COVID-19 Vigilance: Towards Better Risk Assessment and Communication During the Next Wave

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Abstract Since December 2019, SARS-CoV-2 infections have altered many aspects of our societies. Citizens were faced with circumstances to which even experts and scientists did not yet know the answers and were applying the scientific method to make daily steps of progress towards better understanding the threat and how to contain it. Within a year, several vaccines were produced to protect individuals from the virus, thereby resolving the most important medical problem. However, not just medical issues call for the application of the scientific method. The management of epidemics also can, and in fact should, benefit significantly from a science-based approach. The novel complexity of the situation left us torn between permissive and authoritarian approaches of containment, and it is still subject to debate what works best and why. In our contribution, we model the emerging complexity of the epidemics and propose a scientific-based data driven approach that aims to aid the decision makers in their focus on the most relevant issues and thus helping them to make informed and consistent decisions. The resulting monitoring and control system, termed COVID-19 vigilance, helps with risk assessment and communication during regional COVID-19 outbreaks. The system is based on the Cynefin decision complexity framework and the universal process model, and it uses several mathematical models that describe epidemic spreading. Different future scenarios are used to predict the impact of realistic, optimistic, and pessimistic outcomes, in turn allowing for a more efficient communication of involved risk.

Keywords: COVID-19, epidemics, risk assessment, communication, resampling method.

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1 Introduction

Starting from Hubei province in China in December 2019, the novel SARS-CoV-2 virus has been spreading all over the world (Wu et al., 2020). Many countries have had fast increasing numbers of confirmed cases since March 2020. Across the world, the COVID-19 pandemic is causing excess deaths, placing a burden on societies and health systems, and harming the economy. Overwhelming evidence shows that not only public health, but also society and the economy benefit greatly from low COVID-19 case numbers (Priesemann et al., 2020). To decrease the number of newly infected, it is important to align understanding, communication, and management of constrained resources related to COVID-19 epidemics.

In this article, we present such unifying principles on which science works. Thus, we aim to open a way to reality changing collaboration between scientists of different domains, who understand the data and can base their expert opinions on it, decision makers, who can convert expert opinions into action, and public, who is most affected by, yet least informed about the decision processes and the resulting status of the epidemic. The paper is organized as follows; in Section 2, we present the Cynefin decision complexity framework and illustrate its relevance to the COVID-19 epidemics. In Section 3, we rephrase the universal process model that has been introduced in previous contributions at this conference (Fic Žagar, Bokal, 2019). We apply this model to illustrate how societies relying on past recipes in the presence of new complexity may contribute to sacrificing the lives of individuals. However, a scientific learning process may counteract that effect. Our key contribution results in a monitoring and control system of COVID-19 vigilance, elaborated in the setting of the universal process model. In Section 4, we explain the goals of the monitoring and control system explained in Section 3. These goals are made specific using a mathematical method describing the spread of the epidemic. We conclude in Section 5 with some insights for strategic management of epidemics that results from implementing the above monitoring and control process, if implemented in the decision processes under increased complexity and uncertainty. These insights are based on expertise from other similar decision contexts and would require further research for their verification.

2 Complexity of decision making

COVID-19 disease has affected all the aspects of our lives. The usual, every day, simple situations have become more complex. Individuals observe the changed complexity and struggle to find sense in it. To overcome the issued confusion, we apply the sense-making framework Cynefin that explicitly addresses the complexity of decision contexts, as introduced in (Snowden, 2007). It is designed to aid the process of reaching the decision by categorizing the complexity of the situations that require decisions by individuals, groups, or societies. In this section, we present the Cynefin framework, and establish its relevance to COVID-19 decision processes.

2.1 The Cynefin framework

The process of reaching a decision in a given decision context depends on the predictability of consequences of that decision. The Cynefin framework is a conceptual model used to aid decision-making by categorizing the predictability of the outcomes of possible decisions (French, 2017). Each decision is embedded into the decision context, which contributes to the outcome of the decision. The degree to which the decision maker can predict the final outcomes depends on her understanding of this decision context. This understanding is directly linked to the complexity of the decision context as perceived by the decision maker. The Cynefin framework introduced in (Snowden, 2007) and later augmented in (French, 2017) categorizes decision contexts into five complexity domains. The first two, simple and complicated, contain decision contexts in which the outcomes of decisions can be predicted at decision time. The next two, complex and chaotic, contain decision contexts in which the outcomes cannot be predicted at the decision time. The final complexity domain, the center of disorder, contains decision contexts in which the predictability is not yet understood. This is illustrated in Figure 1. Complexity domain the decision context belongs to, defines the approach with which it makes sense to face the challenges of operating in it. The proposed decision aiding process that we elaborate in the next paragraphs draws on research into systems theory, complexity theory, network theory and learning theories (Snowden, 2007).

