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Big data for human security: The case of COVID-19

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A R T I C L E   I N F O

A B S T R A C T

The COVID-19 epidemic has changed the world dramatically since societies are changing their behaviour according to the new normal, which comes along with numerous challenges and uncertainties. These uncertainties have led to instabilities in several facets of society, most notably health, economy and public order. Measures to contain the pandemic by governments have occasionally met with increasing discontent from societies and have triggered social unrest, imposing serious threats to human security. Big Data Analytics can provide a powerful force multiplier to support policy and decision makers to contain the virus while at the same time dealing with such threats to human security. This paper presents the utilisation of a big data forecasting and analytics framework and its utilisation to deal with COVID-19 triggered social unrest. The paper is an extended version of paper Cárdenas et al. (2021) presented at the 2021 International Conference on Computational Science.

1. Introduction

Global challenges and emergencies such as climate change, epidemics and natural and man-made calamities present unprecedented governance issues. Going back in time to 2019, the world changed completely because a thitherto virus (SARS-CoV-2 or COVID-19) took people, institutions and governments by surprise. The high contagiousness and rapid spread of the virus and the lack of appropriate treatments resulted in a global pandemic that affected societies not only the healthcare sector, but also in strategic areas that they had not anticipated they would be impacted so seriously, such as the economy and the public order. Governments across the globe took strict decisions aimed at containing the disease and avoiding massive infections, such as curfew, lockdowns or measures such as 'stay at home' or clustering domestic territories according to its infection rates [1]. Such containment measures have been accompanied by varying degrees of social discontent and unrest, violent manifestations of which in the forms of demonstrations and riots have been witnessed across the globe [2–4]. Most countries witnessed severe knock-on effects of the pandemic, such as rising levels of unemployment and even sometimes food shortages, which accelerated the internal instability scenarios.

The negative social and economic effects of the pandemic also provided a pretext for intensifying pre-existing social discontent and unrest., e.g. the Black Lives Matter movement or the demonstrations in Hong Kong, and eventually jeopardised human security.

Policy and decision-makers need to have at their disposal technological tools to act as force multipliers and enable them to gain insights about disasters and unfolding situations and assess the threat to human security [5–7]. Big Data technologies can provide a powerful means in this endeavour [8,9]. As a result, the last decade has witnessed the development of several computational platforms that utilise Big Data analytics to derive insights about disruptive events that can trigger social unrest [10–14].

Aspiring to contribute to the global effort towards tools for the prediction and interpretation of disruptive events and human security crises, in earlier work we have presented a framework and associated workflow for the analysis of social media data (Twitter) to derive intelligence insights, the outcomes facilitate the dissection of complex human security problems that can be used to inform the courses of action by the decision-makers.

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In this paper, the framework, referred to as *Eunomia*, is utilised to analyse events related to the COVID-19 pandemic. At the time of writing, the pandemic had resulted in more than four million deaths worldwide [20], triggered multiple protests, while its impact on economic and food security was still unfolding.

The paper is an extended version of [21] and its aim is to further refine and test the robustness and applicability of the framework in forecasting and analysing global disruptions such as the COVID-19 pandemic. The new material in this paper, compared with [21] is the following: (a) A more complete discussion on human security components which constitutes the theoretical domain basis for the technical work presented in the paper (Section 2); (b) A more detailed description of the Conceptual Framework components (Section 3.1); (c) a new use case in a different cultural, political and socio-economic context, namely the COVID-19 related protests in Pakistan in March 2020 (Section 4.1).

The rest of the paper is organised as follows. In Section 2 a description of COVID-19 and its impact on human security is provided. Section 3 outlines the proposed human security analysis framework. Section 4 presents experimental results from the analysis of three case studies, the protests in Pakistan, Michigan and Texas respectively. Section 5 concludes the paper, outlining some limitations of the current system and pointers to future work.

2. Human security and pandemics

Human security is a complex concept that has been discussed and debated in academia and international organisations for more than two decades with hereto no commonly agreed exact definition of the term [4,22–32]. This paper adopts the human security agenda and theoretical framework first proposed by the United Nations in the 1994 UN Development Programme (UNDP) Human Development Report [33]. Seven main components of the human security environment were identified in that report, namely: health security, public order, environmental security, communal security, food security, personal security and political security. These components are also inline with the 2030 Agenda for Sustainable Development adopted by the United Nations in 2015 as a universal call to action to protect the planet, and ensure that by 2030 all people enjoy peace and prosperity [34]. This group of seven components are all related to fundamental human rights, place the individual and the people at the centre and facilitate a thorough, and yet still relatively straightforward, way to view, understand and intervene to prevent likely human security threats. To give characteristic examples of each component, assuring a basic income (economic security), providing physically convenient and economically affordable access to food (food security), assuring an environment free of disease and infection (health security), universal access to sanitary water supply and clean air (environmental security), guaranteeing security from physical violence and threats (personal security), protecting people’s freedoms and cultural identity (political and communal security), are critical factors in ensuring stability and avoiding internal disruptions of a society. The fragile equilibrium between the various human security components tends to be a critical factor of a country’s developmental pace. Since there is no development without security, the importance of tracking and understanding the threads of those human security components on which the stability of a state depends is evident.

Pandemics such as COVID-19 are recognised as serious human security threats [3,4,35]. Fig. 1, provides a schematic description of the impact of COVID-19 on human security components. It illustrates the main thesis of this paper, that the study and analysis of the human security components requires a holistic approach, since the initial severe disruption of one component, here the health component, has knock-on effects on multiple other components, for example, erosion of trust in public institutions, riots, raising unemployment, financial instability, disruption of the supply chains, and even secondary disruption of the health component from factors such as lack of medicines, or disruption in the operations of the human health systems.

