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Tracking the evolution of crisis processes and mental health on social media during the COVID-19 pandemic

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ABSTRACT

The COVID-19 pandemic has affected all aspects of society, bringing health hazards and posing challenges to public order, governments, and mental health. This study examines the stages of crisis response and recovery as a sociological problem by operationalising a well-known model of crisis stages in terms of a psycho-linguistic analysis. Based on an extensive collection of Twitter data spanning from March to August 2020 in Argentina, we present a thematic study on the differences in language used in social media posts and look at indicators that reveal the distinctive stages of a crisis and the country response thereof. The analysis was combined with a study of the temporal prevalence of mental health related conversations and emotions. This approach can provide insights for public health policy design to monitor and eventually intervene during the different stages of a crisis, thus improving the adverse mental health effects on the population.

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1. Introduction

The COVID-19 crisis has affected all aspects of society, bringing health hazards and posing challenges to public order, governments, and mental health. Crisis can serve as both threats and opportunities. Despite the tangible risks to the public, crisis also draw awareness about the threats, which can be used to steer people towards productive and socially beneficial behaviours (Spence et al. 2015). Over the last years, social media has become a part of the daily life of millions of people as a medium for exchanging messages in social platforms and reporting events as they occur (Palen and Hughes 2018). In this sense, the COVID-19 pandemic is the first event in history in which people have been massively expressing their thoughts and concerns worldwide. Hence, there is an unprecedented opportunity to study this pandemic in light of the social media activity it generates and how the propagation of COVID-related content connects with existing knowledge about crisis processes, mental health, and other societal behaviours (e.g. emotions, crime).

Several studies have aimed at identifying, modelling and understanding the varying stages through which crisis arise, evolve and dissipate (Spence et al. 2015). These models have been useful for understanding the response efforts, as each stage has its particular needs, requiring distinct strategies and resources (Neal 1997). Nonetheless, these models have also practical

limitations to explain how particular stages are faced by a social collective or community, during the development of a crisis. A common approach here is to study the needs and opportunities of a given community, as manifested by their individuals, government actors and other environmental factors.

In this context, the analysis of textual exchanges in social media provides rich information of individuals' online (and perhaps offline) behaviours. This analysis can provide insights into how crisis perception evolves, how individuals cope with the crisis, and what their needs are, among other possibilities (Gruebner et al. 2017; Jin 2009). Social media is also changing how people manifest and communicate aspects related to their mental health state (De Choudhury, Counts, and Horvitz 2013a; Gkotsis et al. 2017; Naslund et al. 2020). For example, nowadays, individuals are more prone to self-identify as suffering from a disorder and communicate with others sharing similar experiences, which allows observing the mechanisms underlying mental health conditions during crises from different perspectives. Similarly, as governments struggle to develop effective messaging strategies to support society, analyzing how society perceives and responds to those messages becomes crucial for decision-makers (Li, Hughes, and Howe 2018; Palen and Hughes 2018; Reuter, Hughes, and Kaufhold 2018).

In this work, we present a study and a supportive approach for characterising crises, like the COVID-19 pandemic, based on language usage in social media. The approach allows human actors to monitor the evolution of a crisis through its different stages and eventually plan for interventions, helping to improve the mental health effects of the crisis. To that end, our study aims at examining: i) the prevalence and evolution of mental health, ii) the evolution of emotions, and iii) the stages of crisis response as a sociological problem.

A key aspect of our approach is the operationalisation of a model of crisis stages in terms of lexicons for psycho-linguistic text analysis. To do so, we performed a thematic study on the differences in language use in social media posts regarding mental health conditions, emotions and crisis stages. These dimensions of analysis are captured via *lexical categories*, referred to as *markers*, which link social media contents to well-known lexicons. The study is based on an extensive Twitter dataset collected from March to August 2020, containing commonly used hashtags belonging to specific user accounts related to Argentina (Tommasel, Rodriguez, and Godoy 2020). This analysis was combined with a study of the temporal prevalence of mental health conversations (for example, related to depression), which shed light on the relationship between the crisis stages and the individuals' mental health. Furthermore, we developed a heatmap-like visual metaphor for tracking the evolution of the crisis stages as a function of different dimensions of the target model. We believe that this work can contribute to a better understanding of the manifestation of psychological processes related to crises as they reflect on Spanish-based social media. The focus on the Spanish language offers a broader picture of how social media is used around the world during crises, contributing to the body of research, which generally focuses on the English language (Reuter, Hughes, and Kaufhold 2018). Thus, it can support the design of public health policies for preserving the mental well-being of individuals during crises. Furthermore, the proposed approach is not tied to the Argentinian case study, and it can be applied to other large-scale data streams or even incorporate alternative disaster models.

The rest of this article is organised as follows. Section 2 presents background concepts of both mental health and sociological crisis models and some related works. Section 3 describes the approach for operationalising the selected psych-social theories and its application to the collected tweets. Then, Section 4 presents the performed analysis. Finally, Section 5 gives the conclusions, and discusses limitations of the study and future lines of work.

2. Background and related work

Since the beginning of the health crisis due to the COVID-19 pandemic, social media has been a rich source of information for analyzing the phenomenon and mitigating its effects. Datasets of different sizes and characteristics have been released to support studying the social phenomenon around this pandemic. The sampling and collection of social media data enable researchers (and other actors) to examine different aspects of people's reactions to the pandemic and their direct and indirect consequences, as expressed through the use of language in social texts. As an example, Li et al. (2020) analyzed psychological characteristics for two weeks before and after the declaration of the COVID-19 outbreak in China on January 2020. Weibo original posts during such period were sampled to explore the impacts of COVID-19 on people's mental health. The prevalence of LIWC (Pennebaker, Francis, and Booth 2001) categories was compared the week before and after the mentioned date, considering categories related to emotions (e.g. positive or negative emotions, anxiety, anger) and concerns (e.g. health, family, friends). As expected, the study showed that negative emotions (anxiety, depression, and resentment) and sensitivity to social risks both increased, whereas positive emotions (happiness) decreased. The focus of concerns also drifted as people were more concerned about health and family and less about leisure and friends. Hou et al. (2020) also analyzed Weibo posts using LIWC to assess public emotion responses to epidemiological events, government announcements, and control measures between December 2019 and February 2020. The psycho-linguistic features observed in the study were negative emotions (i.e. anxiety, sadness, anger) and risk perception (i.e. drives). All features manifested periods of high prevalence within 24 h after the triggering event took place. Aiello et al. (2020) empirically tested the model proposed by Strong (1990), according to which any new health epidemic resulted in three social epidemics: fear, moralisation, and action. The authors characterised the three social epidemics based on the use of language on social media through lexicons. Their goal was to embed epidemic psychology in real-time models (e.g. epidemiological and mobility models).

Recently, social media has also been used to understand health outcomes through quantitative techniques that predict the presence of specific mental disorders and their symptoms (Chancellor and De Choudhury 2020). Evidence indicates that the rigorous application of even simple natural language processing, computational linguistics, and psycho-linguistics techniques

can yield insights into mental health disorders (Coppersmith, Dredze, and Harman 2014; De Choudhury, Counts, and Horvitz 2013a; Losada and Gamallo 2020). For example, in the case of depression detection Losada and Gamallo (2020) evaluated the performance of different lexicons (including semantically enhanced variants and embeddings similarity), while De Choudhury, Counts, and Horvitz (2013a) trained a traditional classification technique based on features derived from social media text (e.g. emotions, linguistic style). Coppersmith, Dredze, and Harman (2014) trained traditional classifiers using lexicons and language models to detect post-traumatic stress disorder, depression, bipolar disorder, and seasonal affective disorder.

Other works have used more advanced models, such as neural networks (Lin et al. 2017; Zogan et al. 2021). Zogan et al. (2021) proposed a hierarchical deep learning model to detect depression based on social media text and user behaviour features (e.g. social interactions, emotions, topic modelling). According to the authors, not all shared content is crucial for the detection task and could even negatively affect the trained model. In this context, the model leveraged extractive and abstractive summarisation strategies to create a condensed representation of the relevant and non-redundant posts. Lin et al. (2017) used a neural network to leverage social media content and social interaction information (e.g. posting behaviour, social engagement, network topology, social influence) for stress prediction. The study showed differences in the connectivity and complexity of social interactions for stressed and non-stressed users.

Although most of the techniques in the literature achieve good performance in detecting mental health disorders, they do not usually provide explanations regarding what induced the model to positively identify a given disorder. Recently, in this regard, Song et al. (2018) and Turcan, Muresan, and McKeown (2021) proposed explainable and interpretable depression and stress models, respectively. Song et al. (2018) focused on an attention neural network to detect and interpret signs of depression. Detection was based on features derived from the social media content (e.g. explicit mentions of symptoms, sentiments, and writing style). Explanations were based on the assumption that depression symptoms are not always explicitly exhibited in social media but might manifest through only a few shared posts. Then, interpretations aimed at identifying those posts showing salient signs of depression based on their feature weights on the attention mechanism. On the other hand, Turcan, Muresan, and McKeown (2021) designed different neural network architectures

to enhance depression detection by complementing it with an emotion detection model. Interpretability was provided through the LIME technique (Local Interpretable Model-agnostic Explanations) (Ribeiro, Singh, and Guestrin 2016), which identified the word categories (based on LIWC) with the most decisive influence in both stress and non-stress classifications.

