Developing a mental health index using a machine learning approach: Assessing the impact of mobility and lockdown during the COVID-19 pandemic

Krishnadas Nanath [a], Sreejith Balasubramanian [a], Vinaya Shukla [b], Nazrul Islam [c,*], Supriya Kaitheri [a]

[a] *Middlesex University Dubai, United Arab Emirates*
[b] *Middlesex University Business School, UK*
[c] *Department of Science, Innovation, Technology and Entrepreneurship, University of Exeter Business School, UK*

A B S T R A C T

Governments worldwide have implemented stringent restrictions to curtail the spread of the COVID-19 pandemic. Although beneficial to physical health, these preventive measures could have a profound detrimental effect on the mental health of the population. This study focuses on the impact of lockdowns and mobility restrictions on mental health during the COVID-19 pandemic. We first develop a novel mental health index based on the analysis of data from over three million global tweets using the Microsoft Azure machine learning approach. The computed mental health index scores are then regressed with the lockdown strictness index and Google mobility index using fixed-effects ordinary least squares (OLS) regression. The results reveal that the reduction in workplace mobility, reduction in retail and recreational mobility, and increase in residential mobility (confinement to the residence) have harmed mental health. However, restrictions on mobility to parks, grocery stores, and pharmacy outlets were found to have no significant impact. The proposed mental health index provides a path for theoretical and empirical mental health studies using social media.

1. Introduction

The coronavirus disease 2019 (COVID-19), first reported in China in December 2019, has developed into a deadly global pandemic that is changing the fabric of life and societies worldwide (World Health Organization, 2020a). The pandemic, which started as a physical health crisis, is profoundly affecting mental health, resulting in conditions such as depression and anxiety (United Nations, 2020; World Health Organization, 2020b). For example, more than one-third of the participants surveyed in the US, Germany, and the United Kingdom have highlighted mental health as one of their main concerns during the COVID-19 pandemic (Statista, 2020). Studies have reported depression and loneliness levels to have doubled, tripled, or even quintupled compared to pre-COVID-19 times (McKinsey and Company, 2020), and levels of anger, grief, stress, insomnia, boredom, confusion, irritability, hopelessness, nervousness, and restlessness have also increased (World Health Organization, 2020b; McKinsey and Company, 2020; CDC, 2021; The Health Foundation, 2020). Such mental health disorders have also

been observed in previous crises. For example, the SARS pandemic in 2003 and the global recession in 2008 caused an increase in alcohol and substance abuse, self-harm, and suicidal behavior (Armbruster and Klotzbücher, 2020; Harvard Health, 2020). Understanding and strengthening the mental health of citizens during crises is important for governments and should be an integral part of any crisis response strategy (Chancellor and De Choudhury, 2020; World Health Organization, 2020b).

Lockdown is central to the mitigation measures implemented by governments worldwide during the COVID-19 pandemic to contain the spread of the virus and protect public health. Among the various lockdown measures, restrictions on 'mobility' were the most evident and controversial. First, international borders were closed for travel by land, sea, and air. However, the spread of the virus did not end there, soon becoming a local phenomenon. In most countries, especially those hit the hardest, people could not leave their homes during the lockdown (Armbruster and Klotzbücher, 2020). In sum, there was a new global reality in which mobility (mostly taken for granted) was severely

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curtailed. The involuntary nature of this immobility (referred to as the 'mobility index' in this paper) has severe implications for the mental health of the population and therefore requires closer attention (Lowe and Deverteuil, 2020). Other key lockdown measures (referred to as the 'lockdown strictness index' in this paper) that impact mental health include the closing of businesses, schools, universities, and recreational facilities; stringent surveillance (testing and contact tracing); social distancing measures such as limits on public and private gatherings; and the need to wear protective equipment such as face masks (Hale et al., 2020). Despite its significance, there have been limited efforts among practitioners and academics to understand lockdown-related mental health issues *vis-à-vis* physical health issues. For example, of the trillions of dollars passed by the US Congress in emergency coronavirus funding, only a minuscule proportion was allocated for mental health (Washington Post, 2020).

Moreover, there is a lack of consensus on the impact of lockdowns on the mental health of the population. Scholars argue that it will have a detrimental effect; they claim that the lockdown could instill fear, such as the fear of losing livelihoods, fear of being unable to work or being dismissed from work during the lockdown, and fear of being separated from their loved ones. In other words, the impact of social isolation and economic stagnation on mental health resulting from lockdowns could be worse than the fear of the virus itself and the deaths caused by the pandemic. Wang et al. (2020a) found that more than 50% of respondents had experienced psychological distress, including depression and anxiety, when China adopted some of the most aggressive lockdown measures, including stay-at-home orders and mandatory quarantine.

However, proponents of lockdowns claim that mental health issues are primarily due to concerns related to the fear of falling ill and dying, fear of infecting others, and fear of losing loved ones because of the virus. Hence, they claim that stringent lockdown measures could improve people's mental health because of the perceived lower risk of contracting the virus and the hope of curbing the pandemic (YouGov, 2020; Mækelæ et al., 2020). For example, a YouGov (2020) survey found that people had a positive attitude toward lockdown measures, viewing them as an effective method to reduce COVID-19 fatalities. This is evident from the increase in voluntary self-isolation and the voluntary reduction of social contacts (Laato et al., 2020).

These limited and conflicting findings imply that governments and public health authorities are uncertain about the impact of lockdowns on the mental health of the population during the COVID-19 pandemic. The impact of lockdowns and mobility-related restrictions on mental health has significant implications for the way lockdowns are implemented, such as stringency, timing, and duration of the lockdown period; thus, a clear understanding is vital.

Finally, it is unclear how social media usage affects the mental health of the population during the COVID-19 pandemic. There is a lack of consensus in the literature regarding the impact of social media on mental health; some scholars argue that prolonged social media use has a detrimental effect on the mental health of the user, leading to anxiety, depression, or stress (Dhir et al., 2018, 2019) resulting from social media addiction (Longobardi et al., 2020), dependency on social media for almost everything (Arora et al., 2020), and heightened exposure to misinformation (Kouzy et al., 2020), among others.

Even so, proponents of social media highlight the critical role it plays in the rapid dissemination of vital information and constructive discussions about the COVID-19 pandemic (Das and Ahmed, 2020), and in offering an online social support network for those in need during the pandemic (Khaleej Times, 2021). For instance, Erevik et al. (2020) found an inverse relationship between the number of online friends and depression symptoms, suggesting that having more online friends may protect against the development of depressive symptoms. A clear understanding of the effect of social media in amplifying or dampening pandemic-induced mental health issues is critical for governments and businesses to decide whether to rely heavily on social media as part of their COVID-19 response strategy.

Studies have relied on traditional clinical approaches, such as questionnaire-based mental health surveys, to assess the impact of the lockdown and social media use on the mental health of the population. Subjective methods, such as surveys that ask about respondents' opinions and attitudes, have several drawbacks. For instance, surveys use relatively small samples and are prone to self-reporting bias and a lack of voluntary participation (Leroux et al., 2012; Wang et al., 2020a, 2020b). Hence, generalizing these findings to the entire population is difficult. In addition, mental health studies typically adopt a cross-sectional survey design (or single-shot study), making it difficult to track changes in the population's mental health over a period (Dhir et al., 2019; Tandon et al., 2020). Moreover, the survey research approach is time-consuming, and detection of early warning signs of a large population's mental health issues, and thus, provision of timely interventions, is difficult. Similar concerns related to early identification, detection, and longitudinal tracking are also witnessed for objective measures such as suicide rates, psychiatric hospitalization rates (e.g., in-hospital stay or discharge data), and availability of health resources (e.g., number of psychiatrists or psychiatric beds *per capita*), as capturing and reporting these measures can be cumbersome (Tannenbaum et al., 2009) and may not adequately represent the full spectrum of those facing mental health issues.

Given the limitations of traditional approaches, new and emerging approaches have started to utilize data from social media, where much of this conversation now occurs, to examine the mental health of the population. Content-rich, user-generated data on social media platforms such as Twitter offer a valuable source of information to capture the mental health issues of the broader population with relative ease compared to traditional approaches (Chancellor and De Choudhury, 2020). However, despite its promise, the use of such data during pandemics/outbreaks is still in its infancy. A few studies have used social media data (tweets in particular) to examine mental health issues related to events such as an influenza outbreak (Chew and Eysenbach, 2010), vaccination (Love et al., 2013), the spread of flu symptoms (Sadilek et al., 2012), and insights about diseases (Paul and Dredze, 2011). However, these studies have defined and captured mental health in various ways. Otherwise, there was no consistency regarding what constitutes a mental health issue, and none developed a standard mental health index, an approach that is critical for assessing trends in the population over time, especially during the COVID-19 pandemic, because of its ever-changing and evolving nature.

