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## Editor's Letter

COVID has impacted families, countries, geo-political regimes, and the planet at-large. In academics the impact was devastating to sustaining instruction quality levels and research. Furthermore, the pandemic has transformed human society in ways that are not yet fully examined or understood. In response, the Journal on Policy and Complex Systems organized and facilitated the voices of senior researchers, those new to the field of complexity, and current students in computer science. The purpose of the gathering was to explore, discuss, and to present research goals and how to best meet the challenges of conducting quality research during pandemic times. A call to action was communicated to top researchers across the globe and students to participate in a virtual mini conference on Complexity, Policy, and COVID-10 in April of 2021. Senior researchers from 4 continents participated along with over 15 computing students from UNC Charlotte. This resulted in surprising emergent outcomes with dialogues rich in depth and possibilities how to best move forward research-wise during these trying times. However, the most helpful and hopeful perspectives came from students who were thusly inspired by the challenges of the pandemic and how they could best contribute to the betterment of society.

In order to remove barriers associated with research during this pandemic, we have organized a special issue for researchers to share nascent essays on preliminary research they were conducting. Additionally, we chose to include peer-reviewed research that was completed during these times, in order to show where complexity research may be headed. Finally, by including student perspectives, which is usually ignored in academic journals, we have included student essays to show the perspectives, potential, promise of student scholars.

Halloran and Castaneda first addresses simplifying complexity during COVID-19, in *Simplifying Complexity in COVID-19 Policy Narratives: Challenges Presented by Policy Agenda Setting Processes for Complex Adaptive Systems Research*. Vardavas, de Lima, Davis, Parker, and Baker's further investigate adaptations in *Modeling Infectious Behavior: Need to Account for Behavioral Adaptations in COVID-19 Models*. Next Ogibayashi tackles *Can Agent-Based Models Enable Scientific Policymaking on an Understanding of Causal Mechanisms?*

The problem of uncertainty is approached by Venegas in *Automatic Discovery of Attention Flows Under Policy Uncertainty*. Then Salinas, Tejada, Encinas, and Garibay focus on a country level of analysis perspective in *Policy Guidelines to face COVID-19 in Peru: A Complex Systems Perspective*. The final essay contributed by Kaufman, Kaufman, and Koutsovoulou delve in the specialty area of negotiations between labor and management during COVID-19 with *Labor-Management Negotiations in COVID Times: Anticipating Power balance Effects*.

The pandemic allowed for some to conduct research and have their work peer-reviewed. First, Vardavas, de Lima, and Baker researched health and economic outcomes in *Could Periodic Nonpharmaceutical Intervention Strategies Produce Better COVID-19 Health and Economic Outcomes?* Then what about how up-to date we are with the policy instruction and policy research? Davis, McDonald, Pendleton-Julian, O'Mahony, and Osoba offer *A Complex-Systems Agenda for Teaching and Conducting Policy Studies*.

Finally to consider is wisdom by Conrad Hall, "You are always a student, never a master. You have to keep moving forward." In response, for the first time students essays were included for the purpose of highlighting divergent strains of thought and our collective hope for the future. Cubero acknowledges that even during a pandemic sex trafficking flourishes. Her essay of *Human Trafficking on the Dark Web: What Is It and How Can It Be Prevented?* provides a needed reminder of the pervasiveness and possibilities to remedy the issue. Lastly Dahlem explores the topic of *The Digital Divide During the COVID-19 Pandemic*.

Sincerely,

Liz Johnson, Managing Editor and Joseph Cochran, Associate Editor

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## **Carta de los editores**

**E**l COVID ha impactado a familias, países, regímenes geopolíticos y al planeta en general. En el ámbito académico, el impacto fue devastador para mantener los niveles de calidad de la instrucción y la investigación. Además, la pandemia ha transformado la sociedad humana en formas que aún no se han examinado o comprendido por completo. En respuesta, la Revista de Políticas y Sistemas Complejos organizó y facilitó las voces de los investigadores de alto nivel, los nuevos en el campo de la complejidad y los estudiantes actuales en ciencias de la computación. El propósito de la reunión fue explorar, discutir y presentar los objetivos de la investigación y cómo enfrentar mejor los desafíos de realizar investigaciones de calidad durante tiempos de pandemia. Se comunicó un llamado a la acción a los mejores investigadores de todo el mundo y a los estudiantes para participar en una mini conferencia virtual sobre complejidad, políticas y COVID-10 en abril de 2021. Participaron investigadores senior de cuatro continentes junto con más de 15 estudiantes de computación de UNC Charlotte. Esto resultó en sorprendentes resultados emergentes con diálogos ricos en profundidad y posibilidades de cómo avanzar mejor en la investigación durante estos tiempos difíciles. Sin embargo, las perspectivas más útiles y esperanzadoras provinieron

de los estudiantes que, por lo tanto, se sintieron inspirados por los desafíos de la pandemia y la mejor manera de contribuir al mejoramiento de la sociedad.

Con el fin de eliminar las barreras asociadas con la investigación durante esta pandemia, hemos organizado un número especial para que los investigadores compartan ensayos incipientes sobre la investigación preliminar que estaban realizando. Además, optamos por incluir la investigación revisada por pares que se completó durante estos tiempos, para mostrar hacia dónde se puede dirigir la investigación de la complejidad. Finalmente, al incluir las perspectivas de los estudiantes, que generalmente se pasan por alto en las revistas académicas, mostramos las perspectivas, el potencial y la promesa de los estudiantes académicos.

Halloran aborda primero la simplificación de la complejidad durante COVID-19, en *Simplificación de la complejidad en las narrativas de políticas de COVID-19: desafíos presentados por los procesos de establecimiento de la agenda de políticas para la investigación de sistemas adaptativos complejos*. Vardavas, de Lima, Davis, Parker y Baker investigan más adaptaciones en *Modelado de comportamiento infeccioso: necesidad de tener en cuenta las adaptaciones de comportamiento en modelos COVID-19*. A continuación, Ogibayashi aborda ¿Pueden los modelos basados en agentes permitir la formulación de políticas científicas sobre la comprensión de los mecanismos causales?

Venegas aborda el problema de la incertidumbre en el descubrimiento automático de los flujos de atención en situaciones de incertidumbre política. Luego, Salinas, Tejada, Encinas y Garibay se enfocan en una perspectiva de análisis a nivel de país en *Lineamientos de Política para enfrentar COVID-19 en Perú: Una Perspectiva de Sistemas Complejos*. El ensayo final aportado por Kaufman, Kaufman y Koutsovoulou profundiza en el área de especialidad de las negaciones entre la mano de obra y la administración durante COVID-19 con *Negociaciones entre la mano de obra y la administración en COVID Times: Anticipando los efectos del equilibrio de poder*.

La pandemia permitió a algunos realizar investigaciones y hacer que sus trabajos fueran revisados por pares. Primero, Vardavas, de Lima y Baker investigaron los resultados económicos y de salud en ¿Podrían las estrategias periódicas de intervención no farmacéutica producir mejores resultados económicos y de salud del COVID-19? Además, durante toda la pandemia, los principales problemas a los que se enfrentan las familias y los jóvenes fueron la impartición de pedagogía, el acceso a las clases en línea y el seguimiento de la participación de los estudiantes en las clases virtuales.

Davis, McDonald, Pendleton-Jullian, O'Mahony y Osoba ofrecen *Una Agenda de Sistemas Complejos para Enseñar y Realizar Estudios de Políticas*.

Finalmente, hay que considerar la sabiduría de Conrad Hall: "Siempre eres un estudiante, nunca un maestro. Debes seguir adelante." En respuesta, por pri-

mera vez se incluyeron ensayos de los estudiantes con el propósito de resaltar las corrientes de pensamiento divergentes y nuestra esperanza colectiva para el futuro. Cubero reconoce que incluso durante una pandemia el tráfico sexual florece. Su ensayo sobre la trata de personas en la Dark Web: ¿qué es y cómo se puede prevenir? proporciona un recordatorio necesario de la omnipresencia y las posibilidades de remediar el problema. Por último, Dahlem explora el tema de la brecha digital durante la pandemia COVID-19.

Atentamente,

Liz Johnson, editora gerente y Joseph Cochran, editor asociado

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## 编者按

新型冠状病毒病（COVID）已对家庭、国家、地缘政治制度以及绝大多数人造成影响。其影响对维持学术界教学质量和研究而言是巨大的。此外，大流行以尚不清晰的方式改变了人类社会。作为响应，《政策与复杂系统期刊》组织并帮助高级研究者、刚接触复杂性领域的学者，以及计算机专业学生发声。此举旨在探究、讨论并提出研究目标，以及探讨如何以最佳方式迎接大流行期间进行高质量研究一事所面临的挑战。2021年4月，本刊举行了一场主题为“复杂性、政策和新冠肺炎”的小型网络会议，并邀请了全球顶尖研究者和学生参与。来自4个大陆的高级研究者和北卡罗来纳大学夏洛特分校的15名计算机专业学生参加了这次会议。会议带来了意想不到的初步结果—极具深度的对话内容和关于如何在大流行期间以最佳方式进行研究的一系列机遇。不过，最有帮助和希望的视角来自与会学生，他们从关于大流行挑战以及如何以最好的方式对社会作贡献的讨论中深受启发。

为消除大流行期间的研究障碍，本期特刊为研究者提供平台分享他们所进行的初步研究进展。此外，我们收录了在大流行期间完成的、经过同行评审的研究，以期展示复杂性研究可能的发展方向。最后，通过收录学术期刊中经常忽视的学生文章，我们展示了学生作为学者的视角、潜能和希望。

Halloran在《简化新冠肺炎政策叙事中的复杂性：政策议程设置过程为复杂适应系统研究带来的挑战》（Simplifying Complexity in COVID-19 Policy Narratives: Challenges Presented by Policy Agenda Setting Processes for Complex Adaptive Systems Research）一文中首次研究了新冠肺炎期间的复杂性简化。Vardavas、de Lima、Davis、Parker和Baker在《传染性行为建模：衡量新冠肺炎模型中的行为适应》（Modeling In-

fectious Behavior: Need to Account for Behavioral Adaptations in COVID-19 Models) 一文中进一步研究了行为适应。接下来, Ogibayashi 撰写了《基于agent模型能在理解因果机制的基础上让科学决策成为可能吗?》(Can Agent-Based Models Enable Scientific Policymaking on an Understanding of Causal Mechanisms)。

Venegas在《政策不确定性背景下注意力流的自动发现》(Automatic Discovery of Attention Flows Under Policy Uncertainty) 一文中研究了不确定性的问题。Salinas、Tejada、Encinas 和Garibay在《应对秘鲁新冠肺炎的政策指南: 复杂系统视角》(Policy Guidelines to Face COVID-19 in Peru: A Complex Systems Perspective) 一文中聚焦于国家层面的分析视角。最后一篇文章由Kaufman、Kaufman和Koutsovoulou 撰写, 他们在《新冠肺炎期间的劳资协商: 预期权力平衡产生的效果》(Labor-Management Negotiations in COVID Times: Anticipating Power Balance Effects) 一文中分析了新冠肺炎期间劳资协商这一特殊领域。

一些学者在大流行期间进行了研究并通过了同行评审。Vardavas、de Lima 和Baker 在《定期非药物干预策略能产生更好的新冠肺炎卫生结果和经济结果吗?》(Could Periodic Nonpharmaceutical Intervention Strategies Produce Better COVID-19 Health and Economic Outcomes?) 一文中研究了卫生和经济结果。此外, 大流行期间家庭和年轻人所面临的主要问题包括教学交付、网络课程获取、以及对网络课堂中的学生参与加以监督。

最后, 值得思索的是Conrad Hall的名言“你永远是一个学者而不是大师。你必须一直努力前进”。作为响应, 本刊首次将学生文章收录在内, 以期强调不同的思想和我们对未来的集体希望。Cubero认为, 即使在大流行期间, 性贩运也在不断发生。她的文章《暗网上的人口贩运: 它是什么并能如何加以预防?》(Human Trafficking on the Dark Web: What Is It and How Can It Be Prevented?) 提醒需要毅力和机会来解决这一问题。Dahlem探究了“新冠肺炎大流行期间的数字鸿沟”(The Digital Divide During the COVID-19 Pandemic) 这一主题。

真诚地,

编辑主任Liz Johnson和副主编Joseph Cochran



# **Simplifying Complexity in COVID-19 Policy Narratives: Challenges Presented by Policy Agenda Setting Processes for Complex Adaptive Systems Research**

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## ABSTRACT

This essay considers the problem of communicating complex systems within policy narrative formation processes. The systems of systems implicated by the COVID-19 pandemic are highly amenable to complex systems analysis. However, the dynamic response of policymakers and interested parties in a crisis situation tends toward reductionism in a way that limits the application of complex systems thinking in the policy process. This essay identifies questions related to public communication, complexity, and public policy as critical to the field of complex systems and public policy, and proposes a number of directions for the field of complexity and public policy in addressing those practical questions.

**Keywords:** public policy; policy narratives; agenda setting; framing; complexity; COVID-19

# Simplificación de la complejidad en las narrativas de políticas de COVID-19: desafíos presentados por los procesos de establecimiento de la agenda de políticas para la investigación de sistemas adaptativos complejos

## RESUMEN

Este ensayo considera el problema de comunicar sistemas complejos dentro de los procesos de formación de narrativas políticas. Los sistemas de sistemas implicados por la pandemia de COVID-19 son muy susceptibles de análisis de sistemas complejos. Sin embargo, la respuesta dinámica de los formuladores de políticas y las partes interesadas en una situación de crisis tiende hacia el reduccionismo de una manera que limita la aplicación del pensamiento sistémico complejo en el proceso de políticas. Este ensayo identifica cuestiones relacionadas con la comunicación pública, la complejidad y las políticas públicas como críticas para el campo de los sistemas complejos y las políticas públicas, y propone una serie de direcciones para el campo de la complejidad y las políticas públicas al abordar esas cuestiones prácticas.

**Palabras clave:** política pública; narrativas de políticas; configuración de la agenda; enmarcado; complejidad; COVID-19

## 简化新冠肺炎政策叙事中的复杂性：政策议程设置过程为复杂适应系统研究带来的挑战

### 摘要

本文研究了政策叙事形成过程中复杂系统传播的问题。新冠肺炎（COVID-19）大流行造成的体系（systems of systems）十分适用于复杂系统分析。不过，一场危机中决策者和利益方的动态响应往往倾向于还原主义，限制复杂系统思考在政策过程中的应用。本文认为，与公共传播、复杂性和公共政策相关的问题对复杂系统领域而言至关重要；并为复杂性和公共政策领域提出一系列应对这些实际问题的方向。

关键词：公共政策；政策叙事；议程设置；建构；复杂性；新冠肺炎（COVID-19）

## **Introduction**

“Complex causal explanations are not very useful in politics ...”  
— Stone (1989, p. 289)

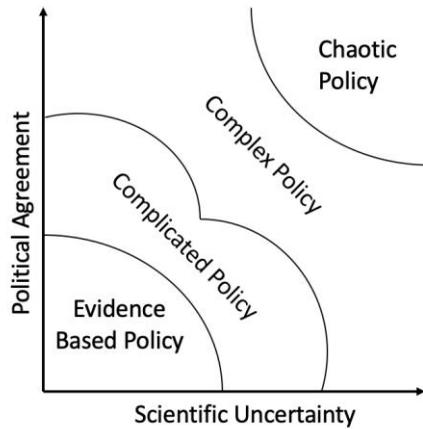
**I**n the first half of 2020, the COVID-19 pandemic dramatically changed life across the globe as individuals, families, medical and public health professionals, businesses, schools, and governments scrambled to respond. COVID-19 and the response thereto implicated an extensive network of complex adaptive systems (hereafter “CAS”) across a complicated hierarchical spatiotemporal geography where policy actions and inactions shaped disease dynamics both inside and outside of local systems. In other words, COVID-19 response unquestionably requires the complexity lens for both effective disease mitigation and comprehensive analysis. At the same time the nature of COVID-19 and the global response highlights the essential importance of complexity sciences, it also exposes a critical deficit at the nexus of policy and complex systems: ineffective communication of complexity to policy makers and to the general public.

Policy discourses around COVID-19 quickly devolved into simplified binary positions such as safe/unsafe, open/closed, effective/ineffective, scientific/unscientific, and controlled/uncontrolled, which flattened complex systems out of the narratives, provided incomplete or misleading information, and resulted in policy agendas that either were aiming for practically

unattainable goals (e.g., control of the pandemic) or were dismissed as impossible (e.g., “lockdowns” and universal individual-level mitigation). Politicians and agency experts across many levels of government implored the public to “trust the science,” a message that, itself, held the false promise of some scientific certainty clarifying all of the unknowns surrounding COVID-19. These simplified discourses played no small role in channeling policy into responses which were muddled, parochial, and ineffective, and which eroded public trust in both the government and in the scientific community.

To address these simplifying tendencies so that complex problems can be appropriately addressed by complexity-based solutions, CAS researchers must become effective and informed participants in the problem definition, narrative formation, and agenda setting fields of the policy process. Problems do not define themselves and prioritization of action on the policy agenda is not objective. Instead, these develop out of contested processes where multiple voices act to shape narratives and agendas (Kingdon, 2014; Rochefort & Cobb, 1993). CAS research must be one of those active and effective voices.

In this essay, we seek to identify questions related to public communication, complexity, and public policy as critical to the field of complex systems and public policy. We will briefly sketch an outline of the literature related to policy narratives and then propose an agenda to develop more effective communication to policy makers and the



Adapted from Stacey (1993)

Figure 1: Stacey Diagram

general public about policy and complex systems.

## Covid-19, Complexity, and Public Policy Agendas

The COVID-19 case is illustrative of an ongoing challenge to applications of complexity theory in public policy. Specifically, COVID-19 demonstrates the attraction of policy narratives toward simple linear causal models. As illustrated in the classic Stacey Diagram (Figure 1), complexity in policy making occurs when there is either a high degree of political disagreement or a low degree of certainty in the steps required to address a particular policy problem (Stacey, 1993). Policy agendas operate along both the axis of agreement and the axis of certainty, within streams of problem definition, policy formation, and political possibility (Kingdon, 2014). The Stacey Diagram illustrates the challenge of

deploying complex thinking in public policy by underscoring a fundamental point about political agenda setting: possibilities in policy action are intertwined with how agendas are set and how problems are formulated (Stone, 1989). The agenda setting literature is thick with cautionary admonishments that simplicity increases the chances of responsive policy action: keep causal chains short, articulate tight linkages between actions and effect, and clearly specify the problems and the fixes (Stone, 1989; Kingdon, 2014). In other words, policy prospects are improved when the narrative formation and agenda setting can stay closer to the “evidence-based policy” quadrant of the Stacey Diagram where policy decisions are known, can be categorized, and have predictable results.

Therein lies peril, however, if policy problems tend toward this simple frame and the science oversells the certainty of effective evidence-based

responses. The failure of the promises of simple causation erodes public trust and adds further complications to policy responses. Thus, as with COVID-19, policy problems that are complicated, complex, or chaotic present significant challenges to agenda setting, clear narrative formation, and ultimately an effective policy response.

This framing and agenda setting process is not mere aesthetics: the formulation of the problem definition and issue narratives essentially determine policy possibilities and, ultimately, policy action (Stone, 2012; Rochefort & Cobb, 1993). Rapidly-evolving narrative formation processes were critical to the responses of governments and public health agencies in the early days of the COVID-19 pandemic (Maor & Howlett, 2020). And where complexity scientists saw iterative and dynamic, predictable, but not necessarily knowable, channels of disease mitigation, public faith was repeatedly shaken by the lack of certainty and rapidly changing patterns of guidance and response. The early development of COVID-19 policy narratives has been examined in the context of World Health Organization communications, in policy sensemaking in Denmark, and in the messaging of four U.S. states (Yiu, Yiu, & Li, 2020; Rubin & de Vries, 2020; Mintrom & O'Connor, 2020). In Denmark, the public communication of risk assessment was sometimes placed at odds with the public health goal of mitigating surging COVID-19 cases, highlighting differences in sensemaking which led to treating a complex problem like a complicated one (Rubin & de Vries, 2020).

In the case of California, Florida, New York, and Texas, the framing contests around the COVID-19 were clearly locking in narratives around government responses. Narratives ranged from Governor DeSantis of Florida actively working to minimize COVID-19 and encourage skepticism of mitigation measures to Governor Newsome of California consistently communicating both the dynamics and seriousness of the pandemic and proactively enacting mitigation policy (Mintrom & O'Connor, 2020). This developing literature summarizes difficulties in effectively communicating uncertainty within a complex systems frame and underscores the tendency of policy systems to drift toward “certain” problem definitions and policy interventions premised on simple linear causal relationships.

### **Policy Narrative and Complexity**

There is well-established literature within agenda setting which views the question of agenda setting through the complex systems lens. The work of Frank Baumgartner and his colleagues typifies this kind of thinking, where complex causation and emergence are used to describe policy processes (Baumgartner, et al., 2011; Baumgartner, et al., 2009). Complexity theory, unsurprisingly, is useful in identifying the boundaries of evidence-based policy, and in understanding the limits of simple causation in policy action (Cairney & Geyer, 2017; Colander & Kupers, 2014). While complexity has been frequently used as an

analytical tool, substantially less work has been done in the effective dissemination of CAS thinking in narrative formation and agenda setting processes—even as the consequences of over-simplified policy narratives frustrate researchers (Ewert, 2019; Leach, Scoones, & Stirling, 2009).

The crux of the narrative formation problem for complexity researchers is best stated by Deborah Stone in her classic article “Causal Stories and the Formation of Policy Agendas,” in which she writes,

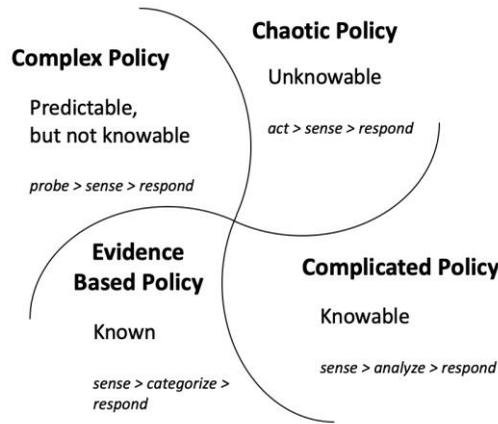
[c]omplex causal explanations are not very useful in politics, precisely because they do not offer a single locus of control, a plausible candidate to take responsibility for a problem, or a point of leverage to fix a problem. Hence, one of the biggest tensions between political science and real-world politics. The former tends to see complex causes of social problems, while the latter searches for immediate and simple causes. (Stone, 1989, p. 289).

The idea of immediate, simple causes with single loci of control or single points of leverage cuts directly against the essence of complexity research and the effective application of CAS analysis in the policymaking realm. CAS repeatedly reminds us that most policy problems cannot be reductively simplified into those single points of control or leverage, and that attempts to manage policy problems as simple and lin-

ear are often counterproductive (Byrne, 2005).

Getting policy makers and the general public to respond to policy problems in all of their richness in the processes of narrative formation and political agenda setting is, itself, a CAS problem (Leach, Scoones, & Stirling, 2009). Where the public and policy makers may see an ineffective, trial-and-error approach to a problem, CAS researchers may understand that dynamic, iterative approaches are essential to addressing an emerging policy problem. CAS identifies multiple locations of influence and offers solutions that are not based on cause-and-effect or control but on probabilities and shepherding. CAS thinking continually pushes against simple linear causal explanations.

An ongoing effort is underway to sensitize policy makers to complexity and its ubiquity within the world of social policy, and to provide them with effective strategies to conceptualize and take action in the face of CAS problems (see, e.g., Keating & Katina, 2019; Kurtz, 2018; Pharis, 2018; Ansell & Geyer, 2017; Chaffin, Gosnell, & Consens, 2014; Innes & Booher, 2010; Lagomarsino, Nachuk, & Kundra, 2009). For example, the Cynefin Framework is a heuristic tool used to orient complexity within a frame of policy response (Snowden & Boone, 2007). Cynefin (Figure 2), developed within the organizational management literature, is an ecological representation of policy domains. Cynefin breaks policy problems into the same four categories as the



Adapted from Snowden & Boone (2007)

*Figure 2: Cynefin Framework*

Stacey Diagram: Evidence-based policy, complicated policy, complex policy, and chaotic policy. These categories offer both a diagnosis of the type of policy problem and approaches to managing that problem. Complex policy problems are identified as those which are knowable but not directly predictable, and where responses should include an iterative feedback process of probing, sensing, and responding as a way to avoid reductive interventions (Van Beurden, et al., 2013). Cynefin and the Stacey Diagram provide legible and useful heuristics to communicate complexity in policy action, but neither directly address the broader problem of incorporating CAS thinking into policy narrative development and political agenda setting.

The COVID-19 pandemic has underscored the urgency of efforts to make complexity more legible to policymakers and managers, and has identified the need to think beyond policy maker education and identify ways to effective-

ly communicate complex systems and complex causality to the general public. This urgency is complicated further in emergency situations like COVID-19 as people in the general public seek to fill information vacuums (Andrade, et al., 2020). In emergent situations, people tend to deal with uncertainty by relying on their own intuitions synthesized through familiar information sources (e.g., personal connections, social networks, and news sources), making them increasingly susceptible to streams of misinformation. For the field of CAS in public policy to advance, we must directly confront these complications.

### **Communicating Complexity in Policy: Ways Forward?**

**T**here are clear gaps in our knowledge which need to be filled. As the empirical foundation of CAS research continues to become more rigorous and more clearly applicable to contemporary policy problems the need

to fill these communication-related gaps becomes more urgent. We identify, in particular, the critical importance of intentional and effective inclusion of complex systems discourse within the narrative framing and agenda setting processes of public policy development. And, conversely, we identify problems of narrative framing and agenda setting as intrinsically interwoven with high quality CAS research as applied to public policy. We discuss those two areas of emphasis in turn.

***Getting policymakers and the public to think in systems: Agenda setting and narrative in a complex world***

In order to effectively respond to dynamic policy situations, which implicate complexity, a substantial amount of groundwork is required to ready CAS concepts for incorporation within policy narrative formation and agenda setting. This is in appreciation of the fact that the time to establish a foothold within the policy agenda is not at the moment of critical policy need, but that the policy agenda is a dynamic process where iterative contacts over time will establish the salience of CAS thinking to policy problems.

Dissemination and education efforts are critical to increase the overall literacy in complexity. We should continue to actively engage in public scholarship which identifies complex policy

problems and discusses how responses to complex problems differ from simple or complicated problems; make education a part of each interaction that we have with policy stakeholders;<sup>1</sup> and advocate for and establish curricula which familiarizes students at all levels with concepts related to CAS and policy. These efforts can be amplified by strengthening networks of policy-makers, journalists, educators, and key members of the general public through outreach.

Ansell & Geyer (2007)<sup>2</sup> propose a number of 'key premises' for the application of pragmatic complexity to policy problems, which identify different modes of policy action depending on the level of complexity and the certainty of the knowledge in that domain. Those key premises for policy realms of higher complexity and lower certainty include: (a) Application of iterative and adaptive responses; (b) Encouraging the inclusion of multiple stakeholders and perspectives; (c) Development of robust information infrastructure. While we don't argue for the universal application of pragmatic complexity, we do suggest these 'key premises' as areas for development in CAS research which, in some ways, already are strengths of the field. How can we effectively communicate contingency—that complex policy problems are not one intervention and done—and that adaptations across multiple iterations of response are nor-

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1 See the special issue of *Complexity Governance & Networks* (volume 4, 2018) that is dedicated to the special problems of and approaches to teaching complexity in a variety of contexts.

2 We do not wholly endorse the frameworks provided by Ansell & Geyer and Byrne. They are cited here as one set of approaches to thinking about practical application of CAS in policy discourses. More work should be done to develop alternative frameworks.

mal for complex policy problems? How do we strengthen the interdisciplinary posture of the field to include the perspectives (and the needs) of multiple stakeholders? How do we develop information systems which connects our knowledge with policymakers and translates and disseminates our knowledge to the general public, and which allows us to receive actionable feedback from those stakeholders (Byrne, 2009)? All of these questions will require intentional engagement and adaptive responses as the field of complexity and public policy continues to develop.

***Focusing on narrative and agenda setting: The role of complex adaptive systems research***

CAS research will continue to engage dynamic policy problems and offer perspectives on the management of complex policy problems. Researchers must continue to develop effective, policy-actionable research which clarifies the utility of CAS to policymakers in analyzing and responding to policy problems (Wulczyn, 2020; Wulczyn & Halloran, 2017).

At the same time, we must also work to develop evidence directly on the question of effective policy explanations from the CAS perspective. It is important to consider the ways in which we are communicating about CAS. Message development, review, dissemination, and adaptation should be critical components of how we are thinking about the interrelationship between public policy and CAS thinking (Vanderford, Nastoff, Telfer, & Bonzo,

2007). We should adopt a posture where we consider feedback loops in policy messaging on CAS—reflecting and intentionally adapting our communications processes—and share knowledge about effective and ineffective strategies in communicating with stakeholders. *The Journal on Policy and Complex Systems* is an excellent forum for these conversations, and space for ongoing reflection about effective public/policy communication about CAS should be carved out within these pages.

As CAS researchers, we should directly incorporate within all of our work acknowledgement of the policy agenda setting process and the understanding of the necessity for intentional engagement of that process. We strongly believe that CAS research offers critical insights into important policy problems, and we think it is clear that effective application of this body of knowledge requires our ideas to be an integral part of the policy agenda. While the work of network building and dissemination discussed above is one critical component of that, engagement within our research on how to advance our work within the broader policy agenda is similarly important. We suggest that a clear effort be made within each research article to clearly articulate, in simple terms, the application of complexity concepts contained within the article. We think of this inclusion of a complexity ‘elevator pitch’ as an opportunity to cooperatively and iteratively hone our skills at communicating complexity to our policy audience—that is policymakers, the media, and the general public.

Finally, as we have previously noted, the fundamental problem complexity, narrative formation, and agenda setting is one of CAS. Are there ways to push against the tendency of policy narratives to drift away from complexity? There is a considerable opportunity to apply the lens of CAS directly to the narrative formation and agenda setting processes. Focusing some research efforts on the application of complexity theory to systems of public communication, narrative formation, and agenda setting will help clarify the ways in which CAS thinking and research can be applied in those critical areas. We are in the midst of a research project where we are using a complexity lens to examine the narrative formation and agenda setting process related to the return to in-person learning in Chicago Public Schools following building closures due to the COVID-19 pandemic. We hope to identify mechanisms in which these

processes acted to reduce the complexity of the circumstances so that future responses to CAS problems can learn from and adapt to those tendencies.

## **Conclusion**

**T**he COVID-19 pandemic and the policy response thereto highlighted a significant number of challenges in the effective response of policy systems to emergent and complex problems of public policy. Critical among those is the identification of complex problems and the management of those problems within the frame of complexity. For CAS thinking and research to become more effective parts of the policymaking process—especially in emergent and quickly-evolving policy settings—we must become more active and successful at integrating complexity within narrative formation and agenda setting processes.

## **References**

Andrade, E., Barrett, N., Edberg, M., Rivera, M., Latinovic, L., Seeger, M., Goldman-Hawes, A., and Santos-Burgoa, C. (2020). Mortality reporting and rumor generation: an assessment of crisis and emergency risk communication following Hurricane Maria in Puerto Rico. *Journal of International Crisis and Risk Communication Research*, 3(1), 15–48.

Ansell, C., and Geyer, R. (2017). ‘Pragmatic complexity’: A new foundation for moving beyond evidence-based policy making? *Policy Studies*, 38(2), 149–67.

Baumgartner, F., Jones, B., Wilkerson, J., Brouard, S., Green-Pedersen, C., and Walgrave, S. (2011). Comparative studies of policy dynamics. *Comparative Political Studies*, 44(8), 947–72.

Baumgartner, F., Breunig, C., Green-Pedersen, C., Jones, B., Mortensen, P., Nuytemans, M., and Walgrave, S. (2009). Punctuated equilibrium in comparative perspective. *American Journal of Political Science*, 53(3), 603–20.

Byrne, D. (2005). Complexity, configurations, and cases. *Theory, Culture, & Society*, 22(5), 95–111.

Cairney, P., and Geyer, R. (2017). A critical discussion of complexity theory: how does complexity theory improve our understanding of politics and policymaking? *Complexity, Governance, and Networks*, 3(2), 1–11.

Chaffin, B., Gosnell, H., and Cosens, B. (2014). A decade of adaptive governance scholarship: synthesis and future decisions. *Ecology and Society*, 19(3), 56–69.

Colander, D., and Kupers, R. (2014). *Complexity and the art of public policy*. Princeton University Press.

Ewert, B. (2019). Underlying assumptions in health promotion policymaking. In Ewert, B., and Loer, K. (eds.), *Behavioural policies for health promotion and disease prevention*. Palgrave/MacMillan.

Innes, J. and Booher, D. (2010). *Planning with complexity*. Routledge.

Keating, C., and Katina, P. (2019). Complex system governance: concept, utility, and challenges. *Systems Research and Behavioral Science*, 36, 1–19.

Kingdon, J. (2014). *Agendas, alternatives, and public policies* (2nd ed.). Pearson Education Limited.

Kurtz, C. (2018). Are we ready for complexity? *Policy and Complex Systems*, 4(1), 135–54.

Lagomarsino, G., Nachukm, S., and Kindra, S. (2009). *Public stewardship of private providers in mixed health systems*. Synthesis Report from the Rockefeller Foundation—Sponsored initiative on the role of the private sector in health systems in developing countries. Rockefeller Foundation.

Leach, M., Scoones, I., and Stirling, A. (2010). Governing epidemics in the age of complexity: narratives, politics, and pathways to sustainability. *Global Environmental Change*, 20(3), 369–77.

Maor, M., and Howlett, M. (2020). Explaining variations in state COVID-19 responses: psychological, institutional, and strategic factors in governance and pub-

lic-policy making. *Policy Design and Practice*, 3(3), 228–41.

Mintrom, M., and O'Connor, R. (2020). The importance of policy narrative: effective government responses to Covid-19. *Policy Design and Practice*, 3(3), 205–27.

Pharis, C. (2018). Complex analytics and public policy: cautions and opportunities going forward. *Journal on Policy and Complex Systems*, 4(2), 1–15.

Rocheffort, D., and Cobb, R. (1993). Problem definition, agenda access, and policy choice. *Policy Studies Journal*, 21(1), 56–71.

Rubin, O., and de Vries, D. (2020). Diverging sensemaking frames during the initial phases of the COVID-19 outbreak in Denmark. *Policy Design and Practice*, 3(3), 277–96.

Snowden, D., and Boone, M. (2007, November). A leader's framework for decision making. *Harvard Business Review*, 69–76.

Stacey, R. (1993). Strategic management and organizational dynamics. *Financial Times/Prentice Hall*.

Stone, D. (2012). Policy paradox: the art of political decision making (3rd ed.). W.W. Norton Publishing.

Stone, D. (1989). Causal stories and the formation of policy agendas. *Political Science Quarterly*, 104(2), 281–300.

van Beurden, E., Kia, A., Zask, A., Dietrich, U., and Rose, L. (2013). Making sense in a complex landscape: how the Cynefin Framework from Complex Adaptive Systems Theory can inform health promotion practice. *Health Promotion International*, 28(1), 73–83.

Vanderford, M., Nastoff, T., Telfer, J., and Bonzo, S. (2007). Emergency communication challenges in response to Hurricane Katrina: lessons from the Centers for Disease Control and Prevention. *Journal of Applied Communications Research*, 35(1), 9–25.

Wulczyn, F. (2020). Race/Ethnicity and Running Away from Foster Care: Children and Youth Services Review, 105504. <https://doi.org/10.1016/j.childyouth.2020.105504>

Wulczyn, F., and Halloran, J. (2017). Modeling complexity in human-built systems: new approaches, new findings in foster care. *Journal of Policy and Complex*

*Systems*, 3(2), 105–19.

Yiu, R., Yiu, CP., and Li, V. (forthcoming 2021). Evaluating the WHO's framing and crisis management strategy during the early stage of COVID-19 outbreak. *Policy Design and Practice*.



# Modeling Infectious Behaviors: The Need to Account for Behavioral Adaptation in COVID-19 Models

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*Keywords:* COVID-19, modeling, infectious disease, behavioral adaptation

## Modelado de conductas infecciosas: la necesidad de tener en cuenta la adaptación conductual en los modelos COVID-19

*Palabras clave:* COVID-19, modelado, enfermedades infecciosas,  
adaptación conductual

## 传染性行为建模：衡量新冠肺炎 模型中的行为适应

关键词：新冠肺炎（COVID-19），建模，传染病，行为适应

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**T**he current COVID-19 pandemic affects billions of people worldwide, and its unprecedented scale and duration are causing extraordinary disruptions to lives and livelihoods. Policymakers have taken comparably extraordinary measures to mitigate the spread of the virus (SARS-CoV-2) by implementing a range of nonpharmaceutical public health interventions (NPIs), from partial closings of business to complete lockdown and mask-wearing (Aledort et al., 2007). NPIs continue to be critically important

as new vaccines roll out in an attempt to reach herd immunity as quickly as possible. Several models have been developed to help policymakers compare interventions such as NPIs and vaccination. Such models attempt—dependent on various uncertain assumptions—to forecast cases, deaths, and medical supply needs; predict the timing of peaks in cases; and estimate if and when to expect additional waves or surges. However, a key limitation of many existing models is that they do not directly integrate adaptive behavioral components to account for how risk perceptions, protective behaviors, and compliance with interventions change over time and ultimately influence transmission. Patterns of COVID-19 transmission shape the subsequent patterns of behavioral responses to the disease and, in turn, are shaped by such responses. Changes in risk perceptions during the pandemic affect behaviors, including adherence to NPIs and willingness to vaccinate. Also, the effects that NPIs have on a population activities have led to pandemic fatigue and a decline in compliance with recommended restrictions (Alagoz et al., 2020; Crane et al., 2021; Kantor and Kantor, 2020). Moreover, perceptions of the risks and benefits of vaccination change, increasing or decreasing the vaccine hesitancy that undermines attempts to reach herd immunity (Yaqub et al., 2014). Decision-makers are faced with the daunting task of interpreting model predictions while simultaneously estimating how the behavioral responses should alter predictions. Despite considerable uncertainties, it may be possible to

improve these estimates by explicitly modeling behavioral responses to intervention, rather than merely varying parameters such as willingness to be vaccinated. Useful explicit modeling will require tapping new sources of data as we recommend in this article.

To elaborate, because the anticipation of behavioral responses can change policy recommendations, new transmission models that factor in the interplay between behaviors and disease dynamics are needed. To properly investigate the trade-offs of different policies, models must be grounded in causal epidemiological and behavioral theory and data (Manheim et al., 2016). Further, models need to factor in the many interacting uncertainties surrounding the virus and the vaccines, such as seasonal effects, the duration of natural and vaccine-based immunity, and the emergence of more transmissible strains. Early evidence suggests that immunity generated by the vaccines could be short-lived and that the vaccine is somewhat more effective at reducing severity than transmission (Hall et al., 2021; Tande et al., 2021). Emerging evidence also suggests that current vaccines may be less effective in protecting against specific variants, although they effectively prevent the most severe reactions and death (Wibmer et al., 2021). Hence, it seems increasingly likely that the virus will enter long-term circulation and become endemic, and that people will need to be vaccinated regularly with updated vaccines, as for seasonal influenza (Kissler et al., 2020; Scudellari, 2020).

