probability is denoted by θ_d. Furthermore, in the model, the given word $w_{d,n}$ over a fixed vocabulary conditioned on the observed factor $z_{d,n}$, follows a Dirichlet distribution with parameter η: $\beta k \sim Dir(\eta)$. The joint likelihood is then known to be the following [84,85]:

$$P\ (\theta, \beta, w, z) = \Pi\ (\theta d|\alpha)\ Dd = \Pi\ (\beta k|\eta)\ Kk = \Pi\ (zd, |\theta d) P(wd, n|zd, n)$$

However, in practice, most of the factors, such as anxiety brought by job loss, substance abuse due to social rejection, mental illness due to prolonged physical disease, etc. are correlated. In order to unveil these correlated factors, we used the correlated topic model (CTM), where the assumption of independent factors is relaxed [44,45]. Furthermore, based on the principle of "Expectation-Maximization" and assuming a Gaussian distribution, we also deployed a structural topic model (STM) for latent factor extraction [44,49]. Finally, we identified experts with a background in clinical psychology and share the outputs of all the above three approaches with them. To identify each factor, the list of words most relevant to the corresponding factor was arranged in a descending order of importance and shared with those experts. Based on their knowledge, they assigned a context or identity to each. The three experts had independently identified the above factors with significant congruence. The few differences were then jointly discussed with the first author and resolved before the statistical investigation.

3.3. Model building

In order to validate the hypotheses, we adopt a pure econometric approach. The final outcome or the dependent variable is dichotomous which represents two classes: depression and suicidal tendencies, observed as baseline to extreme mental health conditions, respectively. Given the binary outcome, logistic regression is used to establish the relationship between the identified factors and the dependent variable. The analysis is carried on the R platform using the 'glmnet' package [86]. The factors are the independent constructs (variables), while each message (or tweet) of self-expression serves as a proxy for the respondent. The probability or the orientation of each message towards the corresponding factor commonly known as topic proportion is treated as in dependent variables for the statistical model [87,88]. Given that the probability ranges between 0 and 1, there is no need for any further standardization of the data. Table 2 reports an exemplification of descriptive summary of the scores of each tweet/message towards the seven factors.

Likewise, the above procedure is adopted to build a similar model with emotional valence as an additional variable. The aim is to compare the coefficients of the identified factors alone and also in the presence of the proposed mediating variable. If the coefficients significantly decrease after adding the mediating variable, there is statistical evidence

Table 2
Descriptive statistics summary of topic proportion corresponding to the uncovered factors.

Descriptive Measures	Psychological Disorders	Financial Issues	Parenting Problems	Lockdown Anxiety	Pandemic Anxiety
Mean	0.095228	0.167542	0.082856	0.068349	0.110961
Median	0.048492	0.151648	0.050414	0.034591	0.078915
Mode	0.027699	0.469529	0.121235	0.010037	0.069837
Standard Deviation	0.110122	0.110314	0.083619	0.080155	0.095941
Sample Variance	0.012127	0.012169	0.006992	0.006425	0.009205
Kurtosis	5.527523	0.162429	4.278758	5.500719	2.990237
Skewness	2.198053	0.7391	1.899491	2.187177	1.621614
Range	0.947236	0.690598	0.704976	0.610373	0.7094
Minimum	0.004168	0.00477	0.002415	0.001572	0.002717
Maximum	0.951404	0.695368	0.707391	0.611945	0.712117
3rd Quartile	0.116471	0.234341	0.109638	0.085823	0.148484
1st Quartile	0.025527	0.078961	0.024689	0.016613	0.041071

of a mediating relationship [79]. Finally, we build the two models and statistically investigate the change in magnitude of coefficients. A paired *t*-test is employed to verify the statistical significant difference in the coefficients of the factors with and without the mediating variable in the model [89]. To ensure research rigor and test for robustness, we also perform the Barron and Kenny test of mediation [90,91]. With respect to our objective to understand the order of importance of variables, it is essential to capture their impacts. However, the order is indecisive from the magnitude or the significance level of each coefficient [79,85,89]. Thus, we use a forward selection model to generate this econometric insight [85]. In a forward selection approach, the model starts with the intercept and adds a variable that best reduces the cross-entropy [86]. We again conduct this analysis in the R platform using the MASS package where Akaike Information criterion (AIC) is chosen as a basis for variable importance [79,85]. We summarize the entire research design in Fig. 1.

4. Results and findings

In this section, we elaborate on the findings of this study. As discussed above, we uncovered the underlying factors of mental health using LDA, CTM, and STM. This analysis was performed for both pre- and post-COVID-19 contexts, on posts of self-expression on social media. After exploring and identifying these latent factors, their impact on mental health was measured using the forward stepwise logistics regression. Mental health is the binary dependent variable indicating baseline and critical mental illness: depression and suicidal ideation, respectively. Furthermore, as per our postulation based on the theories of affective neuroscience and emotional disorder, we tested the mediating role of emotional valence between the factors and the dependent variable. Based on the primary motivation, we investigated the post-COVID-19 landscape. For a relative comparison, the entire analysis was repeated for the scenario before the onset of COVID-19.

4.1. Post-COVID analysis

Using the established list of keywords, recent tweets were pulled using an API of the R platform. However, Twitter had enforced some download restrictions[1] to maintain reliability and reduce downtime. As a consequence, we could retrieve only 8440 tweets. Further, we resorted to the secondary source for robust testing, and derived more generalisable findings and filtered all messages with COVID-related keywords. This search strategy resulted in 1440 messages from the Reddit message board. We finally aggregated 9880 messages of self-expression related to mental health after the onset of COVID-19. To answer the first and the second research questions, topic modelling was carried out to explore the factors underlying the dependent variable. We used the three predominant techniques, namely LDA, CTM, and STM, for a more comprehensive and unbiased exploration of the underlying factors leading to depression and suicidal ideation. To begin with, we report the findings under LDA.

4.1.1. Econometric model using LDA-based factors

As already discussed in the previous section, we narrowed down to seven factors. This was the sub-optimal choice based on the perplexity score and exclusivity of words. We sent the list of top words in a decreasing order of likelihood of occurrence (beta scores) under each factor to three experts in clinical psychology. The experts worked independently on the set of words to isolate the underlying factors. Later, these experts were asked to work together to select the acceptable number of factors and their names. The experts had an overlapping inference with minor disagreement. The first author then moderated the discussion as a group meeting, and finally, the group agreed on the following factors, namely: "psychological disorder, pessimism, pandemic anxiety, and lockdown anxiety". We carried out the logistic regression to investigate the impact of these factors on suicidal ideation and depression as the dependent variables. The analysis tested hypotheses H1, H2, H3, H5 and H6. Next, using econometrics, we also answered the third research question and tested for the mediating role of emotional valence between the identified factors and dependent variables. Fig. 2 depicts the model and the coefficients.

The findings depicted in Fig. 2 highlighted several interesting observations about suicidal tendencies and depression, as exhibited on social media. Combining them, all the factors explained 65% variation in the dependent variable, which mathematically represents the log of odds of depression vs. suicidal ideation. Since this was a classification model, we reported the Nagelkerke's[2] R-squared as the measure for model strength. Further, the model's explanatory power improved to 76% with emotional valence as the mediator. However, the factors were not significant in conjunction with the mediating variable (emotional valence).

