Complex Quality Improvement Networks: Government Responses to Covid-19 Modelled as Complex Adaptive System Behaviour

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COMPLEX QUALITY IMPROVEMENT NETWORKS: GOVERNMENT RESPONSES TO COVID-19 MODELLED AS COMPLEX ADAPTIVE SYSTEM BEHAVIOUR

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Abstract—**Worldwide government policy response both to and during the COVID-19 crisis has been variable. Proposing a new model for observing complex adaptive system (CAS) behaviour that is populated with publicly available policy response data from the first five months of 2020, this paper examines the application and effectiveness of different approaches employed by some governments. This study finds evidence of CAS characteristics and a consistent system response function suggesting high sensitivity CAS activity amongst nations successfully responding to COVID-19. The CAS sensitivity is evident across diverse physical geographies, population densities and systems of government. Identification of consistent CAS behaviour patterns under extreme circumstances offers a potentially useful tool that can complement epidemiological management when calibrating policy settings.**

Keywords— ***Complex adaptive systems, COVID-19 policy responses, complex system sensitivity, CQIN***

I. INTRODUCTION

The first five months of 2020 offer an unfortunate but thankfully rare opportunity to examine global government response to COVID-19 through the lens of complex adaptive systems (CAS) [1]. Observers may choose to identify a system as a CAS when some combination of the following criteria is present: (i) *A large network of autonomous agents;* (ii) *dynamic, entangled, non-linear interactions;* (iii) *a high rate of change;* (iv) *emergent higher-order effects;* (v) *the ability to adapt and learn;* (vi) *self-organisation;* (vii) *coevolution;* (viii) *temporality,* and (ix) *system history* [1-5]. Healthcare systems, governments and whole nations are frequently described as examples of CAS [4, 6]. The sudden emergence of a highly contagious virus like COVID-19, about which very little was initially known, was also an extremely complex problem that even through the tortuously mixed messages in the mainstream media we were told demanded a swift and coordinated response. Unfortunately, a more difficult test of complex problem solving under pressure is difficult to imagine.

Wide variation exists for how each country responded to the threat of COVID-19. Some countries reacted immediately and with policies that may have initially been viewed as draconian, including: Taiwan, South Korea and Israel. Taiwan, still acutely aware of their massive death toll from SARS only a decade earlier had remained vigilant and was one of the first and most stringent of early responders [7]. South Korea (SK) initially had an infection rate second only to China. However, the SK government's response, starting in late February, saw advanced information technology being used to trace individuals and enforce quarantine, rapid rt-PCR testing of citizens, and the use of adaptive legislation that while considered extreme and privacy-eroding, became an effective tool in halting spread of the disease in only a single month [8, 9]. In early February Israel began to close sea and land borders, preventing anyone but citizens from deboarding airplanes [10]. Anti-terror phone tracking legislation and an enforced quarantine with either a location and contact tracing app or home-detention style ankle bracelets was mandated for all persons confirmed infected, and those who had recently returned from overseas. These measures almost entirely arrested Israel's secondary infection rate [11].

In stark contrast were countries like the United States of America (USA), United Kingdom (UK), Italy and Sweden. While Sweden made an early and active choice not to take stringent measures that would impact their economy, like enforced lockdown [12, 13], the responses for each of the other three have been characterised in the media as: *a series of missteps*; *slow*; *unresponsive*; and even *bad luck* [14, 15, 16].

The independently captured COVID-19 government response data provides the basis for an experiment to measure and compare CAS behaviour across multiple samples. Early characterisations of urgency and seriousness for the 'pandemic' in the mass media condensed learning cycles that might normally be expected to unfold over months or even years into timeframes of only days and weeks. It is perhaps obvious to know that very fast action is essential when seeking to prevent exponential growth in case numbers, but this knowledge can be complemented by a nuanced understanding of whether a nation's aggregate responses demonstrate successful adaptation to the problem or have occurred at the most expedient pace.

Given the presumed stakes, the cost/benefit analysis of government responses is both critical and extremely difficult and every government will come to their own conclusions as to how quickly the highest (economic and social) cost policies are required. In relation to the case number signal, understanding whether current policy settings are actually working and having awareness for whether the system is capable of additional rapid adaptation may prevent further unnecessary economic and human cost. We describe this as the *sensitivity of the system* and propose development of reliable measures for system sensitivity as a useful contribution to future pandemic management, to be employed alongside conventional epidemiological, economic and political considerations. The purpose of this study is to identify characteristics of CAS behaviour within the ideal experimental environment provided by international government policy responses to COVID-19.