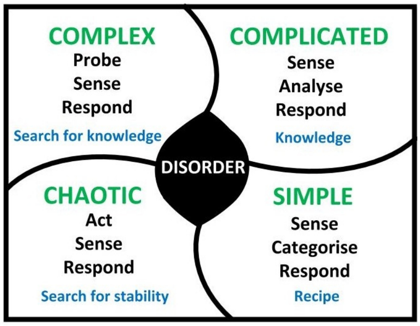

Figure 1: The Cynefin framework.
Source: [Fic Žagar, Bokal, 2021].

The decision contexts that feature predictable consequences of decisions are either simple or complicated. In simple contexts, the consequences of decisions are trivially predictable. Hence, the decision is reached by identifying the problem, categorizing it into one of the available solution pathways, and applying the known recipes of that solution pathway. Examples of such simple decision contexts abound in any bureaucracy. In complicated decision contexts, the consequences of decisions are predictable, but foresight requires expert knowledge and in-depth analysis that establishes the known causal connection and finds an appropriate solution pathway that is not commonly known. An example of a decision context that features complicated complexity is medicine.

Decision contexts in which consequences of decisions are not predictable in the Cynefin framework belong to the complex or chaotic decision domain. Of these, complex domains feature sufficient structure and emerging knowledge that allows consequences of decisions to be analyzed and understood retrospectively. In such a domain, Snowden recommends experimentation, observation of results, and response to observation as a mode of action (Snowden, 2007). Many business situations fall into this category, and most scientific inquiry. Characteristic to chaotic domains are blurred cause-and-effect relationships. In such domains, it is crucial to recognize the area of stability and move towards it with our actions, so Snowden recommends the following sequence: action, observation, and response to observation. In chaotic decision domains of society, stability is usually achieved through charismatic or authoritarian actions. The latter enforce stability, while the former induce stability through voluntary participation in moving to order, usually appealing to people's beliefs or preferences. The center of disorder represents situations where there is no clarity about which of the other domains apply. In the center of disorder, the primary goal is to gather more information, so that the decision maker can characterize the complexity domain the decision context he is facing belongs to, and then take an appropriate action.

2.2 Increased complexity of decision-making due to COVID-19

The presented definitions of complexity domains the decision contexts belong to indicate that COVID-19 epidemic has impacted complexities of several decision contexts. Even the simplest things, like having a coffee with a colleague to discuss a project are no longer simple. With no COVID-19 epidemics, the crucial parameter of the decision is quality of discussion over time consumed: a positive decision for coffee has a very predictable outcome of in-depth discussion while pleasantly consuming a warm drink, while the alternative of just briefly discussing over phone or videoconference spends less time but offers less in-depth discussion and certainly less pleasure. Outcomes of both possible decisions are completely predictable in the absence of COVID-19.

However, with the possibility of COVID-19 infection, the complexity of the decision context increases. Before tests were available, the outcome of the positive decision was impossible to predict, unless both participants were in isolation for the two weeks prior to meeting. After the meeting, however, they could observe and explain the outcomes: either the meeting was sans COVID-19, or they realized one attended infected and the other likely contracted the disease. This possibility characterizes the COVID-19 augmented decision context for having a coffee with no possibility of testing as complex. With the possibility of testing, the outcome of each decision becomes predictable after applying expert knowledge, represented by the test.

