Data-driven modeling of public risk perception and emotion on Twitter during the Covid-19 pandemic

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Abstract

Successful navigation of the Covid-19 pandemic is predicated on public cooperation with safety measures and appropriate perception of risk, in which emotion and attention play important roles. Signatures of public emotion and attention are present in social media data, thus natural language analysis of this text enables near-to-real-time monitoring of indicators of public risk perception. We compare key epidemiological indicators of the progression of the pandemic with indicators of the public perception of the pandemic constructed from ~ 20 million unique Covid-19-related tweets from 12 countries posted between 10th March – 14th June 2020. We find evidence of psychophysical numbing: Twitter users increasingly fixate on mortality, but in a decreasingly emotional and increasingly analytic tone. We find that the national attention on Covid-19 mortality is modelled accurately as a logarithmic or power law function of national daily Covid-19 deaths rates, implying generalisations of the Weber-Fechner and power law models of sensory perception to the collective. Our parameter estimates for these models are consistent with estimates from psychological experiments, and indicate that users in this dataset exhibit differential sensitivity by country to the national Covid-19 death rates. Our work illustrates the potential utility of social media for monitoring public risk perception and guiding public communication during crisis scenarios.

Keywords: Risk perception, Twitter, Covid-19, natural language processing, psychophysics, regression analysis, linguistic networks

1 Introduction

The Covid-19 pandemic has brought about widespread disruption to human life. In many countries, public gatherings have been broadly forbidden, mass restrictions on human movement have been introduced, and entire industries have been paralysed in attempting to lower the peak stress on healthcare systems [1]. However, the degree to which these restrictions have been enforced by law has varied over time and by location, and their success in mitigating public health risks depends on the extent of cooperation on the part of the public.

A key determinant of the public’s behaviour and their cooperation with state-imposed social restrictions is the public’s emotional response to, and their perception of the the risk presented by, the pandemic. However, the evolution of emotions and risk perception in response to disasters is not well-understood, and there is a need for more longitudinal data on such responses with which this understanding can be improved [2]. Our goal is thus to contribute to bettering this understanding, and we do so by exploring the empirical relationships present between the progression of the Covid-19 pandemic and the public’s perception of the risk posed by the pandemic.

We explain our findings in terms of the existing body of literature surrounding public perception of risk, disasters, and human suffering in cognitive psychology. In particular, we draw from psychophysics, the field that studies the relationship between stimulus and subjective sensation and perception [3]. The search for psychophysical “laws” of perception has existed since at least the mid-19th Century with the proposing of the Weber-Fechner law [4], which posits that the smallest perceptible change $ds$ in a physical stimulus of magnitude $s$ is proportional to $s$. Thus, the perceived magnitude $p$ of such stimuli follows

$$ dp \propto \frac{ds}{s}. $$

(1)

In the continuum limit, this implies that $p$ grows logarithmically with the physical magnitude $s$ of the stimulus. More recently, empirical studies by S. S. Stevens [5] supported, instead, a
power law relationship between human perception of a stimulus and the physical magnitude of the stimulus:

\[ p \propto s^\beta. \]  

(2)

Summers et al. [6] extended this concept to human sensitivity to war death statistics and found that a power law with exponent \( \beta = 0.32 \) best fit the data. A number of further studies have corroborated the extension of these psychophysical laws describing the subjective perception of physical magnitudes to the subjective evaluations of human fatalities [7, 8, 9]. In all of these, perception is a concave function of the stimulus, meaning that the larger the stimulus magnitude, the more it has to change in absolute terms to be equally noticeable. Thus, perception is considered relative rather than absolute, implying that our judgments are comparative in nature. This observation has been shown to account for deviations from rationality in economic decision-making [10].

These proposed psychophysical laws of human perception present an opportunity for monitoring a population’s response to a disaster scenario such as the Covid-19 pandemic. By evaluating the goodness of fit of these models to data on the perception of the progression of the pandemic, and determining the parameter values of such fits, we can describe the sensitivity of populations to the state of such crises, with important implications for risk communication and disaster management.

To this end, we make use of a massive Twitter dataset consisting of user-posted textual data to study the public’s emotional and perceptual responses to the current public health crisis. Twitter provides convenient access to the conversation amongst members of the public across the globe on a plethora of topics, and many authors are studying several aspects of the public’s response to the pandemic with it. Twitter is a particularly appropriate tool under conditions of physical distancing requirements and furlough schemes, where online communication has become more than ever a central feature of everyday life. Moreover, results from psycholinguistics and advances in natural language processing techniques enable the extraction of psychologically meaningful attributes from textual data. With this dataset, our general approach is to offer a quantitative, spatiotemporal comparison between indicators of the state of the pandemic and the topics and psychologically meaningful linguistic features present in the discussion surrounding Covid-19 on social media on a country-by-country basis, for a selection of countries.

1.1 Related work

Our work is novel in that, to our knowledge, it is the first to use a large social media dataset spanning multiple countries to model the perceptual response of countries’ citizens to the pandemic in the context of risk perception. To date, empirical validation of the aforementioned psychophysical laws has largely taken place in controlled laboratory settings, in which decisions, actions, and scenarios are artificial or hypothetical. Our work thus contributes to the body of literature surrounding risk perception by investigating these laws in a naturalistic setting.

However, there have been numerous authors using social media to analyse the public response to the Covid-19 pandemic. This includes work that has focused on the psychological burden of the social restrictions. For instance, Stella et al. [11] use the circumplex model of affect [12] and the NRC lexicon [13] to give a descriptive analysis of the public mood in Italy from a Twitter dataset collected during the week following the introduction of lockdown measures. In addition, Venigalla et al [14] has developed a web portal for categorising tweets by emotion in order to track mood in India on a daily basis.

Others have instead focused on negative emotions, as in the work of Schild et al. [15], where they study the rise of hate speech and sinophobia as a result of the outbreaks. More specifically on perception, Dryhurst et al. [16] measured the perceived risk of the Covid-19 pandemic by
conducting surveys at a global scale ($n \sim 6000$) and compared countries, finding that factors such as individualistic and pro-social values and trust in government and science were significant predictors of risk perception. de Bruin and Bennett \cite{17} perform similar work in the United States. The closest work we have been able to find to our own is that of Barrios and Hochberg \cite{18}, in which the authors combine internet search data with daily travel data to show that regions in the United States with a greater proportion of Trump voters exhibit behaviours that are consistent with a lower perceived risk during the Covid-19 pandemic. Despite the above, we have been unable to find work that combines large-scale social media data with linguistic analysis to offer a spatiotemporal, quantitative analysis of emotion and risk perception during the Covid-19 pandemic across multiple countries.