II. Related Works

Complex systems can be classified as natural (an ecosystem), engineered (the internet) or social (cities, governments and organisations). Within the category of complex adaptive social systems, the self-awareness, agency and intentionality of the system actors is an additional structural feature of the system [5, 6]. Localised healthcare improvement activity and the national pandemic responses each exhibit social CAS features, with the difference being the scale of the system and available measurement and intervention opportunities.

One implication we could draw from CAS literature is that CAS may be unsuited to conventional improvement approaches such as statistical process control or Plan-Do-Study-Act (PDSA) cycles, which are built for use on mechanistic systems models. Mechanistic systems can be analysed in a reductionist mode, that is, by isolating the individual parts [5, 6, 17]. Any firm boundary between mechanistic and complex systems is open to challenge, and the literature is not settled on whether the underlying issue is *appropriateness* of a method such as PDSA in a complex healthcare setting, or the skill with which the method is *applied* [18, 19]. A plausible argument can be made that the iterative system responses we observe in this study still represent a recognizable form of PDSA, albeit one that is explicitly dealing with CAS phenomena. Demonstrating the applicability of existing and familiar improvement approaches (in at least some complex settings) may allow for faster action under pressure.

Unsurprisingly, the healthcare complexity literature reveals an emphasis on the agent activity expected within a social CAS, and the frameworks and models in use reflect this. Complex network analysis is now routinely applied to healthcare contexts [20]. However, perhaps the most prominent recent mode of healthcare complexity research is a focus on uncertainty, situational awareness, decision making and leadership, via frameworks such as Cynefin [21]. Cynefin describes situations as known, knowable, complex or chaotic, and maps appropriate actions to the type and levels of uncertainty involved [22, 23]. Complexity principles are also invoked independently of any integrated framework, to analyse or describe phenomena of interest within a study. This was the finding of Thompson et al. [24] in their 2016 scoping review of complexity theory in health services. This review also reported qualitive studies being twice as common as quantitative studies. Relationships and self-organisation were the two most commonly referenced complex system attributes [24]. The difficulties in applying complexity theory in general, and CAS theory in particular, remain prominent in the recent literature, with human agency, effective measurement and establishing system intervention points all identified as challenges [6, 25, 26]. The COVID-19 pandemic can also be viewed as both a logistical and operational management problem (literally, in the supply chain sense). This domain also has an established research tradition incorporating CAS thinking [27, 28]. The CAS model proposed by Nair & Reed-Tsochas represents a recent evolution of this thinking and we have incorporated their definition of system boundaries into the new model presented in this work [28]. This feature allows for simple representation of lightly or heavily coupled systems that must coevolve with the defined CAS [4].

Policy responses to COVID-19 require complex agent networks to coordinate their actions in response to problems and perceived threats in the presence of high levels of uncertainty and multiple communication and problem solving challenges. It is to be expected that crystal clear communication and trust are therefore emphasised as truly vital success factors in the COVID-19 policy responses [29, 30]. To succeed, these highly effective agent networks also need to expertly navigate from the unknown to the known via adaptive learning cycles [4, 31, 32]. For these reasons we investigated a new model that could provide a framework for examining the outcomes of select countries during the first 5 months of 2020.

III. The Complex Quality Improvement Network (CQIN) Model for Adaptive Helathcare Systems

To provide a means of collecting information on complex system behaviour, we developed the *complex quality improvement network* (CQIN) model, whose purpose is to provide a generalisable framework to observe and measure problem solving in complex social systems. Fig. 1 presents the CQIN model as an agent network (G) with two feedback loops, one for the primary signal of interest (A-B-C-E-F) and a separate path for process performance signals (A-D-E-F). The separate process and outcome feedback paths are an important feature of the model given the emergent nature of the outcome signal. It is necessary not only to know that something is working (or not), but also to know why. An example of this second feedback path would be supply chain information for COVID-19 testing readiness e.g. testing kit raw materials. In the CQIN model, multiple system signals are detected and interpreted, any required change actions are determined and then implemented, all in a continual cycle. Signal detection, problem solving and implementing solutions are mediated via the agent network (G) and moderated by the external environment of the CAS (I). Differentiating the CQIN model from simple mechanistic feedback loops, our social CAS has a large network of autonomous agents sending, receiving and interpreting the signals, high rates of change, non-linear outputs, high variation in outcomes, self-organisation and time-dependent behaviour. There are clear examples of this CAS-like activity [2, 4 5, 33] in the Government COVID-19 responses. While the generic components of the CQIN Model are presented in Fig. 1, each component is mapped to the COVID-19 policy responses and measures as described in Table 1.