Existing COVID-19 models use one of two general mathematical approaches for projections: statistics-based models that rely largely on data and curve fitting, and mechanistic models grounded in epidemiological micro-foundations and causal mechanisms. Purely data-driven statistical models (including those based on machine learning (ML) algorithms) generally have better short-term predictive performance, but limited capacity to explain counterfactual conditions and policy interventions. To explore and compare trade-offs of different policies and “what if” scenarios relative to each other, models need to be grounded in causal epidemiological and behavioral theory and data (Pearl, 2009).

Two types of mechanistic epidemiological models are (i) population-based models (PBM) and (ii) individual-level agent-based models (ABMs). Most of the COVID-19 mechanistic models have been deterministic PBM variants of the SEIR model, where the population is divided into such compartment classes as susceptible, exposed (latent), infectious, and removed (e.g., recovered and died) (Adiga et al., 2020). More recently, ABMs based on SEIR-type classes have been developed to explore intervention policies at the individual-level. Both the PBMs and the ABMs have been very useful for comparing policy interventions affecting testing, tracing, NPI, and vaccine prioritization strategies.

A PBM uses a top-down approach to depict disease dynamics at a macroscopic, system level. The ABM

approaches have used less abstraction and been more bottom-up, considering each individual in the environment as an agent with its own infection state and behavior (Auchincloss and Garcia, 2015). Deterministic PBMs are formulated using coupled ordinary differential equations (ODEs) and are less computationally demanding, quicker to develop, and faster to run than ABMs, and their results are often easy to interpret. PBMs are therefore valuable for exploring and comparing a large set of intervention policies. They also relate well to the macro-level factors that policymakers deal with. However, since they model aggregate groups of people, they are not well-suited to addressing individual-level disease transmission dynamics. A PBM’s disease transmission rate assumes the law of mass-action (i.e., that rate is proportional to the product of relevant concentrations). It also makes assumptions about how different groups of people, or population strata mix and under what circumstances (e.g., home, school, work). These are generally modeled using mode-specific mixing-matrices that control the different levels of homogeneous mixing between the population strata. In contrast, ABMs can better reflect a broader range of epidemiological heterogeneities that affect transmission patterns, such as the role of super-spreaders; importantly, they can explicitly model contact networks (Pastor-Satorras et al., 2015). Hence, ABMs allow individuals belonging to the same population group to have very different social mixing properties. Depending on data availability, ABMs can have better predictive

power than PBMs and can be used to explore more targeted intervention policies (Bonabeau, 2002). However, this improved predictiveness depends on numerous assumptions and, thus, requires more data. PBMs and ABMs can complement each other when used together in a multi-model approach and mitigate some structural uncertainties (Gambhir et al., 2015). Ideally, ABMs can generate simulated data permitting recognition of developments that can then be abstracted for inclusion in the analytically convenient PBMs (Davis and O'Mahony, 2019). Towards this goal, modelers have combined ABMs and PBMs into hybrid models of infectious disease transmission (Bobashev et al., 2007). These hybrid models switch between the two approaches over time and allow integration across multiple scales of description. Hybrid models are computationally faster than pure ABMs but still allow for individual-level analysis of emerging population structures.

Despite the rapid advancements in COVID-19 models and forecast tools, very few models directly include adaptive behavioral effects and how risk perceptions influence transmission dynamics. Both PBMs and ABMs can be coupled with models describing behaviors that are affected by and affect the disease transmission dynamics (Manfredi and D'Onofrio, 2013). For example, in PBMs behavioral changes that influence the contact rate during the epidemic can be modeled by allowing the transmission rate parameter to change in response to observed epidemiological state variables such as model outputs for reported cases and deaths

(Kwuimy et al., 2020). Simple parametric models of behavior consider an exponential or a reverse-sigmoid decline in transmission rate with increasing deaths (Getz and Dougherty, 2018). These models consider how contact rate declines in the early stages of the epidemic. Other behavioral effects can be included to model increased mixing due to fatigue in complying with NPIs. However, PBMs models use equations intended to be descriptive of entire groups of people: individuals that belong to the same population group are described by the same behavioral equations and parameter values. Moreover, the adaptive behaviors of each population group only respond to the current epidemiological state variables. Hence, PBMs do not allow for different behaviors to develop due to different histories of otherwise identical individuals that belong to the same population group. ABMs allow explicit specification of micro-level behavioral mechanisms that affect public risk perceptions and individual protective behaviors and attitudes. Moreover, similar individuals in an ABM develop different behaviors due to their different histories.

Whether people are willing to vaccinate strongly affects disease transmission dynamics. Hence, modeling how vaccination willingness is affected by context, events, and policies is crucial in estimating a voluntary vaccination policy's effectiveness. Coupling transmission models of infectious diseases with models of vaccination decisions has been a growing field of research. Early models in behavioral epidemiology considered rationally self-interested

individuals who use deductive reasoning and maximize their utility function when deciding to vaccinate for pathogens that provide permanent immunity (Bauch and Earn, 2004). Subsequent models considered influenza, where vaccination provides only temporary immunity and where individuals use inductive reasoning to make their yearly vaccination-related decisions by adapting to the changing epidemiology that they, in part, help form (Vardavas et al., 2007). For example, individuals choose to vaccinate based on their personal histories with influenza and the vaccine. If they did not vaccinate in the previous year and think they contracted the flu, they are more likely to vaccinate in the current season. On the other hand, if they were vaccinated in the previous season but think that they contracted the flu anyway, or perceive a low risk of contracting the flu because unvaccinated friends did not get the flu, they will be less likely to vaccinate in the current season. These models showed how heterogeneities in vaccination behaviors could emerge in otherwise homogeneous populations and some authors conclude that influenza epidemics cannot be prevented by voluntary vaccination without incentive-based programs (Breban et al., 2007).

Researchers have since been adding more realism to these models by including important sources of heterogeneities. Most notably, they consider how people's behaviors spread over complex social contact networks and affect disease transmission chains (Bhattacharyya and Bauch, 2012; Wang et al., 2016). This is also partly due to

how risk perceptions and protective behaviors are affected by social networks (Bruine de Bruin et al., 2019). For example, through a process of imitation, influenza vaccination behaviors and hesitancy can spread over social networks, further affecting disease transmission dynamics (Cornforth et al., 2011). If COVID-19 becomes endemic, there will be a growing need for new COVID-19 models that consider how behaviors spread over networks and explore incentive-based policies that target key people to vaccinate. These could be a combination of the most vulnerable to severe COVID-19 and those identified as highly connected and most likely to spread the virus. Prevailing models that consider the current acute phase of COVID-19 disease transmission have favored targeting the most vulnerable (Bubar et al., 2021; Kohli et al., 2021). However, other studies have shown that under certain conditions (high vaccine availability, high vaccine effectiveness to prevent transmission), prioritization of vaccinating the highly connected could rapidly cut transmission chains and indirectly protect the most vulnerable (Gulden et al., 2021; Matrajt et al., 2020).

Generally, disagreements between COVID-19 model projections and policy recommendations are due to differences in model architecture, assumptions and how data informs the models. A diverse set of publicly available data-sets have been used to inform COVID-19 models. These include time-series of case reporting and deaths, transmission estimation, and prognosis from epidemiological, de-

mographic, and mobility data, as well as social media data used for sentiment analysis and knowledge-based semantic analysis from the collection of scholarly articles covering COVID-19. Mixing matrices and the contact networks and how these change over time are critical model inputs. To better fit time-series data, modelers often use time-varying mixing parameters that are either informed by proxies to mixing (e.g., mobility data) or directly fitted to data. This approach allows modelers to fit case and death time-series. The reasoning behind this method is that infectious mixing is an unobserved process affected by many time-varying variables such as individual preferences, policy, and fatigue. Therefore, instead of modeling the relevant processes that affect mixing endogenously, one should use the available data such that the effective mixing time-series fits observed time-series. However, this approach does not result in an endogenous explanation of why the behavior changed in the past, and how it might change in the future. Moreover, if modelers are not careful, they may attribute changes in other parts of the system to changes in mixing. For example, if modelers use death time-series to calibrate a mixing parameter, they might attribute changes in mortality rates to changes in mixing. This problem, known as omitted variable bias in causal inference, is often not discussed in papers employing mechanistic models.

Better data-sets containing behavioral information are required to address the pressing need for new reliable COVID-19 models that include

adaptive responses. We argue that interdisciplinary researchers should work together to design and field longitudinal surveys tailored to inform simulation models for this purpose. These surveys would capture how public perceptions of risk, protective and preparedness behaviors, public trust, knowledge, and misinformation change with the evolving epidemic, social network influences and personal experiences. Interdisciplinary research teams designing the surveys should bring together behavioral scientists, epidemiologists, policy researchers, mathematicians, and statisticians. The RAND Corporation is using this approach to develop an ABM of influenza vaccination decision. It has conducted a 4-year, 8-wave longitudinal survey fielded from Fall 2016 to Spring 2020 on the decision to vaccinate for influenza and influenza infection outcomes. The study is called FluPaths and its data is freely publicly available through RAND's American Life Panel (RAND Corporation, 2014). Pre-season questions included respondents' intentions to vaccinate, risk perceptions of catching influenza, and whether they received a recommendation to vaccinate from a health care professional. Post-influenza season questions included whether respondents were vaccinated, whether vaccination resulted from a healthcare professional's advice, whether they thought they caught influenza (and if so, whether they were tested for it and were prescribed antiviral medication). FluPaths surveys collected detailed information on each respondent's social network structure (including alter-alter ties) and assessed the influence of net-

work experiences on the respondent's risk perceptions and attitudes regarding influenza and vaccination over time.

Novel ML methods can generate network structures informing the ABM. For example, they can combine egocentric network data sets from the surveys like FluPaths containing the behavioral responses to socio-centric large-scale networks representing large U.S. cities with socio-demographic features (Hartnett et al., 2020). Further, the surveys inform the adaptive behavioral mechanism of the ABM, which can be based on an Adaptive Control of Thought - Rational (ACT-R) framework. ACT-R provides a realistic and mechanistic behavioral model of human cognition grounded in reinforcement learning (i.e., an area of ML), representing the evolution of individuals' experiences, perceptions, and preferences in disease protective measures (Ritter et al., 2019). It brings together multiple psychological theories that account for human perception, learning, memory, decision making, and action. ACT-R models memory activation, retrieval, and mismatch (i.e., retrieval of the wrong information) based on experience frequency and recency, which is well-aligned to modeling how behaviors change in response to changing epidemiological outcomes, information, and risk perceptions. Hence, these tailored surveys lead to a natural convergence between computational simulation modeling, large data, and ML.

So far, in this paper, we have not addressed the pervasive problem of uncertainty. Even if the modeling

improvements we suggest prove to be valid, there will be profound limitations on how well they will predict the course of disease under alternative interventions (Steinmann et al., 2020). Actual developments will depend on many factors such as actual infectiousness by pathogen variant, which population groups are most affected, the actual effectiveness of public-service announcements, government credibility, and world events. This will be another instance when public policy reasoning is beset with deep uncertainty (Lempert, 2019; Marchau et al., 2019). Model-based analysis may still be very insightful for describing and understanding what has happened, the many possible ways in which matters may unfold under different interventions, and what intervention packages (including built-in monitoring and preparation for adaptation) will be most robust across the uncertainties. A variety of methods are now well developed for what is now called robust decision-making (RDM). However, they are most effective when the model being used is relatively simple, with perhaps ten rather than dozens or hundreds of uncertain inputs. In such cases, it is possible to explore the consequences of all the combinations of input values and find relatively robust strategies. With this in mind, we see great value in pursuing the enhanced ABM approach that we have described above to represent better the complicated cause-effect relationships among interventions, events, entities and their reasoning, agent networks, agent behavioral changes, and the course of the disease. However, we also urge that

experiments with such a relatively detailed model be used to suggest a much simpler model useful for exploratory analysis of policy options (Davis, 2019). Even the simplified model might have aggregate agents, a primitive network or a simplified equivalent, and different contexts reflecting “phase transitions” in the more microscopic model.

In summary, since public willingness to embrace such measures as social distancing, mask-wearing, and vaccination will be so crucial in managing the continuing COVID epidemic over time, and since deep uncertainties afflict many assumptions about the models and their parameter values, we conclude that

1. New agent-based COVID-19 models should include explicit causal mechanisms reflecting how policies affect public behaviors (in both desirable and undesirable ways), affecting subsequent disease epidemiology; these models should be approximated by somewhat simpler models that are amenable to wide-ranging uncertainty analysis;
2. New tailored longitudinal surveys should be conducted and analyzed with novel machine-learning methods specifically designed to inform empirically these enriched models with difficult-to-predict adaptive behaviors;
3. Policy analysis should use the models and the methods of decision-making under deep uncertainty (DMDU) to compare alternative COVID-19 policies—identifying robust policies, i.e., policies that seem likely to prove effective under a broad range of assumptions.

Such improved models, data, and analytical methods could substantially improve the ability to compare alternative intervention strategies.

## References

- Adiga, A., Dubhashi, D., Lewis, B., Marathe, M., Venkatramanan, S., & Vullikanti, A. 2020. Mathematical Models for COVID-19 Pandemic: A Comparative Analysis. *Journal of the Indian Institute of Science* 100, 793–807. <https://doi.org/10.1007/s41745-020-00200-6>
- Alagoz, O., Sethi, A.K., Patterson, B.W., Churpek, M., & Safdar, N. 2020. Effect of Timing of and Adherence to Social Distancing Measures on COVID-19 Burden in the United States. *Ann. Intern. Med.* 174, 50–57. <https://doi.org/10.7326/M20-4096>
- Aledort, J.E., Lurie, N., Wasserman, J., & Bozzette, S.A. 2007. Non-pharmaceutical public health interventions for pandemic influenza: an evaluation of the evidence

base. BMC Public Health 7, 208. <https://doi.org/10.1186/1471-2458-7-208>

Auchincloss, A.H., & Garcia, L.M.T. 2015. Brief introductory guide to agent-based modeling and an illustration from urban health research. *Cad. Saude Publica* 31 Suppl 1, 65–78. <https://doi.org/10.1590/0102-311X00051615>

Bauch, C.T., & Earn, D.J. 2004. Vaccination and the theory of games. *Proc Natl Acad Sci U A* 101, 13391–4.

Bhattacharyya, S., & Bauch, C.T. 2012. Mathematical models of the interplay between individual vaccinating decisions and disease dynamics: a need for closer integration of models and data. *Hum. Vaccines Immunother.* 8, 842–844. <https://doi.org/10.4161/hv.19616>

Bobashev, G.V., Goedecke, D.M., Feng Yu, & Epstein, J.M. 2007. A Hybrid Epidemic Model: Combining the Advantages Of Agent-Based And Equation-Based Approaches, in: 2007 Winter Simulation Conference. Presented at the 2007 Winter Simulation Conference, pp. 1532–1537. <https://doi.org/10.1109/WSC.2007.4419767>

Bonabeau, E. 2002. Agent-based modeling: Methods and techniques for simulating human systems. *Proc. Natl. Acad. Sci.* 99, 7280–7287. <https://doi.org/10.1073/pnas.082080899>

Breban, R., Vardavas, R., & Blower, S. 2007. Mean-field analysis of an inductive reasoning game: application to influenza vaccination. *Phys. Rev. E Stat. Nonlin. Soft Matter Phys.* 76, 031127. <https://doi.org/10.1103/PhysRevE.76.031127>

Bruine de Bruin, W., Parker, A.M., Galesic, M., & Vardavas, R. 2019. Reports of social circles' and own vaccination behavior: A national longitudinal survey. *Health Psychol. Off. J. Div. Health Psychol. Am. Psychol. Assoc.* 38, 975–983. <https://doi.org/10.1037/hea0000771>

Bubar, K.M., Reinholt, K., Kissler, S.M., Lipsitch, M., Cobey, S., Grad, Y.H., & Larremore, D.B. 2021. Model-informed COVID-19 vaccine prioritization strategies by age and serostatus. *Science* 371, 916–921. <https://doi.org/10.1126/science.abe6959>

Cornforth, D.M., Reluga, T.C., Shim, E., Bauch, C.T., Galvani, A.P., & Meyers, L.A. 2011. Erratic flu vaccination emerges from short-sighted behavior in contact networks. *PLoS Comput Biol* 7, e1001062. <https://doi.org/10.1371/journal.pcbi.1001062>

Crane, M.A., Shermock, K.M., Omer, S.B., & Romley, J.A. 2021. Change in Reported Adherence to Nonpharmaceutical Interventions During the COVID-19 Pandemic, April–November 2020. *JAMA*. <https://doi.org/10.1001/jama.2021.0286>

Davis, P.K., & O’Mahony, A. 2019. Improving Social-Behavioral Modeling.

Gambhir, M., Bozio, C., O’Hagan, J.J., Uzicanin, A., Johnson, L.E., Biggerstaff, M., & Swerdlow, D.L. 2015. Infectious Disease Modeling Methods as Tools for Informing Response to Novel Influenza Viruses of Unknown Pandemic Potential. *Clin. Infect. Dis.* 60, S11–S19. <https://doi.org/10.1093/cid/civ083>

Getz, W.M., & Dougherty, E.R. 2018. Discrete Stochastic Analogs of Erlang Epidemic Models. *J. Biol. Dyn.* 12, 16–38. <https://doi.org/10.1080/17513758.2017.1401677>

Gulden, T.R., Hartnett, G.S., Vardavas, R., & Kravitz, D. 2021. Protecting the Most Vulnerable by Vaccinating the Most Active. RAND Corp. <https://doi.org/10.7249/PEA1068-1>

Hall, V., Foulkes, S., Charlett, A., Atti, A., Monk, E.J.M., Simmons, R., Wellington, E., Cole, M.J., Saei, A., Oguti, B., Munro, K., Wallace, S., Kirwan, P.D., Shrotri, M., Vusirikala, A., Rokadiya, S., Kall, M., Zambon, M., Ramsay, M., Brooks, T., Group, S.S., Brown, C.S., Chand, M.A., & Hopkins, S. 2021. Do antibody positive healthcare workers have lower SARS-CoV-2 infection rates than antibody negative healthcare workers? Large multi-centre prospective cohort study (the SIREN study), England: June to November 2020. *medRxiv* 2021.01.13.21249642. <https://doi.org/10.1101/2021.01.13.21249642>

Hartnett, G.S., Vardavas, R., Baker, L., Chaykowsky, M., Gibson, C.B., Giroi, F., Kennedy, D.P., & Osoba, O.A. 2020. Deep Generative Modeling in Network Science with Applications to Public Policy Research. RAND Corp. <https://doi.org/10.7249/WRA843-1>

Kantor, B.N., & Kantor, J. 2020. Non-pharmaceutical Interventions for Pandemic COVID-19: A Cross-Sectional Investigation of US General Public Beliefs, Attitudes, and Actions. *Front. Med.* 7. <https://doi.org/10.3389/fmed.2020.00384>

Kissler, S.M., Tedijanto, C., Goldstein, E., Grad, Y.H., & Lipsitch, M. 2020. Projecting the transmission dynamics of SARS-CoV-2 through the postpandemic period. *Science* 368, 860–868. <https://doi.org/10.1126/science.abb5793>

Kohli, M., Maschio, M., Becker, D., & Weinstein, M.C. 2021. The potential public

health and economic value of a hypothetical COVID-19 vaccine in the United States: Use of cost-effectiveness modeling to inform vaccination prioritization. *Vaccine* 39, 1157–1164. <https://doi.org/10.1016/j.vaccine.2020.12.078>

Kwuimy, C.A.K., Nazari, F., Jiao, X., Rohani, P., & Nataraj, C. 2020. Nonlinear dynamic analysis of an epidemiological model for COVID-19 including public behavior and government action. *Nonlinear Dyn.* 101, 1545–1559. <https://doi.org/10.1007/s11071-020-05815-z>

Lempert, R.J. 2019. Robust Decision Making (RDM). [https://www.rand.org/pubs/external\\_publications/EP67834.html](https://www.rand.org/pubs/external_publications/EP67834.html)

Manfredi, P., & D’Onofrio, A. 2013. Modeling the interplay between human behavior and the spread of infectious diseases. Springer, New York.

Manheim, D., Chamberlin, M., Osoba, O.A., Vardavas, R., & Moore, M. 2016. Improving Decision Support for Infectious Disease Prevention and Control: Aligning Models and Other Tools with Policymakers’ Needs. RAND Corporation.

Marchau, V.A., Walker, W., Bloemen, P.J., & Popper, S.W. 2019. Decision Making Under Deep Uncertainty: From Theory to Practice. Springer, New York.

Matrajt, L., Eaton, J., Leung, T., & Brown, E.R. 2020. Vaccine optimization for COVID-19: Who to vaccinate first? *Sci. Adv.* 7, eabf1374. <https://doi.org/10.1126/sciadv.abf1374>

Pastor-Satorras, R., Castellano, C., Van Mieghem, P., & Vespignani, A. 2015. Epidemic processes in complex networks. *Rev. Mod. Phys.* 87, 925–979. <https://doi.org/10.1103/RevModPhys.87.925>

Pearl, J. 2009. Causality. Cambridge University Press.

RAND Corporation, 2014. The American Life Panel. <https://www.rand.org/research/data/alp.html>

Ritter, F.E., Tehranchi, F., & Oury, J.D. 2019. ACT-R: A cognitive architecture for modeling cognition. *WIREs Cogn. Sci.* 10, e1488. <https://doi.org/10.1002/wcs.1488>

Scudellari, M. 2020. How the pandemic might play out in 2021 and beyond. *Nature* 584, 22–25. <https://doi.org/10.1038/d41586-020-02278-5>

Steinmann, P., Wang, J.R., van Voorn, G.A., & Kwakkel, J.H. 2020. Don’t try to

predict COVID-19. If you must, use deep uncertainty methods. *Rev. Artif. Soc. Soc. Simul.* 17.

Tande, A.J., Pollock, B.D., Shah, N.D., Farrugia, G., Virk, A., Swift, M., Breeher, L., Binnicker, M., & Berbari, E.F. 2021. Impact of the COVID-19 Vaccine on Asymptomatic Infection Among Patients Undergoing Pre-Procedural COVID-19 Molecular Screening. *Clin. Infect. Dis.* <https://doi.org/10.1093/cid/ciab229>

Vardavas, R., Breban, R., & Blower, S. 2007. Can influenza epidemics be prevented by voluntary vaccination? *PLoS Comput. Biol.* 3, e85. <https://doi.org/10.1371/journal.pcbi.0030085>

Wang, Z., Bauch, C.T., Bhattacharyya, S., d'Onofrio, A., Manfredi, P., Perc, M., Perra, N., Salathé, M., & Zhao, D. 2016. Statistical physics of vaccination. *Phys. Rep., Statistical physics of vaccination* 664, 1–113. <https://doi.org/10.1016/j.physrep.2016.10.006>

Wibmer, C.K., Ayres, F., Hermanus, T., Madzivhandila, M., Kgagudi, P., Oosthuisen, B., Lambson, B.E., de Oliveira, T., Vermeulen, M., van der Berg, K., Rossouw, T., Boswell, M., Ueckermann, V., Meiring, S., von Gottberg, A., Cohen, C., Morris, L., Bhiman, J.N., & Moore, P.L. 2021. SARS-CoV-2 501Y.V2 escapes neutralization by South African COVID-19 donor plasma. *Nat. Med.* 1–4. <https://doi.org/10.1038/s41591-021-01285-x>

Yaqub, O., Castle-Clarke, S., Sevdalis, N., & Chataway, J. 2014. Attitudes to vaccination: a critical review. *Soc. Sci. Med.* 1982 112, 1–11. <https://doi.org/10.1016/j.socscimed.2014.04.018>

# Can Agent-Based Modeling Enable Scientific Policy Making Based on an Understanding of Causal Mechanisms?

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*Keywords:* agent-based modeling, scientific policy, causal mechanisms, social systems

## ¿Puede el modelado basado en agentes permitir la formulación de políticas científicas basadas en la comprensión de los mecanismos causales?

*Palabras clave:* modelado basado en agentes, política científica, mecanismos causales, sistemas sociales

## 基于agent模型能在理解因果机制的基础上让科学决策成为可能吗？

关键词：基于agent建模，科学政策，因果机制，社会系统

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**M**any social problems depend on government policy. In democratic societies, government policy should essentially aim to allow people of all levels to lead spiritually- and materially-rich and safe lives. However, this is not the case in reali-

ty. Most countries have various social problems, including remarkable wealth inequality between rich and poor and the issue of social welfare, which appear to be becoming increasingly serious. Underlying these problems is the fact that the true causal mechanisms of var-

ious phenomena in society are not well understood or shared among people, and the policy-making process is likely to be designed for those who have vested interests or powers. It is therefore desirable to correctly understand the causal mechanisms underlying the emergence of social and economic phenomena, based on which social and economic policy by the government is scientifically backed.

In both natural and social systems, there exists a cause and causal mechanism for the occurrence of each phenomenon. In the fields of natural science and engineering, hypotheses and equation-based models concerning these causal mechanisms have been proposed based on observation of the behavior of various phenomena, which are verified by a series of controlled experiments. Thus, natural science and engineering comprise accumulated knowledge and data on the causal mechanisms of various phenomena. The background that various hypotheses have been proved by experiments, owing to which the causal mechanism of each phenomenon has been clarified, is that natural phenomena' behavior is universal and unchanged over time and space. For example, the light speed is constant and does not change with place or time. The same is true for various laws of nature. Because of this principle, hypotheses concerning causal mechanisms could be proved true or not by researchers worldwide without depending on the time and space.

Conversely, in the fields of social science and economics, various phenomena are caused by decision-mak-

ers' behaviors and their interactions, which change with time and place and depend on the heterogeneity of individual intentions. In principle, it is therefore impossible to conduct controlled experiments such as those for natural phenomena in the social world. This implies that a traditional approach is in principle insufficient to clarify the causal mechanism of social phenomena. Furthermore, the causal mechanisms between the causes and effects related to social phenomena are complicated because the human behavior that causes changes in the state of society depends on the state of society itself, and the manner of dependence varies across individuals; therefore, there is a limit to expressing such mechanisms with a simple set of equations.

Agent-based modeling (ABM) is a powerful approach for elucidating the causal mechanisms of social phenomena. ABM is a method where an artificial society is constructed using a computer, based on assuming the actions of multiple decision-makers and reproducing the emergence of various macro phenomena. If the assumed input conditions do not include macro factors other than the behavior of the decision-maker (i.e., if the model is 100% bottom-up), it is, in principle, possible to build a model so that the causal relationship emergent in the artificial society could be same as that in the actual system.

The history of ABM dates back to John von Neumann's theory of "self-reproducing automaton" (1966). Cellular automata devised based on this theory are considered to provide the roots of

ABM. One of the earliest models was Thomas Schelling's ethnic segregation model (1971). Subsequently, "Growing Artificial Societies" written by J. M. Epstein and R. Axtell (1996) and "Simulation for the Social Scientist" by N. Gilbert and K. G. Troitzsch (2005) were published. In these books, the ideas of building a model by abstracting the real world to some extent and that a model can be roughly classified into abstract, middle range, and facsimile models in terms of the degree of precision were proposed. However, criticisms regarding the validity of ABM have been reported, including the argument that ABM cannot specify the necessary conditions for reproducing a specific macro phenomenon because of its inherent functional complexity (R. E. Marks, 2007). Therefore, many researchers seem to consider that although ABM is effective in offering hints on the emergent mechanisms of phenomena in the real world, it is not sufficiently reliable for elucidating the causal mechanisms to replace the traditional approach of economics. ABM has so far received little recognition as a promising methodology that can be used for deciding public policies, except for one paper entitled, "Economy needs agent-based modeling" by J.D.Farmer et al. (2009).

However, as many modelers have probably experienced, ABM emerges different macro phenomena with different input conditions that are assumed. It is also noted that not all factors of the input condition change the characteristics of the macro phenomenon that is the output. Among the factors for a certain input condition, the set of factors indis-

pensable for the emergence of the macro phenomenon are considered the cause of the macro phenomenon in question; therefore, there is a causal relationship between the input condition that consists of a set of indispensable factors and the macro phenomenon. In this context, the input condition comprises the types of agents, their behavioral rules, and attribute variables. Because the combination of these factors can provide a model structure simulating a real system, the input condition will be referred to as a model structure below.

If we perform a series of computer experiments that systematically change the model structure and elucidate the structure that is indispensable for reproducing the characteristics of a macro phenomenon observed in the real world, the causal relationship between the model structure and the macro phenomenon clarified in the model can be considered to represent the causal relationship in the real world. Next, by considering the reason why factors in the model structure clarified by computer experiments are indispensable, it is possible to gain a better understanding of the causal mechanism of that phenomenon.

The author has found that there are indispensable model structures for reproducing various socio-economic phenomena. Considering why the model structure was indispensable confirmed that the extracted causal mechanism was reasonable. Shown below are some research examples.

First, to reproduce the equilibrium of the prices in a goods market,

indispensable factors are: (1) consumer's low price-oriented consumption behaviors and (2) producer's inventory management-oriented determination behaviors of production volume and price. Next, to reproduce the business cycle (i.e., the periodic fluctuation of gross domestic product (GDP)), indispensable factors in addition to (1) and (2) above are the following four factors: (3) producer's judgment for investment based on demand forecast for the expansion of production capacity, (4) producer's wage-increasing behavior when profits are increased, (5) producer's bank financing for investment (i.e., credit creation), and (6) the existence of an upper limit on credit creation. Conditions (3) and (4) imply the existence of productivity improvement and the accompanying increase in wages. Conditions (5) and (6) imply the existence of funds that need to be repaid. In other words, when funds are supplied to the market by bank borrowing, the economy expands because of a virtuous cycle of increased investment, wages, and demand. When borrowing becomes excessive, the amount of funds returned to banks exceeds the amount of borrowed funds, and funds are absorbed from the market to banks. The economy, therefore, declines because of a vicious cycle of reduced investment, lower wages, and lower demand.

In addition to the above, the indispensable model structures for income tax cuts and corporate tax cuts to increase GDP have also been studied. The indispensable model structure to reproduce the positive effect of income tax reduction on GDP is the in-

clusion of inefficiency in government expenditure in addition to the factors described above. Here, government spending inefficiency is defined in the model as the ratio of firm subsidy to total expenditure, where firm subsidies are funds that the government unnecessarily and sometimes unintentionally distributes to business sectors without expecting their economic value. In the case of households, the inefficiency in expenditure corresponds to one minus marginal propensity to consume. The research result indicates that income tax reduction increases GDP only when government expenditure inefficiency is more significant than that of the household. This implies that the household's funds raised by income tax reduction are more effectively consumed in the market than the government's case. The indispensable factors to reproduce the positive effect of corporate tax reduction are, in addition to the inefficiency in government expenditure, the existence of executive compensation, financing for investment from internal funds as well as from the bank, and mitigation of credit restriction. These are the factors that realize that the funds distributed to firms by corporate tax reduction are more effectively consumed in the market in the form of executives' consumption and firms' investment than the case owned by the government.

In summary, the indispensable model structure elucidated by a series of computer experiments indicates the mechanism of tax cuts' effect is as follows. The income tax cuts and corporate tax cuts increase GDP when the government's funds supplied to the

private sector through tax cuts increase demand in the market through the private sector's investment and consumption, which seems reasonable. Factors related to the labor market, such as corporate bankruptcy and the unemployment rate, are not indispensable factors for reproducing the effect of the corporate tax cut.

Another example is the indispensable model structure for the bullying phenomenon. The macro phenomenon observed in the bullying phenomenon is the emergence of five groups: bullies, the bullied, complete bystanders, persons who go along with the bullies, and those with the bullied. The indispensable model structure for the emergence of these five groups is as follows: (1) People tend to tune with and exclude others; these tendencies vary from agent to agent and unique to each agent; (2) The act of excluding others is performed only if the opponent is weaker than the agent. Furthermore, analysis of the frequency of exclusion and being excluded suggests that those with a strong tendency to bully others are those with strong tendencies to tune with others and exclude others. Those who are more likely to be bullied have a weak tendency to tune with others and a weak tendency to exclude others. These results are generally consistent with previous research based on questionnaires and similar approaches reported so far and are considered a reasonable mechanism.

Recently, the author constructed an ABM model for corona infection. The feature of this model is that it con-

siders not only the contact infection of people, but also the number of viruses, virus elimination by immunity, and enhancement of immunity by antibody production. The latter factors are the factors involved in the recovery process. Determining the model structure based on medical knowledge confirmed that this model successfully reproduced expansion and convergence of the pandemic and features of time differences of the accompanying peaks in the number of newly infected persons, the number of newly recovered persons, and the number of infected persons. This model assumed that the number of viruses eliminated in each period by immunity was proportional to the number of viruses in the body. Here, if the number of viruses eliminated in each period is assumed to be a constant value, then the number of newly recovered persons does not exceed the number of newly infected persons, and therefore the pandemic does not converge. That is, the assumption that the number of viruses eliminated from the body by immunity increases with the increasing number of viruses in the body appears to be indispensable for reproducing the convergence of the pandemic. This assumption corresponds with the fact that if the viruses enter the body because of infection, the body temperature rises and immunity increases accordingly. The literature shows that a 1° C increase in body temperature increases immunity five-fold. For this reason, it is important to distinguish infected persons from healthy persons, and suppress the frequency of contact between the two groups to prevent the spread of

infection. Monitoring body temperature is effective in addition to PCR tests (Polymer Chain Reaction test) to identify infected persons because body temperature might sensitively rise even if the number of viruses entered into the body is small.

As shown in the above example, it is possible for ABM to identify an indispensable model structure for reproducing the macro phenomenon observed in the real system by a series of computer experiments in which input conditions are systematically changed. Then, by considering the reason why the model structure is indispensable, we can gain a better understanding of the causal mechanism of various phenomena in society.

The validity of ABM has been argued since its development, but it is considered possible to use ABM to accumulate knowledge on the causal mechanism of specific socio-economic macro phenomenon by clarifying the model structure that is indispensable for reproducing the qualitative characteristics of that phenomenon. By accumulating such knowledge, it may be believable that social science and economics will become a system of truth related to the causal mechanism of the behavior of the socio-economic system, not just a set of theories. In further application, the same approach will enable quantitative reproduction of macro phenomena. When reproducing the quantitative characteristics of macro phenomena with a model, the combination of the numerical values of the attribute variables included in the input

conditions needs to be clarified by a series of computer experiments based on the indispensable model structure for the qualitative reproduction of the phenomenon. In this context, numerical values can be represented by relative numerical values, such as the ratio to a specific reference value. Such a specific reference value includes the total population and total amount of funds in the system.

This principle of ABM for elucidating the causal mechanism mentioned above is considered applicable even for the biological system, including the human disease phenomenon. In the human body, various symptoms accompanied by disease correspond to the characteristics of the macro phenomenon. The behaviors of internal organs or cells may be the input condition for the emergence of various diseases. The causal mechanism could be clarified by the same procedure mentioned above. First, a model should be constructed with the assumption based on the medical knowledge on the disease's emergence as precisely as possible. A set of indispensable factors to reproduce the emergence of a particular disease should be clarified by a series of computer experiments. By considering why such a set of factors is essential for the emergence of the disease symptoms, it might be possible to better understand the causal mechanism of the disease's emergence. This approach may complement the medical approach because the human body is a complex system. The traditional method may have a limit to some extent in clarifying the causal mechanism of the diseases.

*Can Agent-Based Modeling Enable Scientific Policy Making  
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In the policy-making process, it is possible to determine effective policies by a set of “what-if” analyses by predicting the effect of the policies included in the input conditions using the model structure clarified for each macro phenomenon. This approach will contribute to constructing a truly democratic society for all.



# Automatic Discovery of Attention Flows Under Policy Uncertainty

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## ABSTRACT

The failures of governance processes and societal values made evident during the first year of the Covid-19 pandemic have a commonality: the equally challenged processes for disseminating information under uncertainty. This paper demonstrates an applied AI-genetic algorithmic workflow to discover attractors in the attention economy, with applications to policy communications.

**Keywords:** complexity, attention flows, COVID-19, public policy

## Descubrimiento automático de flujos de atención bajo incertidumbre política

## RESUMEN

Las fallas de los procesos de gobernanza y los valores sociales que se hicieron evidentes durante el primer año de la pandemia de Covid-19 tienen un punto en común: los procesos igualmente desafiados para difundir información en condiciones de incertidumbre. Este artículo demuestra un flujo de trabajo algorítmico genético-IA aplicado para descubrir atractores en la economía de la atención, con aplicaciones a las comunicaciones de políticas.

**Palabras clave:** complejidad, flujos de atención, COVID-19, política pública

# 政策不确定性背景下注意力流的自动发现

## 摘要

新冠肺炎（COVID-19）大流行第一年里，治理过程和社会价值出现的失败有一个共同点：信息传播过程在不确定性情境下受到同等程度的挑战。本文应用一项人工智能遗传算法工作流程，以期发现注意力经济中的吸引力因素，并将该工作流程应用于政策传播。

关键词：复杂性，注意力流，新冠肺炎（COVID-19），公共政策

## Introduction

What have you learned one year into the pandemic? “We had a failure of governance process, and, a failure of societal values.” It may sound like a harsh post-mortem, generalized with the benefit of hindsight, until we learn that those are the words of Prof. Yaneer Bar-Yam, president of the New England Complex Systems Institute and leader of EndCoronavirus. This group published the first policy note on Covid-19 back in January 2020 and launched the initiative that has brought together 4,000 volunteers and includes scientists, engineers, medical doctors, and citizens. In their paper “Systemic risk of pandemic via novel pathogens—Coronavirus”, published on January 26, 2020, Joseph Norman, Yaneer Bar-Yam, and Nassim Nicholas Taleb exercised foresight when they advised for what could have been perceived as extreme measures at the time “If you have uncertainty and the absence of evidence, it should lead you

to more precaution” (Bar-Yam January 26, 2020). Moreover, the experience of running endcoronavirus.org and its multiple spin-off projects has given this team an unusual opportunity to witness the gaps in decision-making in our organizations and countries—verify how the points got connected.

The failures they describe are in no small part related to coordination problems—it turned out that we were not only over-connected in our travel networks, but we are also wired in our communication networks in ways that make calibration on simple facts a very difficult task. In the paper “Factoring Attention Price into Investment Decisions,” (Venegas, Krabec, and Čížinská 2018), this author discussed the idea of *attention-trust trade-offs* largely inspired in Fukuyama’s work on trust in the context of the attention economy; Herbert A. Simon’s clever observation that “What information consumes is rather obvious: it consumes the attention of its consumers. Hence a wealth of information creates a poverty of

attention and a need to allocate that attention efficiently among the overabundance of information sources that might consume it.”; and Kevin Kelly’s famous assertion that “the money in this networked economy...follows the path of attention, and attention has its own circuits.”

The motivation for this line of research is to answer: how can we create early alert systems to discover the critical nodes in those attention circuits? i.e., where a network intervention could be performed for optimal policy reach or for identifying vulnerabilities to attention attacks and malicious manipulation of public opinion? It turns out that evolutionary dynamics is how complexity arises (Bar-Yam 2002), so it may sense to use the same evolutionary process to map the system and discover the drivers. In the paper, we show how to use symbolic regression via genetic pro-

gramming and click-stream data to increase policy delivery effectiveness under uncertainty.

## Method

### *The Covid-19 attention economy*

To understand the demand-for-information side, we use The Global Consumer Survey by Statista, which is a worldwide online survey among internet users between 18 and 64. (Statista 2020)

### What people wanted to know

At the beginning of the pandemic, a large share of the public wanted to know about *Testing for Covid-19*, which was the dominant topic at 50%. But the combined percentage of respondents interested in policies (for work, travel, school) was much larger, 76%.