Similar changes in complexity apply to time-framed decision contexts belonging to the complicated domain. They depend upon expert participation, which may be prolonged due to experts contracting the disease. Consequences of decisions in such contexts are no longer predictable as the time they require is exposed to risk. As the time and other outcomes of the analysis can be understood after the project, the complexity of the decision context has increased to the complex domain. For previously complex decision contexts, introducing COVID-19 may preserve the complexity. This happens for instance, when it only introduces the risk of prolonging the projects due to possible disease, and when the prolongation itself does not affect the complexity. In such cases, the consequences of the decision can still be explained after they are observed. But the complexity of decision contexts can also be increased from complex to chaotic. This applies, for instance, to decision contexts involving public participation. Marketing experts may have understood the statistics of population participation triggers and developed models and questionnaires using which the participation may have been understood after it was observed. However, these models may no longer be valid due to new circumstances that significantly affect public engagement. Hence, even explanations after the observed participation may sound reasonable, but not necessarily valid. For such chaotic decision contexts, the Cynefin framework suggests finding new stability that will at least allow explaining of the observed consequences of the decisions, if not their predictability. If this stability means returning into decision contexts without COVID-19, Cynefin recommends either authoritarian or charismatic measures to contain the spread of the disease. The latter builds upon the voluntary participation approach, which has been adopted by Sweden and, in some aspects, the USA. There, it does not seem to have prevented COVID-19 accelerated dying, as measured by comparing the death rate to the long-term average death rate in similar periods of the year (Sang-Wook, 2020; Goldstein and Lee, 2020). Strict containment regimes that issue certain levels of lockdown as soon as indications of uncontrolled spread appear, such as New Zealand, Taiwan, or Vietnam, seem to yield better results (Wikipedia 2020a, Wikipedia 2020b, Wikipedia 2020c).

3 Universal process model

Our development of the universal process model started with a conference article (Fic Žagar, Bokal, 2019), where we addressed Hoffman's grim perspective of veristic views of science as evolutionary inferior to utilitaristic view of business (Hoffmann et al., 2015). Their proposed experiments confirmed to be true, showing that veristic strategies can aid innovation that may evolve to outperform strictly utilitaristic insights. However, combining the verism with utilitarianism is the ultimate evolutionary winner, as we demonstrate in (Fic Žagar, Bokal, 2021). In this section, we first summarize the definition of universal process model, and then adapt it to a proposal of a COVID-19 vigilance learning monitoring and control system that can be used to contain the epidemics.

3.1 Definition

The universal process model generalizes the models of decision processes from the theory of artificial intelligence. The world state W is first mapped to goods and knowledge to focus on relevant entities. Goods and knowledge are then mapped into the space of perceptions X, resulting in the agent's perceived image of the state of the world $x_t = P(k_t)$. This image is then used in the decision process of the agent (Hoffman et al, 2015). Thus, the square world states – (focus) – knowledge – (perception) – world images – (decision) – action – (implementation) – world states in Figure 2 represents the functioning of a perceiving agent that distinguishes between reality and the perceived image of it. By performing cycles in this square, the agent updates its image of the world using perception methods (measurement, observation, communication). On this basis, decisions between possible activities are made. The implementation of these activities leads to a change in the state of the world, which completes the focus-perception-decision-implementation cycle (Fic Žagar, Bokal, 2021).

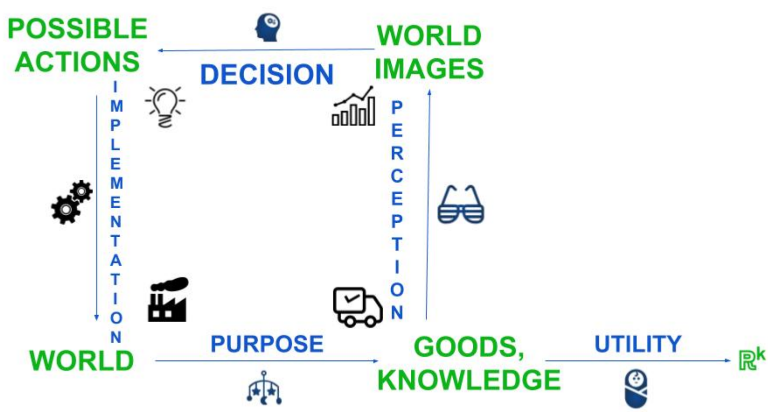

Figure 2: Universal process model
Source: [Fic Žagar, Bokal, 2021]

The mentioned model assumes the external world can be represented by a measurable space, W. An agent acting in the world W maximizing utility U is modelled with a 6-tuple A = (K, X, F, G, P, D), where K is the space of needed goods and knowledge, X is the space of agent's possible perceptions and G is a semigroup of agent's actions as before. Similarly, as W, K, X, and G are measurable spaces. Then F, P, and D are agent's focus, perception, and decision operators. In highest generality, they are modelled as Markov kernels F: W →K, P: K → X, D: X → G. This model is shown on Figure 2 (Fic Žagar, Bokal, 2021).