Of all the above factors, psychological disorder, and pessimism were the most important variables for the model, respectively (all *p*-values <2e-16). We also uncovered two important and COVID-19 specific factors in the model: pandemic anxiety and lockdown anxiety. We specifically found that, "One unit of growing fears about the virus spread and its after-effect, such as lockdown, would lead to 5.14 and 3.63 units increase, respectively, in the log of odds of suicidal ideation over depression." The above findings are critical from the mental health perspective of the population at large. Such well-defined quantitative relationships between COVID-19 based precursors and mental illness had never been reported in the extant literature.

[1] https://help.twitter.com/en/rules-and-policies/twitter-limitshttps://developer.twitter.com/en/docs/twitter-api/rate-limits

[2] https://www.ibm.com/docs/en/spss-statistics/24.0.0?topic=model-pseudo-squared-measures

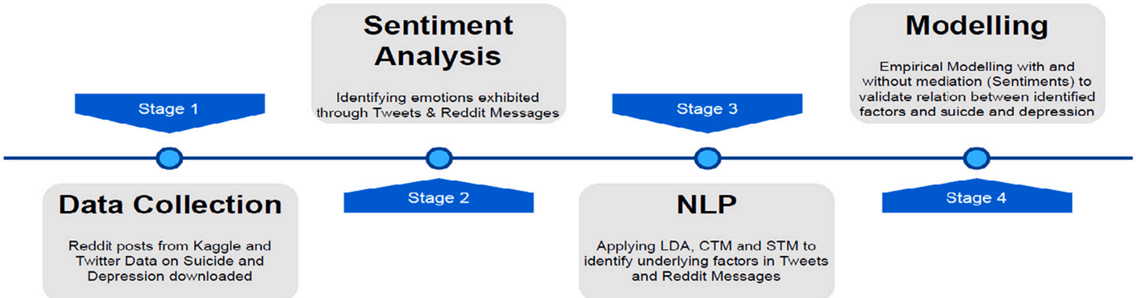

Fig. 1. Summary of Research Design to unveil the factors underlying mental health from messages of self-expression on social media.

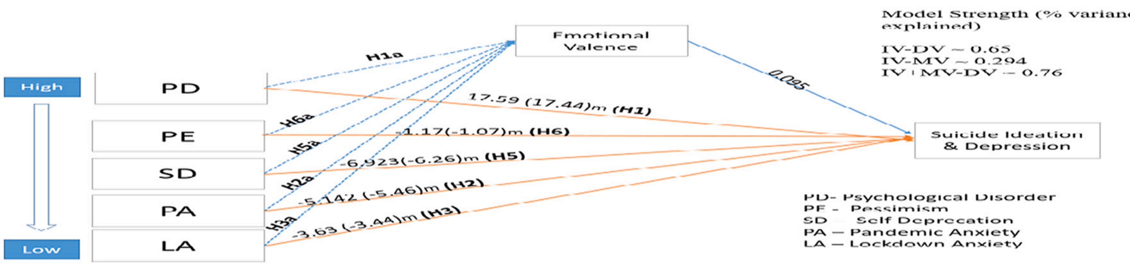

Fig. 2. Post-COVID model diagram of latent factors (in decreasing order of importance) using LDA.

4.1.2. Econometric model using CTM-based factors

As discussed earlier, we know that CTM is used to explore the possible correlated factors. The list of words in the decreasing order of likelihood of occurrence for the corresponding factors was sent to the same experts, who agreed on eight factors in this case. These factors with decreasing importance were: family chores, pandemic anxiety, pessimism, psychological disorder, substance abuse, and lockdown anxiety. We addressed the first research question by performing the logistic regression with suicidal ideation and depression as the dependent variable. To address the third research question, we tested for the mediating role of emotional valence. Fig. 3 depicts that the most important factors were family chores and pandemic anxiety (all p-values $<$2 e-16). The latent factors, when aggregated, explained 65% of the total variance in mental health conditions. Using the Baron and Kenny method, we observed that the mediating relationship of emotional valence was insignificant [90,91]. The inference result further uncovered the following: “If the pandemic anxiety of an individual increases by a single unit, the log of odds for the individual’s depressive tendency increases by 25 units (25.66). Similarly, if the lockdown anxiety of the individual increases by a single unit, the log of odds of the individual’s depressive tendencies increases by 28 units (27.78).” These two revelations remain a significant finding of this work.

4.1.3. STM factors based econometric model

The final analysis of the post COVID scenario was based on the STM output. The experts agreed on the five factors in this case. The factors in a decreasing order of importance (Fig. 3-right panel) are given below: psychological disorder, parenting problems, financial issues, pandemic anxiety, and lockdown anxiety. The most compelling factors which led to suicidal and depressive behaviors were psychological disorder and financial issues (p-values$<$2e-16). The latent factors together explained a 66% variation in baseline to critical mental health issues. The model strength increased with the application of the mediation variable; however, the mediating relationship was insignificant as the coefficients were not statistically different in the presence of emotional valence. Pandemic anxiety and lockdown anxiety were factors that significantly affected suicidal ideation and depression in this case well. A unit increase in pandemic or lockdown anxiety would increase the log of odds of depression over suicidal tendency by 2 and 9 units, respectively. Both of these factors were found to be critical throughout the post-COVID scenario.

Looking at the three modelling findings, the most critical variables post -COVID across all models were: psychological disorder, pessimism, family chores, financial issues, parenting problems, pandemic and lockdown anxiety. Apart from pandemic and lockdown anxiety, all other hidden factors were found to be historical precursors to depression and suicidal ideation. It should be noted that in a variety of survey-based work and expert opinions, these factors act as antecedents of depression and suicidal ideation [24,25,36,69]. In the following subsection, we discussed the results of the pre-COVID analysis.

4.2. Pre-COVID analysis

In this sub-section, we investigated the underlying factors and their impact on mental health prior to the onset of COVID. For this part of the study, we collected more than three hundred thousand pre-labeled posts from the Reddit message board. The posts were available from Dec 16, 2008 (creation) till Jan 2, 2021 and were collated using Pushshift API [92,93]. The messages were categorised as: depression, SuicideWatch, and teenagers. Initially, we pruned the messages pertaining to the ‘teenagers’ label and were left with approximately two hundred fifty thousand posts. However, a bulk of them had a limited information-carrying capacity. On a physical screening done by the first two authors, most of the posts were linked to images and videos concerning mental distress. These posts included references and hyperlinks. The next group of posts included special characters, a limited number of characters, as well as general and neutral terms. Such messages had no explicit indication of mental health concerns. Lastly, after investigating the meta data of these messages conveying self-expression, we selected messages whose number of characters, sentiments, and the eight basic emotions were higher than a particular threshold, the third quartile value in this case. The sole objective was to analyse expressions which convey detailed thoughts and feelings. Finally, we obtained 16,706 pre-COVID messages on depression and suicidal ideation. We repeated our analysis using the three (LDA, CTM, STM) approaches to identify the factors underlying mental health.