Beyond the Covid-19 pandemic, our work is related to a small but growing body of literature on the use of data science in understanding human emotion and risk perception. In such work, natural language analysis has succeeded in supporting established linguistic theories such as the importance of the distribution of words in a vocabulary as a proxy for knowledge \cite{19}, and regarding the relation between the uncertainty of events and the emotional response to their outcome \cite{20, 21}. For instance, using textual data from Twitter, Bhatia found that unexpected events elicit higher affective responses than those which are expected \cite{22}. In another instance, the same author conducted experiments with 300 participants and predicted the perceived risk of several risk sources using a vector-space representation of natural language, concluding that the word distribution of language successfully captures human perception of risk \cite{23}. Similar work has been conducted by Jaidka et al. \cite{24} in the area of monitoring public well-being, in which they compare word-based and data-driven methods for predicting ground-truth survey results for subjective well-being of US citizens on a county-level basis using a 1.5 billion Tweet dataset constructed from 2009 to 2015.

The remainder of this paper is laid out as follows. In Section \ref{data} we present the data set used in the subsequent analysis. In Section \ref{methods} we provide further details on the approach followed to explore the relationships between indicators of the state of the pandemic and the public’s perception of the pandemic, and discuss possible explanations for our observations by drawing on psychological literature. In Section \ref{discussion} we summarise and offer concluding remarks, along with a discussion of the limitations of the current work and suggestions for avenues of future work.

\section{Data}

\subsection{Twitter dataset}

In the following analysis, we make use of the set of tweets gathered by J. Banda et. al \cite{25}, which are obtained and maintained using the Twitter free Stream API\footnote{The free Stream API randomly samples around 1\% of the total tweets for the given queries}. At the time of writing, this data set consists of $\sim 80$ million original tweets spanning from March 11, 2020 to June 14, 2020. Data is collected according to the following query filters\footnote{A number of publicly available Twitter datasets have emerged in relation to the pandemic. We chose to work with this dataset since it used the most generic query terms among all the publicly available datasets we considered, and we wanted the least amount of bias possible for our analysis.}: “COVID19”, “Coronavirus-Pandemic”, “COVID-19”, “2019nCoV”, “CoronaOutbreak”, “coronavirus”, “WuhanVirus”, “covid19”, “coronaviruspandemic”, “covid-19”, “2019ncov”, “coronaoutbreak”, “wuhanvirus”.

For our analysis, we consider only the English and Spanish tweets with a non-empty self-reported location field. We process every self-reported location using OpenStreetMaps \cite{26} and remove non-sensical locations (e.g. “Mars”, “Everywhere”, “Planet Earth”). This allows us to group the remaining tweets by country and proceed with our analysis on a country-by-country
Table 1: Per-country summary of the Twitter dataset constructed from the repository maintained by Banda et al. [25].

| Country      | Language | Number of Tweets | Unique Users |
|--------------|----------|------------------|--------------|
| Argentina    | Spanish  | 846,706          | 194,818      |
| Australia    | English  | 701,072          | 97,027       |
| Canada       | English  | 1,209,712        | 195,507      |
| Chile        | Spanish  | 342,013          | 60,235       |
| Colombia     | Spanish  | 466,477          | 103,845      |
| India        | English  | 1,806,685        | 344,894      |
| Mexico       | Spanish  | 1,133,350        | 187,064      |
| Nigeria      | English  | 754,152          | 133,797      |
| South Africa | English  | 354,613          | 78,447       |
| Spain        | Spanish  | 1,697,049        | 274,010      |
| United Kingdom | English | 3,490,703     | 631,017      |
| United States | English & Spanish | 6,297,720 | 1,397,410 |
| **Total**    |          | 19,072,850       | 3,699,071    |

To assure the statistical significance of our analysis, we keep the countries with the highest number of tweets for each language, resulting in a geolocated Twitter dataset of ~ 20 million tweets posted by ~ 4 million users on 12 different countries, which we summarise in Table 1.

### 2.2 Epidemiological data

We measure the progression of the pandemic with the number of Covid-19 confirmed cases and deaths for all the countries in our analysis. The data was made publicly available by Our World in Data repository [27]. In particular, we take the daily Covid-19 cases and deaths, both in linear and logarithmic scale, since these are four epidemiological indicators that are most frequently used to summarise the state of the pandemic, and are therefore frequently encountered by the public.

### 3 Analysing the public’s perception of the pandemic

In this section, we study the public’s perception of the pandemic on a country-by-country basis, using the countries with the highest number of tweets in the observation period (see Table 1). We do this on a country-by-country basis since the pandemic has often invoked nation-level responses, making nation-level analysis the most natural geographic scale. Our broad approach is to inspect and compare the linguistic features of the tweets released by users in the Twitter dataset described in Section 2.1 with the epidemiological data described in Section 2.2.

#### 3.1 Defining perception from linguistic inquiry

Our goal is to explore the public’s perception of the pandemic. To do this, we analyse the linguistic features present in the textual data generated by Twitter users, and map these features to psychologically meaningful categories that are indicative of the Twitter users’ perception. Here, we are assuming that the words used by these Twitter users are indicative of their internal cognitive and emotional states [28], which is supported in [23] where they predict the perception of risk using text data. Thus, we quantify the linguistic content of each tweet.
using the Linguistic Inquiry and Word Count (LIWC) program [29]. LIWC has been widely adopted in several text data analyses, and it has proven successful in applications ranging from measuring the perception of emotions [30] to predicting the German federal elections using Twitter [31].

LIWC operates as text analysis program that reports the number of words in a document belonging to a set of predefined linguistically and psychologically meaningful categories[28]. For our purposes, a document is a tweet $d_i^t$ posted on date $t$ and from a user based in country $i$. LIWC represents documents as an unordered set of words, and a LIWC category $l$ is similarly a set of words associated with concept $l$. For a given document $d_i^t$, the linguistic score $p_l^i$ for category $l$ is the percentage of words in $d_i^t$ that belong to $l$:

$$p_l^i(d_i^t) = \frac{|d_i^t \cap l|}{|d_i^t|} \cdot 100. \tag{3}$$

There are many such categories $l$, including Family, Work, and Motion. We capitalise such category titles, and use the titles to refer to either the set of words associated with that category or to refer to the category itself. Linguistic scores from Eq. (3) for individual tweets will be noisy, as they are short documents. Moreover, we are interested in the average response of the population of a country. For this reason, we group the tweets by country $i$ and by date $t$, and denote these sets of tweets as $D_i^t = \{ d_{i'}^t' \mid i' = i, t' = t \}$. We then compute the National Linguistic Score (NLS) for category $l$ as the average of the linguistic scores over documents in $D_i^t$ relative to an empirically observed Twitter base rate $p_l^B$:

$$p_l^i(t) = \frac{100}{|D_i^t|} \sum_{d \in D_i^t} p_l^i(d) - p_l^B \cdot p_l^B. \tag{4}$$

The base rates $p_l^B$ for the use of words on Twitter associated with category $l$ are given in [29]. Using Eq. (4) for all the selected linguistic categories, we construct multidimensional country-level time series that represent the evolution of the public perception of the pandemic, similar to the linguistic profiles introduced by Tumasjan et al. [31].

