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Crises social sensing: longitudinal monitoring of social perceptions of systemic risk during public health crisis

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ABSTRACT

Monitoring how different people – as ‘social sensors’ – evaluate and respond to crisis such as pandemics, allows tailoring crisis communication to the social perceptions of the situation, at different moments. To gather such evidence, we proposed a index of social perceptions of systemic risk (SPSR), as an indicator of a situational threat compromising risks to physical health, psychological health, the economy, social relations, health system, and others. This indicator was the core of a social sensing approach applied to crisis situations, implemented during the COVID-19 pandemic through a content analysis of more than 130.000 public comments from Facebook™ users, in COVID-19 related publications. This content coding allowed creating a SPSR index monitored during a one-year descriptive longitudinal analysis. This index correlated with co-occurring events within the social system, namely epidemiological indicators across measurement cycles (e.g. new deaths; cumulative number of infection cases; Intensive Care Unit hospitalizations) and tended to reflect the epidemiological situation severity (e.g. with the highest level registered during the worst pandemic wave). However, discrepancies also occurred, with high SPSR registered in a low severity situation, i.e. low number of hospitalizations and deaths (e.g. school year beginning), or low SPSR in a high severity situation (e.g. 2nd pandemic wave during Christmas), showing other factors beyond the epidemiological situation contributing to the social perceptions. After each ‘crisis period’ with SPSR peaking, there was a ‘restoration period’, consistently decreasing towards average levels of the previous measurement cycle. This can either indicate social resilience (recovery and resources potentiation) or risk attenuation after a high-severity period. This study serves as preliminary proof of concept of a crises social sensing approach, enabling monitoring of social system dynamics for various crisis types, such as health crisis or the climate crisis.

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Introduction

Crisis are often not a result of a single danger/hazard but rather multiple dangers/hazards that may emerge in co-occurrence and/or sequentially. Crisis also do not often involve a single risk but rather multiple co-occurring and/or sequential emerging risks. All these may have an effect that goes beyond the sum of its the 'parts' (i.e. additive effect) and interact in a way that implies the emergence of something 'new' within the social system, something that some would define as a "polycrisis" (Homer-Dixon, Renn, Rockström, & Janzwood 2022). Accordingly, crisis may be characterized by the emergence of systemic risks, i.e. 'the embeddedness of any risk to human health and the environment in a larger context of social, financial and economic risks and opportunities' (Renn 2021, 127), which has been shown to occur in past crisis (e.g. financial crisis; Renn et al. 2019) and current public health crisis such as the COVID-19 pandemic (Renn 2021, 2022, 15). However, as Renn (2022, 15) referred: '(...) a graphic representation and simulation of evolving systemic risks and a participatory deliberative approach of inclusive risk governance are needed in order to prevent, mitigate, or control systemic risks'. Indeed, despite much discussion around the concept of systemic risks (Renn et al. 2022), there is still a lack of understanding of how non-experts/the public perceive systemic risks emergence and evolution across time, during crisis. In the study presented here, we aimed to contribute to this, by presenting a proposal for monitoring social perceptions of systemic risk (Schweizer, Goble, & Renn, 2022), during the COVID-19 pandemic. This may allow tailoring communications to how the social system evaluates and responds to evolving events during a crisis, i.e. to the social system 'crisis template' at a certain point in time and across time.

Crisis social sensing

The Social Amplification of Risk Framework (SARF; e.g. Kasperson et al. 1988, 2022; Pidgeon and Barnett 2013), has been proposed as a 'lens' through which crisis dynamics can be understood. This is because it 'identifies categories of mediator/moderator which intervene between the risk event and its consequences and suggests a causal and temporal sequence in which they act. Information flows through first various sources and then channels, triggering social stations of amplification, initiating individual stations of amplification, precipitating behavioural reactions' (Breakwell and Barnett 2001, 3). In this regard, there is still a lack of understanding of what exactly occurs at the individual and social stations of amplification. If the processes underlying risk amplification at these stations were to be better understood, we would be able to predict and effect change in the lifecycle of a hazard (Breakwell and Barnett 2001), such as SARS-CoV-2 (coronavirus) as an emerging biological hazard that caused the COVID-19 public health crisis to emerge.

To gain a better understanding of the COVID-19 crisis dynamics and how systemic risks were perceived, we applied a social sensing approach to crisis situations proposed by Gaspar et al. (2021). This considers humans as sensors of such evolving changes within the social system, with data collected through this way allowing evidence-based risk and crisis communications and crisis management. We present here results of one year of crisis social sensing grounded on an indicator of social perceptions of systemic risk (SPSR), during the COVID-19 pandemic. Particularly, we aimed to explore (1) at what point a crisis – or crises within a crisis – was perceived or 'sensed' has having emerged in the social system, during the first year of the COVID-19 pandemic. Accordingly, there is still no clear understanding by crisis managers and decision-makers at which point individuals perceive and there is consensus that a crisis has emerged (Gaspar, Barnett, and Seibt 2015; Seeger, Reynolds, and Sellnow 2009; Sellnow and Seeger 2013) and if and why this perception changes over time. In this regard, the Norm Deviation Approach (Gaspar, Barnett, and Seibt 2015) proposed that to determine whether a crisis is perceived as having emerged, at the various levels of the social system, individuals should perceive a situation that: (1) deviates from what is considered 'normal' (norm deviation), (2) is evaluated as adding new demands requiring

the mobilization of resources to cope with these, and (3) consequent responses from people, groups/communities, and organizations, which would not normally occur (Blascovich and Mendes 2000; Blascovich 2008).

Moreover, we aimed to explore (2) how the evaluation of the situation as a threat, based on indicators of SPSR, changed with events co-occurring within the social system (e.g. pandemic waves). This was based on the viewpoint of social media users who commented on a set of Facebook™ publications concerning the epidemiological situation. This latter aspect of threat evaluation, follows from the DeCodeR framework (Domingos et al. 2020) assumptions. This was proposed as a theory-driven mixed-method framework, grounded on the Biopsychosocial Model of Challenge and Threat (BPS Model; Blascovich 2008; Blascovich and Mendes 2000), that could enable exploring and coding verbal or written expressions indicators of perceptions and appraisals of the personal and situational demands, and of the resources to cope with these. This framework was proposed in the context of extreme hot weather events, but could be adapted to other extreme natural or man-made events in the context of crisis situations. Traditionally, the research using the BPS Model studies demands and resources perceptions and appraisals based on psychophysiological indicators (e.g. cardiovascular indexes of challenge and threat), and primary versus secondary self-reported appraisal ratings (e.g. Blascovich and Mendes 2000; Blascovich and Tomaka 1996; Tomaka et al. 1993, 1997). This framework was later adapted by Domingos et al. (2020) to monitor verbal and written expressions of demands vs. resources perceptions during extreme events (e.g. extreme weather; epidemics/pandemics; social emergency situations, etc.). From this, communications should be customized to the: (1) perceptions of demands – referring to the danger (e.g. harm to health), uncertainty (e.g. regarding what is happening), and effort required by the situation (e.g. performing extra actions); and (2) perceptions of resources (personal/social) – referring to knowledge, skills and abilities (e.g. problem solving), personal characteristics or positive dispositions (e.g. psychological resilience and optimism), and external support (e.g. informational, institutional) required to cope with the demands placed by the situation during crises. Similarly to extreme weather events or other natural or human caused crisis, during health crisis events such as disease outbreaks and epidemics, people may also feel the need for information, equipment, and other personal and social resources to cope with the demands that emerged. Depending on their own characteristics and/or those of the situation, people may perceive their resources as sufficient and appraise the situation as a challenge (e.g. a situation they believe they can cope with), or alternatively, they may find their resources to be non-existent or insufficient, thus appraising it as a threat (e.g. a situation they believe that can be hard or even impossible to cope with).

Accordingly, there are indicators that individuals who appraised the COVID-19 pandemic as a threat may have come to perceive aspects of their everyday lives as stressors and/or as more negative (Brose et al. 2021), compared to the previously 'normal' pre-pandemic situation. Differently, appraising the pandemic as a challenge, may provide benefits in how the situation is evaluated and the response to it. Research in non-crisis related domains showed such benefits in association with communication, particularly fear appeals – a type of messaging frequently implemented in crisis situations, despite the doubts raised concerning its effectiveness (e.g. Ruiter et al. 2014). In fact, Putwain, Symes, and Wilkinson (2017) showed, for example, that a challenge appraisal of fear appeals predicted better performance and behavioural engagement in an examination task, with the opposite occurring for threat appraisals. Hence, challenge appraisals may be an important condition for higher adherence to protective recommendations in crisis situations, which should be further explored in future research.

Hence it is relevant to monitor perceptions of demands posed by changing circumstances during health crisis such as the COVID-19 pandemic and the individual and social resources perceived to be available to cope with these, as elements of a social representation of risk (Barnett and Breakwell 2003; Barnett and Vasileiou 2014; Breakwell 2010; Joffe 2003; Joffe and Haarhoff 2002). By grounding this monitoring on humans as social sensors or specifically, as

crisis social sensors, we can have a sense of when a crisis emerges and how its characteristics are perceived to evolve over time, within social systems (Aven et al. 2015).

Social sensing during the COVID-19 pandemic

A social sensors approach (e.g. Galesic et al. 2021; Gaspar et al. 2021) is based on the idea that it is possible to reliably observe physical, psychological, and social phenomena at scale, as interpreted by the collective intelligence of all individuals/groups within the social system, e.g. through the lens of social media users. This assumes that human beings can recognize, observe, describe, and report/interpret a wider spectrum of events than physical sensors can (Wang et al. 2019). Accordingly, social sensors present an increasingly important potential, as they may allow to describe and predict societal trends (Galesic et al. 2021).