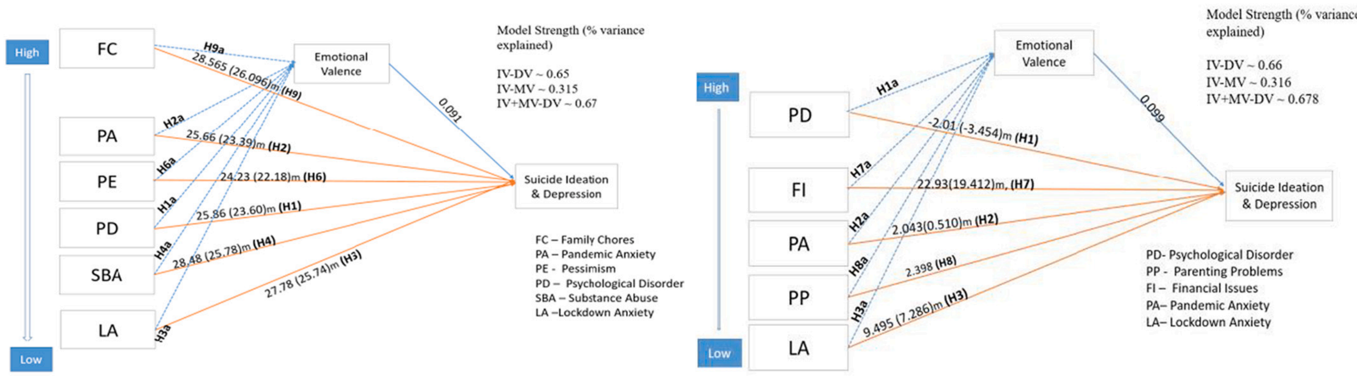

Fig. 3. Post-COVID-19 model diagram of latent factors (in decreasing order of importance) using CTM and STM, respectively.

4.2.1. *Pre-COVID analysis using LDA*

As with the earlier methodology, themes obtained through LDA were sent to three independent experts. These experts were different from the earlier instances to reduce bias due to preconceived notions. The experts identified the two major factors as: psychological disorders and pessimism. Other than these two factors, the experts also found traces of social anxiety, personality issues, social rejection, and relationship dissolution in the Tweets. We did not test hypotheses for these antecedents due to two reasons: Firstly, all of these factors were shown to be associated with psychological anxiety and pessimism in the extant literature. Secondly, the evidence of the existence of these antecedents was fleeting and unclear. Hence, we described the role of these antecedents not as hypotheses but as implications in the discussion and conclusion sections of this paper. Psychological disorders and pessimism have historically been antecedents to mental health issues, although the picture had been fragmented thus far. In this study, we aggregated these factors to investigate their impact on the dependent variable representing suicidal ideation and depression. Fig. 4 presents the results obtained with a mention of the model strength and impact of the corresponding factors.

To answer the second research question, we identified the most important factors as: psychological disorder and pessimism. The factors together explained 2.9% of the variation in the dependent variable. On adding emotional valence as the mediator, the model's explanatory power increased to 3.8%. Moreover, the magnitude of coefficients also decreased significantly in the presence of emotional valence. Furthermore, based on the Baron and Kenny method [90,91], we confirmed that emotional valence mediated the relationship between the six identified latent factors and the dependent outcome.

4.2.2. *CTM factors based econometric model*

Repeating the same process using CTM, the following six factors were identified: loneliness, personality issues, social rejection, stressful events, psychological disorders, and difficult childhood. Out of these six antecedents, concrete evidence was available only for psychological disorder. In continuation with the proposed methodology, the factor was then used as an explanatory variable to regress using sigmoid transformation against mental distress. Fig. 4 exhibits the results obtained and the strength of the relationship(s). CTM-based latent factors explained 4.8% of the variation in the dependent variable, while explanatory power increased to 5.1% with the inclusion of the mediating variable. Psychological disorder was found to be significant and remained the most important factor concerning mental distress.

4.2.3. *STM factors based econometric model*

Finally, we explored the factors using STM for the pre-COVID context. In this case, the experts identified the following seven factors: pessimism, critical illness, academic peer pressure, parenting problems, financial issues, social anxiety, and relationship dissolution. Out of these factors, pessimism, parenting problems, and financial issues were deemed most important by the experts and were considered for modelling. The output is reported in Fig. 5 below.

The factors identified using STM explained 8.8% variance in the dependent variable. At the same time, the explanatory power of these factors was increased to 9.2% in the presence of emotional valence as the mediator. All the factors: pessimism, parenting problems, and financial issues were found to be significant upon modelling. In order to comprehend the varied results and several tests of hypotheses, we report the summary in Table 3 below. It is interesting to note that hypotheses pertaining to the mediating role of emotional valence after the onset of COVID have not been supported. The remaining hypotheses significantly support our postulation corresponding to both of the research questions.

5. Theoretical and managerial implications

We discussed some profound observations concerning the first research question exploring the factors underlying mental health. It is interesting to note that in most cases, the impact of lockdown anxiety on an individual was higher than the impact of the pandemic itself. Looking at the coefficients, we concluded that though the pandemic did cause depression in people, the impact of lockdown was much greater. This could be attributed to the mandatory self-isolation, loneliness, and monotonous activities of individuals [94,95]. From a managerial viewpoint, this holds significance when handling teams remotely during the ongoing pandemic. Organisations should focus on regular counselling of their employees to ensure a healthy work-life balance. Support should be made available to understand duress and underperformance during these testing times.

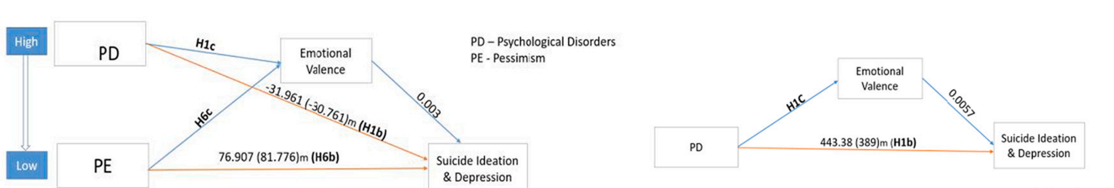

Fig. 4. Pre-COVID model diagram of latent factors (in decreasing order of importance) using LDA and CTM, respectively.

Fig. 5. Pre-COVID model diagram of latent factors (in decreasing order of importance) using STM.

Table 3
Summary of the nine hypotheses test conducted in this study. The *p*-values are reported in brackets in the order of LDA, CTM and STM models, respectively.

Variable Description	Post-COVID		Pre-COVID	
Mediator	–	EV	–	EV
Psychological Disorder	H1 - Supported (2e-16,2e-16,0.00725)	H1a- Not Supported	H1b - Supported (0.00309,2e-16)	H1c- Supported (0.004399,2e-16)
Pessimism	H6 - Supported (0.0433,2e-16)	H6a - Not Supported	H6b- Supported (2e-16,2e-16)	H6c - Supported (2e-16,2e-16)
Self-Deprecation	H5 - Supported (2e-16)	H5a - Not Supported		
Pandemic Anxiety	H2 - Supported (2e-16,2e-16,0.00710)	H2a - Not Supported		
Lockdown Anxiety	H3 - Supported (3.95e-11,2e-16,2e-16)	H3a - Not Supported		
Family Chores	H9 - Supported (2e-16)	H9a - Not Supported		
Substance Abuse	H4 - Supported (2e-16)	H4a - Not Supported		
Parenting Problems	H8 - Supported (0.01221)	H8a - Not Supported	H8b - Supported (2e-16)	H8c - Supported (2e-16)
Financial Issues	H7 - Supported (2e-16)	H7a - Not Supported	H7b- Supported (5.34e-05)	H7c - Supported (6.63e-05)
Sample Size	9880	9880	16,706	16,706

The variable importance reflected that lockdown anxiety remained secondary to the pandemic-related anxiety. Fear of COVID-19 contraction, community spread, associated physical suffering, and rising death toll overshadowed the impact of lockdown restrictions on mental health. Given that lockdown was a fallout of the pandemic, the latter demonstrated a superior explanatory power. Interestingly, we also found traces of neurotic disorder in the antecedents of suicidal ideation and depression in the post COVID-19 scenario. This could be due to the atypical inertia towards changing lifestyle, resulting from lockdown and isolation experiences. Family chores were recognised as factors only in the post-COVID-19 analysis. This can be attributed to the continued proximity to the rest of the family members. There were several instances of frequent clashes due to unfairly distributed household responsibility, opinion discordance, and lack of individual personal space as reported during the pandemic [94–96].