In Figure 1, we show the collection of NLSs for a selection of relevant linguistic categories. We observe clear trends that, in most cases, are synchronized between countries and languages. In particular, most categories associated with emotion – notably Affect, Anger, Anxiety, Positive emotion, Negative emotion, and Swear words (swearing is associated with frustration and anger [32]) – have their highest scores in mid-to-late March, when the World Health Organisation (WHO) announced the pandemic status of Covid-19 and most Western countries introduced more stringent social restrictions [1]. These scores decay thereafter, indicating a relaxation of the emotional response in the conversation. This is consistent with results reported by Bhatia regarding the affective response to unexpected events [22]. A qualitatively similar trend can be seen in the Social processes panel, the category involving “all non-first-person-singular personal pronouns as well as verbs that suggest human interaction (talking, sharing)” [29].

We also observe that health-related categories such as Death and Health show an overall rising trend, with Death rising most rapidly throughout March. These categories, with the exception of Positive Emotion and Health, peak again in the United States at the end of May, coinciding with the murder of George Floyd and the subsequent Black Lives Matter protests. Such universal trends are not apparent by visual inspection in the Money, Risk, and Sadness panels. An additional feature of these plots is the absolute scale of these values: in all cases, there is a significant percentage change from their baseline values, with large percentage

3For the English-language tweets, we make use of the 2015 English dictionary. For the Spanish-language tweets, the most recent dictionary is the 2007 edition, which has fewer categories than the 2015 English dictionary.
increases observed initially in the use of words associated with Anxiety and later with Death, and a moderate percentage increase in the use of words associated with Risk.

3.2 Comparing the public’s perception with epidemiological data

In this section, we explore the relationship between the NLSs described in Section 3.1, which we use as a proxy for the public’s perception, and the intensity of the pandemic, which we assume is the stimulus triggering this perception. Our measure of the intensity of the pandemic is the number of Covid-19 cases and deaths from the data described in Section 2.2.

A straightforward way of approaching this relationship is by computing the correlations between the NLSs and the epidemiological data in a per-country basis, and we show the average across countries of these per-country correlations in Figure 2. On the one hand, we observe significant negative correlations in emotionally charged categories (e.g., Swear words, Anger, Anxiety, Affective processes), indicating a decay in emotion as the pandemic intensifies. Conversely, categories related with health and mortality (Death, Health) and analytical thinking (Analytic) show significant positive correlation.

3.2.1 Psychophysical numbing

We believe the trends we observe in Fig. 1 and the correlations we observe in Fig. 2 are consistent with the notion of psychophysical numbing. This term was introduced by Robert Jay Lifton [33], and developed by Paul Slovic [7, 8] in the context of human perception of genocides and their associated death tolls, to describe the paradoxical phenomenon in which people exhibit growing indifference towards human suffering as the number of humans suffering increases. By inspecting the correlations between the NLSs and the epidemiological indicators, we find that as the pandemic intensifies – in the sense of an increasing number of cases and deaths reported daily – our emotional response diminishes, as expected from a psychophysical numbing phenomenon.

Specifically, we observe negative correlations between almost all components of the NLSs associated with affect – Affective processes, Anger, Anxiety, Negative emotion, Positive emotion, and Swear words – and the epidemiological data. By inspecting Figure 1, we see that every country exhibits similar downward trends in these components and, with the exception of Anxiety, are all significantly lower than their baseline values throughout the observation period. This unusually low and decreasing Affect word count is accompanied, conversely, with a growing awareness of the morbidity of the situation in that we observe significant positive correlations between the Death NLSs and the daily national cases and deaths, indicating that the decrease in affect occurs simultaneously with and despite an attentional shift towards Covid-19 related mortality. We also observe a simultaneous increase in the Analytic component of each English-language dataset over this same period, indicating a movement towards more logical and analytical, rather than intuitive and emotional, thinking.

The potential implication of this is that the public is less perceptive of the risk that the pandemic poses to public health, since their emotional response is reduced and reducing.

4 When analysing these correlations, we found that, overall, the cumulative cases and deaths correlate better with most linguistic categories than the daily data. However, while this is sensible in the early stages of the pandemic, it is unlikely to remain the case over a long time horizon due to humans’ finite memory. We therefore proceeded with our comparison using the daily epidemiological data alone for this reason.

5 The only exception is the cross-country average of the Sadness component of the NLSs, which is positively correlated with the epidemiological indicators and appears to be driven only from Argentina’s, Chile’s, and Colombia’s increasing use of words related to Sadness. The remaining countries remain stationary at a lower-than-baseline value for this component.

6 Unfortunately, the Spanish LIWC dictionary does not yet have an Analytic category.
Figure 1: Time series for the NLSs for the countries as indicated by the legend. Each panel shows the individual linguistic categories. The units on the $y$-axis represent the percentage change of the National Linguistic Scores (NLS) on our data with respect to the LIWC baselines for Twitter (see Eq. (4)).
Figure 2: Correlation coefficients between epidemiological indicators and national linguistic scores (NLSs) averaged across all countries. *“Risk” and “Analytic” are only available for the English-language LIWC. These two categories are thus averages across English-language countries only.

For example, Van Bavel et al. [35] and Loewenstein et al. [36] describe that risk perception is driven more by association and affect-based processes than analytic and reason-based processes, with the affect-based processes typically prevailing when there is disagreement between the two modes of thinking. The negative correlations between the intensity of the pandemic and affective processes, together with its positive correlation with the prevalence of analytic processes, suggests that public risk communication could be adjusted to re-balance the degree of affective and analytic thinking amongst members of the public to achieve favourable risk avoidance behaviour and, consequently, favourable public health outcomes.