In many countries, COVID-19 monitoring systems to evaluate changes in the pandemic situation are often grounded on epidemiological indicators (e.g. incidence; transmission rates; lethality rates; number of hospitalizations). Fewer examples exist of monitoring the evaluations and responses of individuals, groups/communities, and organizations, in the form of what is called epidemic 'nowcasting', i.e. 'assessing the current state by understanding key pathogenic, epidemiologic, clinical and socio-behavioral characteristics of an ongoing outbreak' (Wu et al. 2021). Since 2020, the COVID-19 pandemic has allowed an increase in such approaches through which the results are used for crisis management and communication, and to developed evidence-based health policies. An important example is the behavioural insights survey tool develop by the World Health Organization (2020) which has been used in many countries around the world. More recently, a pandemic risk perception scale (Vieira et al. 2021) was also developed, broadening the scope if such measures to encompass not only the perception of health risks but also of other relevant risks emerging during a pandemic, such as: infection risk, emotional health risk, health system risk, financial risk, and alimentary risk (Vieira et al. 2021).

Although such survey-based approaches are important, they should be complemented with data that can be collected and analysed in real time - nowcasting - rather than retrospectively. In this regard, social media data collection presents various advantages by enabling real-time access to spontaneous reactions from different individuals, groups/communities, and organizations to various unexpected (e.g. 'breaking news') and potentially stressful events (e.g. exponential increase in infection rates, hospitalizations and/or deaths due to COVID-19) that occur at specific moments in time (Gaspar et al. 2014). Hence, social media provides access not only to evaluations and responses at various levels of the social system (intra and inter-individual; intra and inter-group; and intra-inter organizational/regional/national levels) but also to more 'natural' and spontaneous reactions than collected by other methods (e.g. surveys). One approach that was proposed in this regard, with the goal of collecting social sensors data through social media, was the ResiliScience approach (Gaspar et al. 2021).

To implement 'crises social sensing', this approach considers that data can be collected by organizations responsible for crisis management and communication (e.g. health authorities) in four different components: (1) Detection; (2) Evaluation; (3) Response; and (4) Learning. In this article, we focus only on the first two. According to Gaspar et al. (2021, 48): 'the "detection" component, implies assessing indicators that a crisis was perceived has having emerged (e.g. norm deviation)'. Through this, crisis management can implement strategies and activities (e.g. for people who did not perceive it) that enable such perception, to promote appropriate responses. In the 'evaluation' component, crisis sensing should determine which crisis template or templates exist at a certain point in time and what are the required changes in such template(s) to foster appropriate responses. For the 'detection' component, the social media data collection can focus on evaluating increases in theme-centred discourse (e.g. keywords associated with the disease or its symptoms, such as 'coronavirus', 'fever', 'cough') in co-occurrence with an

increase in theme-centred negative affect (e.g. negative and positive sentiment associated with SARS-CoV-2 or COVID-19, including expressions of fear and others). For the 'evaluation' component, the social media data collected can focus on monitoring the prevalence of expressions of demands and the resources to cope with these (e.g. expressions of danger, uncertainty, effort vs. expressions of external support, knowledge/skills and dispositions).

The advantage of considering these components of the ResiliScience approach in comparison to other existent approaches, is that most of the existent approaches (e.g. Li et al. 2020; Rovetta and Bhagavathula 2020; Tan, Raamkumar, and Wee 2021; Tsao et al. 2021): (1) focus narrowly on physical health risks but not broadly on systemic risks (i.e. not only on physical health but also on psychological health, economy, social relationships, etc.); (2) focus on a small variety of emotional responses, predominantly negative (e.g. fear of COVID-19), only allowing access to a simplified/partial version of reality; (3) have a predominant focus on the demands and risk factors (e.g. perceived vulnerabilities) and less on resources and protective factors (e.g. indicators of resilience).

Study goals

There is a need for social sensing approaches to crisis that allow a broader understanding of the social perceptions of systemic risks (SPSR; Schweizer et al. 2022) during health crisis, as an indicator of how threatening the situation is perceived at a moment in time and across time. To contribute to this, this study serves as a preliminary proof of concept of the SPSR index at the core of a crises sensing approach, using data collected through information and communication technologies such as social media, which can be applicable to other types of societal crisis (e.g. extreme events associated with climate change; Gaspar, Yan, and Domingos 2019). The approach presented here was developed to be a human-based data extraction and analysis but that has the potential to be applied as a hybrid human-computer analysis, upon automatization of the extraction and human coding component. This may allow timely and real-time data extraction and analysis, essential in crisis situations and social emergencies. Given that the data was extracted from social media, this has also the potential to extend the explanatory power of SARF, as it was developed before the emergence of global digital platforms (Kasperson et al. 2022). In addition to contributing with such approach, we aimed to respond to two exploratory research questions to allow expanding the knowledge about social perceptions during the COVID-19 pandemic:

RQ1. At what point there was an increase in COVID-19 related discourse (keywords) identified through Google Trends™, indicative of a perceived norm deviation (as a first stage of a perceived crisis emergence)?

RQ2. How did the social perceptions of systemic risk indicator derived from Facebook™ comments, changed longitudinally in co-occurrence with epidemiologically relevant pandemic events?

Particularly with regard to question 2, as shown in previous studies concerning other health crises (Gaspar et al. 2016; Gaspar et al. 2014; Gaspar, Barnett, and Seibt 2015), we expect the social perceptions to change in co-occurrence with situational changes (e.g. risk/crisis communications issued by health authorities; situational reports concerning number of people affected; public health measures to control the disease outbreak), i.e. that although these are perceptions of the situation, at least part of these are based on the evaluation of facts that occur in the surrounding social environment.

Materials and methods

We performed a mixed methods quantitative-qualitative analysis of data extracted from social media, particularly publicly available Facebook® messages/comments. To do this, we created a

quantitative indicator of social perceptions of systemic risk (SPSR), based on a ratio calculated from the coded demands vs. resources expressions identified through a qualitative content analysis. This indicator was subjected to a longitudinal analysis of its evolution in co-occurrence with pandemic relevant events.

This research project and the corresponding data extraction and analysis procedure, was approved by the Ethics Committee for Health from the Catholic University of Portugal with the project reference number 86. Because the social media collected data was publicly available, the participants comments were published in public Facebook™ pages and in accordance with Facebook™ privacy policy, participants were aware that their comments were publicly available, the ethics committee did not consider the need for informed consent to be collected from these. This would be the case, as long all data collected was anonymized and appropriate measures were taken by the researchers, for the participants not to be identified in any way.

Data extraction procedure

Grounded on step 1 of the ResiliScience approach (Gaspar et al. 2021) – Detection – an initial data collection procedure aimed at determining preliminary indicators of whether a crisis was starting to be perceived has having emerged, i.e. perceived norm deviation. The goal was to track an increase in coronavirus related keywords used in searches, as an indicator of an increased attention to the topic and thus, as a proxy to a perceived norm deviation (as the first indicator of crisis perception). Keywords used in Google™ web searches between 1 and 30 January 2020 that were tracked using the Google Trends™ platform, included words related to the virus, the geographical origin of the first detected cases and symptoms associated with the disease at the time, namely: ‘Coronavirus’, ‘Pneumonia’, ‘China’, ‘Cough’ and ‘Fever’.

Grounded on step 2 of the ResiliScience approach – Evaluation – a second data collection procedure was implemented, aimed at determining whether a threat was being perceived has having emerged. For this, discourse on social media was extracted and monitored from January onwards. Complementarily, a chronogram of pandemic relevant events was updated for more than one year, between the initial reports of a disease outbreak in China and the first official case detected in Europe in 24 January 2020, up to one year after (4 March 2021) when the first cases were officially confirmed in Portugal (2 March 2020). The goal was to match it with changes in the crisis events appraisals overtime, operationalized in the form of the SPSR indicator, tracked through the social media analysis.

From January 2020 to March 2021, 134,154 user-generated publicly available comments, in response to 776 COVID-19 communications published on Facebook™ by the Portuguese Directorate-General for Health (DGH) and by seven representative national media outlets with Facebook™ pages and with digital news sharing (Correio da Manhã; Expresso; Observador; Público; RTP Notícias; SIC Notícias; TVI24), were extracted and analysed. For the media outlets selection and to achieve heterogeneity and nationwide representativeness, three criteria were used for their selection: (1) include all three open channel nationwide TV news broadcasters’ brands (RTP, SIC and TVI), with a page available on Facebook; (2) include the most watched/read paper news brands (daily publication: Correio da Manhã; weekly publication: Expresso) and digital news brand (Observador), with a page available on Facebook. Moreover, all eight brands were in the list of the most trusted news brands in 2020, in the following order (OberCom 2020): RTP Notícias (1st); SIC Notícias (2nd); Expresso (3rd); Público (6th); TVI24 (9th); Observador (12th); Correio da Manhã (15th).