Some works have also used natural language techniques to explore the effects of human-made as well as natural disasters in social media. For instance, Gruebner et al. (2017) aimed to identify specific basic emotions from Twitter for the greater New York City area during Hurricane Sandy in 2012. Lin and Margolin (2014) used geo-coded tweets over an entire month to study how Twitter users from different cities expressed three emotions (fear, sympathy, and solidarity) in reaction to the Boston Marathon bombing in 2013. De Choudhury et al. (2013b) created a depression lexicon using a labelled collection of Twitter posts associated with symptoms, among other dimensions. Furthermore, the crisis lexicon CrisisLex (Olteanu et al. 2014) was created from the sampling of Twitter communications that can lead to greater situational awareness during this kind of crisis. These works are mainly oriented to provide real-time tools based on social media to assist during emergencies and, eventually, provide guidelines for first responders.

Disasters and crises have been described as occurring in phases or stages (DeWolfe 2000; Neal 1997), which assign order and rationality to the complex reality of disasters and the human responses to them. Phases aim to identify periods in the unfolding of a crisis, serving to classify the impact or the actions addressing them (Kelly 1999). Considering a temporal dimension, Drabek (2012) made a fourfold division of disaster phases: preparedness, response, recovery, and mitigation. The first stage, preparedness, involves actions tending to reduce the effects of a potential disaster. The response phase occurs in the immediate aftermath of a disaster and involves actions in response to challenges caused by disasters (e.g. lack of communications). Then, a phase of recovery takes place in which things start to return to normal. Mitigation, in turn, refers to sustained actions to reduce or eliminate long-term risks from a disaster occurrence and its effects.

Phases should not be considered discrete events, in which social change is caused by a particular episode but a series of events. In this context, the linear division between phases could not represent the reality of every reported or analyzed event (Neal 1997), as it might not be easy to find a standard set of measures that identify or

quantify how society evolves through a crisis. In this sense, phases might overlap and should not include an objective time definition. Instead, as each crisis and society combination is different, the duration and transition between phases should be adjusted to the ‘social time’, which accounts for the needs or opportunities of societies (Dynes 1970; Neal 1997).

As crises develop, a range of personal emotions often emerges in response to the situation itself and the social disruption and uncertainty it causes. Crises disrupt the quality of life and create a burden of mental health conditions (Spence et al. 2015). In this sense, exposure to a crisis can be a stressor that affects individuals’ expectations about the future, challenging their world views and triggering emotional reactions (Scott and Weems 2013). For example, works as (Park 2012) found initial evidence that people posted about their depression on social media and observed what words dominated the discussion about symptoms. Posts often provide details about sleep, eating habits, and other forms of physical ailment, which are known to be associated with depressive episodes. Likewise, (Aldarwish and Ahmad 2017) predicted depression starting from nine categories related to possible symptoms, such as sadness, loss of interest, appetite, sleep, thinking, guilt, tiredness, and suicidal ideation. In this context, social media offers the opportunity to monitor and understand the mechanisms underlying mental health conditions during crises on a massive scale. This kind of monitoring is also the first step to propose preventive actions that can provide ‘virtual’ support to affected individuals.

From the precedent works, we recognise the potential of social media posts for understanding the different stages of a crisis and mental health-related aspects in a community. One of the challenges here is the bi-directional linkage between a given social theory (or model) and the ‘reality’ as reflected in the texts of the posts so that the theory becomes actionable for the crisis. On one side, a given theory can provide a structure or framework to reason about the vast flow of posts in social media. On the other hand, the empirical data extracted from the posts can instantiate the different parts of a theory for a given crisis (such as the COVID-19 pandemic), and help to track the evolution of crises as prescribed by that theory. A systematic analysis of the data can suggest courses of action for managing the crisis or even signal adjustments to the underlying theory. In this work, we take a step towards this vision by studying a large dataset of COVID-19 tweets and proposing an analysis pipeline that integrates text processing, psycho-linguistic lexicons, and visualisation techniques.

3. Material and methods

This section describes the proposed approach for characterising the crisis phases from the language used on social media for analyzing the prevalence of mental health, emotions and crisis discussions. The approach is schematised in Figure 1, and it involves the following steps: 1) data collection and pre-processing, 2) operationalisation of sociological theories into lexicons, 3) matching and scoring the pre-processed tweets according to the lexicons, and 4) analysis of the results (time series and heatmaps).

This approach is guided by three research questions, each related to whether psycholinguistic techniques can provide evidence of different aspects of the dimensions under analysis, i.e. mental health, emotions, and crisis.

- RQ1: Mental health. To what extent social media reflects changes in anxiety, stress, and depression markers, as the COVID-19 crisis evolved? Are there changes in the manifestation of the selected disorders?
- RQ2: Emotions. How does the prevalence of emotions change as the COVID-19 crisis evolved? Are there changes in the prevalence of negative or positive emotions?
- RQ3: Crisis Stages. Do crisis stages manifest on social media? Can the crisis stages of a society be analyzed based on social media behaviours?

The remainder of this section provides details of the steps of the proposed approach.

3.1. Data collection

Analyses were based on the *SpanishTweetsCOVID-19* data collection, a large-scale sample of data shared in Twitter during the COVID-19 pandemic in Argentina. We chose Twitter as it is one of the most commonly used social media sites, and its role as a public, global and real-time means of communication provides a glimpse of contemporary society as such (Weller et al. 2014). Twitter additionally enables easy access to its data in comparison to other social media sites.

The collection provides a broad perspective on the dynamics and events during this health crisis in Argentina between March 1 and August 31, 2020. The collection covers the beginning of the COVID-19 situation, which started with the announcements of the first contagions and deaths, until over 160 days of lock-down. The first restrictions began on March 14 when airports were closed. The total lock-down started a week later, in March 20. Lock-down status was systematically

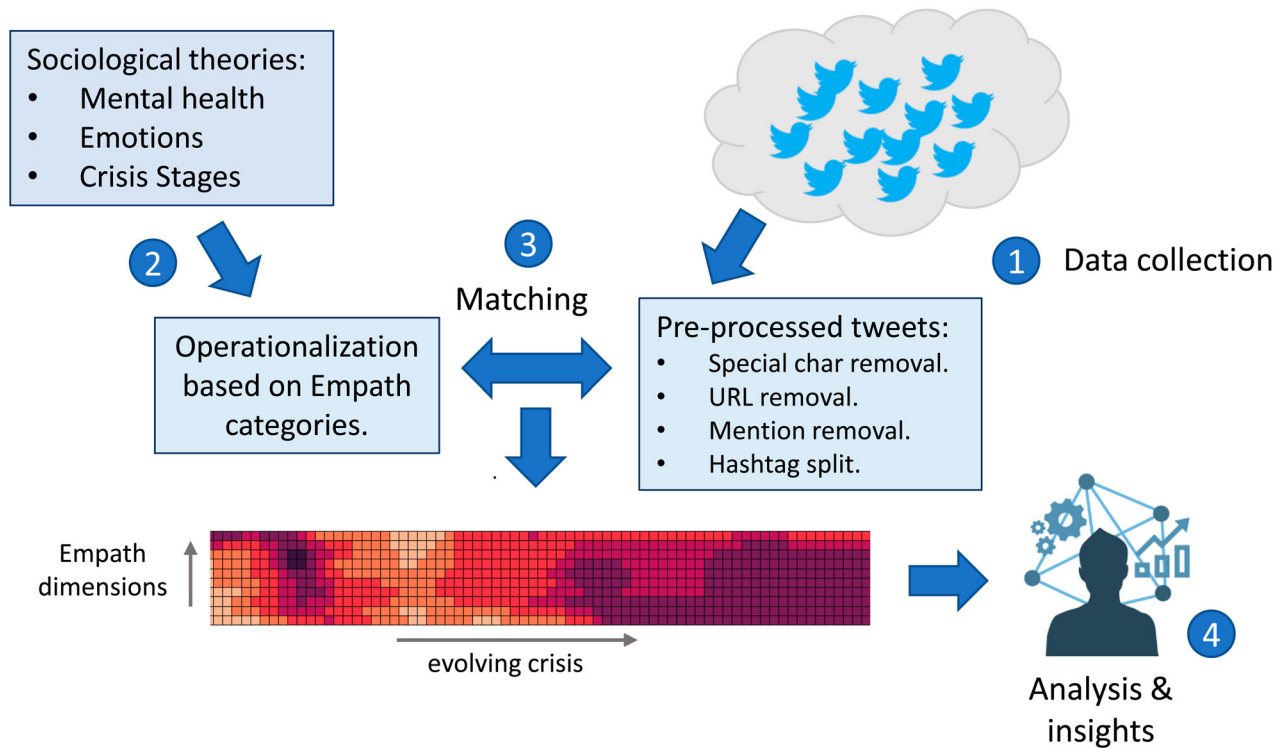


Figure 1. Schematic diagram of the proposed approach.

extended every 2 or 3 weeks. No sportive activity was allowed. Schools were closed for the whole period. In April, while Argentina was one of the top-10 countries with the most contagions, face masks started to be mandatory. Also in April, the government announced different public assistance benefits. In May, some restrictions were lifted only to be reinstalled in June. June saw the beginning of protests against the government, which continued during the whole period.

SpanishTweetsCOVID-19 includes more than 145 million tweets, and it is publicly available in Mendeley (Tommasel, Rodriguez, and Godoy 2020).¹ The dataset comprises Spanish tweets, complemented with geographical information and the possibility of deriving content-based relations between users from the tweet sharing activity. The raw data belonging to the 145 million Twitter posts were retrieved from the Twitter

API using the *Faking it!* tool², which internally uses Twitter4J for easily integrating with the Twitter API.³

The collecting process was based on the Twitter Streaming service, which provides real-time access to the shared tweets. The stream was filtered according to the parameters shown in Table 1. The inclusion criteria were the following: tweets had to be identified as written in Spanish, include any of the selected keywords, or refer to a selected user belonging to the official Argentinian government offices or media. We also considered the retrieval of tweets located inside the Argentina geographical bounding box. The original tweets represented only 19% of the dataset, while retweets accounted for 70%. The remaining tweets corresponded to replies. Tweets were not homogeneously distributed across the observed period. While the tweets in March represented less than 1% of the total collected tweets,

Table 1. Queries used for collecting the data.