3.2.2 Word co-occurrence network analysis

To support our claim that these observations are attributable to psychophysical numbing, we construct word co-occurrence networks using tweets in our dataset. Given a set $\mathcal{T}$ of tweets, the word co-occurrence network $G(\mathcal{T})$ is represented by a weighted adjacency matrix $A(\mathcal{T})$ in which the nodes are words belonging to the Death and Affect LIWC dictionaries. Entry $A_{ij}(\mathcal{T})$ counts the number of co-occurrences between words $i$ and $j$ across all tweets in $\mathcal{T}$, and is computed as

$$A_{ij}(\mathcal{T}) = (B(\mathcal{T})^T B(\mathcal{T}))_{ij},$$

where $B_{tk}(\mathcal{T})$ counts the number of instances of word $k$ in tweet $t \in \mathcal{T}$. We ignore self-edges by imposing $A_{ii} = 0$, since it is the relationship between distinct words that is of interest. (See Appendix B.1 for further details on the construction of these networks.) If the psychophysical numbing effect is legitimate, we expect that words in the Death dictionary co-occur more frequently with other Death-related words and less frequently with words in the Affect dictionary. We construct three such networks by aggregating the word co-occurrences over three distinct periods: 11th March to 9th April 2020, 10th April to 23rd May, and 24th May to 13th June. As we discussed previously, the first period coincides with the pandemic status of Covid-19 declared by the WHO and has a high Affect score but a low and increasing Death score; the second one has a high and relatively stable Death score and a decreasing Affect score; and the third has a high Death score but one in which the Affect scores and some of its subcategories (e.g. Anger, Anxiety, Negative emotion) increase again, which we attribute – at least partly –
to the public response to the murder of George Floyd and the subsequent Black Lives Matter protests. In constructing these networks, we weight each country equally by taking a random sample of approximately 300,000 tweets from each country.

11th March - 9th April In this network (see Fig. 3a) we see two main clusters emerging. The first consists mostly of words associated with Death (left), and the second of words associated with Affect (right). The appearance of some of the Affect-related words in the Death cluster can be explained given the context of the pandemic. For example, the word “positive” is likely used in reference to the number of people that have tested positive for Covid-19, which is closely related to the conversation around Covid-19 cases and deaths. Similarly, the word “panic” is likely reflecting the early conversations around panic-buying of household goods, for example toilet paper and hand-sanitiser, and the word “isolat*” is likely used in calls for symptomatic individuals to self-isolate. Thus, while some instances of Affect-related words that appear in this predominantly Death-based community are harder to explain without appealing to the existence of a true subjective experience of affect amongst the Twitter users (e.g. “risk*”), the most important (in terms of node degree) of these Affect-related words are more likely being used here in an affect-free sense and are appropriately grouped with Death-related words here given the context of the pandemic. Thus the community structure we observe is consistent with our hypothesis of a separation between words belonging to the Death and Affect dictionaries.

10th April - 23rd May In this network (see Fig. 3b), the two-cluster structure seen in the previous snapshot remains, with the cluster more centered on Death on the left and a cluster corresponding to almost exclusive use of Affect-related words on the right. The size of the Death-related cluster has increased relative to the Affect-based community, reflecting the higher Death NLS during this period. Two new and important Affect-related nodes appear in the Death-based community for this time period: “care” and “fail*”. These can once again be plausibly explained by the context of the pandemic. For example, the appearance of the word “care” in the Death-related community can be explained in terms of the conversation surrounding the health care system and death care industries, the number of Covid-19 patients being admitted to intensive care units, and – particularly for the United Kingdom – the number of deaths that have occurred in care homes for the elderly. These are all clearly related to Covid-19 deaths, and the word “care” in this context most likely constitutes part of the noun and topic of conversation rather than any expression of emotion. The word “fail*” could reflect the discussion around failures on the part of governments to respond with sufficient vigor to the public health crisis – e.g. in terms of a failure to impose social restrictions in a timely manner or to meet testing quotas or quotas on the provision of personal protective equipment for key workers. For example, the polling company YouGov finds that approximately 50% of respondents felt during this period that the US and UK governments had been handling the pandemic well, and that these numbers decreased throughout this period to approximately 45% [37]. This does not however exclude the possibility that the appearance of “fail*” indicates a subjective emotional experience: it is possible that Twitter users that fixate on government failures are doing so as a result of a sense of outrage with regard to these perceived failures. Whether such outrage is motivated specifically by the human fatalities themselves or is merely a manifestation of broader political hostilities and polarisation in modern society remains open.

Thus, while the appearance of “sure*”, “fail*”, and some other minor Affect-related terms in the Death-community may be truly indicative of emotion in the conversation around Covid-19 fatalities, the presence of many of the most highly co-occurring Affect-related words in this predominantly Death-related community could be explained by their appearance in common phrases related to Covid-19 fatalities, e.g. the “death care” and “health care” industries, “care homes”, “testing positive” for the virus etc. These words, therefore, do not necessarily reveal
emotion in the current context. We thus argue once again that this co-occurrence network and its community structure shows that Death- and Affect-based words are well-separated, consistent with our claim of psychophysical numbing.

**24th May - 14th June** Our argument remains unchanged for this period (see Fig. 3c). The only notable difference for this period is that a significant proportion of the conversation surrounding death is focused on the political issues that inspired the Black Lives Matter protests and the protests themselves. This is apparent from the appearance of the word “protests” in the left-hand side’s Death-related community.

Altogether, this analysis demonstrates that words indicating a subjective emotional/affective experience and words related to death are well-separated in this Twitter data, which is consistent with the notion of psychophysical numbing as an explanation for the trends and correlations observed in Figures 1 and 2. For completeness, we include the equivalent co-occurrence graphs for the Spanish-language tweets in Appendix B.2 from which similar conclusions can be drawn.

### 3.3 Modeling psychophysical numbing

In the previous section, we demonstrated our finding that as the pandemic intensifies, the proportion of words that appear in the set of Tweets posted in each country that indicate emotion diminishes over time. This indicates that the actual emotional response to the pandemic diminishes as the intensity of the pandemic increases, implying a psychophysical numbing effect. We supported this explanation by showing that the word co-occurrence networks induced by our set of tweets host a community structure that separates words in the Death and Affect dictionaries, suggesting that people do not talk about Covid-19 deaths in a highly emotional tone. The following sections model the relationship between the progression of the Covid-19 pandemic and the Twitter users’ perception using grounded theories of psychophysical numbing.

#### 3.3.1 The Weber-Fechner law

Our analysis suggests that the public’s perception of the progression of the pandemic is logarithmic or, at least, sublinear. From Figure 2, we observe that the correlation magnitudes between NLSs and epidemiological data are generally larger in absolute value whenever the latter are taken in logarithmic scale. To exemplify this observation, we show in Figure 4 the $z$-scores\(^7\) of the Death NLSs and of the logarithm of the daily number of deaths and cases within each country.