Predicting and analysing a crisis is a complex task that gains more relevance and importance when the centre/core of a state (people) can potentially be affected. Digital technologies and Big Data analytics can play a crucial role in the timely spotting of early sparks of societal instability, which later may evolve into human security issues. The rest of the paper discusses such an approach for the analysis of COVID-19 related societal disruptions. The framework utilises Machine Learning techniques and Natural Language Processing to analyse data harvested from multiple sources, including Social Networking Sites (SNS), such as Twitter and Instagram, Independent Websites (IW), and online data from Non-Profit Organisations.

3. The Eunomia framework for human security analysis

The power and influence of information technologies have changed the world because they link individuals through digital channels such as websites or social networking services to share ideas and beliefs. This communication cycle works as a valuable tool that can summon big groups of people, and during a catastrophic scenario, it may lead to disruptive episodes that threaten the fragile internal balance of the affected state. A key fact to highlight is that the nature of such events triggers a content demand surge which turns the Internet into a complex and disarranged milieu because the information is conveyed through a variety of flavours such as blogs, websites, video-sharing platforms or social networking sites [36].

During a crisis, data is crucial to augment our understanding of the crisis situation as it unfolds in real-time. Numerous examples can illustrate the way social media has been used during disasters or demonstrations, ranging from earthquakes to social unrests [37–39]. The Eunomia framework has aspired to bridge well-established theories from social and political sciences, and big data analytics to provide a holistic decision support framework and empower competent shareholders in their efforts to predict and manage human security crises [15–19,21]. The framework consists of two main stages as illustrated in Fig. 2. An initial phase (Warning Period) examines in real-time data from online activity, in a time-continuous manner to the extent that this is feasible, and spots changes in societal behavioural characteristics. When certain thresholds have been surpassed, it triggers an alert whereupon a subsequent ‘Crisis Interpretation’ phase inactivated. This starts to collect and analyse information from a variety of sources, such as web resources and social networking services, and extracts in-depth insights that can help the decision-makers to better understand the unfolding crisis. The following sections illustrate the different elements of this system.

3.1. Analysing a crisis

A crisis may be defined as an event where the affected group of people witnesses a disruption of routine, social structure, norms and values [36]. The COVID-19 pandemic had all the characteristics of a crisis, albeit of higher magnitudes, both in terms of how deep were the changes in certain behavioural aspects of people’s lives, and in terms of their geographical extent. Creating a holistic view of a crisis, encompassing all the affected human security elements, can provide enough insight to explain and interpret the crisis and its impact.

Table 1 summarises the insights that can be provided by the current implementation of the Eunomia framework. The next subsections discuss in more detail all the stages involved, as outlined in Fig. 2, and correspond to the columns of Table 1.
3.1.1. Event polarisation and early warning alert (Q1)

Early warning systems typically encompass disaster risk assessment, hazard forecast, prediction and monitoring, risk communication and emergency preparedness activities [40–42]. Natural and anthropogenic (human-induced) hazards can lead to disasters [36], which can represent a human security threat in the worst scenario. In the case of COVID-19 there has been an intense debate to classify it according to the two previous categories. Irrespective of the posture, the core point is identifying when individuals are heading towards a point of no return, which means that human security components have been altered. Frustration, anger, alienation are all factors that may unleash polarised collective behaviour, such as protests or riots [43]. Timely detection of societal instability sparks represents a core element of dealing with human security problems, as it enables the early prediction of likely major incidents, giving time to the authorities to decide the best course of action to diminish secondary effects. Preparedness for a human security crisis is a crucial step for which states must be ready.

The early warning stage of the Eunomia framework is based on an alert mechanism to identify tipping points, which are situations where the unfolding of events acquire their own irreversible dynamic [44]. In this mechanism, an alert is issued when a certain threshold has been exceeded on three key components: Global Polarisation (GP), Social Media Connectedness (SMC) and Human Security Impact (HSI) (Fig. 3) [15].

Due to the vast nuance of personal views conveyed during a crisis, interpreting messages offers a way to construe subjective information. The first stage (GP) examines individuals’ opinions based on a sentiment analysis process. As part of this stage, a data cleansing procedure has a preponderant role by removing stop words and URLs, replacing contractions and abbreviated words, and correcting errata.

Premised on a preceding calibration process, which is supported by the analysis of numerous incidents, a global polarisation index is used as a threshold to determine if the studied event has surpassed the pre-established limit, in which case the SMC process is activated.

Then, through the prism of a deep learning model, the SMC stage identifies when individuals felt attracted to the incident by considering that disruptive ideas have remained on trends for more than four continuous hours. However, to see through the deep learning model mentioned earlier, a binary classifier process comes into action. This artificial model analyses language text samples and performs the classification procedure to identify when comments are related to attracting intergroup attention or the call of masses, which is closely linked to the variable “people” of the human security components, as described in [15].

In a similar fashion to the preceding component (GP), a pre-defined threshold has been defined by examining multiple disruptive events. Then, the following stage (HSI) comes to the scene when the threshold, as mentioned earlier, has been exceeded.
The HSI step classifies the data corpus into ten human security aspects (health, public order, transport, economy, people, defence, environment, government, information and life) using unsupervised and supervised learning processes. Finally, using a preconfigured scale determines if human security components have been compromised.

3.1.2. Radical behaviour (Q2, Q3 and Q4)

A disaster, a crisis or a health crisis (pandemic) are triggers that tend to ramp up the exchange of data and relevant information, which is crucial in the immediate aftermath of an incident [45]. In the middle of these chaotic scenarios, messages containing a vast nuance of ideas, beliefs and thoughts are conveyed. Within this variety of disseminated topics, calls to violence messages are also transmitted. From a human security perspective, the viral propagation of this type of content can represent a severe threat. Because the idea to assassinate a person, destroy critical infrastructure or even exchange ammunition or weapons are activities that can travel from the virtual to the real world and unleash instability scenarios that might affect the human security components.