The CQIN model is not proposed *sui generis*; it has been synthesised from CAS literature with four structural foundations. These are: 1) *cybernetic control systems* [34, 35]; 2) *complex agent networks* [4, 33]; 3) *learning classifier systems* [3, 4]; and 4) *the CAS boundary representation of Nair and Reed-Tsochas* [28]. CQIN is thus an intentional merging of conceptual models from general and complex systems theory research traditions. The aim of the synthesis

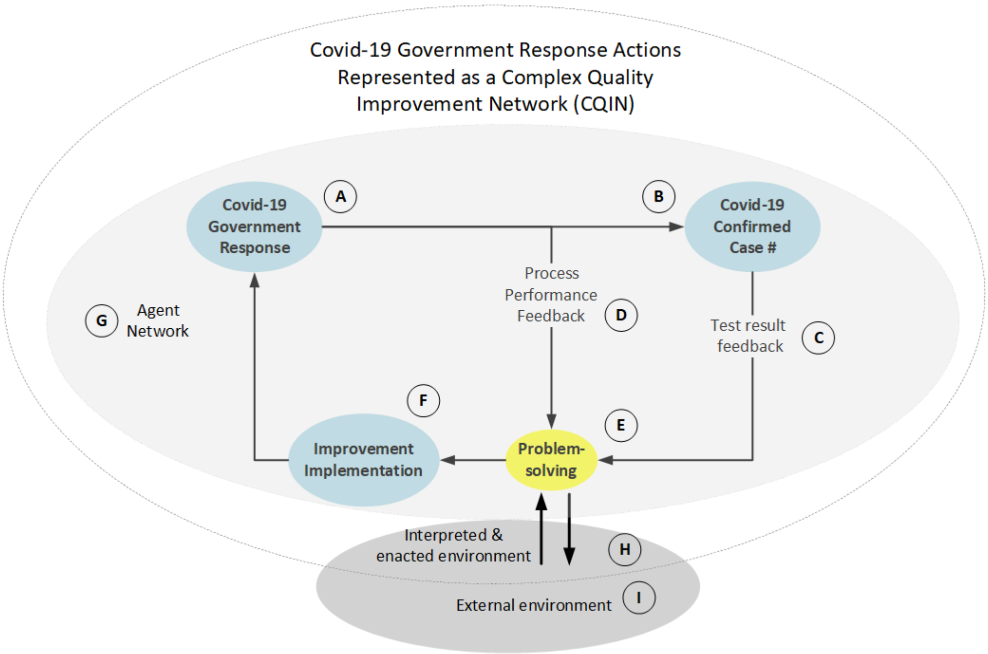


Fig. 1. The complex quality improvement network (CQIN) model

TABLE 1. COMPONENTS OF THE CQIN MODEL FOR GOVERNMENT COVID-19 RESPONSES

CQIN Model Component	**COVID-19 Public Health Context**	**Data Elements in the COVID-19 Context**
(A) Healthcare processes	COVID-19 public health actions: policy responses and measures	Travel restrictions, containment measures, public communications, contact tracing, social distancing rules, test type, frequency, sampling/test criteria.
(B) Outcomes signal	Primary Metric: Case numbers	Confirmed case numbers, probable case numbers, true positives, true negatives, false positives, false negatives.
(C) Outcomes feedback	COVID-19 diagnostic test result path	Case number results and trends shared across network.
(D) Process feedback	Process performance; Issues feedback path	Testing rates, error rates, policy compliance/non- compliance.
(E) Problem solving	Problem-Solving (Adaptive response): Issue detection, interpretation, problem-solving analysis	Not visible at the macro level of observation. May be able to be inferred by overall problem-solving effectiveness and publicly available information.
(F) Improvement action	Implementation of next problem-solving step	Measurable as iterative changes to actions taken over time.
(G) Agent network	Distributed network of clinicians, epidemiologists and decision-making authorities	Not measurable at the macro level of observation. Some inference or descriptive data available.
(H) Perceived system boundary	The boundaries of the microsystem as perceived by the agent network.	Not directly measurable at the macro level of observation. Dynamic and subjective.
(I) External environment	Activity beyond the CAS, e.g. public behavior, coupled systems	Not directly measurable at the macro level of observation, but the moderating effect on requested change actions may be able to be inferred.

is to situate the adaptive learning mechanism within a broader framework that can collect useful empirical CAS data at different granularities of measurement.

By choosing international governmental policy responses to COVID-19 as our concrete example in this study, we must acknowledge the limitation of working with high-level observations. The thousands of detailed relationships and mechanisms within the agent network, and their problem-solving details, are unknowable. A feasible strategy within the context of our case study is to treat the agent network and adaptive responses as a black box, where only the inputs, outputs, and the sum of the box behavior over time are observable. Such an approach has successful precedents in algorithmic data analytics [36]. In this CAS, the confirmed case number acts as the emergent outcome of the complex system behaviour and hence the signal to the system for the next action. This modified view of CQIN is illustrated as a moment in time snapshot in Fig. 2, which represents the South Korean Government COVID-19 response at 1000 confirmed cases.