The general correspondence between all three normalised features in each country is striking.\(^8\) We propose that this can be explained in terms of the Weber-Fechner law\(^4\), which is a quantitative statement with its origins in psychology and psychophysics regarding humans’ perceived magnitude \(p\) of a stimulus with physical magnitude \(s\). It states that a human’s perception of the magnitude of a stimulus varies as the logarithm of the physical magnitude \(s\) of the stimulus, meaning we are more sensitive to ratios when comparing different physical magnitudes than we are to absolute differences. In the continuum limit, Eq. (1) gives the following functional form for the Weber-Fechner law:

\[
p(t) = k \log \frac{s(t)}{s_0} + R(t), \tag{6}
\]

---

\(^7\)Recall that the $z$-score of a sequence of observations \(Y = (y_1, \cdots, y_T)\) is given by \(Z = (Y - \mu_Y)/\sigma_Y\), where \(\mu_Y\) and \(\sigma_Y\) are the mean and standard deviation of \(Y\), respectively.

\(^8\)We note that the correspondence is weaker for Australia, Nigeria, and South Africa due to the relatively low number of cases in these countries (see Fig. 9 in the Appendix for reference). The correspondence is also weaker in Spain, for two reasons: due to its revision of the number of cases in late May, resulting in a day of “negative deaths”; and due to their having recorded a day with no Covid-19-related deaths, which was a significant event given that Spain had seen many deaths until that point.
Figure 3: Snapshots of the word co-occurrences associated with Death (green labels) and Affect (red labels) for English-language tweets aggregated across all analyzed countries in three different time windows (see sub-captions). The nodes are coloured according to their community label as obtained by maximising modularity with the Louvain algorithm [38]. We filtered edges with weight below 20 co-occurrences for visualisation purposes.
Figure 4: Panel time series for $p_i^{\text{Death}}(t)$ (blue), the logarithm of the daily deaths (orange), and the logarithm of the daily cases (green). Each panel presents a different country, with the country name provided in the subplot title. The correlation between $p_i^{\text{Death}}(t)$ and the national daily death rate is given in parentheses for each country. Data is smoothed with a 3-day moving average and standardized with their z-score to make them visually comparable. Vertical lines represent peaks in the death discourse caused by exogenous events (see main text for details) which we remove from the time series.
Table 2: Results from the fit of the Weber-Fechner law to the observed relationship between the Death NLS and the logarithm of the daily number of deaths in each country (see Figure 4). Overall, this model best describes the relationship between the daily number of deaths local to each country and the Death NLS.

| country         | \( k \)  | \( s_0 \) | 95% CI \( k \) | \( t \)  | \( P > |t| \) | \( R^2 \) | NRMSE | \( n \) |
|-----------------|--------|--------|--------------|--------|---------|--------|-------|-----|
| Argentina       | 1.044  | 0.0080 | 0.758 – 1.329 | 7.29   | 0.0     | 0.421  | 0.113 | 75  |
| Australia       | 1.042  | 0.1047 | 0.508 – 1.576 | 3.94   | 0.0003  | 0.275  | 0.171 | 43  |
| Canada          | 0.596  | 0.4477 | 0.508 – 0.683 | 13.53  | 0.0     | 0.683  | 0.105 | 87  |
| Chile           | 0.575  | 0.0001 | 0.412 – 0.737 | 7.05   | 0.0     | 0.395  | 0.149 | 78  |
| Colombia        | 0.604  | 0.0011 | 0.436 – 0.772 | 7.18   | 0.0     | 0.414  | 0.144 | 75  |
| India           | 0.332  | 0.0061 | 0.264 – 0.4    | 9.69   | 0.0     | 0.543  | 0.128 | 81  |
| Mexico          | 0.846  | 0.0300 | 0.742 – 0.95   | 16.2   | 0.0     | 0.775  | 0.101 | 78  |
| Nigeria         | 0.457  | 0.0003 | 0.168 – 0.747  | 3.16   | 0.0025  | 0.147  | 0.222 | 60  |
| South Africa    | 0.282  | 0.0001 | 0.127 – 0.436  | 3.64   | 0.0005  | 0.171  | 0.183 | 66  |
| Spain           | -0.016 | inf    | -0.198 – 0.165 | -0.18  | 0.8593  | 0      | 0.198 | 82  |
| United Kingdom  | 0.752  | 5.241  | 0.61 – 0.894   | 10.54  | 0.0     | 0.555  | 0.143 | 91  |
| United States   | 0.788  | 4.2478 | 0.672 – 0.905  | 13.43  | 0.0     | 0.677  | 0.126 | 88  |

where \( k \) and \( s_0 \) are real-valued parameters and \( R(t) \) the residual. Parameter \( k \) determines the sensitivity of perception to changes in the stimulus \( s \), while \( s_0 \) determines the minimum threshold that the stimuli \( s \) must overcome in order to be perceived. The residual term \( R(t) \) is a random variable representing noise not directly captured by the stimulus. For instance, exogenous events can trigger abrupt peaks in the Death score. This is the case, for example, with the murder of George Floyd in the United States, or the peak in Nigeria around April 17th 2020, triggered by a number of prominent African figures dying from Covid-19 around that day, including the Nigerian President’s top aide (see [39]).

In order to test the Weber-Fechner law, we fit a linear regression model to \( p_i^{Death}(t) \), the Death NLS time series in country \( i \), and log \( s_i(t) \), the daily number of deaths in the same country, and summarize the results of these fits in Table 2. We find that Eq. (6) accurately models the data, with significant coefficients (\( p \)-value < 0.01) for all countries except Spain. The sensitivity parameter \( k \) has the same order of magnitude for all significant countries. However, the country with the lowest \( k \) is \( \sim 3 \) times less sensitive than the highest, indicating that Twitter users in different countries may react differently to the evolution of the pandemic. The minimum stimuli threshold \( s_0 \), on the other hand, is always small: most countries, except for the United States and the United Kingdom, need only one Covid-19 death in a given day in order to be perceived. Conversely, the United States and United Kingdom need approximately 5 and 6 deaths to be perceived, which is small compared to the thousands of daily deaths registered in these countries during the observation period.