The analysis and extraction of radical expressions unveil personality traits together with other core societal aspects that facilitate the crisis interpretation process. In line with this idea, and following the workflow illustrated in Fig. 4, five different components are interconnected to detect radical behavioural traits: Instability Scenarios, Entity Extraction, Wordlists Creation, Analytics, and Data Interpretation [16].

These interlinked stages are supported by dissimilar computational techniques (such as deep learning, natural language processing, supervised and unsupervised learning), and opens up a route to understanding the radicalised environment by providing the following intelligence information:

1. Creation of instability scenarios.
2. Identification of affected entities (people, locations, or facilities).
3. Identification of likely affected entities due to their proximity to the incident.
4. Dissection of the intentions expressed towards an entity.
5. Analysis of the dissemination degree of the crisis (widespread or local incident).
6. Detection of violent expressions.
7. Classification of violent expressions.
8. Necessities shared by individuals amid the crisis.

It is pertinent to note that the nature of the events can bias the extraction of meaningful insights, as expressions and vocabulary conveyed during a political protest, a disaster or a crisis such as a pandemic are diametrically opposite but rich in specialised words. Word specialisation derived from these dissimilar scenarios brings to the table some disadvantages. Firstly, a continuous process of wordlists update needs to be performed since the detection of necessities requires two elements, a verb and a noun. The verb indicates the action that people want to do, and the noun refers to the object/thing that will receive the action (see Fig. 5).

The necessity of a specialised wordlist is displayed in Fig. 5, where both messages are related to people’s needs amidst an incident. On the one hand, a generic term ‘food’, but on the other hand, a specialised word that gained more relevance (popularity) because of the COVID-19 pandemic, ‘PPE’.

A second limitation is that the detection and classification of violent terms can be affected similarly to the previous case. By considering the same verb-noun structure, entities, which in this case are the nouns who received the action, can adopt multiple forms (time-dependent language expressions).

3.1.3. Ideology (Q5)

Information traffic surges in the digital channels during a disaster and a crisis since individuals want to share messages related to a vast nuance of topics such as meteorological and seismological information or even political views of an incident [36]. Nevertheless, those posts’ ideas, thoughts, and beliefs gain special attention when the disruptive content is directed towards other groups or even authorities. This collective set of emotions/comments can denote appraisals of superiority/inferiority, goal obstruction/injustices, or hostility, as described in [46,47]. Protests and violent events derived from societal problems (e.g. Black Lives Matter) or natural disasters (e.g. pandemics) are two examples of incidents. These disturbing plots have a particular interest as hostility traits may be present and maybe red flags that indicate that the stability of a state may have been compromised and a crisis is forthcoming [46,47]. In addition, such disruptive situations may evolve due to the fact that people do not empathise with decisions or activities performed by those who hold the “proper authority”, which can be
or information outlets) as the raw material to analyse the human resources (websites, social networking services, independent websites) and identify likely human security instability features. This method utilizes web security components, which work as an indicator of the presence of ideological traits of hostility and authoritarianism. Then a variational autoencoder model separates ideological traits with unforeseen patterns (anomalies), see Fig. 6. Next, the outcomes are compared against precalibrated thresholds that come from the examination of other incidents to determine the presence of the aforementioned ideological features.

3.1.4. Web insights (Q6)

The analysis of data deluge coming from multiple communication channels is a common problem that many organizations that are in charge of preparing emergency and human security plans are not prepared to deal with. Social media platforms have a preponderant role in this huge communication arena as millions of people have established networks to disseminate information, which outlines the complexity of analysing such a massive volume of data.

Within this heterogeneous mixture of communication channels, the complexity increases when a person posts a message since it may refer to another source (website or social networking service) that contains complementary information that reinforces the very essence of the message. In view of such complex scenarios, examining the message-embedded informational sources plays a significant role since it helps identify likely human security instability features.

The horizontal escalation analysis contributes to spot such instability insights by examining the increase in the number of human security components escalation described above, which may have been used as a mouthpiece to propagate the data throughout the crisis timespan.

The architecture of the web insights procedure begins with the extraction of URLs; then, those digital sources are grouped according to a pre-classified dictionary. Afterwards, a series of machine learning processes analyse the extracted content to perform two core subprocesses. The first one aimed at identifying/classifying violent phrases. The second one determines if the disruptive term relates to an entity of interest as critical infrastructure, people, or a location.

Finally, a multiclass text classification process spots which human security components are being affected and determine an increase in them, which can be construed as a horizontal escalation, see Fig. 8.

4. Deploying Eunomia and experimental results

The goal of the Eunomia framework is to monitor the state of the society at any particular moment and in case of an alert, to derive deeper insights about the situation and the threat it may constitute to human security. This section presents the deployment of Eunomia in two different cases of societal disruptions triggered by the COVID-19 pandemic. These cases have been selected to reflect two different cultural and socio-economic contexts: Asia and the USA.

The first case examines the protests in Pakistan in 2020, where the authorities deployed armed forces to enforce countrywide lockdown measures, and as a result, regional protests took place.

The second case investigates protests in the United States of America (Michigan and Texas), when societal disruptions were triggered due to discontent with restriction measures at the State level, imposed to control the spread of COVID-19.