Daily publications on each of these eight sources were manually screened, enabling the selection of eligible publications for comment extraction, i.e. publications directly related with

the COVID-19 pandemic. In situations where the manual screening was not possible (e.g. due to high volume of publications) a keyword search procedure on the eight sources' Facebook™ pages was created; and a broad set of keywords were defined to search for relevant publications that fitted the criteria and used consistently across all eight sources. These keywords were updated throughout the pandemic as new terminologies emerged and others stopped being used (e.g. from 2019-nCoV to SARS-CoV-2) and included: '2019-nCoV'; 'coronavirus'; 'COVID'; 'SARS'; 'SARS-CoV-2'; 'pandemic'; 'bulletin'; 'situation report'; 'numbers'; 'DGH'; 'vaccine'.

The DGH Facebook™ publications concerning COVID-19 were defined as the main reference for the comments' extraction process, as these were the main social media information source for sharing information concerning the epidemiological situation on a certain day (e.g. when there was a steep increase in daily cases of infections) or a weekly summary. Criteria for selecting relevant publications for comment extraction in all the eight sources were, in the following order: (1) publications focusing on DGH communications and recommendations about the pandemic or the virus; (2) publications about the pandemic evolution in the country; (3) publications about geographically localized disease clusters and epidemiological situation; (4) publications about national topics directly related with the disease or the virus that were considered epidemiologically relevant during the extraction period (e.g. economic and social risks associated with national lockdown measures); (5) publications about the pandemic evolution in other countries, specifically focused on countries with greater proximity and population mobility with Portugal (e.g. Spain or the United Kingdom); (6) publications about international topics related with the disease or the virus that were considered epidemiologically relevant during the extraction period; (7) publications about the evolution of the pandemic worldwide. Comment extractions from publications that had more than one theme in the title (e.g. 'infections rise in Portugal, 153,000 dead in the US, five firefighters injured') or that where extremely politicized (e.g. requests for government cabinet resignations) were avoided.

The data extracted were aggregated into 101 units of observation corresponding to periods of four days each between 26 January 2020 and 4 March 2021, in order to: (1) capture the perceptions diversity and heterogeneity, to enable greater consistency in the comments' sample size (e.g. reach a minimal comment sample size per analysis cycle, as not all days tended to generate enough comments, especially in periods where the epidemiological situation was perceived as less negative); (2) ensure examples from all eight sources were extracted (e.g. avoiding situations where publications in a given source did not generate codable comments for a given day); and (3) provide coders enough time to manually code the extracted comments and produce the data reports for DGH. On the other hand, extending the extraction to larger periods (e.g. weekly) would have the effect of 'diluting' reactions to specific events, whenever the epidemiological situations was serious. This is because in those periods, many relevant events would occur on a daily basis, and could result in outdated information for crisis managers, thus hindering decision making and the application of measures in due time. Thus, a 4-day period was selected as a 'balanced' unit of observation, by allowing enough comments diversity without losing uniqueness in event perceptions and responses. In each of these periods, a sampling quota for the number of comments extracted from each source was determined to be from 100 to 200 comments, to allow a minimum diversity in comments within each extraction source, in each day. Overall, in each 4-day period, a minimum of 1000 comments were extracted (average of 250 per day) to achieve a large and consistent sample of comments across data collection periods.

The extraction tool used was the 'exportcomments.com' platform, which allowed comments to be extracted through the publication link of the selected data source. The free version of this platform was used, which allows extracting the 100 first comments of a specific Facebook™ post. Extracting only the 100 first comments from each post, allowed to use the same extraction criteria for all the 776 COVID-19 communications published on Facebook™ that were the basis

for the comments extraction. Also, because on social media many publications lead to arguments between the commenter's, by extracting only the first 100, we increased the probability of extracting individual comments focused on the post, rather than comments to comments. Nevertheless, if these were captured in the sample, they would be excluded if they did not comment on the epidemiological situation (e.g. if they had a direct 'attack' to someone who commented before them). After performing the extraction of 100 comments per post, the Excel file with the comments extracted by 'Export Comments' was downloaded. Then they were placed, in chronological order, in a database and distributed in sheets of periods of 4 consecutive days, to serve as the basis for the coding process. This data is available at <https://osf.io/znb54/files/osfstorage/62e3c41c3f1ed302d0411691>

Lastly, epidemiological data was collected for 93 data collection periods of 4-day cycles (out of the 101 initially determined), configuring a total of 372 days, between 2 March 2020 (the first registered cases in Portugal) and 4 March 2021. This included: the cumulative number of daily SARS-CoV-2 infection cases and the cumulative number of daily COVID-19 hospitalizations in Intensive Care Units (in both cases representing the number of cases identified in one day, added to the number of cases identified in the previous day); total number of new daily COVID-19 deaths; and the R_t representing the daily SARS-CoV-2 Effective Reproduction Number. All daily results concerning these indicators were averaged for each 4-day cycle. This data is available upon request to the authors and was collected from publicly available sources, namely the R_t collected from the National Institute for Health Dr. Ricardo Jorge made available through their webpage, and the remaining data from the Portuguese Directorate-General for Health.

Data coding and analysis procedure

The comments analysis was carried out creating a coding procedure and scheme adapted from the DeCodeR approach (Domingos et al. 2020) for use in health crisis such as disease outbreaks and epidemics (coding scheme available in the [Supplementary material](#), Appendix I).

The original framework was developed in context of extreme hot weather events using a sample of 159 participants (33 male; 126 female). Participants were first requested to think about an extreme hot weather event and then asked to verbally describe the demands posed by the event they thought about and the resources they had to cope with such demands. Grounded on the BPS Model of Challenge and Threat's definitions of demands and resources (Blascovich and Mendes 2000), participants verbal responses were coded in categories and sub-categories of Demands (Danger; Effort; Uncertainty) and Resources (Knowledge, Abilities, and Skills; Dispositions; External Support). The coding process was performed by two independent judges followed by the assessment of their interrater reliability level (Cohen's $\kappa = .91$). After that the coding units were also coded into third-order categories, previously identified and defined from the available data, by two independent judges, achieving acceptable levels of interrater reliability (Cohen's $\kappa = .96$). The goal of this procedure was to solve minor divergencies in the coding process and allow for a better specification of the type and nature of the expressed demands and resources perceptions (i.e. different functions and qualities inside the same category level).

In the adapted version of this framework applied to health crisis, rather than using interviews as the data collection technique, the procedure considered comments extracted from Facebook. However, it applied the same coding procedure, given that the data was in a written form (i.e. written reports). Each comment was coded into one of two higher-order categories (Level 1) and one of three corresponding subcategories within each (Level 2): (a) L1a. – Demands (L2a. Danger; L2b. Effort; L2c. Uncertainty); (b) L1b. – Resources (L2d. – Knowledge, abilities & skills; L2e. – Dispositions; L2f. – External support). The unit of analysis was the comment (i.e. a phrase or paragraph), with only one code being attributed to each comment (e.g. Comment X coded as L2a; Comment Y as L1b; etc.). For every 4-day period, the data was coded by two independent judges, who initially performed a coding training session with a third person trained in

the coding system. After the training, each of the two judges coded a sample of 100 comments separately, which was then compared to assess the level of agreement. When achieving an agreement above 80%, each judge coded individually different comments samples, which were then aggregated into one sample. During one year of coding, a team of two people permanently performed the coding/analysis, and whenever one person exited and another joined the team, the training and validation procedure was repeated. To assess inter-coder reliability, Krippendorff's Alpha was determined for three specific moments during the whole data collection period, after an initial joint coders training: 1) coding performed by coders A1 vs. A2 – Demands A1 vs. A2 = .95, Resources A1 vs. A2 = .99; 2) coding when two new members joined the team performed by coders A1 vs. A3 (July–August, 2020) – Demands A1 vs. A3 = .98, Resources A1 vs. A3 = .97; performed by coders A1 vs. A4 (August–September, 2021; Note this latter period is outside the scope of the current manuscript data analysis but was introduced to provide an additional reliability indicator) – Demands A1 vs. A4 = .98, Resources A1 vs. A4 = .98).

After the qualitative content coding into numbers representing the higher and lower order categories described, a threat ratio was calculated by dividing the total number of comments coded as Demands (D) by the total number of comments coded as Resources (R), for each units of analysis (4-day cycle): $\text{Threat} = D/R$. Based on the assumptions of the BPS model, it was determined that: (1) Values above 1 indicate the presence of more indicators of Demands than of Resources ($\text{Demands} > \text{Resources}$), configuring the assessment of the situation as a Threat; (2) Values equal to or lower than 1 indicate the presence of less indicators of Demands than of Resources ($\text{Demands} < \text{Resources}$), configuring the assessment of the situation as a Challenge. Based on this, high values of SPSR can be considered indicative of the situation being appraised as a Threat, while low values are indicative of a Challenge appraisal. To facilitate this indicator's interpretation, we classified the results into four different levels: 0–1=Low SPSR; 1–3=Medium SPSR; 3–6=High SPSR; > 6=Very High SPSR. This is grounded on the BPS Model assumption that when the situation is assessed as a challenge ($\text{Demands} < \text{Resources}$), values are below 1 and when the situation is assessed as a threat ($\text{Demands} > \text{Resources}$), values are above 1. Our proposal differs from this, by breaking down the values above 1 into three levels of SPSR. This was done with a practical purpose of providing decision makers and health authorities with a simpler and clearer interpretation, to determine the priority to be given to risk and crisis communications activities and resources in each period, based on the increased needs in this regard. After the extraction, coding and calculation of the SPSR indicator for each analysis unit (4-day cycles), a report synthesizing the analysis and issuing recommendations for crisis/risk communication based on that cycle's results, was provided to the DGH for assisting decision-makers and serve as the basis for evidence-based risk and crisis communication, and crisis management. The longitudinal descriptive analysis and co-occurring chronogram of events was publicly shared by the DGH in their webpage dedicated to COVID-19.