Extracted pre-COVID-19 factors included social anxiety, social rejection, and stressful life events, among others. Owing to the ongoing COVID-19 pandemic, the relevance of these factors had gone down considerably since socialising and inter-personal interactions were restricted. Hence, it was no surprise that these factors did not emerge in the post-COVID-19 analysis and we did not conduct hypotheses tests corresponding to them. Furthermore, we observed in the STM-based exploration that financial burden was a significant factor both pre- and post-COVID-19 mental health outcomes. We deduced that one unit increase in pre-COVID-19 financial issues led to a 0.782 unit increase in the log of odds of suicidal ideation, while post-COVID-19 financial issues depicted a polar opposite finding. Specifically, one unit increase in post-COVID-19 financial issues led to almost 23 unit increase in the log of odds of depressive thoughts. During the pandemic, job loss triggered mental illness, but not as severely as job loss in the pre-pandemic world. There are historical evidences that financial loss had a significant impact on suicidal thoughts, but reduction in income may not have been as severe [97,98]. Even in though the mass panic and the concerns of economic stress significantly increased, the evidence for suicidal ideation was much lower than the prediction [99]. On these lines, a possible reason could be that pandemic had led to loss of income more than job losses. After its onslaught, various help-seeking and distress-prevention campaigns had mediated the worries of suicidal ideation, when controlled for demographic variables [100]. Various governments have launched unemployment insurance programs to offer financial assistance to compensate job loss due to COVID-19. Such initiatives aim to provide economic security to individuals who lost jobs under the clause "through no fault of theirs[3]". These monetary schemes[4] have the potential to alleviate a significant portion of the financial burden on individuals and households. Consequently, the impact of job loss and financial issues during the COVID-19 was observed to have slighter mental concerns. In summary, we inferred that Government schemes to compensate for unemployment and job loss due to the pandemic, effectively prevented suicidal tendencies in individuals.

In a clear differentiation from the post-COVID-19 results, no pandemic-specific factors were observed in the pre-COVID-19 messages of self-expression. Another primary differentiation was witnessed for the overall explanatory power. Post-COVID-19, latent factors explained more than two-thirds of the variance in the dependent variable, while the latent factors marginally explained pre-COVID-19 mental health issues. This strongly indicated that the study at hand could successfully capture the underlying factors of mental health concerns in the context of COVID-19. We also acknowledge that many other latent factors concerning mental distress could not be captured before the outbreak of COVID-19.

Additionally, emotional valence as the mediating variable was insignificant in the post-COVID-19 analysis; whereas, in pre-COVID-19 context, emotional valence was significant across the three models. This could be attributed to the context of the pandemic leading to depression or suicidal ideation without a significant role in intense emotions. Our discussion with the clinical psychology experts also revealed fascinating insights into the psyche of people. Given that the context played a part in triggering most of the stress and anxiety, people

[3] https://thewire.in/labour/unemployment-insurance-india-us-uk-COVID-19-pandemic

[4] https://oewd.org/employees-impacted-COVID-19https://esd.wa.gov/newsroom/COVID-19https://www.usa.gov/unemployment#item-214601

were still hopeful of better days ahead. This hopefulness somehow regulated their emotions, and thus could be the reason for an insignificant mediating relationship post COVID-19.

We also delved into the messages for significant factors such as parenting problems observed both in pre- and post-COVID-19 contexts. Before the pandemic onset, lack of attention and affection deprivation were the triggers of parenting concerns. In contrast, lack of personal space for children and continued proximity to the parents, were precursors of parenting problems throughout the Lockdown. This section underscores the hidden insights gleaned from the findings of this study. Theoretical contributions of this study include the formulation of relevant and precise hypotheses using NLP and econometric modelling approaches. The order of importance of the latent factors based on their capability was uncovered to explain the variance in depression and suicidal ideation. The findings also uncovered the impact of each identified factor in order to aid decision-making by health policy formulators and business managers.

The policy implications of our results include highlighting the necessity of government-funded social security which reduced the suicidal tendencies in individuals who had lost their jobs. For businesses, we inferred that supports to employees through counselling, incentives, and job security were critical in keeping employee morale high amidst the COVID-19 pandemic.

6. Conclusion, limitations, and future directions

History bespeaks that previous pandemic outbreaks and their impact had outlasted the viruses themselves. More than the physical ailments and deaths caused due to them, they had overbearing psychosocial changes that impacted mental health. The increased incidence of psychological problems and anxiety associated with the infection; the social restrictions, economic impacts, etc., were aggravated with the virus spread and left a longer impact on humankind. The above reasons had raised global concerns on mental health and the need to identify novel precursors of depression and suicidal tendencies during COVID-19. Identifying factors affecting mental health and causing suicidal ideation was hence very critical for timely intervention and suicide prevention. Note that the risk factors may not have directly led to suicide, but may have triggered a myriad of psychological, social, neuroscientific, and economic implications for mental distress [5,7,10]. Thus, the need to have an in-depth understanding of stressors of mental distress, arising from the COVID-19 outbreak was crucial and timely. Moreover, the impact of historically documented stressors may change as the COVID-19 pandemic spread. It, therefore, makes this study far more important for healthcare policy makers, government agencies, as well as business managers, to take cognisance of the various preventive and corrective measures adopted to fight COVID-19-induced mental stress within individuals.

We grounded our research in the psychological theories of emotional dysregulation and affective neuroscience. These theories had previously established the role of incidents leading to intense emotions and ultimately influencing human behaviour. The extant literature and our understanding of the theories of emotional dysregulation and affective neuroscience allowed us to formulate research questions before proceeding to conduct the empirical analyses.

We specifically observed that the pandemic and lockdown anxiety remained a significant factor leading to poor mental health outcomes during the COVID-19. Before COVID-19, other psychopathic factors such as social rejection and social phobia (non-significant) were extracted. However, they were absent post-COVID. Consistent with the past works, psychological disorder was found to be a predominant factor both before and after the onset of the pandemic. Parenting concerns were recognised as a significant factor in both contexts; nevertheless, the underlying reasons were distinct: pre-COVID-19, it was the lack of attention by the parents while post-COVID-19 it was intruding into personal space of their children. This was confirmed by manually probing the social media posts, both pre- and post-pandemic. Although financial burden was a factor both before and after the COVID-19 outbreak, its significance in our data from after the onset offered a thought-provoking takeaway, particularly for the policy makers and government agencies. It was observed that financial burden led to higher odds of suicidal ideation pre-COVID-19, whereas, during the pandemic, job loss and financial constraints increased the odds of depressive thoughts. The financial assistance provided to the sufferers through unemployment insurance provided economic palliative during the pandemic.