**Table 1.** Which of the following aspects of the COVID-19 / Corona pandemic, do you feel you need more information on? Source: Statista Global Consumer Survey March 2020, (multi-pick) Base: all respondents.

|  | United States of America |         | United Kingdom |         | Germany  |         | China    |         |
|--|--------------------------|---------|----------------|---------|----------|---------|----------|---------|
|  | absolute                 | percent | absolute       | percent | absolute | percent | absolute | percent |
| Base   | 7,155                    | 100%    | 7,159          | 100%    | 7,083    | 100%    | 4,262    | 100%    |
| <i>COVID-19 / Corona in general</i>                          | 2,256                    | 32%     | 1,591          | 22%     | 1,491    | 21%     | 2,944    | 69%     |
| How to handle personal hygiene                               | 712                      | 10%     | 506            | 7%      | 577      | 8%      | 2,126    | 50%     |
| <i>Policies for businesses</i>                               | 1,459                    | 20%     | 1,033          | 14%     | 1,181    | 17%     | 1,500    | 35%     |
| Policies for schools / kindergarten                          | 1,053                    | 15%     | 1,021          | 14%     | 1,116    | 16%     | 1,806    | 42%     |
| <i>Policies for travel</i>                                   | 1,579                    | 22%     | 1,758          | 25%     | 1,576    | 22%     | 1,009    | 24%     |
| Policies for working   | 1,336                    | 19%     | 1,509          | 21%     | 1,284    | 18%     | 1,729    | 41%     |
| <i>Risks to your health</i>                                  | 2,234                    | 31%     | 1,873          | 26%     | 1,845    | 26%     | 2,391    | 56%     |
| Rules for social distancing                                  | 1,246                    | 17%     | 1,118          | 16%     | 1,096    | 15%     | 1,535    | 36%     |
| <i>Shopping availability</i>                                 | 2,013                    | 28%     | 1,826          | 26%     | 1,272    | 18%     | 1,646    | 39%     |
| Testing for COVID-19 / Corona                                | 3,543                    | 50%     | 3,272          | 46%     | 2,917    | 41%     | 2,446    | 57%     |
| <i>What to do if you show symptoms for COVID-19 / Corona</i> | 2,142                    | 30%     | 1,236          | 17%     | 1,848    | 26%     | 2,348    | 55%     |
| Other  | 232                      | 3%      | 274            | 4%      | 250      | 4%      | 26       | 1%      |
| <i>Don't know</i>  | 937                      | 13%     | 1,283          | 18%     | 1,393    | 20%     | 65       | 2%      |
| Not Applicable   | 0                        | 0%      | 0              | 0%      | 0        | 0%      | 0        | 0%      |

### Which were the preferred sources of information?

They were consuming more Covid-related information on TV (68%) and News

websites (51%) than in scientific sources. However, most of the information was accessed online, with scientific and medical websites accounting for 23%.

**Table 2.** What sources do you actively use to keep informed about the COVID-19 / Corona pandemic? (multi-pick) Base: all respondents.

|   | United States of America |         | United Kingdom |         | Germany  |         | China    |         |
|---|--------------------------|---------|----------------|---------|----------|---------|----------|---------|
|   | absolute                 | percent | absolute       | percent | absolute | percent | absolute | percent |
| Base  | 7,155                    | 100%    | 7,159          | 100%    | 7,083    | 100%    | 4,262    | 100%    |
| Apps  | 580                      | 8%      | 546            | 8%      | 596      | 8%      | 2,653    | 62%     |
| Blogs   | 371                      | 5%      | 234            | 3%      | 319      | 5%      | 621      | 15%     |
| Friends and acquaintances                       | 1,838                    | 26%     | 1,221          | 17%     | 1,911    | 27%     | 1,513    | 35%     |
| News websites                                   | 3,617                    | 51%     | 3,947          | 55%     | 3,759    | 53%     | 3,066    | 72%     |
| Newspapers and magazines (print)                | 1,449                    | 20%     | 1,512          | 21%     | 2,144    | 30%     | 947      | 22%     |
| Online forums                                   | 732                      | 10%     | 464            | 6%      | 748      | 11%     | 1,431    | 34%     |
| Podcasts  | 549                      | 8%      | 277            | 4%      | 583      | 8%      | 319      | 7%      |
| Radio shows                                     | 949                      | 13%     | 1,296          | 18%     | 2,648    | 37%     | 931      | 22%     |
| Scientific / medical journals                   | 758                      | 11%     | 471            | 7%      | 745      | 11%     | 513      | 12%     |
| Scientific / medical websites                   | 1,657                    | 23%     | 987            | 14%     | 1,659    | 23%     | 835      | 20%     |
| Search engines (e.g. Google)                    | 2,387                    | 33%     | 1,640          | 23%     | 2,330    | 33%     | 2,023    | 47%     |
| Social media                                    | 2,434                    | 34%     | 1,734          | 24%     | 1,635    | 23%     | 2,565    | 60%     |
| TV  | 4,877                    | 68%     | 5,370          | 75%     | 5,339    | 75%     | 2,861    | 67%     |
| Other   | 138                      | 2%      | 111            | 2%      | 88       | 1%      | 19       | 0%      |
| I do not keep actively informed about the virus | 241                      | 3%      | 230            | 3%      | 298      | 4%      | 45       | 1%      |
| Not Applicable                                  | 0                        | 0%      | 0              | 0%      | 0        | 0%      | 0        | 0%      |

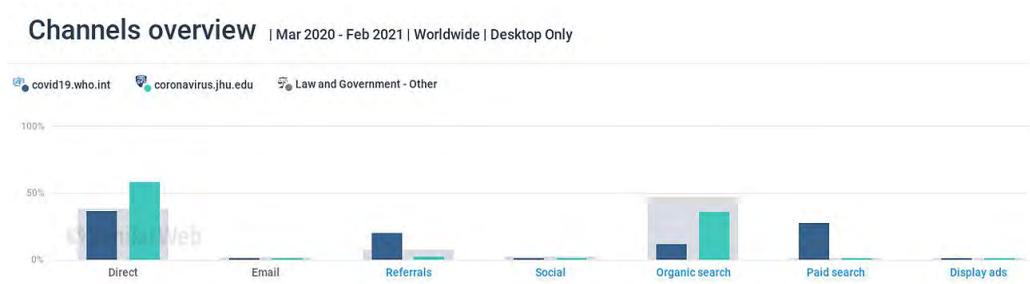
### Web attention flows

Using clickstream data from web panel data providers (Similarweb 2021) we are able to make an exploratory data analysis of the behavior of internet users, the consumers of information.

Scientific websites will rarely receive the whole share of traffic as direct visits (the 23% reported in Table 2); usually, they will receive visitors that begin

the journey with a search in Google or other search engines (Organic Search), who come from other sites (Referrals), follow Social networks links, or arrive via paid advertisement.

As a case in point, when comparing Covid resources sites, Johns Hopkins has a larger share of direct visits than the World Health Organization. It also has more direct visitors than the average for government websites.



**Figure 1.** Web traffic sources to Covid19.who.int and Coronavirus.jhu.edu, compared to a benchmark of Government sites. Source: SimilarWeb.

On the other hand, WHO attracts more visitors using paid ads, matching the search intent of people

with specific bids on terms; the top ad positions are gained by bidding for policy-related keywords.

Table 3. Paid Google Search ads. Accessed February 2021. Source: SimilarWeb

| Ads (11)   | Domains | Landing Page  | Keywords   | Position ↑ |
|--|---------|---|--|------------|
| 1<br>www.who.int/covid-19/q&as<br>Information about COVID-19 - World Health Organization - who.int<br>Official Public Service Announcement on Coronavirus from the World Health Organization   Learn about Symptoms, Prevention, Travel Advisory and Common FAQs on Coronavirus   Your questions answered   Official WHO website   Official info on COVID-19           | who.int | www.who.int/news-room/q-a-detail/q-a-corona-viruses   | 4 keywords:<br>covid policy   covid 19 vaccine news   list how ai is used in combating covid 19   multiple covid patients in one room      | 1          |
| 2<br>www.who.int/covid-19/q&as<br>Information about COVID-19 - World Health Organization - who.int<br>Official Public Service Announcement on Coronavirus from the World Health Organization   Learn about Symptoms, Prevention, Travel Advisory and Common FAQs on Coronavirus   Recommendation from WHO   Your questions answered   Learn about Coronavirus          | who.int | www.who.int/news-room/q-a-detail/q-a-corona-viruses   | 5 keywords:<br>covid policy   coronavirus impact on banks what should they do   covid meter   best multivitamin for covid   covid-19 essay | 1          |
| 3<br>www.who.int/covid-19/workplace<br>Workplace & COVID-19 - Get guidance, video and signs - who.int<br>Learn how employers can protect their employees & measures recommended in the workplace   Action now will help protect your employees and your business. Learn more on WHO website   Learn about Coronavirus   Your questions answered   Official WHO website | who.int | www.who.int/news-room/q-a-detail/q-a-tips-for-health-and-safety-at-the-workplace-in-the-context-of-covid-19 | 1 keywords:<br>covid policy  | 1          |

In turn, Johns Hopkins attracts most of the visits referred (or initiated) by other websites. The composition of that traffic (and audience) differs no-

toriously, too; for instance, 63.3% vs. 11.7% of the visits originate in news media sites.

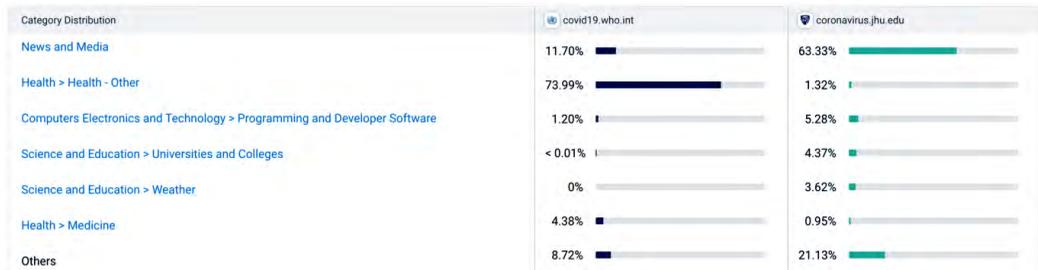


Figure 2. Incoming web visits distribution comparison(desktop), March 2020 to February 2021. Source: SimilarWeb

## Genetic programming modeling Symbolic Regression

From Complexity Science, we know that the space of possibilities is equivalent to information. While it is always

possible to connect the dots in hindsight, we need a way to narrow the space to gain foresight. A start point is to identify driving variables and derive quantitative expressions.

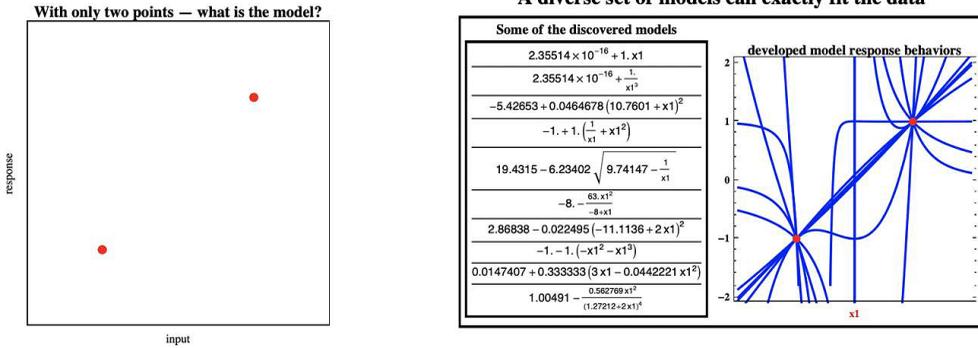


Figure 3. Creative hypothesis generation. Source: Evolved Analytics

For modeling, we use Data Modeler, the Mathematica genetic programming package. Symbolic Regression can identify driving variables and return quality models. The expressions obtained do not suffer from artificial constraints and assumptions of a priori knowledge (e.g., polynomials) that are the norm in conventional econo-

metrics and machine learning methods. (EvolvedAnalyticsLLC 2020)

In this framework, Accuracy is measured by the error ( $R^2$ ) and Complexity refers to structural complexity—the visitation length of the number of nodes passed through from the root node to each of the leaves.

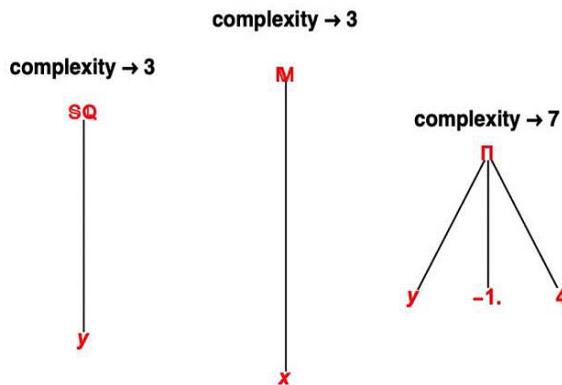


Figure 4. Sample tree structure of the model genotype; operators are Square, Minus, and Product

### Empirical hypotheses generation

To create our model, we use web panel data to put together a list of 489 websites that referred traffic/provided visitors to the website of the The Johns

Hopkins Coronavirus Resource Center, CRC (Coronavirus.jhu.edu). The site dashboards are widely used and Research!America named the CRC a recipient of its “Meeting the Moment for Public Health” award (Research!Amer-

ica 2021) . The dataset contains daily time series with the number of web visitors from November 2020 to February 2021; data for the modeling target, Coronavirus.jhu.edu, is available since March 2020 when the site was launched.

A sample of the variables shows how there are shapes in the series that appear to match the target very closely (contemporaneous peaks).

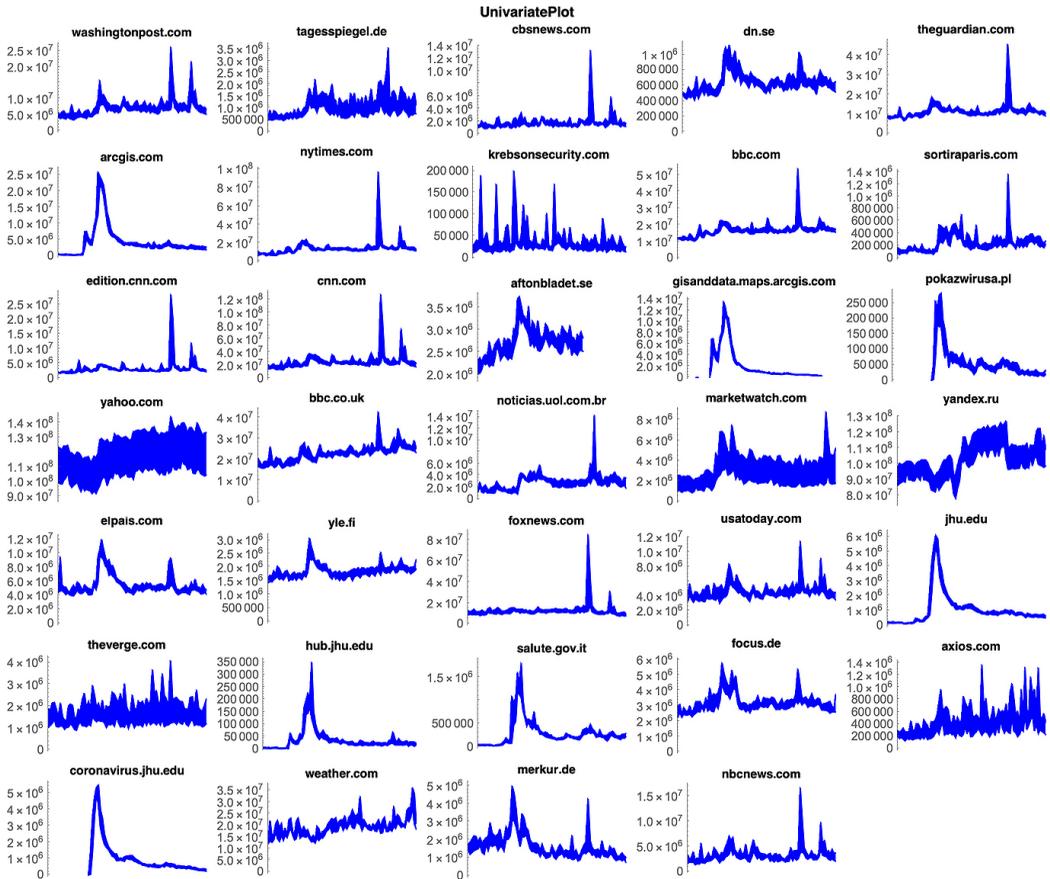


Figure 5. Website visits time series

The correlation is strong among health policy sites in countries such as CRC and other Johns Hopkins sites and Poland and Italy.

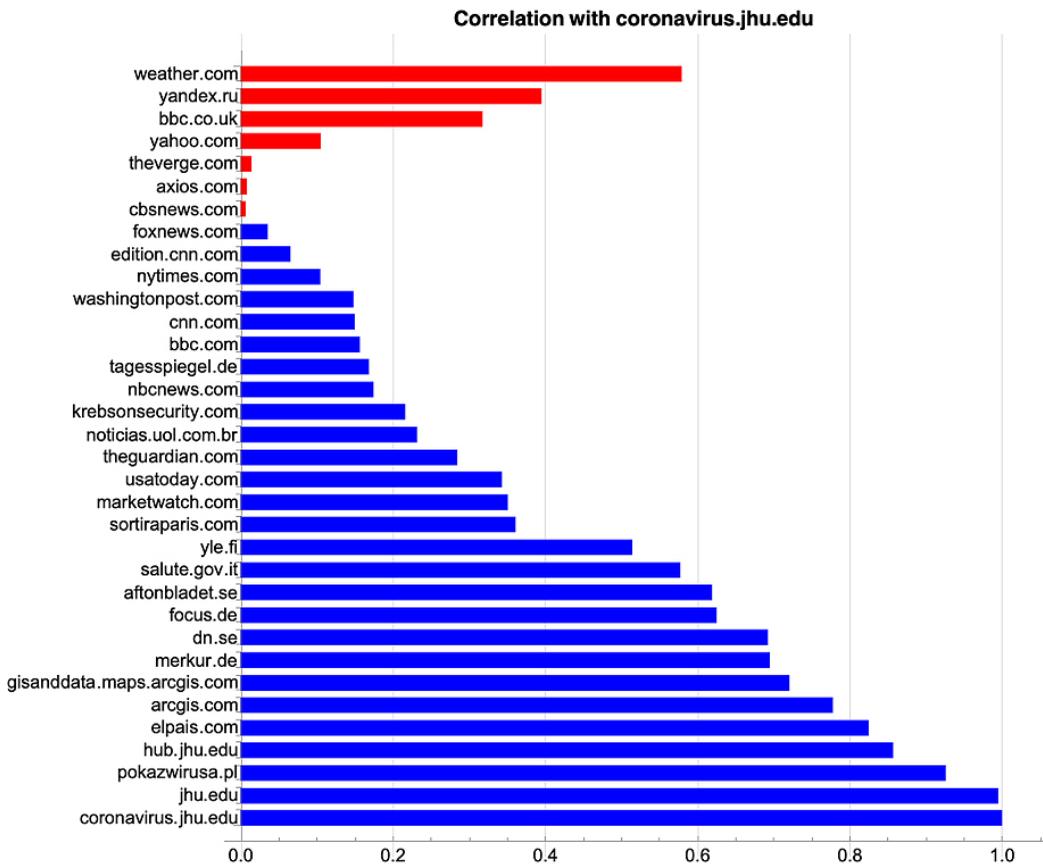


Figure 6. Correlation chart. Red are anti-correlations

By running the first round of modeling, a group of candidate driver variables is discovered. Note that we are modeling a causal relationship: the re-

sponse of the target variable directly depends on the incoming visits from the sites included in the empirical model.

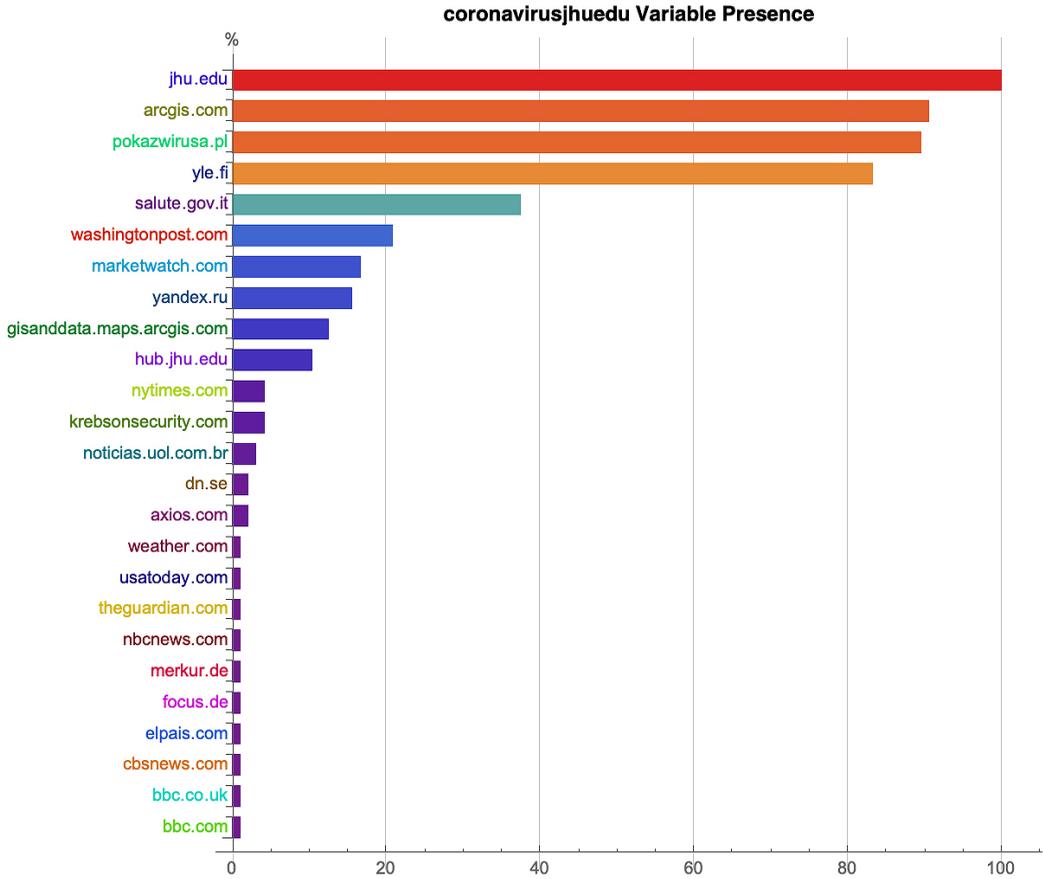


Figure 7. Drivers

We found surprises: for instance, the dependence on a mapping software vendor (partnership with Arcgis) and the site’s utility to the general public in Finland (via local news site yle.fi)—both sites appear in over 80% of the models. Nevertheless, even in the case

of sites too large to be correlated (as the Russian search engine Yandex), a relationship emerges—probably the general public in Russia started finding utility in CRC resources, so after the result was indexed, more people started using the site.

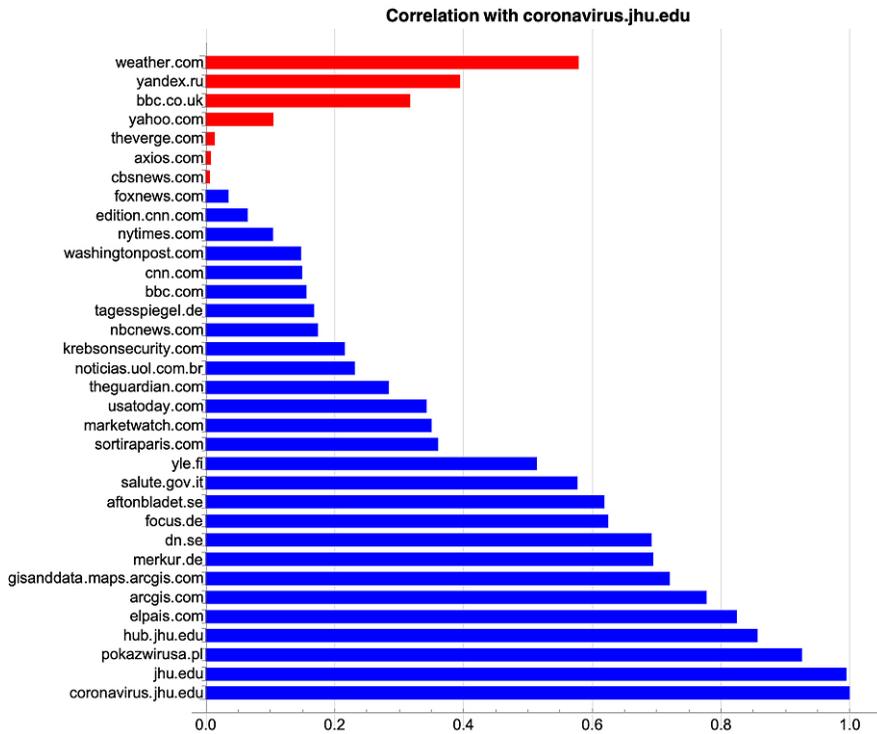


Figure 8. Models quality plot

## Discussion

In total, 719 models were generated; however, we need to narrow the field, so we focus our search on the

best candidates. There are 96 models in the knee of the Pareto that are both simple and accurate.

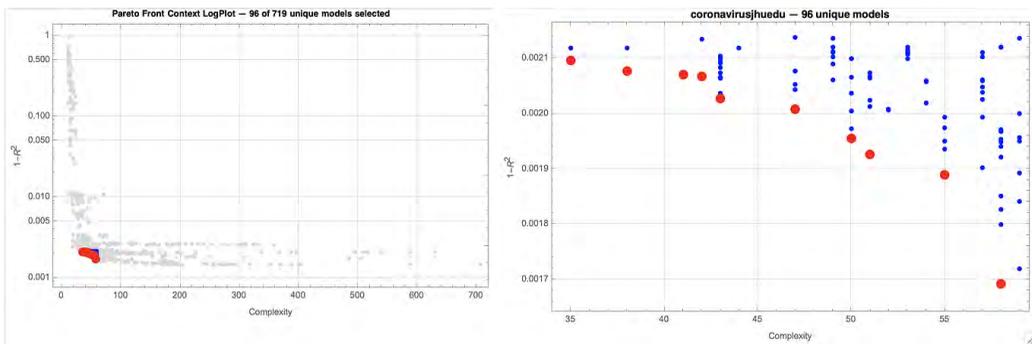


Figure 9. Models in Focus

Several expressions provide the same accuracy but have different levels of complexity. Since our purpose is

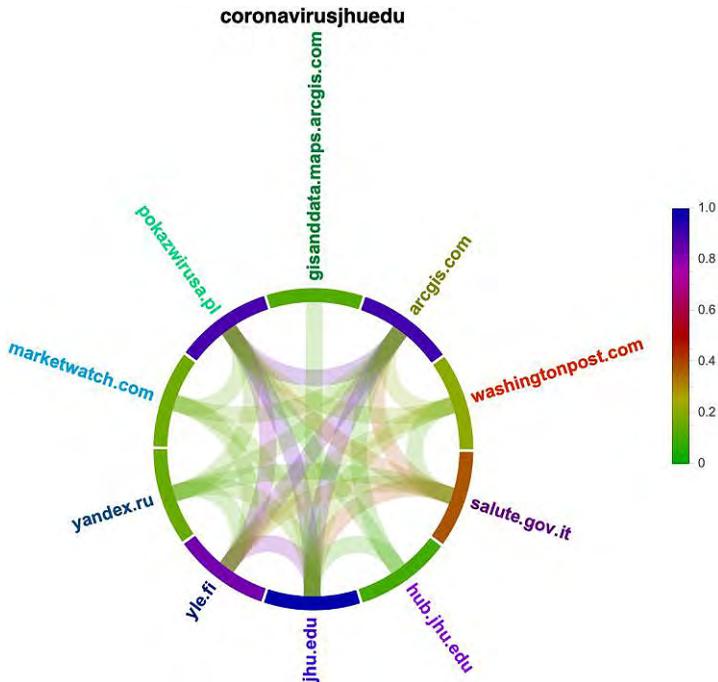
about understanding rather than purely predictive, we concentrate on the prevalent variable relationships.

**Table 4.** Model report: 6 independent evolutions, 3 minutes model development.

| coronavirusjhuedu |                  |       | Function  |
|-------------------|------------------|-------|---|
| Complexity        | 1-R <sup>2</sup> |       |   |
| 1                 | 35               | 0.002 | $-390870.25 - (3.41 \times 10^{-2}) \text{arcgis.com} + 1.04 \text{jhu.edu} + 0.75 \text{pokazwirusa.pl} + \frac{3.33 \times 10^{11}}{\text{yle.fi}}$   |
| 2                 | 38               | 0.002 | $-13568.90 - (3.43 \times 10^{-2}) \text{arcgis.com} + 1.04 \text{jhu.edu} + (4.08 \times 10^{-8}) \text{bbc.com} \text{pokazwirusa.pl} - 0.10 \text{yle.fi}$   |
| 3                 | 41               | 0.002 | $-(3.30 \times 10^{-9}) - (3.73 \times 10^{-2}) \text{arcgis.com} + 1.05 \text{jhu.edu} + (3.01 \times 10^{-15}) \text{arcgis.com} \text{pokazwirusa.pl} \text{weather.com} - 0.10 \text{yle.fi}$   |
| 4                 | 42               | 0.002 | $-274716.26 - (3.21 \times 10^{-2}) \text{arcgis.com} + 1.03 \text{jhu.edu} + \frac{1.21 \times 10^{10}}{\text{salute.gov.it}} + \frac{1778103.80 \text{pokazwirusa.pl}}{\text{yle.fi}}$  |
| 5                 | 43               | 0.002 | $-405699.33 - (3.27 \times 10^{-2}) \text{arcgis.com} + 1.04 \text{jhu.edu} + 0.76 \text{pokazwirusa.pl} + \frac{8.91 \times 10^9}{\text{salute.gov.it}} + \frac{2.81 \times 10^{11}}{\text{yle.fi}}$   |
| 6                 | 47               | 0.002 | $-179235.24 - (3.24 \times 10^{-2}) \text{arcgis.com} + 1.04 \text{jhu.edu} + 408.89 \sqrt{\text{pokazwirusa.pl}} + \frac{1.77 \times 10^{10}}{\text{salute.gov.it}} - (1.50 \times 10^{-3}) \text{yandex.ru}$                                    |
| 7                 | 50               | 0.002 | $-145848.45 - (3.23 \times 10^{-2}) \text{arcgis.com} + 1.03 \text{jhu.edu} + \frac{1.73 \times 10^{10}}{\text{salute.gov.it}} - (1.39 \times 10^{-3}) \text{yandex.ru} + \frac{1958948.30 \text{pokazwirusa.pl}}{\text{yle.fi}}$                 |
| 8                 | 51               | 0.002 | $-276140.47 - (3.30 \times 10^{-2}) \text{arcgis.com} + 1.03 \text{jhu.edu} + 0.85 \text{pokazwirusa.pl} + \frac{1.40 \times 10^{10}}{\text{salute.gov.it}} - (1.33 \times 10^{-3}) \text{yandex.ru} + \frac{2.69 \times 10^{11}}{\text{yle.fi}}$ |
| 9                 | 55               | 0.002 | $-62806.83 + 227934.41 \text{gisanddata.maps.arcgis.com} + 1.05 \text{jhu.edu} - 227934.47 \sqrt{\text{gisanddata.maps.arcgis.com}^2 + \text{jhu.edu}} - (1.02 \times 10^{-2}) \text{marketwatch.com}$  |
| 10                | 58               | 0.002 | $2922.04 + 303918.91 \text{gisanddata.maps.arcgis.com} + 0.99 \text{jhu.edu} - 303918.99 \sqrt{\text{gisanddata.maps.arcgis.com}^2 + \text{jhu.edu}} + (2.48 \times 10^{-7}) \text{jhu.edu} \text{pokazwirusa.pl}$                                |

Attention flows arise from any of the sites where incoming visits to the attractor (the CRC site) originate; however, there is also a quantifiable interplay between sources, with more prevalent variable combinations among inter-

national news sites—this makes sense since there is less competition for attention in countries where Covid policy resources in the native language may be scarce.



**Figure 10.** Variable Association at 0.1 significance level

## **Conclusions**

**A**ny meaningful policy intervention to the fabric of society begins with understanding how attention flows. The discovery process could be a daunting task unless augmented intelligence techniques are utilized. Here we demonstrated an

effective approach that uses the mechanisms of evolution to generate creative hypotheses while providing a quantitative measure of the Complexity of the system under study—which can serve organizational planners and public policy-makers to define priorities and achievable specific goals.

## APPENDIX

### **A selection of Prof. Yaneer Bar Yam Video Transcript Points**

#### *COVID-19: How to Win*

Governments can say that they want communities to do some things (New England Complex Systems Institute, 2020). But the community has to make the decision that it wants to do it. Government should be representing and helping the community.

New England Complex Systems Institute. (2020, September 10). COVID-19: How to Win [Video]. YouTube. [https://www.youtube.com/watch?v=X\\_0tTXfbGPA](https://www.youtube.com/watch?v=X_0tTXfbGPA)

#### *Green Zone Strategy*

Need not wait for government to do it. If local community takes responsibility, then can go ahead and make their green zone (New England Complex Systems Institute, 2020).

New England Complex Systems Institute. (2020, September 8). Green Zones Strategy to Crush COVID-19 [Video]. YouTube. <https://www.youtube.com/watch?v=SbpCoLi9VD0>

#### *Firefighting and Covid-19: Getting rid of the virus and keeping numbers low*

Recommends a five-week complete lockdown for countries to contain coronavirus (New England Complex Systems Institute, 2020). This was implemented in Ireland, Iceland, New Zealand, etc. Lockdown can be eased in areas that are able to contain the virus, he calls them Green Zones. It has to be a community decision, cannot wait for the government.

New England Complex Systems Institute. (2020, September 25). Crushing COVID-19 [Video]. YouTube. <https://www.youtube.com/watch?v=rp-d-9Qxllg>

#### *Guidelines for High-risk institutions*

Many aspects covered in this study by University of Michigan (published in Journal of American Geriatrics Society) were covered in the EndCoronavirus.org's Guidelines for High Risk Care Institutions (Stephane Bilodeau 2020). These were highlighted as successful measures that played a crucial role in containing the outbreaks of Covid 19 in the study facilities. One of these included the facility's leadership regularly communicated about testing and results with residents and healthcare professionals. Other aspects included in the guidelines were screening questions to quickly identify the risks.

Stephane Bilodeau. (2020, October 16). Nursing Homes Study and ECV Guidelines Update by Stephane Bilodeau [Video]. YouTube. <https://www.youtube.com/watch?v=lc7R9qNR9zg>

### **Yaneer Bar-Yam and Nassim Nicholas Taleb discuss making decisions with uncertainty and how acting early would cost less.**

Need to understand scaling, that a cure for an individual is not the same as a cure for a community, that some risks percolate and go up much faster than others (New England Complex Systems Institute 2020). And in a risk domain, do not use naïve scientific evidence. You need much stiffer requirements. The asymmetry is not something everyone gets, that uncertainty on one side is not the same as uncertainty on another side. If you have uncertainty and the absence of evidence, it should lead you to more precaution. At a systemic-level, you should worry about risks that are explosive and fat-tailed. There is a structural difference between the uncertainty when you don't know what things are happening, and the certainty when you actually see what is coming at you. The precautionary principal should not be used for trivial matters. People who think strategically and understand that bad things can happen, yesterday is not same as tomorrow, that's the people we need executing the current situation.

New England Complex Systems Institute. (2020, March 21). Nassim & Yaneer discuss making decisions with uncertainty and how acting early would have cost less [Video]. YouTube. <https://www.youtube.com/watch?v=FUGHKX0clhU>

### **Yaneer Bar-Yam and Nassim Nicholas Taleb discuss super spreaders, optimism on lock downs, and ergodicity.**

Leaving out tail-events by not having a fat-tail distribution is critical to real modeling of an outbreak that includes the kind of dynamics we are seeing here (New England Complex Systems Institute 2020). If you base the analysis of an outbreak before the earliest period of time, before a super spreader event happens, then you are mis-estimating the parameters. Because once there is a super spreader event, it increases the sampling of the tail. On the way up, you do not know who is infected, so the dynamics are described by a certain set of equations. But on the way down, you have isolated people so you know who is infected. So the same equations do not hold. Because you mainly have transmission within families, not so much within the public at large. So the whole framework of the equations has to change.

New England Complex Systems Institute. (2020, March 19). Nassim & Yaneer discuss super spreaders, optimism on lock downs, & ergodicity [Video]. YouTube. [https://www.youtube.com/watch?v=LX\\_bqMQfWlw](https://www.youtube.com/watch?v=LX_bqMQfWlw)

## **WellenbrecherJetzt ZeroCovid Germany discussions with End-Coronavirus founder Yaneer Bar-Yam - 1**

We have eliminated many of the diseases we used to have. We have done that by fighting them using different tools. One is social action where we separate people and prevent transmission, and the other is by vaccination (WellenbrecherJetzt #NoCovid Deutschland 2021). We want to take this strategy of elimination, and if we take this strategy, that guides our thinking and what we should do. The process (of lockdown) does not take very long, and because it does not take very long, the idea that we have to trade off between economic effect and health effect is wrong. That is a misconception. If it takes you a long time to solve the problem, then you have anyway hurt the economy. But in a short period of time if you can get to a condition where you no longer have the disease, then the economy and the public both can be healthy. At any time we are 4-6 weeks away from removing the disease. If we take very strong and concerted efforts, we will get rid of it. The disease pushes us to a point where we have to shut down; but every moment in time before that, we could have shut down. The decision is to get the disease down to a point where you no longer have to use strong restrictions to control it. Then you don't have to use restrictions that are holding back the economy. While making it go down fast, it is important that everyone is on board to do this. People should know what the goal is, not just that there are restrictions. Early case identification, isolation and quarantine are important tools. We want to stop transmission completely. The second is making sure it stays down. That is where tools like contact tracing, mass testing. It is always better to fight a few cases than to fight many cases. If you get it to zero, then use what we call a Green Zone strategy. Use limited travel restrictions. As we get to zero, there are going to be some places that have cases and some that have no cases. So we want to make zones where once you get to zero, you protect it using non-essential travel restrictions. So then you are able to open up specific areas, then you open up the travel between them. It doesn't take very long. We have seen many countries do this, Western nations like New Zealand and Asian countries like Vietnam and Thailand. There is no circumstance that hasn't had this work. It's just a question of taking the right places. We know this is extremely difficult in major slums. But there have been places where it has been successful in major slums. It's a question of adapting the method, realizing what the goal is, and making sure people understand there is an opportunity to get rid of the disease. Europe has not faced an outbreak like this in many years. So there isn't the expertise. What you do is sit down with the people who have done this, and see if you can apply it to your place. It is not as difficult as it seems. It is a misconception that this takes very long. What is important is to make the decision what to do. Once you make that decision, the execution steps becomes the way you work towards the goal, and it becomes easier and easier as you go forward. Anybody who says it cannot be done, they should be faced with what was done in other places, and asked why it was

possible to do it there. It is also possible to improve upon what the successful one have done, and do it even faster. Mass vaccinations is still some time away, and if we wait for the vaccinations, there are new challenges. The virus mutates, and as the virus mutates, it can be more rapidly transmitting. The best strategy is to act the fastest. Why should we compromise and let it be longer than it has to be. We want to take the economic hit quickly, rapidly, and open up to normal. Then we will have less problems, less vulnerabilities, less new problems. Every time we wait, the situation for us gets worse and the situation for the virus gets better.

