Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID-19. The COVID-19 resource centre is hosted on Elsevier Connect, the company's public news and information website.

Elsevier hereby grants permission to make all its COVID-19-related research that is available on the COVID-19 resource centre - including this research content - immediately available in PubMed Central and other publicly funded repositories, such as the WHO COVID database with rights for unrestricted research re-use and analyses in any form or by any means with acknowledgement of the original source. These permissions are granted for free by Elsevier for as long as the COVID-19 resource centre remains active.
Anticipating human resilience and vulnerability on the path to 2030: What can we learn from COVID-19?

Stefano Armenia\textsuperscript{a,}\textsuperscript{*}, Steven Arquitt\textsuperscript{b}, Matteo Pedercini\textsuperscript{b}, Alessandro Pompei\textsuperscript{c}

\textsuperscript{a} Link Campus University, Rome, Italy
\textsuperscript{b} Millennium Institute, Washington DC, USA
\textsuperscript{c} Sapienza University of Rome, Rome, Italy

\textbf{ARTICLE INFO}

\textbf{Keywords:}
Misperception of feedback and delays
Behavioural pattern awareness
Systems thinking
System dynamics
COVID-19
Climate change

\textbf{ABSTRACT}

The COVID-19 pandemic is causing unprecedented damage to our society and economy, globally impacting progress towards the SDGs. The integrated perspective that Agenda 2030 calls for is ever more important for understanding the vulnerability of our eco-socio-economic systems and for designing policies for enhanced resilience. Since the emergence of COVID-19, countries and international institutions have strengthened their monitoring systems to produce timely data on infections, fostering data-driven decision-making often without the support of systemic-based simulation models. Evidence from the initial phases of the pandemic indicates that countries that were able to implement effective policies before the number of cases grew large (e.g. Australia) managed to contain COVID-19 to a much greater extent than others. We argue that prior systemic knowledge of a phenomenon provides the essential information to correctly interpret data, develop a better understanding of the emerging behavioural patterns and potentially develop early qualitative awareness of how to react promptly in the early phases of destructive phenomena, eventually providing the ground for building more effective simulation models capable of better anticipating the effects of policies. This is even more important as, on its path to 2030, humanity will face other challenges of similar dynamic nature. Chief among these is Climate Change. In this paper, we show how a Systems Thinking and System Dynamics modelling approach is useful for developing a better understanding of these and other issues, and how systemic lessons learned from the COVID-19 case can help decision makers anticipate the destructive dynamics of Climate Change by improving perceptions of the potential impacts of reinforcing feedback and delays, ultimately leading to more timely interventions to achieve the SDGs and mitigate Climate Change risks.

\section{Introduction}

COVID-19 caught most countries off-guard and has caused human and economic loss unprecedented in the modern era (Ayittey, Ayittey, Chiwero, Kamasah, & Dzuvor, 2020). As this paper is being written, almost 300 million cases have been diagnosed globally, and approaching 5.5 million COVID-related deaths recorded (WHO, 2022). The increasingly integrated socio-ecological system that we are part of is being shocked to such an extent that it is difficult to foresee the ultimate impacts of the pandemic. The IMF reports that economic lockdowns necessitated by the pandemic have caused the greatest global recession since the Great Depression (IMF, 2020).

\* Corresponding author.
\textit{E-mail addresses:} s.armenia@unilink.it, armenias@mac.com (S. Armenia).

\url{https://doi.org/10.1016/j.futures.2022.102936}

Received 1 July 2021; Received in revised form 11 January 2022; Accepted 24 March 2022

Available online 1 April 2022

\textsuperscript{0}016-3287/\textcopyright{} 2022 Elsevier Ltd. All rights reserved.
With the slow but steady dissemination of highly effective vaccines, the end of the COVID-19 pandemic may be in sight. Still, COVID-19 has hugely impacted global social and economic development and has hampered the delivery of the Sustainable Development Goals (Fenner & Cernev, 2021). On its path to 2030 and beyond humanity will likely face other challenges that from a systems standpoint are of similar nature, making the lessons of COVID-19 ever more relevant. The rapid spread of locusts causing massive damage to food crops; the quick diffusion of fake information through social media that moves public opinion; the escalation of diplomatic, commercial, and military tensions between opposing countries; debt accumulation and default; the housing and stock-market bubbles; are just a few examples of systemic problems with core characteristics similar to the COVID-19 pandemic that cause them to quickly spiral out of control if not managed with urgency.

While the emphasis of policymakers is now on containment and mitigation efforts, the pandemic shock can surely provide important lessons for longer-term policy development and important insights on the systemic structures that characterize the critical early phases of destructive phenomena. By observing the pandemic from a broader and more systemic perspective, we can gather evidence about the archetypal characteristics of the relevant socio-ecological systems and their resilience to shocks. Notwithstanding the fact that governments acted very late in the initial stages of the pandemic, the relatively quick dynamics of COVID-19 has made it possible for all of us to easily become aware of its presence and its behaviour, as we could witness its almost immediate effects on our lives, thus reducing the effects of our initial misperception of feedback, coupled with the phenomenon’s inherent systemic delay. With climate change, lessons are still yet to be learned, as its effects are still too sparse and there continues to be much uncertainty among the non-scientific community regarding the effects and even the reality of climate change itself (de Vries, 2010).

This has much to do with how humans learn, or fail to learn, from their mistakes. We are often unable to learn from our experience because the acquisition of experience is a complex process (Boyd & Fales, 1983); moreover, science and technology are often not capable of fully supporting us in our ability to anticipate the outcomes of pressing global problems (Turiman, Omar, Daud, & Osman, 2012). Given this, and assuming that simulation tools can be valuable for anticipation (Sargent, 2010), how can we ensure that such tools will support us in producing reliable predictions (hence minimizing risks) in the presence of data that is uncertain (Puntowicz & Ravetz, 1993) even in the age of big data and extreme digital transformation? (Deacon, Van Assche, Papineau, & Gruezmacher, 2018; Kitchin, 2014; Roth, Dahms, & Welz, 2019a; Roth, Schwede, Valentinov, Žazar, & Kaivo-oja, 2019b).

In this context, the adoption of a systems paradigm for predictive model design and simulation (see Fuller, 2017) can effectively exploit available data and describe the phenomena under study (Pruyt, Cunningham, Kwakkel, & De Brujin, 2014). This can be the case as long as policy makers adopt the right modelling process, considering and balancing the level of detail, the boundaries of the model’s scope, and the possibility to conduct sensitivity analysis (Rahmandad & Sterman, 2008).

In this paper we concentrate on the all-important first steps of a modelling process. We have made use of the systemic approach advocated by Fuller (2017) in order to reflect on how we perceive and assess risks, and how it can be possible to avoid potential damages due to delayed interventions. In particular, we address relevant knowledge and methodological gaps concerning the need to accurately understand structural systemic mechanisms underlying complex issues, in order to identify more effective policies that could in future be tested and simulated through more appropriate models. We argue that better knowledge of the underlying systemic structure that embodies the root cause of problems can help decision makers develop better decision support systems and hence more effective and timely solutions. An early understanding of those structures can facilitate the identification of emerging behavioural patterns before the most evident symptoms appear, thus allowing timely intervention (Armenia & De Angelis, 2013). Even in the age of big data, the value of systems models, even if purely qualitative, is key to understanding, learning, and possibly improving our decision making processes.

While acknowledging the great importance of quantitative simulation and analysis in the process of policy development (Pedercini, Zuellich, Dianati, & Arquitt, 2018; Rahmandad & Sterman, 2008), we maintain that important insights on the systemic nature of the issues at stake can also be effectively and earlier identified with a quantitative systemic analysis, which in turn can usefully guide the development of simulation models. Therefore, in this work, we take a higher-level perspective, analysing a few simple, but still very relevant, systemic mechanisms from which we can infer important insights that will be useful to later characterize simulation models that aim at producing effective predictions of our future.