Similar to other empirical studies, this work is also not free from limitations. First, it relied on secondary data on pre-COVID-19 messages (due to the restricted access to historical messages on social media websites). Second, our data analysis and implications form a “bird’s eye-view”

of the problem as we had not taken into consideration specific communities, regions or age groups for this study. Researchers may explore these mentioned groups in the future. Furthermore, the ongoing research on COVID-19 has created data sources of different kinds. Researchers may make use of them to study the patterns that emerge on social media as how lockdowns ease across the world. New challenges such as the individuals’ work-life balance [101,102] in the post-COVID-19 pandemic workspace as well as how recent graduates (who studied online during the pandemic) performed in the workplace would be interesting problems to explore in the future.

Appendix A. Appendix

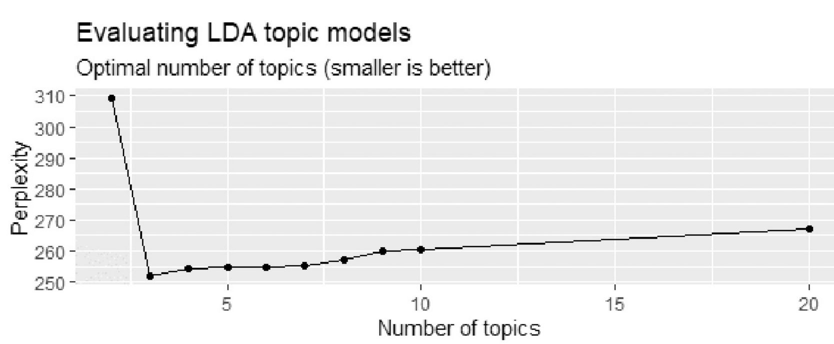

Fig. A1. Perplexity score to decide number of factors underlying mental health.

Variable Description	post-COVID			pre-COVID		
	LDA	CTM	STM	LDA	CTM	STM
Pyschological Disorder	17.59	25.86	-2.01	-31.961	443.38	-
Pessimism	-1.17	24.23	-	76.907	-	4.08
Self Deprecation	-6.923	-	-	-	-	-
Pandemic Anxiety	-5.142	25.66	2.043	-	-	-
Lockdown Anxiety	-3.63	27.78	9.495	-	-	-
Family Chores	-	28.565	-	-	-	-
Substance Abuse	-	28.48	-	-	-	-
Parenting Problems	-	-	2.398	-	-	2.63
Financial Issues	-	-	22.93	-	-	-0.782
Social Anxiety	-	-	-	-45.756	-	0.436
Perso-lity Issues	-	-	-	-39.816	-	-
Social Rejection	-	-	-	60.079	-	-
Relationship Dissolution	-	-	-	101.002	-	-1.04
Loneliness	-	-	-	-	177.01	-
Stressful Events	-	-	-	-	168.87	-
Difficult Childhood	-	-	-	-	160.26	-
Critical Illness	-	-	-	-	-	2.56
Neurotic Disorder	-26.613	21.52	-6.575	-	-	-
Academic Peer Pressure	-	-	-	-	-	-1.75
Emotional Valence						
Sample Size	9880	9880	9880	16706	16706	16706
Model Strength (R^2)	0.65	0.65	0.66	0.038	0.051	0.0902

Fig. A2. Coefficients of factors for logistic regression for LDA, CTM and STM Models.

anticipation	disgust	fear	joy	sadness	surprise	trust	negative	positive
Min. :0.000	Min. :0.000	Min. : 0.000	Min. :0.000	Min. :0.000	Min. :0.000	Min. :0.000	Min. : 0.000	Min. : 0.000
1st Qu.: 1.000	1st Qu.: 1.000	1st Qu.: 1.000	1st Qu.: 1.000	1st Qu.: 2.000	1st Qu.: 0.000	1st Qu.: 1.000	1st Qu.: 3.000	1st Qu.: 2.000
Median : 3.000	Median : 2.000	Median : 3.000	Median : 2.000	Median : 4.000	Median : 1.000	Median : 3.000	Median : 6.000	Median : 4.000
Mean : 4.156	Mean : 2.823	Mean : 4.681	Mean : 3.167	Mean : 5.521	Mean : 1.841	Mean : 4.335	Mean : 8.358	Mean : 6.812
3rd Qu.: 6.000	3rd Qu.: 4.000	3rd Qu.: 6.000	3rd Qu.: 4.000	3rd Qu.: 8.000	3rd Qu.: 3.000	3rd Qu.: 6.000	3rd Qu.: 11.000	3rd Qu.: 9.000
Max. :71.000	Max. :60.000	Max. :106.000	Max. :52.000	Max. :86.000	Max. :32.000	Max. :85.000	Max. :173.000	Max. :164.000

Fig. A3. Descriptive summary of emotions and sentiment scores for the pre-COVID context.

References

[1] A. Kumar, T.-M. Choi, S.F. Wamba, S. Gupta, K.H. Tan, Infection vulnerability stratification risk modelling of COVID-19 data: a deterministic SEIR epidemic model analysis, Ann. Oper. Res. (2021) 1–27.

[2] T.-M. Choi, Fighting against COVID-19: what operations research can help and the sense-and-respond framework, Ann. Oper. Res. 1–17 (2021).

[3] O.M. Araz, T. Lant, J.W. Fowler, M. Jehn, Simulation modeling for pandemic decision making: a case study with bi-criteria analysis on school closures, Decis. Support. Syst. 55 (2013) 564–575.

[4] A. Rai, The COVID-19 pandemic: building resilience with IS research, MIS Q, Manag. Inf. Syst. 44 (2020). III–VIII.

[5] D. Banerjee, J. Rao, T.S.S. Rao, The dual pandemic' of suicide and COVID-19: a biopsychosocial narrative of risks and prevention, Psychiatry Res. 295 (2021).

[6] J. Que, K. Yuan, Y. Gong, S. Meng, Y. Bao, L. Lu, Raising awareness of suicide prevention during the COVID-19 pandemic, Neuropsychopharmacol. Rep. 40 (2020) 392–395.

[7] E.A. Holmes, et al., Multidisciplinary research priorities for the COVID-19 pandemic : a call for action for mental health science, 2020, pp. 547–560, https://doi.org/10.1016/S2215-0366(20)30168-1.

[8] G.W. Evans, Projected behavioral impacts of global climate change, Annu. Rev. Psychol. 70 (2019) 449–474, https://doi.org/10.1146/annurev-psych-010418-103023.

[9] C.W.N. Saville, Ecological social capital does not predict geographical variance in increases in depression following the 2008 financial crisis, Br. J. Psychol. 112 (2021) 163–179.

[10] M. Berk, E. Vieta, O.M. Dean, Suicide risk and prevention during the COVID-19 pandemic 7 (2020) 468–471, https://doi.org/10.1016/S2215-0366(20)30171-1.

[11] W.D.S. Killgore, S.A. Cloonan, E.C. Taylor, F. Fernandez, M.A. Grandner, N. S. Dailey, Suicidal ideation during the COVID-19 pandemic: the role of insomnia, Psychiatry Res. 290 (2020), 113134.

[12] 2020 World Health Organization, COVID-19 and Violence Against Women: What The Health Sector/System Can Do?, 7 April 2020, https://doi.org/10.21608/jdl.2020.105116, 2020.