Lastly, we performed a time series regression analysis to examine the SPSR trend along each of the 4-day periods. We specifically estimated the linear and curvilinear (quadratic and cubic) time effects and controlled for the autoregressive association of SPSR with its earlier occurrence in the periods.

Results

The first year of the COVID-19 pandemic in Portugal: timeline of relevant events

To better understand the chain of events that co-occurred with the longitudinal progression of the SPSR index, a summary of relevant pandemic occurrences during one year of the pandemic in Portugal and other relevant events that co-occurred with it, are presented next (Table 1). These included for example relevant societal marks, such as the characterization(s) of the public health situation by the World Health Organization (WHO) or the beginning and end of national lockdown periods, and also epidemiological events such as rapid and high increases in daily

Table 1. Timeline of relevant events during the COVID-19 pandemic first year in Portugal.

Period	Events
24 January to 5 March 2020	January 24 – First official case detected in Europe (France) January 30 – WHO declares a ‘Public Health Emergency of International Concern’ March 2 – First registered cases of COVID-19 in Portugal
6 March to 4 August 2020	March 11 – WHO declares ‘Global Pandemic’ March 13 – ‘Alert state’ declaration by the Portuguese Government March 18 – ‘Emergency state’ declaration by the Portuguese Government+first national lockdown/home confinement March 26 – Portuguese Health authorities (DGH) declare the beginning of the ‘Mitigation stage’, i.e. low level of control over the epidemic situation, signaled by uncontrolled community transmission April 10 – Highest number of cases registered in the then designated pandemic ‘first wave’ May 3 – ‘Calamity state’ declaration by the Portuguese Government+gradual lifting of home confinement measures (4 May to 1 June 2020) August 3 – First day without COVID-19 deaths since 16 March (first registered death)
5 August to 23 October 2020	August 4–10 & 28–31 – Heatwaves periods with a consequent increase in mortality rates August 11 – announcement of the Sputnik V vaccine creation September 21 – School year beginning and daycare centers reopening October 14 – ‘Calamity state’ declaration by the Portuguese Government+increase in nationwide restrictive measures (4 May to 1 June 2020)
24 October to 18 December 2020	November 4 – Highest number of cases registered in the then designated pandemic ‘second wave’ November 5 – ‘Emergency state’ declaration by the Portuguese Government+additional nationwide restrictive measures December 4 – Announcement of specific restrictive measures for Christmas and new-year’s eve December 17 – Health minister announces the vaccination program initiation between December 27–29
19 December 2020 to 20 February 2021	December 26 & 28 – First batch of vaccines arrives in Portugal (26); vaccination started on the 28th. December 23 to January 11 – Prolonged cold spell January 14 & 18 – Announcement of new restrictive measures January 21 – Decision made to close all schools+second national lockdown/home confinement January 29 – Highest number of cases registered in the then designated pandemic ‘third wave’ February 20 – Announcement of the national lockdown/home confinement extension
21 February to 8 March 2021	March 1 – The mark of 35% of people over 80years vaccinated, was announced. March 2 – One year of the pandemic in Portugal, since the first registered cases of COVID-19

number of infections, Intensive Care Units (ICU) hospitalizations, deaths and Rt (SARS-CoV-2 Effective Reproduction Number) changes. The events were divided into the six periods, considered for the descriptive analysis shown ahead.

Preliminary validation

A Pearson Correlation analysis was performed to identify statistical relationships between the epidemiological data and the crises sensing data collected during one year, thus providing a preliminary indicator of convergent validity of the SPSR measure, with epidemiological relevant events. Results shown in [Table 2](#) demonstrated that SPSR correlated with all epidemiological indicators except for Rt, i.e. SPSR had a significant relationship with the characteristics of the public health crisis across time.

Indicators of crisis emergence

In Portugal, searches for the term ‘Coronavirus’ intensified from 21 January 2020 onwards and peaked on 25 January 2020. Since 21 January 2020, there were more than 139.000 searches on

Table 2. Descriptive statistics and correlations between epidemiological indicators, systemic risk appraisal and related measures.

Variable	<i>n</i> ^a	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Danger	372	22.92	6.55													
2. Effort	372	64.39	7.69	-.88**												
3. Uncertainty	372	11.91	3.71	.02	-.40**											
4. Knowledge & capacities	372	30.30	11.21	.19	-.22*	.22*										
5. Positive dispositions	372	49.29	11.7	-.15	.34**	-.35**	-.61**									
6. External support	372	20.40	10.14	-.04	-.16	.16	-.39**	-.49**								
7. Demands	372	83.83	4.66	.19	-.06	-.39**	-.16	.09	.07							
8. Resources	372	16.16	4.66	-.19	.06	.39**	.16	-.09	-.07	b						
9. SPQR	372	5.69	1.99	.17	-.08	-.41**	-.16	-.07	.26*	b	b					
10. Cumulative daily number of SARS-CoV-2 infection cases per 4-day cycle ^c	372	8667.57	12099.42	.10	-.12	-.30**	-.12	-.16	.33**	.45**	-.45**	.69**				
11. Cumulative daily number of COVID-19 hospitalizations in Intensive Care Units per 4-day cycle ^c	372	1016.30	989.98	-.03	-.16	.08	-.01	-.32**	.39**	0.14	-.14	.32**	.77**			
12. Total number of new COVID-19 deaths per 4-day cycle	372	2166.89	3024.86	.01	-.14	-.03	-.08	-.34**	.48**	.26*	-.26*	.51**	.88**	.90**		
13. <i>R</i> _t – 4-day average of the daily SARS-CoV-2 Effective Reproduction Number	372	1.04	0.21	.29**	-.12	-.32**	-.26*	.34**	-.11	-.01	.01	.03	-.07	-.46**	-.30**	

^aThe sample represents 101 data collection periods of 4-day cycles.

^bCorrelations between Resources, Demands and SPQR were not included given that the latter is constructed based on the D/R ratio and because the former represent a proportion as a function of the total number of R and D.

^cThis cumulative value represents the number of cases identified in one day, added to the number of cases identified in the previous day, for a 4-day cycle.

p*< .05, *p*< .01.

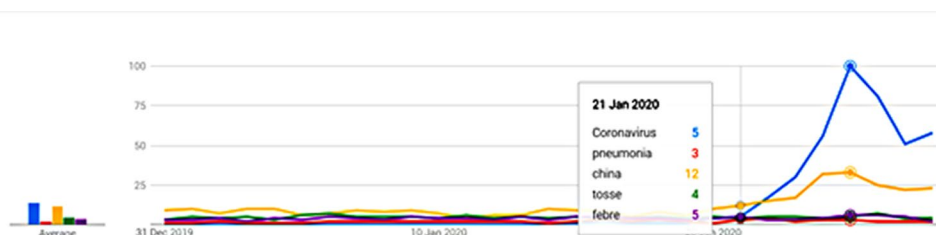


Figure 1. Variation of search terms 'Coronavirus' (blue), 'Pneumonia' (red), 'China' (yellow), 'Cough' (green) and 'Fever' (purple) on the Google search engine, from January 1–30, 2020. Source: Google Trends.

the 'New Coronavirus' (as named at the time) grounded on terms such as: 'China Virus', 'Coronavirus', 'Coronavirus symptoms', 'Coronavirus Portugal'; 'Corona'. On the 23rd and 24th of January 2020, 'Coronavirus' was the term most frequently searched for as shown in the next figure (Figure 1).

From these results, it can be considered that a norm deviation started being socially perceived close to 25 January 2020 which, along the events that co-occurred at the time, could potentially mark a period in which the conditions for a crisis to be perceived, were emerging. However, because perceived norm deviation is not enough for a situation to be perceived as a crisis (Gaspar, Barnett, and Seibt 2015), it was also important to assess evaluations of the social system, with regards to the emerging demands and the resources to cope with these. This is shown next.

Longitudinal changes in social perceptions of systemic risk in co-occurrence with the epidemiological situation

The results from a longitudinal descriptive analysis of the SPSR evolution during the COVID-19 pandemic in Portugal between January 2020 and March 2021, is presented below. This represents the period starting on 26 January 2020 after the perceived norm deviation mark described before, and finalizing with the first official cases of COVID-19 identified in Portugal on 2 March 2020, a few days before the official declaration of the emergence of a pandemic by the WHO.

For the six analysis cycles considered, configuring time blocks between relative minimums of observed SPSR, the SPSR values for each period and their underlying demands vs. resources indicators that enabled their calculation, can be seen in Table 3.

In addition to the average values for each of six time periods for the analysis, the next figure (Figure 2) presents the detailed analysis for each of 4-day periods in each of these six global periods, with a proposed threat level scale. The time periods identified in the yellow level in the graph, represented periods in which the epidemiological situation was not perceived as threatening, as indicated by the SPSR measure. Periods with results within the red level, were identified when the situation was potentially perceived as extremely threatening.

Table 3. Average values for SPSR level, and percentage of demands vs. resources indicators, in each of six periods during the COVID-19 pandemic first year in Portugal.