The analysis of these cases aim to demonstrate the robustness and applicability of the framework for forecasting and analysing important real-world events: would the framework have been able to provide the competent authorities enough notice and insights to deal with the then-forthcoming crisis? The results support the paper’s premise that an insightful examination of imbalances in human security components contributes towards the timely detection of likely human security issues. The analysis also provides interested stakeholders postmortem insights about COVID-19 social crises with the view to contribute to the global effort to tackle this disruptive situation.
4.1. Protests in Pakistan

In early March 2020, small bursts of societal instabilities began to appear in Pakistan due to political views regarding health care sector problems, which were exacerbated by the pandemic. Tensions escalated, and on March 23, 2020, the army was deployed to assist civilian authorities to enforce lockdown measures after all provincial governments ordered a complete or partial lockdown to curb the spread of coronavirus disease (COVID-19) [52].

4.1.1. Data cleansing

The first stage of the analysis begins with the collection of 78,910 tweets, written in English, between 19th and 31st of March 2020, considering hashtags linked to the incident as shown in Fig. 9. Since tweets are unstructured data, the raw text was processed following the steps described below: (1) URLs were extracted; (2) RT and mention terms were removed; (3) contractions were replaced, for instance, is not: is not; (4) punctuation marks were removed; (5) emoticons were replaced by suitable terms; (6) duplicated messages were removed; (7) Internet slang was replaced by complete expressions using a preconfigured dictionary, for example, AFAIK: “as far as I know”, ASAP: “as soon as possible”, or BBL: “be back later”.

4.1.2. Early warning alert (Q1)

Fig. 10 depicts the analysis of the collected tweets for the incident in Pakistan, between the 19th and 31st of March 2020. On March 23rd, 2020, the local government deployed its army to enforce the lockdown measures imposed to contain the spread of COVID-19. As depicted in Fig. 10, the Alert Mechanism would raise a red flag (alert) two days before the government deployed its military personnel, suggesting that a crisis escalation could have been detected.

Observing Fig. 10, it is important to note that a surge in activity in the digital channels (such as a surge in negative sentiment tweets) does not necessarily show a crisis escalation. As explained in Section 3.1.1, the alert mechanism of Euonomies is based on examining three elements: Global Polarisation (GP), Social Media Connectedness (SMC) and Human Security Impact (HSI). It is the thresholds of these three elements that determine the presence of a tipping point.

4.1.3. Radical behaviour (Q2, Q3 and Q4)

The information disseminating during an incident or a crisis, often involves text that includes violent expressions, which embody the feelings and the ideas of a wider mass of people. Thus, a key element in our approach lies in extracting radical terms, as described in [16].

Q2. As shown in Table 2, a day before the Pakistani government deployed military personnel, people were posting regarding the lockdown in Karachi, and after the deployment of the armed forces, protesters were disseminating messages related to locking the Masjid mosque.

Q3. To avoid the further spread of COVID-19 among the population, lockdown measures were enforced on March 23rd. When our system triggered a red alert on March 21st, individuals were broadcasting messages associated with the evasion or violation of the lockdown. Their posts contained content indicating refusal, disagreement, defiance, and dissuasion, while the idea of taking to the streets to demand the withdrawal of the measures was also propagated during the following days.

Q4. Finally, as the pandemic affected people’s health, various health-related demands were also mentioned during the protests in Pakistan. On March 21st, individuals were asking for ventilators and other specialised equipment, such as (PPE), to help the health services cope with the crisis, see Table 2.

4.1.4. Ideology (Q5)

The public demonstrations in Pakistan against the restrictions imposed by local authorities struggling to contain the coronavirus, are examples of events where individuals shared their beliefs and ideas through digital channels. Within this environment, detecting ideological traits such as hostility and authoritarianism, along with radical expressions, can suggest the onset of a crisis, see Fig. 11. Following the framework described in Section 3.1.3, hostility and authoritarianism scores were computed and compared against a set of predefined thresholds [19].

Fig. 11 summarises measurements on ideological traits. On March 20th, a day before the alert was triggered, traits of hostility and authoritarianism were spotted. A day after, both ideological features increased considerably. These features continued to exceed the predefined thresholds, and on March 23rd, when the armed forces were deployed to enforce the lockdown measures, disgust and aggressiveness, which are components of hostility and authoritarianism, respectively, both witnessed a considerable surge.
4.1.5. Web insights (Q6)

During an incident, various digital channels are used to propagate ideas and beliefs, ranging from websites to social networking services. During the protests in Pakistan, people used social networking services as the primary communication channel, and as Fig. 12 shows, the health component was the most affected, from 19th to 24th of March. Moreover, from a horizontal escalation point of view, from March 20th to March 21st (when the alert was triggered), there was an increase in the number of affected human security components, from five to six. Such an increment suggests human security instability.

4.2. Protests in the United States of America

Two incidents that occurred in Michigan and Texas in April 2020 were studied. In both cases, citizens protested after local governments imposed lockdown rules, notwithstanding other types of restrictions previously introduced to tackle the pandemic.
### Table 2
Disruptive Expressions extracted using Word Embeddings and Direct Object during the protests in Pakistan.

| Location | Dates (2020) | March 19 | March 20 | March 21 | March 22 | March 23 | March 24 | March 25 | March 26 |
|----------|--------------|----------|----------|----------|----------|----------|----------|----------|----------|
| Pakistan |              | Aware ->People | Maintain ->Precaution | Impose ->Curfew | Trigger ->Riots | Lockdown ->Karachi | Enforce ->Lockdown | Lift ->Curfew |
|          |              | Violating ->Lockdown | Provide ->PPE | Disagree ->Curfew | Discover ->Antidote | Take ->Streets | Close ->Mosque | Impose ->Lockdown |
|          |              | Use ->Sanitisers | Take ->Precaution | Implementing ->Curfew | Declare ->Lockdown | Fight | Impose | Protest |
|          |              | Avoid ->Lockdown | Enforce ->Lockdown | Impose ->Lockdown | Impose ->Lockdown | Protest |
|          |              | Endure ->Lockdown | Impose ->Lockdown | Refuse ->Lockdown | Impose ->Lockdown | Protest |
|          |              | Use ->Sanitisers | Take ->Precaution | Implementing ->Curfew | Declare ->Lockdown | Fight | Impose | Protest |
|          |              | Avoid ->Lockdown | Enforce ->Lockdown | Imposing ->Lockdown | Dissuade ->Lockdown | Enforced ->Lockdown | Disobey | ->Lockdown |
|          |              | Enforce ->Lockdown | Impose ->Lockdown | Disobey ->Lockdown | ->->Lockdown | ->->Lockdown | ->->Lockdown | ->->Lockdown |
|          |              | Endure ->Lockdown | Use ->Sanitisers | Take into consideration ->Precaution | Impose ->Lockdown | Protest |

In the case of Texas, rallies were organised to show disagreement with the local lockdown measures, and the participants demanded the reopening of the economy [53,54].