[13] M.J. Heisel, E. Neufeld, G.L. Flett, Reasons for living, meaning in life, and suicide ideation: investigating the roles of key positive psychological factors in reducing suicide risk in community-residing older adults, Aging Ment. Health 20 (2016) 195–207.

[14] Y. Sun, S.-Y. Lin, K.K.H. Chung, Does Emotional Well-Being Mediate between the Association of Peer Support and Depressive Symptoms in University Students during COVID-19 Pandemic?, 2020.

[15] R. Ren, W. Hu, J. Dong, B. Sun, Y. Chen, Z. Chen, A systematic literature review of green and sustainable logistics: bibliometric analysis, research trend and knowledge taxonomy, Int. J. Environ. Res. Public Health 17 (2020), https://doi.org/10.3390/ijerph17010261.

[16] Y.K. Lin, H. Chen, R.A. Brown, S.H. Li, H.J. Yang, Healthcare predictive analytics for risk profiling in chronic care: a Bayesian multitask learning approach, MIS Q. Manag. Inf. Syst. 41 (2017) 473–495, https://doi.org/10.25300/MISQ/2017/41.2.07.

[17] H. Rettie, J. Daniels, Coping and Tolerance of Uncertainty : Predictors and, 2020.

[18] G. Arslan, M. Yıldırım, A. Tanhan, M. Buluş, K.-A. Allen, Coronavirus stress, optimism-pessimism, psychological inflexibility, and psychological health: psychometric properties of the coronavirus stress measure, Int. J. Ment. Heal. Addict. (2020) 1–17.

[19] J. Goh, J. Pfeffer, S.A. Zenios, J. Goh, The relationship between workplace stressors and mortality and health costs in the United States, Manag. Sci. 62 (2016) 608–628.