IV. Analysis of COVID-19 Policy Responses and Measures in Selected Countries Using the CQIN Model

A. Hypothesis

It will be possible to observe and formally describe the relationship between the confirmed COVID-19 case numbers and the iterative government policy responses.

In the context of CQIN, the confirmed case numbers represent the system signal and the policy responses represent the cumulative signal detection, problem-solving and adaptation of the system. To confirm the hypothesis, the following observations are expected:

1. There is evidence of adaptation in the form of increased or reduced stringency and multiple iterative response cycles relative to the case number signal.
2. Adaptation cycles are non-linear, due to the underlying complex network structures, the information spreading (sharing) rate, and the overall system learning rate.
3. There is moderation of the effectiveness of similar government responses across the sample group, representing the coevolution of external systems required for the responses to be effective, for example, population compliance.
4. There are critical state transitions within the adaptive responses.
5. There is a mix of successful and unsuccessful strategies, with observable relationships between case numbers, response index severity, the number of response iterations and the timing of responses.

B. Methodology

This work draws on publicly available data from the University of Oxford Blavatnik School of Government's "Variation in government responses to COVID-19" dataset; specifically, the Oxford COVID-19 Government Response

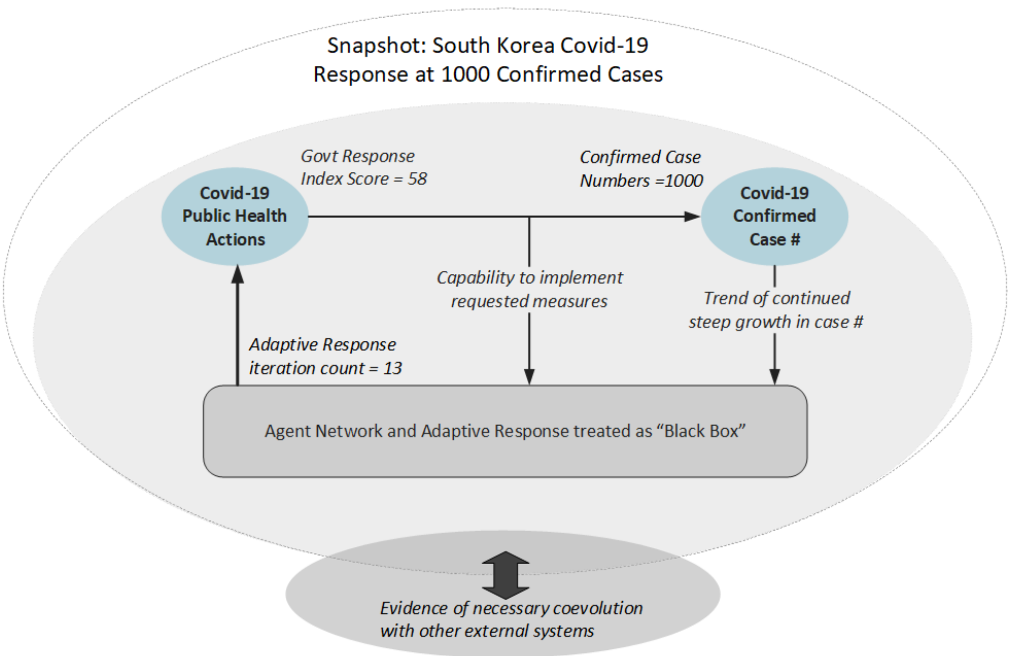


Fig. 2. The CQIN model in terms of the COVID-19 policy context

Tracker (OxCGRT) [37]. The OxCGRT provides a view across countries and time of the various government responses to COVID-19 in the form of four composite indices of the various policies. We selected the overall government response index which contains all the identified containment and closure, health system, and economic response measures. The overall response index was therefore best suited to the aim of the study, which was to observe all responses, not just the stringency levels.

In the context of the CQIN model, the confirmed case numbers provide the improvement signal, with "flattening the curve" as the improvement objective. Case numbers are acknowledged as dependent on each countries' testing policy during the time window selected. Mortality rates were rejected as an outcome measure given the lack of standardized reporting across countries [38] and the dependence on treatment. In this time series view of the CQIN, the 'problem' to be solved is preventing or suppressing the initial spread of the disease, i.e. flattening the curve. A sample of 12 countries was chosen using a positive and negative deviation approach to compare countries that successfully limited case numbers quickly with countries who struggled to achieve this. To more fully demonstrate application, the case study maintains a wide range of geographic spread, country size, population densities and COVID-19 case numbers.