By contrast, in Michigan, a convoy of thousands of motorists drove from all over the state to protest the governor’s stay-at-home order extension. The protest, known now as Operation Gridlock, involved clogging with their vehicles the streets surrounding the Michigan State Capitol, including the Capitol Loop, and it drew human attention [55].

#### 4.2.1. Data cleansing

A data corpus of six million tweets written in English was collected, covering the dates from 10th to 20th April 2020, by considering hashtags such as #covid, #coronavirus, #coronavirusoutbreak and #coronaviruspandemic. Then, two data subsets were extracted from the anterior dataset, each subset containing tweets with a unique combination of specific parameters, such as hashtags that were linked to the studied entities (locations), as depicted in Table 3.

Once these two subsets have been created, tweets appertained to the former clusters were cleansed in a similar fashion to Section 4.1.1.

#### 4.2.2. Early warning alert (Q1)

The Alert Mechanism of Eunomia as described in Section 3.1.1 has been applied in the two incidents in the USA.

**Michigan.**

Fig. 13. It shows that the system would generate an alert on 14th April 2020, a day before protests began because the governor’s “stay at home” order was declared, and five days before protests escalated (19th April 2020). The triggered alarm suggests that the internal cohesion amongst human security components has been disrupted.

**Texas.**

As depicted in Fig. 13 II on 11th April 2020, an alert was triggered by the early warning process, eight days before protests against Coronavirus policies intensified (19th April 2020).
Incitement to actions affecting various public thoroughfares, such as blocking roads or taking to the streets, were also present, such as demands to reopen, lift the quarantine, and liberate masks while protesting; moreover, messages suggesting the location of the protest, namely Michigan, were conveyed too.

On the 18th and 19th April 2020, demands related to the lift of the lockdown and messages urging to continue protesting against the imposed measures were spread. In addition, some other ideas were present, such as demands to reopen, lift the quarantine, and liberate from the lockdown. Incitement to actions affecting various public thoroughfares, such as blocking roads or taking to the streets, were also present.

Q4. Lastly, messages where individuals conveyed their personal needs for PPE (personal protective equipment), or urge for action towards a cure for COVID-19 were shared likewise, see Table 4.I.

Texas.

Q2. Radical behavioural traits revealed that individuals expressed ideas linked to reopening a specific location, namely, Texas, see Table 4.II. According to Levin’s classification [56], the verb “need” expresses that a person desires something. Following Levin’s analysis, on April 17th 2020, messages were posted conveying the desire that a different location, Michigan, would join the incident. As argued in [57], this mention of different locations, suggests that the state is dealing with a widespread event.

Q3. Social media users (Twitter) expressed concepts connected to the demand of allowing business in the city, lifting the quarantine, and contempt towards Coronavirus, as described in Table 4.II. On the other hand, in the following days (17th, 18th and 19th April 2020), messages that instigate violations of the lockdown, urge protest and boycott, close schools, wear PPE, and spread the frustration, were shared.

Q4. Concerns about health were also transmitted, related for example to the need for more nurses, and the rise of deaths.

4.2.4. Ideology (Q5)

In order to begin the dissection of ideology in the COVID-19 datasets, a sentiment analysis process was performed, then tweets with negative polarisation were selected accordingly. In both cases, negative sentiments played the predominant role; Michigan had the highest percentage with 51%, while Texas had 35%. Then authoritarianism and hostility traits were computed using the methodology and thresholds proposed in our previous study [19]. When the calculated variables of authoritarianism (aggressiveness, submission and conventionalism) and hostility (anger, contempt and disgust) were above the predefined thresholds, the results were deemed to suggest that the aforementioned ideological traits were present.

Michigan.

A day after the early warning alert was triggered (April 14th 2020), signs of authoritarianism and hostility were detected (April 15th 2020), the same date that the local government imposed the lockdown, see Fig. 14.

Texas.

On April 11th 2020, ideological traits were detected, the same date that the early warning alert was triggered, see Fig. 14. This specific point turns into a modular axis, since people were concerned about competing aspects such as the COVID-19 death toll, and lifting the quarantine, see the radical behaviour analysis in Section 4.2.3 and Table 4.II. Regarding authoritarianism, it should be noted that in both of the studied cases, aggressiveness was above 60% of the precalculated threshold, while the other two variables showed irregular increments. The consistent increase in aggressiveness suggests that people were conveying messages indicating prejudice/intolerance against a specific topic [49], here a lockdown, a curfew, or a quarantine, see Table 4.

4.2.5. Web insights (Q6)

During an incident or a health crisis such as COVID-19, individuals and organisations use digital channels to disseminate information and data such as breaking news, messages or pictures, the analysis of which can help understand whether a crisis is escalating over time. Hence, as described in Section 3, the web insights methodology proposed in our previous work [16] enables the study of the horizontal escalation of human security components. Following the methodology there, URLs were classified according to a comprehensive list of entities created over the Wikidata knowledge base. Then, a web scrapping process was conducted to retrieve the content of such web resources.