The novelty of our work lies in identifying major systems mechanisms relevant to both COVID-19 and Climate Change through the application of a Systems Thinking and qualitative System Dynamics approach. A specific focus on the qualitative dynamics of reinforcing feedback loops and delays was adopted because, although there are also balancing loops that fill out the big picture of the problem, the work is intended to grasp the ‘onset’ part of the problem (i.e. when the reinforcing loops start generating exponential growth) which is the most critical phase for policy makers to make a difference with their decisions. The target audience for this work goes beyond those accustomed to using Systems Thinking and System Dynamics and extends in particular to policy and decision makers. Knowing in principle that there are or there will be balancing loops acting does not really change much in the eyes of policy makers when pressured by the strength of a current-acting dominant reinforcing dynamic.

Our aim is thus to show that lessons learned from COVID-19 dynamics through a Systems Thinking lens should be seriously taken into account by decision makers in order to derive important insights for the lessons “not yet learned” of Climate Change dynamics. We argue that the main underlying systemic structures, especially related to the onset phases of the two phenomena, are basically the same (dominant reinforcing feedback loops that are snowballing the systems towards epidemiological or ecological disaster), and that their differences are mainly determined by the intrinsic delays between action and effect that characterize dynamic systems. This can be seen, in particular, when comparing the two cases in terms of mitigation vs. adaptation policies. In both cases, mitigation policies tend to be more cost-effective if performed in time, while once the positive feedback loops pick-up speed, only the more costly and partially effective adaptation policies are possible. Still, the inertial qualities of the two systems are very different. For COVID, the inertia is relatively small, the frequent cycles show that with adequate measures, exponential growth patterns can be rapidly turned around. For
Climate Change, the huge inertia of the system implies on the one hand a slower build-up, on the other hand a much longer time to turn-around even when the right policies are in place.

We maintain that Systems Thinking (Senge, 1990) and System Dynamics (Forrester, 1961) should be taken into account for an early understanding of the dynamics of complex phenomena, hence developing a clear awareness of what it means to “anticipate” and forecast behaviour over time (Fuller, 2017). If we fail to understand how a system’s structure works (Sterman, 2000), we fail to grasp the real extent of its dynamics, which means failing to later develop effective computer simulation models on which to test our strategies, and ultimately becoming aware only too late of the real extent of what is going on. Ultimately, this is the type of modelling mindset we would like to reflect upon with this paper, and we do this through the comparison of two qualitative models built with a Systems Thinking and qualitative System Dynamics approach.

In Section 2 (Context and previous research), we analyse previous studies on the value of systemic approaches in simulation and introduce two case studies (COVID-19 and Climate Change) by analysing relevant recent literature.

In Section 3 (Methodological background and approach), we first describe the adopted methodological background (Systems Thinking and System Dynamics) with particular emphasis on the analysis of reinforcing and balancing feedback loops and the influence of delays in feedback systems. Then we move on to analyse the systemic structures behind the evolution of the COVID-19 pandemic, describing how the devastating effects of a new, highly infectious pathogen on a globally unprotected population were further catalysed by unprepared governments and delayed intervention to such a degree as to make COVID-19 a global pandemic (Lazzerini & Putoto, 2020). Ultimately, we do not develop a simulation model; rather we develop two novel Causal Loop Diagrams (characteristic of qualitative Systems Thinking) that will facilitate an understanding of an issue like Climate Change by comparing with lessons learned from COVID-19. In turn, we will also reflect on the advantages of the modelling mindset and approach of Systems Thinking and System Dynamics.

In the case of COVID-19, we will show how the contagion “system” is driven by reinforcing feedback loops that without prompt and focused early mitigation cause the exponentially explosive and uncontrollable growth of the pandemic (Homer & Hirsch, 2006). Finally, based on the lessons learned from the COVID-19 dynamics, we generalize the roles of reinforcing feedback loops and delays in policy application to other problems addressed by the Agenda 2030, with specific reference to global Climate Change.

In Section 4 (Results and discussion) we synthesize the core aspects of the COVID-19 and Climate Change cases into generalizable systemic principles that can be applied when developing (not only SD-based) simulation models aiming to tackle many problematic systems.

In Section 5 (Conclusions) we provide comments on how an early yet effective qualitative systemic approach to systems understanding can ultimately equip us to produce more effective simulation models that can help us learn from past or current critical situations that are apparently different but similar at the system-level; and that leveraging on lessons-learned from similar archetypical structures across seemingly different phenomena can provide us with a basis for systems understanding and awareness (thus mitigating the effects of our inherent misperception of feedbacks and delays) so to better assess potential policy impacts and put in place timely and effective interventions.

2. Context and previous research

The use of simulation tools and the subsequent decision-making process are a manifestation of the human need to act in the face of complexity and risk. However, it is uncertain whether this troubleshooting process always leads to the most correct solution possible, even when supported by a large amount of data. Although Big Data initiatives are currently showing promising results, for example, clinical (Aguair de Sousa & Katan, 2021), environment (Soler et al., 2021), manufacturing (Li et al., 2021); there is still some scepticism regarding their real capabilities. Some authors argue that Big Data contributions to forecasting reliability are still marginal (Junqué de Fortuny, Martens, & Provost, 2013), as it is considered highly context-dependent (i.e. Big Data quality depends on the intended use/application) and that presumptions of objectivity and accuracy are misleading (Boyd & Crawford, 2012). Furthermore, the ability to infer the behaviour of the system being modelled and its relationship with other systems, is linked foremost to the mental models (Senge, 1990) of the decision maker who conceptualizes the problem, as well as those of the model maker who creates the simulation model, performs simulations and presents the results and recommendations.

Modelling and simulation intended to support decisions through forecasting and scenario analysis, must therefore be weighed with the introduction of knowledge elicited from the actors who enter the process. Therefore, poorly posed problems generate poor solutions, which lead to poor knowledge, which further worsens the decision-making process, making it less and less aligned with the reality of the facts (Foreman, 2013). The risk is to develop a completely misaligned perception of the seriousness of the risks concerning the problem, as well as the perception of the delayed effects emerging in the system. It is worth mentioning that this work has no ambition to explain the reasons why the decision-making process is so difficult in such situations, rather its aim is to qualitatively analyse the systemic effects of delay perception (which is under the domain of decision-making) and how it manifests itself in presence of a rapidly evolving phenomenon (in particular, systemically determined by the presence of a reinforcing feedback loop structure). Feedback and delay (mis-)perception is, in fact, an important common factor that ties together the various elements and examples that are presented inside this work.

As mentioned, in order to show how systemic paradigms are key to an early understanding of potentially destructive phenomena and to the later development of simulation models that are effective in their prediction capability, we will introduce and analyse two cases that are similar in their systemic and archetypal structures, and that can help us understand how critical a systems perspective is when developing simulation models to understand how the system really works, even before their simulation is carried out. These are the COVID-19 pandemic and Climate Change.
Regarding the global COVID-19 crisis, there are already some studies that partly describe the difficulties and limitations related to overreliance on certain models and simulations developed (perhaps too quickly) during the first phase of the pandemic by governments in the context of their usual decision-making processes. Rajan et al. (2020) analysed the composition of the task forces that have been created by various governments, summarizing the evidence that they found in a few very relevant points. First, there is a widespread preponderance of politicians, virologists and epidemiologists in the task forces, while experts in other areas of health such as mental health, child health, chronic diseases, preventive medicine and gerontology have been overlooked, not to mention experts in areas other than those of health (i.e.: systems engineers). Furthermore, the vast majority of the members of the COVID-19 task forces come from universities and government institutes where they conduct research in the classic sense of the term, that is, under conditions of clinical or laboratory experimentation. Such studies are often far from the reality and experiences lived by the groups of society that are most severely affected by the potential measures adopted, for example those in isolation. Finally, the study showed little transparency regarding the sources of information that the decision-making bodies were consulting and the truthfulness of the data used. The study concludes by emphasizing the need for a multidisciplinary approach in the research activity regarding the COVID-19 crisis, which is not simply a health problem but also a social one. Of the same opinion are Norheim et al. (2021), who agree that although a timely lockdown can be very effective in limiting the health threat of COVID-19, such actions should be further investigated as they greatly limit freedoms and can seriously affect economic growth, access to social services, level of employment, mental well-being of the population, as well as quality of education. Furthermore, the need for intervention by some governments in response to COVID-19 has questioned and weakened democratic processes, so much so that trust in political and scientific authorities is going through difficult times, especially in countries where policies have been late and therefore less effective in containing the emergency. Gao and Yu (2020) highlighted the importance of sub-provincial governments in providing rules to facilitate collective action and promptly coordinating health services in emergency situations. They underline that, for example in the case of Wuhan, local governments still rely on traditional administrative systems, hampering responses to the epidemic and the speed of implementation. For this reason, they recommend the creation of a Public Health Emergency Preparedness organization for local governments that includes the participation of stakeholders outside the bureaucratic system.