WellenbrecherJetzt #NoCovid Deutschland. (2021, January 2). How to END the crisis (Part I: Scientific Perspective) - Prof. Schneider and Prof. Bar-Yam [Video]. YouTube. [https://www.youtube.com/watch?v=AZ\\_MIIJL2MQ](https://www.youtube.com/watch?v=AZ_MIIJL2MQ)

### **What can we do about the coronavirus (COVID-19)?**

In China and South Korea, they controlled by taking an area where there was an outbreak and completely locking it down, for three or four weeks so that makes it tough to transmit (New England Complex Systems Institute, 2020). And they prevent travel so that people do not carry the virus to other areas. And then you do a lot of testing, both where you have lockdown and even where you do not have lockdown, and ensure all those who have symptoms are isolated individually and get the medical care they need. If you wait to do these, it's going to get a lot worse because the virus multiples exponentially by a factor of 10 every week.

New England Complex Systems Institute. (2020, March 16). What can we do about the coronavirus (COVID-19)? [Video]. YouTube. <https://www.youtube.com/watch?v=fXUVFqKKcBM>

### **How do we protect our family from COVID-19?**

It has to start by discussing with them what the disease is and how dangerous it is, to understand how it is changing the world (New England Complex Systems Institute, 2020). And we do have to change how we act. It starts from being aware how it transmits. And you would not know who is sick because they have mild symptoms and are not showing them, but you may get sick from them. And that has happened a lot. So, we have guidelines, both for individuals and how they deal with the environment and for protecting your family by creating a safe space.

New England Complex Systems Institute. (2020, March 16). How do we protect our family from COVID-19? [Video]. YouTube. <https://www.youtube.com/watch?v=bIThSYMIDH4>

### **Why isn't the coronavirus like the Flu?**

About 10% of the people who have coronavirus have to go into intensive care and

be on ventilators and about 20% have to be in hospitals (New England Complex Systems Institute, 2020). That would overwhelm hospitals. Also, unlike flu which exists as a steady percent, coronavirus infections can grow at an explosive rate.

New England Complex Systems Institute. (2020, March 16). Why isn't the coronavirus like the flu? [Video]. YouTube. <https://www.youtube.com/watch?v=qygMBL4wJik>

### **What should businesses do in response to the outbreak?**

Companies often wait for an employee to get a case of Covid before deciding to send employees to work from home (New England Complex Systems Institute, 2020). Waiting for that to happen is a bad situation. And companies should work with the authorities to ensure there is rapid testing. If companies go to the government and go to the local authorities and say that we really want rapid testing for our employees to make sure that they are okay, that's going to be important. In industries like hospitality where people are in contact, the whole business process has to change.

New England Complex Systems Institute. (2020, March 16). What should businesses do in response to the coronavirus outbreak? [Video]. YouTube. <https://www.youtube.com/watch?v=R37lZ8hmw38>

## References

Bar-Yam, Y. and Taleb, N. January 26, 2020. “Systemic Risk of Pandemic via Novel Pathogens – Coronavirus: A Note, New England Complex Systems Institute”, January 26, 2020.

Venegas, P., Krabec, T., and Cizinska, R. 2018. “Factoring Attention Price into Investment Decisions”. *International Advances in Economic Research* 24 (4): 379–80. <https://doi.org/10.1007/s11294-018-9707-7>.

Bar-Yam, Y. and Taleb, N. 2002. “Complexity Rising: From Human Beings to Human Civilization, a Complexity Profile, in Encyclopedia of Life Support Systems (EOLSS)”. *Developed under the Auspices of the UNESCO EOLSS Publishers*, Oxford, UK.

Statista. 2020. “Global Consumer Survey 2020”. *Accessed March 2021*. [www.statista.com](http://www.statista.com).

Similarweb. 2021. “Similarweb Data Methodology”. In . <https://support.similarweb.com/hc/en-us/articles/360001631538-Similarweb-Data-Methodology>.

EvolvedAnalyticsLLC. 2020. “DataModeler.” In *Version 9.5*. Rancho Santa Fe, CA USA.

Research!America. 2021. “Johns Hopkins Coronavirus Resource Center - 2021 Meeting the Moment for Public Health Award”. In . <https://www.researchamerica.org/johns-hopkins-coronavirus-resource-center-2021-meeting-moment-public-health-award>.

# Policy Guidelines to Face COVID-19 in Peru: A Complex Systems Perspective

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*The only true globalization that would serve the human race is the understanding of humanity's intellectual and moral solidarity.*

—Edgar Morin

## ABSTRACT

In March 2020, the COVID-19 pandemic is declared in Peru, beginning quarantine and a multidimensional crisis that has claimed more than 50,000 deaths in the country.

The pre-pandemic scenario in Peru is characterized by the growing dehumanization of life, dehumanization of knowledge, the commodification of basic needs, among other aspects.

A proposal is inquired to help us understand the complex dynamics of the pandemic and its consequences in Peru. Greater awareness of local and global public health and a change of path that leads us to policies for humanity and policies for civilization are required to regenerate life in Peru and the world.

**Keywords:** COVID-19, complexity, complex dynamic systems

## Lineamientos de política para enfrentar COVID-19 en Perú: una perspectiva de sistemas complejos

### RESUMEN

En marzo de 2020, se declara la pandemia COVID-19 en Perú, iniciando cuarentena y una crisis multidimensional que ha cobrado más de 50.000 muertes en el país.

El escenario pre-pandémico en el Perú se caracteriza por la creciente deshumanización de la vida, la deshumanización del conocimiento, la mercantilización de las necesidades básicas, entre otros aspectos.

Se solicita una propuesta que nos ayude a comprender la compleja dinámica de la pandemia y sus consecuencias en el Perú. Se requiere una mayor conciencia de la salud pública local y global y un cambio de rumbo que nos lleve a políticas de humanidad y políticas de civilización para regenerar la vida en el Perú y el mundo.

**Palabras clave:** COVID-19, complejidad, sistemas dinámicos complejos

## 应对秘鲁新冠肺炎的政策指南：复杂系统视角

### 摘要

2020年3月，秘鲁宣布新冠肺炎大流行，隔离和多维度危机随即开启，目前这场危机已让超过5万人丧生。

大流行来临前秘鲁的情形包括以下特征：逐渐增加的对生命的非人性化、对知识的去人性化、以及基本需求的商品化等。

需要一个提议帮助我们理解大流行的复杂动态及其对秘鲁产生的影响。需要提升地方和全球公共卫生的意识、进入引领我们采取人道政策和文明政策的变革之路，以振兴秘鲁和全球生命。

**关键词：**新冠肺炎（COVID-19），复杂性，复杂动态系统

## 1. Introduction

The Severe Acute Respiratory Syndrome COVID-19 (SARS-CoV-2) emerged in the city of Wuhan, Hubei, China, in December 2019. Since then, governments have taken unprecedented measures in response to the COVID-19 outbreak, which has spread throughout the world causing the confinement of the world's population and a multidimensional crisis, as well as the collapse of health systems. Since December 2020, new mutations of the virus have been identified in England, South Africa, and Brazil, which have generated new uncertainties.

This epidemiological phenomenon has revealed the fallacies of our beliefs, showing us how the fabric of life in nature is woven. We are living the consequences of humanity's irrational persistence in forging an unsustainable society.

In the last decades of the twentieth century, a new global "scientific-technical revolution" emerged, characterized by a synergy between quantum mechanics, computer science and molecular biology, and by the development in information levels globally. The epistemic frameworks of mainstream science did not serve to address the complex dynamics of natural and social phenomena that underlie our existence, such as climate change, social conflicts, and the behavior of viruses (AIDS, Ebola, etc.). In the search for answers to these non-deterministic phenomena, the science of complexity emerges, complex dynamic systems,

chaos theory, etc., which cause a change in the structures of knowledge and in the foundations of knowledge.

To face the pandemic, humanity needs a change of path, an individual and social metamorphosis, and a change in our relationship with nature, which would contribute to new policies.

## 2. Situation of COVID-19 in Peru

The Peruvian government made the first patient official on March 6, 2020. As of June 21, 2021, the Peruvian Ministry of Health reported 2,033,606 cases of contagion and 190,906 deaths.

The evolution of daily new cases of Covid-19 (Figure 1) shows the dynamism of the virus. Initially, the government implemented strong quarantine measures, but these were lessened in the months of May and June 2020, thereby increasing contagion. As of June 30, 2020, the quarantine was officially suspended, a situation that contributed to a massive contagion, which has increased with travel, public transport and the reactivation of the economy. As of January 2021, the second wave began due to the new strains of the virus that have caused the collapse of the health system again and forced staggered quarantines.

COVID-19 began in Lima and quickly spread through the regions, generating a tragic situation due to the insufficient capacity of the regions to deal with the pandemic because of the precariousness of the health sector. Throughout Peru, this pandemic has

revealed the great social crisis and true misery that exists in the country, which lacks basic services for survival.

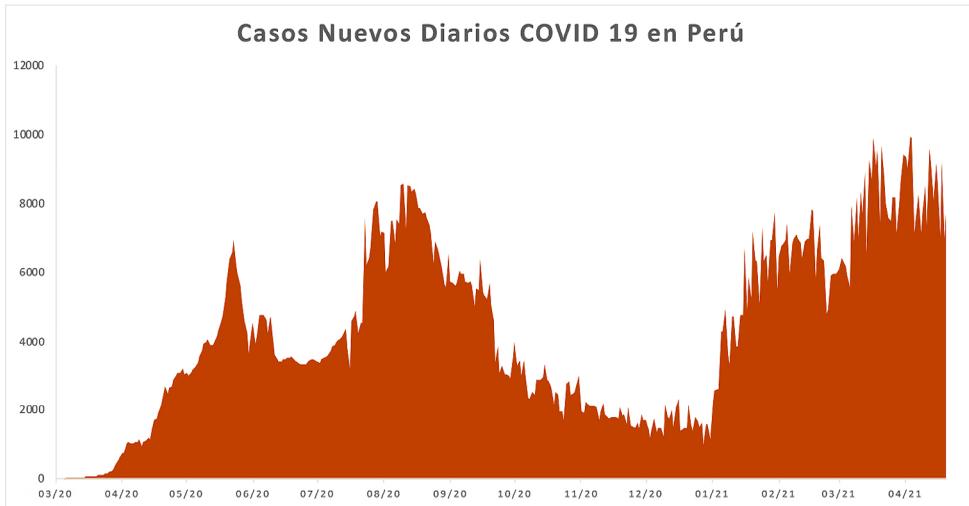


Figure 1 New Daily Cases of Covid-19 in Perú  
Source: Ministry of Health, Perú

### 3. Pre-pandemic scenario in Peru

What has been experienced in the global pandemic by Covid-19, the suffering of the population, being one of the countries in the world with the highest number of deaths and hardest hit by the pandemic, questions us about what is the meaning of life? How are we living? What level of self-sufficiency for health and food is developing in the world and in Peru? What policies should be given to improve the human condition and overcome the crisis?

#### a) *The dehumanization of life*

Michael Porter, at CADE 2010, pointed out that Peru's growth was an illusion because it was due to the expan-

sion of foreign investment in already established sectors or the purchase of existing companies, rather than the creation of new companies and jobs. Porter warned us of the long-term dangers for the Peruvian economy because of the low productivity, poor education, a poor health system, weak physical infrastructure, social inequality, crushing corruption, and a high level of informality.<sup>1</sup> His words would be premonitory in the face of the effects of the global pandemic, which has shown the inability of the State, its institutions and a large part of the population to respond to this multidimensional crisis.

With the pandemic, the effects of the dehumanization of life emerged more clearly. Millions of Peruvians did not have the basic elements to deal with

1 <https://econoblognet.blogspot.com/2010/11/michael-porter-en-cade-2010-diagnostico.html>

the effects of Covid-19, being crowded on the outskirts of cities without access to water, soap, food and work.

Thousands of migrants in Lima, when survival jobs disappeared and without any unemployment protection insurance, returned to their places of origin, where the ancestral values of community life still exist, and they know that they will be welcomed to share food, pain, and maybe death. Defying the norms of containment of the pandemic, the migrants began their return on foot, which was called “the exodus of hunger.” The State did not have enough planes or national transport to support the transfer.

Blind thinking, the instrumental reason for power and profit created a political crisis in the country. When the presidential vacancy took place, the largest citizen protest of our time in the entire territory originated, breaking all strategy to contain the contagion.

### *b) The dehumanization of knowledge*

According to Edgar Morin, one of the serious problems facing humanity is the rationalization that only knows the calculation and ignores individuals, their bodies, their feelings, and their souls (8, 9). The way in which we build knowledge based on the dominant education, has not helped humanity to understand the complex dynamics of the world, life, the biosphere and human nature and leads us to a planetary crisis.

According to Aníbal Quijano, globalization began with the discovery of America, and launched a new pattern of world power. Western culture and its

methods are the only ones recognized to create valid knowledge, since indigenous practices for the creation of knowledge, social and spiritual practices were made invisible and punished. The loss of their own cultural references and the imposition of the idea of race generated a process of dehumanization and marginalization of important sectors of the population. (13)

In Europe, influenced by the ideas of Descartes and Newton, Western culture built knowledge by seeking order, discarding contradictions, fragmenting the whole, reducing and rejecting uncertainty in emerging processes.

### *c) The commodification of basic needs*

According to the World Health Organization, health is not only the absence of diseases or illnesses but is also linked to the quality of life and individual and collective well-being. It is the emergent result of well-being of interactions / feedbacks of biological, psychological, political, economic, social, environmental, cultural, etc. conditions, where the living and coexistence of humanity takes place.

The pandemic in Peru has exposed serious social problems and serious deficiencies in the health system. The policies implemented since 1990 to apply the neoliberal model in Peru, aimed to reduce the role of the State and its social responsibilities, leaving everything to market regulation. In practice, the costs of private health systems have become more expensive, and the State

has neglected the Public Health System. The cost of living has risen, reducing the level of satisfaction of basic needs.

Despite being one of the countries with the greatest biodiversity in the world and with a high quality of food products, we face serious problems of malnutrition, anemia, obesity, and chronic resistant tuberculosis. Anemia affects 43.6% of children under three years of age, becoming a public health problem.<sup>2</sup>

Another of the serious problems to confront the pandemic is the low cultural level of the population. 50% of basic educational service is private. The commodification of education based on the fragmentation of knowledge and life has diminished its quality. According to international tests, 7 out of 10 children do not have good reading comprehension. There is a large gap between the education of the elites, which is very expensive, and the education of the great majority.

Working conditions are very difficult (low wages, outsourcing, etc.). 72% of work in Peru is informal. According to the Peruvian Institute of Economics (IPE), 12 million Peruvians are vulnerable and poor, so these sectors of the population could not endure the quarantine for a long time because they had to go out to seek survival.

#### ***d) Recursive and organized corruption and crime***

Bad education and lack of work have contributed to the increase in crime in recent decades, not only in quantity but also increasingly violent. The entry into the country of international mafias has increased citizen insecurity. However, the linear and fragmented view with which the crime problem is approached is not going to solve it. Not only are more police required on the streets but more education, culture, love, food and work.

A great battle is taking place in the country to stop corruption. In recent years, five presidents and many officials have been imprisoned. According to the Government Accountability Office, Peru lost more than 23,000 million to corruption in 2019.<sup>3</sup>

#### ***e) Loss of community education and ethics***

Peruvian society is very fragmented and of great cultural diversity. The heritage of Andean Amazon education, which still exists in many native communities, has been marginalized. In human settlements, people survive the pandemic with the Andean-Amazonian practices of solidarity, reciprocity, the common pot, mutual help, singing, and dancing that always accompany community activities. This way of dealing with uncertainties and challenges of life and nature, makes it possible for them to continue to exist for thousands of years.

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2 <https://rpmesp.ins.gob.pe/index.php/rpmesp/article/view/3281/2906>

3 <https://www.gob.pe/institucion/contraloria/noticias/187607-n-344-2020-cg-gcoc-contraloria-peru-pierde-anualmente-s-23-000-millones-por-corrupcion-e-inconducta-funcional>

Another aspect that has been lost is ethics, which is based on responsibility and commitment to the other, to society, to life, which is the cause of many of the crises that humanity faces. According to Morin, every action increasingly escapes the will of its author as it enters the game of the inter-retroactions of the environment in which it intervenes. Any action goes beyond the intention or desire of the author, depending on the environment where it occurs, and its consequences are unpredictable in the short and long term (8, 9).

#### **4. Inquiring about epistemic frameworks to understand the pandemic**

According to Mitchell and Garibay, complex dynamic systems are complex phenomena, non-linear, far from equilibrium, with multiple variables that self-organize in recursive loops, with collective properties emerging from the whole, which are not found in the parts of the system. These properties cannot be explained from the individual properties of its constituents; they adapt and evolve (7).

The Covid-19 pandemic is a complex dynamic system that arises from the leap from the level of reality of the virus to the level of reality of the human species, generating interactions and feedback in multidimensional recursive loops, in a self-eco-organizing process of biological, health, political, social, economic, agriculture systems, among others, shown in Figure 2. All

these processes are carried out simultaneously, performing local and global functions. In this way, emerging behaviors surface (drama of hunger, economic crisis, unemployment, increase in poverty, etc.), which are due to collective behavior and feed back into all systems, at the local, regional and global levels, affecting health, life and all social practices of humanity.

From an ontological approach, we must not forget our limitations to know the real world, the planet and the universe. The coronavirus has shown us the fragility of the human condition and the impossibility of global markets to solve global problems such as the pandemic. A reform of thought is essential to change the instrumental reasoning of calculation and profit for an ethical and humanistic reasoning, which increases the solidarity of the human species and community life in order to survive Covid-19.

In this sense, we must learn with greater interest the Seven Complex Lessons in Education for the Future proposed by Edgar Morin: detecting error and illusion; principles of pertinent knowledge; teaching the human condition; earth identity; confronting uncertainties; understanding each other; and ethics for the human endeavor.<sup>4</sup>

To overcome the pandemic, we require greater awareness of public health locally and globally. The common destiny of humanity in the face of vital and mortal problems requires a Policy of Humanity based on the concept of

<sup>4</sup> <https://unesdoc.unesco.org/ark:/48223/pf0000123074>

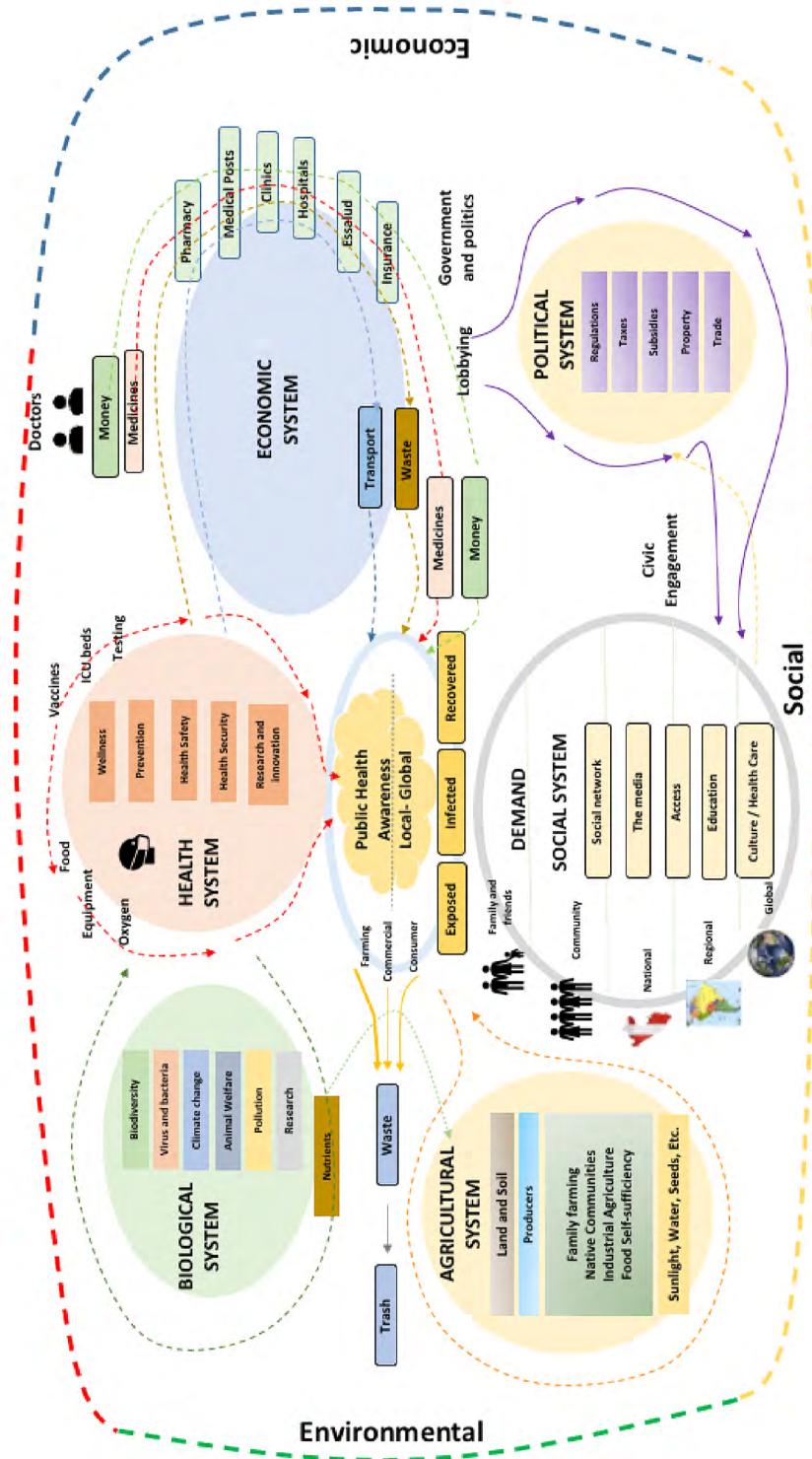


Figure 2 An inquiry into the complex dynamic system of Covid-19 pandemic<sup>5</sup>

<sup>5</sup> Based on Link A, Platkin C, Kwan A, Cather A, and Lindstrom L. (2018). Health and Technology: Feeding an Urban Population. Hunter College New York. City Food Policy Center, Hunter College.

Land-Homeland (10), which should be the symbiosis of all the best that has been produced by the various civilizations and help us to improve the dialogic, between the individual-egocentric and the community-altruistic, inherent to the human condition.

## **5. Conclusions and recommendations**

**I**n the pre-pandemic scenario, there are two processes that are transforming the world from a complex interaction, on the one hand, the process of globalization, inclusive for mass consumption but exclusive for access to the benefits of wealth and work and, on the other hand, the emergence of the identities of native people and the spontaneous explosive social movements that demand vindications.

We need approaches that allow us to demonstrate the complex, emerging behavior of the various agents and their interrelationships in order to know the real dimension of the evolution of the virus and its effects in all areas of human and planet life.

There is a lot of pain in humanity, but there is also love, solidarity, heroic actions by doctors, health personnel and police. In addition, art, songs, poetry of life emerge to strengthen the body and soul. Hopefully, we will learn that life, health and education should not be commodified. It is our duty to humanize life in all its manifestations.

The good living of native communities is based on the principles of: (a) interconnection, or the intercon-

nected dynamics of life, according to which members of all communities have something to give and need something to exist; and (b) complementarity, in which everyone fulfills a role of harmony, equilibrium, living in peace and community. The science of the 21st century has shown that nature does not operate from competitiveness and separation but from collaboration and interrelation.

The world needs a change of direction. Market forces will not be able to provide the complex answers that humanity is obliged to conceive to improve living conditions. We must change the instrumental means-ends rationality for a humanistic ethical rationality; as well as moving from the market economy to a humane and solidary economy.

Globalization is in crisis and due to the serious consequences it generates, it should be regulated. A more humane alternative globalization is required, accompanied by de-globalization in food and health matters. A policy of protection and self-sufficiency for food and health (medicines, masks, and vaccines) must be ensured, among other policies to improve the quality of life on the planet.

The dehumanization of life and its commodification must be changed with policies of humanity that join together the best of all civilizations to regenerate life on the planet, awakening good living, solidarity, responsibility, coexistence. Policies of civilization are also required to reform our way of thinking and acting in the world of

Western culture and Westernized peoples, as one of the ways to save the existence of the human species on earth.

## **References**

- [1] Bastián González-Bustamante. (2020). Evolution and early government responses to COVID-19 in South America. *World Development*.
- [2] Castell, Manuel. (2000). *Globalization, society and politics in the information age*. Binnacle.
- [3] Gunaratne, C. and Garibay, I. (2020). Evolutionary model discovery of causal factors behind the socio-agricultural behavior of the Ancestral Pueblo. *PLoS ONE*, 15 (12): e0239922
- [4] International Labour Organization. (2020). *Technical Note. Impact on the labour market and income in Latin America and the Caribbean*. Second edition.
- [5] Link, A., Platkin, C., Kwan, A., Cather, A., and Lindstrom, L. (2018). *Health and Technology: Feeding an Urban Population*. Hunter College New York. City Food Policy Center, Hunter College.
- [6] Maturana, H. (2014). *Transformation in Coexistence*. Argentina. Granica Editions.
- [7] Mitchell, Melanie. (2009). *Complexity, A Guided Tour*. New York. Oxford University Press.
- [8] Morin, Edgar. (1981). *Introduction to complex thinking*. Barcelona. Editorial GEDISA.
- [9] Morin, Edgar. (1999). *Seven Complex Lessons in Education for the Future*. UNESCO.
- [10] Morin, Edgar. (2011). *The route for the future of humanity*. Barcelona. Paidós.
- [11] Nicolescu, Basarab. (1996). *The Transdisciplinarity Manifesto*. Paris: Du Rocher Edition.
- [12] Prigogine, Illya, and Isabelle Stengers. (1983). *The New Alliance: Metamorphosis of Science*. Editorial Alliance.

- [13] Quijano, Aníbal. (2014). Issues and horizons. From the historical - structural dependence to the coloniality / decoloniality of power. Latin American Council of Social Sciences - CLACSO.
  
- [14] Rajabi, A., Mantzaris, A.V., Mutlu, E. C., and Garibay, I. (2020). Investigating dynamics of COVID-19 spread and containment with agent-based modeling. medRxiv the Preprint server for health sciences. <https://doi.org/10.1101/2020.08.18.20177451>
  
- [15] Salinas, Teresa. (2018). Chapter 10, “Sustainability Learning Based on an Andean Amazonian Worldview. *Academia and Communities: Engaging for Change Innovation in Local and Global Learning Systems for Sustainability Learning Contributions of the Regional Centers of Expertise on Education for Sustainable Development*, ed. Fadeeva, Zinaida, Galkute, Laima and Chhokar, Kiran B. (Tokyo: United Nations University Institute for the Advanced Study of Sustainability, 2018). Print ISBN: 978-92-808-4589-1 e-ISBN: 978-92-808-4584-6



# **Labor-Management Negotiations in COVID Times: Anticipating Power Balance Effects**

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## **ABSTRACT**

We focus on the impact of the COVID pandemic on the dynamics of labor-management negotiations. We have previously used a network model to generate anticipatory scenarios of the trajectories and outcomes of multi-party labor relations occurring in European Union countries such as France. U.S. labor-management negotiations are usually two-party, between management and one union (even if several exist). We argue here that, as a consequence of COVID on the economy and unemployment rates, French companies may have practically converged to the American two-party style as unions coalesce and focus on employment preservation as their highest priority. Consequently, we generate two-party negotiation scenarios which are applicable both in France and in the U.S. We explore how COVID consequences affect the union-management balance of power.

*Keywords:* dynamic network model of negotiations, Labor relations, Anticipatory scenarios

# **Negociaciones laborales-gerenciales en tiempos de COVID: Anticipar los efectos del equilibrio de poder**

## **RESUMEN**

Nos enfocamos en el impacto de la pandemia de COVID en la dinámica de las negociaciones laborales. Anteriormente, hemos utilizado un modelo de red para generar escenarios anticipatorios de las

trayectorias y resultados de las relaciones laborales multipartidistas que ocurren en países de la Unión Europea como Francia. Las negociaciones entre trabajadores y empresas en los Estados Unidos suelen ser bipartitas, entre la dirección y un sindicato (incluso si existen varios). Argumentamos aquí que, como consecuencia de COVID en la economía y las tasas de desempleo, las empresas francesas pueden haber convergido prácticamente al estilo bipartidista estadounidense a medida que los sindicatos se fusionan y se centran en la preservación del empleo como su máxima prioridad. En consecuencia, generamos escenarios de negociación bipartita que son aplicables tanto en Francia como en los EE. UU. Exploramos cómo las consecuencias de COVID afectan el equilibrio de poder entre sindicatos y administración.

**Palabras clave:** modelo de red dinámica de negociaciones, Relaciones laborales, Escenarios anticipatorios

## 新冠肺炎期间的劳资协商：预期权力平衡产生的效果

### 摘要

我们研究了新冠肺炎大流行对劳资协商动态产生的影响。我们之前使用过一个网络模型，用于对欧盟国家（例如法国）中多方劳动关系的轨迹和结果创造预期场景。美国的劳资协商通常由管理层和一个工会进行（即使存在多个工会）。我们主张，在新冠肺炎对经济和失业率造成的影响下，鉴于各工会联合在一起并将就业保护作为其首要重点，法国公司可能已相互聚集形成了类似美国的劳资协商方式。因此，我们创造了既适用于法国又适用于美国的双方协商场景。我们探究了新冠肺炎的后果如何影响工会-管理层之间的权力平衡。

关键词：协商动态网络模式，劳动关系，预期场景

French labor-management negotiations (LMN), for which Kaufman et al. (2020) proposed a dynamic network model of trajectories and outcomes, are similar in some respects with the U.S.: the economic contexts—and in particular unemployment levels—affect labor relations in both countries. Additionally, unionization rates in recent years have been similar, hovering around 10%. However, there are some differences, meaningful enough that each situation warrants its own model.

In the U.S., each union periodically negotiates contracts formally with management, not necessarily annually. Contract-related disputes get resolved during contract implementation. National and local union chapters are organized by professions (e.g., construction workers, teachers, state workers). Politically, they are mostly aligned with the Democratic Party, regardless of their respective individual members' political preferences. The negotiations exhibit principal-agent difficulties: the rank-and-file union members may fail to ratify a contract negotiated by their representatives (Lax & Sebenius, 1991; Ensmiger, 2001) when they feel their interests have not been adequately represented. We note that in any organization there may be several unions, but individual employees do not have

a choice between them: they belong to the union corresponding to their profession. For example, state universities typically have a faculty union, a staff union, and at times a graduate assistants union. Negotiations with management are conducted (almost) independently.<sup>1</sup>

French LMN are termed “social dialog” (e.g., Laroche, 2009; Thuderoz, 2020). In any organization, several unions compete for members among workers and mid-managers. The unions interact continually with management at the negotiation table and behind it, formally at annual contract negotiations, and informally in shaping working conditions. Conflicts arise between labor and management representatives and also between unions, and between unions and their respective constituents (principal-agent conflicts). Power dynamics hinge on organizations' internal conditions, on the shifting national economic, political, and regulatory context, and on the national-level union leaderships, which largely align with different political parties. In any organization, individual members' political orientation tends to drive personal choice of union affiliation. Compared to the U.S., France has a similar rate of unionization,<sup>2</sup> but a higher level of state interventionism, strong labor legislation, and very conflictual labor relations often accompanied by prolonged multi-sector strikes.

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1 In some cases, as in the university example, the staff union may hold off on agreement, waiting to see what the faculty union obtains, to increase pressure on management. However, they do not cooperate or negotiate jointly.

2 According to the U.S. Bureau of Labor Statistics, in 2020 the U.S. employees' union membership rate was 10.8 (the same as France in 2018, according to OECD statistics). Public sector workers' unionization rate was 34.8%; the corresponding private sector rate was 6.3%. In total, 14.3 million workers belonged to a union.

Negotiators in any context need to anticipate outcomes in order to select robust strategies—those likely to work for a range of possible contingencies (Kaufman et al., 2019). In contrast, a strategy optimized for a specific set of contingencies is non-robust—it runs the risk of failing if those specific contingencies do not materialize. In the U.S., to devise a negotiation strategy, two groups (union and management) have to keep track of each other's interests, alternatives, and power, all shifting in time. French LMN negotiations are multiparty. Management and the several unions have shared and competing interests. Consequently, negotiations are more complex, with diminishing outcome predictability in real time. In both cases, the ability to anticipate outcomes and paths leading to them helps negotiators prepare robust strategies.

Using a hybrid (quantitative-qualitative) approach, we constructed a dynamic model of French multi-party LMN for the French divisions of a multinational company (Kaufman et al., 2020). With qualitative data from interviews, we anticipated trajectories of recurring conflicts among management and several unions. The trajectories varied with the (qualitatively assessed) degree of internal cohesion of management and unions respectively, intergroup relationships, and the context conceptualized as ambient “temperature.” We continue this project by investigating how the COVID-19 pandemic—an unexpected and prolonged shock with far-reaching, global political and socio-economic consequences—has affected and continues to impact

French LMN dynamics in general, and in the case study.

The COVID virus was discovered at multiple locations between January and March 2020 (e.g., Randazzo et al., 2020). According to wastewater analyses in several countries (e.g., Medema et al., 2020), it appears to have struck during 2019—hence the name COVID-19. One year later, despite large-scale vaccination in many countries, normalcy is not yet in sight in many respects, including employment. World-wide, unemployment has risen sharply, and states' resources have been heavily taxed to respond to exacerbating and new needs.

From 4.4% in March 2020, the U.S. unemployment rate rose to 14.7% by April 2020. It stood at 6% in March 2021 (cf. Statista). On one hand, some jobs no longer exist, as COVID forced closure of numerous businesses, while other businesses have incurred losses and had to reduce their workforce. On the other hand, unemployment benefits coupled with fear of the virus combine to cause reluctance to return to, or seek work, even when it is available in some sectors. As a result of these and other factors, those seeking employment may have difficulty finding jobs that match their skills, while those still employed may feel at risk. This situation is not unlike that experienced in the European Union. For example, in France—the locus of our case study—unemployment stood at 8% at the end of 2020, having come down from a COVID high of 9.1, but with a relatively high level of underemployment (Montpellier, 2021) which

puts pressure on the number of available jobs in 2021.

We ask here: does the continued presence of the COVID pandemic affect labor-management negotiations (LMN)? And can our dynamic model help anticipate LMN trajectories and outcomes under the new circumstances? We draw on new qualitative information from our multi-year French case study and adapt the network model to the new contextual conditions, to anticipate negotiation dynamics and possible conflict trajectories and outcomes. We begin by describing the original model (Kaufman et al., 2020) and how it was changed to capture the prolonged global COVID shock. We use the new model to generate trajectories and outcomes of LMN. Due to COVID restrictions, we were unable to collect sufficient on-site data to validate the new scenarios. Therefore, our contribution remains theoretical until we can return to the case study site. We discuss our findings and explore ways to test and improve it, and to also apply it to U.S. data.

## **The Model**

**T**he notion underlying our model is that complex systems appearing chaotic at one observation level exhibit qualitative patterns at a higher observation level. It is not explanatory in the sense of deriving causal links to be used for prediction. Rather, it is anticipatory, yielding scenarios of possible futures that can be incorporated in negotiation strategies.

The model anticipates trajectories in time of the negotiating groups' average stances  $s$  towards a package of issues under negotiation, from  $s=1$  (most preferred by unions) to  $s=-1$  (most preferred by management). The range midpoint  $s=0$  corresponds to a preference for a compromise package. Group members try to persuade each other to their own stance and take account of other groups' average stances. Union constituents (Figure 1a, level 1) negotiate with their representatives (level 2). Union reps negotiate with management negotiators (level 2). In time, depending on intra-group cohesions and the inter-groups mutual influences, and context (temperature) average group preferences  $s$  evolve toward mutual intransigence, openness to cooperation, or even "capitulation." Settlements are likely when stances converge.

The LMN model for the French company before the pandemic considered at least two unions, their representatives, and management negotiating with each other (Figure 1a). The stance trajectories varied with the groups' internal levels of cohesion and with contextual "temperature." For example, with a weakly cohesive management and high union groups' internal cohesions, agreement occurred closer to the unions' terms. Management could use this anticipated scenario to formulate a strategy that reduces the Unions' advantage. Similarly, Unions could use this information to strategize how to exploit their advantage. Indeed, some case study respondents found this insight useful and could see how to improve their negotiation strategy.

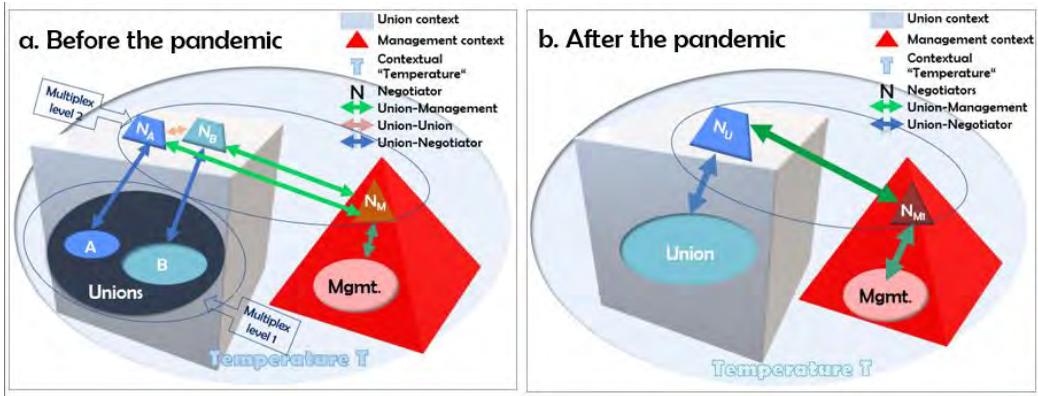


Figure 1 Negotiating groups and their relationships

We hypothesize that the COVID pandemic, raging for at least one year, has affected internal group cohesions, the relationships among groups, and the context of negotiations (temperature) as follows (Figure 1b):

- Instead of competing, Unions have coalesced around a key shared interest—minimizing job losses; nevertheless, the new Union bloc, formed of groups with previously divergent interests, may be less cohesive in negotiating with Management than the previously separate union groups;
- Expected revenue losses may lead to increased management’s intransigence;
- Heavy economic losses nationally and political turmoil have reduced some previous political constraints for the unions, equivalent to a higher contextual “temperature.” Unions may have become more flexible and cooperative with each other and with management, and less bound by their respective national leadership.

## The Case Study

New information from one French Division of the multinational company we have studied indicates that the Company is facing simultaneously several destabilizing crises—the *gilets jaunes* movement (end of 2020), COVID (2020-21), and a recent fire at one plant. Consequently:

- Serious company financial losses (from a sharp drop in orders) are expected to affect recovery, requiring creative responses in the short run;
- Operations have been constrained by new COVID sanitation requirements, and by their costs;
- The need to face the crises has strengthened the relationship between Unions and management, who are relying on each other to restart and to continue the activities;
- The level of trust between Union and Management negotiators has increased as they work together

toward the common goal of emerging from the combined crises;

- Unions are re-thinking their relationship with management, renouncing some of the inter-union competition but also losing some of the internal cohesion;
- Expecting employment losses, the Unions together with Management are now *co-constructing* decisions regarding working conditions—a first for the company.
- The Unions’ flexibility has been enhanced by the current disarray among leadership at the national level.