Michigan.

It can be seen in Figs. 15.I and 15.II, that only two media resources were embedded in people’s messages while posting a tweet, namely Independent Websites (IW) and Social Networking Services (SNS).

On April 14th 2020, when the early warning alert was triggered, SNS (Instagram and Twitter) were used to convey that one human security component was being affected, in this case, health. One day later, messages posted on those social media sites showed that four human security components were unbalanced (information, defence, business and health). Such increment in the number of affected components (from one to four), demonstrates a horizontal escalation, which according to [51] may represent a disruptive situation, see Fig. 15.I.
It should be noted that both business and government components had the highest intensities, which may complement the behavioural traits previously extracted that referred to violating the lockdown and the disagreement towards that measure (see Table 4.I).

On the other hand, IW showed on April 15th 2020, that three human security components were affected, namely defence, information and government, with the government having the highest intensity figure. The result suggests that those web resources were providing a more detailed description of the government’s activity (see Fig. 15.II).

On the following days (17th, 18th and 19th April 2020), both IW and SNS published content affecting the health and information components. The result is relevant since, on April 19th, COVID-19 cases began to spike [55]. By contrast, only SNS revealed information about two other components (people and public order), as displayed in Fig. 15.I.

### Table 4

Disruptive Expressions extracted using Word Embeddings and Direct Object (Texas and Michigan).

| Location | Dates (2020) | Location | Dates (2020) |
|----------|--------------|----------|--------------|
|          | April 10 | April 11 | April 12 | April 15 | April 16 | April 17 | April 18 | April 19 |
| I. Michigan | April 10 | April 11 | April 12 | April 15 | April 16 | April 17 | April 18 | April 19 |
| Location | Dates (2020) | Location | Dates (2020) |
|----------|--------------|----------|--------------|
|          | April 10 | April 11 | April 12 | April 15 | April 16 | April 17 | April 18 | April 19 |
| Location | Dates (2020) | Location | Dates (2020) |
|----------|--------------|----------|--------------|
|          | April 10 | April 11 | April 12 | April 15 | April 16 | April 17 | April 18 | April 19 |

**Fig. 14.** Ideological traits (Michigan and Texas).

**Texas.**

Figs. 16.I, 16.II and 16.III show that three digital web resources were used by people to disseminate information amidst the protests, namely, IW, SNS and Non-Profit Organisations.

As mentioned earlier, the early warning alert and the emergence of ideological traits happened on the same date (11th April 2020). Unlike the previous case, the Independent Websites were used more intensively and they unveil that two human security components were disrupted, business and health; while SNS showed that only the business component was affected, with 80% less intensity than in IW.

Visible changes were displayed between 13th and 18th April 2020, as the IW and SNS showed an increased number of affected components, which exposed a horizontal escalation across the human security factors, which went from two affected factors to five for the IW, and from one to four for SNS.

In addition, Non-profit organisations played a crucial role on the 18th and 19th April 2020, because topics in business and health were
affected by them. Moreover, intensity health levels had a considerable increase of 85%, while, by contrast, health levels in SNS and IW showed little change, around 7% on average. Such a difference indicates that Non-profit organisations were stressing issues linked to health.

Finally, it should be noted that on April 19th, when the highest burst of online activity took place (see Fig. 13. II), SNS were used to convey more messages linked to people, as indicated by an increase of 70%; whereas IW was focused on disseminating data related to the information component, which had an increment close to 28%.

5. Summary and discussion

As COVID-19 has so clearly demonstrated, pandemics constitute a severe human security threat, and they can become breeding grounds for societal instabilities, which can affect multiple human security components. Given the complexity of analysing and detecting human security threats, and motivated by the importance of providing relevant information to facilitate the decision-making process, this paper has presented a holistic analytics framework for analysing human security aspects.

In the era of digital media, social networks and other communication channels use the Internet to disseminate information faster than ever before. They act as a multiplier of ideas, thoughts, beliefs, and, therefore, they disseminate ideologies that can turn into violent actions or societal disruptions. Quite often, such disruptions feedback into their initial trigger, as is the case with the COVID-19 pandemic, where the infection rate can increase as a result of the aforementioned societal instabilities. In turn that leads to other human security elements being impacted in parallel, such as economic and food security.

This paper has discussed the utilisation of the framework for analysing human security aspects in the context of COVID-19. Two real-world cases were considered where authorities’ measures to contain the disease via lockdowns resulted in protests and social unrest. The cases represent different cultural, political and socio-economic contexts. The results have demonstrated the ability of the system to provide early warning well in advance of the manifestations of social unrest. It also demonstrated its capacity to provide insights enabling a better understanding and interpretation of the crisis.

The presented framework constitutes an effort to demonstrate the feasibility and robustness of proposed approach. This work has pointed to a number of challenges that still need to be addressed.

One aspect that characterises human beings is the ability to constantly learn new concepts and incorporate them to address new and varied scenarios. Similarly, society has to deal with a wide variety of events that include demonstrations or riots, but whose genesis responds to such a dynamic nature that is hard to adapt to. One way to illustrate this is the disruptive nature of the COVID-19 pandemic which introduced, new issues, discussion topics and new terminology used to convey information. Analysing such complex scenarios requires computational models with adaptive capabilities since new vocabulary, information and knowledge need to be incorporated to update the models as incidents and their nature is continuously evolving/changing and new data is generated. This is exacerbated by the different cultural, political and socio-economic contexts that result in different communication nuances. However, the Alert mechanism described in Section 3.1.1 is based on a static and offline configuration for the calculation and calibration of the different components and thresholds involved. There are two major issues with this approach. Firstly, a low
fixed value of the thresholds may lead to false alarms; conversely a high value may reduce false alarms but will reduce the notice period to very close to the event. An alternative approach would therefore be desirable whereby the models constantly absorb new data, and learn and adapt to new situations. One way to achieve this is by enriching the SMC substage with adaptive capabilities that would enable the incorporation of knowledge through incremental learning and would allow the adaptation of thresholds that trigger the alert. Work in this direction (utilising Q-learning) is already underway.