Language	es
Keywords (including their hashtag versions)	quedateencasa, covid, covid-19, casa rosada, cuarentena, barbijo, máscara, salud, coronavirus, solidaridad, argentina, caso, muert, infectado, infectada, test, testeo, testeomasivo, tapaboca, médico, enfermera, viruschino, virus, virus chino, jubilado, pandemia, mayorescuidados, tapatelaboca, cuidarteescuidarnos, desarrollo social, cancilleria argentina, argentinaunida
Users	LANACION, msalnacion, alferdez, casarosada, infobae, lanacion, clarincom, kicillofok, gcba, felipe sola, c5n, mauriciomacri*, cfkargentina*, Chequeado*, DiputadosAR*, HCDiputadosBA*, MDSNacion*, Migraciones AR*, MindefArg*, MindeTransporte*, MinSeg*, msnarg*, MinGenerosAR*, MinInteriorAR*, MinTrabajoAR*, msalnacion*, elcancillercom*, filonewsOK*

* were added to the query in July.

tweets in June peaked to a 25% of the total. For our analyses, only original tweets and replies were considered, as they are the ones in which writers provide sufficient content to evaluate aspects related to the crisis evolution and mental health. Table 2 summarises the statistics of the collected dataset, excluding retweets. Hashtags were only present in 19% of the tweets. An inspection of the data showed that neither official government accounts, politics, nor media included hashtags in most of their tweets. The median number of shared tweets per user was 2, while 40% of the accounts tweeted over the median.

The collected tweets were pre-processed to remove special characters, URLs, and mentions. Hashtags were kept without the numeral symbol and were split into their constituent words. After inspecting randomly selected tweets, spelling corrections were not applied as most of the tweets were correctly written, and abbreviations were scarce.

3.2. Operationalisation of psychological theories

The language used in social media for expressing opinions, personal situations, and communicating with others provides signals about a person's state of mind. In this sense, lexicons are a rich tool for analyzing language in social texts across various categories, including emotions, concerns, and health-related issues. Existing language lexicons have been widely used in psychometric studies as well as sentiment analysis. Some examples are the Linguistic Inquiry and Word Count (LIWC) (Pennebaker, Francis, and Booth 2001), Emolex (Mohammad and Turney 2013), the Prosocial Behavior Lexicon (Frimer, Schaefer, and Oakes 2014), and LEW list (Francisco and Gervás 2013), among others. When no training data is available, domain-specific lexicons play a fundamental role in the automated analysis of texts, and in our case, in understanding the person behind the text.

Table 2. Statistics of the collected dataset.

Tweets	Start date: 1 March 2020 – End date: 31 August 2020		
	Original:	Retweets:	Replies:
	29,712,138	106,361,088	15,815,975
	(with quotes:		(with quotes:
	8,947,933)		414,984)
	With media:	With mentions: 19,494,778	
	7,578,945		
	With URL:	With places: 102,241	
	9,917,012		
	With hashtags:	Avg. number of hashtags per tweet: 46	
	8,621,975	Avg. frequency of hashtags: 13	
Users	Total: 6,977,032		
	Min tweets per user: 1	Avg. tweets per user: 4.5 ± 8.4	Max tweets per user: 167

In this study, the psycho-linguistic analysis of social texts was based on the multiple categories provided by two specific lexicons:

- *Empath* (Fast, Chen, and Bernstein 2016; Fast, Chen, and Bernstein 2017) covers a broad, human-validated set of 200 emotional and topical categories drew from common concepts in ConceptNet (Liu and Singh 2004) knowledge base and Parrott's hierarchy of emotions (Parrott 2001). Categories have several seed terms representing the concept, which can be further expanded to obtained similar categorical terms. Empath categories showed to be highly correlated with similar categories in LIWC and EmoLex.

As the Empath lexicon is only available in English and considering the experiences reported by Perczek et al. (2000), who analyzed the reliability of Spanish translation from English for psychometric scales and lexicons, we automatically translated the Empath categories and their associated words to Spanish. For this translation, we relied on the IBM Watson Language Translator.⁴ Then, the authors independently checked the resulting translations for inconsistencies. Given the gendered nature of Spanish, if a word in a category was associated with a specific gender, we also added the words corresponding to the other gender and a gender-neutral version (if it exists in Spanish). Although we could have instead translated the collected tweets to Spanish, such task would have required considerable efforts given the data volume even with the help of automated tools.

- *SentiSense Affective Lexicon* (de Albornoz, Chugur, and Amigó 2012a; de Albornoz, Plaza, and Gervás 2012b) consists of synsets from WordNet⁵ labelled with an emotional category. This lexicon consists of 2,190 synsets tagged with 14 emotional categories derived from the ones proposed by Arnold (1960), Plutchik (1980) and Parrott (2001).

Since SentiSense Affective Lexicon is integrated with the WordNet Spanish version, it can be directly applied to the analysis of our tweets. These markers are the ones used for the study of the positive and negative emotions dimensions.

The goal of operationalizing the crisis stages and mental health theories was to represent each dimension of analysis (i.e. each mental health disorder, emotion type and crisis stage) based on a set of lexical categories (or markers). This task was accomplished in three steps, namely: 1) adaptation and expansion of lexicons based on a thematic encoding and categorisation; 2)

contextualisation of the expanded lexicons based on semantic similarity; and 3) association between the expanded lexicons and the Empath categories that will be used later in the analysis of the pre-processed tweets. The contextualisation of the expanded lexicons was based on *FastText*⁶ embeddings. The goal here was to capture the context in which the words in the lexicon appear to gather a more accurate picture of how individuals express aspects related to crisis evolution and mental health. For each word in our lexicons, we selected the top-10 most similar terms in *FastText* based on the traditional Wikipedia model. Finally, we matched each of the expanded terms to the Empath categories to automatically retrieve the top-10 most prevalent categories for each dimension, i.e. the categories with the highest number of shared words with the lexicons. We refer to the selected categories as *markers* for the associated lexicon. The original lexicons, expansions, and the translated Empath categories can be found in the corresponding companion repository.⁷ The following subsections describe the operationalisation of the mental health and crisis stages.

3.3. Mental health

In public mental health terms, the primary psychological impact of the COVID outbreak has been elevated rates of stress and anxiety (Asmundson and Taylor 2020). However, due to public health policies, such as social distancing and the uncertainty generated by social and economic situations, a rise in depression, levels of loneliness, addictions, and suicidal behaviours can be expected. Thus, in this study, we focused on anxiety, stress, and depression as the three main concerns regarding mental health in the population.

As previously mentioned, several works (Aldarwish and Ahmad 2017; De Choudhury et al. 2013b; Park

2012) have relied on lexicons to automatically analyze the level of depression in texts from social networks. Based on such lexicons and the characterisations, symptoms, and manifestations of each selected disorder as defined by the National Institute of Mental Health⁸ and the Anxiety and Depression Association of America⁹, each author manually performed a hand-coding analysis of each disorder. This activity generated independent lists of keywords (one list per author) that were combined using a voting strategy as follows. For each keyword selected by any of the authors, it was included in the lexicon if it had been chosen by the majority of the authors (3 out of 4 authors). In the case of a keyword chosen by only two authors, its appropriateness was put up for discussion with the remaining authors to decide whether it should be added. In this way, we ensured a consensus on the base words included in the lexicons. Afterwards, the resulting lexicons were augmented using *FastText* to include descriptions of the manifestations of the selected mental health disorders and other words commonly used to provide context to the expressions, in order to understand how people express health related aspects (Lin et al. 2016; Losada and Gamallo 2020). At last, we matched each of the expanded lexicons to the top-10 Empath categories to define the markers for each dimension. Table 3 shows a summary of the words associated with each disorder and the corresponding Empath categories.

3.4. Crisis stages

Several authors have studied the sociological responses to natural disaster events (Drabek 2012; Richardson 2005) based on surveys, interviews, and narratives. Nowadays, social media presents new ways to explore the communications during a crisis (Niles et al. 2019).

Table 3. Mapping of mental health issues to *Empath* categories.

Mental disorder	Associated keywords	Associated markers
Anxiety	anxiety, medication, depression, meds, panic attack, falling, heart, fear, apprehension, nervousness, restlessness, suffering, uncertainty, unease, worry, tension, wound-up, frustrated, irritability, sleep problems, pounding heartbeat, sweating, trembling, shaking, nightmare, frightening thoughts, angry outburst, trauma, loss of interest, eating habits, demoralise	sadness, nervousness, fear, suffering, horror, disappointment, health, confusion, shame, anger
Depression	depression, boring, sadness, painful, unhappy, suicide, dissatisfaction, confused, unsatisfactory, cry, die, hopeless, indecisive, impatience, reluctant, fatigue, palpitation, useless, underestimated, disappointed, withdrawal, insomnia, drowsiness, dizziness, nausea, seizures, antidepressant, medication, apathetic, demanding, guilty, shame, remorse, demands, loss of satisfaction, complaining, tachycardia, fatigue, emptiness, restless, pain, sedative, unhappiness, detach	sadness, suffering, shame, neglect, emotional, disgust, torment, nervousness, disappointment, pain
Stress	stress, agony, anxiety, burden, fear, intensity, nervousness, tension, worry, affliction, apprehensiveness, distension, fearfulness, impatience, mistrust, nervous, interruptions, expectations, agonised, alienation, alone, anger, angry, anguish, antidepressant, disinterest, distracted, done with life, doomed, down, downhearted, drained, drugs, hopeless, fatigue, fear, pessimistic, terrified	sadness, nervousness, anger, suffering, fear, shame, torment, neglect, disgust, health

Following the crisis stages defined by Neal (1997), we attempted to characterise them based on the communicative ways in which the social collectives organise themselves (Richardson 2005).