We explore theoretically how these changes might affect LMN (Figure 2). Inter-group Union-Management

relations can be symmetrical (equal in strength) or asymmetrical, yielding different dynamics. Using the new qualitative information as a basis for assumptions, we generate COVID-time stance trajectories and outcome scenarios.

Corresponding to the qualitative indications received from the company in our case study we assume that in COVID times, Unions and their representatives are more “on the same page” than in normal times. They have practically become one negotiating bloc. In turn, Management in turn is assumed to have be more cohesive than the new Union bloc. The latter is assumed to have gained in flexibility. Figure 2 shows the two-group system’s trajectory in time with repeated rounds of negotiations at low and high temperatures.

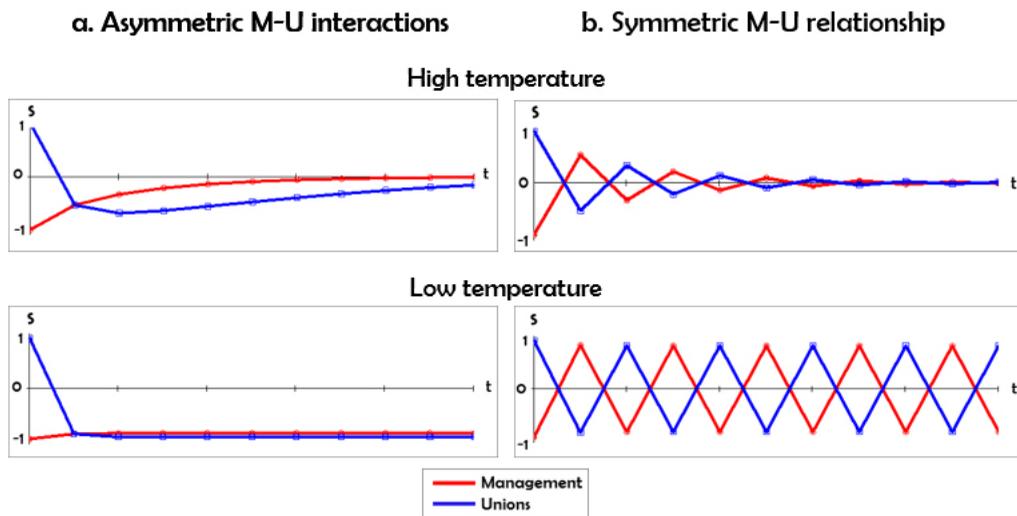


Figure 2 Trajectories of groups’ stances

We consider two types of Union-Management relations: asymmetric, and symmetric. In the asymmetric case (Figure 2.a), we assume the Union bloc

to be influenced by the Management to a higher degree than the Management by the Union. At low temperature (meaning that both the Union and Manage-

ment feel constrained by the prevailing conditions) the Unions bloc will align with Management and converge on a settlement closer to the management's preferred contract. At high temperature, both Union and Management find options for mutual gains and settle for a compromise.

In the symmetric case (Figure 2.b), we assume the Union bloc to be influenced by the Management to the same degree as the Management is influenced by the Union. Then at low temperature, where both feel constrained in what they can concede, Union and Management positions oscillate out of phase, failing to converge to a settlement. At high temperatures however, Union and Management settle for a compromise contract.

## Conclusions

Using the dynamic multi-group model with assumptions based on information from the

French case study, we found theoretically that changes the parties' stances and Union-Management relationship during the COVID pandemic have affected the negotiation dynamics yielding meaningfully different trajectories and outcomes than before the pandemic. The realignment of unions into one bloc facing management in contract negotiations renders the French LMN structure in COVID times similar to the U.S. configuration.

At the next stage of this project, we will seek more information from Union and Management actors in our case study to validate our theoretical outcomes. We will also investigate the new normal when it prevails: will LMN relationships revert to the pre-COVID dynamics, or will they be altered for the longer run, after Unions and Management have experienced the benefits and drawbacks of increased cooperation during COVID?

## References

- Bureau of Labor Statistics. (2021). Union Members Summary. Last visited on April 19, 2021. <https://www.bls.gov/news.release/union2.nr0.htm>
- Ensminger, J. (2001). Reputations, trust, and the principal agent problem. *Trust in Society*, 2, 185-201.
- Evan, W. M. & MacDougall, J. A. (1967). Interorganizational conflict: a labor-management bargaining experiment. *Journal of Conflict Resolution*, 11(4), 398-413.
- Kaufman, S., Koutsovoulou, M., & Kaufman, M. (2020). Multi-Group Labor-Man-

agement Negotiations: Model and Case Study. *Journal on Policy and Complex Systems*, 6(1).

Kaufman, M., Kaufman, S. & Diep, H. T. (2019). Multi-Group Conflict Paths: Anticipatory Scenarios of Attitudes and Outcomes. *Journal on Policy and Complex Systems* 5(2): 5-21.

Laroche, P. (2009). *Les relations sociales en entreprise*. Dunod.

Lax, D. A. & Sebenius, J. K. (1991). Negotiating through an Agent. *Journal of Conflict Resolution*, 35(3), 474-493.

Medema, G., Heijnen, L., Elsinga, G., Italiaander, R., & Brouwer, A. (2020). Presence of SARS-Coronavirus-2 RNA in sewage and correlation with reported COVID-19 prevalence in the early stage of the epidemic in the Netherlands. *Environmental Science & Technology Letters*, 7(7), 511-516.

Montpellier, C. (2021). France: Don't be fooled by the fall in the unemployment rate. <https://think.ing.com/articles/france-the-fall-in-the-unemployment-rate-is-not-really-good-news>, last visited on April 19, 2021.

Randazzo, W., Cuevas-Ferrando, E., Sanjuán, R., Domingo-Calap, P., & Sánchez, G. (2020). Metropolitan wastewater analysis for COVID-19 epidemiological surveillance. *International Journal of Hygiene and Environmental Health*, 230, 113621.

Statista. (2021). Monthly unemployment rate in the United States from March 2020 to March 2021. <https://www.statista.com/statistics/273909/seasonally-adjusted-monthly-unemployment-rate-in-the-us/>, last visited on April 19, 2021.

Thuderoz, C. (2020). Considering ordinary negotiation in the workplace. *Negotiations* (1), 99-115.



# **Could periodic nonpharmaceutical intervention strategies produce better COVID-19 health and economic outcomes?**

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## ABSTRACT

We developed a COVID-19 transmission model to compare the effects of nonpharmaceutical public health interventions (NPIs) on health and economic outcomes. An interdisciplinary approach informed the selection and use of multiple NPIs, combining quantitative modeling of the health and economic impacts of interventions with qualitative assessments of other important considerations (e.g., cost, ease of implementation, equity). We used our model to analyze strategies that periodically switch between a base NPI and a high NPI level. We find that this systematic strategy could have produced similar health outcomes as static strategies but better social welfare and economic outcomes. Our findings suggest that there are opportunities to shape the tradeoffs between economic and health outcomes by carefully evaluating a more comprehensive range of reopening policies.

*Keywords:* COVID-19, economic outcomes, health outcomes, nonpharmaceutical interventions

## **¿Podrían las estrategias periódicas de intervención no farmacéutica producir mejores resultados económicos y de salud del COVID-19?**

## RESUMEN

Desarrollamos un modelo de transmisión de COVID-19 para comparar los efectos de las intervenciones de salud pública (NPI) no farmacéuticas en los resultados económicos y de salud. Un enfoque

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interdisciplinario informó la selección y el uso de múltiples ISFL, combinando modelos cuantitativos de los impactos económicos y de salud de las intervenciones con evaluaciones cualitativas de otras consideraciones importantes (por ejemplo, costo, facilidad de implementación, equidad). Usamos nuestro modelo para analizar estrategias que cambian periódicamente entre un NPI base y un nivel alto de NPI. Encontramos que esta estrategia sistemática podría haber producido resultados de salud similares a los de las estrategias estáticas, pero mejores resultados económicos y de bienestar social. Nuestros hallazgos sugieren que existen oportunidades para dar forma a las compensaciones entre los resultados económicos y de salud al evaluar cuidadosamente una gama más completa de políticas de reapertura.

**Palabras clave:** COVID-19, resultados económicos, resultados de salud, intervenciones no farmacéuticas

## 定期非药物干预策略能产生更好的新冠肺炎卫生结果和经济结果吗？

### 摘要

我们提出一个新冠肺炎（COVID-19）传播模型，用于比较非药物公共卫生干预（NPIs）对卫生和经济结果产生的效果。通过跨学科方法选择和使用不同NPIs，并对干预产生的卫生和经济影响进行定量建模，同时结合有关其他重要考量因素（例如成本，执行难度，公平）的定性评估。我们使用模型分析定期在基准NPI和高NPI层面切换的不同策略。我们发现，这一系统性策略能够产生与静态策略相似的卫生结果，以及更高的社会福利和经济结果。我们的研究发现暗示，通过仔细评估更全面的经济重新开放政策，有可能影响经济结果和卫生结果之间的得失。

**关键词：**新冠肺炎（COVID-19），经济结果，卫生结果，非药物干预

## 1. Introduction

**C**oronavirus disease 2019 (COVID-19) is unprecedented in terms of scale and speed, affecting millions worldwide. Until recently, vaccines and effective treatments for COVID-19 were unavailable. National leaders have had to take extraordinary measures to mitigate the virus's spread and prevent health care systems from being overwhelmed. Policy-makers have implemented a range of nonpharmaceutical public health interventions (NPIs). These interventions include partial closings (e.g., schools and non-essential businesses, prohibiting large gatherings, quarantining the most vulnerable) and complete lockdown (e.g., placing all residents under stay-at-home orders). The goal of NPIs is to delay and reduce the peak number of cases per day, reduce pressure on health services, and allow time for vaccines to be distributed [1]. If NPIs are relaxed too soon, a new wave of infections may occur. However, NPIs have wide-ranging effects on the health, economy, and social well-being of populations, which has led to growing pandemic fatigue and a decline in adherence to NPIs since they were first initiated [2, 3]. Decision-makers are faced with tough decisions, such as how to sequence, relax, and possibly reinstate mitigation measures. Exacerbating these decisions are significant uncertainties, including new variants and behavioral responses to extended interventions.

Mathematical and simulation models of COVID-19 transmission dynamics are invaluable tools to help de-

cision-makers forecast and compare intervention outcomes, predict the timing of peaks in cases and deaths, medical supply needs, and if and when we should expect additional waves. They enable the projection and comparison of population-level outcomes over hypothetical scenarios. Model outcomes include the incidence and prevalence of the infection over time and for different population groups. The hypothetical scenarios can consist of the impact of varying pharmaceutical and nonpharmaceutical public health interventions, distributing vaccines, and the emergence of new strains.

We developed a COVID-19 transmission Population-Based Model (PBM) used as part of a web-based COVID-19 decision support tool that compares the effects of different nonpharmaceutical public health interventions (NPIs) on health and economic outcomes. An interdisciplinary approach informed the selection of NPI portfolios, combining quantitative modeling of the health/economic impacts with qualitative assessments of cost, ease of implementation, and equity. An in-depth description of our approach was previously published as a RAND report describing how the PBM, the economic model, and a systematic assessment of NPIs informed the web tool [4].

We expanded our original model [4] to account for additional uncertainties and consider an expanded set of NPI strategies. In this paper, we consider periodic NPI strategies. These are strategies whereby the enacted NPI

systematically changes at fixed intervals between low and high stringency levels. Recent research has demonstrated that high-frequency periodic NPIs [5] have the potential to mitigate COVID-19 resurgences while providing more predictability and alleviating the damaging effects on economic activity and social well-being. We use our updated model to explore if a periodic strategy could have provided benefits compared to fixed strategies in mitigating the virus's transmission by keeping a low value for the effective reproductive number ( $R_t$ ) and close to one.<sup>1</sup> We find that a periodic strategy can dominate fixed strategies, improving health and days spent under restrictions. This could have led to improvements in economic outcomes due to both the reductions in the days spent under restrictions and the greater certainty of planned restrictions' timing and duration.

The paper is structured as follows. First, we provide an overview of our model structure. Then, we briefly analyze a set of illustrative scenarios, including periodic and fixed strategies, identifying if the periodic strategies used by other modelers [5] produce similar results in our model. Finally, we provide detailed information on our mathematical model and present sensitivity analyses.

## 2. Model Overview

Theory-based epidemiological models use a theoretical understanding of biological and social processes to represent a disease's clinical and epidemiological course. The most typical model considers the population in four different disease states: susceptible, exposed, infected, and Removed (SEIR). Our PBM incorporates several extensions to the SEIR model of disease transmission. It is formulated deterministically by coupled ordinary differential equations (ODEs) and integrated numerically by solvers for stiff problems [6–9]. We extend the SEIR framework to better describe COVID-19 transmission by adding additional disease states and considering population strata based on age and chronic conditions. The PBM models the effects of different NPIs on health outcomes and income loss, from partial closings to complete lockdown. Unlike many other COVID-19 models, we simulate the impact of NPIs on different mixing modes (such as home, school, and work) separately, allowing us to model various interventions flexibly. Our PBM also includes population strata and specify mixing pattern heterogeneities across the population strata and for each mode. These heterogeneities included in our model allow us to set the NPI more specifically, with mixing rates reduced differentially by mixing mode. Our model is designed

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<sup>1</sup> The effective reproductive number ( $R_t$ ) found from population-based models provides an indication of the average number of secondary infections produced by a typical case of an infection in a population during the course of the epidemic. When  $R_t > 1$  we get a growing number of new infections.

to help policy-makers understand the effects of NPIs, weigh trade-offs among them, make decisions about which

NPIs to implement, and estimate how policy-makers should enforce long-term interventions to control the virus.

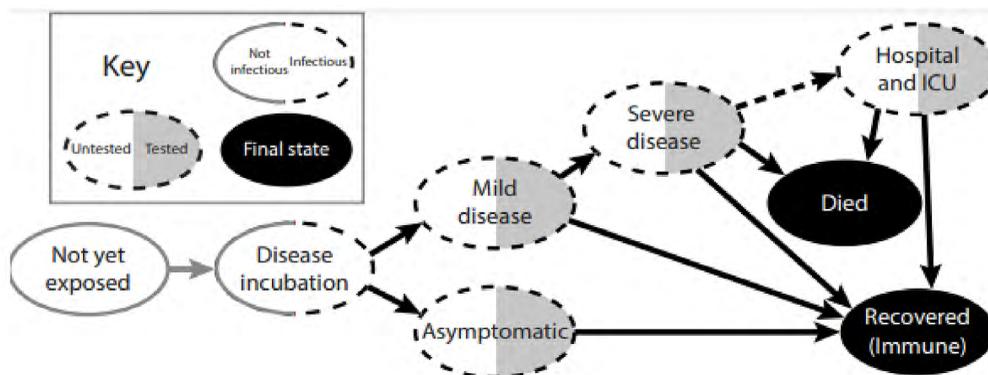


Figure 1: COVID-19 PBM disease states

Figure 1 shows a simplified illustration of the disease states included in the first basic version of our PBM. The model includes a pre-symptomatic highly infectious state that is part of the incubation phase, which leads to either an asymptomatic state or a state with mild symptoms, a fraction of which continues to severe disease. Most of those who develop severe symptoms are hospitalized. Non-hospitalized severely-symptomatic either recover or die. The hospitalized state includes compartments for both the main hospital and the ICU, where individuals are admitted if they were to develop critical symptoms. Capacities can be set for the hospital and ICU beyond which no additional patients can be added. At each of the infectious states, individuals can be tested for COVID-19. Each compartment comprises ten population strata, five age groups, and two health states (those with and without at least one chronic condition). These strata allow the model to simulate how the

disease impacts different population groups, including differences in population size, mixing mortality rate, and the proportion who are asymptomatic. Disease progression rates are based on figures given in the literature and are sampled from distributions if uncertain. The force of infection (the rate that susceptible individuals become exposed) is characterized by how many infectious people are in each state, each state's transmissibility, and mixing levels. We estimate transmissibilities for each state based on biological and social factors. For instance, viral loads are highest early in the disease [10], so these states have higher biological transmissibility. We assume that those who receive positive tests or exhibit symptoms have lower social transmissibility because they take measures to limit others' exposure. The total transmissibility of a state is the product of biological and social transmissibilities. The population-weighted sum of transmission is proportional to the number of new infections.

**Table 1.** Nonpharmaceutical intervention levels.

| <b>NPI Level</b>  | <b>Description</b>  |
|---|---|
| Level 1: No Intervention  | No Intervention.  |
| Level 2: Close schools  | All schools are closed.   |
| Level 3: Close schools, bars, and restaurants; and ban large events   | In addition to school closures, all bars' and restaurants' dine-in services are closed, only allowing for take-out options. Also, large gatherings are banned.                              |
| Level 4: Close schools, bars, and restaurants; ban large events; and close nonessential businesses  | In addition to school, bar, and restaurant closures, all nonessential businesses are closed.  |
| Level 5: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and shelter in place for the most vulnerable            | In addition to the closure of all nonessential businesses, a shelter in place is recommended for the vulnerable population, including the elderly, children, and other at-risk populations. |
| Level 6: Close schools, bars, and restaurants; ban large events; close nonessential businesses; and shelter in place for everyone but essential workers | In addition to the interventions above, shelter in place order is issued for everyone but essential workers   |

In our model, NPIs are portfolios of restrictions mandated at the state level, as described in table 1. The set of NPIs levels used by each state is characterized by a discrete set of intervention levels ranging from 1 (no intervention) to 6 (close schools, bars, restaurants, and non-essential businesses; and issue a shelter-in-place order for everyone but essential workers). Each intervention level is associated with mixing matrices that describe how strata interact with each other in six different settings: household, work, school, commercial, recreation, and other. Interventions are

modeled as changing the level of mixing which occurs in each of these settings. For instance, closing schools reduce school and work mixing but increases home mixing. Given the specified model structure, the NPI time-series, and the mixing matrices, we calibrate our model for each state using time series of reported deaths. Our Supplemental Information provides a detailed description of the mathematical formulation of our model.

### 3. Exploring Periodic NPI Strategies

This section presents an illustrative retrospective analysis of policies that can be tested with the model, using California as an example. They illustrate that alternative plausible NPI strategies could have produced improved outcomes during 2020 in the absence of vaccines. The purpose of this analysis is two-fold. First, it demonstrates how our model can trace many-objective trade-off curves to support the analysis of reopening strategies. Second, this analysis demonstrates that a periodic switching of NPIs could have shifted society towards more desirable trade-off curves. That is, it could have led to a Pareto-improvement<sup>2</sup>.

We explore two types of strategies that policy-makers could have followed to manage NPIs in 2020. The first set of strategies are “fixed” NPI levels. This type of strategy holds the NPI level constant over time. Although this strategy has not been followed in California explicitly, the NPI mandates imposed in California are best approximated in our model by setting the NPI level to three. This NPI level was stable between July of 2020 through the end of the year. It represents our baseline scenario and is the scenario we used to calibrate our model.

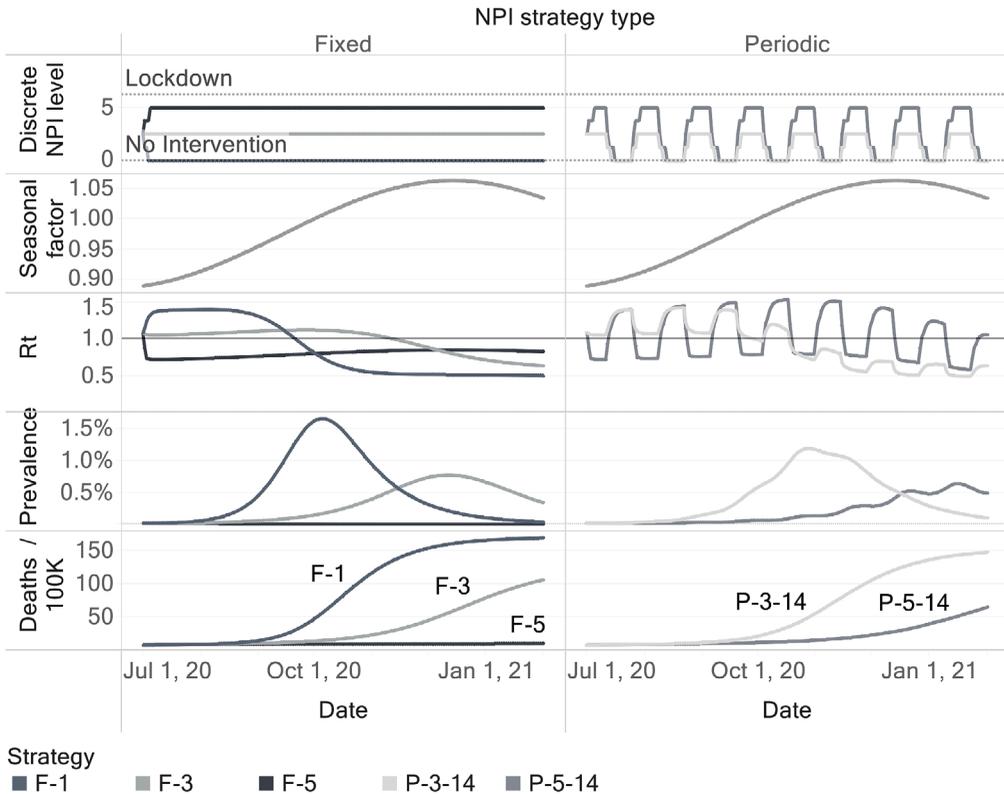
Fixed NPIs are not, however, the only way to control the pandemic. Alternatively, one could use periodic

strategies to curb transmission [5]. A periodic NPI can represent a strategy wherein society goes into more severe periods of NPIs then relaxes to lower levels of stringency. This strategy’s rationale is that those newly infected during the relaxed periods would take a few days before becoming infectious themselves. The enforcement of stringent NPIs would then limit the virus’s time and possibilities to spread further from these infectious individuals before they either recover or are hospitalized. This periodical switching would systematically reduce transmissions and force the dynamics of the epidemic to be controlled by the strategy’s frequency.

In essence, a periodic strategy uses the natural timescales of disease progression and infectivity to induce a synchronization phase that helps align when people are more likely to be infected together, allowing for the social distancing NPIs to be more effective. An example of a similar strategy includes schools adopting a hybrid learning model wherein students go to school every other week. Similarly, restaurants could open for indoor dining periodically. In the absence of vaccines, such policies may be desirable. They would provide stability, regularity, and increased predictability for businesses to plan against. The policies could, in principle, help suppress the transmission of the virus and simultaneously reduce uncertainties in economic activity.

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2 Consider the trade-off between deaths and lockdown days, a strategy A is Pareto dominated if there is some other strategy B that would decrease the number of deaths for the same number of lockdown days or decrease the number of lockdown days for the same number of deaths. Strategy B would be a Pareto-improvement over strategy A.



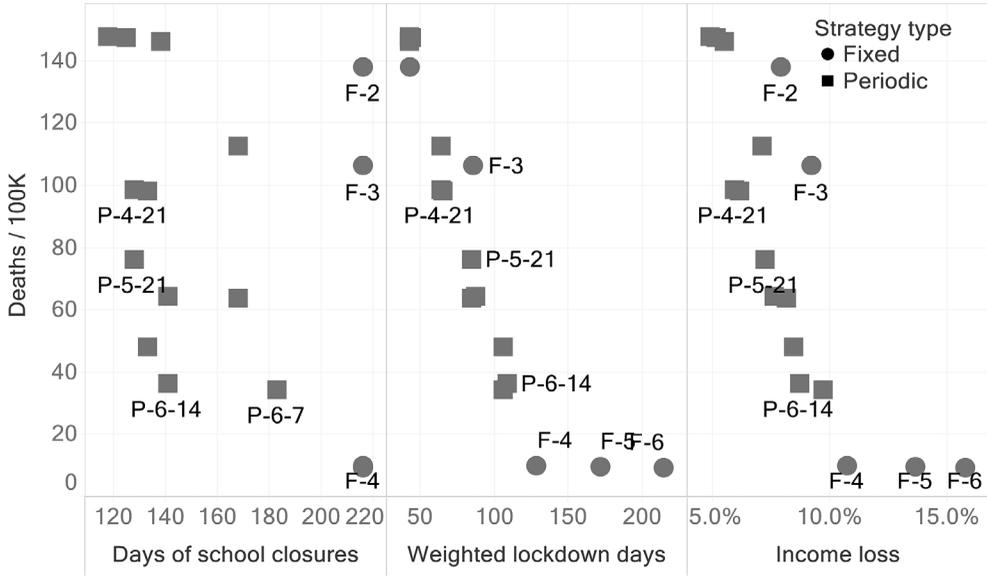
**Figure 2: Model Dynamics with Fixed and Periodic NPIs:** Fixed NPI strategies are coded with an “F” followed by the intervention level included in the NPI. Periodic NPI strategies are coded with a “P” followed by the maximum NPI level in the periodic strategy and the period in days. In that case, P-3-14 means that the state will switch between the NPI levels 3 and 1 every 14 days.

Figure 2 illustrates the dynamics of periodic and fixed NPI strategies. The fixed NPI strategies represented in the figure suggest that under the NPI level three,  $R_t$  closely followed one and increased towards the end of December, driven by our model’s seasonal effect. Because  $R_t$  was close to one in the model, a departure from the current NPI level would be expected to produce a significant departure from the  $R_t = 1$ . Therefore, a policy that reopens the state (F-1) would be expected to produce a spike in prevalence and subsequently

in the number of deaths. A more stringent, constant policy (F-5) would be expected to reduce the number of deaths.

As figure 2 shows, the periodic strategy P-5-14 switches between NPI levels 1 and 5 every two weeks. This switching causes  $R_t$  to oscillate such that prevalence does not increase unchecked. As a consequence, the number of deaths is controlled. The choice of two weeks is based on the typical timescale describing the disease progression for most infected people. However, other choices for the periodicity could be explored.

*Could Periodic Nonpharmaceutical Intervention Strategies Produce Better Covid-19 Health and Economic Outcomes?*



**Figure 3: Tradeoff surface implied by alternative policies.** The vertical axis presents the number of Deaths / 100k at the end of the simulation run (Feb. 2021) in California. The horizontal axis contains several proxies that represent alternative criteria to evaluate the costs of NPIs. Across all these criteria, we find that periodic NPIs tend to dominate fixed NPIs.

When judging alternative strategies, policy-makers often have to weigh multiple criteria to make decisions, so one needs to translate model outcomes to meaningful criteria. One criterion could be the number of days of school closures, which has been an important concern during the COVID-19 pandemic. However, the number of days of school closures does not distinguish scenarios where non-essential businesses are closed for long periods, so other proxies for welfare loss are needed. One approach could be to use weights for each NPI level, such that those weights are proportional to the marginal daily welfare loss induced by each NPI level. Suppose we define the weights such that one day under lockdown is equivalent to a weight of one, and define that one

day under no restrictions is equivalent to zero. We can then compute a proxy to social welfare that we can use to judge alternative strategies. Our weighted lockdown days metric corresponds to this criterion.

There are other plausible ways to compute NPI costs. NPIs arguably induce income loss. Our third metric uses the income loss under each NPI level estimated by a general equilibrium model [11] to account for the economic consequences of NPI restrictions. Although all these proxies are imperfect measures of social welfare loss induced by NPIs, our conclusions do not rely on their precision but on the assumption that NPI costs are increasing in the level of restriction. This structural assumption allows us to illuminate trade-offs

and reveal Pareto-dominated strategies that rely on the structure of the epidemiological model<sup>3</sup>.

Figure 3 demonstrates that using a small set of alternative measures can support those decisions and reveal Pareto-dominated strategies. Strategy F-3, our baseline strategy, is Pareto-dominated by a wide range of strategies that oscillate between the NPI level of 5 and 1, using many periods, which is in line with prior research [5].

We analyzed periodic strategies to illustrate that alternative NPI strategies could Pareto-dominate fixed strategies and shift the trade-off surface among health and economic/social outcomes if implemented with high levels of compliance. Based on our analysis, policy-makers could have used periodic NPIs to manage the COVID-19 pandemic producing the same health outcomes while allowing essential activities, such as in-person education, to have happened in a controlled manner. Our analysis demonstrated that alternative NPI strategies could shift the trade-off curves among the relevant outcomes.

Including social welfare loss measures induced by NPIs in analyses seeking to inform COVID-19 reopening decisions is essential. Only includ-

ing health outcomes in those analyses leaves the task of weighing other concerns to the policy-maker, who may or may not be able to do so consistently. Metrics of welfare loss induced by NPIs can be either derived directly from the model outcomes (e.g., days of school closures) or by using a weighted sum based on the NPIs stringency level, potentially using economic models in our prior work [4]. Our analyses provide a general guide to policy-makers that is valid despite the uncertainties that prevent us from providing precise estimates. As figure 3 demonstrated, if one ignores all the horizontal axes under the argument that those estimates might be imprecise, policy-makers might not be properly informed that alternative policies dominate some policies. This statement and the pattern seen in the trade-off curves do not rely on the precision of economic estimates but the theory-based epidemiological model structure

There are limitations to our analysis. First, we do not consider practicality: these periodic strategies might be regarded as unfeasible, impractical, or undesirable by policy-makers and the public. This consideration is significant because the strength of the periodic NPIs relies on the ability to abrupt-

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3 One might estimate the costs of NPIs using a willingness to pay or similar approach. As long as those weights are monotonically increasing (e.g., people are not deriving utility from NPI restrictions), our substantive findings would hold. While estimating more precise welfare costs of NPIs and using those costs as weights might be valuable to compare benefits from NPIs to costs, we doubt that these weights would be stable over time. Still, as long as these weights are monotonically increasing functions of the NPI level *at any point in time*, our substantive results would hold. Because these weights are highly uncertain and potentially not constant, we refrain from aggregate all outcomes under a single social welfare metric in our analyses as a traditional Cost-Benefit analysis would do. Instead, we assess Pareto-efficiency and seek strategies that dominate other strategies across a set of outcomes

ly reduce mixing, which can only be achieved with a high compliance level. Further, people may shift their mixing to the open periods reducing or even canceling the mitigation effects on transmission intended by the periodic NPI policy. The trade-off curves we present also should not be seen as static. Many other factors that have been held constant in our analysis might shift this curve.

Widespread adoption of high-quality masks, for example, would shift every point inwards, making society systematically better off. The emergence of new, more transmissible variant strains can shift the curve outwards. A more stringent strategy to eliminate com-

munity spread and prevent re-seeding (such as New Zealand's strategy) can remove the health-economic trade-offs curve completely if successfully implemented. Adaptation measures to prevent transmission within schools would also shift this curve, strengthening periodic strategies even more attractive to allow in-person education. Moreover, the introduction of vaccines also shapes this trade-off curve over time. As vaccination roll-out advances, the marginal benefit of an additional day under stringent NPIs will decrease. Accounting for the vaccination dynamics will be essential to guide society to a new normal through a robust reopening plan.

## **Contributions**

Raffaele Vardavas (Ph.D.) led the effort in conceptualizing and formulating the model structure and led the overall modeling effort. Pedro Nascimento de Lima (MSc) led the model implementation and model analysis effort. Lawrence Baker (MSc) led the effort in informing the model with data and parameter values found in the literature. All authors contributed equally to this research work and to this article.

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## References

- [1] Julia E. Aledort, Nicole Lurie, Jeffrey Wasserman, and Samuel A. Bozzette. Non-pharmaceutical public health interventions for pandemic influenza: An evaluation of the evidence base. *BMC public health*, 7:208, August 2007. ISSN 1471-2458. doi: 10.1186/1471-2458-7-208.
- [2] Matthew A. Crane, Kenneth M. Shermock, Saad B. Omer, and John A. Romley. Change in Reported Adherence to Nonpharmaceutical Interventions During the COVID-19 Pandemic, April- November 2020. *JAMA*, January 2021. ISSN 1538-3598. doi: 10.1001/jama.2021.0286.
- [3] Bella Nichole Kantor and Jonathan Kantor. Non-pharmaceutical Interventions for Pandemic COVID-19: A Cross-Sectional Investigation of US General Public Beliefs, Attitudes, and Actions. *Frontiers in Medicine*, 7, July 2020. ISSN 2296-858X. doi: 10.3389/fmed.2020.00384.
- [4] Raffaele Vardavas, Aaron Strong, Jennifer Bouey, Jonathan William Welburn, Pedro Nascimento de Lima, Lawrence Baker, Keren Zhu, Michelle Priest, Lynn Hu, and Jeanne S. Ringel. The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19: A Decision Support Tool for State and Local Policymakers. <https://www.rand.org/pubs/tools/TLA173-1.html>, 2020.
- [5] Michelangelo Bin, Peter Y. K. Cheung, Emanuele Crisostomi, Pietro Ferraro, Hugo Lhachemi, Roderick Murray-Smith, Connor Myant, Thomas Parisini, Robert Shorten, Sebastian Stein, and Lewi Stone. Post-lockdown abatement of COVID-19 by fast periodic switching. *PLOS Computational Biology*, 17(1): e1008604, January 2021. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1008604.
- [6] Peter N. Brown, George D. Byrne, and Alan C. Hindmarsh. VODE: A Variable-Coefficient ODE Solver. *SIAM Journal on Scientific and Statistical Computing*, 10(5):1038–1051, September 1989. ISSN 0196-5204. doi: 10.1137/0910062.
- [7] Alan C. Hindmarsh and Linda R. Petzold. Algorithms and software for ordinary differential equations and differential-algebraic equations, Part II: Higher-order methods and software packages. *Computers in Physics*, 9(2):148–155,

March 1995. ISSN 0894-1866. doi: 10.1063/1.168540.

- [8] L. F. Shampine and C. W. Gear. A User's View of Solving Stiff Ordinary Differential Equations. *SIAM Review*, 21(1):1–17, January 1979. ISSN 0036-1445. doi: 10.1137/1021001.
- [9] Karline Soetaert, Thomas Petzoldt, and R. Woodrow Setzer. Solving Differential Equations in R: Package deSolve. *Journal of Statistical Software*, 33(1):1–25, February 2010. ISSN 1548-7660. doi:10.18637/jss.v033.i09.
- [10] Xi He, Eric H. Y. Lau, Peng Wu, Xilong Deng, Jian Wang, Xinxin Hao, Yiu Chung Lau, Jessica Y. Wong, Yujuan Guan, Xinghua Tan, Xiaoneng Mo, Yanqing Chen, Baolin Liao, Weilie Chen, Fengyu Hu, Qing Zhang, Mingqiu Zhong, Yanrong Wu, Lingzhai Zhao, Fuchun Zhang, Benjamin J. Cowling, Fang Li, and Gabriel M. Leung. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nature Medicine*, 26(5):672–675, May 2020. ISSN 1546-170X. doi: 10.1038/s41591-020-0869-5.
- [11] Aaron Strong and Jonathan William Welburn. An Estimation of the Economic Costs of Social-Distancing Policies. May 2020.



## Supplemental Information:

### Could periodic nonpharmaceutical intervention strategies produce better COVID-19 health and economic outcomes?

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#### Abstract

In this supplemental information document we provide a detailed description of the mathematical formulation of our COVID-19 transmission Population-Based Model.

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# 1 The Mathematical Formulation of the Model

## 1.1 Model disease states and progression

Individuals in our population are divided into fourteen key compartments listed in Table 1. We assume that individuals in the  $P$  and  $I_A$  compartments are fully asymptomatic and thus are unaware of being infectious. In our model, individuals in  $I_{Sm}$  have mild symptoms, including a dry cough and a fever, while those in  $I_{Ss}$  are assumed to have severe symptoms that include shortness of breath in addition to a dry cough and a fever. The sum of the population in all of the states gives the total

| Disease State $X$ | Description                                  | Infectious $X_I$ | Diagnosed |
|-------------------|--|------------------|-----------|
| $S$               | Noninfected and susceptible.                 | No               | No        |
| $E$               | Exposed and infected but not yet infectious. | No               | No        |
| $P$               | Presymptomatic infectious.                   | Yes              | No        |
| $I_{Sm}$          | Nondiagnosed Infected with mild symptoms.    | Yes              | No        |
| $I_{Ss}$          | Nondiagnosed infected with severe symptoms.  | Yes              | No        |
| $Y_{Sm}$          | Diagnosed infected with mild symptoms.       | Yes              | Yes       |
| $Y_{Ss}$          | Diagnosed infected with severe symptoms.     | Yes              | Yes       |
| $H$               | Hospitalized not in the intensive-care unit. | Yes              | Yes       |
| $H_{ICU}$         | Hospitalized in the intensive-care unit.     | Yes              | Yes       |
| $I_A$             | Nondiagnosed infected asymptomatic.          | Yes              | No        |
| $Y_A$             | Diagnosed infected asymptomatic.             | Yes              | Yes       |
| $R_S$             | Recovered who were symptomatic.              | No               | Yes & No  |
| $R_A$             | Recovered who were asymptomatic.             | No               | Yes & No  |
| $D$               | Those who have died.                         | No               | Yes & No  |

Table 1: Disease states included in the model. The dependence on time  $t$  is implicitly assumed.

population  $N$ . In our model we assume that each state variable gives the proportion of the population belonging to that state. Therefore, instead of tracking the dynamics of each compartment's population sizes, we track the population densities. We express this as  $\sum_X X(t) = N = 1$ , where  $X \in \{S, E, X_I, R_A, R_S, D\}$  labels the population compartments and  $X_I \in \{P, I_{Sm}, I_A, I_{Ss}, Y_{Sm}, Y_A, Y_{Ss}, H, H_{ICU}\}$  labels the subset of compartments that are infectious.

In the Population-Based Model (PBM), the susceptible that get infected enter state  $E$  at a rate known as the force of infection  $\lambda$  described in the section 1.2. As for all the transition rates in our PBM,  $\lambda$  is specified as a per-person transition probability per unit time. Figure 1 illustrates disease progression in the early stages of COVID-19 infection. They progress to the presymptomatic infectious state  $P$  at a rate  $v$ . As an individual-level interpretation of this transition, the mean duration, also known as the mean dwelling or sojourn time that newly infected individuals stay in disease state  $E$  is given by  $v^{-1}$ . Those in the presymptomatic infectious state  $P$  either remain asymptomatic and transition to state  $I_A$  at a rate  $\gamma_A$ , or develop mild symptoms and transition to state  $I_{Sm}$  at a rate  $\gamma_S$ .