To create the system response measure, we took the OxCGRT government response index time-series view from 01 January 2020 to 31 May 2020 and measured the *transitions* in index levels as tangible evidence of action (the change in policy setting). These transitions represent iterations of the CQIN adaptation cycle, implemented by the underlying complex agent network including health and government officials. Two important points must be made about the selected data. First, as Hale et al. [39] stress, the government response index levels are not intended to pass judgement on the appropriateness or effectiveness of the government responses. They merely track the range of responses in a standardised manner. Second, the COVID-19 pandemic remains a global crisis at the time of writing, and it continues to circulate around the world in multiple waves.

Some of the countries that were initially successful in flattening the curve have subsequently experienced ongoing challenges suppressing the virus. For others, the time window chosen may not yet reveal the success or failure of their efforts. The conclusions drawn from this research focus only on the initial 5 months of 2020 as a rare period of exceptionally intense activity that can be accessed as a snapshot of complex adaptive system behaviour, within the given time window. We intend to continue our measurement across the full time series of the pandemic to extend and develop our initial findings.

C. Results

Formal mathematical analysis of the policy response-case number function is the subject of ongoing research by our team. For the present discussion, we have assessed the reliability of the plotted data using a generalised additive model (gam), to establish confidence levels for the response means [40, 41]. Fig. 3. shows a high sensitivity example (Spain) compared to a low sensitivity example (USA) in Fig. 4, after each has been fitted to a gam.

The dotted curves in Fig. 3 and Fig. 4 represent the 95% confidence intervals for the mean gam curve. Comparing the curves to the plotted data it is quickly apparent that the confirmed case numbers are not a reliable predictor variable for the USA response. We then prepared two charts for each of our 12 sample countries. The first chart is an x-y scatterplot:

$$y = f(x)$$

The government response transition count is the response variable (y), and the confirmed case numbers are the predictor variable (x). The second chart is a combined time series view showing confirmed case numbers, the government response stringency index level, and the count of response transitions over time. A complex non-linear relationship between the variables is revealed. Viewed together the charts provide a view not only of the effectiveness of the government responses in suppressing case numbers, but also the *sensitivity* of the complex adaptive system to the case numbers as the primary system signal requiring a response. We have divided the countries into two categories: high sensitivity and low sensitivity responses. Table 2 presents the high sensitivity systems, where we can see a signature 3-part system response function in all cases – the very fast implementation of an initial set of measures, at very low case numbers, then ongoing responses at a significantly slower rate, and then a third phase of increasingly frequent responses. This final third of the system response curve may represent either an increasing or decreasing of the government response level, depending on successful flattening of the case curve. Table 3 presents the low sensitivity response category, where we see that the second and third phases of the system response are absent (USA, Canada, Singapore Sweden), or in the cases of the UK and Brazil, present but clearly not yet effective in flattening the curve.