Departing from the crisis stages defined and characterised by Drabek (2012), Richardson (2005) and DeWolfe (2000), and the crisis lexicon proposed by Olteanu et al. (2014), each of the authors manually hand-coded each of the crisis stages. From the selected sources, we obtained keywords related to the four traditional crisis stages: preparedness (including aspects related to planning and warning), response (including aspects related to impact, the heroic and disillusionment sub-stages), recovery, and mitigation. When creating the lexicons, we only kept those words related to actions, sentiments, and emotions from the crisis lexicon, removing all terms associated with a particular type of crisis (e.g. tornado, flood, explosion, storms, among others). The selected keywords included: i) aspects related to the functional aspects of each of the stages by the different actors (e.g. individuals, society, government), ii) aspects related to the perceptions and concerns during a crisis (e.g. the false sense of security that felt during the preparedness phase), and iii) aspects related to mental health. Similarly as for the mental health dimension, this coding activity generated independent lists of keywords for each crisis stage, which were combined using the described voting strategy. The resulting lexicons were also augmented using *FastText* and matched to the Empath categories to retrieve the 10 most prevalent categories for each crisis stage.

Table 4 shows a summary of the words associated with each disorder and the corresponding Empath markers. As observed, some markers are shared across stages, meaning that the concepts or keywords describing a given stage might be also relevant to the others. This implies that stages are not linearly divided, as Neal (1997) and Kelly (1999) stated.

3.5. Matching the tweets and categories

To answer our research questions, we analyzed the matching between the Empath and emotional markers associated with each lexicon and the tweets. We considered that a tweet matched a marker if at least one word (of the tweet) belonged to such marker. Multiple word occurrences were ignored as they might be rare due to the restrictions on tweet length, which might not adequately reflect the actual intensity of the marker. To summarise the marker prevalence on a particular day, we computed the percentage of daily tweets matching the marker. As an example, Figure 2 shows tweets¹⁰ for any given day in which the words associated to

Empath markers are highlighted. In the example, tweets are checked against four markers (*health*, *nervousness*, *pain* and *emotional*). For instance, *COVID* and *PCR* in the first tweet match with the *health* marker. In the general case, a given tweet can contribute to zero, one or more markers. Based on the matching, we computed the prevalence of each marker for that day. The markers are subsequently aggregated for analyzing the dimensions. For instance, *health* and *nervousness* correspond to the anxiety dimension, while *nervousness*, *pain* and *emotional* correspond to the depression dimension. Due to the matching procedure, a tweet might be indirectly linked to different dimensions (as in the case of the first and second tweets), which makes sense in practice when short texts expose multiple aspects related to the disorders. However, the occurrence of this phenomenon is deemed low, mainly because of the restricted tweet length.

Once the matching for a marker over the entire time span was computed, we obtained a time series distribution for the marker, which models the sequence of observations of a given marker (or dimension) during the defined time window. On average, in the collected dataset, 189.260 tweets were shared per day, with a maximum monthly average of 396.228 in June and a minimum average of 800 in March. To reduce the impact of day-to-day variations and weekly periodicity in the time series, for each marker we computed the gradient over the one-week smoothed time series. This smoothing better exposes the characteristics of the time series, as it responds more slowly to recent changes, which favours the observation of more consistent behaviours over longer periods (in opposition to instantaneous shifts).

Given the smoothed time series for each marker, we proceeded to compute the time series corresponding to the analyzed dimensions. To do so, we averaged the gradients for all markers to obtain the overall gradient of the dimension. Gradients allowed us to measure the magnitude of change (either an increment or decrement) of the time series. Finally, to identify the phases of each dimension, we looked at breakpoints or peaks in the series. These peaks represent points in time in which the values of the markers varied altogether with respect to previous observations, presumably due to COVID-19 related events. For example, the first anxiety peak appeared in the days following the first COVID case in Argentina and the first lockdown restrictions. We only kept those peaks whose prominence values were higher than the mean plus one standard deviation (Palshikar et al. 2009). Due to the smoothing of the series, peaks not only respond to events of their particular day but also to events of the previous days.

Table 4. Mapping of crisis stages to *Empath* categories.

Crisis Stage	Associated keywords	Associated markers
Preparedness	government, responsibility, society, public belief, we, faith in authority, lack of concern, family, curiosity, safety, acceptance, anticipation, resources, response, anticipation, hoard, preparedness, think, anxiety, worry, futility, helplessness, protective, control, overwhelmed, warning, impact, unreal, sense of security, information, track, control, reality, plan, devise, strategy, idea, liability, importance, duty, care, charge, restrain, power, prospect, contemplation, expectancy, premonition, promise, presentiment, preoccupation, sensation, change, defensive, avoidance, realistic, vigilance, disbelief, normality bias, interpretations, naturalise the threat, denial, danger, information, perception, diversity, confirmation efforts, misinterpretation, refusal, warning, threat, adaptation, panic, consequences, credibility, vulnerable, vulnerability, unsafe, fearful, no control, protection, guilt, self-blame, advice, alarm, alert, caution, guidance, indication, notification, avoidance, panic, ready, alertness, forewarning, expectation, provision, awareness, prevision, foreseeing, consequence, advice, recommendation, suggestion, forecast, attention	fear, sadness, nervousness, horror, neglect, aggression, anticipation, disappointment, communication, trust
Response	fear, hoarding, credibility, active, anxiety, entrapment, powerlessness, impotence, isolation, dependency, adaptive, responsible, emotional disturbance, dazed, stunned, apathetic, passive, immediate, extreme, gratitude, help, concern for family and community, susceptibility, irritability, anger, angry, sadness, withdrawal, obsessive preoccupation, safety, loss of interest, depression, resistance to authority, feeling, inadequacy, panic, afraid, help, medication, depression, mental, mind, way, life, time, side effects, meds, music, nervousness, restlessness, suffering, uncertainty, unease, worry, sleep problems, sweating, trembling, shaking, shortness of breath smothering, choking, being out of control, frightening thoughts, trigger, easily startled, angry outburst, anger, trauma, stress, loss of interest, angst, sadness, concern, disinterest in life, distress, fearful, unknown, hazard, concerned, demoralise, shock, disconcerting, safety, rapport, government, volunteer, aid, attend, charge, repair, palliate, reform, limits of assistance, mental health, exhausted, exhaustion, stress, discouragement, fatigue, problems, frustration, antidepressant, medication, shame, remorse, lonely, lonesome, inept, inhuman, insensate, irritable, intense, intolerable, miserable, grief, rage, purposelessness, upset, disorientated, i, me	sadness, suffering, nervousness, fear, shame, neglect, disgust, anger, health, disappointment
Recovery	victim, perception, recovery, disengagement, recurrence, fear, anxious, legal implications, financial state, depression, shocked, distress, demoralisation, overacting, loss of appetite, difficulty in sleeping, shaky, trouble, irritability, sweating, anger, headache, stomach trouble, diarrhea, constipation, alcohol, tobacco, smoking, drugs, pills, tranquilisers, insomnia, restless, sleep, dependency, clinging, despair, preoccupation, sensitivity, death, hostility, apathy, home, enclosed, people, street, irritation, living, agitation, tears, sorrow, worry, recover, migraine, burden, sarcasm, jokes, guilt, tension, inept, government, politics, conflicts, restrictions, breakup, attention to present, levelling of society, i, we, community identification, society, community, looting, robbery, death, grief, nightmares, need to talk, crime, talk, optimism, religion, guilt, phobias, planning, explanation, increase action, local governments, power, law, economics, normal, restoration, future, improving, renewal, resurgence, revival, blame, who, blame	sadness, suffering, disgust, anger, nervousness, irritability, disappointment, fear, neglect, rage
Mitigation	awareness, salience, underestimate, stability, experience	love, anticipation

4. Data Analysis

This section presents the psycho-linguistic analysis of: i) the prevalence and evolution of mental health markers, ii) the evolution of emotions, and iii) the stages of crisis response as a sociological problem.

4.1. Mental health

The first research question is about the extent to which tweets contain references to mental health problems, how such references evolve over time with the COVID-19 pandemic, and whether perceptible changes could be observed in the prevalence of the markers associated with the mental health problems. In

particular, we analyzed references to anxiety, depression, and stress, three of the most commonly studied mental illnesses or disorders.

Figure 3 presents the temporal distribution of the *Empath* markers for the three disorders during the span March-June, as well as the peaks detected using such markers. The darker the area, the higher the prevalence of the associated markers. The analysis does not include the span of July-August due to the different magnitude orders across markers prevalence.¹¹ As Argentina moved into 100 days of lockdown (late June), markers showed an increment in their prevalence, which hindered the analyses and eclipsed the changes in the preceding months. Table 5 shows the correspondence between the discovered

	Health	Nervousness	Pain	Emotional
My dad is dead and we got COVID. Our PCR tests took too long! Who is responsible for the anxiety and pain that the whole situation caused my kids?	✓	✓	✓	-
Citizens followed all the rules. We stayed at home, we became ill, we suffered anxiety and depression. So, who is to blame for the contagions?	✓	✓	✓	-
The eternal lockdown stresses me out! I am crying just like in my worst anxious and stressed moments.	-	✓	-	✓
You should tell that to every family suffering and getting depressed due to the economic situation!	-	-	✓	-
Daily prevalence of markers	50%	75%	75%	25%

Figure 2. Matching example between tweets and mental health markers.

peaks and events in Argentina related to the COVID-19 pandemic and the accompanying political and economic situation.