Another challenging issue is the consideration of language expressions as they can involve a myriad of nuances due to regionalisms or because new or non-trivial words come to light as a result of new disruptive events (e.g. PPE or Personal Protective Equipment, in the case of COVID-19). Incorporating techniques as such incremental learning would create the dynamic models that respond to these types of core challenges. The current system is able to deal with only the English language. The current system is only able to deal with the English language, which significantly limits its scope in English speaking populations. It is therefore important that other languages are incorporated.

Future work will address the aforementioned challenges and will fully integrate and automate the different components of the framework, utilising additional data analytics approaches and developing dashboards that can form part of intelligent emergency operation centres.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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References

[1] S. Kharroubi, F. Saleh, Are lockdown measures effective against COVID-19? Front. Public Health 8 (2020) 549692, https://doi.org/10.3389/fpubh.2020.549692, Published 2020 Oct 22.
[2] P. Peretti-Watel, V. Seror, S. Curtaredona, O. Launay, J. Raude, P. Verger, et al., Attitudes about COVID-19 lockdown among general population, France, 2020, Emerg. Infect. Diseases 27 (1) (2021) 301–303, http://dx.doi.org/10.3201/eid2701.210377 (2021).
[3] Marco Di Liddo (Ed.), The Impact of Covid-19 on Human Security, Center for International Studies (CeSI), 2021.
[4] E. Newman, Covid-19: A human security analysis. Global society, Routledge, 2021, http://dx.doi.org/10.1080/13600826.2021.2000304.
[5] I. Kureshi, G. Theodoropoulos, E. Magina, G. O'Hare, J. Roche, Towards an info-symbiotic framework for disaster risk management, in: The 19th IEEE/ACM Interhuman Symposium on Distributed Simulation and Real Time Applications, DS-RT 2015, Xinhua Interhuman Hotel, Changdu, China, October, 2015, pp. 14–16.
[6] T. Töth, G. Theodoropoulos, S. Bol, I. Kureshi, A. Ghandar, Global challenge governance: Time for big modelling? in: 2019 IEEE 18th Interhuman Conference on Cognitive Informatics & Cognitive Computing, KCCI-CC, Milan, Italy, 2019, pp. 244–253.
[7] Peter J. Haas, Georgios Theodoropoulos, Introduction to the special issue for towards an ecosystem of simulation models and data, ACM Trans. Model. Comput. Simul. 30 (4) (2020) 20, http://dx.doi.org/10.1145/3425907.3425908, 3, 2020.
[8] H. Roef, Uncomfortable Ground Truths: Predictive Analytics and Human Security, Brookings human security report, 2020.
[9] B. Akhgar, G. Saathoff, H. Arabnia, R. Hill, A. Staniforth, P. Bayerl, Application of Big Data for Human Security: A Practitioner’s Guide To Emerging Technologies, Butterworth-Heinemann, 2015, Paperback ISBN: 9780128019733, 10.
[10] Project PERICLES: Policy recommendation and improved communication tools for law enforcement and security agencies preventing violent radicalisation, European Commission, https://cordis.europa.eu/project/id/740773.
[11] CEWS homepage, 2021, https://ntm.cn/3owTJ8L. Last (Accessed 10 January 2021).
[12] S. Muthiah, et al., EMBERS at 4 years: Experiences operating an open source indicators forecasting system, in: Proceedings of the 22nd ACM SIGKDD, New York, NY, USA, 2016.
[13] X. Zhang, J. Li, X. Zhang, J. Fu, D. Wang, Construction of a geopolitical environment-simulation and prediction platform coupling multi-source geopolitical environmental factors, Sci. Technol. Rev. 36 (3) (2018).
[14] D. Van Puyvelde, S. Gouldart, M.S. Hossain, BEyezond the buzzword: big data and human security decision-making, Interhuman Aff. 93 (6) (2017).
[15] P. Cárdenas, G. Theodoropoulos, B. Obara, I. Kureshi, Defining an alert mechanism for detecting likely threats to human security, in: IEEE Interhuman Conference on Big Data, USA, 2018.
[16] P. Cárdenas, G. Theodoropoulos, B. Obara, Web Insights for human security: Analysing participative online activity to interpret crises, in: IEEE Interhuman Conference on Cognitive Informatics and Cognitive Computing, Italy, 2019.
[17] P. Cárdenas, G. Theodoropoulos, B. Obara, I. Kureshi, Analysing social media as a hybrid tool to detect and interpret likely radical behavioural traits for human security, in: IEEE Interhuman Conference on Big Data, USA, 2019.
[18] P. Cárdenas, G. Theodoropoulos, B. Obara, I. Kureshi, A conceptual framework for social movements analytics for human security, in: The Interhuman Conference on Computational Science, 2018.
[19] P. Cárdenas, G. Theodoropoulos, B. Obara, I. Kureshi, Unveiling ideological features through data analytics to construe human security instabilities, in: IEEE Interhuman Conference on Big Data, USA, 2020.
[20] World health organization. WHO coronavirus (COVID-19) dashboard. World health organization homepage, 2021, https://bit.ly/3pGWvCa. Last (Accessed 28 October 2021).
[21] P. Cárdenas, B. Obara, I. Ivrissimtzis, I. Kureshi, G. Theodoropoulos, Big data for human security in the era of COVID-19, in: Computational Science – ICCS 2021, 2021.