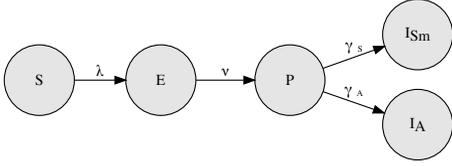


Figure 1: Initial disease progression stages. At the individual level, the mean duration that infected individuals stay in disease state  $P$  is given by  $[\gamma_S + \gamma_A]^{-1}$ , and the probability of developing mild symptoms is given by  $\gamma_S \cdot [\gamma_S + \gamma_A]^{-1}$ . We assume that testing the presymptomatic for COVID-19 results in a false negative outcome. Consequently, all those who are presymptomatic are unaware of their infected and infectious state. The formulation of the first three ODEs describing our PBM are

$$\dot{S} = -\lambda S, \tag{1}$$

$$\dot{E} = \lambda S - vE, \tag{2}$$

$$\dot{P} = vE - (\gamma_S + \gamma_A)P. \tag{3}$$

The asymptomatic and unaware of having been infected,  $I_A$  progress to the recovered state  $R$  at rate  $\xi_A$ . The asymptomatic are assumed to stay infectious until they recover. Figure 2 illustrates the disease progression of the asymptomatic. A proportion  $\zeta_A(t) \cdot [\zeta_A(t) + \xi_A]^{-1}$  of the asymptomatic are diagnosed with having COVID-19. This proportion of individuals transition to state  $Y_A$ . The testing rate  $\zeta_A(t)$  is not constant but implicitly depends on time, due to dynamic testing policies. These individuals most likely get tested because they suspect or are informed by health-care workers engaged in contact-tracing to have recently been in contact with someone diagnosed with COVID-19. Those who enter disease stage  $Y_A$  progress to the recovered state  $R$  at rate  $\xi_A^*$ . The transition rate  $\xi_A^*$  is faster than  $\xi_A$  and accounts for the elapsed duration of mild symptoms prior to being diagnosed. These diagnosed asymptomatic are aware of having been infected and of being infectious. Therefore, they are assumed to engage in increased social distancing behavior described in the section 2.2.4 on the disease transmission model. The ODEs describing the asymptomatic disease progression are

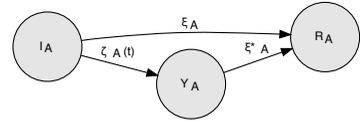


Figure 2:

$$\dot{I}_A = \gamma_A P - [\xi_A + \zeta_A(t)] I_A, \tag{4}$$

$$\dot{Y}_A = \zeta_A(t) I_A - \xi_A^* Y_A. \tag{5}$$

Figure 3 illustrates the disease progression of the symptomatic. The non-diagnosed mildly symptomatic,  $I_{Sm}$  either progress to the recovered state  $R$  at a rate  $\xi_m$  or develop severe symptoms and

progress to state  $I_{S_s}$  at a rate  $v$ . Some are tested at a rate  $\zeta_S(t)$  and diagnosed with having COVID-19. These transition to state  $Y_{S_m}$  and become aware of their infection state. As before,  $\zeta_S(t)$  is not a constant but is assumed to implicitly depends on time. Our model assumes that those mildly symp-

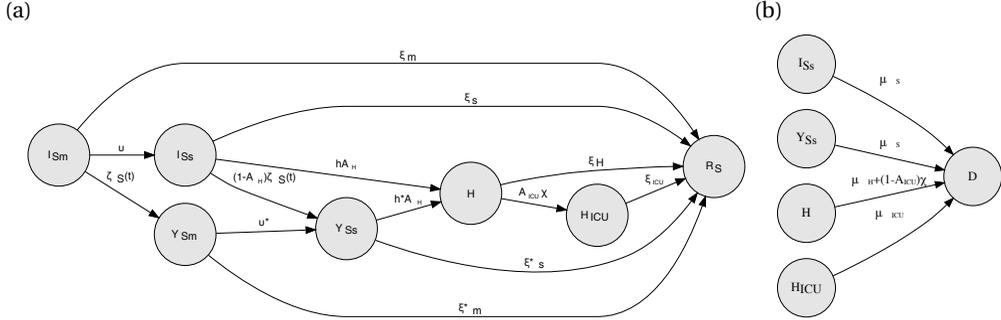


Figure 3: Model flow of disease progression of the infected symptomatic with transitions that lead to the recovered state  $R$  and the died state  $D$  shown respectively in panels a and b.

tomatic that get diagnosed will also progress to the recovered state  $R$  at a rate  $\xi_m^*$  or develop severe symptoms and transition to state  $Y_{S_s}$  at rates  $v^*$ . These rates are respectively faster than  $\xi$  and  $v$  to account for the elapsed duration of mild symptoms prior to being diagnosed. The ODEs describing the non-hospitalized with mild symptoms are

$$\dot{I}_{S_m} = \gamma_S P - [v + \xi_m + \zeta_S(t)] I_{S_m}, \quad (6)$$

$$\dot{Y}_{S_m} = \zeta_S(t) I_{S_m} - [v^* + \xi_m^*] Y_{S_m}. \quad (7)$$

Most of the non-diagnosed severely symptomatic  $I_{S_s}$  are hospitalized at a rate  $hA_H$ . When they enter the hospital they are diagnosed with COVID-19. The percentage of severe cases hospitalized remains constant as long as the hospital has not reached its capacity in terms of available beds. The dichotomous variable  $A_H$  indicates whether the hospital is accessible to COVID-19 patients ( $A_H = 1$ ) or whether it has reached its bed capacity and no longer accepts new COVID-19 patients ( $A_H = 0$ ). If the hospital is at capacity, the severely symptomatic patients that would have otherwise been hospitalized are tested at a rate  $(1 - A_H)\zeta_S(t)$ . Once the hospital is no longer at capacity, these diagnosed patients are hospitalized at a rate  $h^*A$  which is faster than rate  $h$  as these diagnosed patients are likely to have waited longer to be hospitalized than the non-diagnosed. A minority of the severely symptomatic never access the hospital. Some of these patients recover but most die at home. We assume that the transition rates to the recovered state  $R$  is  $\xi_s$  and to death  $D$  is  $\mu_s$ . These rates also apply to those diagnosed and severely symptomatic as the majority of those in state  $Y_{S_s}$  are diagnosed while having mild symptoms. The ODEs describing the non-hospitalized with severe symptoms are

$$\dot{I}_{S_s} = v I_{S_m} - [\zeta_s + \mu_s + hA_H + (1 - A_H)\zeta_S(t)] I_{S_s}, \quad (8)$$

$$\dot{Y}_{S_s} = (1 - A_H)\zeta_S(t) I_{S_s} + v^* Y_{S_m} - [\xi_s^* + \mu_s + h^*A_H] Y_{S_s}. \quad (9)$$

Patients that are hospitalized may develop critical symptoms. Like for the hospital, the ICU can also reach capacity, at which point it takes no more patients until it has free beds. Provided there are available ICU beds, these hospitalized critical patients transition into the ICU at a rate  $\chi A_{ICU}$ . As with hospital accessibility, we use the dichotomous variable  $A_{ICU}$  to indicate whether the ICU is accessible ( $A_{ICU} = 1$ ) to COVID-19 critical patients or whether it has reached capacity ( $A_{ICU} = 0$ ). Hospitalized patients that do not require the ICU either transition to the recovered state  $R$  at a rate  $\xi_H$ , or transition to death  $D$  at a rate  $\mu_H$ . The transition rate  $\mu_H$  is assumed to be small because very few patients die in the hospital without having accessed the ICU first, provided that the ICU is not at capacity. We assume that patients who recover in the ICU move immediately to the recovered compartment rather than back to the hospital. This ensures that individuals do not make multiple trips to the ICU. The transition rate to the recovered state  $R$  is  $\xi_{ICU}$ . Therefore, the time spent in the  $H_{ICU}$  compartment represents both the ICU and the time spent recovering after intensive care in the hospital. The actual transition rates from the hospitalized to the recovered state  $R$  and death  $D$  depend on whether the ICU is accessible. When the ICU is closed, we assume that all those who required ICU access will die until the ICU is reopened. Hence, the general transition rate from  $H_{ICU}$  to death  $D$  is  $\mu_H + \chi(1 - A_{ICU})$ . The ODEs describing the hospitalized are

$$\dot{H} = A[hI_{S_s} + h^*Y_{S_s}] - [\mu_H + \chi + \xi_H]H, \quad (10)$$

$$\dot{H}_{ICU} = A_{ICU}\chi H - [\mu_{ICU} + \xi_{ICU}]H_{ICU}. \quad (11)$$

When the hospital is at capacity ( $A_H = 0$ ), patients that develop critical symptoms are more likely to die at home. This requires modifying the rate  $\mu_s$  based on the hospital accessibility indicator variable  $A_H$ . The implementation of our PBM can take this into account where the death rate  $\mu_s$  in state  $I_{S_s}$  is increased to  $\mu_s + h\chi/(\chi + \xi_H)$ . A similar increase in the death rate applies in state  $Y_{S_s}$ . However, unlike for the ICU, the duration of having no accessibility to the hospital is likely to be short because hospitals can adapt spaces and create new bed accommodations in a way that is not possible for the ICU. Hence, the ODEs we present and describe here do not consider this increased mortality rate. Therefore, the ODEs describing the recovered and those that die are

$$\dot{R}_A = \xi_A I_A + \xi_A^* Y_A, \quad (12)$$

$$\dot{R}_S = \xi_m I_{S_m} + \xi_m^* Y_{S_m} + \xi_s I_{S_s} + \xi_s^* Y_{S_s} + \xi_H H + \xi_{ICU} H_{ICU}, \quad (13)$$

$$\dot{D} = \mu_S(I_{S_s} + Y_{S_s}) + [\mu_H + (1 - A_{ICU})\chi]H + \mu_{ICU}H_{ICU}. \quad (14)$$

We assume that the expected time for the diagnosed and asymptomatic  $Y_A$  to transition to the recovered state  $R$  is shorter than the expected time for the same transition to the recovered state of the undiagnosed asymptomatic  $I_A$ . Similarly, the expected time for  $Y_{S_m}$  to transition to either state  $Y_{S_s}$  or the recovered state  $R$  is shorter than the expected time for those in  $I_{S_m}$  to transition to either state  $I_{S_s}$  or the  $R$  is. We model this by setting  $\xi_A^* = \kappa_\xi \xi_A$ ,  $\xi_m^* = \kappa_\xi \xi_m$  and  $v^* = \kappa_\xi v$  where the value of  $\kappa_\xi$  is sampled in a range of values greater than one. As for interpretation, when  $(\kappa_\xi - 1)/\kappa_\xi$  is multiplied by the expected duration before the next clinical disease progression, it gives the expected time duration when an infected person is likely to be diagnosed with COVID-19.

## 1.2 Modeling SARS-CoV-2 transmission

Following the approach taken in standard compartmental models of infectious diseases, the force of infection  $\lambda$  describes SARS-CoV-2 transmission. The force of infection is characterized by how infectious people in each disease state infect others. In our formulation, the force of infection is the product of two parameters. The first parameter is the contact mixing rate, representing the number of daily contacts people make with others. The second parameter is biological transmissibility, which defines the probability of transmission between an infectious and a susceptible person when they come in contact. Each disease state would have a different contact mixing rate and transmissibility. We express the force of infection as

$$\lambda(t) = \sum_{X_I} c_{X_I} \beta_{X_I} X_I(t) = c_{eff} \beta_{eff} \sum_{X_I} m_{X_I} X_I(t), \quad (15)$$

where the coefficient  $c_{X_I}$  represents the social mixing contact rate and  $\beta_{X_I}$  represents the transmissibility of infectious people in disease state  $X_I$ .

The expression for the force of infection simplifies by assuming an effective contact rate  $c_{eff}$  and an effective  $\beta_{eff}$  transmissibility. The product of these two  $c_{eff} \beta_{eff}$  is assumed to characterize the rate of infections caused by an undiagnosed asymptomatic infected person in either state  $P$  or  $I_A$ . Rates of infections in the other disease states are characterized using  $m_{X_I}$  coefficients that give the multiplicative effect on infectivity with respect to the primary infectious state or an asymptomatic state. For example,  $m_{S_S}$  gives the overall average multiplicative infectivity of a symptomatic severe individual relative to an asymptomatic individual. This multiplicative factor combines the effect of decreased social mixing with increased biological transmissibility. We choose the asymptomatic untested individual as our reference because they are unaware of their positive status and thus do not change their social mixing behavior acting as though they are not infected. Hence  $m_P = m_{I_A} = 1$ . We estimate the values of the multiplicative factor of the other disease stages by considering how the transmissibility and the social mixing contact rate change relative to the presymptomatic case.

Changes in viral load are used to estimate the transmissibility of each of the disease states. Studies have shown that viral loads peak in the primary infectious stage and decrease monotonically after the onset of symptoms. See section 2.2.3 for more details on relative infectivity.

The value of the effective infectivity  $c_{eff} \beta_{eff}$  and its range is estimated from the basic reproductive number  $R_0$ . This number is defined at the individual-level and represents the average number of secondary infections caused by an infectious person during the disease invasion phase. This phase represents the early stage of the epidemic when susceptible individuals surround each infectious person. At the population-level,  $R_0$  represents a threshold parameter. Whether its value is larger or smaller than one, this threshold parameter indicates whether an outbreak will invade the population and become an epidemic or whether it is likely to extinguish before becoming a full-blown epidemic. The distinction between the individual-level definition and the basic reproductive number's threshold property does not always align and can be very consequential, leading to incorrect conclusions. A large body of literature provides a detailed discussion on the basic reproductive number, its uses, limitations, and misconceptions [1–5].

In simple mathematical models of infectious diseases, such as Susceptible-Infected-Removed (SIR) or SEIR models,  $R_0$  can be expressed as the product of three terms  $R_0 = c\beta\tau_I$  where  $\tau_I$  represents the duration of the infectious phase. This expression assumes that the contact rate  $c$  and the transmissibility  $\beta$  takes the same value for all the infectious compartments. This is the case for the SIR and SEIR models but it is not the case for our COVID-19 PBM. Our COVID-19 model considers more-infectious compartments with different contact mixing and transmissibility values and compartments that branch off from each other. We express  $R_0$  in terms of  $c_{eff}\beta_{eff}$  as

$$R_0 = c_{eff}\beta_{eff}\tau_{eff}, \quad (16)$$

where  $\tau_{eff}$  represents a typical time-scale that considers the diversity of both disease transmission and progression across the different disease states. It can be interpreted as the effective infectious period for an equivalent SEIR model with a single infectious compartment, with contact rate  $c_{eff}$  and the transmissibility  $\beta_{eff}$ . Consequently, in our model  $\tau_{eff}$  is not equal to the duration of the infectious period  $\tau_I$  because the former accounts for the changes in transmissibilities in each infectious compartment, namely the  $m$  multiplicative factors. The expression for  $\tau_{eff}$  is given at disease invasion and hence considers the case where testing rates  $\zeta_A(t)$  and  $\zeta_S(t)$  are zero. The next section, appendix 1.3, describes the next-generation method and gives the mathematical expression for  $\tau_{eff}$  at disease invasion in terms of the transmission and progression parameters. Hence, by knowing the input transmission and progression parameter values, we can compute the duration  $\tau_{eff}$ . By knowing the value of this duration and an estimated input value of  $R_0$  we can compute the value of  $c_{eff}\beta_{eff}$ .

To extract an estimate for the value of  $R_0$ , we use the number of reported cases during the epidemic's early stages. In the disease invasion phase, the growth in cases is exponential. Hence, the log of the case counts and the log of the death counts increase linearly with time. An estimate for the growth rate  $r$  is obtained by linear regression of the log of these counts with time. Mathematically,  $R_0$  is related to  $r$  by the following expression

$$R_0 = 1 + r(\tau_E + \tau_I), \quad (17)$$

where  $\tau_E + \tau_I$  represents the typical duration for which a person is infected and is the sum of the duration of the noninfectious incubation phase  $\tau_E$  and the duration of the infectious phase  $\tau_I$  [4]. The value of  $\tau_I$  depends on the disease progression times and, more specifically, on the dwelling or sojourn times of compartments representing infectious states.

### 1.3 The expression for $\tau_{eff}$

To find the expression for  $\tau_{eff}$ , we apply the next-generation method [6, 7] to the model described by the set of coupled ODEs given in Eqs 1-14. We first rearrange the order of our ODEs and focus only on the equations describing infection states. We then construct the matrices  $\mathbf{M}$  and  $\mathbf{V}$  respectively, describing the disease transmission and progression terms. The equations, together with the matrices, are shown on the next page. A representation of the Jacobian matrix  $\mathbf{J}^*$  of our system of ODEs taken at disease-free equilibrium point (i.e.,  $S = 1$ ) is given by

$$\mathbf{J}^* = \mathbf{M} \cdot [-\mathbf{V}]^{-1}. \quad (18)$$

The expression for  $R_0$  is found by finding the largest eigenvalue of  $\mathbf{J}^*$ . At the disease-free equilibrium point, and soon after, at disease-invasion, the hospital and ICU is not at capacity and there is no testing for COVID-19. Hence the expression for  $R_0$  is found by setting  $A_H = A_{ICU} = 1$  and  $\zeta_S = \zeta_A = 0$ . Using this simplification we find that

$$\tau_{eff} = \frac{a[\gamma_A bc + \xi_A(bc + m_{Sm}\gamma_S c + v m_{Ss}\gamma_S)] + \xi_A A_H h v m_h \gamma_S}{\xi_A(\gamma_A + \gamma_S) abc}, \quad (19)$$

where the coefficients  $a, b$  and  $c$  are given by

$$\begin{aligned} a &= (\mu_H + \xi_H), \\ b &= (\xi_m + v), \\ c &= (A_H h + \mu_H + \xi_S), \end{aligned}$$

and

$$R_0 = c_{eff} \beta_{eff} \tau_{eff}.$$

We can also find an expression for the effective reproductive number  $R_t$ . Generally  $R_t = R_0 S$ . However, we cannot use equation 19 for  $\tau_{eff}$  and to get  $R_t$  because it is only valid at disease invasion where we assumed no testing and full accessibility to the hospital and ICU. We can derive a complete expression for  $\tau_{eff}$  that considers testing rates and hospital accessibility using the next-generation method. Such expression is algebraically long and complicated, and we choose not to include it here. A Mathematica notebook providing the full expression is available upon request.



## 1.4 The Population Stratified Model

The population in our model can be partitioned into subpopulations. We consider multiple population groups or strata within each compartment. Each stratum specifies the population-based on common characteristics, such as demographic, social, economic, and pathological states. The specific strata we consider are described in section 2.1. The structure of the population stratified model is expressed as an array of ODEs, where the disease progression dynamics for each stratum are expressed by equations 1-14. The reformulation to a strata-dependent PBM extends the model from the more conventional version of a single-strata compartment model that assumes homogeneous mixing and implicit interactions within the population.

The modeled population is described by the proportion of people in each stratum. These proportions are given by the one-dimensional array  $\mathbf{v}$  where the element  $v_i$  represents the proportion of the population belonging to strata  $i$ . Since we are tracking population densities, the sum of all the elements of the  $\mathbf{v}$  is equal to one. We will refer to  $\mathbf{v}$  and other strata-specific one-dimensional arrays as vectors in the disease state space  $X$ . Therefore, each disease state is also expressed as a vector. For example, the vector  $\mathbf{P}(t)$  represents the presymptomatic state, and the element  $P_i$  represents the proportion of the presymptomatic population belonging to strata  $i$ .

Some parameter values and settings that enter the model differ across the strata. The heterogeneity introduced by the strata-dependent parameters plays a crucial role in the disease progression and transmission dynamics and is used to better characterize the epidemiology of COVID-19. Differences across strata include parameter values describing pathological transition rates, including the proportion of the infectious in each stratum that stay asymptomatic (i.e.,  $\gamma_A$  and  $\gamma_S$ ), the proportion of the symptomatic that develop severe symptoms and need hospitalization (i.e.,  $\nu$ ), and the fatality rates (i.e., the  $\mu$  parameter values). The flexibility of our model allows users to easily specify other parameters that depend on the strata. For example, protective behaviors such as willingness to get tested can be specified by stratum.

The strata-dependent parameters are also expressed as vectors and are used to specify the strata-specific transition rates between disease states. For example, the vector giving the strata-specific transition rates from state  $\mathbf{P}$  to state  $\mathbf{I}_A$  is expressed as  $\gamma_A \odot \mathbf{P}$ , where  $\odot$  denotes the element-wise multiplication. Equivalently, this can be expressed by matrix multiplication as  $\text{diag}(\gamma_A) \cdot \mathbf{P}$  where the operator  $\text{diag}$  represents vector diagonalization. By following this notation, the PBM's ODEs can be expressed in vector notation, remaining mathematically concise.

Heterogeneity in disease transmission is introduced by the strata-dependent mixing contact rates describing the variations in how people belonging to the different population strata mix with each other. This heterogeneity is described by a mixing matrix  $\mathbf{M}$ . The matrix element  $M_{ij}$  denotes the proportion of contacts of individuals in population strata (or row)  $i$  with those in population strata (or column)  $j$ . The sum across each row in the mixing matrix is a sum of proportions, and hence equals one (i.e.,  $\sum_j M_{ij} = 1$ ). In addition to the mixing matrix, we have a normalized contact vector  $\boldsymbol{\kappa}$ . The vector element  $\kappa_i$  denotes the proportion of all daily contacts (or duration of contacts) in the population made by individuals in stratum  $i$ , and hence, the sum of the vector elements is one (i.e.,  $\sum_i \kappa_i = 1$ ). The matrix multiplication of the diagonalized vector  $\boldsymbol{\kappa}$  with  $\mathbf{M}$  gives the contact matrix  $\mathbf{K}$ ,

expressed by

$$\mathbf{K} = \text{diag}(\boldsymbol{\kappa}) \cdot \mathbf{M} = \boldsymbol{\kappa} \odot \mathbf{M}. \quad (20)$$

The contact matrix  $\mathbf{K}$  is a symmetric matrix where the sum across the rows is equal to the vector  $\boldsymbol{\kappa}$ . For off-diagonal elements  $i$  and  $j$ , the sum  $K_{ij} + K_{ji}$  gives the proportion of all daily contacts between strata  $i$  and  $j$ . For diagonal elements, the same proportion is given by  $K_{ii}$ . Under the disease-free status-quo conditions everyone is susceptible. Hence  $\mathbf{v} = \mathbf{S}$ , and the overall daily effective contact rate is proportional to  $\mathbf{S}^T \cdot \mathbf{K} \cdot \mathbf{S}$ . During the disease transmission dynamics, we are instead interested in the contacts between the susceptible population  $\mathbf{S}$  and each of the infectious states  $\mathbf{X}_I$ . Hence the daily effective contact rate between susceptible and infectious people is proportional to  $\mathbf{S}^T \cdot \mathbf{K} \cdot \sum_{X_I} \mathbf{X}_I$ . We denote the coefficient of proportionality by  $k_\lambda$ . Taken together with transmissibility  $\beta_{eff}$  and the transmissibility multiplier  $m_{X_I}$ , we can express the force of infection vector for our strata dependent PBM as

$$\boldsymbol{\lambda}(t) = k_\lambda c_{eff} \beta_{eff} \mathbf{K} \cdot \sum_{X_I} m_{X_I} \mathbf{X}_I(t). \quad (21)$$

Equation 21 replaces equation 15 for our strata-specific PBM and the transition rate from  $S$  to  $E$  given in equation 1 is re-expressed as

$$\dot{\mathbf{S}}(t) = -\boldsymbol{\lambda}(t) \odot \mathbf{S}(t). \quad (22)$$

The coefficient of proportionality  $k_\lambda$  is related to the base-line total daily contact rates. We estimate  $k_\lambda$  at disease-invasion by calibration to the observed data and assume that it stays constant during the dynamics. Instead, changes in mixing rates due to social-distancing NPI and behavioral responses are accounted for by changes in the contact matrix  $\mathbf{K}$ .

## 1.5 Mixing Modes

People mix in different settings, or mixing modes. Modes have different levels of social interaction and different strata compositions. For instance, in schools mixing is primarily between children, whereas in commercial settings mixing occurs between all ages. Our PBM considers six different modes of social mixing: household, school, work, commerce, leisure, and other. Based on the data described in Section 2.1 we can create matrices describing the average daily contacts between each stratum in each mixing mode. We decompose these matrices into a set of row normalized mixing matrices  $\mathbf{M}_m$ , column normalized contact vectors  $\boldsymbol{\kappa}_m$ , and scalar mode weight  $w_m$  for each mixing mode labeled by the index  $m$ . The total contact matrix,  $\mathbf{K}$  is a weighted sum of the mode-specific contact matrices  $\mathbf{K}_m$ , and given by

$$\mathbf{K} = \sum_m w_m [\boldsymbol{\kappa}_m \odot \mathbf{M}_m] = \sum_m w_m \mathbf{K}_m, \quad (23)$$

The weights,  $w_m$  give the proportion of contacts (or duration of contacts) of how people mix over the different mixing modes. Under the disease-free status-quo conditions these weights sum to one, hence  $\sum_m w_m = 1$ .

## 1.6 Modeling Nonpharmaceutical interventions (NPIs)

When the initial outbreak becomes an epidemic, governments may choose to impose nonpharmaceutical interventions (NPIs) which limit how people can mix. The goal of NPIs is to delay and reduce the peak number of cases and hospitalizations per day by shifting individuals to locations where there are few unique contacts. Hence, we model the effects of NPIs by decreasing the weights associated with various mixing modes. For example, an NPI policy that closed schools, restaurants, and bars is modeled by reducing the weights associated with the school, commerce, and leisure mixing modes. Mixing matrices measure the number of unique contacts, not time spent in a mixing mode, therefore weights are not conserved. NPI interventions, such as confining people to their households, reduce the total number of unique contacts such that the mixing mode weights sum to less than one. To model the impact of reduced mixing from NPI level  $n$  on mode  $m$ , we define a diagonal matrix  $\Phi_m^{(n)}$ . The diagonal elements of  $\Phi_m^{(n)}$  specify the reduction in mixing for each stratum in mode  $m$  relative to the disease-free state. For interventions that apply to all strata (i.e. where each stratum changes their mixing by the same proportion), such as the closure of schools, all diagonal elements of  $\Phi_m^{(n)}$  have the same value. In cases where interventions apply to some strata and not others: such as when only front-line essential workers are expected to attend their workplaces, the diagonal elements of  $\Phi_m^{(n)}$  take on different values, each specifying the strata-mode specific impact of the NPI. Hence the expression for  $\mathbf{K}^{(n)}$  that accounts for the impact of NPIs is:

$$\mathbf{K}^{(n)} = \sum_m w_m \left\{ (\Phi_m^{(n)})^{\frac{1}{2}} \mathbf{K}_m (\Phi_m^{(n)})^{\frac{1}{2}} \right\}. \quad (24)$$

In the disease-free state, specified by NPI-level one (i.e.,  $n = 1$ ) the  $\Phi_m^{(1)}$  matrix is equal to the identity matrix where all diagonal elements are equal to one.

The matrix  $\Phi_m^{(n)}$  is square-rooted and then multiplied on either side of the contact matrix  $\mathbf{K}_m$  so that the contact matrix is symmetric. The matrix  $\Phi_m^{(n)}$  represents multiplicative factors that reduce the strength of the interactions along the network edges. It is obtained by the individual-level reductions specified on the network vertices. Two vertices bound each edge, and hence the overall edge-level reduction of the interactions is given by multiplying the two vertex-level reductions. These reductions are represented by the term  $(\Phi_m^{(n)})^{\frac{1}{2}}$  in mixing on either side of the strength of the edge, and given by the matrix  $\mathbf{K}_m$ .

We allow the effectiveness of NPIs to vary by state. The effectiveness of the NPIs,  $\theta$ , is defined through a calibration process. We narrow the ranges used as priors in the calibration process by exploring a wide range of parameter combinations using a Latin Hypercube Sample and by observing that values outside those ranges consistently produced biased death results. The calibrated contact matrix  $\mathbf{K}_c^{(n)}$  is:

$$\mathbf{K}_c^{(n)} = \frac{\mathbf{K}^{(1)}}{\theta \left( \frac{\mathbf{K}^{(1)}}{\mathbf{K}^{(n)}} - 1 \right) + 1} \quad (25)$$

When  $\theta = 1$ ,  $\mathbf{K}_c^{(n)} = \mathbf{K}^{(n)}$ . For other values,  $\theta$  approximately geometrically scales the distance between  $\mathbf{K}^{(n)}$  and zero mixing, while leaving  $\mathbf{K}_c^{(1)} = \mathbf{K}^{(1)}$  for any  $\theta$ . For instance, a value of  $\theta = 2$

yields a  $\mathbf{K}_c^{(n)}$  approximately half the size of  $\mathbf{K}^{(n)}$  for  $n \neq 1$ . This functional form allows us to account for the physical and cultural differences between states which may yield different NPI effectiveness and compliance levels.

After the initial wave of lockdowns in March and April 2020, many states slackened restrictions. However many behaviors to reduce transmission, including mask-wearing, aversion to crowded spaces, and other adaptation measures remained after the lockdowns were lifted. To account for this we compute the final contact matrix  $\mathbf{K}_f^{(n)}$  as a weighted average of the contact matrix under the highest NPI  $\mathbf{K}_c^{(h)}$  and the current NPI  $\mathbf{K}_c^{(n)}$ :

$$\mathbf{K}_f^{(n)} = b_h \mathbf{K}_c^{(h)} + (1 - b_h) \mathbf{K}_c^{(n)}. \quad (26)$$

The relative weight  $b_h$  of the highest NPI matrix is calibrated through the same process as the NPI effectiveness parameter. Finally, to prevent NPIs from changing instantaneously in the model and causing discontinuities inappropriate for an ODE, we make the NPI level  $n_c$  a continuous stock variable with rate  $\dot{n}_c = (n^* - n)/l$ , where  $n^*$  is a target NPI level and  $l$  determines how fast the NPI level can be changed. Therefore, the mixing matrix we use is a weighted average between the ceiling NPI level mixing matrix  $\mathbf{K}_f^{\lceil n_c \rceil}$  and the floor NPI level  $\mathbf{K}_f^{\lfloor n_c \rfloor}$  weighted by the distance between  $n_c$  and its ceiling.

## 2 Informing the model

### 2.1 Mixing Matrices and Population Strata

We model mixing in the population using mixing matrices. A mixing matrix describes the amount of contact that occurs between each of the population strata. We consider six different mixing locations: household, work, school, commercial, recreational, and other. We use two sources for mixing matrices within the baseline scenario. The first source is a mixing matrix based on the locations of a synthetic population in the city of Portland, Oregon provided by the Network Dynamics and Simulation Science Laboratory (NDSSL) at Virginia Polytechnic Institute and State University [8]. The second data source is based on self-reported survey data from eight European countries [9]. These results were then extrapolated to create mixing matrices for 152 countries, including the United States [10]. We use the US matrix as our second data source.

States typically apply NPI and vaccination policies to specific groups. To ensure that we could represent state policies, we transformed these averaged matrices to represent the nine non-aggregated strata shown in table 2. Creating different matrices for each state would be time-consuming and unnecessary for the analyses we aim to perform with the model. Instead, we created a single set of matrices using the US populations, though the size of each stratum is allowed to vary by state. The averaged matrices contain strata by age group and chronic condition. We aggregated these strata into three age groups (age  $\leq 17$ ,  $18 \leq \text{age} \leq 64$ , age  $\geq 65$ ). To create ‘employed’ and ‘not employed’ strata we split mixing in the ‘working age  $18 \leq \text{age} \leq 64$ ’ strata. In every mixing mode except work, we split working-age mixing in proportion to the population who were employed or not employed. This is equivalent to assuming that average levels of mixing in the household, school, commercial,

recreational, and other settings are the same for employed and unemployed individuals. Work mode mixing was assigned entirely to the employed strata. Based on BLS data [11] approximately 10% of workers are younger than 20 or older than 65, these workers and their work mixing was aggregated into their respective age groups.

We further split the employed strata into Front-line essential workers (FLEW) and other workers. All mixing was split in proportion to population, equivalent to assuming that FLEW and other workers have similar mixing patterns. We assumed that FLEW would only mix with other FLEW at work and, similarly, that non-FLEW workers would only mix with other non-FLEW workers. This was based on the Cybersecurity & Infrastructure Security Agency (CISA) guidance which indicates that most essential industries are composed entirely of essential workers [12]. We assumed that those workers with chronic high-risk conditions have mixing behaviors identical to their colleagues without high-risk conditions.

| <b>Non-aggregated Strata</b>                         | <b>US Unique Population (millions)</b> | <b>Aggregated Strata</b>              |
|--|--|---------------------------------------|
| Young  | 73.4                                   | Young                                 |
| FLEW without high-risk conditions                    | 36.0                                   | FLEW                                  |
| Employed, but not FLEW, without high-risk conditions | 60.0                                   | Working age                           |
| Not employed without high-risk conditions            | 33.2                                   | Working age                           |
| Old without high-risk conditions                     | 11.8                                   | Old                                   |
| FLEW with high-risk conditions                       | 14.1                                   | FLEW                                  |
| Employed, but not FLEW, with high-risk conditions    | 37.6                                   | Working age with high-risk conditions |
| Not employed with high-risk conditions               | 20.8                                   | Working age with high-risk conditions |
| Old with high-risk conditions                        | 37.6                                   | Old                                   |

Table 2: Model strata and corresponding populations

## 2.2 Model parameters

Parameters indicate how people move between states in the model. These include disease progression rates, the proportion of individuals who enter more severe disease states, and the relative infectivity of each stage.

Parameter estimates were selected from a review of the literature and with the input of RAND experts. To carry out sensitivity analyses of the parameters and to calibrate the model, we constructed a large set of independent case runs, each with a different and unique combination of model parameter

values. Parameter values for the case runs are sampled using a Latin-Hypercube approach [13, 14]. We use either a uniform or a beta-PERT (Program Evaluation and Review Technique) distribution to sample the model parameter value, as specified within a sensitivity analysis range [15]. In the latter case, the reference value is used to specify the mode of the beta distribution used for our parameter value sampling. The model formulas shown are based on the parameters in Figures 1, 2, and 3. Summaries of parameter estimates, sources, and sensitivity are shown in Tables 3, 4, 5 and 6

### 2.2.1 Duration parameters

Duration parameter estimates are shown in Table 3 and specify how fast individuals advance through the disease phases.

| Parameter   | Mode | Sample Range | Sample Dist | Formula  | Sources         |
|---|------|--------------|-------------|--|-----------------|
| Duration in days of incubation phase  | 5    | 4 - 6        | PERT        | $\frac{1}{v} + \frac{1}{\gamma_A + \gamma_S}$  | [16–19]         |
| Proportion of incubation phase which is non-infectious  | 60%  | 50 - 70%     | PERT        | $\frac{\gamma_A + \gamma_S}{\gamma_A + \gamma_S + v}$  | [17, 20]        |
| Infectious duration in days of asymptomatic and mild disease  | 5    | 4 - 7        | PERT        | $\frac{1}{\xi_A}$  | [17–19, 21, 22] |
| Expected days spent in hospital (including ICU) at hospitalization  | 8    | 6 - 10       | PERT        | $\frac{1}{\xi_H + \mu_H + A_{ICU}\chi} \times \left(1 + \frac{\chi}{\xi_{ICU} + \mu_{ICU}}\right)$ | [19, 23]        |
| Expected days spent in the ICU at ICU admission as a proportion of expected days spent in the hospital at hospitalization | 90%  | 80 - 100%    | PERT        | $\frac{\xi_H + \mu_H + A_{ICU}\chi}{\xi_{ICU} + \mu_{ICU} + \chi}$                                 | [19, 23]        |
| Months before loss of natural immunity  | 20   | 10 - 40%     | PERT        | $\rho$   | [24]            |

Table 3: Disease duration parameter estimates

Estimates are for the mean duration of the phase length, rather than for any individual’s phase lengths. The incubation phase, or pre-symptomatic phase, is the time from exposure to the virus to the appearance of the first symptoms. We assume that immediately after exposure individuals are not infectious, but that they become infectious before exhibiting symptoms. Some research suggests that the pre-symptomatic phase is the most infectious period [25], we explore this more in Section 2.2.3. We assume that the infectious periods are the same length for those with mild disease or who are asymptomatic [25]. As shown in Figure 3 all individuals who develop severe disease must first pass

through the mild disease phase. The mean duration of mild disease is similar to the mean delay between symptom onset and hospitalization [17–19, 21–23], so we assume that individuals are admitted almost immediately to the hospital after entering the severe compartment of the model.

We describe hospital and ICU stays through two parameters. The first includes the expected time spent in the hospital at hospitalization, which includes some expectation of ICU admission. The second parameter is the expected time spent in the ICU at ICU admission as a fraction of the first parameter. For COVID-19 a significant proportion do not enter the ICU and ICU stays are long [23, 26], so the second parameter is a large fraction of the first. The parameters are constructed in this manner so that the length of ICU and hospital stays are not independently sampled.

### 2.2.2 Prognosis parameters

Prognosis parameter estimates are shown in Table 4 and specify what fraction of individuals enter different phases, such as whether individuals with mild disease recover or develop severe disease.

| Parameter   | Mode | Sample Range | Sample Dist | Formula                                   | Sources           |
|---|------|--------------|-------------|---|-------------------|
| Proportion of infections which are asymptomatic                                 | 25%  | 15 - 50%     | PERT        | $\frac{\gamma_A}{\gamma_A + \gamma_S}$    | [19, 27–29]       |
| Proportion of symptomatic infections which are severe (require hospitalization) | 5%   | 3 - 7%       | Uniform     | $\frac{v}{v + \xi_m + \mu_S}$             | See Section 2.2.2 |
| Proportion of severe cases which are critical (require ICU admission)           | 32%  | 26 - 38%     | PERT        | $\frac{\chi}{\chi + \xi_H + \mu_H}$       | [19, 26]          |
| Initial proportion of critical cases which result in death                      | 75%  | 70 - 80%     | PERT        | $\frac{\mu_{ICU}}{\xi_{ICU} + \mu_{ICU}}$ | [26, 30, 31]      |
| Reduction in ICU death proportion as treatment improves                         | 50%  | 40 - 60%     | PERT        | N/A                                       | [30]              |
| Time period over which treatment improves (months)                              | 6    | 4.8 - 7.2    | PERT        | N/A                                       | [30]              |

Table 4: Disease prognosis parameter estimates

We define severe disease as requiring hospitalization and critical disease as requiring ICU admission. The proportion of asymptomatic individuals used in this model is substantially lower than early estimates. Recent systematic reviews have found that many early studies overestimated the fraction of symptomatic individuals because they applied restrictive criteria for symptoms or did not observe participants for long enough to determine if they were asymptomatic or presymptomatic [27–29].

The proportion of symptomatic infections which result in hospitalization has not been reliably estimated in the literature. Available estimates find high rates (19%) but are likely biased due to selection effects which undersample mild cases [32]. Merely looking at the ratio of cumulative hospitalizations to cumulative positive tests in US (among states who report both metrics) as of February 2020 [33]

shows a symptomatic hospitalization rate of around 6% (accounting for the proportion symptomatic shown in Table 3). The real figure is likely significantly lower than this number because we observe a higher fraction of hospitalizations due to COVID-19 than we do COVID-19 infections.

### 2.2.3 Relative Infectivity parameters

The relative infectivity, the daily expected infections of susceptible, varies by disease state. We conceptualize infectivity as having two components: contact mixing, how likely people are to mix with others, and biological transmissibility, the probability of transmission between an infectious and a susceptible person given a contact. The infectivity is the product of these components. We define infectivities relative to the asymptomatic state.

To calculate biological transmissibility we rely on viral load data and estimates of the number of infections in the presymptomatic period. We use viral load data from individuals who tested positive [25], assuming that the average test occurs 3 days after initial exposure [19]. Based on relationships between biological transmissibility observed in other infectious diseases, we assume that the functional form for the relative biological transmissibility,  $\beta_{1,2}$  between the viral load in two states,  $VL_1$  and  $VL_2$  is:

$$\beta_{1,2} = \delta^{Log_{10}\left(\frac{VL_2}{VL_1}\right)}, \quad (27)$$

where  $\delta$  is a calibration parameter. Several studies have estimated that the fraction of infections caused during the presymptomatic period is approximately 45% [34, 35]. We choose  $\delta = 1.92$  such that 45% of infections are caused in the presymptomatic phase once contact mixing is accounted for. We also assume that those who are asymptomatic have biological transmissibility only 75% of those who have mild symptoms based on estimates by the CDC [22].