As regards anxiety (Figure 3a), the time series the emergence of darker areas in the days following the confirmation of the first COVID case and previous to the suspension of activities and the official declaration of lock-down (between March 7 and March 14). These events led to the first peak around March 8. As observed, the increment in prevalence mainly affected the markers of *confusion*, *horror*, *disappointment*, and

nervousness. On the other hand, the less affected markers were *suffering* and *health*. The burst in *anger* in early March could respond to declarations of the Health Minister underestimating the virus and to a COVID political event by which the President was assigned ‘special faculties’ to dictate acts of law and discretionally make budget allocations. These observations match the ones made by Aiello et al. (2020) after detecting the first contagion in the US, when there was a peak of anger, fear, and anxiety, which decreased after the lock-down declaration.

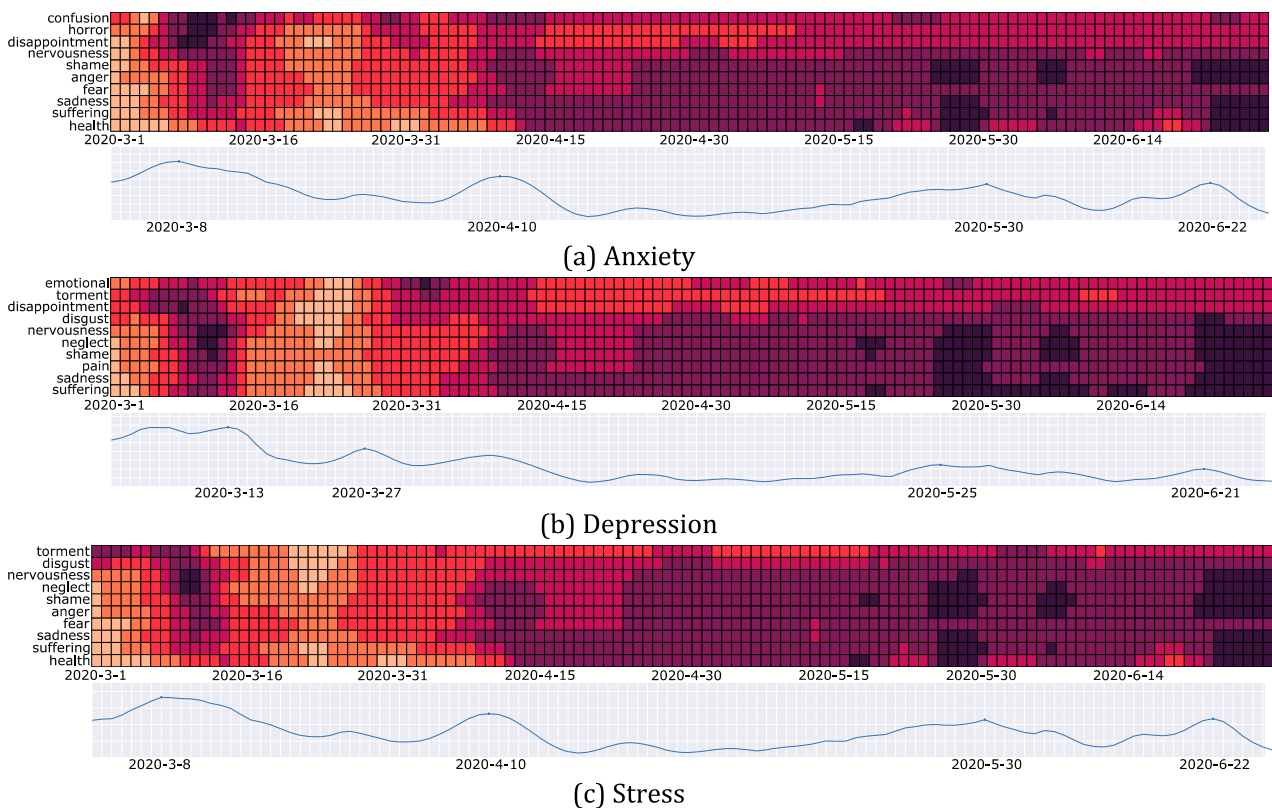


Figure 3. Prevalence of the Empath categories for the three analyzed mental health disorders.

After the announcement and start of the first lock-down (March 20 – March 21), the least prevalent marker was *disappointment*, while the intensity of the *nervousness*, *sadness*, *suffering* and *health* markers decreased. An analysis of tweets showed the faith that people had in the government decisions, optimistic beliefs in lock-down, and gratefulness for how the government was taking care of the population. These observations match those of a survey¹² collected in Argentina at the end of March, where people reported an increased sense of security against COVID-19 and a higher awareness regarding the preventive actions than those at the start of the lock-down. As the lock-down continued, we can observe an increment in the conversations about *health* and *suffering*, followed by *confusion*, *fear*, and *anger*. Reaching the 100 days of lock-down (June 27), the prevalence of *suffering*, *health*, and *anger* reached their highest values for a continuous week.

In a context with high anxiety markers, the increment in the prevalence of the *health* marker could relate to the phenomenon known as ‘health anxiety’ (Asmundson and Taylor 2020). This phenomenon arises from the misinterpretation of perceived body sensations and changes combined with the consumption of inaccurate or exaggerated information from the media (Asmundson and Taylor 2020a; Asmundson and Taylor 2020b). These observations are in accordance with Asmundson and Taylor (2020b), who reported an increment in health anxiety, particularly in areas where the number of people affected by COVID-19 was continuously increasing. Health anxiety can manifest in individuals as maladaptive behaviours (e.g. the avoidance of health care even with genuine symptoms¹³, or the hoarding of particular sanity items¹⁴). Then, at a societal level, health anxiety can lead to mistrust of public authorities, which can influence the success or failure of the public health strategies. In this context, it is critical that decision-makers understand how health anxiety affects the responses of individuals and society to health recommendations (Rajkumar 2020).

As shown in Table 5, the anxiety peaks could be explained by a sequence of events. Most of them were related to the situation of the Argentine capital city (called Ciudad Autónoma de Buenos Aires, or CABA) and the most prominent state (called Buenos Aires), which defined the lock-down path for the rest of the country. In the mapping, there are also events related to debt negotiation (which altered the rate exchange of the Argentine peso and thus goods prices) and to citizen demonstrations in reaction to the President’s decisions. An individual analysis of markers revealed that, even though peaks appeared simultaneously, their prominence was different. In this sense, the *health*

marker presented the most prominent peaks, followed by *fear*.

When observing depression (Figure 3b), the trends are similar to those of anxiety due to the shared markers. Nonetheless, the distributions showed a higher prevalence of most categories since early April, when lock-down was extended for 15 extra days, limiting the allowed activities. The topics discovered around those days expressed concerns regarding both health and the economic situation. The highest prevalence was observed for *sadness* and *suffering* across most of the period. Given the restrictive nature of the adopted policies, the population started to express their discouragement. For example, when reaching the 100 days under lock-down in late June, a high prevalence of 60% of markers was observed. Conversely, *emotional*, *torment*, and *disappointment* did not show a high prevalence across the time span.

The peaks for depression are close to those of anxiety, including a new one on March 27. As Table 5 shows, that date marks the first week of lock-down and a televised President’s announcement in which he declared the first lock-down extension for two additional weeks. When individually analyzing the markers, both *suffering* and *sadness* showed the most prominent peaks. Finally, stress markers (Figure 3c) showed a highest prevalence for the most extended period. As for depression, the detected peaks match those of anxiety. Similar to anxiety, the peaks corresponding with the individual markers were dominated by the *health* marker, followed by *suffering* and *fear*.

Recent evidence has suggested that people kept under lock-down experiences can exhibit significant levels of anxiety, anger, confusion, depression, and stress (Salari et al. 2020). In this context, as the COVID-19 lock-down situation evolved, the variations observed in the markers for each of the selected mental disorders showed that social media reflects the events in the real world, thus helping to answer RQ1. This is further confirmed by the matching between relevant COVID-19 events in Argentina and the changes in the prevalence of markers. These observations agree with those of Barzilay et al. (2020), who discovered through surveys and questionnaires symptoms of anxiety, depression, and stress in the population. Similarly, Adams and Adams (1984), Nolen-Hoeksema and Morrow (1991) and Jeong et al. (2016) determined through surveys and interviews changes in stress and depression markers through the crisis period. In addition to the direct COVID-19 situation, the high levels of anxiety and stress could also relate to lock-down economic consequences (Mucci et al. 2016). Furthermore, the evolution of the manifestations of the mental health disorders also had a

Table 5. Events associated to peaks observed for the mental health analysis.