[20] A.T.A. Cheng, T.H.H. Chen, C.C. Chen, Psychosocial and psychiatrie risk factors for suicide: case-control psychological autopsy study, Br. J. Psychiatry 3 (2001) 86.
[21] G. Coppersmith, C. Harman, M. Dredze, Measuring post traumatic stress disorder in twitter, Proc. 8th Int. Conf. Weblogs Soc. Media, ICWSM (2014) 579–582 (2014).
[22] K.B. Coffman, L.C. Coffman, K.M.M. Ericson, The size of the LGBT population and the magnitude of antigay sentiment are substantially underestimated, Manag. Sci. 63 (2017) 3168–3186.
[23] Y.-P. Huang, T. Goh, C.L. Liew, Hunting Suicide Notes in Web 2.0 - Preliminary Findings, 2008, pp. 517–521, https://doi.org/10.1109/ism.workshops.2007.92.
[24] S. Mohanty, G. Sahu, M.K. Mohanty, M. Patnaik, Suicide in India - a four year retrospective study, J. Forensic Legal Med. 14 (2007) 185–189, https://doi.org/10.1016/j.jcfm.2006.05.007.
[25] A.H. Hagstrom, P.M. Gutierrez, Confirmatory factor analysis of the multi-attitude suicide tendency scale, J. Psychopathol. Behav. Assess. 20 (1998) 173–186, https://doi.org/10.1023/A:1023078314714.
[26] S. Sharma, A. Powers, B. Bradley, K.J. Ressler, Gene × environment determinants of stress-and anxiety-related disorders, Annu. Rev. Psychol. 67 (2016) 239–261, https://doi.org/10.1146/annurev-psych-122414-033408.
[27] S. Traynham, A.M. Kelley, C.P. Long, T.W. Britt, Posttraumatic stress disorder symptoms and criminal behavior in U.S. army populations: the mediating role of psychopathy and suicidal ideation, Am. J. Psychol. 132 (2019) 85–95.
[28] S. Moro, G. Pires, P. Rita, P. Cortez, A text mining and topic modelling perspective of ethnic marketing research, J. Bus. Res. 102 (2019) 49–58, https://doi.org/10.1016/j.jbusres.2019.01.053.
[29] M. Bogaert, M. Ballings, D. Van den Poel, A. Oztekin, Box office sales and social media: a cross-platform comparison of predictive ability and mechanisms, Decis. Support. Syst. 147 (2021), 113517, https://doi.org/10.1016/j.dss.2021.113517.
[30] A. Castillo, J. Benitez, J. Llorens, X.R. Luo, Social media-driven customer engagement and movie performance: theory and empirical evidence, Decis. Support. Syst. 145 (2021), 113516.
[31] M. Chau, T.M.H. Li, P.W.C. Wong, J.J. Xu, P.S.F. Yip, H. Chen, Finding people with emotional distress in online social media: a design combining machine learning and rule-BASED classification, MIS Q. Manag. Inf. Syst. 44 (2020) 933–956.
[32] R. Davidson, D. Pizzagalli, J. Nitschke, K. Putnam, DEPRESSION: perspectives from affective neuroscience, Annu. Rev. Psychol. 53 (2002) 545–574, https://doi.org/10.1007/978-0-230-80178-3_5.
[33] E.H. Bos, P. de Jonge, R.F.A. Cox, Affective variability in depression: revisiting the inertia–instability paradox, Br. J. Psychol. 110 (2019) 814–827, https://doi.org/10.1111/bjop.12372.
[34] S.H. Spence, A. De Young, C. Toon, S. Bond, Longitudinal examination of the associations between emotional dysregulation, coping responses to peer provocation, and victimisation in children, Aust. J. Psychol. 61 (2009) 145–155, https://doi.org/10.1080/00049530802259076.
[35] S. Muthana, H. Al-samarraie, A. Ibrahim, W. Alnumay, A. Paul, A lexicon-based approach to detecting suicide-related messages on twitter biomedical signal processing and control a lexicon-based approach to detecting suicide-related messages on twitter, Biomed. Signal Process. Control. 65 (2021), 102355, https://doi.org/10.1016/j.bspc.2020.102355.
[36] R. Dinga, et al., Predicting the naturalistic course of depression from a wide range of clinical, psychological, and biological data: a machine learning approach, Transl. Psychiatry 8 (2018) 1–11, https://doi.org/10.1038/s41398-018-0289-1.
[37] C.-Y. Lee, Y.-C. Chiang, A. Li, X. Li, Y.-T. Wu, Y.-J. Lin, Y. Zhao, X. Zhang, Influence of humor expression on suicidal ideation among adolescents: mediating effects of depressive emotion and positive emotion, BMC Psychiatry. 20 (2020) 421.
[38] T.-M. Choi, Risk analysis in logistics systems: a research agenda during and after the COVID-19 pandemic, Transp. Res. E Logist. Transp. Rev. 145 (2021), 102190, https://doi.org/10.1016/j.tre.2020.102190.
[39] O.M. Araz, T. Choi, D.L. Olson, F.S. Salman, Role of analytics for operational risk management in the era of big data, Decis. Sci. 51 (2020) 1320–1346.
[40] L. Kang, Y. Xiao, H. Sun, J. Wu, S. Luo, N. Buhigiro, Decisions on train rescheduling and locomotive assignment during the COVID-19 outbreak: a case of the Beijing-Tianjin intercity railway, Decis. Support. Syst. (2021), 113600, https://doi.org/10.1016/j.dss.2021.113600.
[41] R. Kumar, S.G. Deb, S. Mukherjee, Do words reveal the latent truth? Identifying communication patterns of corporate losers, J. Behav. Exp. Financ. 26 (2020), 100291, https://doi.org/10.1016/j.jbef.2020.100291.
[42] S. Mukherjee, R. Kumar, P.K. Bala, Managing a natural disaster: actionable insights from microblog data, J. Decis. Syst. (2021) 1–16, https://doi.org/10.1080/12460125.2021.1918045.
[43] A. Sharma, N.P. Rana, R. Nunkoo, Fifty years of information management research: a conceptual structure analysis using structural topic modeling, Int. J. Inf. Manag. 58 (2021), 102316, https://doi.org/10.1016/j.ijinfomgt.2021.102316.
[44] D.M. Blei, Probabilistic topic models, Commun. ACM 55 (2012) 77–84, https://doi.org/10.1145/2133806.2133826.
[45] J. Liu, Q. Gu, Package ‘ CTM,’, 2016, pp. 1–5.
[46] M.E. Roberts, B.M. Stewart, D. Tingley, Stm: an R package for structural topic models, J. Stat. Softw. 91 (2019), https://doi.org/10.18637/jss.v091.i02.
[47] D.M. Blei, A.Y. Ng, M.I. Jordan, Latent Dirichlet allocation, J. Mach. Learn. Res. 3 (2003) 993–1022, https://doi.org/10.1016/B978-0-12-411519-4.00006-9.
[48] R. Kumar, R. Thakurta, Exfoliating decision support system: a synthesis of themes using text mining, Inf. Syst. E-Bus. Manag. (2021), https://doi.org/10.1007/s10257-020-00490-4.
[49] A. Sharma, N.P. Rana, R. Nunkoo, Fifty years of information management research: a conceptual structure analysis using structural topic modeling, Int. J. Inf. Manag. 58 (2021), 102316, https://doi.org/10.1016/j.ijinfomgt.2021.102316.
[50] M. Shevlin, et al., Stocks, anxiety, depression, traumatic stress and COVID-19-related anxiety in the UK general population during the COVID-19 pandemic, BJPsych Open. 6 (2020).
[51] P. Hyland, M. Shevlin, O. McBride, J. Murphy, T. Karatzias, R.P. Bentall, A. Martinez, F. Vallières, Anxiety and depression in the Republic of Ireland during the COVID-19 pandemic, Acta Psychiatr. Scand. 142 (2020) 249–256.
[52] C.K. Ettman, S.M. Abdalla, G.H. Cohen, L. Sampson, P.M. Vivier, S. Galea, Prevalence of depression symptoms in US adults before and during the COVID-19 pandemic, JAMA Netw. Open 3 (2020) e2019686.
[53] S. Özdin, Ş. Bayrak Özdin, Levels and predictors of anxiety, depression and health anxiety during COVID-19 pandemic in Turkish society: the importance of gender, Int. J. Soc. Psychiatry. 66 (2020) 504–511.
[54] Y.-J. Cai, T.-M. Choi, A United Nations' sustainable development goals perspective for sustainable textile and apparel supply chain management, Transp. Res. E Logist. Transp. Rev. 141 (2020), 102010, https://doi.org/10.1016/j.tre.2020.102010.
[55] M.É. Czeisler, R.I. Lane, E. Petrosky, J.F. Wiley, A. Christensen, R. Njai, M. D. Weaver, R. Robbins, E.R. Facer-Childs, L.K. Barger, Mental health, substance use, and suicidal ideation during the COVID-19 pandemic—United States, June 24–30, 2020, Morb. Mortal. Wkly Rep. 69 (2020) 1049.
[56] W.D.S. Killgore, S.A. Cloonan, E.C. Taylor, M.C. Allbright, N.S. Dailey, Trends in suicidal ideation over the first three months of COVID-19 lockdowns, Psychiatry Res. 293 (2020), 113390.
[57] T.C.K. Huang, C.H. Huang, Y.T. Chuang, Change discovery of learning performance in dynamic educational environments, Telemat. Inform. 33 (2016) 773–792, https://doi.org/10.1016/j.tele.2015.10.005.
[58] P.A. Geoffroy, N. Hoertel, B. Etain, F. Bellivier, R. Delorme, F. Limosin, H. Peyre, Insomnia and hypersomnia in major depressive episode: prevalence, sociodemographic characteristics and psychiatric comorbidity in a population-based study, J. Affect. Disord. 226 (2018) 132–141, https://doi.org/10.1016/j.jad.2017.09.032.
[59] M. Pompili, et al., Substance abuse and suicide risk among adolescents, Eur. Arch. Psychiatry Clin. Neurosci. 262 (2012) 469–485, https://doi.org/10.1007/s00406-012-0292-0.
[60] D. Kealy, M.S. Treeby, S.M. Rice, Shame, guilt, and suicidal thoughts: the interaction matters, Br. J. Clin. Psychol. (2021), https://doi.org/10.1111/bjc.12291 n/a.
[61] C.J. Bryan, B. Ray-Sannerud, C.E. Morrow, N. Etienne, Guilt is more strongly associated with suicidal ideation among military personnel with direct combat exposure, J. Affect. Disord. 148 (2013) 37–41, https://doi.org/10.1016/j.jad.2012.11.044.
[62] E.C. Chang, T. Yu, A.S.-M. Najarian, K.M. Wright, W. Chen, O.D. Chang, Y. Du, J. K. Hirsch, Understanding the association between negative life events and suicidal risk in college students: examining self-compassion as a potential mediator, J. Clin. Psychol. 73 (2017) 745–755, https://doi.org/10.1002/jclp.22374.
[63] M.S. Bhatia, S.K. Verma, O.P. Murty, Suicide notes: psychological and clinical profile, Int. J. Psychiatry Med. 36 (2006) 163–170, https://doi.org/10.2190/5690-CMGX-6A1C-Q28H.
[64] C.C. Choo, K.M. Harris, P.K.H. Chew, R.C. Ho, Clinical assessment of suicide risk and suicide attempters' self-reported suicide intent: a cross sectional study, PLoS One 14 (2019), e0217613, https://doi.org/10.1371/journal.pone.0217613.
[65] A. Malmberg, S. Simkin, K. Hawton, Suicide in farmers, Br. J. Psychiatry 175 (1999) 103–105, https://doi.org/10.1192/bjp.175.2.103.
[66] P.S.F. Yip, K.C.T. Yang, B.Y.T. Ip, Y.W. Law, R. Watson, Financial debt and suicide in Hong Kong SAR1, J. Appl. Soc. Psychol. 37 (2007) 2788–2799.
[67] L. Sher, The impact of the COVID-19 pandemic on suicide rates, QJM An Int. J. Med. 113 (2020) 707–712.
[68] Y.-C. Shin, D. Lee, J. Seol, S.-W. Lim, What kind of stress is associated with depression, anxiety and suicidal ideation in Korean employees? J. Korean Med. Sci. 32 (2017) 843.
[69] E.K. Moscicki, Identification of suicide risk factors using epidemiologic studies, Psychiatr. Clin. North Am. 20 (1997) 499–517, https://doi.org/10.1016/S0193-953X(05)70327-0.
[70] K.W. Lai, C. McBride-Chang, Suicidal ideation, parenting style, and family climate among Hong Kong adolescents, Int. J. Psychol. 36 (2001) 81–87.
[71] M.L. Heggeness, Estimating the immediate impact of the COVID-19 shock on parental attachment to the labor market and the double bind of mothers, Rev. Econ. Househ. 18 (2020) 1053–1078.
[72] M.E. Larsen, T.W. Boonstra, P.J. Batterham, B. O'Dea, C. Paris, H. Christensen, We feel: mapping emotion on twitter, IEEE J. Biomed. Heal. Inform. 19 (2015) 1246–1252, https://doi.org/10.1109/JBHI.2015.2403839.
[73] B. O'Dea, S. Wan, P.J. Batterham, A.L. Calear, C. Paris, H. Christensen, Detecting suicidality on twitter, Internet Interv. 2 (2015) 183–188, https://doi.org/10.1016/j.invent.2015.03.005.
[74] S.M. Weiss, N. Indurkhya, T. Zhang, F. Damerau, Text Mining: Predictive Methods for Analyzing Unstructured Information, Springer Science+Business Media, New York,USA, 2010.