Contact mixing changes by disease phase because individuals may be incapacitated COVID-19 or may voluntarily reduce their mixing to avoid infecting others. We assume that those who are presymptomatic or asymptomatic do not modify their mixing relative to those who have not yet been exposed to the virus. Those with mild symptoms reduce mixing by 40%, those who are tested positive by 80%, those who are severe (but not yet hospitalized) by 90%, and those who are hospitalized by 95%. The reduction for those who are hospitalized is larger than for those who are waiting for hospitalization because hospital staff is expected to have better protective equipment than home carers. The infectivities relative to the asymptomatic phase are shown in Table 5.

### 2.2.4 Other parameters

We randomly sample several other parameters from distributions. These are shown in Table 6 and pertain to testing rates, and the effectiveness of NPIs within that state. See Section 1.6 for more details.

In our most recent model runs, we do not assume constraints on the availability tests. Hence we assume constant rates for  $\zeta$ ,  $\zeta_S$ , and  $\zeta_A$ . During December 2020 and January 2021, the total daily rate of tests in the US ranged between 1.5 and 2 million tests a day, and the positive rate was 10%. We assume the infectious duration of the mild disease is between 4 and 7 days, and between 33% and 66% of the mildly symptomatic infected individuals seek to get tested during this time. Using these numbers,

| Infectivity of phase relative to asymptomatic phase | Mode | Sample Range | Sample Dist | Sources          |
|---|------|--------------|-------------|------------------|
| Pre-symptomatic infectious                          | 2.07 | 1.65 - 2.48  | PERT        | [19, 25, 34, 36] |
| Mild symptomatic                                    | 0.83 | 0.66 - 1.00  | PERT        | [19, 25, 34, 36] |
| Severe symptomatic                                  | 0.14 | 0.11 - 0.17  | PERT        | [19, 25, 34, 36] |
| Hospitalized  | 0.07 | 0.06 - 0.08  | PERT        | [19, 25, 34, 36] |
| Tested mild symptomatic                             | 0.28 | 0.22 - 0.33  | PERT        | [19, 25, 34, 36] |
| Tested severe symptomatic                           | 0.14 | 0.11 - 0.17  | PERT        | [19, 25, 34, 36] |
| Tested asymptomatic                                 | 0.20 | 0.16 - 0.24  | PERT        | [19, 25, 34, 36] |

Table 5: Relative infectivity parameter estimates

we estimate that the per-person detection rate of the mildly symptomatic  $\zeta_S$  ranges between 0.06 to 0.13 per day. Using the 10% positive rate and the infectious duration of asymptomatic disease ranging between 4 and 7 days, we estimate that the per-person detection rate of the asymptomatic  $\zeta_A$  ranges between 0.01 and 0.012 per day.

| Parameter  | Mode  | Sample Range  | Sample Dist | Formula        |
|--|-------|---------------|-------------|----------------|
| Per person daily detection rate for those not yet exposed      | 0.002 | 0.001 - 0.004 | PERT        | $\zeta$        |
| Per person daily detection rate for those who are asymptomatic | 0.01  | 0.005 - 0.04  | PERT        | $\zeta_A$      |
| Per person daily detection rate for those who are symptomatic  | 0.2   | 0.1 - 0.8     | PERT        | $\zeta_S$      |
| Increased progression rate for tested individuals              | 2     | 1.33 - 4      | PERT        | $\kappa_\zeta$ |
| Effectiveness of NPIs  | 2     | 0.5 - 3.5     | PERT        | $\theta$       |

Table 6: Other parameter estimates

### 2.2.5 Strata-specific parameters

Some parameters vary by strata. For instance, it's well known that young children have significantly decreased COVID-19 mortality relative to elderly populations [37]. We allow the proportion of asymptomatic cases, severe disease (hospitalization) probability, and mortality to vary by age and mortality to vary by chronic condition. We generate these parameters by first establishing age-based infection fatality rates (IFRs) from the literature [37] and incorporating IFR multipliers for cormorbidities by age [38]. We also use clinical fraction (symptomatic proportion) estimates by age to estimate the relative

probability of being asymptomatic by strata [39]. Finally, we rely on hospital occupancy data to determine the probability of hospitalization [40]. This is imperfect, because we are implicitly assuming that disease exposure was the same for each age group. However, we could find no estimates of hospitalization probability given infection by age. Given the overall IFR, the probability of being symptomatic, and the probability of being hospitalized given symptoms, we then calculate the probability of death given hospitalization.

Table 7 shows the multipliers used for each strata, relative to the population weighted average. These multipliers are fixed, but are used in conjunction with the randomly varying mortality, asymptomatic, and severe disease probabilities in Table 4

| <b>Strata</b>                            | <b>Asymptomatic</b> | <b>Severe Disease Given Symptoms</b> | <b>Mortality Given Severe Disease</b> |
|--|---------------------|--------------------------------------|---------------------------------------|
| Young                                    | 1.285               | 0.078                                | 0.063                                 |
| FLEW                                     | 1.029               | 0.931                                | 0.234                                 |
| Working age without high-risk conditions | 1.029               | 0.931                                | 0.023                                 |
| Working age with high-risk conditions    | 1.029               | 0.931                                | 0.839                                 |
| Old                                      | 0.525               | 1.598                                | 1.862                                 |

Table 7: Strata-specific parameter multipliers

## References

- [1] Romulus Breban, Raffaele Vardavas, and Sally Blower. Linking population-level models with growing networks: A class of epidemic models. *Physical Review E*, 72(4):046110, October 2005. doi: 10.1103/PhysRevE.72.046110.
- [2] Romulus Breban, Raffaele Vardavas, and Sally Blower. Theory versus data: How to calculate  $R_0$ ? *PloS One*, 2(3):e282, March 2007. ISSN 1932-6203. doi: 10.1371/journal.pone.0000282.
- [3] O. Diekmann, J. A. P. Heesterbeek, and J. A. J. Metz. On the definition and the computation of the basic reproduction ratio  $R_0$  in models for infectious diseases in heterogeneous populations. *Journal of Mathematical Biology*, 28(4):365–382, June 1990. ISSN 1432-1416. doi: 10.1007/BF00178324.
- [4] J.m Heffernan, R.j Smith, and L.m Wahl. Perspectives on the basic reproductive ratio. *Journal of The Royal Society Interface*, 2(4):281–293, September 2005. doi: 10.1098/rsif.2005.0042.
- [5] Jing Li, Daniel Blakeley, and Robert J. Smith? The Failure of  $R_0$ . *Computational and Mathematical Methods in Medicine*, 2011, 2011. ISSN 1748-670X. doi: 10.1155/2011/527610.
- [6] P. van den Driessche and James Watmough. Reproduction numbers and sub-threshold endemic equilibria for compartmental models of disease transmission. *Mathematical Biosciences*, 180(1): 29–48, November 2002. ISSN 0025-5564. doi: 10.1016/S0025-5564(02)00108-6.
- [7] An introduction to compartmental modeling for the budding infectious disease modeler: Letters in Biomathematics: Vol 5, No 1. <https://www.tandfonline.com/doi/full/10.1080/23737867.2018.1509026>.
- [8] M. V. Marathe. Synthetic Data Products for Societal Infrastructures and Proto-Populations: Data Set 2.0. Technical Report NDSL-TR-07-003, Network Dynamics and Simulation Science Laboratory, Virginia Polytechnic Institute and State University, 1880 Pratt Dr, Building XV, Blacksburg, VA, 24061, 2014.
- [9] Joël Mossong, Niel Hens, Mark Jit, Philippe Beutels, Kari Auranen, Rafael Mikolajczyk, Marco Massari, Stefania Salmaso, Gianpaolo Scalia Tomba, Jacco Wallinga, Janneke Heijne, Malgorzata Sadkowska-Todys, Magdalena Rosinska, and W. John Edmunds. Social Contacts and Mixing Patterns Relevant to the Spread of Infectious Diseases. *PLOS Medicine*, 5(3):e74, March 2008. ISSN 1549-1676. doi: 10.1371/journal.pmed.0050074.
- [10] Kiesha Prem, Alex R. Cook, and Mark Jit. Projecting social contact matrices in 152 countries using contact surveys and demographic data. *PLOS Computational Biology*, 13(9):e1005697, September 2017. ISSN 1553-7358. doi: 10.1371/journal.pcbi.1005697.
- [11] BLS. Employed persons by detailed occupation and age. Technical report, Bureau of Labor Statistics, 2020.

- [12] CISA. Guidance on the Essential Critical Infrastructure Workforce. <https://www.cisa.gov/publication/guidance-essential-critical-infrastructure-workforce>, December 2020.
- [13] C. J. Sallaberry, J. C. Helton, and S. C. Hora. Extension of Latin hypercube samples with correlated variables. *Reliability Engineering & System Safety*, 93(7):1047–1059, July 2008. ISSN 0951-8320. doi: 10.1016/j.ress.2007.04.005.
- [14] Alexander Hoare, David G. Regan, and David P. Wilson. Sampling and sensitivity analyses tools (SaSAT) for computational modelling. *Theoretical Biology and Medical Modelling*, 5(1):4, February 2008. ISSN 1742-4682. doi: 10.1186/1742-4682-5-4.
- [15] W. Cottrell. Simplified Program Evaluation and Review Technique (PERT). *Journal of Construction Engineering and Management*, 125(1):16–22, 1999. doi: 10.1061/(ASCE)0733-9364(1999)125:1(16).
- [16] Wei-jie Guan, Zheng-yi Ni, Yu Hu, Wen-hua Liang, Chun-quan Ou, Jian-xing He, Lei Liu, Hong Shan, Chun-liang Lei, David S.C. Hui, Bin Du, Lan-juan Li, Guang Zeng, Kwok-Yung Yuen, Ru-chong Chen, Chun-li Tang, Tao Wang, Ping-yan Chen, Jie Xiang, Shi-yue Li, Jin-lin Wang, Zi-jing Liang, Yi-xiang Peng, Li Wei, Yong Liu, Ya-hua Hu, Peng Peng, Jian-ming Wang, Ji-yang Liu, Zhong Chen, Gang Li, Zhi-jian Zheng, Shao-qin Qiu, Jie Luo, Chang-jiang Ye, Shao-yong Zhu, and Nanshan Zhong. Clinical Characteristics of Coronavirus Disease 2019 in China. *New England Journal of Medicine*, 382(18):1708–1720, April 2020. ISSN 0028-4793. doi: 10.1056/NEJMoa2002032.
- [17] Chanu Rhee, Sanjat Kanjilal, Meghan Baker, and Michael Klompas. Duration of SARS-CoV-2 Infectivity: When is it Safe to Discontinue Isolation? *Clinical Infectious Diseases: An Official Publication of the Infectious Diseases Society of America*, August 2020. ISSN 1058-4838. doi: 10.1093/cid/ciaa1249.
- [18] Andrew William Byrne, David McEvoy, Aine B Collins, Kevin Hunt, Miriam Casey, Ann Barber, Francis Butler, John Griffin, Elizabeth A Lane, Conor McAloon, Kirsty O’Brien, Patrick Wall, Kieran A Walsh, and Simon J More. Inferred duration of infectious period of SARS-CoV-2: Rapid scoping review and analysis of available evidence for asymptomatic and symptomatic COVID-19 cases. *BMJ Open*, 10(8), August 2020. ISSN 2044-6055. doi: 10.1136/bmjopen-2020-039856.
- [19] CDC. COVID-19 Pandemic Planning Scenarios. <https://www.cdc.gov/coronavirus/2019-ncov/hcp/duration-isolation.html>, February 2020.
- [20] Lirong Zou, Feng Ruan, Mingxing Huang, Lijun Liang, Huitao Huang, Zhongsi Hong, Jianxiang Yu, Min Kang, Yingchao Song, Jinyu Xia, Qianfang Guo, Tie Song, Jianfeng He, Hui-Ling Yen, Malik Peiris, and Jie Wu. SARS-CoV-2 Viral Load in Upper Respiratory Specimens of Infected Patients. *New England Journal of Medicine*, 382(12):1177–1179, March 2020. ISSN 0028-4793. doi: 10.1056/NEJMc2001737.

- [21] Min-Chul Kim, Chunguang Cui, Kyeong-Ryeol Shin, Joon-Yong Bae, Oh-Joo Kweon, Mi-Kyung Lee, Seong-Ho Choi, Sun-Young Jung, Man-Seong Park, and Jin-Won Chung. Duration of Culturable SARS-CoV-2 in Hospitalized Patients with Covid-19. *New England Journal of Medicine*, 0(0): null, January 2021. ISSN 0028-4793. doi: 10.1056/NEJMc2027040.
- [22] CDC. Coronavirus Disease 2019 (COVID-19). <https://www.cdc.gov/coronavirus/2019-ncov/hcp/planning-scenarios.html>, February 2020.
- [23] Christel Faes, Steven Abrams, Dominique Van Beckhoven, Geert Meyfroidt, Erika Vlieghe, and Niel Hens. Time between Symptom Onset, Hospitalisation and Recovery or Death: Statistical Analysis of Belgian COVID-19 Patients. *International Journal of Environmental Research and Public Health*, 17(20), October 2020. ISSN 1661-7827. doi: 10.3390/ijerph17207560.
- [24] Jennie S. Lavine, Ottar N. Bjornstad, and Rustom Antia. Immunological characteristics govern the transition of COVID-19 to endemicity. *Science (New York, N.Y.)*, January 2021. ISSN 1095-9203. doi: 10.1126/science.abe6522.
- [25] Ashish Goyal, E. Fabian Cardozo-Ojeda, and Joshua T. Schiffer. Potency and timing of antiviral therapy as determinants of duration of SARS CoV-2 shedding and intensity of inflammatory response. *medRxiv*, page 2020.04.10.20061325, April 2020. doi: 10.1101/2020.04.10.20061325.
- [26] Semagn Mekonnen Abate, Siraj Ahmed Ali, Bahiru Mantfardo, and Bivash Basu. Rate of Intensive Care Unit admission and outcomes among patients with coronavirus: A systematic review and Meta-analysis. *PLOS ONE*, 15(7):e0235653, July 2020. ISSN 1932-6203. doi: 10.1371/journal.pone.0235653.
- [27] Eric A. Meyerowitz, Aaron Richterman, Isaac I. Bogoch, Nicola Low, and Muge Cevik. Towards an accurate and systematic characterisation of persistently asymptomatic infection with SARS-CoV-2. *The Lancet Infectious Diseases*, 0(0), December 2020. ISSN 1473-3099, 1474-4457. doi: 10.1016/S1473-3099(20)30837-9.
- [28] Oyungerel Byambasuren, Magnolia Cardona, Katy Bell, Justin Clark, Mary-Louise McLaws, and Paul Glasziou. Estimating the extent of asymptomatic COVID-19 and its potential for community transmission: Systematic review and meta-analysis. *Official Journal of the Association of Medical Microbiology and Infectious Disease Canada*, 5(4):223–234, December 2020. ISSN 2371-0888. doi: 10.3138/jammi-2020-0030.
- [29] Diana Buitrago-Garcia, Dianne Egli-Gany, Michel J. Counotte, Stefanie Hossmann, Hira Imeri, Aziz Mert Ipekci, Georgia Salanti, and Nicola Low. Occurrence and transmission potential of asymptomatic and presymptomatic SARS-CoV-2 infections: A living systematic review and meta-analysis. *PLoS medicine*, 17(9):e1003346, September 2020. ISSN 1549-1676. doi: 10.1371/journal.pmed.1003346.

- [30] Leora I. Horwitz, Simon A. Jones, Robert J. Cerfolio, Fritz Francois, Joseph Greco, Bret Rudy, and Christopher M. Petrilli. Trends in COVID-19 Risk-Adjusted Mortality Rates. *Journal of Hospital Medicine*, 16(2):90–92, February 2021. ISSN 1553-5606. doi: 10.12788/jhm.3552.
- [31] R. A. Armstrong, A. D. Kane, and T. M. Cook. Outcomes from intensive care in patients with COVID-19: A systematic review and meta-analysis of observational studies. *Anaesthesia*, 75(10): 1340–1349, October 2020. ISSN 1365-2044. doi: 10.1111/anae.15201.
- [32] Stephanie Bialek, Ellen Boundy, Virginia Bowen, Nancy Chow, Amanda Cohn, Nicole Dowling, Sascha Ellington, Ryan Gierke, Aron Hall, Jessica MacNeil, Priti Patel, Georgina Peacock, Tamara Pilishvili, Hilda Razzaghi, Nia Reed, Matthew Ritchey, and Erin Sauber-Schatz. Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020. *Morbidity and Mortality Weekly Report*, 69(12):343–346, March 2020. ISSN 0149-2195. doi: 10.15585/mmwr.mm6912e2.
- [33] The COVID Tracking Project. <https://covidtracking.com/>, access date: 2020-07-01.
- [34] Xi He, Eric H. Y. Lau, Peng Wu, Xilong Deng, Jian Wang, Xinxin Hao, Yiu Chung Lau, Jessica Y. Wong, Yujuan Guan, Xinghua Tan, Xiaoneng Mo, Yanqing Chen, Baolin Liao, Weilie Chen, Fengyu Hu, Qing Zhang, Mingqiu Zhong, Yanrong Wu, Lingzhai Zhao, Fuchun Zhang, Benjamin J. Cowling, Fang Li, and Gabriel M. Leung. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nature Medicine*, 26(5):672–675, May 2020. ISSN 1546-170X. doi: 10.1038/s41591-020-0869-5.
- [35] Miriam Casey, John Griffin, Conor G. McAloon, Andrew W. Byrne, Jamie M. Madden, David Mc Evoy, Áine B. Collins, Kevin Hunt, Ann Barber, Francis Butler, Elizabeth A. Lane, Kirsty O’Brien, Patrick Wall, Kieran A. Walsh, and Simon J. More. Pre-symptomatic transmission of SARS-CoV-2 infection: A secondary analysis using published data. *medRxiv*, page 2020.05.08.20094870, June 2020. doi: 10.1101/2020.05.08.20094870.
- [36] T. C. Quinn, M. J. Wawer, N. Sewankambo, D. Serwadda, C. Li, F. Wabwire-Mangen, M. O. Meehan, T. Lutalo, and R. H. Gray. Viral load and heterosexual transmission of human immunodeficiency virus type 1. Rakai Project Study Group. *The New England Journal of Medicine*, 342(13):921–929, March 2000. ISSN 0028-4793. doi: 10.1056/NEJM200003303421303.
- [37] Megan O’Driscoll, Gabriel Ribeiro Dos Santos, Lin Wang, Derek A. T. Cummings, Andrew S. Azman, Juliette Paireau, Arnaud Fontanet, Simon Cauchemez, and Henrik Salje. Age-specific mortality and immunity patterns of SARS-CoV-2. *Nature*, (7844):1–6, November 2020. ISSN 1476-4687. doi: 10.1038/s41586-020-2918-0.
- [38] Selene Ghisolfi, Ingvild Ingvild Almas, Justin Sandefur, Tillman von Carnap, Jesse Heitner, and Tessa Bold. Predicted COVID-19 fatality rates based on age, sex, comorbidities, and health system capacity. *medRxiv*, page 2020.06.05.20123489, June 2020. doi: 10.1101/2020.06.05.20123489.

- [39] Nicholas G. Davies, Petra Klepac, Yang Liu, Kiesha Prem, Mark Jit, and Rosalind M. Eggo. Age-dependent effects in the transmission and control of COVID-19 epidemics. *Nature Medicine*, 26 (8):1205–1211, August 2020. ISSN 1546-170X. doi: 10.1038/s41591-020-0962-9.
- [40] CDC. COVID-19 Hospitalization and Death by Age. <https://www.cdc.gov/coronavirus/2019-ncov/covid-data/investigations-discovery/hospitalization-death-by-age.html>, February 2020.

# **Reforming the Teaching and Conducting of Policy Studies to Deal Better with Complex Systems**

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## ABSTRACT

The teaching and conduct of policy analysis needs updating to account better for the special challenges of social problems occurring in complex adaptive systems. Drawing on topics central to this journal, we suggest changes relating to (1) worldview when conceiving and posing problems, (2) the basis for reasoning and inference within a worldview, (3) analytic style for conducting inquiry (e.g., addressing uncertainty and comparing options), (4) the character of the models used, and (5) the questions asked of the models.

**Keywords:** complex systems, computational social science, decision analysis, decision support, deep uncertainty, exploratory analysis, policy analysis, policy modeling, robust decision making, system thinking, worldview in modeling and analysis.

## Reforma de la enseñanza y realización de estudios de políticas para lidiar mejor con sistemas complejos

### RESUMEN

La enseñanza y realización del análisis de políticas debe actualizarse para tener en cuenta mejor los desafíos especiales de los problemas sociales que ocurren en los sistemas adaptativos complejos. Basándonos en temas centrales de esta revista, sugerimos cambios relacionados con (1) la cosmovisión al concebir y plantear problemas, (2) la base para el razonamiento y la inferencia dentro de una cosmovisión, (3) el estilo analítico para realizar indagaciones (por ejemplo, abordar la incertidumbre y comparando opciones), (4) el carácter de los modelos utilizados y (5) las preguntas formuladas a los modelos.

**Palabras clave:** sistemas complejos, ciencias sociales computacionales, análisis de decisiones, soporte de decisiones, incertidumbre profunda, análisis exploratorio, análisis de políticas, modelado de políticas, toma de decisiones sólida, pensamiento sistémico, cosmovisión en modelado y análisis

## 对政策研究的教学和实施加以改革—更好地应对复杂系统

### 摘要

政策分析的教学和实施需要改革，以期更好地解释复杂适应系统中社会问题所带来的特殊挑战。基于本刊的核心主题，我们建议在以下方面进行变革：（1）与构想问题和提出问题相关的世界观，（2）世界观下推理和推断的基础，（3）进行调查（例如应对不确定性和比较选项）时的分析方式，（4）所使用模型的特征，以及（5）对模型提出的问题。

关键词：复杂系统，计算社会科学，决策分析，决策支持，深度不确定性，探索性分析，政策分析，政策建模，稳健决策，系统思考，建模和分析中的世界观

## 1. Introduction

### 1.1 Purpose

Thirty years after awareness of complex adaptive systems (CAS) burgeoned as the result of work at the Santa Fe Institute, the realm of policy studies has not yet assimilated adequately the new insights. We are rethinking such matters at our graduate school, which is transforming its approach to teaching PhD students of policy analysis. This paper presents complexity-related items on which changes in teaching, practice, and scholarly writing seem important. Tried-and-true methods and mindsets will remain apt in many cases, but we focus on where we believe that change is warranted.

In what follows we define our terms for discussing CAS. In Sections 2-5 we then consider issues relating to (1) world view when conceiving and posing problems, (2) the basis for reasoning and inference within a world view (e.g., the relative role of theory and data), (3) analytic style for conducting inquiry (e.g., treatment of uncertainty and the way in which options are compared), (4) the character of the models used (e.g., analytic, system-dynamics, and agent-based models) and (5) the questions asked of the models.

### 1.2 Definitions

We see complex adaptive systems (CAS)

as systems with nonlinear interactions involving adaptive animate components, interactions that lead to emergent macroscopic properties. We see CAS as a subset of complex systems more generally.<sup>1</sup> Terminology and distinctions vary across authors, but Table 1 summarizes those we use in this paper.

As a side note, we do not characterize complex systems as “systems that are more than the sum of their parts” because *most* systems have this property. An automobile is not an automobile without its propulsion, steering, and braking subsystems.

## 2. Worldview

Analyst worldview has profound effects on any study. We touch on worldview issues related to system thinking, confronting complexity in CAS, and seeing decision making as a continuing process reflecting values and objectives; knowledge and uncertainty; and limits on the controllability of systems.

### 2.1 System Thinking

Readers of this journal will agree that we policy analysts should see the world in system terms. As an example, a systems approach to improving education considers not just class size, but also, e.g., teacher quality, school governance, curriculum and pedagogy, teaching materials, the physical plant, student safety in school or in transit, parent in-

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<sup>1</sup> Examples of emergence without animate system elements are sand grains assembling into a pattern of rippled dunes (Camazine et al., 2001), the Bénard cells arising from convection in a heated liquid (Nicolis & Prigogine, 1977), and the superfluidity of liquid Helium.

**Table 1.** Simple, Complicated, Complex, and Complex-Adaptive Systems

| Characterization  | Numbers       | Nonlinearities | Adaptive elements | Emergent phenomena                                     | Examples  |
|---|---------------|----------------|-------------------|--|---|
| Simple system   | Small         | No             | No                | No   | A printer-computer system with plug-and-play                                    |
| Complicated system  | Large         | Yes            | No                | No   | Troublesome furniture or barbecue grills to be assembled; intricate assemblages |
| Complex system  | Usually large | Yes            | No                | Yes (may be due to inanimate features)                 | Modern automobiles and aircraft; dissipative systems in chemistry               |
| Complex adaptive system (CAS) (subset of complex systems) | Usually large | Yes            | Yes               | Yes (due to animate or artificial intelligence agents) | Human body, social organizations, nations                                       |

volvement, and the home environment. A systems approach is often aided by viewing matters through such different frames as material, social, and mental lenses (Pendleton-Jullian & Brown, 2018a; Pendleton-Jullian & Brown, 2018b).

The need for systems thinking was stressed decades ago with the advent of systems analysis (Quade & Boucher, 1968), policy analysis (Quade & Carter, 1989; Walker, 2000), and System Dynamics (Forrester, 1963; Sterman, 2000). Remarkably, however, system thinking is often not visible in modern-day policy studies.

CAS-informed system thinking is essential when we seek transforma-

tional changes. Rather than occurring directly, such changes may emerge after changes initiated at levels where human beings have agency. Those human actions interact with other aspects of the system, including top-down and mid-level policies and constraints. The changes may occur as sequential increments over time, or may be more rapid. Bringing about beneficial transformations requires fearlessness along the way—designing, implementing, doing, learning, adapting, and often trying new ideas (Pendleton-Jullian & Brown, 2018a; Pendleton-Jullian & Brown, 2018a; Pendleton-Jullian & Brown, 2018b) (particularly Ch. 11 of the latter).<sup>2</sup> Because this is all quite challenging, a major initiative in the re-imagin-

<sup>2</sup> As an example, General Stanley McChrystal transformed the Joint Special Operations Center (JSOC) during the war in Afghanistan. He reframed the challenge as a fight for information, a stra-

ing of our graduate school is having a specialist stream dedicated to effecting real and sustainable change, in part through partnering with communities. It is not enough to appreciate a problem and analyze options. As noted decades ago, it is necessary to *act* constructively in designing, choosing, and implementing options over time (Checkland, 1999, p. A5).

## ***2.2 Confronting Complexity and Wicked Problems***

Policy analysis is mostly about social phenomena occurring in complex adaptive systems (CAS). Seldom, however, does current policy analysis represent the emergent behaviors that loom large in CAS thinking. Econometric analysis, for example, highlights elasticities in a stable system without contemplating how new incentive structures can spawn changes of organization and process—e.g., the rise of the order-from-Amazon economy and the collapse of department stores and shopping malls. These occur as people adapt to new technology and new circumstances.

Recognizing systems and adaptation is still not enough. The problems in policy analysis are often *wicked*: difficult to define and inherently unsolvable in the usual sense (Rittel & Webber, 1973). When wicked problems are successfully addressed, it is not because “the” solution is identified but because stakeholders have agreed on compromise actions that will be good enough

for all to accept (or at least tolerate). This is the stuff of soft system methodology (SSM) or soft Operations Research (Ackoff, 2008; Checkland, 1999; Churchman, 1961; Rittel & Webber, 1973; Rosenhead & Mingers, 2002). The practice of policy analysis in the United States has lagged in dealing with soft system issues, but related matters have been championed in the language of learning organizations (Senge, 2006; Schoemaker, 1995), and system thinking for social change (Stroh, 2015; Meadows & Wright, 2008) (Chapter 7 of the latter, “Dancing with Systems”).

## ***2.3 Decision making as a Continuing and Messy Process***

Another aspect of analyst worldview is an image of how decision making occurs. Policy analysis often proceeds as though a single decision is to be made. Social systems, however, change—sometimes abruptly and in surprising ways. Major course corrections may then be necessary and management of CAS should be conceived accordingly. This arguably relates to the incrementalist approach of “muddling through” (Lindblom, 1959; Lindblom, 1979) and to the approach of economist/philosopher Amartya Sen, who urges practical incremental improvements that operate over time to move in a favorable direction (Sen, 2009).

We resonate with these authors, but use the terminology of planning for adaptiveness. Teaching related skills is very different from teaching how

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tegic principle of “It takes a network to defeat a network.” Results were dramatic but did not defeat the insurgency.

to optimize a problem given fixed assumptions. Such planning can include scheduling branch-point decisions and building capabilities that allow responses to unpredictable developments (Davis, 1994a; Davis, 2003) or the use of dynamic-pathway and related methods (Haasnoot et al., 2013). Prospects for adaptive strategies can be compared as a function of possible developments and a measure of regret, a subtle concept definable in significantly different ways (Groves et al., 2019, pp. 33-34).

These methods anticipate surprises and a sequence of actions over time that are likely to be troublesome. Progress is possible, but the process may be prolonged and messy. This contrasts with an image of study, decide, act, and be done with it.

#### ***2.4 The Values and Objectives That Drive Decisions***

Decision making depends on judgments about how to improve matters. Typically, these are discussed in terms of utilities, core concepts in traditional policy analysis (Nyblade et al., 2019). Stakeholders, however, often do not know their utility functions and no such utility function may even exist! After all, the concept of utility function depends on the stability of values, but values evolve with experience and events. A corporation may come to value its employees' quality of life; union members may come to value their company's commercial success. Nations may come to value strategies that are at once tough for deterrent purposes but also not threatening to other countries.

Values inform the objectives and goals set when making policy choices. Some are broad (e.g., better health for Americans), whereas others are more specific (e.g., making prescription drugs more affordable). Conceiving objectives in multiple levels is necessary—to see both forest and trees and to establish concrete objectives at different levels of detail. A difficulty is that collections of seemingly unobjectionable value-laden objectives often harbor deep conflicts or unresolvable trade-offs (e.g., data privacy vs. data utility, procedural fairness vs. equality of outcomes).

In classic policy analysis, “the” objective may be seen as a composite utility to be optimized. In a world of complex problems, however, we have multiple objectives that are often in tension and controversial. Successful compromise is about *balancing* considerations acceptably (a social matter), not optimizing.

#### ***2.5 Knowledge, Uncertainty, and Disagreement***

Policy analysis often proceeds as though much is known and only a few items are uncertain enough to worry about explicitly. In truth, the uncertainties in policy problems are frequently ubiquitous, large, and not amenable to best-estimate analysis. This was noted early in defense planning (Davis, 1994b; Davis, 2014), in a visionary technologist's paper about reforming policy analysis (Bankes, 1993), and in climate-change studies that led to powerful new methods (Lempert et al., 2003; Groves & Lempert, 2007). A core concept is that

of deep uncertainty (Bankes, 2002), defined in the 2003 study as follows (page vii):

*Deep uncertainty: the condition in which “analysts do not know or the parties to a decision cannot agree upon (1) the appropriate models to describe interactions among a system’s variables, (2) the probability distributions to represent uncertainty about key parameters in the models, or (3) how to value the desirability of alternative outcomes.”*

Confronting deep uncertainty alters one’s world view and the way one goes about policy analysis, in both defense work and social-policy studies.

### **2.6 Moderation in the Search for Control**

As a last item on worldview, we note that past generations of policy analysts have been trained to think in terms of top-down interventions with predictable consequences. For those sensitive to the character of CAS, the way ahead seems more treacherous and the very concept of control should be approached with humility because consequences of interventions will often be surprising and sometimes distinctly counterproductive. An interesting example involving attempts to conserve rain forests appeared recently in this journal (Zia & Kauffman, 2018).

This has implications for implementation. Although the need for monitoring and feedback has long been recognized, implementation has often

been seen as a separate, pedestrian, and less prestigious subject by policy analysts. If, however, we expect to be surprised and dismayed by some consequences of interventions, we should be vigilant in watching for troublesome indicators and prompt in adapting. Expertly guided adaptive implementation then becomes part of sequential decision making. National governments are notoriously ill-suited for rapid adaptation, so this will often require more decentralization of interventions to states, communities, non-government organizations (NGOs), and commercial companies. Maintaining continuity of focus is a major challenge, since leaders often rotate out or are promoted to other responsibilities.

## **3. Basis for Reasoning**

**G**iven a worldview, how does an analyst reason about a problem?

### **3.1 Theory, Data, Association, and Causation**

A long-standing schism exists between those who study policy problems with the statistical tools of social and health sciences and those who are more dependent on theory-building. The schism can be described, roughly, as data-driven versus theory-driven inquiry (Davis & O’Mahony, 2019, p. 23).

Much current policy analysis is based on data-driven econometrics and other forms of statistical analysis. An example is evidence-based decision making, as when the efficacy of health

treatments is judged by data from randomized control trials. This is in contrast with policy analysis that considers alternative future scenarios when evaluating options—as is routine in defense planning (Davis, 2014), corporate strategic planning (Schwartz, 1995; Schoemaker, 1995), and studies of climate change (IPCC, 2014). Empirical data plays only a limited role because empirical data on the future of changing systems is, let us say, sparse.

Both data-driven and theory-driven work have their place, but the ideal is a hybrid that includes theory-informed data analysis and theoretical work that draws effectively on empirical information. Making that kind of hybrid activity easier to pursue is a major challenge for social-science modelers, technologists, and scientists (Davis & O'Mahony, 2019). Meeting that challenge will depend partly on CAS-sensitive teaching of causal theory (cause-effect reasoning, not the causal inference of statistics).

The need for causal theory transcends our concern about CAS. Correlational data has distinct limitations and many questions cannot even be asked without causal models. These include questions about the effects of alternative interventions or other policy actions (Pearl, 2009; Pearl & Mackenzie, 2018). Several other problems exist with the evidence-based focus in policy analysis. First, it may stifle innovation

that seeks to try new things or the application of common-sense cause-effect reasoning. Second, historical-empirical data is sometimes misleading as evidenced by “once-in-a-century” storms now occurring annually. Third, the data may not be representative. Such problems have been described by an insider’s critique of past efforts to promote evidence-based practices (Brooks, 2016).

Returning to the theme of doing better in dealing with CAS, the need for increased causal system modeling should be evident because we seldom have adequate data to understand the effects of interventions in social systems. We need theory to help anticipate troublesome feedbacks, possible instabilities, and other complications. Theory is also necessary to sort out ambiguous cause-effect directionality, which is common in complex systems. Fortunately, theory need not be precise to be useful in such respects. How good it needs to be is context-sensitive.

### *3.2 Types of Theory*

We refer to “theory,” but many connotations exist. In the social sciences, the myriad definitions cause severe but often-unnoticed confusion (Abend, 2008). Often, the word refers merely to discrete hypotheses or speculations (sometimes thoughtful and sometimes quarter-baked).<sup>4</sup> In another usage (and in everyday language), the word is often used disparagingly, as in “Well, in

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3 Although treated intuitively here, the subject of causality is deep and subtle (Cartwright, 2004; Halpern, 2016).

4 A more expansive view sees theory as “a device for interpreting, criticizing, and unifying established laws, modifying them to fit data unanticipated in their formulation, and guiding the enter-

theory such and such should be true, but—of course—we all know that...” This is in contrast with such disciplines as physics in which settled theory is deeply respected and refers to an integrative and coherent set of principles by which to understand knowledge in a broad domain. We see special need for increasingly good theories of the integrated and coherent variety.

It is often claimed that the difference is that this is not possible in social science because context matters so dramatically. Context, however, is as crucial in physics as in social science. It is just that in physics the variables defining context are better understood and specified, with the cases being distinguished sharply. Sharpening treatment of social-science context is undeniably difficult, but not impossible. Incremental gains can be valuable well short of finding the elusive Grand theory.

#### **4. Analytic Style**

**A**nalytic style has many dimensions, but we touch on the false dichotomy between analysis versus synthesis, the meaning of rigor, the treatment of uncertainty and disagreement, the way options are compared, and the questions asked of models.

##### ***4.1 Analysis Versus Synthesis, a False Dichotomy***

In this paper we use the term “analysis” to mean

*a detailed examination of anything complex in order to understand its nature or to determine its essential features: a thorough study* (Merriam Webster on-line dictionary).

In this meaning, analysis is not just about decomposition. *Good* analysis, in our usage, requires creativity, integration, and synthesis—and, often, a system view of complex problems. Our definition does not accept the distinction between analysis and synthesis that is sometimes drawn. Also, we see “reductionism” favorably, as an important part of studying complex systems, as when Herbert Simon described the human body as a nearly decomposable system (Simon, 1996) or physicists seek to understand the universe by, in part, studying its elements and relationships among them (Weinberg, 1994). Also, the most holistic of physicians (internists) need to understand both parts and the whole, as do system engineers.

To be sure, it is sometimes more insightful to focus on the whole and interactions at the level of the whole, rather than seeking explanation from below. Some social phenomena are best understood without going into individual characteristics and behaviors. This is less different from other domains than is sometimes realized. Scientists work at the thermodynamic level without ever discussing molecular phenomena, even though thermodynamics can be understood in terms of quantum statistical

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prise of discovering new and more powerful generalizations.” (Kaplan, 2013, p. 295).

mechanics. A clinical psychologist may discuss changing a patient's life patterns and behaviors without going into psychoanalysis and childhood trauma. In the investment world, it is sometimes more pragmatic to react to system-level signals (e.g., trends in prices, wages, and employment) than to attempt analysis of poorly understood microscopic causal relationships.

## 4.2 Character of Analysis: Quantitative versus Qualitative, and Matters of Rigor

### 4.2.1. Quantitative versus Qualitative?

Early systems analysis and policy analysis focused unduly on quantitative analysis. This was seen as an antidote to emotional and sometimes parochial arguments, and to be necessary for rigor. This emphasis had negative side effects because many important variables are inherently imprecise and difficult to measure (e.g., love, hate, loyalty). As famously noted by Jay Forrester when referring to soft variables,

*To omit such variables is like saying that they have zero effect—probably the only value that is known to be wrong!* (Forrester, 1971, p. 57)

An example of soft factors in 2020-2021 is the effect of national leaders' behaviors and random anecdotes on the public's mask-wearing in the COVID-19 pandemic.

Scathing critiques of early systems analysis and rational-choice theory have argued that they omitted dis-

cussion of values other than narrowly defined self-interest (Amadae, 2003). To the extent that the critiques were true, they would have shocked such decision theorists as John Stuart Mill and Herbert Simon, both of whom interpreted utility far more broadly, to include altruism (Mill, 1863, p. Chapter 2; Simon, 1993).

A related point is that qualitative considerations are profoundly important in defining the context in which issues arise and policies are considered. What solutions are acceptable depends on local culture. Does the proposed solution fit (or can it at least be related to) a narrative that resonates in the community? If not, problems are likely.

### 4.2.2. Rigor

A next issue is the need to re-interpret the concept of rigor. Noting the negative connotations of rigor (being formulaic, austere, strict), we should instead interpret it in terms of being "logical, coherent, and the result of considering all relevant information" (a meaning familiar in philosophy). This is different from meticulously calculating effects on one variable while blithely assuming that all other things remain equal.

Good rigor is not necessarily quantitative or precise. Well-structured qualitative treatment will sometimes be apt, as when describing the approximate circumstances under which intervention in a complex and unstable adaptive system will have unpredictable consequences. It is better to formulate theory that includes important soft factors than to ignore them.