\(^9\)In doing so for Spain, we ignore the epidemiological data on 25th May 2020. This is because this day is unusual in that a downwards revision of the number of deaths was introduced, making it a “negative death” day. We also remove outliers that are identifiable as driven by exogenous shocks e.g. George Floyd’s murder at the end of May.
### Table 3: The results from the fit of a power law to the relationship between the Death NLS and the national daily death count. This is the best model in some cases, though is outperformed by the Weber-Fechner law most times. *While we fit this model assuming a log-log relationship between \( p \) and \( s \), we compute \( R^2 \) with linear \( p \) to make it comparable to the model implied by the Weber-Fechner law (see Eq. (10) in Appendix A for details). This may cause negative values of \( R^2 \) as is the case for Spain.

| Country       | \( \beta \) | \( \nu \) | 95% CI \( \beta \) | \( t \) | \( P > |t| \) | \( R^2* \) | NRMSE | \( n \) |
|---------------|-------------|------------|--------------------|-------|-------------|----------|--------|------|
| Argentina     | 0.164       | 2.21       | 0.121 – 0.208      | 7.59  | 0.0         | 0.411    | 0.114  | 75   |
| Australia     | 0.363       | 0.99       | 0.181 – 0.546      | 4.02  | 0.0002      | 0.259    | 0.173  | 43   |
| Canada        | 0.288       | 0.37       | 0.252 – 0.323      | 16.29 | 0.0         | 0.678    | 0.106  | 87   |
| Chile         | 0.085       | 2.47       | 0.06 – 0.109       | 6.97  | 0.0         | 0.382    | 0.151  | 78   |
| Colombia      | 0.112       | 1.81       | 0.083 – 0.142      | 7.57  | 0.0         | 0.425    | 0.143  | 75   |
| India         | 0.126       | 0.77       | 0.101 – 0.15       | 10.33 | 0.0         | 0.558    | 0.126  | 81   |
| Mexico        | 0.141       | 1.52       | 0.126 – 0.157      | 18.04 | 0.0         | 0.78     | 0.1    | 78   |
| Nigeria       | 0.104       | 1.56       | 0.037 – 0.172      | 3.09  | 0.0031      | 0.143    | 0.223  | 60   |
| South Africa  | 0.087       | 1.11       | 0.037 – 0.136      | 3.52  | 0.0008      | 0.16     | 0.184  | 66   |
| Spain         | 0.014       | 2.14       | -0.03 – 0.059      | 0.64  | 0.5241      | -0.042   | 0.202  | 82   |
| United Kingdom| 0.356       | 0.16       | 0.302 – 0.409      | 13.21 | 0.0         | 0.514    | 0.149  | 91   |
| United States | 0.309       | 0.21       | 0.279 – 0.339      | 20.54 | 0.0         | 0.608    | 0.139  | 88   |

#### 3.3.2 Power-law perception

An alternative functional form for the relationship between human perception \( p \) of a stimulus and the physical magnitude \( s \) of the stimulus is a power law relationship

\[
p(t) = \nu \cdot s(t)^\beta + \tilde{R}(t),
\]

(7)

where \( \nu \) and \( \beta \) are parameters determining the perception from a stimulus of unit magnitude and the growth rate of the perception as a function of the stimulus magnitude, and \( \tilde{R}(t) \) is a residual term. This form has been shown to outperform the Weber-Fechner law in characterising human perception in a number of empirical studies [5]. We also therefore report the results of this model fit to the relationship between the Death NLS \( p_{\text{Death}}(t) \) and national daily death counts \( s_i(t) \) for each country \( i \), reporting our results in Table 3.

In all cases, we observe sublinear exponents \( \beta \) for the perception of the daily deaths data, with significant exponents (\( p \)-value < 0.01) ranging between 0.085 and 0.36. These exponents are of the same order of magnitude as the \( \beta \) of 0.32 reported in [6], where in several laboratory experiments they measure psychophysical numbing in participants’ perception of death statistics. As discussed previously, the data for Spain is unusual for a number of reasons, thus the model does not accurately describe the data in this instance. These results suggest that Twitter users in certain countries are more sensitive to change in the number of deaths than others.

#### 3.3.3 Model comparison

Both the Weber-Fechner law and power-law relationships between the Death NLS and the daily number of reported deaths accurately model the data. Each captures the phenomenon in which “the first few fatalities in an ongoing event elicit more concern than those occurring later on” [10]. By way of comparison, we present in Table 4 the normalised root mean squared errors.
Table 4: Comparison of the normalised root mean squared error (NRMSE) (see Eq. (8)) between the power law model of Eq. (7), the Weber-Fechner model of Eq. (6), and a linear relationship between variables, which we use as a benchmark model. Lower values indicate better-fitting models. Note that, overall, the Weber-Fechner law outperforms the other models. For further details, see Figs. 6 and 7 in Appendix A.

(NRMSE), defined as

\[
\text{NRMSE} = \sqrt{\frac{1}{n} \sum_{t} e(t)^2}
\]

for these models, in addition to a linear model between \( p^\text{Death}(t) \) and \( s_i(t) \) as a baseline “null” model. Here, \( e(t) = p(t) - \hat{p}(t) \) is the model residual, and \( n \) is the sample size. The models are directly comparable in this sense, since each involves only two parameters. Bhatia [41] made a similar model comparison to test psychophysical laws for subjective probability judgements of real-world events, in that case finding that the linear relationship was the best. In our case, however, a linear relationship between \( s \) and \( p \) is significantly worse than the present concave models of perception (see Appendix A for the results of the linear model), reinforcing our hypothesis of psychophysical numbing.

While the Weber-Fechner law is better than the power law model overall, the difference in their goodness of fit – as measured by the NRMSE – is marginal. Both are reasonable descriptions of the observed relationship, and similar conclusions can be drawn from both.

In particular, the parameters \( k \) and \( \beta \) from the Weber-Fechner law and power law, respectively, are analogous in their interpretation as the measure of the sensitivity of the nation’s Twitter users to changes in the national Covid-19 daily death rate. To illustrate this, we rank the countries in our dataset in order of sensitivity to changes in the local death rate, as measured separately by these two parameters, and plot the correlation between the countries’ ranks in Figure 5. Here, low rank indicates high sensitivity to changes in the number of daily deaths nationally. The correlation between the two methods of ranking – according to \( k \), the Weber-Fechner law slope parameters, and according to \( \beta \), the power law model exponents – is high, with correlation coefficient 0.77. This shows that the sensitivity of each country is relatively robust between models. By both measures, therefore, Twitter users tweeting in English and

| Country     | Power Law | Weber-Fechner Law | Linear Relationship |
|-------------|-----------|-------------------|---------------------|
| Argentina   | 0.114     | 0.113             | 0.116               |
| Australia   | 0.173     | 0.171             | 0.175               |
| Canada      | 0.106     | 0.105             | 0.117               |
| Chile       | 0.151     | 0.149             | 0.17                |
| Colombia    | 0.143     | 0.144             | 0.145               |
| India       | 0.126     | 0.128             | 0.125               |
| Mexico      | 0.1       | 0.101             | 0.133               |
| Nigeria     | 0.223     | 0.222             | 0.218               |
| South Africa| 0.184     | 0.183             | 0.188               |
| Spain       | 0.202     | 0.198             | 0.193               |
| United Kingdom | 0.149   | 0.143             | 0.166               |
| United States | 0.139    | 0.126             | 0.179               |
| Mean        | 0.151     | 0.149             | 0.16                |
| Proportion of best fits | 16.7 % | 58.3 % | 25 % |
| Proportion of second-best fits | 66.7 % | 33.3 % | 0 % |
Spanish from Australia and Argentina, respectively, appear to be the most sensitive to changes in the national daily death rate, while Twitter users posting in English from South Africa, India, and Nigeria and in Spanish from Spain and Chile appear to be the least sensitive to these changes.