These perspectives are perfectly in line with what was stated by Waltner-Toews et al. (2020) in the context of post-normal science and what it can do to respond to a threat such as that represented by COVID-19. It is in this context of unpredictable but potentially catastrophic impacts that Funtowicz’s proposal (Funtowicz & Ravetz, 1993) and post-normal science finds specific use, since the aim of post-normal science is not the search and consolidation of a “truth”, by its nature uncertain, but rather the gathering of as much information as possible to act wisely and make informed decisions on the basis of the precautionary principle, considering every legitimate perspective and having consensus as its objective.

On the other hand, some studies fully promote the use of simulation models to determine the best strategies to mitigate the effects of COVID-19. Although the most used epidemiological or mathematical models make it possible to understand the dynamics of the spread of the disease (Ferguson et al., 2020; Singh, Srivastava, Hammouch, & Nisar, 2021) or to decide the number of tests necessary to perform an effective screening on a population (Deckert, Bärnighausen, & Kyei, 2020), a pandemic like the one we are now facing generates an enormous number of problems in various areas not only related to the transmission of the disease and to its mortality. Those problems require different types of models, or rather a holistic perspective, to find the best solutions (Currie et al., 2020). In fact, if it is true that epidemiological models can predict the number of new cases in a sufficiently precise way, it is not equally true that they can help organize beds and medical personnel for intensive care units (ICU) or predict relevant economic impacts in following the measures adopted. The conclusion is that approaches devoted to the anticipation of similar problems must have the prerogative of being able to identify as many modelling instances as possible that can be put into practice (Fuller, 2017). Under this perspective, the possibility to include multiple interdependent (but seemingly separated) system sub-structures becomes key, as is also a methodology (i.e. Systems Thinking) to visualize such interdependencies and analyse (albeit qualitatively) their potential outcomes.

Concerning Climate Change, during the last 50 years it has become increasingly clear that the world is complex by nature and that it has become even more so due to the additional layers of complexity that have been added by humankind since the advent of the industrial revolution. Still, few researchers have tried to understand the global impacts of these additional layers of complexity on the way our entire world will behave in the upcoming decades. In the early 1970s, a small group of researchers at MIT, tried to warn the world’s governments about the risks that our planet would be facing in the years to follow, but their warning went almost unheard, notwithstanding the great resonance of their scientific work (Meadows, Meadows, Randers, & Behrens, 1972). Fifty years later, we have dramatically seen how accurate their predictions were. The Agenda 2030 has more recently raised the attention of humankind around the issue of sustainability, and the scientific community has been able to acquire a multitude of data relevant to the Sustainable Development Goals (SDGs).

We now understand that there are interlinkages among old and new layers of complexity, that certain phenomena are not only local but spread across national boundaries, and that their dynamics need to be addressed globally and through the lens of interdisciplinarity. We have come to understand that we need systemic models describing the potential synergies, complementarities and trade-offs between SDGs (Armenia, Pompei, Castano Barreto, Atzori, & Fonseca, 2019; Hjorth and Bagheri, 2006; Pedercini Arquitt, Collste, & Herren, 2019). However, although as humans we tend to be able to realize or even anticipate a problem, we then often lack the commitment to fully solve it, as doing so requires much effort and energy to steer a system’s behaviour away from its current path. As linear problem solvers, we thus tend to solve issues only one bit at a time and with a local perspective. Hence, we need to use new concepts and tools to address the presence of interdependencies among various phenomena as well as their systems natures, but most of all we have to muster the collective will to fully apply them.
3. Methodological background and approach

Systems Thinking (ST) and System Dynamics (SD) can help us develop a better understanding of the above-mentioned phenomena through the analysis of their systems interdependencies as well as develop an early awareness of the likely behaviour of these phenomena, by addressing two fundamental aspects that quickly bring systems out of equilibrium (and potentially out of planetary boundaries) and that often lead decision-makers to simply decide “not to act”, or to act reactively, often leading to even worse problems later. There are two elements of System Thinking the effects of which our bounded rationality generally does not allow us to grasp: feedback loops (especially reinforcing feedback loops) and delays. Working together feedback loops and delays can generate highly nonlinear behaviour patterns that our intuition often cannot anticipate. In order to address the “no action” decisional issue, we rely on the Systems Thinking approach thanks to its capability (as already mentioned in previous sections) to explain, even just qualitatively, complex phenomena in an easy (and early) way. Other methods (for example, ABM and discrete event modelling and simulation approach) do not have the same early expressive power to describe and capture the qualitative dynamics of a phenomenon (Armenia, Atzori, & Romano, 2015), as in fact most of the times their models need to be simulated in order to capture the emerging dynamics (with all that implies in terms of developing times that sometimes are not compatible with the fast-evolving dynamics of the phenomena that they want to simulate). On the other hand, through the technique known as Causal Loop Diagrams (CLDs) (Richardson, 1999; Serman, 2000), an easy and straightforward ST concept mapping approach used to represent causal interdependencies, we can concentrate on the essential processes and dynamics, and infer, even though qualitatively, the particularly relevant initial behaviour of the system, so important to grasp especially in the early stages of destructive phenomena. Such an ease of use and understanding is of course especially useful for policy makers.

The CLD method is particularly important as it provides the possibility, by mapping causal relationships among the various parts/ aspects of a system, to identify important systemic structures known as Systems Archetypes (Senge, 1990). A Systems Archetype is a structure that displays a(n) (arche)typical behaviour over time, and it is mainly characterized by the feedback loops that compose it.

A feedback loop is defined as a closed sequence of causes and effects, a closed path made of actions and information (Richardson & Pugh, 1981). Think for instance of the causal relation between eggs and chickens. More eggs lead to more chickens, which in turn produce more eggs and so on. This chain of cause and effect is always true if there are no other causal relations that limit the chicken population growth and hence is called a reinforcing feedback loop. If, for instance, wolves were introduced into the system, with the increase of the chickens there would be an increase of the wolves eating them. However, if wolves increase beyond a certain point, the chicken population will then dramatically decrease as they are being eaten by the wolves. In other words, the wolves would generate a balancing feedback loop. A balancing loop generally starts dominating only after a certain threshold (carrying capacity) has been reached in the system. This contributes to the resilience of a system and in general, resilience is strictly connected to balancing or counterbalancing processes (or if that balancing effect in the system is triggered only after a delay - a tipping point), then the system will be deprived of its normal functions. In those situations, for which the carrying capacity is difficult to determine or is inherently too big to be taken into account, the balancing feedback can be provisionally ignored. The dynamics of population growth are typical examples of social and environmental problems, both as a direct (chickens’ growth, or the growth of a population of pathogens in a biological environment) or indirect cause (human population growing and driving the growth of plastics being disposed of in the environment).

A system dominated by a reinforcing feedback loop generates exponential growth. If there are no limiting conditions that activate a counterbalancing process (or if that balancing effect in the system is triggered only after a delay - a tipping point), then the system’s behaviour tends to grow more and more quickly. For this reason, monitoring a threshold in such situations is not sufficient to avoid problems, as given the monitoring time window, it could be too late to realize that the behaviour is getting dangerously close to the threshold. This is why understanding the system’s structure and related behaviour is key, in order to be able to grasp signals of exponential growth even when not evident and hence being able to react more promptly. It is evident how, in systems where the situation can develop very quickly from one moment to the next, that a reaction delay, or even an observation delay, can play a crucial role when it comes to timely intervention. The inclusion of a system’s feedback loops and related delays in simulation models reflects in the model behaviour the dynamics that can unexpectedly lead to the quick growth of a problem.