Period	SPSR	Demands (%)	Resources (%)
26 January to 5 March 2020	4.32	78.73	21.27
6 March to 4 August 2020	5.42	83.81	16.19
5 August to 23 October 2020	5.30	83.68	16.32
24 October to 18 December 2020	6.21	85.73	14.27
19 December 2020 to 20 February 2021	7.08	84.79	15.21
21 February to 8 March 2021	3.81	79.19	20.81

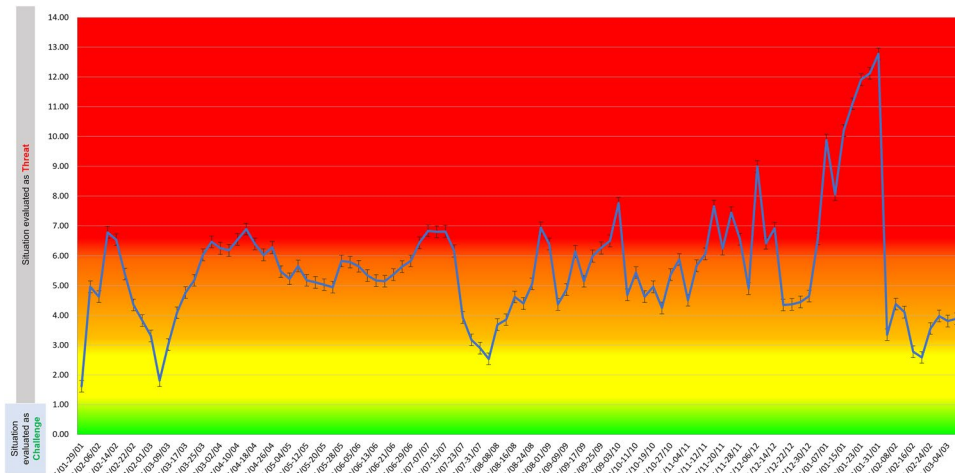


Figure 2. Results from the longitudinal monitoring of the SPSR level, between January 2020 and March 2021. Note: Green = Low SPSR; Yellow: Medium SPSR; Orange = High SPSR; Red = Very High SPSR. Low SPSR = Situation evaluated as challenge; Medium to very high SPSR = Situation evaluated as threat.

Differently, the orange level represents a situation that should be monitored but not necessarily representing an extremely threatening perceived situation.

Overall, the SPSR tended to reflect the epidemiological situation severity, given that the highest values co-occurred with what was popularly known as the first (March–April 2020), second (October–November 2020) and third (January–February 2021) waves of the pandemic in Portugal. Particularly in the third ‘wave’, the highest value in all six global periods was identified. However, discrepancies also occurred, with high levels of SPSR in low severity situations, i.e. low number of hospitalizations and deaths (e.g. when schools opened in September 2020), or low levels of SPSR when a high severity situation emerged (e.g. during Christmas).

Based on the analysis performed across time, and in order to summarize the results, only some relevant results are highlighted below:

- During the ‘first pandemic wave’ in which the number of cases peaked on 10 April 2020, configuring a high-severity situation with a rise in the number of hospitalizations and deaths, there was a subsequent significant decrease from 27 July 2020 onwards, when the SPSR dropped to a low level when zero deaths occurred.
- The 18 March 2020 marked the beginning of the first national lockdown/home confinement, and an increase in the level of SPSR continued to be observed, until 29 March 2020 (6.46). From 25 to 28 May 2020, there was again a marked increase in SPSR, co-occurring with yet another phase of the home deconfinement plan, which lifted some more restrictions, starting from 18 May 2020 (e.g. reopening of schools for 11th and 12th grades; reopening restaurants, cafes and similar). This was potentially perceived as increasing the health risks due to the measures lifting. In the beginning of July 2020 there was a consistent increase, reaching the second highest SPSR value (6.83) recorded in the analysis cycle, which co-occurred with an increase in the number of daily infection cases and the start of new restrictions specifically for the Lisbon Metropolitan Area.
- From 5 August 2020 onwards, there was again a SPSR increase, co-occurring with a period of temperatures above normal in some places in the North and Center of the country observed between 4 and 10 August 2020 (Instituto Português do Mar e da Atmosfera 2020). However, a slight decrease was registered between 13 and 20 August 2020, in co-occurrence with the announcement of the Russian Sputnik V vaccine creation

on 11 August 2020, and a decrease in temperature between 12 and 17 August 2020 (Instituto Português do Mar e da Atmosfera 2020). After 20 August 2020, the SPSR increased again until reaching, on 28 August 2020, the second highest value recorded in the 1-year analysis cycle and the highest value recorded until that point (6.93). This maximum co-occurred, once again, with the heatwave that affected Portugal between 28 and 31 August 2020 (Instituto Português do Mar e da Atmosfera 2020).

- On 3 October 2020 a new maximum was reached (7.76), co-occurring with the beginning of the school year and reopening of daycare centres, as well as the return of political, sports and cultural events along with media discussion on the potential associated violation of safety measures.
- After 4 November 2020, with the peak of 7.497 new infection cases per day and the state of emergency decree on 5 November 2020, in which more restrictive measures were implemented, a new growth trend was observed, which maintained until 6 December 2020, when the highest value until that point was recorded (8.99). A decrease was observed immediately after, co-occurring with the: announcement of the first vaccines arrival in Portugal on 26 December and the vaccination program start on 28 December; apparent reduction of new daily cases; announcement of specific measures for the Christmas and New Year season; and apparent attempt by the population to cope with a 'non-normal' Christmas (e.g. trying to make it as similar as possible to previous years), with an increase also being reported on the number of SARS-CoV-2 tests performed and anecdotal reports of a social "sense of safety".
- The SPSR highest values observed during the first year of the pandemic in Portugal, occurred on 31 January 2021 (12.78). This period was characterized by what was popularly known as the 'third wave' of the pandemic in Portugal, with a peak of 16432 new infection cases on 29 January 2021, configuring a high-severity situation with a rise in the number of hospitalizations and deaths. Also during this period, there was an announcement of new pandemic control measures, schools closing and the second national lockdown. The observed rise in SPSR also co-occurred with a prolonged cold spell that affected Portugal between 23 December 2020 and 11 January 2021 (Instituto Português do Mar e da Atmosfera 2021).
- Towards the approach of the COVID-19 pandemic one-year milestone in Portugal, a series of news emerged regarding the side effects of vaccines, particularly the Astrazeneca® vaccine, which seemingly did not co-occur with changes in SPSR (Instituto Português do Mar e da Atmosfera 2021).

Longitudinal trends exploration

The analysis presented before showed that during the period under study, the COVID-19 pandemic was never evaluated as a challenge but only as a threat, with all values of SPSR above 1. Nevertheless, after performing a mean centring transformation on the data, it can be seen in Figure 3 that there were various periods across time, in which the values of SPSR were above the average determined for the whole analysis period ($M_{SPSR} = 5.69$; $SD = 1.99$). The specific 4-day periods in which this happened, can be seen in Table 4.

In order to further explore the associated patterns in the results, a Time Series Analysis was performed. Regression analysis of the time series revealed a reliable quadratic period effect, confirming that SPSR occurred in waves or cycles (see graphical representation of the quadratic effect in Figure 4 and corresponding results in Table 5). Indeed, SPSR increased significantly from baseline to week 25 ($b = .031$, $SE = .014$, $t=2.173$, $p = .033$), then stabilized without significant change until week 50 ($b = .004$, $SE = .006$, $t=0.621$, $p = .536$) and then changed direction, significantly decreasing after week 50 ($b=-.040$, $SE = .013$, $t=-2.961$, $p = .004$).

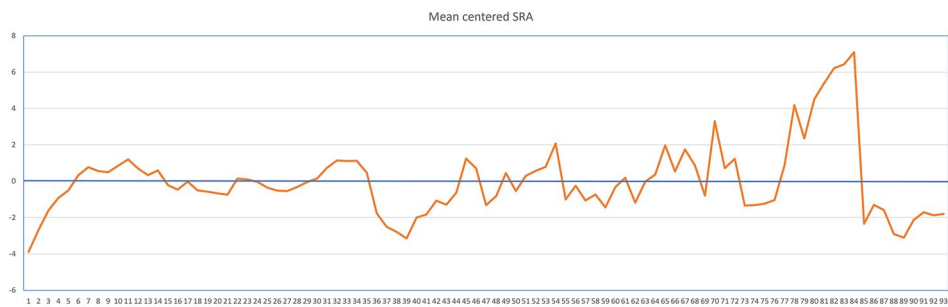


Figure 3. Mean-centred SPSR across the measurement period.

Table 4. Periods in which mean centred SPSR values were above the mean.