These reasons are the motivation for this study, whose specific objectives are as follows: (1) Analyze the mental health condition of the population using their social media posts and develop a novel 'mental health index'; (2) Assess the impact of mobility restrictions and lockdown stringency on mental health; (3) Assess the impact of social media use (follower effects) on the relationship between mobility restrictions, lockdown stringency, and mental health.

This study makes a three-fold contribution. First, it proposes a novel mental health index at a global level using social media, capable of assessing the mental health trends of the population over time with relative ease compared to traditional questionnaire-based self-reporting mental health surveys or objective measures, such as suicide rates and psychiatric hospitalization rates. The mental health index also enables meaningful, rapid, and cost-effective comparisons, generalizability, and transferability of findings across studies. Second, knowledge of the cause-and-effect relationships among COVID-19 mobility restrictions, lockdown stringency, and mental health enables policymakers to make informed decisions about how lockdowns are enforced. Third, the study provides direct evidence and supports the growing call to include mental health concerns in the government's COVID-19 response.

The remainder of this paper proceeds as follows. The next section will discuss the study framework, including the step-by-step development of the mental health index and research hypotheses. The data analysis is detailed in Section 3, and the results are presented in Section 4. We conclude the paper in Section 5 with a discussion of the findings

and their implications, limitations of the study, and suggestions for future research.

2. Development of a mental health index and study hypotheses

This section outlines the study framework and discusses the step-by-step process of developing the mental health index and the hypotheses concerning the link between mobility restrictions, lockdown strictness, social media use, and mental health. The framework adopted in this study is illustrated in Fig. 1. As shown, the framework is divided into three sequential stages, where the output of one stage is the input to the next.

The first stage of the framework deals with tweet extraction and data cleaning to obtain a corpus of filtered tweets, resulting in a final dataset of tweets for the analysis. This process is illustrated in Fig. 2. More details on this stage are provided in Section 3.1, where the choice of keywords and filters is described.

In the second stage, in line with the first research objective, a novel method for arriving at the mental health index score for each tweet in the dataset is developed, contributing to a new variable (feature generation). This is discussed in detail in the following section (Section 2.1). In the third stage, the impact of the lockdown strictness and mobility indices on the computed mental health index, as well as the asymmetric effects of social media use (using follower count as a proxy) on the relationships between the lockdown strictness index, mobility index, and mental health, in accordance with research objectives two and three, respectively. Further details on the predictors of mental health and their hypothesized impacts are discussed in Section 2.2.

2.1. Development of a mental health index

Developing a robust mental health index is critical, given the lack of consensus in the literature on the various approaches to assessing mental health as well as on the key indicators to capture the full spectrum of mental health issues. As discussed, most mental health studies, including those during the COVID-19 pandemic, use either questionnaire-based self-reporting mental health surveys or objective measures such as rates of suicide or psychiatric hospitalization, and the availability of hospital resources (Tannenbaum et al., 2009) as a proxy for understanding mental health issues, and neither adequately represents the mental health issues facing the population and does not lead to timely intervention to improve mental health. Therefore, the first objective of this study was to address this gap.

The key criteria for the development of any good index are that it should be measurable, verifiable, meaningful, rapid, cost-effective, policy-relevant, and capable of assessing population trends over time with relative ease (Tannenbaum et al., 2009). With the broader reach of the Internet and the growth of social media, millions worldwide now express their opinions and states of mind on these platforms. Consequently, mental health-related conversations on social media are a valuable source of information for mental health research (Sarker et al., 2015; Reavley and Pilkington, 2014). According to Kolliakou et al. (2020), the use of data-rich internet sources such as social media is becoming a potentially rapid and cost-effective way to identify population needs and predict or prevent mental health problems. Its usefulness is even greater during the COVID-19 pandemic, as much of the conversation about COVID-19 and related mental health issues now occurs on social media platforms. Evidence shows that social media venting has been on the rise since the beginning of the pandemic, when people are not afraid of strong opinions, including mental health issues such as depression and anxiety (Muses, 2020). Social media feeds allow access to a wider population than traditional clinical approaches do, allowing more timely intervention to address mental health issues (Chancellor and De Choudhury, 2020).
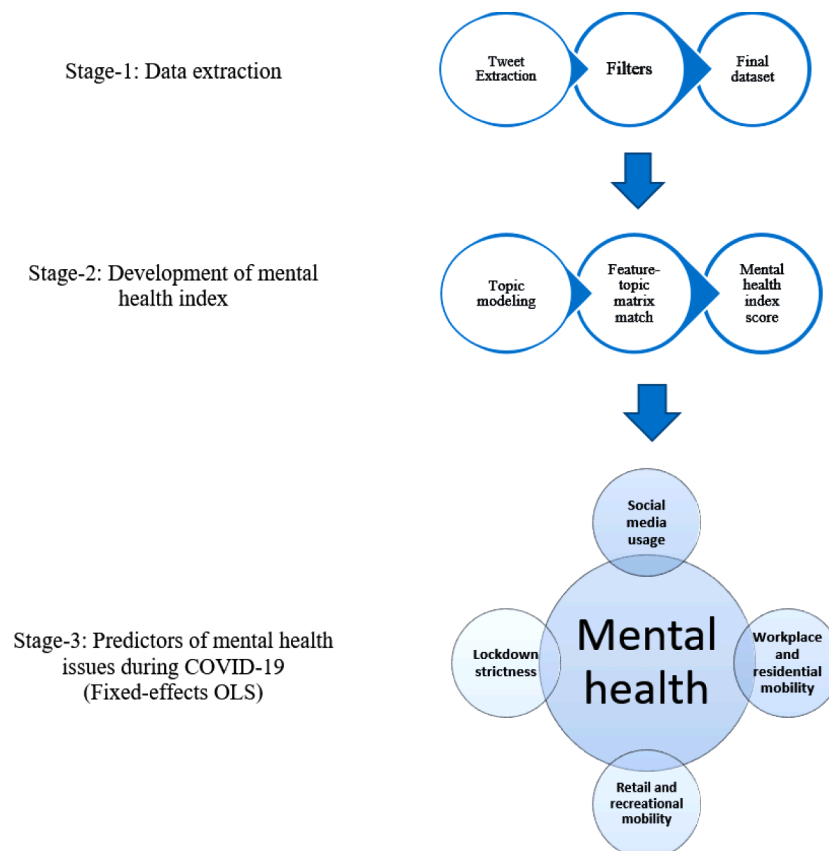

Stage-1: Data extraction

Stage-2: Development of mental health index

Stage-3: Predictors of mental health issues during COVID-19 (Fixed-effects OLS)
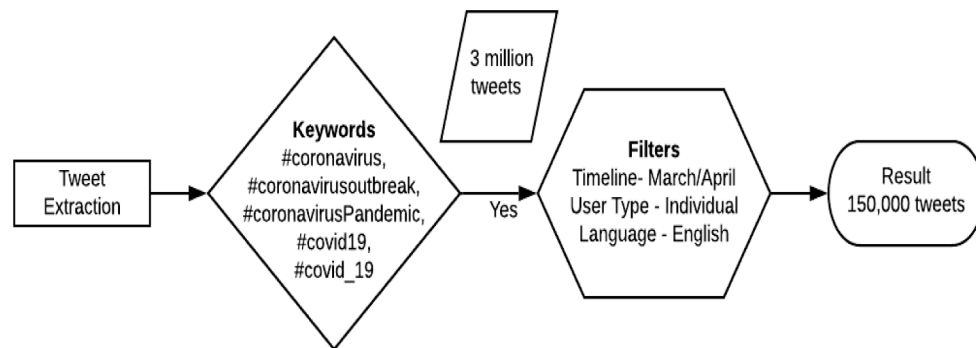
Fig. 1. Study framework.

Fig. 2. Data extraction process.

