Big Data for National Security in the Era of COVID-19

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Abstract. The COVID-19 epidemic has changed the world dramatically as societies adjust their behaviour to meet the challenges and uncertainties of the new normal. These uncertainties have led to instabilities in several facets of society, most notably health, economy and public order. Increasing discontent within societies in response to government mandated measures to contain the pandemic have triggered social unrest, imposing serious threats to national 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 national security. This paper presents the utilisation of a big data forecasting and analytics framework to deal with COVID-19 triggered social unrest. The framework is applied and demonstrated in two different disruptive incidents in the United States of America.

Keywords: COVID-19 · Epidemics · Big Data · National Security · Data Analytics · Machine Learning

1 Introduction

Global challenges and emergencies such as climate change, epidemics and natural and man-made calamities present unprecedented governance issues. The COVID-19 pandemic has demonstrated how a global challenge can disrupt more than 180 countries. Governments across the globe have taken strict decisions aimed at containing the disease and avoiding massive infections, such as curfews, lockdowns, “stay at home” orders, or compartmentalization of domestic territories according to their infection rates [1].

Such measures represent a meaningful way to control the disease, however, they also have a negative effect on people’s lives imposing dramatic changes in the ways of life people had been used to. As a result, containment measures have often be met with varying degrees of social discontent and unrest, from protests and non-compliance actions to more violent manifestations such as demonstrations and riots [2]. A state’s stability could be seriously undermined by such social instability incidents, which may have a negative effect on national security components such as health, economy, and public order [3].

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DOI: 10.1007/978-3-030-77961-0_7

Policy and decision-makers need to have at their disposal technological tools, acting as force multipliers and enabling insights about disasters and unfolding situations, so that an assessment of the scale of the threat to national and international security can be made [4, 5]. Big Data technologies can provide a powerful means in this endeavour [6, 7]. As a result the last decade we have witnessed the development of several computational platforms that utilise Big Data analytics to derive insights about disruptive situations that can trigger social unrest [8–13].

Contributing to this effort, in earlier work we have proposed a framework and the associated workflow for the analysis of social media data (Twitter) to derive insights about disruptive events and potential unrest [14–18]. In this paper, this framework is utilised to analyse the COVID-19 pandemic. Our analysis focuses on two geographical areas where acts of social unrest were witnessed as a result of COVID-19 containment measures, namely Michigan and Texas.

The aims and contributions of this paper are twofold. Firstly, to demonstrate the robustness and applicability of our framework for forecasting and analysing important real-world events such as COVID-19 related unrest: would the framework have been able to provide the competent authorities enough notice and insights to deal with the then unfolding crisis? Secondly, to provide interested stakeholders postmortem insights about COVID-19 social crises with the view to contribute to the ongoing global effort to tackle this disruptive situation.

The rest of the paper is organised as follows; Section 2 briefly discusses the impact of pandemics such as COVID-19 on National Security; Section 3 provides an overview of the framework; Section 4 illustrates the operationalisation of the methodology, examining two events regarding COVID-19 related outbreaks; Section 5 concludes the paper.

2 COVID-19 and National Security

National security threats refer to those activities that endanger the individuals' physical well-being, or compromise the stability of the state. When we place people at the centre of the analysis of how national security is affected, in which case it is also referred to as human security, we typically distinguish between seven different components: economic security, food security, health security, environmental security, personal security, communal security and political security [3]. Instabilities are generated due to the disruption of one or more these components leading to protests, riots and other forms of violence [17, 19]. According to the Global Peace Index [20], civil unrest has doubled over the past decade, and riots, strikes and anti-government protests increased by 244%.

Countries around the world define their domestic security threats based on their internal policies. Pandemics are typically considered national security threats due to their negative social, economic and political impacts [22]. As a global pandemic, COVID-19 represents a serious National Security threat [23]. The negative social and economic effects of lockdowns and curfews have fuelled preexisting social discontent and unrest (e.g. in the Black Lives Matter movement, or the demonstrations in Hong Kong) as well as new anti-lockdown

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DOI: 10.1007/978-3-030-77961-0_7

demonstrations. These demonstrations, in turn, act as super-spreader events, further exacerbating the negative impacts of the pandemic [21].

3 An Overview of the Framework

The methodology described in our previous work [14–18], attempts to enrich the security decision-making process scenario. It analyses national security considering its broad spectrum components, including but not limited to health and public order; enabling in such a way to detect timely tipping points and examine a variety of situations as riots, protests or events linked to health issues such as COVID-19.