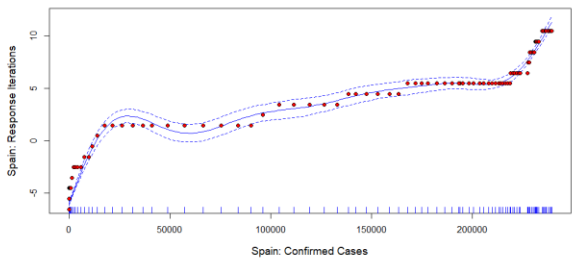


Fig. 3. Spain: Iterative response fitted to a generalised additive model

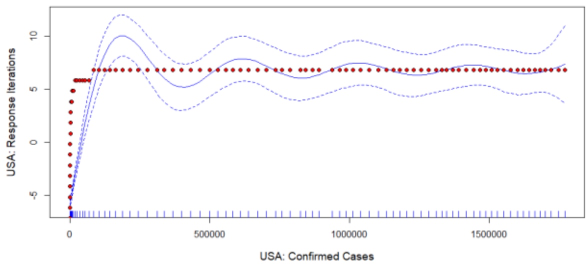


Fig. 4. USA: Iterative response fitted to a generalised additive model

TABLE 2. HIGH SENSITIVITY SYSTEM RESPONSES

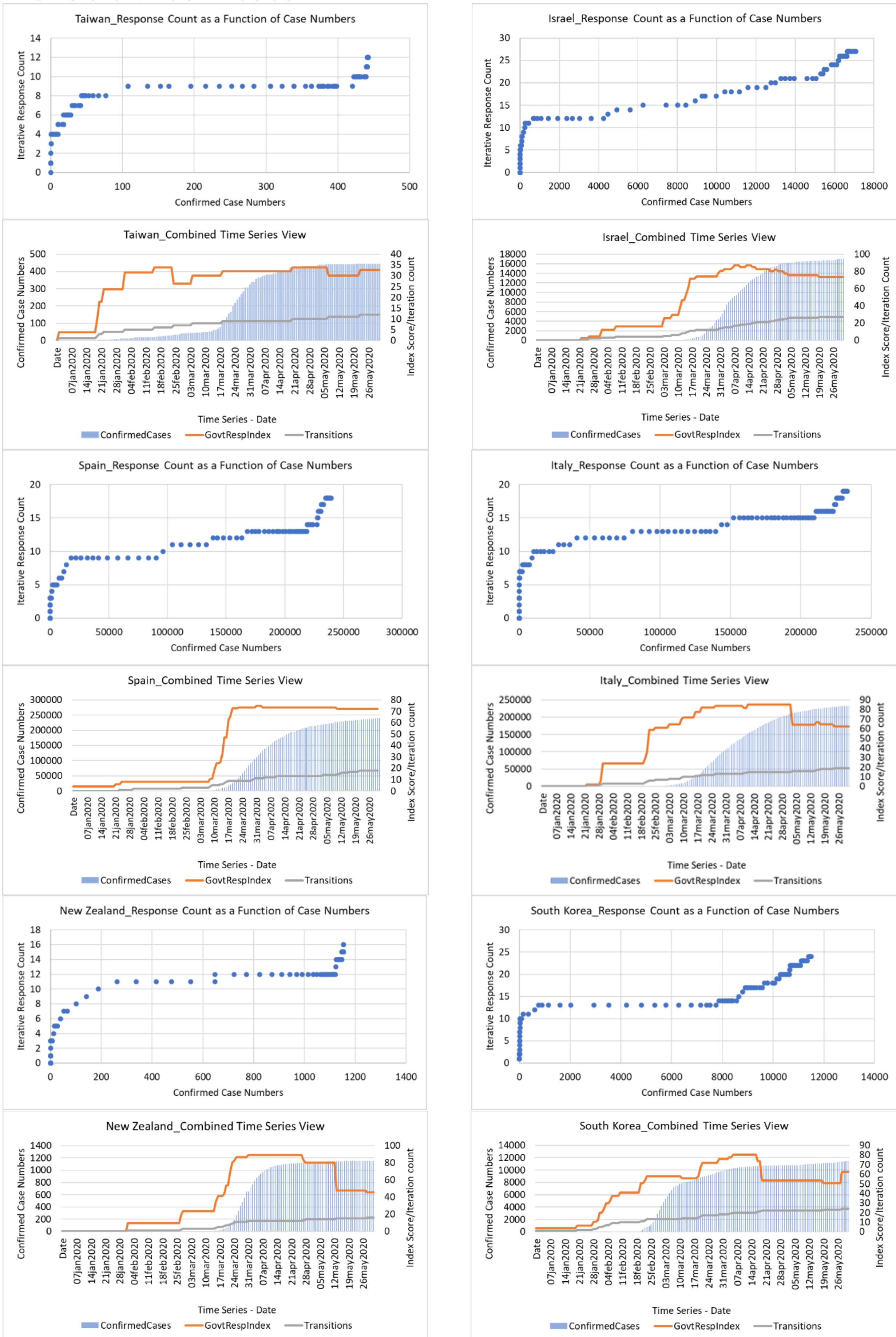
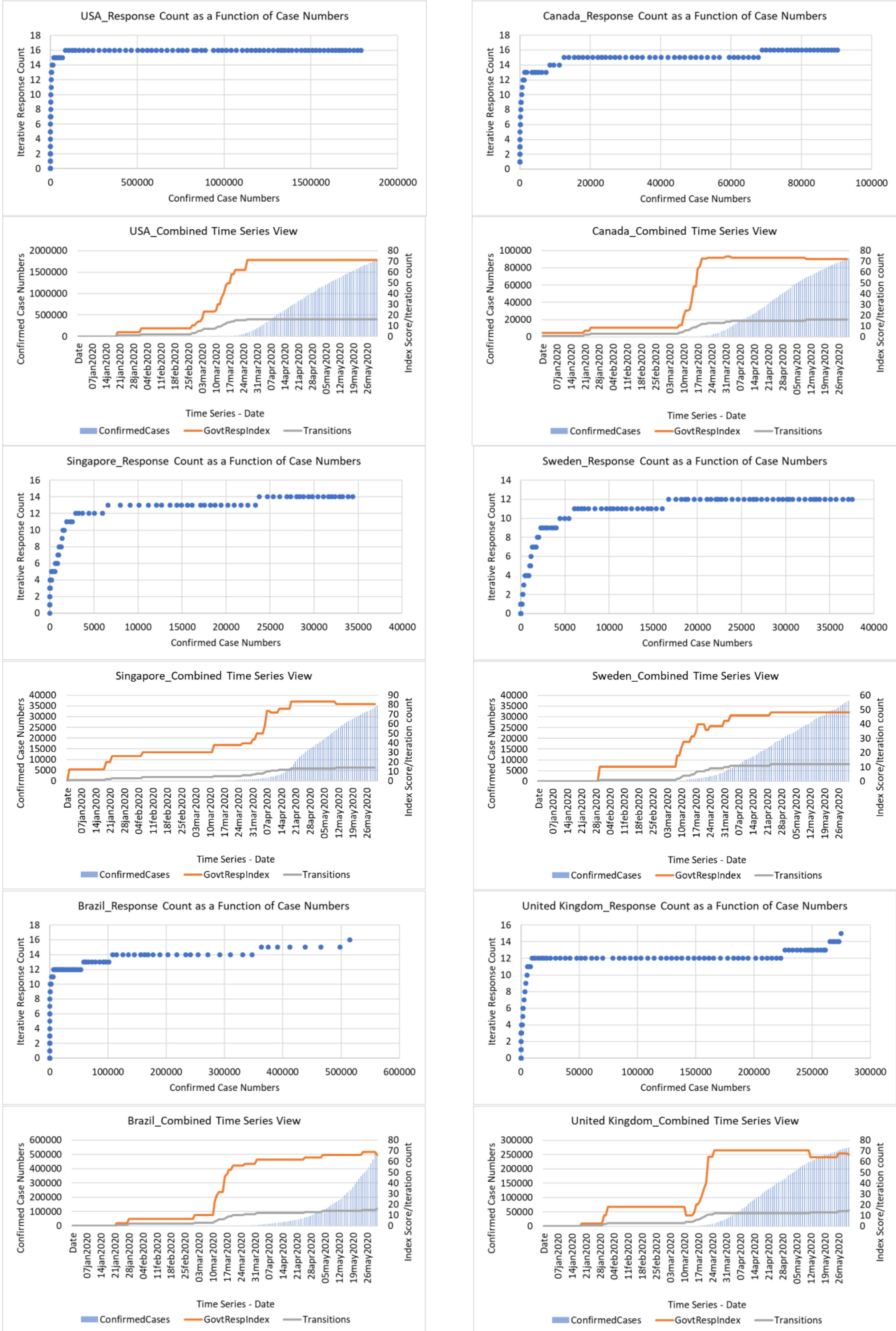