Peaks	Associated events
March 8th	<p>March 3rd. The first COVID-19 case is confirmed in a man who had arrived from Italy.</p> <p>March 4th. The Health Minister announces that the government was not planning on closing schools, suspending shows nor flights coming from affected countries.</p> <p>March 5th. The Health Minister declares that people were over-reacting. The flag carrier (Aerolíneas Argentinas) announced the cancellation of flights connecting Argentina and Italy.</p> <p>March 7th. The first death is confirmed. A 64-year-old man who had travelled to Paris. The COVID case was diagnosed post-mortem.</p> <p>March 8th. Twelve confirmed cases.</p>
March 13th	<p>March 9th. Agricultural producers go on strike due to new taxation policies. The president declares that the strike is violent. The president declares that COVID-19 is posing a serious situation, but people should not over-react. The president allows the start of debt restructuring negotiations.</p> <p>March 11th. The president establishes a lock-down only for those returning from an affected country or region, and affirms that those who break the lock-down will be prosecuted.</p> <p>March 12th. The president announces the establishment of repatriation mechanisms.</p> <p>March 13th. The second death is confirmed.</p>
March 27th	<p>March 21st. According to the president, 'the worst is yet to come'.</p> <p>March 22nd. Governors asks for the army to control the lock-down.</p> <p>March 24th. Riots in several prisons. More agreements regarding the operations of the legislative branch.</p> <p>March 25th. The president threatens companies that do not respect the maximum price limits.</p> <p>March 26th. The aerial space is closed. All borders, airports and ports are closed. Not even the Argentinian people can enter the country.</p> <p>March 27th. The president declares that he is not in a rush to reopen schools.</p>
April 10th	<p>April 4th. Mercosur approves an emergency fund and 45.000 diagnostic tests will arrive.</p> <p>April 5th. A TV special ('Unidos por Argentina', 'United for Argentina') is held to collect donations through the Red Cross. More than 1500 confirmed cases.</p> <p>April 6th. Controversy over purchases made by the government with surcharges.</p> <p>April 8th. More than 800 prisoners are benefited with house arrest for fear of contagions in Provincia de Buenos Aires. The first national diagnostic tests are being developed.</p> <p>April 10th. Second lock-down extension until April 26th. Argentina is in the top-10 countries with the most cases in Latin America.</p>
May 25th	<p>May 18th. Presentation of a new diagnostic kit locally produced.</p> <p>May 19th. New activities are authorised in Buenos Aires. Definitions regarding the authorizations of new activities.</p> <p>May 21st. Negotiations to avoid debt default. Record of contagions in Buenos Aires and CABA.</p> <p>May 23rd. Limits to the public transportation system in CABA. Argentinian GDP is expected to slump up to a 20%. Lock-down extended two extra weeks.</p> <p>May 24th. The government started to provide economic assistance to companies. More than 12,000 confirmed cases.</p> <p>May 25th. The president declares that all economic problems are due to the pandemic and not the imposed lock-down. Commemoration of first independent government in Buenos Aires.</p>
May 30th	<p>May 24th. The government started to provide economic assistance to companies. More than 12,000 confirmed cases.</p> <p>May 25th. The president declares that all economic problems are due to the pandemic and not the imposed lock-down. Commemoration of first independent government in Buenos Aires.</p> <p>May 29th. A group of intellectuals declares that 'democracy is in danger', which causes counter declarations from the government.</p> <p>May 30th. Argentina continues with debt restructuring negotiations to avoid default. Health workers protest against work insecurity and low salaries.</p>
June 21 st	<p>June 15th. The governor of Provincia de Buenos Aires wants to impose an even harsh lock-down, as according to estimations, the health system will collapse in 35 days. The economy ministry is confident on reaching an agreement for the debt restructuration.</p>
June 22nd	<p>June 16th. The government suggests that the lock-down might be in place for at least three more months.</p> <p>June 17th. Restrictions for running according to the number of the national ID. New circulation permit in place. The president blames the runners for the new surge of contagions.</p> <p>June 20th. Protestors against the expropriation of a company.</p> <p>June 22nd. A plan for restricting the lock-down is announced. Almost 50k confirmed cases.</p>

correspondence with the psychological states of a crisis (DeWolfe 2000; Drabek 2012), by which it is expected to first have an anxious phase, followed by stress and depression phases.

4.2. Emotions

Sentiment analysis has been regarded as an effective tool to detect social media content that can contribute to situational awareness, as it can help understand individuals' dynamics (Gruebner et al. 2018). For example, how individuals cope with the causes, effects, and emotional burden of a crisis. Nonetheless, some studies (Gruebner et al. 2018) have argued that it is not enough to solely focus on mental health issues or a global sentiment score. Doing so could miss the complexity of the full

range of emotional responses to the direct effects, and the social, economic and environmental changes caused by crises. Hence, assessing multiple emotion dimensions might provide insights regarding how individuals experience crises or disasters (Gruebner et al. 2017). In this sense, we considered a subset of the SentiSense emotions (shown in Figure 4) for the March-August period. Peaks were detected for positive (i.e. *surprise*, *calmness*, *joy*, *love*, *hope*, *like*, and *anticipation*) and negative (i.e. *despair*, *hate*, *anger*, *sadness*, *fear*, and *disgust*) emotions.¹⁵ The darker the colour, the higher the prevalence of the emotion for such day. Unlike mental health markers, emotional markers did not show a magnitude order increment during July and August.

The emotion evolution shows the appearance of areas with a higher prevalence of emotions in the days

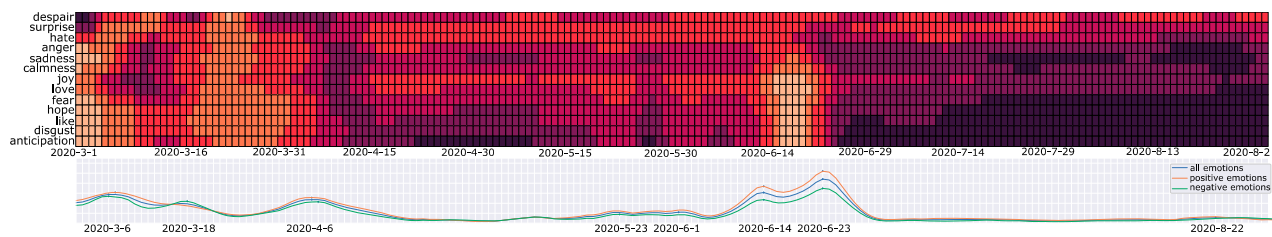


Figure 4. Prevalence of the SentiSense emotions over the span March-August.

following the confirmation of the first case until the announcement of the lock-down, affecting both negative and positive emotions. The high prevalence of positive emotions could relate to the mentioned confidence in the government decisions and the feeling of being taken care of. Simultaneously, there was a slight change in *anticipation*, which could relate to the uncertainty of what to expect during lock-down. The prevalence of emotions is similar to those of the detected Empath markers. For example, in both cases, *anger* and *sadness* showed a high prevalence in mid-March, around the time of the first official prevention measure and lock-down announcements.

In early June, lock-down was extended for its sixth time until the end of June, with new allowed activities for the big cities, including running, individual outdoor sports, and shopping. Unlike the analyzed mental health traits, most emotions showed a low prevalence period in mid-June, which could be related to a sense of optimism

for the newly authorised activities. In late-June contagions increased, leading to another extension of lock-down and the start of the most emotional period. Changes in *fear*, *disgust*, and (to a lesser extent) *hate* dominated the peaks for the negative emotions. Their most significant changes matched those observed for the mental health traits, taking place in early March (at the time of the first COVID-19 related announcements) and mid to late June (when reaching the 100 days of lock-down). Then, *disgust* and *fear* changed in the same magnitude in June. Changes in the remaining emotions were less prominent. *Despair* was the emotion with the least changes. Small peaks were observed for most emotions around the dates of the lock-down extension announcements. By July, none of the negative emotions showed prominent peaks, indicating a sustained level of emotions, with no sudden changes. [Table 6](#) complements [Table 5](#) matching the discovered peaks for emotions with events.

As regards the positive emotions, peaks showed similar trends to those for the negative ones. Both early-March and late-June showed the highest peak density and prominence. Unlike negative emotions, a few *surprise* and *calmness* small peaks appeared in late July and mid-August. These peaks seemed to match different political and economic events. For example, there were peaks around the celebration of Argentina Independence Day (July 9) and the day the President announced a plan for recovering the economic situation after the pandemic (July 11). Then, the *surprise* peaks in August matched the new extensions of the lock-down and the authorisation of new activities in the city.

These observations agree with Gruebner et al. (2018), who found differences in the level of discomfort (represented by six negative emotions: anger, confusion, disgust, fear, sadness, and shame) of social media users before, during, and after a disaster. They observed that negative emotions tended to increase during and after the crisis, contrasting with the emotions during the warning or planning phase before the crisis. Similarly, Gruebner et al. (2017) observed a prevalence of fear and surprise after the disaster (in this case, it could refer to the days after the announcement of the first

Table 6. Events associated to peaks observed for the emotion analysis.

Peaks	Associated events
March 18th	March 13th. The second death is confirmed. March 14th. Schools are to be closed. Borders are closed to non-residents coming from affected countries. March 17th. Citizens are asked not to do tourism.
April 6th	March 31st. Borders are still close for non-residents. Lock-down extension for two weeks. April 2nd. Protests asking for the executive branch of the government to reduce their salaries. April 3rd. University of Buenos Aires presents a plan for returning to activities on June 1st. The judicial branch of the government reduces their salaries. April 4th. Mercosur approves an emergency fund and 45,000 diagnostic tests will arrive. April 5th. A TV special ('Unidos por Argentina', 'United for Argentina') is held to collect donations through the Red Cross. More than 1500 confirmed cases. April 6th. Controversy over purchases made by the government with surcharges.
June 14th	June 8th. Changes in the authorised activities in CABA. The government presents a plan for expropriating a cereal exporter. June 14th. New restrictions in Buenos Aires.
August 22nd	August 17th. Protest in all the country against the government. August 19th. New protest against changes in the judicial branch of government. August 20th. 4% GDP deficit.

lock-down) and an excess of sadness. Additionally, the authors determined that the emotions with the highest prevalence (they referred to them as emotions expressing risks) were anger, fear, sadness, disgust, and surprise, which match the emotions dominating the peaks in our observations. Moreover, the evolution of emotions showed a behaviour similar to that observed by Aiello et al. (Aiello et al. 2020) for the fear social epidemic in the two months between the detection of the first case and the declaration of lock-down, in which fear and anger were prevalent, followed by sadness and some positive emotions. The changes in the prevalence of emotions and the evidence of their interrelations, which are in agreement with other works in the literature, allow answering **RQ2**, reinforcing the role of social media for monitoring emotions and, consequently, derived negative mental health outcomes.