[75] S.W.K. Chan, M.W.C. Chong, Sentiment analysis in financial texts, Decis. Support. Syst. 94 (2017) 53–64, https://doi.org/10.1016/j.dss.2016.10.006.
[76] B. Pang, L. Lee, Presentation: opinion mining and sentiment analysis, Found. Trend Inf. Retr. 2 (2008) 1–135, https://doi.org/10.2200/S00416ED1V01Y201204HLT016.
[77] G. Ertek, X. Chi, A.N. Zhang, S. Asian, Text mining analysis of wind turbine accidents: An ontology-based framework, in: 2017 IEEE Int. Conf. Big Data (Big Data), 2017, pp. 3233–3241, https://doi.org/10.1109/BigData.2017.8258305.
[78] S. Asian, G. Ertek, C. Haksoz, S. Pakter, S. Ulun, Wind turbine accidents: a data mining study, IEEE Syst. J. 11 (2017) 1567–1578, https://doi.org/10.1109/JSYST.2016.2565818.
[79] J.F.J. Hair, W.C. Black, B.J. Babin, R.E. Anderson, Multivariate Data Analysis, 2009, p. 816.
[80] D. Travis, M. Lang, L. Stice-Lawrence, The evolution of 10-K textual disclosure: evidence from latent Dirichlet allocation, Eviden. J. Account. Econ. 64 (2017) 221–245.
[81] H.M. Wallach, I. Murray, R. Salakhutdinov, D. Mimno, Evaluation methods for topic models, in: Proc. 26th Int. Confer- Ence Mach. Learn. Montr. Canada, 2009, 2009, pp. 1–8.
[82] K. Bastani, H. Namavari, J. Shaffer, Latent Dirichlet allocation (LDA) for topic modeling of the CFPB consumer complaints, Expert Syst. Appl. 127 (2019) 256–271.
[83] M. Steyvers, T. Griffiths, Probalistic topic models, in: Latent Semant. Anal. A Road To Mean, 2010, https://doi.org/10.1016/s0364-0213(01)00040-4.
[84] K.P. Murphy, Probabilistic Machine Learning: An Introduction, MIT Press, 2021 (probml.ai).
[85] G. James, D. Witten, T. Hastie, R. Tibshirani, An Introduction to Statistical Learning, Springer Science+Business Media, New York, 2013.
[86] J.H. Friedman, T. Hastie, R. Tibshirani, Regularization paths for generalized linear models via coordinate descent, J. Stat. Softw. 1 (1) (2010).
[87] S. Tirunillai, G.J. Tellis, Mining marketing meaning from online chatter: strategic brand analysis of big data using latent dirichlet allocation, J. Mark. Res. 51 (2014) 463–479, https://doi.org/10.1509/jmr.12.0106.
[88] D.G. Ko, F. Mai, Z. Shan, D. Zhang, Operational efficiency and patient-centered health care: a view from online physician reviews, J. Oper. Manag. 65 (2019) 353–379, https://doi.org/10.1002/joom.1028.
[89] K. Black, Business Statistics for Contemporary Decision Making, Sixth, John Wiley and Sons, Jefferson City, 2010.
[90] J. Chen, X.-L. Shen, Consumers' decisions in social commerce context: an empirical investigation, Decis. Support. Syst. 79 (2015) 55–64.
[91] B. Xiao, I. Benbasat, An empirical examination of the influence of biased personalized product recommendations on consumers' decision making outcomes, Decis. Support. Syst. 110 (2018) 46–57, https://doi.org/10.1016/j.dss.2018.03.005.
[92] A. Zirikly, P. Resnik, Ö. Uzuner, K. Hollingshead, Shared task: predicting the degree of suicide risk in {Reddit} posts, in: Proc. Sixth Work. Comput. Linguist. Clin. Psychol, 2019.
[93] H.-C. Shing, S. Nair, A. Zirikly, M. Friedenberg, H. Daumé III, P. Resnik, Expert, crowdsourced, and machine assessment of suicide risk via online postings, in: Proc. Fifth Work. Comput. Linguist. Clin. Psychol. From Keyboard to Clin, 2018, pp. 25–36.
[94] A.H. Puspitasari, Hamidah, effectiveness of acceptance and commitment therapy to reducing depression in nursing home residents, in: Proc. 3rd Int. Conf. Psychol. Heal. Educ. Soc. Organ. Settings (ICP-HESOS 2018), 2018, pp. 174–179.
[95] M.T. Masud, M.A. Mamun, K. Thapa, D.H. Lee, M.D. Griffiths, S.-H. Yang, Unobtrusive monitoring of behavior and movement patterns to detect clinical depression severity level via smartphone, J. Biomed. Inform. 103 (2020), 103371.
[96] G. DiPetta, Addictions and depression: the paradise lost, Eur. Psychiatry. 30 (2015) 114, https://doi.org/10.1016/s0924-9338(15)30095-x.
[97] C. Turvey, A. Stromquist, K. Kelly, C. Zwerling, J. Merchant, Financial loss and suicidal ideation in a rural community sample, Acta Psychiatr. Scand. 106 (2002) 373–380, https://doi.org/10.1034/j.1600-0447.2002.02340.x.
[98] L. Fiksenbaum, Z. Marjanovic, E. Greenglass, F. Garcia-Santos, Impact of economic hardship and financial threat on suicide ideation and confusion, J. Psychol. Interdiscip. Appl. 151 (2017) 477–495, https://doi.org/10.1080/00223980.2017.1335686.
[99] E.A. Halford, A.M. Lake, M.S. Gould, Google searches for suicide and suicide risk factors in the early stages of the COVID-19 pandemic, PLoS One 15 (2020) 1–8, https://doi.org/10.1371/journal.pone.0236777.
[100] J.A. Lueck, Help-seeking intentions in the U.S. population during the COVID-19 pandemic: examining the role of COVID-19 financial hardship, suicide risk, and stigma, Psychiatry Res. 303 (2021), 114069, https://doi.org/10.1016/j.psychres.2021.114069.
[101] X. Xu, T. Siqin, S.H. Chung, T.M. Choi, Seeking survivals under COVID-19: the WhatsApp platform's shopping service operations, Decis. Sci. (2021), https://doi.org/10.1111/deci.12552 published online.
[102] T.M. Choi, S. Kumar, X. Yue, H.L. Chan, Disruptive technologies and operations management in the industry 4.0 era and beyond, Prod. Oper. Manag. (2021), https://doi.org/10.1111/poms.13622 published online.

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