In the previous section, we established that the complexity of decision-making contexts increased with the presence of COVID-19. The outbreak has altered the world state in a way that the complexity of many decision-making contexts has increased. Until testing was developed and widely applied, outcomes of human interactions involving physical presence were unpredictable, rendering those decision contexts complex or even chaotic. Within new circumstances, science is applying its apparatus to identify the new entities of the COVID-19 reality (such as DNA sampling of the novel virus, its relationship to processes in human and animal cells, its spreading mechanisms, etc.) (Smith et al., 2020; Tilocca et al., 2020). These new concepts and their relationships allow for new perceptions of reality, such as tests indicate whether an individual is contagious or not. These new perceptions that sharpen the initially blurred chaotic image of the world state allow for better decision making, such as whether to self-isolate or not. These decisions affect the reality, most importantly affecting the spread of the virus in the population. The changed state of the world is perceived in the next iteration of the focus-perception-decision-action cycle.

3.2 COVID-19 vigilance, a proposal for a monitoring and control system

A specific proposal for a monitoring and control system termed COVID-19 vigilance is based on the universal process model is shown on Figure 3. First step is to focus on the most critical factor by systematically observing COVID-19 reality, consisting of the epidemic status and other relevant aspects of this chaotic decision-making context. Next step is to create its model, populate it with data, and thus create an image of the world and a prognosis of the future into which different decisions can lead. Based on this understanding, a choice is made among the possible measures to be implemented. The described process impacts the COVID-19 reality.

Once the measures have provided positive results and the most pressing COVID-19 challenge is resolved, we address the next most critical resource and repeat the process described above. This system would gradually transform the critical, unpredictable COVID-19 reality (red on Figure 3) into a predictable new reality (green on Figure 3).

A prototype of such a monitoring and control system was developed during the first wave of COVID-19 epidemics in Slovenia around the open-source infrastructure covid-19.sledilnik.org. However, a key challenge in the implementation of the processes of the described proposal proves to be a simplified understanding of complex and chaotic decision-making domains of the responsible institutions. Therefore, the integration of the developed processes into its decision-making loop was delayed, and the public may have been blinded by the successful containment of the first wave and did not pick on the seriousness of the oncoming second wave in late summer, resulting in one of the highest per capita death rates in the world, which was 1,359.23 deaths per million on January 6th, 2021 ("Coronavirus (COVID-19) deaths worldwide per one million population as of January 6, 2021, by country").

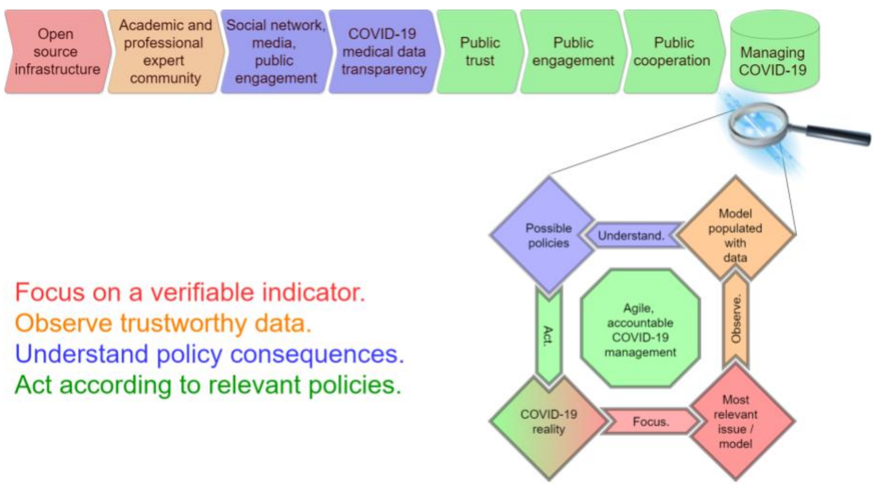

Figure 3: COVID-19 control system
Source: [Own]

With the introduction of such a system, the complexity of the decision-making contexts would gradually return to the domains where they were before the appearance of the COVID-19. The crucial idea of the COVID-19 vigilance monitoring and control system is to introduce a scientific method into this process by making it data driven. This is achieved by identifying relevant concepts in chaotic decision contexts, scientifically verifying their impact in complex decision contexts resulting in tested models, applying models to generate foresight in complicated decision contexts, and by developing generally adoptable and acceptable recipes in simple decision contexts, which the public will accept hopefully with little need for authoritarian measures.