In order to show the fundamental influence of reinforcing feedback loops and delays, we will rely on two specific cases that will enable us to understand the criticality of timely reaction in the design of effective and robust policies in systems dominated by reinforcing feedback.

a) Although the dynamics of COVID-19 pandemic may seem, at first glance, quite linear in its development (population becoming infected, people quarantined and treated until the pathogen disappears or a vaccine is ready), the reality is that the phenomenon is based on specific systemic structures that can be found in other phenomena.

b) Although Climate Change is unfolding over a much longer time horizon, the underlying dynamics created by reinforcing feedback and delayed problem recognition and policy response are similar to the COVID-19 case. Unlike the epidemic, climate change is taking us into new territory, which further delays the local and international consensus-building needed for massive policy response.

At first glance the COVID-19 pandemic and climate change seem worlds apart in terms of causality. However, from a high-level systems perspective the two have much in common and demonstrating this commonality is a novel contribution of this research. COVID-19 contagion progresses over a time horizon of days where climate change involves decades, but both are systemic phenomena driven by powerful reinforcing feedback loops. Both systems are rife with time lags related to problem recognition, consensus building, policy formulation and acceptance, and implementation. Both systems call for urgent action to prevent dire consequences arising from
self-reinforcing stressors.

3.1. COVID-19: a systems perspective

Over the last two years many academics have attempted to address the COVID situation with the help of System Dynamics (SD) models. Almost all the models identified are Stock and Flow models based mainly on the SIR (Susceptible-Infectious-Recovered) model (Anderson & May, 1992).

Some of these models are clearly focused on specific geographic areas. For example, Venkateswaran and Damani (2020) presented an SD model of the COVID-19 pandemic spread in India. Their model highlights the effects of testing, contact tracing, isolating COVID-positive patients, as well as use of mask/better hygiene practices and social distancing. Their conclusion was that an extensive lockdown does not avoid the resurfacing of the pandemic, the best solution for the long period, in the absence of a vaccine, is to make tests available for those who show COVID-19 like symptoms, isolating them if they are positive and tracing all their contacts. Ghaffarzadegan and Rahmandad (2020) developed their SD model in the context of Iran. Although their model seems more simplified than Venkateswaran and Damani’s, it shares some elements, like social distancing and the testing capacity, as well as some conclusions. In fact, they too forecasted that the pandemic may resurface in the absence of sustained contact reductions. Also, Japan has its own specific case study developed by Niwa, Hara, Sengoku, and Kodama (2020), who described with the help of an SD model the regional population dynamics demonstrating the effectiveness of inbound traveller quarantine and resident isolation. As the other studies discussed before, Niwa described the role of intrinsic elements of pandemic dynamics like virus testing, hospitalization and isolation, suggesting at the end of the study that the promptness of government isolation measures in the early stage can effectively reduce the number of infected people and control the epidemic faster. Feng and Lu (2020) came to the very same conclusion with their model based on the Wuhan case, adding that the rapid increase of infection cases found in Wuhan City in the very first stage of the virus outbreak is due to the government’s lack of a prevention and control strategy.

Struben (2020) used multiple time series data (reported cases and deaths, performed tests, and social interaction proxies) from six countries (South Korea, Germany, Italy, France, Sweden, and the US) to develop a behavioural dynamic epidemic model. Other than specifying the different potential statuses of the infected populations, Struben placed particular attention on contact dynamics that varied with differences in the perceived outbreak severity. Therefore, the contacts in the model are strongly influenced by social distancing of the general population, home confinement of suspected cases, quarantining of detected cases and social contact reduction by populations that exhibit symptoms. Thanks to the simulation analysis of different countries, it was possible for Struben to show the critical role of timing and efforts of testing-capacity expansion and social-contact reduction, that explains the wide cross-country variation in outbreak pathways. Moreover, the final advice that emerged from the model is that, in the post peak stage and in the absence of valid pharmaceutical solutions, it would be appropriate to maintain social contacts well below pre-pandemic values.

Although there are differences in terms of elements, level of detail and localization in all these valuable studies, there is one element that is always present and deeply characterizes the pandemic dynamics, i.e., the social contacts. Without contacts the pandemic cannot even start to develop and evolve, therefore this element can be considered as crucial in every model. Having complete control of contacts means that the main feedback loop behind the infection is under control, and not allowed to exceed the tipping point beyond which the exponential dynamic becomes difficult (if not impossible) to stop. An increase in contacts causes a parallel increase in the infection rate which intensifies the disease transmission through increased contact and causes inadequate isolation of non-diagnosed patients and inadequate medication due to the possibility of overflow of medical systems (Niwa et al., 2020).

![Fig. 1. Principal feedback loops underlying dynamics of COVID-19 pandemic growth. The arrows indicate the direction of causality between variables. Arrows (in blue) without an accompanying sign mean that the variables at the base and tip of the arrow tend to change (increase or decrease) in the same direction. Arrows (in red) with negative signs mean that variables at the base and tip of the arrow tend to change in opposite directions. R1 designates a reinforcing feedback loop. B1 designates a balancing feedback loop. The variable Infected population includes both symptomatic and asymptomatic individuals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)](image-url)
Using a Causal Loop Diagram (CLD), we can highlight the main dynamics of a quickly spreading and dangerous disease like COVID-19. This kind of dynamic is typical of important infectious diseases in almost every geographical, social and economic context. This fact makes the COVID-19 issue not a simple national problem but rather an international problem, because it recreates the same dangerous pattern in every geographic area in which it is allowed to spread. None of the world’s nations is out of danger, as long as globalization exists and the various means of transportation between countries are so accessible.

In the following paragraphs, the core feedback loops underlying the spread of the infection are described. The response to COVID-19 is then characterized through additional consciously implemented feedback loops, and by identifying the pernicious time lags which determine the severity and extent of the disease.

The starting point of our analysis is based on the well-known model structure for epidemics, the SIR model (Kermack & McKendrick, 1927). The main assumption of this model is that, when dealing with an active pathogen, the relevant population can be divided into three subgroups: the healthy individuals who can become sick (Susceptible), the individuals already infected (Infected) who have the capability to transmit the disease to healthy ones, and the individuals who have recovered from the disease (Recovered) and are no longer part of the infection cycle, having become immunized after infection. For the purposes of our analysis, we will focus on the Susceptible-Infected (SI) part of the overall model. As already mentioned in the introduction, we do not want to underestimate the balancing loops typical of the SIR model (as they are really part of the “big picture”), rather we want to highlight the importance of the dynamics of the dominant reinforcing loops once the problem starts to be unmanageable, which is a very critical part for decision making. The same can be said about the recovered cases and deaths, which we did not explicitly include in the diagram because (although they indeed do have impacts on the growth dynamics of the pandemic in the long run) and, for the sake of simplicity, we chose to focus more on the timeframe in which the reinforcing loop is dominant and is really feeding the problem: balancing loops, like recoveries and deaths, have indeed the capability to influence the phenomenon, but mostly in a second phase.

Our conceptual starting model, shown in Fig. 1, focuses on the growth and control dynamics of the pandemic. In Fig. 1 the variable Infected population includes both asymptomatic and symptomatic populations.

The diagram shows two feedback loops: a reinforcing loop (R1) and a balancing loop (B1). This structure is typical of a fundamental systems archetype known as the “Limits to Growth” (Meadows et al., 1972). From this archetype we can analyse the impacts of these paired basic loops.

The reinforcing feedback is dominant in the beginning as there are many people who are susceptible to becoming infected, and the virus can spread very quickly through asymptomatic infected who are unaware of their health status.

At a certain “tipping” point, when around 50% of those initially susceptible have been infected, dominance begins to shift toward the balancing feedback loop that exerts limiting effects (in other words, the virus finds it more difficult to spread as most people have already been infected making it less likely that a contact will produce an infection). In the absence of countermeasures, the phenomenon could be easily described by this sub-model alone. In reality, in the presence of similar situations of public danger,

---

**Fig. 2.** Dynamics of policy makers’ reactions. Time delays are indicated by double hash marks. As long as the variable *Gap between perceived and acceptable risk of becoming infected* is greater than zero the policies are implemented.
institutions react by putting in place specific policies to halt or mitigate the problem. This is represented in the causal loop diagram shown in Fig. 2.