Period	Week	Mean centred SRA
22/03–25/03/2020	6	0.34
26/03–29/03/2020	7	0.77
30/03–02/04/2020	8	0.56
03/04–06/04/2020	9	0.49
07/04–10/04/2020	10	0.85
11/04–14/04/2020	11	1.2
15/04–18/04/2020	12	0.7
19/04–22/04/2020	13	0.34
23/04–26/04/2020	14	0.59
26/06–29/06/2020	30	0.14
30/06–03/07/2020	31	0.74
04/07–07/07/2020	32	1.14
08/07–11/07/2020	33	1.11
12/07–15/07/2020	34	1.12
16/07–19/07/2020	35	0.47
25/08–28/08/2020	45	1.24
18/09–21/09/2020	51	0.3
22/09–25/09/2020	52	0.57
26/09–29/09/2020	53	0.8
30/09–03/10/2020	54	2.07
09/11–12/11/2020	64	0.37
13/11–16/11/2020	65	1.97
17/11–20/11/2020	66	0.54
21/11–24/11/2020	67	1.75
25/11–28/11/2020	68	0.86
03/12–06/12/2020	70	3.3
07/12–10/12/2020	71	0.72
11/12–14/12/2020	72	1.23
31/12–03/01/2021	77	0.87
04/01–07/01/2021	78	4.19
08/01–11/01/2021	79	2.36
12/01–15/01/2021	80	4.51
16/01–19/01/2021	81	5.41
20/01–23/01/2021	82	6.22
24/01–27/01/2021	83	6.43
28/01–31/01/2021	84	7.09

Discussion

The analysis presented aimed to provide a first proof of concept of an index that serves as an indicator of social perceptions of systemic risk (SPSR; Schweizer et al, 2022), as the core of a social sensing approach applied to crisis situations. As a preliminary indicator of this, significant correlations were found between the epidemiological data and the crisis sensing data collected during one year. In particular, the SPSR index presented strong to moderate positive and

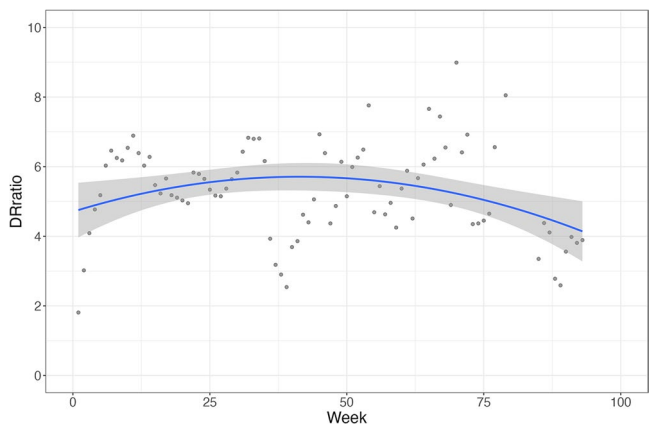


Figure 4. Graphical representation of the quadratic effect identified through a time series analysis of SPSR.

Table 5. Estimated time series effects for predicting SPSR.

Effects	<i>b</i>	<i>SE</i>	<i>t</i>	<i>p</i>	95%CI	
					Lower	Upper
Intercept	5.693	0.199	28.583	.001	5.297	6.090
Linear	0.333	0.341	0.976	0.332	−0.346	1.011
Quadratic	−0.426	0.153	−2.778	0.007	−0.730	−0.121
Cubic	−0.285	0.172	−1.652	0.102	−0.628	0.058

Note. *b* = unstandardized regression coefficients; *SE*=Standard error; *CI*=Confidence interval of *b*.

significant relationships, with the cumulative number of SARS-CoV-2 infection cases, number of new COVID-19 deaths and the cumulative number of COVID-19 hospitalizations in Intensive Care Units, despite the same not occurring for the *R(t)* indicator. This may provide a preliminary indicator of convergent validity of the SPSR measure, namely that social perceptions of systemic risks within the social system may, at least partially, correlate with epidemiologically relevant events co-occurring with it, within the social system.

Regarding the first research question – At what point there was an increase in COVID-19 related discourse (keywords) identified through Google Trends™, indicative of a perceived norm deviation (as a first stage of a perceived crisis emergence)? – the implementation of the ‘detection’ and ‘evaluation’ components of the ResiliScience approach (Gaspar et al. 2021), seemingly showed that there was a socially shared perceived norm deviation around 25 January 2021, as indicated by a significant increase in pandemic related searches as identified through the Google Trends platform. However, as proposed by the Norm Deviation Approach (Gaspar, Barnett, and Seibt 2015), this is a mandatory but not sufficient criteria to conclude that a crisis was perceived to have emerged. For this to occur, there should also be indicators of evaluations that a threat emerged and that people started implementing strategies to cope with it, that they would not normally implement. Based on social media comments monitoring results, this was seemingly shown to take place at the end of January, particularly from the 30 January 2020 to 2 February 2020 analysis cycle onwards, when the SPSR level (grounded on the threat level ratio calculation) was at a high level, becoming very high in mid-February.

Concerning the second research question – How did the Social Perceptions of Systemic Risk indicator derived from Facebook™ comments, changed longitudinally in co-occurrence with epidemiologically relevant pandemic events? – the longitudinal analysis of SPSR derived from Facebook™ users comments in Portugal, throughout one year of the pandemic, showed that it tended to reflect the changes in the epidemiological situation. More specifically and as shown by the time series analysis, when there were pandemic waves (i.e. steep rises in new daily

infections, ICU hospitalizations and deaths), there was also a pattern of SPSR "waves", rather than a linear progression or other data patterns. Accordingly, there were high/very high levels of SPSR in periods when the situation was more serious, namely what was popularly known as the first, second, and third pandemic waves in the first year. However, there were also periods in which this did not happen, for example with high SPSR co-occurring with concerns related to the start of the school year and the return of children to school in September 2020, without the increase in cases that was anticipated by the population.

Overall, these apparently inconsistent results seemingly shows that the SPSR may be influenced by multiple factors that in turn, may have different effects at different times, beyond the characteristics of the epidemiological situation at a certain point in time (e.g. number of hospitalizations and deaths). Hence, in certain periods the perception may be strongly influenced by the epidemiological situation (i.e. number of cases, deaths, etc.) and sometimes more affected by events that co-occur with the epidemiological situation, whether those are perceived as positive for some (e.g. beginning of the vaccination process for certain age groups), or those that are perceived as negative for some (e.g. beginning of more restrictive measures to control the pandemic, such as a national lockdown/home confinement). This should be further assessed in future studies, to understand which factors at different times may be more predictive of the SPSR and which factors consistently predict perception in different moments in time.

Also worth of further studying is the consequences of relatively sharp changes (up and down) in SPSR in relatively shorter time periods, observed mainly between mid-August 2020 and mid-December 2020. Moreover, the results show that after each 'crisis period', in which the SPSR increased consistently until reaching a peak, a 'restoration period' was observed, where SPSR consistently decreased, reaching the average levels of the previous analysis cycle. These results may, on one hand, indicate the social system resilience, i.e. that after each crisis 'peak' there may be recovery and potentiation of perceived resources (e.g. learning, habituation, and increment of positive dispositions, such as optimism and hope). On the other hand, it may also indicate a possible denial/escape from the situation, associated with a social and individual attenuation of risk, with the objective of (re)gaining control over the situation (e.g. Kasperson et al. 1988).

Despite this interpretation, these results also serve as a warning, given that the repetition of several cycles of crisis-recovery can lead to negative consequences for mental health and consequent longer recovery time after each crisis period. Moreover, overtime, it may lead to 'pandemic fatigue', if psychological resources are consumed without being replenished, something that can be further assessed in future studies. Nevertheless, potential negative consequences can be mitigated, if social and personal resources are effectively provided to the public (e.g. what resources are in place, where can they be found or mobilized, how they can be accessed and used), to make recovery more effective. Examples of what can be provided are communication of the social and community resources available to citizens (e.g. the Portuguese NHS 24hour Psychological Support Line, how to reach it, and when to use it); fostering positive dispositions (e.g. by demonstrating the effects of willingness to act, calmness and comprehension, avoiding jumping into precipitated conclusions, respect for others opinions, optimism and hope for the near future); and information that demonstrates greater control of the epidemiological situation and of what is being done by authorities and other entities to protect citizens.

In our view, all these results show the importance of Information and Communications Technologies (ICTs) monitorization and particularly social media, to enable a tailored communication that addresses population concerns and needs to capacitate them for the adoption of mitigation measures (individual and collective behavioural awareness and changes; Gaspar, Yan, and Domingos 2019). Social events such as the first news about the virus that emerged from China, the entry of the virus in Europe, the perceived demands posed by national or regional

lockdowns/home confinement, the 'false sense of safety' felt during 2020 Christmas period when in presence of (perceived healthy) family members along with restrictive measures relaxation and other events, are examples of events that could be targeted with customized risk and crisis communication. An example was the change in how SARS-CoV-2 variants were named (e.g. from "Indian variant" to "Delta variant") and corresponding advice in how to communicate this, proposed by the WHO (2021a, 2021b) due to an emergence of expressions of prejudice and racism towards people from the country where the virus was first detected or from which local virus variants emerged. Implementing such customization, should allow for negative consequences for the social system to be mitigated, while also allowing for an effective control of the epidemiological situation through non-therapeutical measures. In our view, a social sensors approach can be an important tool to address these crises management needs in a timely and evidence-based manner, as preliminary evidence shows that the SPSR index correlates with events occurring within the social system, while also being determined by other relevant factors that should be studied in future studies.

Although the study presented here opens some possibilities for future research, it also has limitations. First, it should be noted that the SPSR level never went below one. This can be partly due to methodological reasons, given that when the data collection started (26 January, 2020), it can be hypothesized that the crisis had already been perceived as such by many people, i.e. they were perceiving more demands than the resources available to cope. Also, the use of one as the cut of point, as proposed by Blascovich and colleagues (Blascovich and Mendes 2000; Blascovich 2008), can be questioned. To respond to this, we performed a data transformation to mean centre the SPSR index across time, which allows using zero as the reference value. It can be inferred that above average values – i.e. above zero – represent more negative (threat) appraisals of the situation and may thus be used as an alternative cut-off point (Gaspar, Barnett, and Seibt 2015; Kasperson et al. 1988; Renn 2011; Pidgeon and Barnett 2013).