4 Examples of critical societal resources

In the previous section, critical factors and a scientific model used to characterize the spreading of COVID-19 disease were mentioned as a most relevant part of monitoring and control system of COVID-19 vigilance. Data about utilization of constrained resources is collected and used to model the epidemics. In this section, we will introduce two key categories of resources needed to overcome the epidemics, healthcare, and public engagement. We discuss their role through the lens of the universal process model.

4.1 Healthcare

The most important critical resources are healthcare capacities. It is crucial to help the infected individuals to recover, especially by treating the severe cases, thus reducing the mortality in the general population, and preserving the health of healthcare employees. Healthcare capacities are divided into 2 groups: primary and secondary constrained resources. Characteristic to primary constrained resources is its direct relationship to the number of individuals in the healthcare process. Hence, primary constrained resources include testing capacity, epidemiologist capacity, hospital capacity, respirator capacity, and intensive care unit capacity. Characteristic to secondary constrained resources is indirect, more vague relationship to the numbers of individuals in the healthcare process. Hence secondary constrained resources include medical personnel capacity, specific institution capacity (such as individual hospitals and elderly homes), protective equipment availability, and possibly some other resources that may be in short supply due to epidemics.

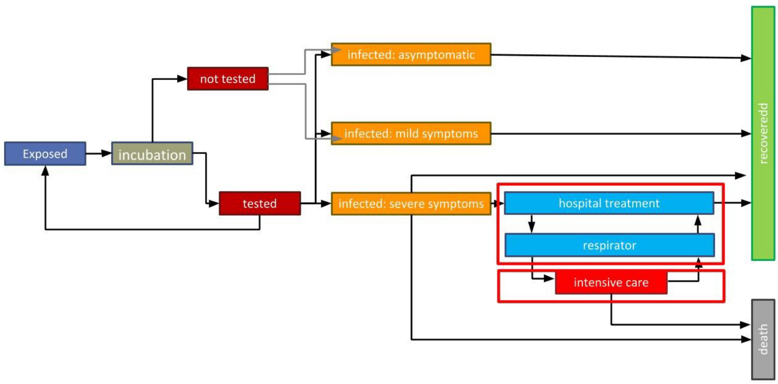

Figure 4: Possible outcomes of the exposure to COVID-19
Source: [Own]

Figure 4 represents the state diagram exposure to COVID-19. Exposed individual is contagious and may infect others with COVID-19 already during the period of incubation. Some individuals at this stage are tested and if found positive, proceed into the next stage according to the seriousness of their symptoms: they can be asymptomatic, with mild symptoms, or with severe symptoms. The severe symptoms are defined as those that require hospitalization, hence anyone with such symptoms is actually tested for COVID-19. This is not true for asymptomatic cases or cases with mild symptoms; only some of those cases get infected, but all can contribute to further spread of the disease. The asymptomatic cases and those with mild symptoms recover without hospital assistance, but when capacity is sufficient, severe cases enter the healthcare system. Some may need just medical attention and observation, some require respirators, and others require intensive care. Given the current data collection, ie. the current image of the world, we do not distinguish those requiring respirators from regular hospitalizations, as respirators were only critical resources early in the epidemics. Hence, the number of hospital beds and the number of intensive care units are the current observed critical healthcare resources.