The framework consists of two main stages (see Figure 1). An initial phase (Warning Period) continuously analyses data and issues an alert when it identifies that specific societal behavioural characteristics exceed a given threshold (tipping point). The system then gets into its next phase (Crisis Interpretation) by collecting information from numerous sources, such as social networking services or websites, to attempt to zoom in and provide more in-depth insights that unveil data to construe the unfolding crisis and support therefore authorities and other stakeholders into making better decisions.

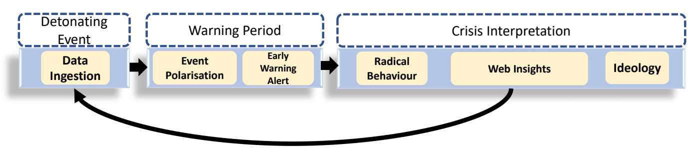

Fig. 1: Conceptual framework, as described in [14–18].

Under the new normal, where COVID-19 tends to modify important behavioural aspects of people's lives, understanding features that directly impact the security of a state becomes crucial. Here, our aim is to use features extracted from our conceptual framework to interpret the health crisis. The characteristics we used here are summarised in Table 1. In the next subsections, we provide a stage by stage overview of the framework.

Insights		Stages			
		Early Warning Alert	Radical Behaviour	Ideology	Web Insights
Q1.	When do people head towards a situation that evokes that both social stability and national security components can be compromised?	✓	-	-	-
Q2.	Which entities are described by people during the crisis?	-	✓	-	-
Q3.	What are the radical behavioural traits being conveyed?	-	✓	-	-
Q4.	What items are being asked for by individuals in social media?	-	✓	-	-
Q5.	Are hostility and authoritarianism traits present during the incident?	-	-	✓	-
Q6.	Do embedded web resources in social media texts disclose that the national security components have a horizontal escalation over time?	-	-	-	✓

Table 1: Insights derived from the Analytics Framework described in [14–18].

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3.1 Event Polarisation and Early Warning Alert (Q1)

As explained in [17, 24, 25], a detonating event is an incident that may trigger a disruptive situation that can lead to social unrest and threaten national security components. The Warning stage aims to identify which human security components are being affected and, if such impact exceeds a certain threshold, to issue an alert.

More specifically, the alert is issued when the three components of Global Polarisation (GP), Social Media Connectedness (SMC) and Human Security Impact (HSI) have reached a predefined threshold, as described in [14]. First, the GP process performs a sentiment analysis procedure, and when the negative polarisation starts fluctuating above a predefined verge, triggers the next step. The SMC step, based on a Deep Learning model, reveals when individuals are engaged towards the incident. Finally, 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, it determines if human security components have been compromised.

Once these three steps have been completed, an alert is issued to indicate that the society is heading towards a tipping point, namely a situation where the crisis tends to affect the components that keep a state's stability, which means a point of no return.

3.2 Radical Behaviour (Q2, Q3 and Q4)

Social media is a complex and disarranged milieu in both normal conditions and during crises [26]. Emergencies/incidents are situations where online activity tends to ramp up significantly [27]. Such bursts of activity can provide information linked to various social aspects, but here those aspects that may unbalance the integrity of a state gain special attention.

Based on the analysis of disruptive expressions, the radical behaviour methodology, as detailed in our previous work [16], comprises eight components: (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) Dissemination degree of the crisis (widespread or local incident), (6) Detection of violent expressions, (7) Classification of violent expressions, and (8) Necessities shared by individuals amid the crisis.

As detailed in [16], the radical behaviour architecture comprises of five stages: Instability Scenarios, Entity Extraction, Wordlists Creation, Content Analytics and Data Interpretation. The sequence of the above mentioned procedures is underpinned by an array of interconnected computational techniques, such as deep learning, natural language processing, supervised and unsupervised learning. It should be noted that the extraction of meaningful insights from the above, depends on the nature of the incident since a violent public disorder or a protest amidst a pandemic have dissimilar roots, and therefore features such as violent expressions cannot be detected with the same frequency.

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As part of the communication cycle, individuals use words or specific terms to embody the situation they have to cope with. We note that the pandemic is affecting not only the way people live and work, but also the way they communicate. Indeed, COVID-19 has drawn to the scene numerous new terms that enrich the everyday vocabulary to the level necessary to convey the message. Therefore, the Wordlist Creation step had to be enriched by adding a comprehensive glossary that included terms such as, case fatality rate (CFR), or personal protective equipment (PPE) [28–30].