As the disease becomes more “visible” with an ever-increasing number of symptomatic individuals and fatalities, institutions become aware of the disease severity and recognize the potentially catastrophic effects that the disease could cause both from social and healthcare perspectives. Therefore, after some delay (due firstly to recognition of the problem and forming consensus about policies), some policies are formulated and approved. It is important to point out that in the case of COVID-19 the spread of infection has begun to move among the population by means of asymptomatic individuals even before the recognition of symptomatic cases, meaning policy makers are already dealing with a significant amount of delay in their response to the disease. After the policies are formulated, there is the need to mobilize the resources that will enable implementation, which contributes further to delayed policy implementation.

The model in Fig. 2 considers three different categories of policies. All of these policies are formulated to counter the snowballing effect of infection shown in feedback loop R1 and to drive the risk of becoming infected to an acceptable level. Defining an acceptable level of risk has been a subject of debate. Businesses hurt by lockdowns and travel restrictions and citizens growing weary of restrictions and inconveniences are pressuring governments to relax lockdowns and other mandates. The notion of infection risk acceptability varies between and within countries; however, there is an increasing acceptance of non-zero risk of infection, and that some amount of illness and death due to COVID-19 will continue to occur into the future (Mallapaty, 2021).

Building on the above, our purpose in Figs. 2–5 is now to put in evidence the roles of feedback loops and time delays in the dynamics of COVID-19 and in the dynamics of pandemic management. For clarity we have applied the same simple risk perception decision rule to all three categories of policies, whereas in reality, multiple indicators would be used (CDC, 2021).

The first policy category targets transmission of the virus through the distribution and use of masks, hand and surface disinfectants and social distancing (as called for in meetings, grocery queues, etc.). These policies act through feedback B2 highlighted in Fig. 3.

These policies have important effects on disease transmission; even when the contact rate struggles to drop, these contacts will result in less danger of contracting the disease. This policy has some delays, for example due to time lags in the supply chain of equipment from producers to consumers (the population), and to some people’s resistance to mask wearing and social distancing recommendations or rules.

The second policy category targets the rate of contact between infective and susceptible individuals through lockdowns of nonessential activities, travel restrictions, and contact tracing and quarantine. These policies exert their influence through feedback loop B3, highlighted in Fig. 4.

The lockdown policy has direct effects on the infection rate (Becoming infected in the causal loop diagrams) because it drastically reduces the contact rate among the population. This is the most effective and prompt policy in the short-term, but it has socio-economic consequences and can be subject to resistance. The travel restriction policy may take the form of an international travel ban with some or all countries. This policy prevents the spread of the disease, safeguarding those countries that are still healthy or have the situation under control. Without the prohibition on transboundary movement of people, the country will be under pressure to continually implement the three policies described above with a likelihood of eventual disease breakout. This was witnessed in Singapore, where early measures to control the virus were highly successful. However, Singapore was slow to close its borders, resulting in a serious outbreak that led to 57,000 cases by September 2020, a greater number than was experienced in Wuhan at that point (Pueyo, 2020). Restrictions may also be put in place on domestic travel. This policy has very serious economic consequences for port and airport services markets and transport markets, as well as for tourism. The policy for testing, tracing and quarantining infected people acts on the population’s infection process by influencing and lowering the likelihood of infected contacts, because once the infected are identified and quarantined, he/she exits the infection process and cannot infect other individuals. This policy is characterized by delays due to making the test available in each city, region or urban agglomeration and the difficulty to effectively trace the positives.

The third policy category targets the susceptible population through vaccination. Vaccination decreases the population that is susceptible to COVID-19 infection. The policy acts through feedback loop B4, highlighted in Fig. 5.

Vaccination is a very effective policy because it eliminates the resources, i.e., the susceptible individuals, that the disease must have to grow. Its limiting action is similar to that of feedback loop B2, but happily without the incidence of disease. Vaccination, however, is fraught with implementation delays. Chief among these are delays due to research and development, trials for efficacy and safety, production and distribution, hoarding vaccine supplies by some nations, and resistance to taking the vaccines.

As mentioned above, the model describes the hidden dynamics of infection spreading disease as well as actions taken in response by decision makers.

In fact, although the reactive policies are of vital importance to contain the pathogenic agent and reduce the potential damages to social and economic dimensions, the recognition of the severity of the situation caused by COVID-19 may push institutions to undertake long term investments to make future responses to pandemics timelier and more effective.

The following long-term investments will reduce time lags and allow more effective implementation of the interventions shown in Figs. 2–5. As shown in Fig. 3, each of those investments will have specific effects on different variables at the reactive level, as follows:

- By investing in permanent monitoring capacity, the decision makers will be faster in detecting new dangerous diseases spreading through the population. Once the number of infected grows over a certain amount at a certain rate, an early warning enabled by continuous monitoring could make the difference.
- Setting aside some reserves of resources for reactive policies, which will be implemented in times of need, means spending less time in securing them during those times.
Fig. 3. Feedback loop B2 is highlighted in bold. Policies for mask wearing, disinfecting hands and surfaces, and social distancing reduce the rate of transmission. This reduces the infection rate causing the infected population to decline over time and contributes to driving down the risk of becoming infected.

Fig. 4. Feedback loop B3 is highlighted in bold. Ramping up lockdowns, travel restrictions, and contact tracing and quarantine reduces the rate of contact between and susceptible individuals. This in turn reduces the rate of becoming infected, the infected population, and the risk of becoming infected.
Advance planning work, supported by investment, increases the effectiveness of implementation of reactive policies in terms of performance and time/resources needed.

Investment in a well-stocked inventory of masks and disinfectants makes the distribution during the infection faster and easier, as well as preventing the emergence and spread of new disease among the population.

Capacity development in vaccine R&D in lower income countries and establishment of distribution networks may improve timely availability of vaccines for the global population.

Knowledge of systems thinking on the part of decision-makers can generate awareness of policy leverage points and the importance of acting swiftly to manage contagious disease epidemics.

As all of us in some way experienced, the initial snowball effect of the pandemic, if uncontested, can result in very severe economic losses and social disorder. This should be enough to understand the importance of the availability of (even if only qualitative) tools capable of addressing the early-stages issues of destructive phenomena like COVID-19, thus allowing decision makers to gain an early awareness of what is at stake and to understand if one or more proposed policies (i.e.: like the ones we presented here) may be of any help.

3.2. Climate change: the influences of feedback and delays

Reinforcing feedback loops are believed to be key drivers of global climate change (Stocker et al., 2001). The Intergovernmental Panel of Climate Change (Stocker et al., 2001) classifies these feedback loops into categories of Atmospheric, Oceanic, Land-surface, Cryosphere, and Coupled Systems feedbacks. One of the most powerful Atmospheric feedback loops identified by the IPCC involves water vapor, itself a potent greenhouse gas (Stocker et al., 2001). In this reinforcing feedback loop rising temperatures increase evaporation and atmospheric water vapor, which in turn causes further temperature rise. In the cryosphere category, a highly publicized feedback loop causing climate change involves the albedo effect in which increasing average temperatures cause a reduction in polar ice cover, reducing albedo and leading to further temperature rise and polar ice melting because less solar energy is reflected from the earth’s surface into space. If prompt mitigative action is not taken to reduce atmospheric GHGs these types of feedback loops have the potential to exacerbate climate change (Van Nes et al., 2015). There is concern that runaway climate change may exceed tipping points (Lenton et al., 2019; Lenton, 2011), points of no return beyond which mitigative actions may be rendered futile due to the huge inertia of the climate system, further driving home the case for urgent global action.