4.1.1 Modelling COVID-19 epidemics

Predictive mathematical models of epidemics are fundamental to understand the progress of the epidemics and to plan effective control strategies (Giordano et al., 2020). These were calculated using collected data along with mathematics under assumptions customized according to the situation (Eržan et al., 2020). Mathematical models of epidemics are usually classified into two categories: stochastic and deterministic epidemic models (Duan et al., 2015). Stochastic epidemic models handle uncertainties in the inputs applied, and the outcomes are probability distributions of potential outcomes (Kamenšak et al., 2021). On the other hand, deterministic epidemic models predict the outcome with certainty (Kermack, McKendrick, 1927). Therefore, to describe the spread of the COVID-19, deterministic epidemic models are more often used. Commonly used is the SIR model, which describes the flow of individuals through three mutually disjunctive compartments of infection: susceptible, infected, and recovered (Kermack, McKendrick, 1927; Batista, 2020). Many modifications of the SIR model are found in literature, including those that there is no immunity upon recovery (SIS model), or where immunity lasts only for a short period of time (SIRS). Furthermore, for many infections, there is a significant incubation period during which individuals have been infected but are not yet infectious themselves. During this period, the individual is in a compartment called exposed. This model is called the SEIR model and is often combined with activation functions to model social factors affecting virus spread and the disease progression (Leskovar et al., 2020; Piovella, 2020, Wu et al., 2020).

Although, the most commonly used to describe the epidemics, the deterministic models are unable to properly describe the uncertainty of the epidemics forecast related to heterogeneous connectivity of the social network and to heterogeneous disease progress of the infected population (Zaplotnik et al., 2020). Therefore, non-epidemic mathematical models are also used to describe the spread of the COVID-19. Some of them are phenomenological models which are data-driven statistical models that use regression analysis, often fitting epidemiological data to exponential or sub-exponential growth observed in the early stages of an epidemic (Kamenšak et al., 2021). Some phenomenological models used to describe the spread of COVID-19 are the logistic growth model (Batista, 2020), exponential model (Perc et al, 2020) and Richards growth model, we use in our analysis (Bokal et al., 2020).

Another used model is the social network model, an individual-based model which mimics the social network of the population in more detail with ensemble-of-simulations of the virus spread (Zaplotnik et al., 2020) and ensemble forecasting, a method used in or within numerical weather prediction (Davidović, 2020).

4.1.2 Stability analysis using bootstrapping method

The models together with the bootstrapping method are combined to assess the probability of the epidemic parameters exhausting the available number of hospital resources in an observed period. The bootstrapping method is one of the approaches to robust and inaccurate forecasting of future scenarios. We generate a model prediction on each synthetic sample. The set of all the predictions obtained gives us probable predictions for the future. However, we do not use any of them as our prediction. Instead, we use the interval within which lies 95% of the predictions of all models that are resampled. The method with assumption of normal error distribution is applied to Slovenia, while also analyzing three hypothetical scenarios of realistic equal continuation, optimistic decline, or pessimistic increase in the number of new infections (Bokal et al., 2020).

Figures 5 indicates that there is a risk to the years-of-agony scenario while keeping the existing measures relatively low, but still not near the end of the pandemic. It would make sense to tighten up the measures to stop the epidemic sooner, as it can take up to two years, given the upper limits of the 95% confidence interval, to last observed new infection.

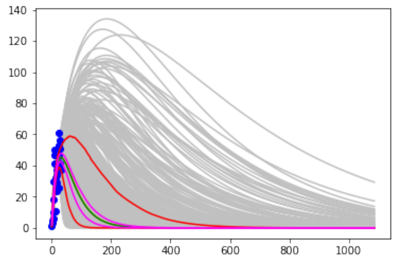

Figure 5: Estimating the reliability of the model using the bootstrapping method. The figure shows original data about newly detected infections (blue), curves of bootstrapping models formed on the basis of synthetically generated patterns similar to those actually observed (gray), curve of the model from actually detected data (orange, overlapped by green), median of gray curves (green), 80% confidence interval (purple) and 95% confidence interval (red)

Source: [Bokal et al., 2020]

Scenarios calculated on the 4th April 2020 are shown on Figure 6. The Figure indicates almost disjunct estimates of the end of the epidemic: realistic scenario says that the end will be between August 2020 and August 2021, optimistic between May 2020 and August 2020, pessimistic between September 2020 and February 2023. An optimistic scenario, led by high responsibility, leads to a rapid recovery and a relatively normal summer. A pessimistic scenario, led by indulgence of responsibilities, can drag the epidemic into years of agony (Bokal et al, 2020)