3.3 Ideology (Q5)

The term ideology usually refers to a set of ideas and beliefs taken from a more complex system of ideas, such as popular sovereignty or nationalism [31]. Another way to approach this concept is by linking it to the processes of giving legitimacy to the power of a dominant group [32]. In both approaches, the term ideology describes fundamental beliefs shared by a social group [33].

During an organised public demonstration or a riot, ideas, beliefs and actions directed against authorities or other groups may emerge [34]. Here, collective emotions denoting appraisals of superiority/inferiority, goal obstruction/injustices, or intolerability, also described in [35] as hostility, play a big role. Protests and other disruptive incidents are two examples of events where hostility may be present and where tints of violence can be a signal of the instability of the state, which in turn may represent the prelude of a crisis [35, 36].

In addition, such disruptive events 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 perceived as a high level of authoritarianism against them, as measured in an aggression, submission and conventionalism scale [37, 38]. Governments around the globe have introduced various measures to contain the virus. Notwithstanding the differences, the nature of the restrictions may generate traits of hostility and authoritarianism, which is why both ideological characteristics will be used in this work, similarly to the methodology proposed in our work [18].

The ideology traits are spotted following a data analytics procedure that involves the processing of emotions in unstructured data (tweets) to identify the internal components of authoritarianism and hostility, followed by a deep generative model (variational autoencoders) centred on separating the ideological features from the rest of the data. Lastly, such information is compared to a precalibrated model to determine the presence of such ideological characteristics.

3.4 Web Insights (Q6)

While a disruptive event occurs, individuals adopt responses shaped by the nature of the incident, which runs from protests and large-scale mobilisations to violent activity. As a result of such activities, human security components get affected, since a violent incident does not only impact a prima facie component such as "public order", but also "health" as some protesters can be hurt as the situation gets nuanced by more aggressive reactions.

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Such an aspect gains importance since national security can be compromised when the number of affected human security components increases over time, which is called horizontal escalation, as described in [39]. Horizontal escalation can be accelerated by the use of web resources (websites, social networking services, independent websites or information outlets), which become a tool to disseminate information and work, for example, as a mouthpiece to organise demonstrations. In the preceding work [15], an architecture aimed at analysing the horizontal escalation of human security components along on-line participative channels was presented. There, a classification model is used to cluster the various human security components from the data corpus, and it yields baseline thresholds to analyse the aforementioned escalation characteristics in future events.

4 Analysing Two COVID-19 disruptive events

As stated earlier, the conceptual framework's main objective 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 national security. With this goal in mind, two incidents of social unrest, which occurred in April 2020 in Michigan and Texas, are studied, both related to COVID-19 outbreak.

The two events were chosen in consideration of the people's reactions. In both cases, citizens protested after local governments adopted lockdown rules, notwithstanding the strict restrictions imposed to tackle the pandemic.

In the case of Texas, rallies were organised to show disagreement against local restriction measures, and people demanded to reopen the economy [40, 41].

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 drew national attention [42].

4.1 Data Collection and Cleansing

A data corpus of six million tweets written in English was collected 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 2.

Once these two subsets have been created, tweets appertained to the former clusters were cleansed following the steps described below: (1) URLs were extracted; (2) RT and mention terms were removed; (3) contractions were replaced, for instance, wasn't: was not; (4) punctuation marks were removed; (5) emoticons were replaced by words; (6) 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".

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Dataset 1 (Michigan ,USA)		Dataset 2 (Texas, USA)	
#michigan	#michiganprotest	#texas	#reopentexas
#liberatemichigan	#michiganlockdown	#opentexas	#stayhometexas
#freemichigan	#michiganshutdown	#texasstrong	#texans

Table 2: Popular hashtags posted on April 2020 linked to two locations, namely, Michigan and Texas. The depicted hashtags in the table involve two tokens, the first one associated with a location and the other with a noun/verb. The two types of tokens are shown in different colours - red and black.

4.2 Early Warning Alert (Q1)

Once an incident is unfolding, the stability of the state can be compromised due to national security components instability, at which point identifying if an event heads toward a significant disruption scenario becomes a primary task. In light of this, the analysis of three indicators, namely, Global Polarisation, Social Media Connectedness and Human Security Impact, enable the identification of the real nature of the event by triggering an early warning alert, as described in Section 3 [14].

Michigan Figure 2.I 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 national security components has been disrupted.