Another limitation is that the comments extracted may have been made as a response to other aspects of the publication content, than to the external events to which it referred. Moreover, 'social media channels and platforms and the traditional print and broadcast news media' have specifically been identified as amplification stations (Kasperson et al. 2022). Nevertheless, a careful selection procedure was implemented to avoid explicit politically motivated publications and other aspects of content not directly concerning the epidemiological situation. Also, to avoid the researcher's publication selection bias, the same selection criteria was used across time, across publication source and by all members of the extraction and coding research team.

Lastly, future research should consider more types of data and levels of analysis. For an effective crisis detection mechanism to be implemented, a 'layering method' as proposed by Breakwell and Barnett (2001) should be applied. Grounded on such method, different 'layers' of data can be collected and interpreted as they co-occur. Such 'Layering method' is an integrative, multidimensional technique for capturing data and identifying relationships, which allows a better understanding of what happens at the different social stations and individual stations of amplification identified in the SARF, and how this may determine behavioural reactions. In order to do this, we need to assess different data layers/levels of analysis both within specific time periods/events and between time periods/events.

The example presented here, showed three layers of data: 1) keyword search behaviours on Google, 2) social media data collection and 3) epidemiological data collection, namely the identification of pandemic relevant occurrences. The analysis of these layers could be complemented with longitudinal surveys as exemplified by the behavioural insights survey tool develop by the WHO (2020), along with data collected through smartphone apps (e.g. Fernandes et al. 2022; Kheirkhahan et al. 2019) and other types of data, to put in place a social sensing mechanism (Galesic et al. 2021; Gaspar et al. 2021; Wang et al. 2019) during crisis situations, based on the

interpretation of various layers of data (Breakwell and Barnett 2001). Still, caution should be taken, given that co-occurrence of changes between layers of data at a point in time and across time, should not be interpreted as causation. It should rather be seen as different pieces of a puzzle that, together, allow having a better ‘picture’ of what is happening within the social system.

Final remarks

Faced with an increasing frequency of emerging risks to health, the economy, and society in general (e.g. systemic risks), the objective of any intervention or communication strategy should always be the assessment of current and future events more as a challenge (i.e. perception of resources as sufficient to cope with current and future demands) and less as a threat (i.e. perception of insufficient or non-existent resources to cope with the demands). A challenge evaluation has been showed to be associated with better performance and behavioural engagement (e.g. Putwain, Symes, and Wilkinson 2017), which may be an important condition for adherence to protective behavioural recommendations shared through crisis and risk communications, particularly concerning the non-therapeutical interventions (Warren and Lofstedt 2021).

Furthermore, such strategies need to ensure that the perceptions and beliefs that citizens have regarding these resources and demands are adjusted to the facts and to the existing scientific evidence. To achieve these, the recommendations must be tailored to both present social perceptions and responses, and anticipate perception and responses to future crises scenarios. Social sensor approaches such as the one presented here, are a relevant part as they allow identifying such perceptions/responses. Also, these approaches have the potential to be grounded on a hybrid human-computer based data extraction and analysis, that may enable real time monitoring of the social system dynamics during crisis situations - nowcasting -, while also having the potential to predict future responses - forecasting.

Conflicts of interest

No potential conflict of interest was reported by the authors.

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References

- Aven, Terje, Yakov Ben-Haim, Henning Boje Andersen, Tony Cox, Enrique López Droguett, Michael Greenberg, Seth Guikema, et al. 2015. "Society for Risk Analysis Glossary." Arlington. <https://www.sra.org/wp-content/uploads/2020/04/SRA-Glossary-FINAL.pdf>
- Barnett, Julie, and Glynis M. Breakwell. 2003. "The Social Amplification of Risk and the Hazard Sequence: The October 1995 Oral Contraceptive Pill Scare." *Health, Risk & Society* 5 (3): 301–313. doi:10.1080/13698570310001606996.
- Barnett, Julie, and Konstantina Vasileiou. 2014. "Making Sense of Risk: The Role of Social Representations and Identity." In *Identity Process Theory: Identity, Social Action and Social Change*, edited by Rusi Jaspal and Glynis M. Breakwell, 357–378. Cambridge: Cambridge University Press. doi:10.1017/CBO9781139136983.022.
- Blascovich, Jim. 2008. "Challenge, Threat, and Health." In *Handbook of Motivation Science*, edited by James Y. Shah and Wendi L. Gardner, 481–493. New York: Guilford Press. <https://www.guilford.com/books/Handbook-of-Motivation-Science/Shah-Gardner/9781593855680/contents>
- Blascovich, Jim, and Wendy Berry Mendes. 2000. "Challenge and Threat Appraisals: The Role of Affective Cues." In *Studies in Emotion and Social Interaction, Second Series – Feeling and Thinking: The Role of Affect in Social Cognition*, edited by Joseph P. Forgas, 59–82. New York: Cambridge University Press.
- Blascovich, J, and J Tomaka. 1996. "The Biopsychosocial Model of Arousal Regulation." In *Advances in Experimental Social Psychology*, Vol. 28, 1–51. Academic Press. doi:10.1016/S0065-2601(08)60235-X.
- Breakwell, Glynis M. 2010. "Models of Risk Construction: Some Applications to Climate Change." *Wiley Interdisciplinary Reviews: Climate Change* 1 (6): 857–870. doi:10.1002/wcc.74.
- Breakwell, Glynis M., and J. Barnett. 2001. *The Impact of Social Amplification on Risk Communication – Contract Research Report 322/2001*. Sudbury: HSE Books.
- Brose, Annette, Elisabeth S. Blanke, Florian Schmiedek, Andrea C. Kramer, Andrea Schmidt, and Andreas B. Neubauer. 2021. "Change in Mental Health Symptoms during the COVID-19 Pandemic: The Role of Appraisals and Daily Life Experiences." *Journal of Personality* 89 (3): 468–482. doi:10.1111/JOPY.12592.
- DGS. 2020. *Princípios Orientadores Para Comunicação de Riscos e Crise Baseados Na Percepção de Risco: Doença Respiratória Aguda Por 2019-NCov*. Lisbon: Direção Geral da Saúde.
- Domingos, Samuel, Rui Gaspar, Hugo Fonseca, and João Marôco. 2020. "DeCodeR Framework: Data Collection and Coding for Demands and Resources Appraisal in Extreme Weather Events." *PsyEcology* 11 (1): 90103. doi:10.1080/21711976.2019.1643988.
- Fernandes, José Marcelo, Jorge. Sá-Silva, André Rodrigues, Fernando. Boavida, Rui. Gaspar, Cristina. Godinho, and Rita Francisco. 2022. "Social Sensing and Human in the Loop Profiling during Pandemics: The Vitoria application." <https://arxiv.org/abs/2207.01920v1>
- Galesic, Mirta, Wändi Bruine de Bruin, Jonas Dalege, Scott L. Feld, Frauke Kreuter, Henrik Olsson, Drazen Prelec, Daniel L. Stein, and Tamara van der Does. 2021. "Human Social Sensing is an Untapped Resource for Computational Social Science." *Nature* 595 (7866): 214–222. doi:10.1038/s41586-021-03649-2.
- Gaspar, Rui, Julie Barnett, and Beate Seibt. 2015. "Crisis as Seen by the Individual: The Norm Deviation Approach/ La Crisis Vista Por El Individuo: El Enfoque de La Desviación de La Norma." *Psyecology* 6 (1): 103–135. doi:10.1080/21711976.2014.1002205.
- Gaspar, Rui, Samuel Domingos, Duarte Brito, Gisela Leiras, Jessica Filipe, Beatriz Raposo, and Miguel Telo de Arriaga. 2021. "Striving for Crisis Resolution or Crisis Resilience? The Crisis Layers and Thresholds Model and Information and Communication Technology-Mediated Social Sensing for Evidence-Based Crisis Management and Communication." *Human Behavior and Emerging Technologies* 3 (1): 40–52. doi:10.1002/hbe2.241.
- Gaspar, Rui, Sara Gorjão, Beate Seibt, Luise Lima, Julie Barnett, Adrian Moss, and Josephine Wills. 2014. "Tweeting during Food Crises: A Psychosocial Analysis of Threat Coping Expressions in Spain, during the 2011 European EHEC Outbreak." *International Journal of Human Computer Studies* 72 (2): 239254. doi:10.1016/j.ijhcs.2013.10.001.
- Gaspar, R., Cláudia Pedro, Panas Panagiotopoulos, and Beate Seibt. 2016. "Beyond Positive or Negative: Qualitative Sentiment Analysis of Social Media Reactions to Unexpected Stressful Events." *Computers in Human Behavior* 56: 179–191. doi:10.1016/j.chb.2015.11.040.
- Gaspar, Rui, Zheng Yan, and Samuel Domingos. 2019. "Extreme Natural and Man-Made Events and Human Adaptive Responses Mediated by Information and Communication Technologies' Use: A Systematic Literature Review." *Technological Forecasting and Social Change* 145 (August): 125–135. doi:10.1016/j.techfore.2019.04.029.
- Homer-Dixon, T, O. Renn, J. Rockström, J. Donges, and S. Jantzwood. 2022. "A Call for an International Research Program on the Risk of a Global Polycrisis." 2022-3, version 2.0. Cascade Institute. <https://cascadeinstitute.org/technical-paper/a-call-for-an-international-research-program-on-the-risk-of-a-global-polycrisis/>
- Instituto Português do Mar e da Atmosfera. 2020. *Resumo Climatológico Agosto e Verão de 2020*. Lisbon: Instituto Português do Mar e da Atmosfera.
- Instituto Português do Mar e da Atmosfera. 2021. *Episódio Frio Persistente: Dezembro 2020 a Janeiro 2021*. Lisbon: Instituto Português do Mar e da Atmosfera.