Among the various social media sources, Twitter has proven to be the most valuable for monitoring and early detection of mental health issues, and for analyzing behaviors, attitudes, and experiences related to mental health, particularly anxiety and depression (Shepherd et al., 2015; Cavazos-Rehg et al., 2016; Kolliakou et al., 2020). Its advantage is that it allows automated analysis of the features of large data sets of posts, including linguistic features such as frequency of words, sentiments, and emotions, followed by machine learning methods (such as support vector machines) to detect mental health issues (Tadesse et al., 2019). Hence, Twitter data are used for the development of the mental health index. First, the various approaches used to capture mental health data from social media platforms are reviewed, and then we propose a method for calculating a mental health index for a given individual post (tweet) on social media.

2.1.1. Capturing mental health issues from social media

The impact of social media on human lives is multifaceted and broad, given that there are approximately 3.78 billion active social media users worldwide (Tankovska, 2021). As a result, behavior on social media and its implications, including mental health, has received wide attention in the past decade. Several studies have investigated the relationship between extensive social media use and psychological well-being (Dhir et al., 2018, 2019; Keles et al., 2020; Liu et al., 2021). Evidence suggests that social media use results in depression, anxiety, and psychological distress. However, studies have reported that anxiety and depression could lead to compulsive social media usage (Tandon et al., 2020). De Choudhury et al. (2013) used social media content to detect and diagnose major depressive disorders. Erevik et al. (2020) used the number of social media connections and frequency of logins to understand the impact of follower count on user depression.

In the literature, we identified four approaches to capture indications of mental health issues from social media data. The first approach combines social media data with questionnaires, where individuals self-report mental illness, and the analysis adds social media posts (De Choudhury et al., 2013; Reece et al., 2017). Most studies using this method used Twitter as a platform, combining it with psychometric mental illness scales such as the Center for Epidemiologic Studies Depression (CESD; Radloff, 1977) and Beck's Depression Inventory (BDI) (Beck et al., 1996). However, these methods are subject to several disadvantages, such as bias in reporting, lack of self-awareness, and unreliability of the scales during a crisis like the COVID-19 pandemic. The second approach extracts data from online forums and discussion websites dedicated to mental health (Bagroy et al., 2017; De Choudhury et al., 2016). As these forums are avenues for people to seek help and discuss problems, they provide useful data for analysis. However, the prediction is limited to individuals who are self-aware of mental health issues. The third approach involves annotators manually examining social media posts to detect depression and stress symptoms (Kern et al., 2016; Hwang and Hollingshead, 2016); mostly using theory-driven or data-driven classifications to identify symptoms (Mowery et al., 2015),

but there is an issue of human bias in rating, and humans cannot process big datasets beyond a specific limit. The fourth approach identifies mental health issues by using self-declared posts on social media. Several individuals are open about their problems, and post tweets such as "I was diagnosed with depression today." Researchers often use topic modeling methods to identify key topics that emerge from self-declared posts (Resnik et al., 2015). For example, it was used to identify post-traumatic stress disorder (PTSD) and depression status (Preoţiuc-Pietro et al., 2015). Similar studies have used psychological dictionaries (Linguistic Inquiry and Word Count (LIWC)) to identify various categories of mental health issues. A summary of these four approaches is presented in Table 1.

Unfortunately, one of the main limitations of these approaches is the presentation of mental health issues as binary, either present or absent in a post. However, issues do not appear as binary in social media posts but on a scale ranging from low to high. Thus, our proposed method is primarily inspired by the combination of methods in the fourth category but also uses the best of all other categories to obtain a mental health score for each post (tweet).

2.1.2. The three-step process for the development of the mental health index

To define the boundary of mental health prediction from social media data, we restrict our analysis to depressive symptoms and psychosocial stressors, the two most common categories of mental health issues discussed in the literature (Mowery et al., 2017). The mental health index quantitative score is calculated for each tweet from our dataset, $C = \{c_1, c_2, c_3 \ldots \ldots c_n\}$. C represents the set of tweet "documents" and c_i represents each tweet in the dataset (each row). The mental health score (MH_i) demonstrates the extent of depressive symptoms and psychosocial stressors, as demonstrated by tweet c_i. A lower value of MH_i indicates a low degree of mental health issues, whereas a higher value indicates a high degree of symptoms demonstrated in the tweet. The calculation of MH_i was a three-step process: a) topic modeling of the tweets resulting in two outputs – feature topic matrix and the transformed dataset normalized as the conditional probability of topics given in a document; b) scanning the depressive symptoms and psychosocial acquired depression (SAD) corpus and matching it with featured text; c) adding the score of top topics that match the previous step to obtain an overall score for the mental health index. The steps are discussed in detail in the following sections.

Step 1: Topic modeling

Topic modeling was the first step, testing for topics in the corpus and examining the featured text. The latent Dirichlet allocation (LDA) algorithm (Blei et al., 2003) was used to control the number of topics and words to ease statistical analysis. One of the objectives of this step is to extract $T = \{t_1, t_2, t_3, \ldots \ldots t_n\}$ topics from tweet dataset C. A tweet Ci can be viewed by its topic distribution in terms of its probability Pi, and the representation can be expressed as:

$$\text{Probability } (C_i \in t_i) = P_i$$
$$\text{tweet document } C = \{c_1, c_2, c_3 \ldots \ldots c_n\} \text{ and topic distribution } T = \{t_1, t_2, t_3, \ldots .. t_n\}$$

Table 1
Various approaches for capturing mental health issues from social media data.

Approach	Description	Key Papers
1: Questionnaires	Combines social media data with a self-reporting questionnaire.	De Choudhury et al. (2013), Reece et al. (2017)
2: Online forums	Extract data from online forums and discussion websites (mental health).	Bagroy et al. (2017) , De Choudhury et al. (2016)
3: Annotators	Annotators manually examine the social media posts for symptoms.	Kern et al. (2016), Hwang and Hollingshead (2016), Burnap et al. (2015)
4: Text Modeling	Use of topic modeling and NLP techniques like sentiment analysis.	Resnik et al. (2015), Preoţiuc-Pietro et al. (2015), Durahim and Coşkun (2015)

Topic modeling also generated a feature topic matrix that contains the featured text and the score of each of the categories in the topics column $\{t_1, t_2, t_3, \ldots .. t_n\}$. The matrix values are probabilities that can be represented in terms of probability (word/feature | topic). The featured text-transform results in a bag of consecutive words called n-grams for a given text corpus. The choice of n-grams was fixed at two (bigrams), as tweets were short, with a limit of 280 characters. It is also essential to choose the correct number of topics (n) to obtain meaningful results (Law and Jain, 2003). We experimented with various values of n in the recommended range of five to 30 and traced back the results to the literature to understand meaningful topics. This method has been used in similar studies that have used topic modeling (Kar, 2020). After several rounds of experimentation, seven topics ($n = 7$) were selected based on their relevance to mental health. Microsoft Azure Machine Learning Studio was used to execute the topic modeling, as it is very efficient in treating big data and uses a cloud interface (browser).

Step 2: Examination of feature topic matrix using the external corpus.

This step involved examining the feature topic matrix and matching the depressive symptoms and SAD corpus to find topics that reflect mental health issues in a tweet. To select the topics from the matrix, we scanned various LIWC dictionaries in the literature and selected the corpus developed by Mowery et al. (2017). The reason for this is twofold. First, a corpus was developed using self-declarations made on Twitter. Second, the two dimensions explored by the corpus were depression and psychosocial stress, which are relevant to this research during the COVID-19 pandemic. The corpus had 110 keywords distributed across the two dimensions and ten categories (see Table 2). Each topic t_i (column) in the feature topic matrix is sorted to identify the top topic features (n-grams or keywords, rows) in each column. The keywords in the chosen corpus were then searched for in the keywords of each topic. All 110 dictionary keywords existed in three (of the seven)

Table 2
Summary of keywords in depressive symptoms and SAD corpus.

Dimension	Common Categories	Sample keywords
Depressive symptoms	Sad mood Change in appetite Sleep issues Psychomotor agitation Fatigue Inappropriate guilt	*Insomnia; restless; jitter; groggy, dazed; guilt; burden; suicide; kill and others.*
Psychosocial stressors	Lack of support group Occupational problems Housing problems Various expressions of sad nature	*Fired, unemployed; pathetic; weep; neglect; fail; fatigue; grief and others.*

topics (t_3, t_5, and t_7). This indicates the strength of these three topics in identifying depressive symptoms and stress disorders.