![Fig. 5. Feedback loop B4 is highlighted in bold. Vaccination reduces the susceptible population, slowing the contact rate between infected and susceptible. This reduces the rate of individuals becoming infected, the infected population and reduces the aggregate risk of infection.](image-url)
The fact that climate change is characterized by webs of feedback loops with embedded time lags makes systems thinking and modelling ideal for climate change analysis, and for communicating the causal mechanisms of climate change to decision makers and the public. The best-known system dynamics models of climate change are those developed by Climate Interactive.\(^1\) The EN-Roads model, developed by Climate Interactive, is a user-friendly system dynamics model designed for learning and awareness building. EN-Roads allows users, ideally in facilitated workshops, to experiment with a wide range of climate change policies and observe simulated outcomes of key climate change indicators (Rooney-Varga et al., 2020). Randers and Goluke (2020) have developed the ESIMO “reduced complexity earth system” climate change model based on system dynamics. ESIMO simulates climate behaviour from 1850 to 2500 under different assumptions of anthropogenic greenhouse gas emissions. ESIMO simulations indicated that runaway permafrost and polar ice feedback loops can drive irreversible climate change even if initial warming is as low as 0.5°C above industrial levels. Meadows, Sweeney, and Mehers (2016) apply systems thinking and games to build understanding of the causes and urgent challenges of climate change. Research by Ballew, Goldberg, Rosenhal, Gustafson, and Leiserowitz (2019) found that systems thinking can be instrumental in fostering acceptance of climate change science across divisive political lines and facilitate a value system that promotes environmental protection.

From a Systems Thinking perspective, we maintain that many of the feedback loops underlying global climate change have strong similarities to the feedback structure underlying the COVID pandemic, all falling under the “Limits to Growth” archetype (Meadows, 2008).

For example, forest fire is considered by researchers to be part of a reinforcing feedback loop contributing to climate change (IPCC, 2019; Liu, Ballantyne, & Cooper, 2019). Fig. 6 shows simplified coupled reinforcing and balancing feedback loops involving forest fire that are very similar in structure to the basic loops for COVID-19 shown in Fig. 1.

Global temperature increases due to radiative forcing caused by atmospheric greenhouse gas concentration that is initially driven by anthropogenic greenhouse gas emissions. Higher atmospheric temperatures increase the potential for forest fire making forest fires more frequent, in particular due to climate change induced drought (IPCC, 2019). Forest fires release CO2, increasing GHG concentrations and, hence, global temperature, putting a reinforcing feedback loop in place (Feedback R1 in Fig. 6). Over time forest afflicted with recurrent fire may shift to shrub lands or other ecological regimes (IPCC, 2019). As forests diminish, a balancing feedback, B1 in Fig. 6, will in time reduce the potential for forest fire in a given region. This limiting process through depletion is similar in structure to the effect of depletion of susceptible in the COVID dynamics shown in Fig. 1.

The release of methane, estimated to be 34 times more effective than CO2 as a GHG (IPCC, 2013), is part of a reinforcing feedback loop that has the potential to exacerbate climate warming (IPCC, 2014; Knoblauch, Beer, Liebner, Grigoriev, & Pfeiffer, 2018). Fig. 7 shows basic feedback loops underlying the permafrost feedback.

The causal loop diagram in Fig. 7 follows the same pattern as for forest fire in Fig. 6 and COVID in Fig. 1. The conditions for permafrost thawing are rising atmospheric temperature and the presence of permafrost. Thawing of permafrost is gradual, indicated in Fig. 7 by the delay hash mark. The reinforcing feedback R1 increases the rate of permafrost thawing, driving up temperature and causing yet more thawing of permafrost. However, permafrost gradually becomes depleted, reducing the conditions for thawing and the rate of thawing (feedback loop B1).

An example of cryospheric feedback involving the well-documented melting off of polar ice is shown in Fig. 8.

The case of the polar ice melting is somewhat different from the other climate change cases shown above but the feedback loop pattern is nearly the same and strongly resembles the case of COVID shown in Fig. 1. The impact on temperature is via albedo rather than GHG. As polar ice cover decreases albedo is lowered, meaning that less insolation is directly reflected into space. Hence, there is greater energy absorption which increases temperature and results in further loss of ice cover. The process is limited by the loss of ice cover represented by balancing feedback loop B1 in Fig. 8.

Reinforcing feedback loops driving climate change may vary considerably in the speed of their impacts. For instance, reinforcing feedback associated with water vapor is considered fast acting whereas feedback associated with polar ice melting is much slower. The differences in speed of climate change reinforcing feedback means that different loops may be dominant at different times. However, all the reinforcing loops impact one another by raising temperature. Fig. 9 is a generalized feedback structure meant to represent multiple reinforcing feedback loops including the examples given and others such as water vapor feedback and feedback from forest die-off.

In Fig. 9, the term environmental stocks is meant to include any type of global ecosystem component, whether biotic or abiotic, that by virtue of being intact or in homeostasis has a stabilizing effect on climate, and by the same token is a source of climate change impetus if subjected to damage or decay. Examples are forests as potential sources of carbon flux if destroyed, permafrost as a potential source of methane emission when thawed, polar ice potentially increases net radiative forcing and global average temperatures if ice coverage is reduced.

In Fig. 9 rising temperature stresses environmental stocks that gradually disintegrate or decay (delay hashmark denotes time lags in this process). The degeneration increases radiative forcing, for example through release of greenhouse gases or decreased albedo in the case of ice cover, that increases temperature and eventually more degeneration of environmental stocks (feedback loop R1). As environmental stocks become depleted their contribution to climate change diminishes (feedback B1).

We can expand the generalized causal loop diagram shown in Fig. 9 to include human response to climate warming, that we can consider a balancing feedback for climate change.

\(^1\) https://www.climateinteractive.org/
Fig. 10 includes human recognition and response to climate warming in the form of a simple balancing feedback loop (B2). Decision-makers recognize that increasing temperature causes risk of social and economic damage (Beard et al., 2021) and design and enact policies to reduce anthropogenic GHG emissions in response.

However, given large short-term costs of reducing GHG emissions, a certain amount of GHG emission is allowed to continue. Often this accepted amount of GHG emissions is determined in international fora and varies between countries, largely dependent on the stage of economic development of the particular country. The Nationally Determined Contributions (NDCs) are nations’ declarations...
on climate change actions they agree to take, set forth in the 2015 Paris Agreement. Nations are expected to update their NDCs every five years reflecting their progressive commitment to mitigating climate change (Mills-Novoa & Liverman, 2019).

Fig. 10 shows that the human recognition of and response to climate change features time lags at every stage. First time is required to recognize and agree that climate change is in fact occurring and that it is causing serious environmental, social, and economic damage. The second tier of time delay in the feedback loop is to design, agree upon and implement mitigation policies. The third-tier delay arises due to working capital lifetimes and inertia in current energy, industrial, and agricultural systems. The fourth-tier time lag is related to the inertia of the climate system itself - greenhouse gases can have a residence time of decades in the atmosphere, and decades will be required for reductions in anthropogenic GHG emissions to affect atmospheric concentrations.

Two components of systems thinking are particularly relevant in the climate change debate: reinforcing feedback that potentially leads to runaway climate change, and the time delays in human recognition and consensus-building that could fatally weaken humanity’s efforts to arrest climate change.

Bill Gates commented in 2014 on the importance of quick action to address climate change:
“…by the time we see that climate change is really bad, [our] ability to fix it is extremely limited. Like with viruses, the problem is latency. The carbon gets up there, but the heating effect is delayed. And then the effect of that heat on the species and ecosystem is delayed. That means that even when you turn virtuous, things are actually going to get worse for quite a while.” (Goodell, 2014).
Gates’ quote points to the massive momentum of climate change, driven in large part by reinforcing feedback loops. Systems thinking and system dynamics modelling, and simulation can help decision makers comprehend the urgency of climate change, and their historic responsibility to take action before it is too late.

4. Results and discussion

We have so far argued how important it is for decision makers to be able to assess early on the potential dynamic behaviour of destructive phenomena (like the COVID-19 pandemic or climate change).

A main tenet of Systems Thinking and System Dynamics is that a system’s structure defines its behaviour over time. Hence, being able to reproduce and analyse systemic structure is key to an early understanding of the issues at stake and for a more effective design of simulation models that are able to provide the right answers (i.e., reliable projections of future outcomes) by “posing the right questions” (i.e., using “less wrong” models - Sterman, 2002). Since similar behavioural patterns can be observed for different systems, one can assume that the systemic structures underlying those systems showing similar behaviours are also similar. As mentioned earlier, such structures are called Systems Archetypes. This does not mean that two different systems are made of the same ‘items’, but that they have a similar structure that causes them to have similar, archetypal, behaviours (Meadows, 2008).

Both cases analysed in the previous section show an important common structure that is known as “the limits to the growth” archetype (Fig. 11).