TABLE 3. LOW SENSITIVITY SYSTEM RESPONSES



D. Discussion

The comparison of both charts for each country shows that the response index amplitude (the orange line) does not fully reveal system sensitivity to case numbers when taken on its own. Time is an unreliable predictor in this context given the significant leading and lag effects present in the system. For example: the initial rapid implementation of multiple measures to prevent the virus spread followed by the time required for implemented actions to be confirmed as working or not. System *sensitivity* may seem obvious at the point countries such as New Zealand, South Korea or Israel loosened their restrictions in May, but the frequent adjustments of Spain and Italy to eventually achieve suppression are much subtler. Mapping the policy transitions onto the x-y plot reveals the consistent relationship to the case numbers, especially through the middle part of the curve. Within the low sensitivity category we can see that the implemented policies failed to contain or suppress the virus, at least within the measured timeframe. Singapore, Canada and Sweden are perhaps special cases here with Singapore and Canada successfully flattening their curves soon after this set of measurements was taken [37]. In contrast to most other countries, Sweden elected to follow an intentional strategy of minimal intervention [13]. The USA, Brazil, and UK curves reveal only a weak relationship between increasing case numbers and further policy actions.

The question of a critical transition in the system arises, i.e. at a certain critical mass of case volume, the ability to suppress the virus becomes exponentially more difficult. This makes intuitive sense based on the epidemiological modelling and underpins the early success stories [16]. However, Italy and Spain demonstrate that suppression was still possible at the 250,000-case level of magnitude and the failure of the UK to achieve similar results is unfortunate. Beyond a critical transition of uncontrolled spread, understanding root causes for failure to contain or suppress cases requires investigation of each country's unique context. Viewed through a complex system lens, the law of requisite variety — where any system regulatory mechanism must have at least the same level of variety as the system itself — is a plausible contributing factor. [35, 42]. The more uniform (or at least interoperable) the key national and regional health and government systems are, the faster agreed policies can be determined and implemented (system regulation). Ensuring the necessary coevolution of networks is also posited as a critical influence; we can treat complex supply chains, or population groups complying with instructions, as coupled networks that must also adapt [4]. With regards to population compliance, the vital role of trust has been identified as influential within the UK pandemic behaviour [30].