Step 3: Deriving the mental health index

The previous steps examined a feature topic matrix with seven topics ($n = 7$). In addition to the matrix, executing the LDA algorithm in Azure Studio also generates the transformed dataset as an output. Each row in this transformed dataset contains a tweet along with the scores across seven discoverable categories (topics). Step 2 revealed that three of the seven topics demonstrated a strong match between depressive symptoms and psychosocial stressors (t_3, t_5, and t_7). Therefore, a score in the transformed dataset across these three topics would demonstrate factor loading, so that the tweet would be assigned to topics t_3, t_5, or t_7. Thus, an aggregation of these scores would reflect the mental health index, where a tweet would exhibit depressive symptoms and psychosocial stressors. This would help achieve one score per tweet, which could be used further for modeling and analysis.

In the final step, the scores of the three topics were added (t_3, t_5, and t_7, each ranging from 0 to 1) in the first output of the topic modeling (LDA-transformed dataset) that contained the tweet document $C = \{c_1, c_2, c_3 \ldots c_n\}$ and topic distribution $T = \{t_1, t_2, t_3, \ldots .. t_n\}$. This addition was possible because of the mutually exclusive nature of the loadings. Therefore, for each tweet C_i, there was a new score, MH_i ($t_3 + t_5 + t_7$), ranging from 0 to 3. A value close to three indicated the highest trace of depressive symptoms and psychosocial stressors and, thus, a greater display of mental health concerns in the tweet. In contrast, a tweet with a mental health index score closer to zero demonstrates minor signs of depressive symptoms and psychosocial stressors.

The execution of all three steps above helped achieve the first objective of developing the mental health index, addressing the gap in the extant literature that primarily focuses on binary indicators (present or absent). With the growth of computing infrastructure and big data technologies, it is essential to deal with social media data at the document level, rather than at the corpus level. Moreover, human coding and intervention are extremely challenging with millions of social media and related data points. Therefore, this method uses natural language techniques to automate the development of a score that is not in binary format. Although this method has been demonstrated for tweets, it contributes to document-level text data. The three steps: (a) topic modeling, (b) examination of feature topic modeling using the SAD corpus, and (c) combining the scores of influential topics to arrive at a mental health index offer a combined process that can be applied to a row-level text dataset. With an appropriate corpus, this method can be extended further to develop a score for topics other than mental health.

Now that we have achieved our first objective of developing a mental health index, our next focus is to define the predictors of mental health issues.

2.2. Predictors of mental health issues during COVID-19

The COVID-19 pandemic has generated an enormous psychological burden for people, and recent studies have reported an increased threat to mental health and pre-existing mental illness (Bäuerle et al., 2020). The rise in mental health issues due to the virus outbreak could be attributed to several factors; the two considered in this study are restrictions on mobility and lockdown stringency, because restrictions on everyday life, such as going out to work, leaving the house, or meeting friends and family, can adversely affect mental health (Veenhoven, 2000). A supportive work environment, professional confidence, and civic engagement have been found to positively influence mental health (Fink, 2014). Similarly, greater social engagement, generally defined as active engagement in a range of interpersonal relationships and social activities, is associated with better mental health (Sani et al., 2012) as it provides people with a sense of meaning, purpose, belonging, and stability (Thoits, 1983) and increases the social support they receive or perceive (Cohen, 2004). Therefore, government restrictions on personal choices have a profound negative impact on mental well-being (Hayward and Elliott, 2014). Several studies have reported a reduction in happiness levels after the COVID-19 lockdown was implemented (Arora and Kathuria, 2020; Greyling et al., 2020a). People tend to feel anxious and unsafe when the environment changes owing to lockdown restrictions (Usher et al., 2020). The more stringent the stay-at-home regulations were, the greater the negative effect they had on the happiness level (Greyling et al., 2020b). Imposed quarantine or isolation is unfamiliar; therefore, it is crucial to explore how these COVID-19 restrictions affect the mental health of the population.

2.2.1. Mobility and mental health

Mobility is an aspect of daily activity. A micro-geographical concept that captures the spatial extent of daily mobility patterns is known as activity space (Schönfelder and Samaga, 2003). An activity space generally consists of all activities performed to satisfy physiological needs (eating, sleeping), institutional demands (work, school), personal obligations (childcare, food, shopping), and personal preferences (leisure activities) (Vilhelmson, 1999). Previous studies have shown that limited daily mobility reflects spatial and social confinement, and can be correlated with a higher risk of depression (Vallée et al., 2011).

The COVID-19 pandemic has resulted in a significant drop in mobility (Borkowski et al., 2020); Aloi et al. (2020) reported a massive reduction in mobility during lockdown after analyzing mobility data. The policies associated with the pandemic, such as working from home, cancelation of public events, restrictions on gatherings, and non-availability of public transport, have affected mobility on an unprecedented scale (Gössling et al., 2020). Although reduced mobility is effective in reducing COVID-19 cases (Tian et al., 2020), its mental health effects remain unexplored. A clearer understanding of the type of mobility restriction that has the greatest impact on mental health could aid the government in the implementation or phased removal of mobility restrictions. For example, understanding mental health issues due to restricted access to parks compared to restricted access to retail stores will have policy implications, but there is a significant gap in understanding the differential impact on the mental health of restricted access to the workplace, recreation, parks, retail, grocery, pharmacies, among others. This is discussed in the following sections.

Impact of the workplace and residential mobility on mental health: One of the most observable changes resulting from the COVID-19 pandemic has been the shift to remote work, across many occupations. Many are teleworking full-time for the first time and physically isolated from coworkers. This includes occupational groups with minimal experience of working from home (e.g., teachers in primary education) as well as, for instance, those working in sales, who may prefer not to work from home but are now forced to do so (Kramer and Kramer, 2020). It is imperative to check how the new work arrangement impacts employees' mental well-being.

Several previous studies have discussed the negative impact of work travel on mental health. The general assumption, therefore, is that the flexibility inherent in working from home generally benefits the individual and family. A few studies have confirmed that work-from-home enables increased autonomy in scheduling paid work, housework, and childcare responsibilities (Hill et al., 2003). Conversely, researchers have argued about the potential mental health benefits of traveling to work, such as daily structure, a sense of worth, and regular supportive social engagement (Modini et al., 2016). The social benefit of interacting with colleagues does not always work in the same way as digital media, and physical disconnectedness from co-workers may cause loneliness and isolation (Marsh, 2021).

Moreover, working from home creates an expectation for the employee to be available at any time (Park et al., 2011; Arlinghaus and Nachreiner, 2014). This may lead to an increase in work; that is, constant availability or working beyond contractually agreed work hours. People tend to extend work hours into evenings and weekends, causing interference with the rhythms of sleep, recovery, and social interaction (Arlinghaus and Nachreiner, 2014). Others may feel the need to find work and squeeze in activities whenever they can. However, without time to disconnect and unplug, there is a high risk of burnout, causing work-related health problems, such as depression, stress, and anxiety (Marsh, 2021). A few studies have indicated the adverse effects of stay-at-home orders on mental health, including depression, due to restricted mobility (Jacobson et al., 2020). Townley et al. (2009) reported that people whose daily activities remain close to home tend to have lower life satisfaction. Hence, we propose the following hypothesis:

H1: Workplace mobility (the ability to travel to work) positively affects mental health.
H2: Residential mobility (or confinement to a residence or nearby) adversely affects mental health.

Impact of retail and recreational mobility on mental health: COVID-19 has shut down a large part of the economy to save lives, and there is evidence that these interventions are effective in curbing the spread of the virus (Fang et al., 2020). Governments worldwide have implemented stay-at-home rules and restrictions on the opening of non-essential services. Even essential trips, such as for groceries, pharmacies, or doctors, were restricted to those with valid permits (CNBC, 2020). It is widely accepted that both long-distance travel (Poletto et al., 2013) and commuting (Yang et al., 2012) spread diseases, particularly those caused by airborne viruses (Germann et al., 2006). However, while long-distance travel could be seen as a non-essential activity and could be limited, daily mobility is deemed non-dispensable (Borkowski et al., 2020).

Google's (2020) COVID-19 community mobility report showed that access to retail and recreational services decreased considerably worldwide after March 2020 (Laato et al., 2020). Retail shopping is a complex consumer behavior that may be either purchase- or non-purchase-related. Due to the restrictions on physical retail space, consumers are learning to improvise and learn new retail habits to cope with COVID-19 restrictions. This includes an increase in online shopping and home deliveries (Sheth, 2020), which is expected to alleviate anxiety and stress related to fears of food and supply shortages, and to prevent unusual consumer behavior such as panic buying before the closure of physical retail outlets (Laato et al., 2020). However, financial anxiety and the need for precautionary savings during the COVID-19 pandemic have led to smaller shopping baskets, a decline in discretionary spending, and a reduction in shopping frequency (Talwar et al., 2021; Kohli et al., 2020). Such changes in consumer behavior may adversely affect consumers' mental health.