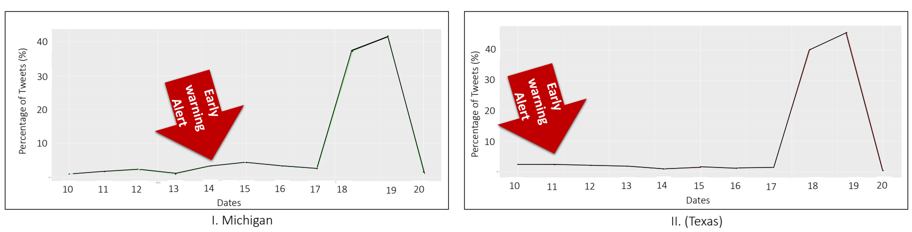

Fig. 2: Early Warning Alert Detection in the events of Michigan and Texas in April 2020.

Texas As depicted in Figure 2.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).

4.3 Radical Behaviour (Q2, Q3 and Q4)

The analysis of radical behavioural traits can lead to critical and actionable insights. Table 1 demonstrates how addressing Q2, Q3 and Q4 enables the identification of entities, behavioural traits and required objects; justifying the use

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of the radical behaviour analysis methodology proposed in our previous work [16] to enrich this part of the analysis.

Location	Dates (2020)							
	April 10	April 11	April 12	April 15	April 16	April 17	April 18	April 19
I. Michigan				Violating -> Lockdown		Stop -> Insanity	Cancel -> Lockdown	Avoid -> Quarantine
				Disagree -> Curfew		Take -> Streets	Protest -> Lockdown	Violating -> Distancing
				Protest -> Rally		Break -> Demand	Take -> Lockdown	Michigan -> Edict
				Protest -> Virus		Protest -> Michigan	Protest -> Distancing	Need -> Lawmaker
						Wear -> Masks	Demand -> Reopening	Break -> Curfew
						Shut -> Now	Liberate -> Lockdown	Want -> Cure
							Block -> Roads	Want -> PPE
							Rally-> Arizona	Take -> Streets
II. Texas		Allow -> Business	Halt -> Covid			Reopen -> Government	Spreading -> Frustration	Hoarding -> PPE
		Avoid -> Corona	Develop -> Diarrhea			Need -> Michigan	See -> Outrage	Open -> Quarantine
		Lifting -> Quarantine	Open -> Employment			Close -> Schools	Wear -> PPE	Observe -> Distancing
		Reopen -> Texas	Help -> Employees				Wear -> Facemask	Protesting -> Coronavirus
		Care -> Lives	Puts -> Halt				Authorizing -> Reopen	Violate -> Lockdown
		Rise -> Deaths						Protest -> Lockdown
		Want -> Nurses						Support -> Boycott
								Make -> Masks
								Rally -> Whattsapp
								Rally -> Austin Texas

Table 3: Disruptive Expressions extracted using Word Embeddings and Direct Object (Texas and Michigan).

Michigan Q2. and Q3. In order to facilitate the narrative, Q2 and Q3 will be presented together. It can be seen in Table 3.I that on April 15th 2020 protesters were conveying messages about violating the lockdown as well as expressing disagreement against the measure. In contrast, two days later messages that expressed an intention to take to the streets were disseminated, coupled with messages that urged people to wear masks while protesting; moreover, messages suggesting the location of the protest, namely Michigan, were conveyed too.

On 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 were 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 3.I.

Texas Q2. Radical behavioural traits revealed that individuals expressed ideas linked to reopening a specific location, namely, Texas, see Table 3.II. According to the Levin's classification[43], 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.

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As argued in [44], 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 3.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.

4.4 Ideology (Q5)

The ideological traits of authoritarianism and hostility reveal important social characteristics. Authoritarianism denotes that individuals do not empathise with decisions or activities performed by those who hold the "proper authority" [37, 38]. Hostility enables the identification of collective emotions which are seen whilst disruptive events take place [35, 36].

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 [18]. Consistently with our previous approach, 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.

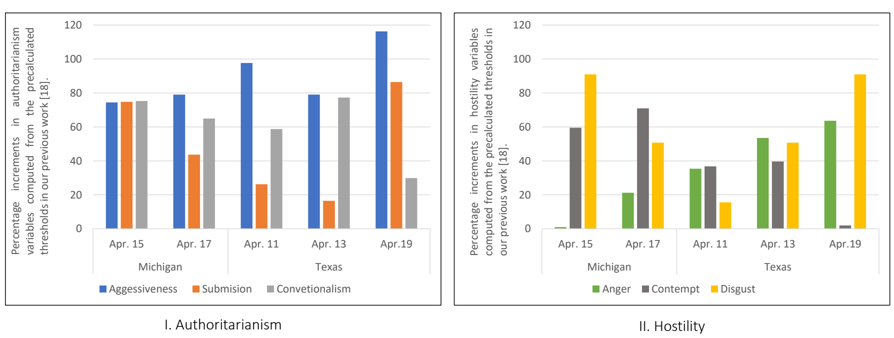

Fig. 3: Ideological traits (Michigan and Texas).