As in the case of this archetype’s behaviour, both for COVID-19 and Climate Change the initially dominant “growing” action is slow at the beginning, and in the case of slow phenomena (characterized by higher delays) almost impossible to tell whether it is different from linear growth if data is sparse and not very precise. But once the “doubling-time” is recognized (that is the time needed for the dynamics to “double” its magnitude - i.e.: the time needed for 100 infected people to become 200), it is then easy to understand its nature. Of course, much depends also on the perception delay of such a doubling-time, which in turn depends on the human capability to adapt physically and psychologically (as well as socially, economically, etc.) to the new conditions.

The ability to become aware, through simulation or even through an early systemic understanding of the real system’s structure, of the presence of a reinforcing feedback in “undercover” action is hence fundamental to anticipate the moment in which it will “explode”, hence becoming almost unstoppable (at least until it triggers a balancing feedback, in some other parts of the system, which, in the cases of pandemics and climate change, might occur only after incurring terrific economic and human costs).

Despite the fact that Italy is recognized today as one of the countries that has best managed the COVID-19 pandemic, in Europe and the entire world, the Italian case of COVID-19 is emblematic of what other countries have done and it is useful for understanding the systemic problems (delays, feedback, etc.) that decision makers encounter every time a crisis occurs. The Italian government (as many others), despite the example of what happened in China, was not initially able to perceive the severity of COVID-19 as it was not able to perceive that an exponential growth was actually occurring. So, despite the fact that the doubling-time was very rapid (around 2–3 days), Italy established a full lock-down only on the 8th of March 2020, 21 days after the epidemics’ breakout, during which COVID-19 underwent free and unopposed exponential expansion. The lock-down policy revealed its result 12 days after, on March 21st, when the curve of Total Infected (Fig. 12) began to flatten as the New Daily Infections started to go down.

It is interesting to note that almost in the same period, similar lock-down policies have determined a similar flattening in neighbouring countries. If decision makers had been able to detect this dynamic earlier, they would have acted earlier. But they perceived how the problem was unfolding only when the numbers of infections and deaths started to become undeniably shocking, that is, becoming frontline news and jarring public opinion (see the meme retrieved from the web in Fig. 13).

However, many other countries were late in recognizing the imminent threat of COVID-19 and in implementing the necessary travel bans. In the United States, for example, there was a delay in recognizing the extent to which the U.S. population was already infected by arrivals from abroad (Du, Javan, Nugent, Cowling, & Meyers, 2020). These delays resulted in further delays in preparation for ensuing irruptions of COVID-19 cases (Pueyo, Lash, & Serkez, 2020).

But, again, this is the problem with delays coupled with reinforcing feedback loops… if you don’t look at the dynamics through a systemic lens, the moment you realize that you’re going to be overcome, it is already too late…!

The presence and impacts of time delays is a highly relevant aspect of a thorough and full-picture understanding of systems behaviours. Generally, in human systems, an action does not produce an instantaneous effect and when such effects are particularly
distant in time (i.e. ice melting at the poles), the ability of humans to perceive them must somehow be supported by tools and methodologies. It is as if we were looking at the stars: the light we see today is due to energy emitted billions of years ago. Anticipating the future effects of actions, and perceiving them in the right way, is key to enabling early and effective intervention for next

Fig. 12. Time series of Total Cases (top) Vs Daily New Infections (bottom) in Italy, starting from the identification of COVID-19 patient-0 on February 15th 2020.
Source: Worldometers.info.

Fig. 13. (a) Meme retrieved from the web, depicting the different perception paradigm when dealing with exponential growth.
(b)Source:https://m.facebook.com/systemdynamics/photos/a.683212415060943/3716852498363571/?type= 3.

S. Armenia et al.
generation policy makers. Anticipation might even include the possibility to forecast (e.g., by simulation) what would happen in the event that a certain policy is implemented, a consolidated “what-if” approach which to minimize risks following action. For this it is critical to have a correct understanding of the system structure and behaviour and it is more effective if the simulation environment is capable of explicitly accounting for the presence of time delays and other dynamics like that of exponential growth (reinforcing feedback) or resistance to change (balancing feedback).

Some delays are intrinsic in the dynamics of a system’s behaviour (i.e., exponential growth can be very small for a long period of time and take some time before growing beyond a certain threshold) but other delays (i.e.: related to intervention) can also be caused by the inability of the decision maker to become aware, in due time, about the change that is happening.

Perception delays combined with intrinsic systems delays produce longer time lags that can become critical (Bengston, Crabtree, & Hujala, 2020). Also, delays might even fall outside our “relevant” time-horizon or out of the scope of our observational capability (i.e., a dynamic of a specific phenomenon might occur, with a long delay and in another country or part of the globe, produce changes that we are not able to readily observe).

In light of the above, it is our strong opinion, already supported by many scientists, that data analysis and inference-based simulation models need to be supported by structural models built through systemic approaches. In this sense, Systems Thinking can help in describing and understanding the structure of a system, and System Dynamics, based on those descriptions and understanding, can seamlessly support, the design of “less wrong” simulatable models that can explicitly address the presence of structures capturing exponential growth dynamics and the influences of delays in the system. So, we argue that Systems Thinking and System Dynamics should be taken into account when it comes to understanding the dynamics of complex phenomena, hence developing a clear awareness of what it means to “anticipate” and forecast behaviour over time (Fuller, 2017). In terms of forecasting challenges (Orrell & McSharry, 2009), if we fail to understand how a system’s structure works, then we fail to correctly infer the real extent of its dynamics, which means on one hand failing to adopt correct (potentially even hybridized with other disciplines, like Agent-based modelling, for example) models on which to test our strategies and, ultimately becoming aware only too late of the real extent of potential disasters.

5. Conclusions

On the path to 2030 and beyond, humanity faces many issues of very diverse nature, demanding multidisciplinary approaches to overcome forecasting challenges and potentially anticipate the impacts of our choices on our own future (World Economic Forum, 2020).

In this paper, we have analysed the commonalities between two seemingly different global problems, the COVID-19 pandemic and Climate Change, and have developed two novel qualitative Causal Loop Diagrams (Systems Thinking models) aimed at producing some reflections on the advantages of a systemic Systems Thinking mindset. We have highlighted the challenges related to addressing problems characterized by dominant reinforcing feedback loops coupled with delays in perception and intervention. In those cases, timely recognition of the nature of the issue from a structural standpoint can provide the basis to design and develop more effective simulation models, hence anticipating potentially adverse and destructive impacts, and more promptly putting in place the necessary countermeasures.

Additionally, we have argued that the use of systemic paradigms like Systems Thinking and System Dynamics can provide the necessary complement to the mere extrapolation of our future state driven by data analysis. Hence, simulating the behaviour of models, validated with current data, can help us in understanding and forecasting what our world will likely be in the complex post-COVID-19 context we are starting to face.

From this perspective, the insights evidenced through this work are the following:

1) COVID-19 and Climate Change display similar archetypal structures that are particularly relevant in describing the critical, early phases of the phenomena
2) Systems Thinking and System Dynamics are extremely useful approaches even when building qualitative models (that include archetypal structural characteristics of complex environments) that make possible an early understanding of the potential evolution of destructive phenomena
3) Being able to correctly identify the presence of reinforcing feedback loops and delays in a system, by means of Causal Loop Diagrams, supports an early understanding of the stakes and helps design realistic simulation models that will support taking timely decisions
4) Using systemic paradigms like Systems Thinking and System Dynamics can thus be very useful and effective when designing predictive simulation models
5) Lessons learned from the study of the dynamics of COVID-19 should warn policy makers not to underestimate the current accelerating dynamics of Climate Change

In summary, decision-making that is driven by data, without properly accounting for the underlying system drivers, may not be effective when issues are growing exponentially and the effect of policies are lagged. Thus, developing an early understanding of the phenomena’s structures based on a sound systemic framework is essential to anticipating adverse/destructive behaviours and hence to effective decision-making.

This paper has also some limitations:
• Our modelling approach is limited to Systems Thinking (ST) and qualitative System Dynamics (SD), expressed through Causal Loop Diagrams (CLDs). An ST model is simulated mentally but often provides the conceptual foundation for the ensuing development of formal mathematical models (quantitative System Dynamics models). Our premise, however, is that ST and CLDs can provide crucial and timely insights that can be made readily comprehensible to policy and decision makers.