Further, online shopping may not necessarily provide shoppers with the same positive experience as visiting shopping centers. This is because shopping centers can promote individual and societal well-being by offering restorative services that promote relaxation and

collaboration (Rosenbaum et al., 2016). Utilitarian and hedonic motives drive retail shopping. The utilitarian aspect of consumer behavior is directed toward satisfying functional or economic needs (Babin et al., 1994). The hedonic perspective views shopping as an emotionally satisfying experience (excitement, arousal, joy, festivity, escapism, fantasy, and adventure) related to shopping activity, regardless of whether a purchase is made (Babin et al., 1994; Kim, 2006). Seeking gratification is one of the main hedonic motivations, and it involves shopping for stress relief, alleviating a negative mood, as a special treatment to oneself (Arnold and Reynolds, 2003), to (temporarily) experience positive emotions, and to relieve a depressive state (Claes et al., 2010; Horváth and Adıgüzel, 2018). The closure of non-essential retail outlets and shopping malls reduces hedonic shopping behaviors, leading to anxiety and depression.

Leisure is essential for psychological health. Leisure, as a free-time, non-obligatory behavior, lessens the impact of minor everyday stressors (Caltabiano, 1994). The primary purposes of recreational activities are enjoyment, fun, personal satisfaction, and revitalization (Leitner and Leitner, 2004), and they have a strong effect on happiness, life satisfaction, physical wellness, loneliness prevention, and emotional stability (Johnson, 2000; Chow, 2002; Luleci et al., 2008; Jacobs et al., 2008; Hunter and Gilen, 2009). Recreational activities can be categorized into physical and cognitive activities (Hunter and Gillen, 2009). Physical recreational activities include adventure, sports, visiting theme parks, and bio-parks, while cognitive recreational activities include book clubs, museums, restaurants, and movie theaters. Evidence shows that exposure to natural places can lead to positive mental health outcomes (Barton and Pretty, 2010). Globally, COVID-19 mobility restrictions have resulted in a significant reduction in recreational mobility.

Thus, this study hypothesizes that:

H3a: Retail and recreational mobility positively affects mental health.
H3b: Mobility to parks positively affects mental health.
H3c: Grocery and pharmacy mobility positively affects mental health.

2.2.2. Lockdown strictness and mental health

Most countries have imposed a lockdown on social and economic activities, although there are differences in the duration and strictness of these restrictions (Oum and Wang, 2020). It has been challenging for governments to balance their health and economic goals (Jones et al., 2020). The results showed that countries that imposed stringent measures were effective in lowering daily COVID-19 infections at the expense of economic progress (Makki et al., 2020). Some countries imposed massive lockdowns, whereas others did not implement strict measures. Strict lockdowns have received support from the perspective of saving lives (Eichenbaum et al., 2020), whereas fewer restrictions and no lockdowns have received support from an economic perspective (Jelnov, 2020).

The restrictions imposed because of the COVID-19 outbreak have caused significant disruptions to individuals, families, communities, and all countries. Government-imposed lockdowns have drastically altered aspects of daily life, which were previously simple and uncomplicated (Usher et al., 2020). Moreover, the longer a person is confined to quarantine, the poorer mental health outcomes are observed in terms of PTSD symptoms, avoidance behavior, and anger (Brooks et al., 2020). Studies conducted during previous pandemics suggest that adverse mental health impacts do not simply stop, but continue after the quarantine period. People continue to pursue a range of avoidance behaviors, such as reduced direct contact with other people and crowds, less social contact, avoiding enclosed and public places, and not returning to work (Marjanovic et al., 2007). Hence, this study hypothesizes the following.

H4: Lockdown strictness adversely affects mental health.

2.2.3. Asymmetrical effects of social media follower count

The social media follower count (used as a proxy for extended social media use) could potentially influence the above hypotheses (H1–H4). However, there is a lack of consensus in the literature on the impact of social media on mental health. Several studies have argued that social media users with a high follower count are likely to become addicted to social media, which in turn may negatively impact the mental health of the user. For instance, Longobardi et al. (2020) found that users with more friends on social media have more mental health issues than those with fewer followers. This is likely to be greater during the COVID-19 pandemic as people with many followers spend significant amounts of time using social media, developing a dependency on social networking sites for social interaction, communication, entertainment, and emotional expression, leading to negative mental health outcomes (Arora et al., 2020). Kouzy et al. (2020) found that misinformation accounted for 24.8% of all the serious tweets related to the COVID-19 pandemic. This risk was acknowledged early by the World Health Organization (WHO), who declared an 'infodemic' (an outbreak of misinformation causing mass anxiety and uncertainty) running in parallel to the viral pandemic. It could be argued that individuals with more social media followers are more likely to be exposed to misinformation or unverifiable information, resulting in 'information pollution', anxiety, and depression (Das and Ahmed, 2020; Lin and Kishore, 2021). For instance, the use of social media for online information seeking is becoming increasingly common, especially during the COVID-19 pandemic. This behavior, referred to as voyeurism or social surveillance, has been found to adversely affect users' mental health, such as fear of missing out (FoMO) (Tandon et al., 2021). A recent study shows an increasing propensity by users to believe in any news, despite the possibility of it being fake (Kumar et al., 2021). A recent study by Kaur et al. (2021a) explored the dark side of social media and found that social media usage is a real concern for young adults, as it could adversely influence users' well-being, including social media fatigue and FoMO. Social media fatigue and FoMO were found to influence fake news sharing behavior on social media (Talwar et al., 2019). Kaur et al. (2021b) highlighted concerns related to the nocturnal use of social media platforms on a user's sleep and the associated problems.

Despite these concerns, several authors have reported the positive role of social media in new product development, SMEs business sustainability, public dissemination and discussion of vital information about the COVID-19 pandemic (Rakshit et al., 2021a, 2021b; Talwar et al., 2022; Yousaf et al., 2022; Das and Ahmed, 2020), as well as in offering an online support network for those in need; for instance, people used social media to support each other during the pandemic (Khaleej Times, 2021). In contrast to Longobardi et al. (2020) findings, Erevik et al. (2020) found an inverse relationship between the number of online friends and symptoms of depression, suggesting that having more social media followers may protect against the development of depressive symptoms. Similarly, Cole et al. (2017) reported the benefits of using social media as a social support medium. While online social support may be beneficial in moderation, those who received excessive social media support during the COVID-19 pandemic had elevated levels of stress, anxiety, and depression (Zhong et al., 2020). Based on these arguments, we propose the following hypotheses:

H5: Follower count will have asymmetrical effects on the hypotheses H1–H4.

3. Data and method

3.1. Data extraction and preparation

Three datasets were used in this study: the Twitter dataset of COVID-19 tweets, Google mobility dataset, and University of Oxford's lockdown strictness index dataset.

To compute the mental health index, a dataset of COVID-19 tweets

Table 3

Data inclusion-exclusion criteria of tweets.

Data Inclusion/ Exclusion	Task	Rationale
Inclusion	Only tweets in the English language were included.	To use the machine learning packages that could apply natural language processing.
Inclusion	Only tweets from the Twitter Web app, mobile apps, and tablets were included.	To avoid any brand communication (from external applications) and include only individual responses.
Exclusion	The tweets with no information on the location of the tweet were excluded.	The country details were needed to match the mobility and lockdown strictness data.
Exclusion	Tweets with no text and only hashtags were removed.	It would be impractical to check symptoms of depression and stress with just hashtags.

was prepared by extracting more than three million tweets over two months: March and April 2020. Similar datasets have been used to discuss social media topics in the context of COVID-19 (Kruspe et al., 2020; Zarei et al., 2020). We used the 'rtweet' package on CRAN to extract the tweets in R studio using Twitter's application programming interface (API) (Twitter, 2020). The hashtags used in the extraction process were #coronavirus, #coronavirusoutbreak, #coronavirusPandemic, #covid19, #covid_19, and #ihavecorona. The tweets were then subjected to inclusion and exclusion criteria to derive a meaningful dataset for this study. A summary of the tasks in the tweeting process is provided in Table 3. After passing the tweets through all inclusion and exclusion criteria, the resulting dataset consisted of 150,000 tweets.