![Figure 5](image)

Figure 5: Comparison of the rank of each country as determined by their $k$ and $\beta$ parameters in the Weber-Fechner and power-law fits, respectively, which determine the sensitivity of Twitter users tweeting from each country to changes in the number of daily reported deaths. Low rank indicates high sensitivity relative to the remaining countries. The correlation between countries’ ranks from both measures is high at 0.77.

4 Discussion and conclusions

We explored the country-by-country relationship between the linguistic features present in a large set of tweets posted in relation to the Covid-19 pandemic, and the progression/intensity of the pandemic as measured by the daily number of cases and deaths in each country we consider. By considering the change, relative to a baseline, in the percentage of words present in each tweet that are associated with a number of psychologically meaningful categories – here called linguistic scores – we observed significant trends that we believe are indicative of a psychophysical numbing effect [7].

We found that the national linguistic scores (NLSs, see Eq. (4)) associated with emotion and affect decrease as the pandemic intensifies. This is in spite of a greater attentional focus on death and mortality and a simultaneous increase in use of words indicating analytic reasoning. We showed, by constructing word co-occurrence networks on different time periods of the pandemic, that words related to death co-occur more frequently with other words related to death than they do with words indicating affect and emotion, and that this separation of affect from the conversation around death is also revealed by the community structure of this network.
This is consistent with the notion of psychophysical numbing, which we believe explains these observations.

We also showed that the psychophysical laws of Weber-Fechner and of power law perception in humans accurately model the relationship between the frequency of words related to death and the actual daily number of Covid-19 deaths in each country. We estimated sub-linear exponents in the power law perception function that are of similar values to values previously estimated from psychological experiments [6]. These exponents, together with parameter $k$ of the Weber-Fechner law (see Eq. (6)), tell us how sensitive the Twitter users in each country are to their national Covid-19 daily deaths, and were seen to vary by country, indicating inter-country differences in risk perception and sensitivity to death rates. Such sensitivities were consistent across models (see Fig. 3) suggesting that these measures of a nation’s Twitter users’ sensitivities to changes in the national death rate are robust features of the data.

Our findings illustrate the signaling power of Twitter, and demonstrate its potential use as a tool for monitoring public perception of risk during large-scale crisis scenarios. With the modelling and visualisation approaches we employ in this paper, policy-makers and public officials could track in near-to-real-time the public’s attitudes towards threats to public well-being and the prevalence of factors important to public perception of risk, including degree of outrage and relative attentional focus on the threat. Our findings also imply a functional form for agent perception of the system state in models of opinion dynamics. This will be instrumental for developing coupled opinion dynamics-epidemiological models, in which the bidirectional relationships between human perception, human behaviour, and epidemic progression are modelled endogenously.

A natural extension to this work would involve nowcasting and/or forecasting of certain economic indicators. It has also been limited in that we assumed that only the national death rate is a significant predictor of perception. A more complete analysis should account for the effect of other countries’ death statistics as a driver of local perception, or more broadly an advancement of a process-level explanation of the cross-cultural differences we observe in the sensitivity to death statistics. This analysis could also be enhanced by relating these measures of risk perception to behavioural data, which – since “people’s behavior is mediated by their perceptions of risk” [10] – may be useful for understanding the role of emotions in driving behaviours that are conducive to public health during crises. Further, a deconstruction of the aggregate indicators we have developed to the state and regional level may be necessary to more accurately characterise the relationship between local crisis progression and human risk perception.

We also stress that the results presented in this paper may be indicative only of the responses of Twitter users posting from each of these countries in each of these languages, so extrapolating these results to the broader population will only be possible with a better understanding of the biases present in, and representativeness of, the dataset at hand.

5 Declaration

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5.3 Competing interests

The authors declare that they have no competing interests.

5.4 Availability of data and materials

The Twitter data used in the manuscript is collected and maintained by Banda et al. at the Panacea Lab [25], and it is available at their website [http://www.panacealab.org/covid19](http://www.panacealab.org/covid19). The data on Covid-19 confirmed cases and deaths were obtained from the “Coronavirus Pandemic (COVID-19)” page of the Our World in Data website [27], and the stable URL for this data is [https://covid.ourworldindata.org/data/owid-covid-data.csv](https://covid.ourworldindata.org/data/owid-covid-data.csv).

5.5 Authors’ contributions

BK and JD both conceived the idea, carried out the analysis, and wrote, read, and approved the final manuscript.

5.6 Abbreviations

- LIWC: Linguistic Inquiry and Word Count.
- WHO: World Health Organization.
- NLS: National linguistic score.

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Table 5: Results for the linear model defined in Eq. (9).

| country      | $a$ (a) | $b$ (a) | 95% CI (a) | $t$ (a) | $P > |t|$ | $R^2$ | NRMSE | $n$  |
|--------------|---------|---------|------------|---------|----------|-------|-------|------|
| Argentina    | 0.057   | 2.603   | 0.04 - 0.074 | 6.79    | 0.387    | 0.116 | 75    |
| Australia    | 0.192   | 0.912   | 0.087 - 0.298 | 3.67    | 0.247    | 0.175 | 43    |
| Canada       | 0.005   | 0.759   | 0.005 - 0.006 | 11.46   | 0.607    | 0.117 | 87    |
| Chile        | 0.005   | 2.969   | 0.003 - 0.007 | 4.58    | 0.216    | 0.17  | 78    |
| Colombia     | 0.016   | 2.147   | 0.011 - 0.02  | 7.11    | 0.409    | 0.145 | 75    |
| India        | 0.002   | 1.074   | 0.002 - 0.003 | 10.14   | 0.566    | 0.125 | 81    |
| Mexico       | 0.003   | 2.428   | 0.002 - 0.003 | 10.97   | 0.613    | 0.133 | 78    |
| Nigeria      | 0.047   | 1.589   | 0.021 - 0.073 | 3.61    | 0.184    | 0.218 | 60    |
| South Africa | 0.006   | 1.295   | 0.002 - 0.01  | 2.95    | 0.119    | 0.188 | 66    |
| Spain        | 0       | 2.248   | -0.0 - 0.001  | 1.98    | 0.047    | 0.193 | 82    |
| United Kingdom | 0.001 | 0.877   | 0.001 - 0.001 | 7.69    | 0.399    | 0.166 | 91    |
| United States | 0      | 1.235   | 0.0 - 0.001   | 6.84    | 0.352    | 0.179 | 88    |

Table 5: Results for the linear model defined in Eq. (9).