The evolution of emotions could also be linked to the psychological states of crisis (DeWolfe 2000; Drabek 2012) by which it is expected to have a sense of *anticipation* in the days leading to the prime event of the crisis, followed by a period of negative emotions associated with states of anxiety. In our case, this period could include the days in between the confirmation of the first case and the announcement of the lock-down. After that, brief periods of optimism can occur, followed once again by a prevalence of negative emotions and stress traits.

4.3. Crisis

Based on the operationalisation of the traditional crisis stages (DeWolfe 2000; Drabek 2012), Figure 5 presents the temporal distribution of references to each of the particular markers for the classical disaster stages (Drabek 2012; Neal 1997): preparedness, response, recovery, and the shared markers across stages, for the March-June period, along with the detected peaks. Regarding the mental health analysis, during July and August we observed different orders of magnitude across the markers, which hinder the observation of changes in the previous months. The overlapping of the categories shared by preparedness, response, recovery showed their coincidences and an interwoven nature. The analysis did not include the mitigation phase as it relates to activities after the recovery of the current event and in preparation for future similar events, which have not started at the time of data collection. Table 6 complements Table 5, matching the discovered peaks for the stages with events Table 7.

Regarding the preparedness phase (Figure 5a and Figure 5d), when considering anxiety, the distribution showed emerging areas with a high prevalence of

anticipation, *trust*, and *nervousness* in the days following the confirmation of the first COVID case and previous to the first official announcements. *Aggression* could be related to *anger*, as both serve as a self-defensive mechanism for coping with the situation. *Anger* could also be explained in terms of the reactions to the political events previously described for anxiety.

When individually analyzing the markers, *communication* presented the most prominent peaks from March until mid-April, which matches the time in which the government promoted safety measures for preventing contagions and the announcements of the first lock-down and the first COVID tests produced locally. During this time, the government supported the idea that Argentina was leading the fight against the COVID and that these efforts were renowned worldwide, which could have spiked the sense of trust. In June, another *communication* peak appeared as contagions increased after the first lock-down flexibilization. This peak seems related to the need of reminding individuals of prevention measures¹⁶ and the consequences of the disease.¹⁷ When observing response (Figure 5b and Figure 5d), a peak appeared after confirming both the first contagions and the first death. Markers increased their prevalence around mid-April (matching the second peak) when lock-down was once again extended, contagions grew gradually, and individuals started to be aware of the possibilities of contagion and the COVID-19 effects. As previously mentioned, the prevalence of *health* could be related to the diffusion of prevention guidelines or the description of physical symptoms or other health complications, along with the phenomenon of health anxiety.

According to Richardson (2005), during a crisis, people might suffer 'survivor's guilt', which might manifest by *shame* for still having a job, for being able to work (the lock-down in Argentina prohibited all activities but a small number of exceptions), which might explain the high relevance of *shame*. Then, *shame* or even self-guilt can be followed by a period in which there is a need to blame someone for the problems. In this case, around mid- and late-June, when several activities were allowed in CABA, the culprit of the new contagions were the runners, which were the target of a blaming campaign in social media. This situation matched a detected peak. The remaining dark areas matched the spans over which the President made announcements regarding the health situation in Argentina and extended the lock-down.

Several theories have explored the relationship between crisis and the prevalence of crime (Prelog 2016). On the one hand, some theories (such as Therapeutic Community) support the claim that both violent

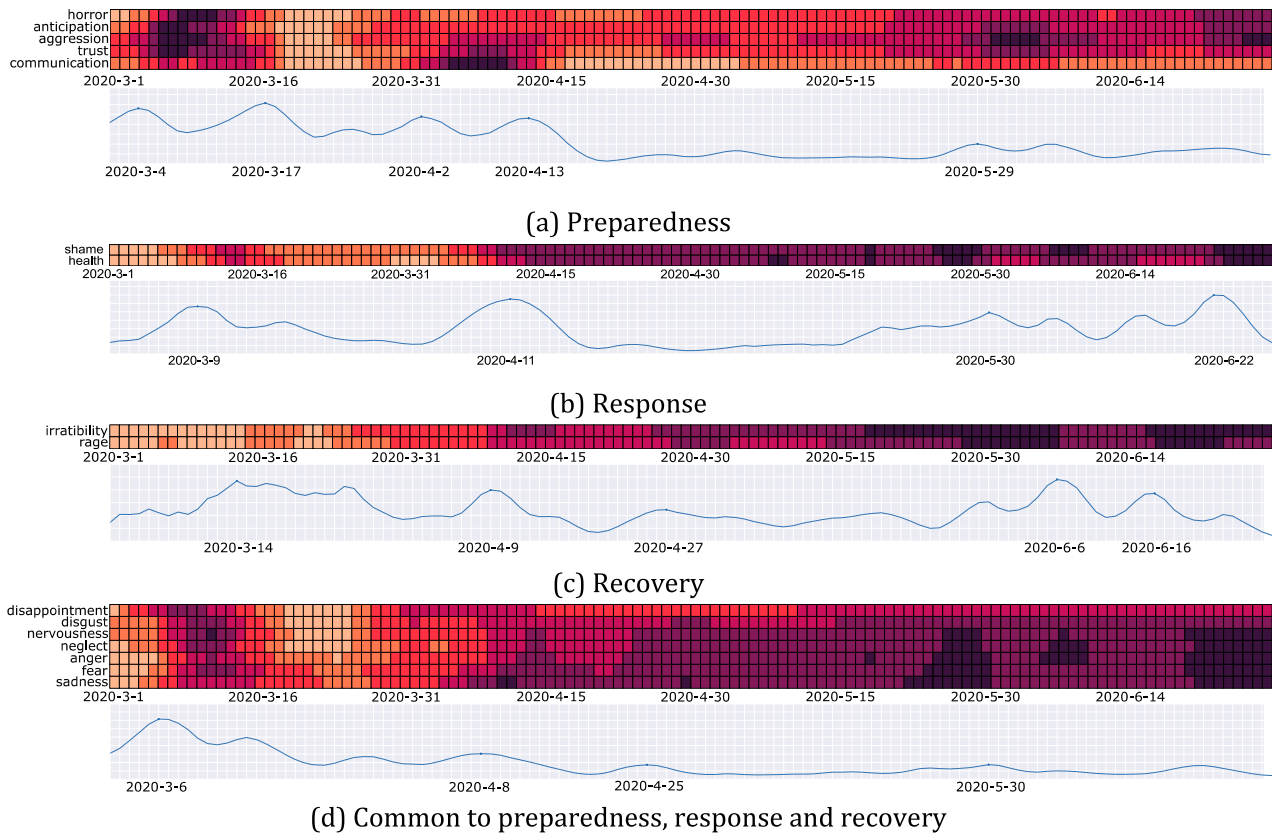


Figure 5. Prevalence of the Empath categories across crisis stages.

Table 7. Events associated to peaks observed for the crises stage analysis.

Peaks	Associated events
April 13th	April 6th. The president justifies the ministries that allegedly paid overprices. Mandatory use of masks. Pope Francis declares that in prisons COVID can cause a 'calamity'.
	April 8th. More than 800 prisoners are released for risk of COVID contagion.
	April 10th. Announcement of the new lock-down extension. Announcement of financial assistance for tourism related companies and sport clubs.
	April 12th. The president replies to the Chilean government that number shown that the applied policies are working. The number of domestic violence reports increases.
	April 20th. The government announces that 3 million extra people has filled for food assistance.
April 27th	April 21st. Plans for a new lock-down extension. Crisis and inflation warnings.
	April 22nd. The health minister affirms that he did not contemplated the possibility of allowing entertainment activities.
	April 25th. Announcement of the new lock-down extension. People is now allowed to go outside one hour a day for a walk.
June 6th	May 30th. Debt negotiations to avoid default.
	May 31th. Government agencies are being investigated for alleged overpricing.
	June 1st. Over 21 million people receive financial help from the government.
	June 4th. The president shares a video announcing the new lock-down extension.
	June 5th. Debt negotiations are continued to avoid default.

and property crime either remain unaffected or decrease after crises, while domestic violence could rise. On the other hand, other theories (such as Social Disorganization) argue that crises can create or aggravate the existing social disorganisation by disrupting the social cohesion and the collective efficacy, rendering the community unable to self-monitor and sanction anti-social behaviour. This implies, in turn, that criminality rates tend to rise due to the lack of controls. A third group of theories (such as Routine Activity) suggests that changes in crime rates result from changes in the socio-structural organisation of everyday activities. These changes reflect the convergence of three necessary elements: the availability of crime targets, the absence of guardians (such as the police), and the presence of motivated offenders.

The analysis of the evolution of crime perception was based on several Empath categories related to crime (i.e. *sexual, aggression, violence, kill, stealing, military, crime, law*). As these categories were already available, no lexicon was created for this analysis. As Figure 6 shows, crime did not seem to be a preoccupation during the early stages of lock-down. This tendency was in line with the government declarations in late March and mid-April stating that thefts decreased due to the

limited circulation in cities. Nonetheless, during late April and May, the prevalence of such markers increased (along with the marker related to government mentions), which could be associated with the release of prisoners for preventing contagions and the rise in crimes against the property by which individuals began to usurp private land.¹⁸ Later in August, the government admitted an increase in criminality.