Next, for the mobility index, we used the Google mobility dataset (Google, 2020), which records actual data on community mobility and shows movement trends by region across different categories of places. For instance, it provides information on the mobility of residents in a country on a given day (time-series data). Similarly, it provides a mobility index for various categories such as retail, transit stations, workplaces, and parks. All datasets were aggregated into one dataset using the common field of country code.

Finally, for lockdown strictness, we used an index published by the University of Oxford (Hale et al., 2020). This shows the strictness of governments worldwide in their containment response to the COVID-19 pandemic and mainly refers to proposed governance and lockdown guidelines. This dataset has been highly cited and used in several studies to understand government responses and pandemic policies (Capano et al., 2020; Ashraf, 2020). The strictness index provides a stringency measure for a country on a given day (time series data).

3.2. Data analysis

The first stage of data analysis involved the computation of the mental health index. The dataset of COVID-19 tweets was subjected to data cleaning along with text pre-processing of the tweets. Azure Machine Learning features were used to execute the text processing, which included removing URLs, verb contraction, removing stop words, normalizing the case to lower case, removing duplicate characters, and preparing the tweets to be subjected to the topic modeling process that helped develop the mental health index. The second step involved calculating a quantitative score to indicate the extent of depression and stress-related symptoms in a tweet. The mental health variable MH_i indicates the quantitative score of tweet C_i. The third step used this MH_i score as a dependent variable to assess the impact of independent variables mobility and lockdown strictness on mental health using a linear regression model (see Fig. 1). The measure of mobility was represented by X_{tc}, where X refers to the residents' mobility index in country c on a given day t. X_{tc} was available for five categories: retail and recreation, grocery and pharmacy, parks, workplace, and residential. This resulted

in the five dependent variables being used in the regression model. The measure of the lockdown strictness index S_{tc} ranges from 0 to 100 and provides the index S on a given day t for a country c. The nine metrics used to calculate the lockdown stringency index are school closures, workplace closures, cancelation of public events, restrictions on public gatherings, closures of public transport, stay-at-home requirements, public information campaigns, restrictions on internal movement, and international travel controls. A lag of two days (t-2) was introduced, as it would take at least two days for strictness policies to impact people in a particular location. The third measure in the list was the online support system, which was measured using the follower count of an individual on Twitter. Table 4 presents a summary of the variables.

For the empirical analysis of the time-series model, fixed-effects OLS was used. The reason for including a fixed-effects model was to account for unobserved country attributes that could affect the mental health index. Therefore, for a country c, on a given day t and tweet i, model (Model 1) can be represented as

$$MentalHealthIndex(MH_i) = \beta_1 Country_i + \beta_2 StrictnessIndex(S_{tc})$$
$$+ \sum_{j=1}^{5} MobilityIndex(X_{tcj}) + FollowersCount_i + \in$$

In the equation above, variable j ranging from one to five represents the five categories of retail and recreation, grocery and pharmacy, parks, workplace, and residential. $Country_i$ represents the inclusion of country-fixed effects to control for unobserved country attributes that might affect the mental health score of an individual tweeting from a given country. We checked the assumption of multicollinearity before proceeding with OLS regression (Hilbe, 2009). The objective was to test for strong relationships between the independent variables. We use the variance inflation factor (VIF) to test this assumption.

Model 1 tested the relationship between the mental health index and other independent variables. We introduced two more models (Models 2 and 3) to compare the potential asymmetrical effects of strictness and mobility index on mental health across high and low online support systems (follower count). To execute Models 2 and 3, we disintegrated the sample into a high support sample and low support sample. Model 2 tested the relationship between strictness and the mobility index on the mental health of users with high online support, while Model 3 tested

Table 4

Summary of independent variables used in the regression model.

Category	Variables	Comments
Strictness Index	Strictness Index (S_{tc}): S is the strictness index on a given day t for a country c	The strictness index S_{tc} ranges from 0 to 100 and provides the index S on a given day t for a country c.
Mobility Index (X_{tc}): X is the mobility index of residents in a country c on a given day t	Workplace	Percentage change (-100 to 100) of mobility in the workplace compared to baseline.
	Residential	Percentage change (-100 to 100) of mobility in residential areas compared to baseline.
	Retail and Recreation	Percentage change (-100 to 100) of mobility in retail and recreational areas compared to baseline.
	Parks	Percentage change (-100 to 100) of mobility in parks compared to baseline.
	Grocery and Pharmacy	Percentage change (-100 to 100) of mobility in grocery and pharmacy areas compared to baseline.
Online support system	Followers Count	Followers of users who have tweeted in this dataset (High=1, Low=0).

the same relationship for users with low online support.

4. Results

Before running our fixed-effects OLS regression, we checked for outliers, observations, or measures that were much smaller or larger than the vast majority of observations. Outlier detection and removal are critical given that a few outliers are sometimes sufficient to distort the study results (Cousineau and Chartier, 2010). We used a well-known visual inspection method for standard outlier detection, namely, the box-and-whisker plot (Murrell, 2005). Visualizations of mobility variables compared on a common scale are presented in Fig. 3. It can be observed that there are some outliers, especially for two categories, namely "parks" and "groceries & pharmacy," which also demonstrated similar distribution patterns. The "workplace" and "retail & recreation" categories demonstrated similar mobility distribution, deviating below the baseline. The "residential" category was the only variable where mobility distribution was above the baseline and demonstrated positive scores. All outliers were removed before analysis.

Next, to check for possible multicollinearity concerns between the independent variables, we computed VIF. VIF is defined as the inverse of tolerance and assesses the extent to which the variance of an estimated regression coefficient increases if the predictors are correlated. Typically, if the VIF value is above 10 (tolerance value less than 0.1), it can be assumed that the regression coefficients are poorly estimated because of multicollinearity (Minitab, 2013). A statistical summary of all the variables used in the model and their VIF scores is presented in Table 5. All scores were lower than 10, indicating that multicollinearity was not a major concern in our analysis.

The statistical summaries (Table 5) also provide insights into the variables used in the analysis. In general, it can be observed that all aspects of mobility decreased during the pandemic (negative average scores) compared to the baseline. High mobility reductions were observed in the workplace and retail categories, while medium reductions were observed in the parks and grocery categories. The only category in which there was an increase in mobility (compared to the baseline) was residential mobility (positive average score). The mobility mean scores across various categories confirm that the sample data points in this study demonstrated the same characteristics as the population during the pandemic. The average strictness index was 76.5, and it can be inferred that overall strictness across all countries included in this dataset was relatively high.

Table 6 presents the results of the fixed-effects OLS regression model (Model 1). All the hypotheses and sub-hypotheses were tested using the same model. The model was controlled for country fixed effects (not

Table 5
Descriptive statistics of model variables.

Variable	Mean	Standard Deviation	VIF
Mental health index	0.685	0.234	–
Workplace (mobility)	-50.620	12.256	7.600
Residential (mobility)	20.828	5.845	5.435
Retail & recreation (mobility)	-53.852	16.775	3.450
Parks (mobility)	-25.181	16.352	1.672
Grocery & pharmacy (mobility)	-25.156	15.323	2.876
Strictness index (t-2) S_{tc}	76.494	9.324	5.329

Table 6
Results of the fixed-effects regression model.

Independent Variable	Beta Coefficient	Standard Error	p-Value	Hypothesis Supported (Yes/No)
(Constant)	0.044	(0.003)	0.000***	–
Workplace	-0.014	(0.001)	0.010**	Yes
Residential	0.018	(0.001)	0.000***	Yes
Retail & Recreation	-0.001	(0.000)	0.048*	Yes
Parks	0.001	(0.000)	0.713	No
Grocery & Pharmacy	0.018	(0.001)	0.459	No
Strictness index (t-2) S_{tc}	-0.003	(0.001)	0.032*	No

Note: Dependent variable: Mental Health Index; robust standard errors in parentheses; ***$P < .01$; **$P < .05$; *$P < .1$.

reported) and standard errors are reported in parentheses. There are some caveats associated with the fixed-effect regression; hence, the recommendations suggested by Hill et al. (2020) were followed for the execution. The overall model was significant with an adjusted R-squared value of 0.068.