**Appendices**

**A Further model comparison**

In this section, we present further results of our models to give a more complete overview of their quality. Besides the Weber-Fechner law and power law models (see Eqs. (6) and (7)), we use the following linear relationship between $s$ and $p$ as our benchmark model

$$p(t) = a \cdot s(t) + b,$$

where $a$ and $b$ are parameters. We summarize our results for the linear model in Table 5.

For all models, we compute the $R^2$ values

$$R^2 = 1 - \frac{\sum_{t=1}^{n} e(t)^2}{(n-1)\sigma_p^2},$$

where $e(t) = p(t) - \hat{p}(t)$ is the model residual, $\sigma_p^2 = \sum_{t=1}^{n} (p(t) - \mu_p)^2/(n-1)$ is the variance of $p(t)$, and $n$ is the sample size. The $R^2$ values for all models are summarized in Table 5. (Note that as the power law model implies a log-normal residual, the $R^2$ values can be negative.) From this table we see that, once again, the Weber-Fechner law is generally a better fit to the data across all countries, but that the power law and Weber-Fechner models are often comparable and significantly better than the linear model.

We also show in Figures 6 and 7 scatterplots of the Death NLSs against the logarithm of the daily number of deaths in each country, with the $y$-axis in linear- and log-scales, respectively. Red lines indicate the line of best fit, with the slope equal to $k$ and $\beta$ in Eqs. 6 and 7, respectively.
| country       | $R^2$ power law | Weber-Fechner law | linear relationship |
|--------------|----------------|-------------------|---------------------|
| Argentina    | 0.411          | 0.421             | 0.387               |
| Australia    | 0.259          | 0.275             | 0.247               |
| Canada       | 0.678          | 0.683             | 0.607               |
| Chile        | 0.382          | 0.395             | 0.216               |
| Colombia     | **0.425**      | 0.319             | 0.28                |
| India        | 0.558          | 0.397             | 0.477               |
| Mexico       | 0.78           | 0.775             | 0.613               |
| Nigeria      | 0.143          | 0.004             | 0.007               |
| South Africa | 0.16           | **0.171**         | 0.119               |
| Spain        | -0.042         | 0                 | **0.047**           |
| United Kingdom | 0.514      | **0.555**         | 0.399               |
| United States | 0.608         | 0.556             | 0.24                |
| Mean         | 0.36           | **0.379**         | 0.303               |
| Proportion of best fits | 41.7 %        | 50 %               | 8.33 %               |
| Proportion of second-best fits | 66.7 %        | 33.3 %             | 0 %                  |

Table 6: Comparison of $R^2$ between the power law model of Eq. (7), the Weber-Fechner model of Eq. (6) and a linear relationship between variables, which we use as a benchmark model. Higher values indicate better models.

Figure 6: Resulting scatter plot for the Weber-Fechner law model fit, where each panel shows a different country with their corresponding NRMSE in parenthesis (the lower the better).
Figure 7: Resulting scatter plot for the \textbf{power law} model fit, where each panel shows a different country with their corresponding NRMSE in parenthesis (the lower the better).
B Word co-occurrence analysis

B.1 Further technical details on co-occurrence network construction

In constructing the word co-occurrence networks presented in Section 3.2.1, we perform basic text preprocessing, including taking the lower-case form of all letters, removing URLs, removing punctuation, and removing the following small set of stopwords from the vocabulary:

```
to, today, too, has, have, like.
```

We retain hashtags, since LIWC also recognises hashtags and because hashtags are an essential aspect to communications on Twitter. It is also necessary to account for the fact that a number of “words” appearing in the LIWC dictionary are in fact regular expressions to which many complete words in the Twitter dataset map. For example, the “word” “isolat*” appears in the English LIWC dictionary, to which each of the following words would map: “isolate”, “isolated”, “isolating”. Thus, construction of the word co-occurrence networks $G_i'$ involves a two-step procedure: first, constructing the raw word co-occurrence networks $G_i$, in which the nodes are words exactly as they appear in the Twitter dataset; and then reducing this to a quotient graph $G_i'$ by contracting nodes in $G_i$ that are matched by the same regular expression in the LIWC dictionary. More formally: the LIWC dictionary implies an equivalence relation $\sim$ on the vocabulary $V$ implied by the Twitter dataset, such that $v \sim u$ for words $v, u \in V$ if both $v$ and $u$ are matched by the same regular expression in the LIWC dictionary. The weights of edges between nodes $v' \subset V$ and $u' \subset V$ in $G_i'$ are then taken to be

$$w_{G_i'}(u', v') = \sum_{u \in u', v \in v'} w_{G_i}(u, v),$$

where $w_{G}(x, y)$ is the weight of edge $(x, y)$ in $G$. Note that $w_{G}(x, y) = w_{G}(y, x)$ and $w_{G}(x, y) = 0$ if $(x, y)$ is not an edge in $G$.

B.2 Word co-occurrence networks for Spanish-language tweets

For completeness, we provide here the word co-occurrence graphs for the Spanish language tweets. We omit a discussion of the results, since similar conclusions can be drawn from these as in the English counterparts.

C Covid-19 epidemiological data

We include this section as a reference for the actual number of deaths in each country for the period we analysed throughout the paper, which we present in Fig. 9.
Figure 8: Snapshots of the word co-occurrences associated with death (“muerte”, green labels) and affect (“afecto”, red labels) for Spanish-language tweets aggregated across all analyzed countries in three different time windows (see sub-captions). The nodes are coloured based on the community labels obtained by maximising modularity using the Louvain algorithm [38]. We filtered edges with weight below 20 co-occurrences for visualisation purposes.
Figure 9: Daily deaths related to Covid-19 for each of the countries in our analysis (see legend) from March 11 to June 14, 2020.