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 Figure 3.

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Texas On April 11th 2020, ideological traits were detected, the same date that the early warning alert was triggered, see Figure 3. 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 subsection 4.3 and Table 3.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 [38], here a lockdown, a curfew, or a quarantine, see Table 3.

4.5 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 III, the web insights methodology proposed in our previous work [15] enables the study of the horizontal escalation of national 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 Figures 4.I and 4.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 national security component was being affected, in this case, health. One day later, messages posted on those social media sites showed that four national 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 [39] may represent a disruptive situation, see Figure 4.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 3.I).

On the other hand, IW showed on April 15th 2020, that three national security components were affected, namely defence, information and government, with 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 Figure 4.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 [42]. By contrast, only SNS revealed information about two other components (people and public order), as displayed in Figure 4.I.

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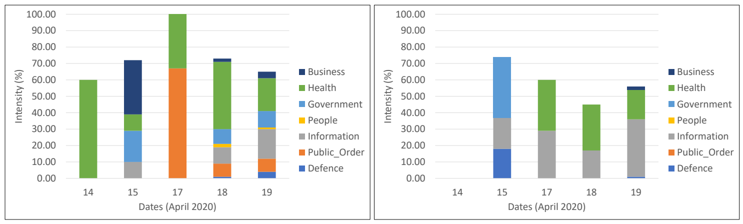

Fig. 4: Horizontal Escalation of the National Security Components during the protests in Michigan (April 2020)

Texas Figure 5.I, 5.II and 5.III show that three digital web resources were used by people to disseminate information amidst the protests, namely, IW, SNS and Non-Profit Organisations.

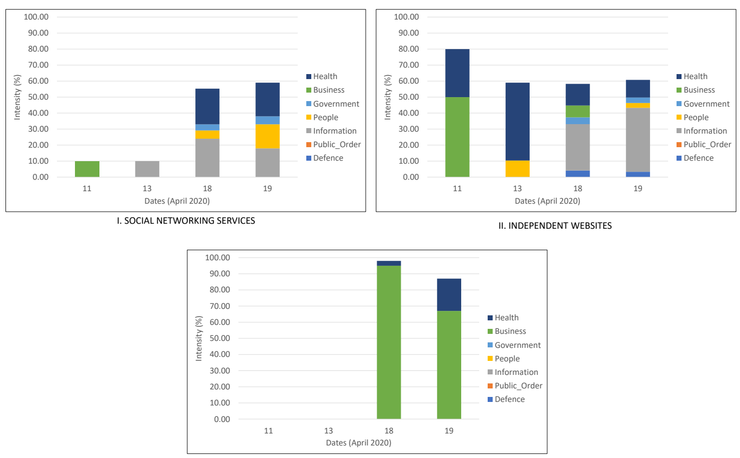

Fig. 5: Horizontal Escalation of the National Security Components during the protests in Texas (April 2020).

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 national 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 national 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.

DOI: 10.1007/978-3-030-77961-0_7

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 Figure 2.II), SNS were used to convey more messages linked to people, as indicated by an increase of 70%; whereas IW were focused on disseminating data related to the information component, which had an increment close to 28%.

5 Conclusions

As COVID-19 has so vividly demonstrated, pandemics constitute a serious National Security threat. Big Data Analytics technologies can provide a powerful force multiplier in the endeavour of competent authorities and stakeholders to manage the pandemic while minimising the security threats it poses.

As a crisis is unfolding, uncertainty is a crucial element and the lack of information is a variable that can obstruct the decision-making process. This paper has discussed the utilisation of a holistic Data Analytics framework for analysing national 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, namely Michigan and Texas. In both cases the system proved its ability to provide early warning well in advance of the demonstrations (six and eight days respectively). It also demonstrated its capacity to provide insights enabling the better understanding and interpretation of the crisis.

Future work will fully integrate and automate the framework, utilising additional analytics approaches and making the various thresholds involved adaptive to the socio-economic context of deployment.

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DOI: 10.1007/978-3-030-77961-0_7

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