The results of workplace mobility on mental health ($b = -0.014, p < .05$) confirmed H1. They found that a reduction in workplace mobility had an adverse impact on mental health during the pandemic. This is in line with the findings of Marsh (2021), who cautioned that physical disconnectedness from coworkers may make an individual feel lonely and isolated. Moreover, work-from-home arrangements may lead to burnout, leading to mental health issues, such as depression, stress, and anxiety.

Similarly, the residential mobility results ($b = 0.018, p < .001$) confirmed hypothesis H2. They indicated that an increase in residential mobility (or confinement to residence or places close to the residence)

Fig. 3. Box-and-Whisker plots of mobility variables.

also increased mental stress during the pandemic. These results align with Jacobson et al. (2020) findings, indicating the adverse effects of staying at home on mental health.

The results of retail and recreation mobility on mental health ($b = -0.001$, $p < .05$) supported Hypothesis H3a. They showed that restrictions on retail and recreational mobility harm mental health. The results support the hedonic perspective of retail shopping, in which consumers enjoy an emotionally satisfying experience such as instant gratification, stress relief, and positive emotions (Babin et al., 1994; Kim, 2006; Arnold and Reynolds, 2003). The findings also support the importance of providing physical and cognitive recreational activities to the population to enhance their mental health (Jacobs et al., 2008; Hunter and Gilen, 2009). However, mobility to parks (H3b) did not show any statistically significant impact on mental health ($b = 0.001$, $p > .05$). Similarly, the results of grocery and pharmacy mobility (H3c) did not demonstrate any statistically significant impact on mental health ($b = 0.018$, $p > .05$); this could be due to the fact that online grocery ordering and home deliveries have become common during the pandemic, and therefore, people have fewer concerns and fears related to running out of necessities and the need to stock up on food (Deák, 2020).

Finally, the impact of lockdown strictness on mental health ($b = -0.003$, $p < .05$) shows that our proposed hypothesis H4 was not supported. Although the relationship was significant, the nature of the impact turned out to be opposite to the hypothesized relationship, that a heightened lockdown strictness level would increase depressive symptoms and psychosocial stressors; instead, stricter lockdown regulations eased the stress levels, resulting in lower mental health problems. The results support the findings of the YouGov (2020) survey, which found that people had a positive outlook on lockdown measures and viewed them as an effective method to reduce COVID-19 fatalities.

To compare the potential asymmetrical effects of social media use using follower count, we executed two additional fixed-effects OLS regression models: Model 2 and Model 3. As shown in Table 7, these models were run after disintegrating the sample into a 'high' number of followers (above average) and a 'low' number of followers (below average). We also conducted an outlier test for the number of followers. Outliers (extremely high follower count) could affect the average and, hence, the categorization of followers. The removal of outliers reduced the average follower count from 14,341 to 8489. After removing outliers, the range of followers varied from 0 to 145,000, and the average number of followers was 13,456. The high online support (above average) and low online support (below average) subsamples comprise 32.36% and 67.64% of the sample, respectively. The testing of assumptions in these models was identical to those used for Model 1. The

chi-square test results of the models suggest that the coefficients from Models 2 and 3 are significantly different (with standardization, $\Delta\chi^2 = 30.2$, $p < .001$). Table 7 presents a summary of the two models (with disintegrated samples).

At the individual variable level, significant asymmetrical effects of follower count were found for the workplace (H1) and residential mobility (H2). As shown in Table 7, an increase in workplace mobility was found to reduce mental health issues. The relationship is stronger for those with a low follower count than for those with a high follower count. Additionally, an increase in residential mobility was found to increase mental health issues. The relationship is stronger for those with a high follower count than for those with a low follower count. In sum, both results show that a higher follower count has a detrimental effect on the mobility-induced mental health of the population. This is in line with the literature demonstrating that those confined to home with many followers are more likely to have mental health issues than those confined to home with fewer followers (Longobardi et al., 2020). The results support the recent literature on the dark side of social media, in that social media could adversely influence users' well-being, including social media fatigue, FoMO, and sleeplessness (Kaur et al., 2021a, 2021b).

5. Discussion and conclusions

This study examined the effects of COVID-19-related restrictions on the mental health of the general population. The results showed that the ability to travel to work reduces depressive symptoms and psychosocial stressors. This is likely because a physical work environment provides people with a sense of belonging, professional confidence, and civic engagement (Fink, 2014). The results also support the argument that traveling to work provides structure, a sense of worth, and regular supportive social engagement (Modini et al., 2016), and that the social benefit of face-to-face colleague interaction is not the same over digital media. The boundary between work and home life is blurred for people who work in the same place as they sleep. Unlike the flexibility that employees enjoy occasionally working from home, doing so for an extended period of time adversely impacts mental health. The study findings showed that an increase in residential mobility (staying at home) adversely affected mental health, especially for those addicted to social media. However, daily mobility outside the neighborhood of residence has been reported to result in fewer mental health issues. This is in line with previous studies that reported the adverse effects of stay-at-home orders (Jacobson et al., 2020) and confining daily activities to close to home (Townley et al., 2009). The results have potential implications for 'work-from-home' policies, as more companies are transitioning from an office-centric culture to more flexible ways of working post-pandemic.

The results of the impact of retail and recreational mobility on mental health show the need to reopen retail and recreational places, as this will not only support the economy and save jobs, but also enhance the mental health of the population. These findings support the notion in the literature that the closure of non-essential retail outlets and shopping malls will reduce hedonic shopping behavior and lead to anxiety and depression (Arnold and Reynolds, 2003; Claes et al., 2010; Horváth and Adıgüzel, 2018). The results also align with studies revealing that an increase in social interactions and involvement in social activities is associated with better mental health (Sani et al., 2012).

However, it was interesting to find that mobility or lack of mobility in parks, groceries, and pharmacies had no significant effect on mental health. In the case of parks, this could be because, although open, they may have severe restrictions in place, such as social distancing, and may not serve their primary purpose of enjoyment, fun, personal satisfaction, or revitalization. Furthermore, the pandemic has accelerated the penetration of e-grocery store services (Deák, 2020), so essential utilities are available. Therefore, the utilitarian aspect of consumer behavior, directed toward satisfying a functional or economic need (Babin et al.,

Table 7
Results of the fixed-effects regression models for disintegrated samples.

Independent variables	High follower count sample (Model 2) Unstandardized coefficients (SE)	Low follower count sample (Model 3) Unstandardized coefficients (SE)
Workplace	-0.010***	-0.016***
	(0.002)	(0.001)
Residential	0.024***	0.011***
	(0.001)	(0.002)
Retail & Recreation	-0.003**	-0.004**
	(0.000)	(0.000)
Parks	0.006	0.003
	(0.001)	(0.001)
Grocery & Pharmacy	0.032	0.021
	(0.001)	(0.002)
Strictness index (t-2) S_{tc}	-0.002**	-0.007**
	(0.001)	(0.001)
Country fixed-effects	Included	Included

Note: Dependent variable: Mental Health Index; robust standard errors in parentheses; ***$p < .01$; **$p < .05$; *$p < .1$.

1994), is likely fulfilled by online stores and home delivery, which could explain why restrictions on mobility to groceries and pharmacies have not impacted mental health.

However, it is counterintuitive that heightened lockdown strictness has improved the mental health of the population, in contrast to the notion in the literature that an increase in lockdown strictness has a detrimental impact on mental health (Usher et al., 2020; Brooks et al., 2020). Instead, strict lockdown measures may have alleviated concerns related to COVID-19, such as the fear of falling ill and dying, infecting others, and losing loved ones because of the lower risk of contracting the virus and the hope of controlling the pandemic (Mækelæ et al., 2020; YouGov, 2020). These results have potential implications for how governments implement future lockdown measures in the event of potential threats from new COVID-19 variants, such as the recent Omicron variant or in the event of a new pandemic.

Finally, the asymmetric effects of follower count on mental health were examined for both residential and workplace mobility. A higher follower count was found to have a detrimental effect on mobility-induced mental health problems. This could be because those with many followers who are confined to home are likely to be more addicted to social media than those with fewer followers (Longobardi et al., 2020), and may also experience social media fatigue and heightened exposure to misinformation, leading to uncertainty and anxiety (Dhir et al., 2019; Kouzy et al., 2020). These results support the growing literature on the dark side of social media and its impact on mental health (Talwar et al., 2019). This includes an increase in information-seeking behavior in social media and the propensity to share news in social media without verifying its facts and authenticity, leading to the spread of fake news, sleeplessness, and FoMO (Tandon et al., 2021; Kaur et al., 2021a, 2021b). These results contrast with those of Erevik et al. (2020), who found an inverse relationship between the number of online friends and symptoms of depression. In addition, the positive impact of workplace mobility on minimizing mental health issues was found to be lower for those with many followers. This could be because users may be addicted to social media in the workplace, with a greater dependency on social networking sites for social interaction, support, communication, entertainment, and emotional expression than on colleagues at the workplace (Arora et al., 2020). The results also indicate a lack of effectiveness of the online support network available on social media platforms for those in need during the pandemic.