[22] E. Newman, Human security: Reconciling critical aspirations with political ‘realities’, Br. J. Criminol. 56 (6) (2016).
[23] S. Tadjbakhsh, A. Chenoy, Human Security Concepts and Implications, Routledge, London, 2006.
[24] M. McIntosh, A. Hunter, New Perspectives on Human Security, Routledge, London, 2017.
[25] D. Andersen-Rodgers, K.F. Crawford, Human Security: Theory and Action, Cambridge University Press., 2016.
[26] D. Gasper, A. Oscar, Human security thinking in practice: Personal security, citizen security and comprehensive mappings, Contemp. Politics 21 (1) (2015) 100–116.
[27] S.N. MacFarlane, Y.F. Hong, Human security and the UN, in: A Critical History, Routledge, London, 2021.
[28] R. Christie, Critical voices and human security: To endure, to engage or to critique? Secur. Dialogue 41 (2010) 169–190.
[29] D. Chandler, Human security: The dog that didn’t bark. Secur. Dialogue 39 (2010) 427–438.
[30] M. Martin, T. Owen, The second generation of human security: Lessons from the UN and EU experience, Int. Aff. 86 (1) (2010) 211–224.
[31] R. Paris, Human security: Paradigm shift or hot air? Int. Secur. 26 (2) (2001) 87–102.
[32] E. Newman, Human security - conflict, critique, and consensus: Colloquium remarks and a proposal for a threshold-based definition, Secur. Dialogue 35 (3) (2004) 373–387.
[33] Human Development Report, United Nations Development Program, Oxford University Press, New York and Oxford, 1994, pp. 22–33.
[34] Transforming Our World: The 2030 Agenda for Sustainable Development, United Nations Report A/RES/70/1, 2015.
[35] L. Klarèevs, C. Clarke, COVID-19 is a threat to human security. Let’s start treating it as such, just security, 2020.
[36] C. Castillo, Big Crisis Data: Social Media in Disasters and Time-Critical Situations, Cambridge University Press., 2016.
[37] H.N. Nguyen, T. Dang, EQSAI: Earthquake situational analytics from social media, in: IEEE Conference on Visual Analytics Science and Technology (VAST), 2019.
[38] L. Tan, S. Ponnam, P. Gillham, B. Edwards, Johnson E., Analyzing the impact of social media on social movements: A computational study on Twitter and the occupy wall street movement, in: IEEE/ACM Interhuman Conference on Advances in Social Networks Analysis and Mining, 2013.
[39] Statista homepage. Most popular social networks worldwide as of 2021, 2021, https://bit.ly/3sfa0Yz. Last (Accessed March 10 (2021).
[40] J.C. Villagrán de León, Early warning principles and practices, in: B. Winner, J.C. Gaillard, I. Kelman (Eds.), Handbook of Hazards and Disaster Risk Reduction and Management, Routledge, Abingdon, 2012, pp. 481–492.
[41] J.C. Villagrán de León, J. Bogardi, S. Dannemann, R. Barter, Early warning systems in the context of disaster risk management, Ländlicher Raum 2 (2006) 23–25.
[42] V. Marchezini, F.E.A. Horita, P.M. Matsuo, R. Trajber, M.A. Trejo-Rangel, D. Olivato, A review of studies on participatory early warning systems (P-EWS): Pathways to support citizen science initiatives, Front. Earth Sci. 6 (2018) 184, http://dx.doi.org/10.3389/feart.2018.00184.
[43] J.M. Jasper, The emotions of protest: Affective and reactive emotions in and around social movements, Sociol. Forum 13 (1998).
[44] E.H. van Nes, B.M.S. Arani, A. Staal, B. Bolt, B.M. Flores, S. Bathiany, M. Scheffer, What do you mean, 'Tipping Point'? Trends Ecol. Evol. 31 (12) (2016) 902–904, http://dx.doi.org/10.1016/j.tree.2016.09.011.
[45] B. Bjerge, N. Clark, P. Finker, E. Raja, Technology and information sharing in disaster relief, PLoS One 11 (9) (2016).
[46] A.H. Maslow, Authoritarian character structure, Soc. Psychol. (1943).
[47] D. Matsumoto, et al., The role of intergroup emotions in political violence, Curr. Dir. Psychol. Sci. (2015).
[48] R.A. Saunders, J. Ngo, The right-wing authoritarianism scale, in: V. Zeigler-Hill, T. Shackelford (Eds.), Encyclopedia of Personality and Individual Differences, Springer, Cham, 2017.
[49] P. Dunwoody, F. Funke, The aggression-submission-conventionalism scale: Testing a new three factor measure of authoritarianism, J. Soc. Political Psychol. (2016) North America.
[50] D. Troest, Emotions of protest, emotions in politics, in: Palgrave Studies in Political Psychology series, Palgrave Macmillan, London, 2013.
[51] J. Patrick, Cullen and erik reichborn-kjennerud, in: MCDC Countering Hybrid Warfare Project:Understanding Hybrid Warfare, Multihuman Capability Development Campaign, 2017.
[52] A. Gul, Pakistan Deploys Army To Deal with Coronavirus Outbreak, The Voice of America, 2020, 23 March.
[53] A. Jeffery, Scenes of protests across the country demanding states reopen the economy amid coronavirus pandemic, 2020, CNBC. 18 April.
[54] Hundreds protest COVID-19 orders at texas capitol, FOX4news homepage, 2021, https://bit.ly/38IA1rl. Last (Accessed 14 January 2021).
[55] B. Hutchinson, Operation gridlock’: Convoy in Michigan’s capital protests stay-at-home orders, 2020, ABCNews. April 16.
[56] B. Levin, English Verb Classes and Alternations: A Preliminary Investigation, University of Chicago Press, Chicago, 1993.

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