- Joffe, H        . 2003. "Risk: From Perception to Social Representation." *The British Journal of Social Psychology* 42 (Pt 1): 55–73. doi:10.1348/014466603763276126.
- Joffe, H        , and Georgina Haarhoff. 2002. "Representations of Far-Flung Illnesses: The Case of Ebola in Britain." *Social Science & Medicine* 54 (6): 955–969. doi:10.1016/S0277-9536(01)00068-5.
- Kasperson, Roger E., Ortwin Renn, Paul Slovic, Halina S. Brown, Jacque Emel, Robert Goble, Jeanne X. Kasperson, and Samuel Ratick. 1988. "The Social Amplification of Risk: A Conceptual Framework." *Risk Analysis* 8 (2): 177–187. doi:10.1111/j.1539-6924.1988.tb01168.x.
- Kasperson, Roger E., Thomas Webler, Bonnie Ram, and Jeannette Sutton. 2022. "The Social Amplification of Risk Framework: New Perspectives." *Risk Analysis* 42 (7): 1367–1380. doi:10.1111/RISA.13926.
- Kheirkhahan, Matin, Sanjay Nair, Anis Davoudi, Parisa Rashidi, Amal A. Wanigatunga, Duane B. Corbett, Tonatiuh Mendoza, Todd M. Manini, and Sanjay Ranka. 2019. "A Smartwatch-Based Framework for Real-Time and Online Assessment and Mobility Monitoring." *Journal of Biomedical Informatics* 89 (January): 29–40. doi:10.1016/J.JBI.2018.11.003.
- Lazarus, Richard S., and Susan Folkman. 1984. *Stress, Appraisal, and Coping*. New York: Springer Publishing Company. https://books.google.pt/books?hl=pt-PT&lr=&id=i-ySQUuUpr8C&oi=fnd&pg=PR5&ots=DgHUqqdgUc&sig=5HjAr-dApuTxdNBgXDArY4nb2FCY&redir_esc=y#v=onepage&q&f=false
- Li, J., Q. Xu, R. Cuomo, V. Purushothaman, and T. Mackey. 2020. "Data Mining and Content Analysis of the Chinese Social Media Platform Weibo during the Early COVID-19 Outbreak: Retrospective Observational Infection Study." *JMIR Public Health and Surveillance* 6 (2): e18700. doi:10.2196/18700.
- Noar, Seth M., Nancy Grant Harrington, and Rosalie Shemanski Aldrich. 2016. "The Role of Message Tailoring in the Development of Persuasive Health Communication Messages." *Annals of the International Communication Association* 33 (1): 73–133. doi:10.1080/23808985.2009.11679085..
- OberCom. 2020. "Reuters Digital News Report 2020 Portugal." Lisbon. https://obercom.pt/wp-content/uploads/2020/06/DNR_PT_2020_19Jun.pdf
- Pidgeon, Nick, and Julie Barnett. 2013. *Chalara and the Social Amplification of Risk*. London: Department for Environment, Food and Rural Affairs.
- Putwain, David W., Wendy Symes, and Hannah M. Wilkinson. 2017. "Fear Appeals, Engagement, and Examination Performance: The Role of Challenge and Threat Appraisals." *The British Journal of Educational Psychology* 87 (1): 16–31. doi:10.1111/BJEP.12132.
- Renn, Ortwin. 2011. "The Social Amplification/Attenuation of Risk Framework: Application to Climate Change." *Wiley Interdisciplinary Reviews: Climate Change* 2 (2): 154–169. doi:10.1002/wcc.99.
- Renn, Ortwin. 2021. "New Challenges for Risk Analysis: Systemic Risks." *Journal of Risk Research* 24 (1): 127–133. doi:10.1080/13669877.2020.1779787.
- Renn, Ortwin. 2022. "The Systemic Risk Perspective: Social Perception of Uncertainty and Tipping Points." In *Strategies for Sustainability of the Earth System*, edited by Peter A. Wilderer, Martin Grambow, Michael Molls, Konrad Oexle, 15–31. Cham: Springer. doi:10.1007/978-3-030-74458-8_2.
- Renn, Ortwin, Manfred Laubichler, Klaus Lucas, Wolfgang Kr        , Jochen Schanze, Roland W. Scholz, and Pia Johanna Schweizer. 2022. "Systemic Risks from Different Perspectives." *Risk Analysis* 42 (9): 1902–1920. doi:10.1111/RISA.13657.
- Renn, Ortwin, Klaus Lucas, Armin Haas, and Carlo Jaeger. 2019. "Things Are Different Today: The Challenge of Global Systemic Risks." *Journal of Risk Research* 22 (4): 401–415. doi:10.1080/13669877.2017.1409252.
- Rovetta, Alessandro, and Akshaya Srikanth Bhagavathula. 2020. "Global Infodemiology of COVID-19: Analysis of Google Web Searches and Instagram Hashtags." *Journal of Medical Internet Research* 22 (8): e20673. <https://www.jmir.org/2020/8/E20673>. doi:10.2196/20673.
- Ruiter, Robert A. C., Loes T. E. Kessels, Gjalt-Jorn Y. Peters, and Gerjo Kok. 2014. "Sixty Years of Fear Appeal Research: Current State of the Evidence." *International Journal of Psychology* 49 (2): 63–70. doi:10.1002/ijop.12042.
- Schweizer, Pia-Johanna, Robert Goble, and Ortwin Renn. 2022. "Social Perception of Systemic Risks." *Risk Analysis* 42 (7): 1455–1471. doi:10.1111/risa.13831.
- Seeger, Matthew W., Barbara Reynolds, and Timothy L. Sellnow. 2009. "Crisis and Emergency Risk Communication in Health Contexts: Applying the CDC Model to Pandemic Influenza." In *Handbook of Risk and Crisis Communication*, edited by Robert L. Heath and H. Dan O'Hair, 493–506. New York: Routledge.
- Sellnow, Timothy L., and Matthew W. Seeger. 2013. *Theorizing Crisis Communication*. 1st ed. New Jersey: Wiley-Blackwell.
- Tan, Soon Guan, Aravind Sesagiri Raamkumar, and Hwee Lin Wee. 2021. "Users' Beliefs toward Physical Distancing in Facebook Pages of Public Health Authorities during COVID-19 Pandemic in Early 2020." *Health Education & Behavior* 48 (4): 404–411. doi:10.1177/10901981211014428.
- Tomaka, J., J. Blascovich, R. M. Kelsey, and Hwee Lin Wee. 1993. "Subjective, Physiological, and Behavioral Effects of Threat and Challenge Appraisal." *Journal of Personality and Social Psychology* 65 (2): 248. doi:10.1037/0022-3514.65.2.248.

- Tomaka, J., J. Blascovich, J. Kibler, and J. M. Ernst. 1997. "Cognitive and Physiological Antecedents of Threat and Challenge Appraisal." *Journal of personality and social psychology* 73 (1): 63. doi:[10.1037/0022-3514.73.1.63](https://doi.org/10.1037/0022-3514.73.1.63).
- Tsao, Shu-Feng, Helen Chen, Therese Tisseverasinghe, Yang Yang, Lianghua Li, and Zahid A. Butt. 2021. "What Social Media Told Us in the Time of COVID-19: A Scoping Review." *The Lancet. Digital Health* 3 (3): e175–e194. doi:[10.1016/S2589-7500\(20\)30315-0](https://doi.org/10.1016/S2589-7500(20)30315-0).
- Vieira, Kelmara Mendes, Ani Caroline Grigion Potrich, Aureliano Angel Bressan, Leander Luiz Klein, Breno Augusto Diniz Pereira, and Nelson Guilherme Machado Pinto. 2021. "A Pandemic Risk Perception Scale." *Risk Analysis* 42 (1): 69–84. doi:[10.1111/RISA.13802](https://doi.org/10.1111/RISA.13802).
- Wang, Dong, Boleslaw K. Szymanski, Tarek Abdelzaher, Ji Heng, and Lance Kaplan. 2019. "The Age of Social Sensing." *Computer* 52 (1): 36–45. doi:[10.1109/MC.2018.2890173](https://doi.org/10.1109/MC.2018.2890173).
- Warren, George W., and Ragnar Lofstedt. 2021. "Risk Communication and COVID-19 in Europe: Lessons for Future Public Health Crises." *Journal of Risk Research*: 1–15. doi:[10.1080/13669877.2021.1947874](https://doi.org/10.1080/13669877.2021.1947874).
- World Health Organization. 2020. *Survey Tool and Guidance Rapid, Simple, Flexible Behavioural Insights on COVID-19*. Copenhagen: World Health Organization.
- World Health Organization. 2021a. "Tracking SARS-CoV-2 Variants."
- World Health Organization. 2021b. "WHO Announces Simple, Easy-to-Say Labels for SARS-CoV-2 Variants of Interest and Concern." <https://www.who.int/news/item/31-05-2021-who-announces-simple-easy-to-say-labels-for-sars-cov-2-variants-of-interest-and-concern>
- Wu, Joseph T., Kathy Leung, Tommy T. Y. Lam, Michael Y. Ni, Carlos K. H. Wong, J. S. Malik Peiris, and Gabriel M. Leung. 2021. "Nowcasting Epidemics of Novel Pathogens: Lessons from COVID-19." *Nature Medicine* 27 (3): 388–395. doi:[10.1038/s41591-021-01278-w](https://doi.org/10.1038/s41591-021-01278-w).