Relating the high-level policy response data to identified local events further supports the claim that countries can demonstrate sensitivity to the case number signal. South Korea experienced a 2nd post-reopening outbreak on the 27th of May, and by the 29th of May reversed its gradual lifting of restrictions and increased its response level [43]. In the case of New Zealand, there was a planned stepwise transition from the highest severity containment (from 'alert level 4' to 'alert level 3') on April 28, and then a further step down to 'alert level 2' on May 14. These step changes, visible in New Zealand's combined chart in Table 2, occurred only after the case numbers were confirmed as stable, following planned two-week incubation periods clear of new cases [44].

All of our sampled countries apart from Taiwan and Sweden eventually reach similar levels of stringency in the index score (viewed on the secondary vertical axis of the combined chart). The different circumstances for Taiwan and Sweden are well known; very successful early suppression in the case of Taiwan and intentionally moderate intervention in the case of Sweden [7, 13]. Revisiting the original hypothesis for our study, Table 4 compares our results with our expected findings:

TABLE 4. SUMMARY OF RESULTS

Expected finding based on the hypothesis	Result
1. There is evidence of adaptation in the form of increased or reduced stringency and multiple iterative response cycles relative to the case number signal	The high sensitivity examples showed a consistent relationship between the signal and the frequency of responses, as opposed to the amplitude/stringency only. The high sensitivity examples include countries successful with early containment (Taiwan, New Zealand) and those that had to work very hard to achieve suppression following initial outbreaks (Spain, Italy)
2. Adaptation cycles are non-linear, due to the underlying complex network structures, the information spreading (sharing) rate, and the learning rate.	The policy response curve reflects a complex multi-step non-linear function that is an aggregate of the many underlying processes.
3. There is moderation of the effectiveness of similar Government responses across the sample group, indicating the coevolution of external systems required for the responses to be effective, for example, population compliance.	It can be seen in the low-sensitivity examples that flattening the curve is not achieved within the measured time window. We have not investigated the underlying reasons but the inability to implement or maintain the chosen measures is perhaps the most plausible factor. For example, local populations unwilling or unable to comply with the measures
4. There are critical state transitions within the adaptive responses	Early preparations relative to case numbers are perhaps obvious, but the continued implementation of actions through the second and third phases is less so. All the sampled countries that successfully flattened their curves demonstrated these additional phases. Beyond a certain scale of outbreak, suppression becomes extremely difficult to achieve (USA, Brazil, UK)
5. There is a mix of successful and unsuccessful strategies, with observable relationships between case numbers, response index severity, the number of response iterations and the timing of responses	We observe a range of outcomes across the unique contexts of each country. Within the high sensitivity countries, the case number curve was able to be suppressed at low case numbers (Taiwan, New Zealand) *and* subsequent to a substantial outbreak (Italy, Spain, South Korea) .

V. Conclusion and Summary

This study demonstrates that CAS theory can be used to observe and interpret complex social system activity. Using the CQIN model, the CAS sensitivity function is straightforward to measure and the study findings are consistent across the sampled countries. Taken together, these results should provide confidence to practitioners and academia about the usefulness of including the CAS perspective for planning, implementing, and controlling system change in complex settings.

Limitations to this study are acknowledged. We have relied on published 3rd party data, which, given the goal of making COVID-19 related data widely available quickly, is of necessity still being refined and validated. It is recognised that the confirmed case numbers were dependent on the testing policies in place and that these varied over time and between countries. Our study is quantitative, analysing macro-level data only. Qualitative enquiry into agent behavior would be beneficial to reliably establish the underlying causal factors for success or failure in the suppression of COVID-19. Reducing the entire set of complex system signals to one predictor and one response variable is a coarse level of measurement; however, this is a simplification that we defend within the unique COVID-19 context and the aims of the study. The case numbers do effectively aggregate the immensely complex system activity. We are continuing this research to include the ongoing suppression efforts over a longer timeline, a wider sampling of countries, and mathematical exploration of the system response function.

Each of the complex adaptive systems measured in our study are unique. It is not possible to generalise a formula to predict outcomes in one country based on a function derived from another country's unique data, and even future outbreaks in the same country will be different. CAS learn and retain history [28, 30], and the lessons from early 2020 will now heavily influence the management of future outbreaks. Careful management of policy settings will always be required to balance the enormous social, health and economic costs of COVID-19 containment and suppression measures.

The intensely concentrated decision making that occurred during the first half of 2020 in response to COVID-19 provided a unique opportunity to study multiple CAS at a macro level. We propose that CAS sensitivity to critical system signals can be measured using the CQIN model, in line with Holland's elegant conceptualisation of CAS as fundamentally defined by signals and boundaries [4]. The ability for any country to quickly establish CAS sensitivity could have an immediate practical benefit. Monitoring CAS sensitivity would be a useful adjunct to established epidemiological control strategies for future outbreaks, enabling fine calibration of the system responses and preventing critical under or over reaction.

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