In social terms, the recovery stage (Figure 5c and Figure 5d) covers the attempts to return to a ‘normal life’ mixed with fear, anxiety, depression, rage, irritation with changes in daily life, and the emergence of conflicts in the community level, among other characteristics (Drabek 2012). In this sense, for this stage, there are two non-overlapping markers, *irritability* and *rage*, which showed a high and continuous prevalence starting in mid-May. By late May, Argentina had already endured five lock-down extensions, and the number of contagions was still on the rise. In parallel, the press conferences led by the government included comparisons to other countries (e.g. Sweden, Chile, Spain, and Brazil) to highlight the good administration of the health situation, which were debunked afterwards. The fact that the markers for response and recovery had a high prevalence around the same periods showed the interwoven nature of phases, and that recovery actions were followed while society was still enduring the impact of the pandemic. For example, as the number of contagions was still rising, the government tried to better equip the health system by providing additional budget and resources to the most affected regions.

The high prevalence of markers associated with the three stages during July and August could be perceived as a return to the early stages of the pandemic. At that time, the reporting of contagions and deaths and the positivity rate started to rise. Simultaneously, the economic situation continued to aggravate as several sectors were unable to resume working. The situation is expressed in social media by an exacerbated prevalence of markers associated with mental health and emotions, as previously showed.

The observed changes in social media activity, the identified mental states and emotions, and the stationary prevalence of the derived markers suggest that Argentina traversed the three classical stages of crises, thus providing evidence for answering **RQ3**. Based on

Table 8. Prevalence of the Empath categories over the crisis stages between March-June.

		<i>preparedness</i>	<i>response</i>	<i>recovery</i>
Associated to <i>preparedness</i>	horror	52.45	9.33	17.83
	aggression	13.53	7.27	15.50
	anticipation	41.02	7.95	22.62
	communication	27.46	1.72	4.06
Associated to <i>response</i>	trust	20.05	2.81	6.99
	shame	13.78	23.74	16.41
Associated to <i>recovery</i>	health	12.59	28.93	39.58
	irritability	11.64	23.75	24.20
Associated to <i>preparedness, response and recovery</i>	rage	3.22	16.03	27.10
	fear	28.33	12.47	14.17
	sadness	14.06	17.80	11.44
	nervousness	25.08	16.46	18.60
	neglect	9.96	16.62	20.52
	disappointment	36.27	5.97	6.57
	anger	4.00	16.00	21.70
Associated to <i>response and recovery</i>	disgust	6.16	12.39	18.90

the analysis, the preparedness stage spanned between early March and mid-April, covering the time when society was still trying to make sense of the situation, and the first prevention measures were adopted after the first cases and deaths. Then, the response stage started mid-April, when lockdown was well established, and the development of national tests and the first economic and political measures were announced. Finally, still in the response stage, a brief recovery stage started in late May and early June, with the first lift of restrictions in the big cities, which signalled the first short steps towards the ‘new normality’. This situation reverted in July, and the response stage took prevalence again as the number of daily contagions rose and more restrictive lock-downs were applied.

To further reinforce relations between the three stages, Table 8 reports the maximum percentage difference between the prevalence of markers in each of the stages compared to the median prevalence of markers across the March-June period. In each row, the maximum value is highlighted. As shown in the table, in most cases the highest percentage difference of a marker was observed for its corresponding stage. The two exceptions are *aggression* and *health*, both showing a higher prevalence in the recovery stage. For those markers shared across stages, the average prevalence differences across phases were lower. In other words, the usage of such markers was more evenly distributed across phases than for those markers associated with a unique phase.

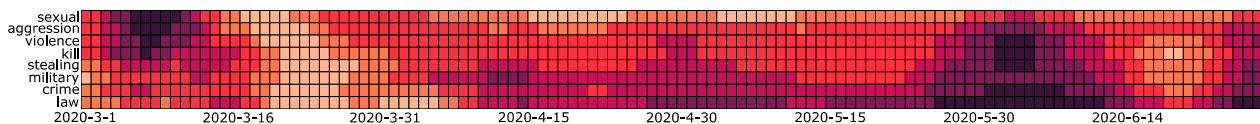


Figure 6. Prevalence of the Empath categories associated to crime over the span March-June.

5. Conclusions

The COVID-19 pandemic has profoundly affected all aspects of society, not limited to physical health but also to mental health, economics (e.g. affecting employment conditions, financial insecurity, and poverty), and even twisting political decisions. More than one year after the start of the pandemic, Argentina has entered the second wave, and restrictions are still in place while contagions increase. In this context, measuring the effects of the pandemic on individuals and societal dynamics is vital to understand the policies employed by the authorities to manage the pandemic, which should aim at achieving a proper balance between disease control and mitigation of adverse socio-economic effects (Holmes et al. 2020). Moreover, government agencies should provide accurate information on the pandemic state, refute rumours promptly and reduce the impact of misinformation, which should result in public security and trust (Salari et al. 2020).

Most studies on the effect of crises and disasters have relied on post-disaster data obtained through surveys or questionnaires (Gruebner et al. 2018) and conducted on a small-to-medium scale, which might cause important information to be missed. We believe that social media can complement these studies by enabling opportunities to track individual behaviour and perceptions over more extended periods, from pre- to post- crisis stages and at a larger scale. Moreover, analyzing social media can help to monitor the spread of the disease, the awareness about the disease and symptoms, and the responses to health and government recommendations and policies. The end goal is to support the design of effective communication interventions (Depoux et al. 2020; Li, Hughes, and Howe 2018; Van Bavel et al. 2020) to provide reassurance and practical advice.

From a theoretical point of view, our analyses provide a contextualisation of the traditional stages of a crisis, showing their corresponding manifestations in social media, and verifying the processes and patterns previously observed through surveys. The analyses also help discovering mental health markers, which can inform the design of health prevention policies (Holmes et al. 2020). The analysis approach presented in this study can, in principle, be applied to any large-scale data stream and have practical implications on the monitoring of individuals' behaviours, perceptions, mental health, and emotions, as valuable indicators to understand mechanisms and propose interventions. As lexicons do not reflect particularities of crises, but rather characterise their generic stages and mental

health expressions, the presented analysis, process, and techniques can be applied to other crises and disasters, provided that social media data can be collected.

The Spanish lexicons for both mental health disorders and crisis stages used in this work are an important asset, and we aimed at keeping the lexicons as neutral as possible. Nonetheless, they could be influenced by the idiosyncrasy of the Argentinian dialect, which might affect the results if applied to resources based on other Spanish variations. Thus, as future work, translations should be revised and refined in order create Spanish resources with a wider applicability. A potential issue in the matching procedure between tweets and markers, whose prevalence then affects the analysis of dimensions, is the fact that markers might be shared across dimensions. Despite this can be a confounding factor for analyzing evolution trends, a preliminary analysis showed that the proportion of tweets with these characteristics is low, and thus they should not affect the overall gradient computation. Nonetheless, we envision a more detailed analysis of the relationships among tweets, their contributions to the daily prevalence of markers, and how they support the dimensions.

There are interesting aspects to consider in future works that could help tackle the limitations of this work. First, we characterised the COVID-19 pandemic in the context of Argentina, limiting the scope of the analysis and disregarding its effect on neighbour countries. It should be possible to compare how the pandemic manifested in other countries and whether the different policies adopted by each government, its political orientation, and the cultural dimensions can condition the evolution of emotions and crisis stages. Second, we focused the analysis on Twitter. Despite having a large number of users in the country, its user base might not be representative of the general population. In this sense, as the government is also present in other social media sites, which aim at different targets. A challenge here is how to include the multiple sites in the analyses to account for different perspectives and extend the scope of the study. In turn, one could investigate whether users in different sites behave similarly. Third, there are ethical concerns regarding the assessment of mental health markers in social media (Guntuku et al. 2017). Even though all collected data is publicly available, there could be risks associated with users' privacy. If not properly managed, the interventions based on these analyses could lead to discrimination, stigmatisation, and violence. Hence, a clear policy of data transparency and protection should be defined and enforced. Fourth, given the existence of cases of fake news that were propagated (even by the government) during the early stages of the pandemic,

it would be interesting to analyze the prevalence and propagation of misinformation and disinformation and how they affect the public perceptions and the coping of the crisis. Fifth, the period of the study is limited to the first wave of COVID-19. Future work could explore even longer periods to assess how crisis perception and mental health indications change as, for example, the second wave hits while vaccines are being distributed, and ultimately analyze the long effects of the pandemic.

Notes

1. Available at: <https://data.mendeley.com/datasets/nv8k69y59d/1>
2. Available at: <https://github.com/knife982000/FakingIt>. Since raw data cannot be publicly shared, Faking It! can also be used to rehydrate the data collection
3. <https://developer.twitter.com/en/docs/twitter-api>
4. <https://www.ibm.com/watson/services/language-translator/>
5. <https://wordnet.princeton.edu/>
6. <https://fasttext.cc/>
7. Due to the requirement of anonymous submission the figures are momentarily located in the following Drive folder: <https://github.com/tommantommasella/SocialCovidArgentina>
8. <https://www.nimh.nih.gov/index.shtml>
9. <https://adaa.org/>
10. The depicted tweets are fictional to avoid breaching the anonymity of users and their shared content. The examples were created based on real tweets included in SpanishTweetsCOVID-19.
11. The figures including a complete time span can be found in the companion repository.
12. <https://cordoba.conicet.gov.ar/wp-content/uploads/sites/25/2020/04/Informe-final-6-de-abril-recortado.pdf.pdf>
13. In this regard, the official government communications asked people to stay at home and avoid attending to hospitals, which resulted in the population avoiding hospitals even when showing symptoms, and hospitals suspending services.
14. To avoid this, in mid-April, the government fixed the prices of hand sanitiser.
15. The peak Figures for each of the individual emotions can be found in the companion repository.
16. Official government spot: <https://twitter.com/msalnacion/status/1272569410407063554>
17. For example, the government created official short videos to discourage people of maintaining social reunions: <https://twitter.com/SantiCafiero/status/1287502460509130752>
18. This rise in land usurpation led to the political problem that until October 2020 was not solved.

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