The outbreak of COVID-19 has greatly affected human life, and the repercussions of this virus are beyond the direct physical threat, as it has a profound detrimental effect on the mental health of the general population, which in turn could reduce life expectancy due to suicide and alcohol and substance abuse (Armbruster and Klotzbücher, 2020; Harvard Health, 2020). The current empirical study offers new insights into how COVID-19 pandemic movement restrictions and stay-at-home rules impacted mental well-being, which will enable practitioners and policymakers to make informed decisions and provide support mechanisms during the pandemic. The significance of this study is even greater given the fact that several countries are experiencing or are likely to experience a second or third wave of infection, and the pandemic could potentially last for several years. This study had several practical and research implications.

5.1. Practical implications

The study is timely, given that considerable challenges lie ahead with the COVID-19 pandemic, with the unknown duration of the pandemic itself and the prospects of global economic recession. The study findings provide direct evidence to support the growing call to include mental health issues in the government's COVID-19 response. These results indicate that policymakers should consider the adverse impact of mental health on the population before introducing severe restrictions, such as confining people to their homes, as well as when planning the phased reopening of the economy. For instance, the results indicate that in

phased reopening, workplace mobility and retail and recreational activities must be prioritized. The findings can be used by governments to anticipate the likely mental health impact of varying levels of lockdown stringency so that pre-emptive measures can be put in place, such as outreach programs and the widespread availability of a variety of mental health and psychological support. The methods adopted in this study are difficult to access through traditional clinical approaches and can detect early warning signs of mental health issues, thus enabling the provision of timely interventions.

The adverse impact of social media usage on mental health highlights concerns related to "infodemic." Governments need to combat the spread of misinformation on social media through stricter laws and penalties. Governments and businesses should also be careful in their own use of social media to share vital pandemic-related information with the public, recognizing social media information overload and fatigue.

5.2. Research and theoretical implication

This study demonstrated the use of social media data to understand the mental health of the population. This extends the work done in social media analytics, where text features and natural language processing are used to predict mental health traits. Further, the research framework theoretically advances the links between mobility, lockdown strictness index, and mental health in a crisis situation. One of the significant contributions of this study is the proposed novel mental health index using social media, which can be automated to assess the mental health of the population. This is a significant contribution given that previous studies linking social media and mental health have failed to propose a robust mental health index, which is meaningful, rapid, cost-effective, and capable of assessing population trends over time with relative ease vis-à-vis traditional approaches. Other researchers have used or adapted the proposed mental health index. Furthermore, the development of a mental health index score that could vary from low to high addresses the gap in the extant literature that primarily focuses on binary indicators (present or absent) to understand mental health issues in social media data posts. We expect the proposed mental health index to provide a path for the theoretical and empirical advancement of mental health studies using social media. Finally, the study demonstrates the importance of interdisciplinary research in the areas of health informatics, natural language processing, big data and predictive analytics, machine learning, artificial intelligence, and human-computer interaction to assess the broad impact of the pandemic on the population.

5.3. Study limitations

This study has some limitations. First, it relies on social media data that have been argued to have fake posts/tweets (albeit low) that could affect the results. Previous studies have highlighted the growing concerns regarding fake news in social media (Talwar et al., 2019, 2020). Second, this study only considered social media data from Twitter, and therefore may not adequately represent the full spectrum of the population, such as social media users active on other platforms, such as Instagram and Facebook. Third, we relied on Google's mobility data, which may not be a complete reflection of the actual mobility in a given location. Fourth, there were several locations for which secondary indicators were not available, which may have affected the overall quality of the results.

5.4. Avenues for future research

Future research could conduct a large-scale survey-based study to test the hypotheses, especially in settings where secondary data are unavailable. Researchers could also test additional parameters related to pandemics that may affect mental health. In addition, longitudinal studies are required to understand the impact of the pandemic on the

mental health of the population with prolonged lockdowns and restrictions. Moreover, using an appropriate corpus, this study method can be extended to develop an index score for topics beyond mental health.

This study's findings also provide future research opportunities on how permanent or long-term work-from-home options might affect employees' mental health and well-being. Further research is required to explore the darker aspects of social media on the population's mental health, such as the recent spread of misinformation in social media on the Omicron variant (Guardian, 2021). Similarly, despite the growing calls in the literature (Talwar et al., 2019, 2020), there has been limited investigation, especially during COVID-19, on instantaneous fake news sharing behavior on social media and its impact on the mental health of the population.

Overall, despite its limitations, this study contributes to the first wave of empirical investigation to understand the impact of COVID-19 restrictions on the mental health of the population.

CRediT authorship contribution statement

Krishnadas Nanath: Conceptualization, Methodology, Data curation, Formal analysis, Writing – original draft. **Sreejith Balasubramanian:** Conceptualization, Formal analysis, Writing – review & editing. **Vinaya Shukla:** Supervision, Writing – review & editing. **Nazrul Islam:** Supervision, Methodology, Validation, Writing – review & editing. **Supriya Kaitheri:** Writing – review & editing, Validation.

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Krishnadas Nanath is an Associate Professor in Data Science at Middlesex University Dubai. He received his Ph.D. from the Indian Institute of Management Kozhikode (IIM K), and his thesis covered the areas of Green IT (Sustainability Analytics) and Cloud Computing. He has experience of teaching Data Science, MIS, and Cloud Technologies area. He has executed several corporate training programs and Data Science consulting assignments with prestigious firms in the UAE (PWC, Landmark Group, National Bank of Fujairah, UAE Exchange, and others) .

Sreejith Balasubramanian is a Senior Lecturer in Supply Chain Management and Chair of the Research Committee at Middlesex University, Dubai. He completed his PhD from Middlesex University Business School, London. His areas of expertise include supply chain, operations management, disruptive technologies, sustainability, and knowledge management. His work has been published in leading academic and practitioner-focused journals, including S*upply Chain Management: An International Journal, Production, Planning and Control,* and *Journal of Knowledge Management*. He has been a consultant for several public and private sector entities, including the Abu Dhabi Chamber of Commerce and Bridgestone Middleseast .

Vinaya Shukla is a Senior Lecturer in Operations and Supply Chain Management at Middlesex University Business School, London. He has a PhD from Cardiff Business School, UK. Prior to academia, he spent many years as a Management Consultant advising clients on how to improve their operations performance. His research interests are in Industry 4.0 and Blockchain, supply chain sustainability, supply chain systems and supply chain risk management. He has published in several prestigious journals including the *International Journal of Production Economics, International Journal of Production Research, Supply Chain Management-An International Journal, Production Planning and Control, International Journal of Logistics Management & Journal of Manufacturing Technology Management* .

Nazrul Islam is Associate Professor of Innovation/Entrepreneurship and an interdisciplinary pathway lead for global political economy at the University of Exeter Business School, England, UK. He holds a PhD in innovation management. His research interest focuses on interdisciplinary fields: the management of technology, innovation and entrepreneurship, the emergence and growth of disruptive and digital technology-based innovation, and SMEs business sustainability. His research was published in the leading international journals, and he has complemented his peer reviewed journal efforts with three books. Prof Islam's research received awards including the 'Brad Hosler Award for Outstanding Paper' from USA; and the 'Pratt & Whitney Best Paper Award' from Canada. Prof Islam serves on the board of directors for Business and Applied Sciences Academy of North America. He is Associate Editor (Lead Bureau Editor for Emerging Technologies) of *Technological Forecasting & Social Change,* and Editor-in-Chief of *International Journal of Technology Intelligence and Planning* .

Supriya Kaitheri is a senior lecturer in Data Analytics and Quantitative Methods at Middlesex University Dubai. Before joining Middlesex, she completed her doctoral studies at the Indian Institute of Management Kozhikode. Her doctoral thesis was in the area of ICT for social development and e-Governance. She was also a Gold medalist in Computer Science and Engineering. She works in the areas of e-Governance, User Technology Readiness, and Data Analytics .