• Our Systems Thinking models focus on small subsets of the almost innumerable feedback loops and delays that characterize the COVID-19 and Climate Change. This is intentional as our purpose is to identify key positive feedback loops that can lead to disastrous consequences when decision makers fail to recognize and take early action in causal relationships that lead to overwhelming exponential growth. This has happened with COVID-19 and will happen with Climate Change unless leaders take prompt actions.

• We have not performed a formal comparison of Systems Thinking and System Dynamics with other modelling and simulation methodologies as we did not want to focus our attention on this rather on the misperception of positive feedback loops and delays. For this we have relied on a previous studies stating the value of Systems Thinking and System Dynamics over other modelling techniques when dealing with certain complex problems around sustainability (Armendart et al., 2015) and when dealing with the need to produce an early understanding of the problems at stake (Armenia & De Angelis, 2013).

Despite the evident delayed action, governments have by now demonstrated that they are able to clearly perceive the COVID-19 problem and have implemented containment policies that will (sooner or later) bring a halt to the spread of the pandemic. COVID-19 has shown to civil society that when we realize that a problem impacts our personal lives, we are more prone to listen through a different mindset, and to collaborate more actively in the related crisis situation.

Unfortunately, a similar commitment is not yet emerging to deal with Climate Change. Although we are currently witnessing an increasing number of alarming signals (increasingly severe wildfires, the reduction of the ice cover at the poles, the loss of animal and plant species, rising sea level, etc.) of a literally burning planet, the policy response is not as strong and clear as it should be to significantly reduce negative impacts. The mechanisms driving Climate Change are certainly multifaceted, and data is more difficult to interpret than for COVID-19.

While the effects of Climate Change are irregular and geographically dispersed, we already know that reinforcing feedbacks are at work accelerating change while the current inertia of Government agreements will unfortunately make effective countermeasures much harder down the road. The delays involved in policy implementation will give even further time to the Climate Change machine.

To conclude, as COVID-19 has brought incommensurable harm to humanity, we can learn from that very expensive lesson and appreciate the urgent need to act before powerful feedback systems driving Climate Change gain further strength. Prompt and focused action in such systems is necessary to avoid enormous costs for our current and future generations.

Acknowledgements

This paper is the sole result of the research conducted by the authors, and no funding was obtained in order to produce this work.

References

Aguilar de Soua, D., & Katan, M. (2021). Promising use of automated electronic phenotyping: turning big data into big value in. Stroke Res. Stroke, 52(1), 190–192.

Anderson, R. M., & May, R. M. (1991). Infectious Diseases Of Humankind: Dynamics and Control. Oxford university press.

Armendartiz, A. S., Atzi, A. S., & Fonseca, J. M. (2019). The rural-urban food systems’ links with the agenda 2030: From FAO guidelines on food supply and distribution systems to a dairy sector application in the area of bogota. System, 7(3), 45.

Ayittey, F. K., Ayittey, M. K., Chiwero, N. B., Kamasah, J. S., & Dzuvor, C. (2020). Economic impacts of Wuhan 2019-nCoV on China and the world. Journal of Medical Virology, 92(5), 473–475.

Ballew, M. T., Goldberg, M. H., Rosenthal, S. A., Gustafson, A., & Leiserowitz, A. (2019). Systems thinking as a pathway to global warming beliefs and attitudes through an ecological worldview. Proceedings of the National Academy of Sciences, 116(17), 8214–8219.

Beard, S. J., Holt, I., Tzachor, A., Kemp, L., Avin, S., Torres, P., & Bellfield, H. (2021). Assessing climate change’s contribution to global catastrophic risk. Futures, 127, Article 102673.

Bengston, D. N., Crabtree, J., & Hujala, T. (2020). Abrupt climate change: Exploring the implications of a wild card. Futures, 124, Article 102541.

Boyd, D., & Crawford, K. (2012). Critical questions for big data in information. Communication and Society, 15(5), 662–679.

Boyd, E. M., & Fales, A. W. (1983). Reflective learning: Key to learning from experience. Journal of Humanistic Psychology, 23(2), 99–117.

CDC. (2021). COVID-19 information metrics for response leadership’s decision making. Centers for Disease Control and Prevention. Accessed 27 June 2021 and availabl at: https://www.cdc.gov/coronavirus/2019-ncov/global-covid-19/leadership-emergency-response.html.

Currie, C. S., Fowler, J. W., Kotiadis, K., Monks, T., Ongra, B. S., Robertson, D. A., & Tako, A. A. (2020). How simulation modelling can help reduce the impact of COVID-19. Journal of Simulation, 14(2), 83–97.

Deacon, L., Van Ache, K., Papineau, J., & Gruenmacher, M. (2018). Speculation, planning, and resilience: Case studies from resource-based communities in Western Canada. Futures, 104, 37–46.

Deckert, A., Bärnighausen, T., & Kyei, N. N. (2020). Simulation of pooled-sample analysis strategies for COVID-19 mass testing. Bulletin of the World Health Organization, 98(9), 590.

Du, Z., Javan, E., Nugent, R., Cowling, B., & Meyers, L. (2020). Using the COVID-19 to influenza ratio to estimate early pandemic spread in Wuhan, China and Seattle, US. EClinicalMedicine, 12 August, 2020.

Feng, Y. & Lu, X. (2020, October). Simulation analysis of the coronavirus disease 2019 (COVID-19) spread based on system dynamics model. In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 498–501). IEEE.

Fenner, R., & Cerneve, T. (2021). The implications of the Covid-19 pandemic for delivering the Sustainable Development Goals. Futures, 128, Article 102726.
Soler, L. S., Silva, D. E., Messias, C., Lima, T. C., Bento, B. M. P., de Souza, J. J., & Almeida, C. (2021). Promising advances of amazonian monitoring systems throughout vanguard technology and scientific knowledge. The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 43, 843–849.

Sterman, J. D. (2000). Business dynamics: systems thinking and modeling for a complex world. New York: Irwin Professional/McGraw-Hill.

Sterman, J. D. (2002). All models are wrong: reflections on becoming a systems scientist. System Dynamics Review: The Journal of the System Dynamics Society, 18(4), 501–531.

Stocker, T. F., Clarke, G. K., Le Treut, H., Lindezen, R. S., Meleshko, V. P., Mugara, R. K., & Holtslag, A. A. M. (2001). Physical climate processes and feedbacks. In IPCC, 2001: Climate change 2001: The scientific basis. Contribution of working group I to the third assessment report of the intergovernmental panel on climate change (pp. 417–470). Cambridge University Press.

Struben, J. (2020). The coronavirus disease (COVID-19) pandemic: simulation-based assessment of outbreak responses and postpeak strategies. System Dynamics Review, 36(3), 247–293.

Turiman, P., Omar, J., Daud, A. M., & Osman, K. (2012). Fostering the 21st century skills through scientific literacy and science process skills. Procedia-Social and Behavioral Sciences, 59, 110–116.

Van Nes, E. H., Scheffer, M., Brovkin, V., Lenton, T. M., Ye, H., Deyle, E., & Sugihara, G. (2015). Causal feedbacks in climate change. Nature Climate Change, 5(5), 445–448.

Venkateswaran, J., & Damani, O. (2020). Effectiveness of Testing, Tracing, Social distancing and Hygiene in tackling covid-19 in india: A System Dynamics Model arXiv Preprint arXiv, 2004, 08859.

de Vries, A. (2010). European territories confronted with climate change: Awaiting the events or timely preparation? Futures, 42(8), 825–832.

Waltner-Toews, D., Biggeri, A., De Marchi, B., Funтович, S., Giampietro, M., O’Connor, M., & van der Sluijs, J. P. (2020). Post-normal pandemics: Why CoViD-19 requires a new approach to science. Recenti Progressi in medicina, 111(4).

World Economic Forum (2020). The Global Risks Report 2020. [https://www.weforum.org/reports/the-global-risks-report-2020].

World Health Organization, (2022) WHO Coronavirus Disease (COVID-19) Dashboard [Online]. Available at: [https://covid19.who.int/] (Accessed: 15 June 2022).