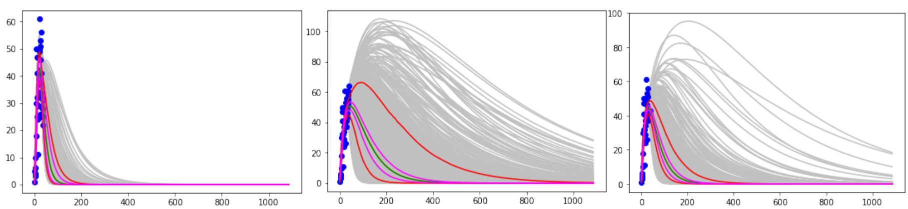

Figure 6: Estimates of reliability assuming an optimistic, realistic, and pessimistic scenario, retrospectively, without rising responsibility. On the horizontal axis is the day of the epidemic, on the vertical axis there is a number of newly detected infections

Source: [Bokal et al., 2020]

4.2 Public engagement

Second category of critical resources contains issues related to public engagement. It relates to communication and adoption of behaviors contributing to stopping the disease spread. The main goal of public engagement is to raise awareness of the need to solve the problem. Any epidemic management strategy relying upon immunity from natural infections for COVID-19 is flawed. (Alwan et al., 2020). In April 2020, (Bokal et al., 2020) proposed public engagement following a shared goal of ending the epidemics before August, which then seemed unlikely. The measures were respected effectively and the first day with no new patients occurred in May (Manevski, Perme, 2020). In November 2020, Sledilnik analysed 3 possible scenarios, which use the estimates of the number of future deaths of individuals as indicator driving public engagement: scenario without newly infected individuals, scenario where the infection spread with the same speed as the previous week and the scenario from March 2020 (Davidovič et al., 2020). Although predictions of significant differences between the cumulative number of deaths were proposed, they did not really reach the public. Therefore, it is important to encourage the accountability of individuals, decision-makers, and groups in discussions on actions. Measures can be drastic if we have a vague picture of the situation, or accurate if we understand the picture of the situation well. The success of these measures depends crucially on the cooperation and involvement of the public. Making the case for the economic and social benefits of reducing case numbers will, if clearly communicated, greatly foster public cooperation (Priesemann et al., 2020).

5 Conclusion

As the world deals with one of the worst public health crises of modern era, the need to plan and prepare for new potentially infectious outbreaks occurs. It is important to develop systems to control and forecast the course of an epidemic, as the probability of a new epidemic rises sharply with population growth and globalization. For instance, in weather forecasting models we invest significantly more despite the much lower costs and sacrifices associated with natural disasters caused by the weather. These systems encourage mass evacuations a few days in advance, thus helping to protect both lives and properties. An example of this investment is project BOBER worth € 33 million, acquired by the ARSO after catastrophic floods in Železniki. New radar for western Slovenia (Pasja ravan), new computing infrastructure (HPC) and new network of automatic measuring stations were developed to be better prepared for such disasters and to be able to predict them at least 1 day in advance (Ministrstvo za okolje in prostor, 2010). But in an epidemic, whose damage is larger than the one caused by the weather, we are completely unprepared with the investment into implementation of forecasting processes negligible in comparison with the aforementioned numbers. It is important to invest in epidemic management systems because more and better measurements, better models, and better computing infrastructure such as a system for recording contacts based on smartphones are needed.

In this article, in the chaos of COVID-19, we connect processes from start to finish in a single process based on the universal process model to help resolve the situation. We called this managing and control process COVID-19 vigilance. The main goal is to first understand and then reduce the complexity of the decision-making contexts which immediately after the COVID-19 epidemics belong to the chaotic domain of Cynefin framework. Even almost a year later, some still persist in such complexity. By introducing new concepts into chaotic decision contexts, enough stability to make it understandable may be established. The relationships between known concepts explained by the models become predictable again, which enables knowledge-based decision-making. New knowledge enables the discovery of good practices, recipes, and continuation of the adjusted old life in new COVID-19 conditions.

In a given situation, science moves toward the goal of reducing the suffering of humanity affected by a common problem, the COVID-19 pandemic. Therefore, the goal of a managing and control system of COVID-19 vigilance presented in this article is to help the decision-makers who have to decide whether to relax, maintain or tighten the measures, as well as any individual suffering from anxiety, caused by changed circumstances. While the proposed control system is in this paper applied to specific instances of COVID-19 epidemics, it has applications in general instances of risk assessment and decision-making under uncertainty.

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