Modelers should contribute to improved rigor, especially by including all key variables. This will mean constructing increasingly integrative theories to test in simulation for their relative ability to explain data conceptually in cause-effect terms, rather than comparing how well data-fitting works for alternative but individually simplistic theories or comparing the coefficients obtained by regression analysis.

A tradeoff exists between maximizing a kind of rigor when testing a narrow theory in a narrow context and instead seeking or testing broader theory for which some data is softer and less controlled. In our view, policy analysis needs relatively more emphasis on the broader constructs and system thinking. This, we believe, will increase the accuracy and policy relevance of analysis, although sacrificing the rigorous statistical precision notoriously<sup>5</sup> demanded in some disciplinary work.

### ***4.3 Confronting Uncertainty and Disagreement***

Everyone agrees on the need to address uncertainty, but for decades system analysts and policy analysts recognized that it was being given short shrift (Miser & Quade, 1988). The methods available have now improved dramatically. A first round of improvements introduced probabilistic methods with subjective probabilities (Morgan & Henrion, 1992). A second round addressed

deep uncertainty, as defined in Section 2. Given these new methods, we should encourage analysis that addresses the many kinds of uncertainty (including disagreement) from the very outset and as a matter of first-order attention.

Often, policy analysis should be identifying strategies with FARness, i.e., strategies that are flexible, adaptive, and robust—with no pretense of optimization. Arguably, assisting policy makers in finding FARness should be an ethical responsibility (Davis, 2014). In different but functionally equivalent language, we should urge robust decision making (RDM)—i.e., seeking strategies that are robust in the broadest sense of that over-loaded term. The RDM concept now has international standing (Marchau et al., 2019).

This search for robust strategies may seem obvious, yet consider how CSS practitioners often think about their simulation experiments. Do they develop their inputs and models so that, from the outset, all the important inputs can be changed readily, and so that model uncertainty can also be addressed (Davis & Popper, 2019)? Or, instead, do they hold nearly everything constant and vary only a few parameters? Doing better will be challenging with current infrastructure for computational social science. Technological innovation will be necessary. Part of this may involve adapting the benefits of high-level languages or tools that make

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5 As an example, correlational research has shown that some states have increased minimum wages without loss of low-paying jobs (Card & Krueger, 1993; Cengiz et al., 2019). Policymakers, however, need theory to describe circumstances under which raising the minimum wage will and will probably have positive consequences (e.g., when profits are good and wage growth has lagged productivity growth) and where they probably will not (Ritholtz, 2019).

uncertainty analysis routine (e.g., visual programming languages). Part may involve scenario-generation apparatuses for ensemble approaches (Bankes et al., 2001), which are now possible to use in near-real time (Groves et al., 2016).

Another important concept is multi-resolution modeling (MRM). It is often possible to have a good but imperfect family of models at different levels of resolution (Davis & Bigelow, 1998). It is then possible to do initial exploration at a high level (low resolution) with perhaps 3-10 variables and to then zoom into detail only where it is worthwhile to do so. This can avert the dreaded curse of dimensionality (Davis, 2014).

Fortunately, many policy makers are comfortable with planning under uncertainty. They value simulation-based analysis and interactive settings that help them to *learn* about connections and possibilities, and to view their problem area coherently. They will use this knowledge as needed along the way, but they have no illusions about the simulations being reliably predictive (Rouse, 2015; Rouse, 2019).

#### **4.4 Comparing Options**

Early systems analysis highlighted cost-benefit and cost-effectiveness analysis. Later, some policy analysis came to emphasize multicriteria policy scorecards (Goeller et al., 1983) and to disparage “adding things up” because an option’s utility is often not a linear sum. Regrettably, that insight has often been lost in favor of formulaic cost-ef-

fectiveness methods. This practice should be supplanted when dealing with CAS issues because it is important to distinguish among qualitatively different criteria and to recognize that system behaviors are related in non-linear and sometimes incommensurate ways. It should become routine to emphasize these matters and to show conclusions as a function of “perspective,” seeing through the eyes of other people as urged long ago by Adam Smith (Smith, 1790, pp. pp. part III, 2nd paragraph).

#### **4.5 Changing the Questions Asked of Models**

In simulation studies, it is standard to observe results and then ask “What if?” questions. With each “What if?” a new simulation can be run, but that may require collecting or negotiating new data, making substantive changes in the model, and other time-consuming activities. If so, policymakers become impatient and disgusted with analysis based on big models (Davis, 2016).

The way ahead is to think from the outset about addressing broader, “Beyond-what-if” questions, such as “Under what circumstances will we achieve our objective?” We can often provide approximate answers with computational experiments and subsequent search for patterns in the results (Groves & Lempert, 2007; Marchau et al., 2019). We can aspire to “region plots” and other mechanisms for preemptively addressing policymaker questions (Davis, 2019). The opportunity exists for many forward-leaning

developments and a number of related efforts have recently appeared (Yilmaz & Ören, 2009; Yilmaz, 2019; Garibay et al., 2019).

An example from JPCS illustrates doing so. An article asks “How Stable Is Democracy?” It is not about forecasting, but rather understanding democracy’s fragility and what constitute troublesome combinations of factors (Grim et al., 2018). Output graphics are what we refer to as region plots, sometimes suggesting the likelihood of “phase transitions” for certain combinations of factor values.

## **5. Character of Models and Model-Based Analysis**

**W**e have discussed worldview, reasoning, and analytic style. Let us now briefly discuss the models used in policy analysis.

### **5.1 Different Classes of Model**

Although statistical models have dominated social science and policy analysis, we see the need for much more extensive use of causal models. Many such approaches are needed as discussed in two modern books (Cioffi-Revilla, 2014; Page, 2018). These may include analytical models, system dynamic models, agent-based models, and network models among others. Research often benefits from using a combination of simple, mid-level, and detailed causal models; and various forms of human gaming (Davis, 2014, pp. 22-25).

### **5.2 Purpose of Models and Related Issues of Validity**

When planning to use a set of different models, we need to keep in mind their different purposes, which include

- Understanding the system and its behavior (Checkland, 1999; Sterman, 2000)
- Designing a system or policy to intervene in a system (Pendleton-Julian & Brown, 2018b)
- Developing strategies, notably robust strategies (Marchau et al., 2019; Davis et al., 2008; Davis, 2014; Groves & Lempert, 2007)
- Communicating and deliberating with stakeholders, as in “convening” (Klitgaard, 2019), use of “policy flight simulators” (Rouse, 2019), or use of interactive web-based tools such as those currently dealing with the COVID-19 pandemic from the University of Washington and a number of other institutions.

Although it is common to hear demands that models be “validated” as though that were a straightforward and unambiguous matter, recent work urges that the validity be assessed separately along dimensions of (1) description, (2) explanation, (3) postdiction, (4) exploratory analysis and coarse prediction, and (5) prediction (Davis et al., 2018).

What do “explain” and “predict” mean in the present context? In the machine-learning and statistics communities, “explanation” refers to a model’s ability to generate estimates that accord

well with data. If the model generates results close to that of new data, it is said to be “predictive.” When talking with a policymaker, however, “explanatory power” should refer to providing understandable and actionable cause-effect relationships. Claiming that a model is predictive should mean that it can anticipate *future* situations— after the system reacts to interventions and changes in various other ways (Osoba & Davis, 2019).

Addressing CAS issues with cause-effect models and addressing uncertainties and disagreements will require different attitudes about internal, external, and measurement validity. It is more important to get major phenomena roughly right, and to anticipate possible negative consequences of intervention, than to fit past data precisely. Measurement error will also be a bigger problem because important variables are hard to define and measure. But omitting them, or pretending that they are represented adequately by more conveniently measured proxies, will be counterproductive. As merely one example, GDP per capita is a poor proxy for understanding the economic well-being of the diverse people in a country. Measurement error is even more troublesome when outcomes important to stakeholders depend on context, history, and tacit cultural norms, including sacred values (Haidt, 2013).

### 5.3 Measures of Outcome from Models

The typical measure of outcome in policy analysis is an expected value. Policy analysis has not paid adequate attention to distributional results. Arguably, the focus on expected value has contributed to policies that have so disadvantaged the middle class as to be among the reasons for the political turmoil in the United States, Great Britain, and elsewhere. To those thinking about CAS, the need to go beyond expected value is even more evident. It is the nature of CAS to exhibit distributions at a given time and to change over time (e.g., as the system’s agents respond to interventions by adapting their behaviors, attempting to a “game the metrics”).

## 6. Conclusions

**T**able 2 summarizes, suggesting an agenda for teaching and conducting policy studies that moves the relative emphasis from where it is now (2d column) toward something more CAS-informed (3d column). The idea is indicated also in Figure 1 by depicting current and future coverage of the teaching spectrum from simple problems to CAS-sensitive thinking, using a 0 to 10 scale. Topics covered in the past remain important, but coverage is extended to the right—not to the extent of dwelling on complete chaos and related mathematics, but enough to appreciate the special issues of dealing with complex adaptive systems.

**Table 2.** Shifting the Balance in Policy Studies

| <b>Issue</b>  | <b>As Seen Now</b>  | <b>CAS-informed perspective</b>   |
|---|---|---|
| <b>Worldview</b>                                    |   |   |
| Nature of system                                    | Simple or complicated, perhaps complex but well behaved   | Complex, adaptive, often not predictable  |
| Problems  | Well posed, solvable                                      | Wicked; solutions, if possible, to be emergent  |
| Stability   | Stable system, once-and-for-all decisions                 | Evolving system with need for continuing decisions  |
| Values  | Known, fixed, simple                                      | To be discovered, complex, conflicting, changing  |
| Objectives  | Optimize over a utility function                          | Balance conflicting considerations acceptably   |
| Knowledge and uncertainty                           | Good, with some uncertainties                             | Deeply uncertain  |
| Control   | Top-down; direct; confident                               | Top-down, bottom-up, sideways; humble; iterative  |
| <b>Basis for Reasoning and Inference</b>            |   |   |
| Basis for inference                                 | Data, correlation   | Causal theory   |
| Types of theory                                     | Simple concepts; discrete hypotheses for narrow phenomena | Integrative, coherent principles for classes of phenomena with contextual specializations |
| <b>Analytic Style</b>                               |   |   |
| Character   | Parsimonious in fitting data accurately                   | Inclusive of important factors, even if uncertain and hard to measure                     |
| Uncertainty analysis                                | On margin as add-on                                       | From outset, with broad exploration   |
| Option comparison                                   | Cost-effectiveness, cost-benefit                          | Multicriteria scoreboards by perspective  |
| <b>Character of Models and Model-Based Analysis</b> |   |   |
| Type  | Statistical   | Diverse causal models and human exercises   |
| Purpose   | Explain and predict in statistical sense                  | Describe, explain, post-dict, explore, and predict  |
| Explanation; prediction                             | Correlations with old and new data                        | Causal explanation and approximate prediction for when system and circumstances change    |
| Focus of outcomes                                   | Expected value  | Distributional effects  |
| <b>Questions Asked of Models</b>                    |   |   |
| Questions   | What if...?   | Under what circumstances...?  |

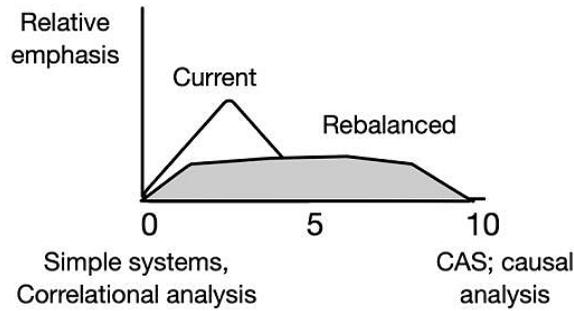


Figure 1: Shifting the Balance of What Is Taught

## References

Abend, G. (2008). The Meaning of “Theory.” *Sociological Theory*, 26(2), 173-199.

Ackoff, R. L. (2008). *Ackoff's Best: His Classic Writings on Management*. John Wiley & Sons.

Amadae, S. M. (2003). *Rationalizing Capitalist Democracy: the Cold War Origins of Rational Choice Liberalism*. University of Chicago Press.

Bankes, S. C. (1993). Exploratory Modeling for Policy Analysis. *Operations Research*, 41(3), 435-449.

Bankes, S. C. (2002). Tools and Techniques for Developing Policies for Complex and Uncertain Systems. *Proceedings of the National Academy of Sciences, Colloquium, Vol. 99, Suppl. 3*.

Brooks, J. (2016). Making the Case for Evidence-Based Decision-Making. *Stanford Social Innovation Review, December 6*.

Camazine, S., Deneubourg, J.-L., Franks, N. R., Sneyd, J., Theraulaz, G., & Bonabeau, E. (2001). *Self-Organization in Biological Systems*. Princeton University Press.

Card, D., & Kreuger, A. B. (1993). *Minimum Wages and Employment: A Case Study of the Fast Food Industry in New Jersey and Pennsylvania* (NBER Working Paper 4509).

Cartwright, N. (2004). Causation: One Word, Many Things. *Philosophy of Science*, 71(5).

Cengiz, D., Dube, A., Lindner, A., & Zipperer, B. (2019). The Effect of Minimum Wages on Low-Wage Jobs: Evidence from the United States Using a Bunching Estimator. *NBER Working Paper, 25434*.

Checkland, P. (1999). *Systems Thinking, Systems Practice (Includes a 30-Year Retrospective)*. John Wiley & Sons.

Churchman, C. W. (1961). *Prediction and Optimal Decision: Philosophical Issues of a Science of Values*. Prentice Hall.

Cioffi-Revilla, C. (2014). *Introduction to Computational Social Science: Principles and Applications*. Springer-Verlag.

Davis, P. K. (1994a). Institutionalizing Planning for Adaptiveness. In P. K. Davis (Ed.), *New Challenges in Defense Planning: Rethinking How Much Is Enough* (pp. 73-100). RAND Corporation.

Davis, P. K. (1994b). *New Challenges in Defense Planning: Rethinking How Much is Enough* (August 11, Trans.). RAND Corporation.

Davis, P. K. (2003). Uncertainty Sensitive Planning. In S. Johnson, M. Libicki, & G. Treverton (Eds.), *New Challenges, New Tools for Defense Decisionmaking* (pp. 131-155). RAND Corporation.

Davis, P. K. (2014). *Analysis to Inform Defense Planning Despite Austerity* (RR-482). RAND Corporation.

Davis, P. K. (2016). *Capabilities for Joint Analysis in the Department of Defense: Rethinking Support for Strategic Analysis*. RAND Corporation.

Davis, P. K. (2019). Lessons on Decision Aiding for Social-Behavioral Modeling. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-Behavioral Modeling for Complex Systems*. John Wiley & Sons.

Davis, P. K., & Bigelow, J. H. (1998). *Experiments in Multiresolution Modeling (MRM)* (MR-1004-DARPA). RAND Corporation.

Davis, P. K., & O'Mahony, A. (2019). Improving Social-Behavioral Modeling. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-Behavioral Modeling for Complex Systems* (pp. 15-48). John Wiley & Sons.

Davis, P. K., O'Mahony, A., Gulden, T., Osoba, O., & Sieck, K. (2018). Priority Challenges for Social-Behavioral Research and Its Modeling. *RR-2208-DARPA*.

Davis, P. K., & Popper, S. W. (2019). Confronting Model Uncertainty in Policy Analysis for Complex Systems: What Policymakers Should Demand. *Journal of Policy and Complex Systems*, 5(2), 181-201.

Davis, P. K., Shaver, R. D., & Beck, J. (2008). *Portfolio-analysis Methods for Assessing Capability Options* (MG-662-OSD). RAND Corporation.

Forrester, J. W. (1971). *World Dynamics* (ISBN: 1563270595 ed.). Wright-Allen Press.

Forrester, J. W. (1963). *Industrial Dynamics*. MIT Press.

Garibay, I., Gunaratne, C., Yousefi, N., & Schinert, S. (2019). The Agent-Based Modeling Canvas: A Modeling Lingua Franca for Computational Social Science. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-Behavioral Modeling for Complex Systems* (pp. 521-544). Wiley and Sons.

Goeller, B. F., et al. (1983). *Policy Analysis of Water Management for the Netherlands, Summary Report* (R-2500-NETH). RAND Corporation.

Grim, P., Liu, M., Bathina, K. C., Liu, J., & Gorder, J. W. I. (2018). How Stable Is Democracy? Suggestions from Artificial Social Networks. *Journal on Policy and Complex Systems*, 4(1), 87-108.

Groves, D. G., & Lempert, R. J. (2007). A New Analytic Method for Finding Policy-relevant Scenarios. *Global Environmental Change*, 17(1), 78-85.

Groves, D. G., Molina-Perez, E., Bloom, E., & Fischbach, J. R. (2019). Robust Decision Making (RDM): Application to Water Planning and Climate Policy. In V. A. W. J. Marchau, W. Walker, P. J. T. M. Bloemen, & S. W. Popper (Eds.), *Decision Making under Deep Uncertainty* (pp. 135-163). Springer.

Haasnoot, M., Kwakkel, J. H., Walker, W. E., & Maat, J. T. (2013). Dynamic Adaptive Policy Pathways: A Method for Crafting Robust Decisions for a Deeply Uncertain World. *Global Environmental Change*, 23(2), 485-498.

Halpern, J. Y. (2016). *Actual Causality*. The MIT Press.

IPCC. (2014). *Climate Change 2014: Synthesis Report*. Intergovernmental Panel on Climate Change (IPCC).

Kaplan, F. (2013). The End of the Age of Petraeus. *Foreign Affairs*, 92(1), 75-90.

Klitgaard, R. (2019). Engaging Corruption: New Ideas for the International Monetary Fund. *Policy Design and Practice*, 2(3), 229-242

Lempert, R. J., Popper, S. W., & Bankes, S. C. (2003). *Shaping the Next One Hundred Years: New Methods for Quantitative Long-term Policy Analysis*. RAND Corporation.

Lindblom, C. E. (1959). The Science of "Muddling Through." *Public Administration Review*, 19(Spring), 79-88.

Lindblom, C. E. (1979). Still Muddling, Not Yet Through. *Public Administration Review*, 222-233.

Marchau, V. A. W. J., Walker, W. E., Bloemen, P. J. T., & Popper, S. W. (Eds.). (2019). *Decision Making Under Deep Uncertainty: from Theory to Practice*. Springer.

Meadows, D. H., & Wright, D. (2008). *Thinking in Systems: A Primer*. Earthscan.

Mill, J. S. (1863). *Utilitarianism*.

Miser, H. J. & Quade, E. S. (Eds.). (1988). *Handbook of Systems Analysis*. North Holland Publishing Company.

Morgan, M. G., & Henrion, M. (1992). *Uncertainty: A Guide to Dealing with Uncertainty in Quantitative Risk and Policy Analysis*. Cambridge University Press.

Nicolis, G., & Prigogine, I. (1977). *Self-organization in Nonequilibrium Systems: from Dissipative Structures to Order Through Fluctuations* (ISBN: 0471024015 ed.). John Wiley & Sons.

Osoba, O., & Davis, P. K. (2019). An Artificial Intelligence/Machine Learning Perspective on Social Simulation: New Data and New Challenges. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social and Behavioral Modeling for Complex Systems* (pp. 443-476). Wiley & Sons.

Page, S. E. (2018). *The Model Thinker: What You Need to Know to Make Data Work for You*. Basic Books.

Pearl, J. (2009). *Causality: Models, Reasoning, and Inference*. Cambridge University Press.

Pearl, J., & Mackenzie, D. (2018). *The Book of Why: The New Science of Cause and Effect* (1 ed.). Basic Books.

Pendleton-Jullian, A., & Brown, J. S. (2018a). *Design Unbound, Volume 2: Ecologies of Change*. MIT Press.

Pendleton-Jullian, A., & Brown, J. S. (2018b). *Design Unbound: Designing for Emergence in a White Water World, Volume 1*. MIT Press.

Quade, E. S. & Boucher, W. I. (Eds.). (1968). *Systems Analysis and Policy Planning: Applications for Defense*. Elsevier Science Publishers.

Quade, E. S. & Carter, G. M. (Eds.). (1989). *Analysis for Public Decisions, 3D Ed.* North Holland Publishing Company.

Ritholtz, B. (2019). Labor Market Is Doing Fine with Higher Minimum Wages – *Bloomberg Opinion*. Retrieved 2019-09-06 from <https://www.bloomberg.com/opinion/articles/2019-01-24/u-s-economy-higher-minimum-wages-haven-t-increased-unemployment>

Rittell, H. W. J., & Webber, M. M. (1973). Dilemmas in a General Theory of Planning. *Policy Sciences*, 4(3), 155-169.

Rosenhead, J. & Mingers, J. (Eds.). (2002). *Rational Analysis for a Problematic World Revisited: Problem Structuring Methods for Complexity, Uncertainty and Conflict, 2nd Edition*. John Wiley & Sons.

Rouse, W. B. (2015). *Modeling and Visualization of Complex Systems and Enterprises*. John Wiley & Sons.

Rouse, W. B. (2019). Human-Centered Design of Model-Based Decision Support for Policy and Investment Decisions. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-Behavioral Modeling for Complex Systems* (pp. 798-808). Wiley.

Schoemaker, P. (1995). Scenario Planning: A Tool for Strategic Thinking. *Sloan Management Review*, 36(2), 25-40.

Schwartz, P. (1995). *The Art of the Long View: Planning for the Future in an Uncertain World*. Doubleday.

Sen, A. (2009). *The Idea of Justice*. Belknap Press, Harvard University.

Senge, P. M. (2006). *The Fifth Discipline: The Art & Practice of the Learning Organization*. Penguin Random House.

Simon, H. A. (1993). Altruism and Economics. *The American Economic Review*, 83(2), 151-161.

Smith, A. (1790). *The Theory of Moral Sentiments (Sixth Edition)*. Dover.

Sterman, J. D. (2000). *Business Dynamics: Systems Thinking and Modeling for a Complex World* (ISBN: 007238915X ed.). McGraw-Hill.

Stroh, D. P. (2015). *Systems Thinking for Social Change*. Chelsea Green.

Walker, W. E. (2000). Policy Analysis: a Systematic Approach to Supporting Policymaking in the Public Sector. *Journal of Multi-Criteria Decision Analysis*, 9, 11-27.

Weinberg, S. (1994). *Dreams of a Final Theory: The Scientist's Search for the Ultimate Laws of Nature*. Vintage.

Yilmaz, L. (2019). Toward Self-Aware Models as Cognitive Adaptive Instruments for Social and Behavioral Modeling. In P. K. Davis, A. O'Mahony, & J. Pfautz (Eds.), *Social-Behavioral Modeling for Complex Systems* (pp. 569-586). Wiley & Sons.

Yilmaz, L., & Ören, T. (2009). *Agent-Directed Simulation and Systems Engineering* (1 ed.). Wiley-VCH.

Zia, A., & Kauffman, S. A. (2018). The Limits of Predictability in Predefining Phase Spaces of Dynamic Social–Ecological Systems: “Command and Control” Versus “Complex Systems”-Based Policy Design Approaches to Conserve Tropical Forests. *Journal on Policy and Complex Systems*, 4(2), 153-170.



# Human Trafficking on the Dark Web: What Is It and How Can It be Prevented?

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*Keywords:* dark Web, human trafficking, sexual exploitation, COVID-19

## Trata de personas en la Dark Web: ¿qué es y cómo se puede prevenir?

*Palabras clave:* dark Web, trata de personas, explotación sexual, COVID-19

## 暗网上的人口贩运：它是什么 并能如何加以预防？

关键词：暗网，人口贩运，性剥削，新冠肺炎（COVID-19）

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### Introduction

While many people seem to believe that slavery is a remnant of an unenlightened past, human trafficking is currently affecting the lives of an estimated over 45 million people globally (Rhodes, 2017). Due to the ease of communications, negotiations, and payments through the Internet, specifically the portion known as the ‘dark web,’ the number of people trafficked every year has skyrocketed. Just for a comparison, the number of people trafficked in the contemporary era is over eleven times as large as the

number of slaves freed after the American Civil War. Furthermore, the onset of COVID-19 resulted in victims having less interactions with higher-paying sex buyers (Meyer, 2020). This meant more interactions with low-paying buyers, which resulted in a need for victims to engage with more buyers to make the same amount of money. More interactions translates into more potential exposure to COVID-19 and threats of violence (Meyer, 2020).

In many ways, the dark web is a manifestation of the negative side of the complexity of the Internet and should stand as a warning for the study of com-

plex systems. When systems reach sufficient complexity, voids will naturally form within the systems that criminals and other malcontents with sufficient knowledge will be able to exploit. In the case of the Internet, these voids effectively account for a massive share of the economy of the Internet, as the criminal economy of the Internet is likely equal in scope to the legal economy of the Internet.

## **Background**

**L**ike many Internet technologies, the dark web was originally designed around utopian dreams to avoid censorship and to facilitate the spread of knowledge and information during the early years of the 21<sup>st</sup> century. Such communications were facilitated by TOR protocols, but criminals quickly figured out that TOR protocols could also be used for sharing illegal information, such as child pornography and pirated copyrighted content. With the development of cryptocurrencies, though, the dark web quickly grew from a place for individual criminals to central hub for organized crime, as cryptocurrencies allowed criminal organizations to transfer funds through the Internet without using traditional banking systems. Combined with the anonymity provided by multiple layers of encryption, the dark web became a haven for illegal activity that has been impossible for governments to effectively police (Rhodes, 2017).

While the dark web may have originally been founded for admirable goals, the fact that it was twisted towards

criminality during its formative years should not surprise anyone. Criminal enterprises thrive in anonymous and secretive environments, especially if they involve activities that society find abhorrent, and it is unlikely that there is any way to remove the criminal element of the dark web without dismantling the entire Internet. Of course, most of the population of the world is unlikely to support such drastic action, even though more and more crime is facilitated by the Internet.

While the economic damage of the dark web is significant, it is important that we do not forget about the trauma experience by the human victims of the dark web, especially the children who find themselves abused for the pleasure of adults. Suspected child sex trafficking has increased by an astounding 846 percent in the five years between 2010 and 2015, according to the National Center for Missing and Exploited Children (Enough is Enough, 2020, para. 14). Around four-fifths of searches on the dark web are estimated to be related to child sexual exploitation (Rhodes, 2017).

In essence, the dark web represents the harm that can be done when a complex system lacks any central guiding authority. While the Internet has been a great tool for many people, allowing people to obtain education and entertainment that would have been unavailable to most of the human species even a quarter of a century ago, the dark web represents the negative externalities associated with the freedoms represented by the Internet. While bil-

lions of people gain a minor benefit from the Internet, hundreds of millions of people suffer a major penalty from the Internet every year, and tens of millions of people suffer horrific violations due because of the anonymity provided to their victimizers and the clients of their victimizers by the anonymity of the Internet.

One of the more disturbing elements of the dark web comes in the facilitation of more extreme forms of pornography. With pornography addiction increasing in part due to the availability of pornography on the Internet, many criminals have turned to offering content that appeals to paying clients with tastes for fetishized and/or violent sex. Since most professionals who work in pornography are unwilling to subject themselves to such treatment, criminals who traffic women and children are willing to supply the content if their clients are willing to pay, resulting in more women and children ending up as unwilling participants in the sex trade (Enough is Enough, 2020). Because of the prevalence of human trafficking in every state in the USA, it is a complex problem that needs to be dealt with on the national level (ECPAT USA, 2019).

## **Technology**

**T**he dark web has become the central hub for human trafficking and child exploitation because the anonymity of dark web, facilitated by cryptocurrency exchanges and encryption networks is ensured by using multiple layers of encryption, makes it impossible for governments to take

down more than a small minority of criminal operators every year (Rhodes, 2017). In the case of the criminal operators that they do manage to take down, governments tend to rely on repurposed technologies that detect anomalous data traffic and/or money laundering rather than tools that directly detect human trafficking and/or child exploitation (Dixon, 2013; Hammonds, 2015). In effect, such tools take advantage of the two major weaknesses of criminal enterprises on the dark web: 1) most Internet activity still operates outside of the dark web, so criminal enterprises will sometimes leave digital tracks that authorities can detect and 2) most financial activities eventually must involve the traditional banking system, so criminal enterprises will sometimes commit financial crimes that authorities can prosecute.

Another beneficial system that could assist in this job is called FlagIt, which during studies has luckily had hopeful results. According to Kejriwal et al. (2017), it works by flagging suspicious pieces of information on the Internet, making it possible to monitor Internet activity more easily. FlagIt seems to outperform the best baseline on the F1-Measure metric by 2-13% on four of the five indicators and is always the best of all adaptive baselines (Kejriwal et al., 2017, p. 5). While such systems are useful, and are important supplements to more traditional investigations, the scale and scope of such programs are limited, and criminal organizations are willing to devote significant resources to avoid detection and capture. Unfortunately, criminal organizations are

likely willing to devote more resources to avoiding detection and capture than governments are willing to spend, so the people that they usually end up catching are the disposable street-level operators.

## **Ethics**

**T**he existence of the dark web represents a massive ethical failure on the part of the governments, companies, and people who benefited from the Internet. Governments bought into the propaganda that the Internet could be a self-regulating utopian society, despite the simple fact that humans are humans and criminals will always seek to exploit new technologies for their financial gain. Internet companies fought government regulation because they wanted to avoid the associated scrutiny and taxation, and they actively promoted the technologies that led to the evolution of the dark web. Finally, the people who used the Internet did not stop to think about the price that other people might have paid for their education and entertainment.

It is important to not forget about the human element of the dark web: the victimizers and the victims. Of course, the perpetrators must be found and prosecuted to the full extent of the law, but that should come secondary to rescuing the victims and providing them with the support services required to make them whole. For too long, societies have treated the victims of sexual oppression and sexual exploitation as criminals while the victimizers could get away with atrocious behavior.

When it comes to the human trafficking facilitated by the dark web, there are multiple different facets of ethics to discuss with this topic, beginning with the treatment of victims. In the case of the victims who are children, there is a need for more access and resources for support services, especially given that many victims are afraid that they will be arrested and/or deported if they seek help (English, 2017). The “T” visa program, which grants some victims of human trafficking a pathway to citizenship, but it relies on the victims cooperating in the prosecution of traffickers, which could be problematic (Richter & Richter, 2003). Many human traffickers belong to criminal organizations that are capable of retaliating against victims, either directly through targeting the victim or indirectly through targeting their families.

Additionally, human traffickers are often quite skilled at manipulating their victims because they often need to get their victims to willingly make the first step. After their victims are in their power, then they will reveal their true purpose (Rhodes, 2017). While the unethical nature of human trafficking is undeniable, it is important to remember that criminals are involved because they are supplying a substantial demand within the population, so it must be acknowledged that there is a significant failure in the ethics of that population. Free trade and globalization allow people to indulge in horrific violations against people that they dehumanize and there are always going to be criminals willing to supply them with the commodities that they desire

(Heller et al., 2018). Of course, this should not be a surprise to anyone who is a student of history, as the wealthy and powerful have always been willing to victimize the poor and vulnerable for their pleasure. In general, a significant proportion of humans will indulge in monstrous behavior if there is not a high probability of financial, legal, or social consequences, which is one of the reasons why the anonymity of the dark web (and the larger Internet) is so useful for people who want to indulge their inner demons.

When analyzing sex trafficking on the dark web, there are couple of concepts that should be forefront in the minds of researchers. First, they have an obligation to society to protect human rights and, by definition, sex trafficking violates the human rights of its victims, as they are treated as profitable commodities rather than people with intrinsic value (ACM, 2018). While privacy should also be considered a human right and should be included in any ethical treatment of the dark web, the right to privacy is less important than the right to life. By focusing on the right to life over the right to privacy, it may be possible to convince computer science professionals to volunteer their time to develop tools that would monitor dark web activity for signs of sex trafficking, which would only help in the fight against sex trafficking through the dark web,

## **Conclusion**

**W**hen we find ourselves examining the influence of the dark web on sex trafficking, we must ask ourselves what is going on and how can we change it? The evidence of sex trafficking is clear, it is a massive industry that is quite profitable for organized crime, and the dark web allows organized crime to exploit supply and demand efficiently and effectively. Since the demand exists in every substantial community, the victims of sex trafficking can be found in every substantial community, and it is an international problem because the victims come from every nation.

Computer science professionals have an ethical duty to come together to create better technologies for tracking sex trafficking through the dark web so that the authorities can catch the criminals involved and save the lives of their victims. Although there are some concerns that these technologies, just as the dark web itself, could be used for malicious purposes, how else is society going to deal with sex trafficking? These systems assist in the catching and the prosecution of the criminals involved in sex trafficking, as well authorities to rescue the victims of these criminals, hopefully before they suffer too much harm. Without government action to provide compensation for their work though, society must depend on computer science professional developing these tools for the good of society, which likely means that the development of these tools will likely be intermittent and slow, as computer science

professionals have limited time and resources.

It is important to remember though that sex trafficking is a tragedy that was created by our dependence on the Internet and, if we wish to retain the use of Internet technologies, this is one of the ills that society must work to mitigate. We are all stakeholders in our technological society because we are all

beneficiaries of technology, so we all bear the responsibility for the ills created by technology. If we seek to be ethical people, we must not only focus the good of the individual but, instead, the good of the global community. Therefore, we must work together as a society to address the ills created by our utilization of technology, such as the sex trafficking facilitated by the dark web.

## References

ACM. (2018). *Code of ethics and professional conduct*. Retrieved from <https://www.acm.org/code-of-ethics>

Dixon, H.B. (2013). Human trafficking and the Internet\* (\*and other technologies, too). *The Judges' Journal*, 52(1). Retrieved from [https://www.americanbar.org/groups/judicial/publications/judges\\_journal/2013/winter/human\\_trafficking\\_and\\_internet\\_and\\_other\\_technologies\\_too/](https://www.americanbar.org/groups/judicial/publications/judges_journal/2013/winter/human_trafficking_and_internet_and_other_technologies_too/)

ECPAT USA. (2019). *Statistics of trafficking and exploitation*. Retrieved from [https://www.ecpatusa.org/statistics?gclid=EAIaIQobChMIxYLMzJuD7AIVEgCGCh1OzwR0EAMYASAAEgLNrvD\\_BwE](https://www.ecpatusa.org/statistics?gclid=EAIaIQobChMIxYLMzJuD7AIVEgCGCh1OzwR0EAMYASAAEgLNrvD_BwE)

English, A. (2017). Mandatory reporting of human trafficking: potential benefits and risks of harm. *AMA Journal of Ethics*, 19(1), 54-62.

Enough Is Enough. (2020). *Sex trafficking*. Retrieved September 25, 2020, from <https://enough.org/stats-sex-trafficking>

Hammonds, J. (2015). An Inquiry into privacy concerns: Memex, the Deep Web, and sex trafficking. *Infosec Writers*. Retrieved from <http://infosecwriters.com/articles/2015/05/13/inquiry-privacy-concerns-memex-deep-web-and-sex-trafficking>

Heller, L.R., Lawson, R.A., Murphy, R.H., & Williamson, C.R. (2018). Is human trafficking the dark side of economic freedom? *Defence and Peace Economics*, 29(4), 355-382.

Kejriwal, M., Ding, J., Shao, R., Kumar, A., & Szekely, P. (2017). FlagIt: A system

for minimally supervised human trafficking indicator mining. *Cornell University*. Retrieved from <https://arxiv.org/abs/1712.03086>

Meyer, L. (2020). Effects of COVID-19 on sex trafficking survivors in St. Louis. Retrieved from <https://www.linkedin.com/pulse/effects-covid-19-sex-trafficking-survivors-st-louis-missouri-meyer/>

Rhodes, L. (2017). Human trafficking as cybercrime. *Agora International of Administrative Sciences*, 4, 23-29.

Richter, W.L., & Richter, L.K. (2003). Human trafficking, globalization, and ethics. *PA Times*, 26(2), 4.



# The Digital Divide During the COVID-19 Pandemic

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*Keywords:* digital divide, COVID-19, systemic inequity

## La brecha digital durante la pandemia COVID-19

*Palabras clave:* brecha digital, COVID-19, inequidad sistémica

## 新冠肺炎大流行期间的数字鸿沟

关键词：数字鸿沟，新冠肺炎（COVID-19），系统性不平等

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### Introduction

“Essential activities moved online (for COVID-19), yet sufficient Internet is an essential public service that remains unattainable for many US households” (Lai & Widmar, 2020, p. 458). The problem is how did COVID-19 amplify the digital divide? The digital divide is a societal problem that occurs when some people have access to and/or ownership of computer technology and when other people similar access and/or ownership (Britannica, 2014). When it comes to the COVID-19, there is an open question concerning how the computer divide has amplified the consequence of the digital divide from historical, scientific, and ethical perspectives.

### Discussion

In addressing COVID-19 in relation to the digital divide, it is critical to address historical, scientific, and ethical perspectives. First, the historical perspective provided the context of when the digital divide appeared and how it evolved in society. The digital divide originally was not a visible issue, as public opinion in the late 1990s and early 2000s saw access to computers and the Internet as a luxury and not a necessity (Strover, 2014). However, some scholars began discussing the digital divide and how widespread it was in the background (Strover, 2014). By 2005, personal computers and Internet access were becoming more prevalent, but 25-30% of people in the most developed

countries still had no access to one or the other (van Djik, 2006).

As scholars began to recognize this gap, these technologies became “a prominent vector of communication, interactions, and participation between citizens and societal entities” (Beaunoyer et al., 2020, p. 2). Thus, this new reliance on technology in society strengthened the digital divide because not only was there a divide between access to technology, but there was a growing social separation that evolved that focused on access to certain communications and activities in society. Over time, the digital divide continued to grow and “evolved beyond access to technology and has expanded to include inequalities in technology skills” (Rogers, 2016, p.197). This evolution in technology will likely continue to contribute to the digital divide because as reliance on computer technology continues to grow, society will become more reliant on people using it will need to perform basic social functions.

Also, before the pandemic, Internet access was not a priority to everyone, and most people were able to function normally without computer technology, though they suffered from some disadvantages (Beaunoyer et al., 2020). The physical quarantine and social distancing measures that followed the pandemic though amplified the digital divide because they made Internet access a vital necessity for commerce, education, employment, and socialization. People who lacked reliable Internet connections were incapable of buying goods, furthering their educa-

tion, earning a living, connecting with friends and family, etc.

Rural areas were hit hard because historically, “substantial segments of rural America still lack the infrastructure needed for high-speed internet” (Perrin, 2019, para. 8). This lack of infrastructure further amplified the impact of the digital divide because urban and wealthier people were able to avoid exposure to the pandemic by working from home while rural and poorer people did not have that luxury. Poorer people were often forced to choose between earning a living to support themselves and their families and avoiding potential exposure to protect themselves and their families.

Internet access has become a necessity for employment and, without high speeds and reliable access, workers lose productivity or are unable able to perform their jobs properly. In addition to the employment aspect of internet access, another key issue has been the migration of medical systems to the online environment. In early 2020, when the pandemic first hit the United States, healthcare appointments started to move to a virtual format when healthcare providers sought to protect their employees and their patients, but many healthcare providers soon realized that many of their patients could not access these visits and systems (Ramsetty & Adams, 2020). The digital divide created a barrier between patients and their healthcare because of their lack of access to certain now-virtual healthcare functions, which could harm their health.

Secondly, a scientific perspective provides insights into how COVID-19 is affecting the digital divide by looking at existing Internet infrastructure, as well as demographics of Internet and computer access. To start with infrastructure, in 2018, over half of rural U.S. residents had broadband speeds that would support four devices according to the FCC, compared to nearly all of urban U.S. residents (Lai & Widmar, 2020). These slower Internet speeds created a large disadvantage for rural residents in the COVID-19 pandemic because it creates difficulties connecting to essential online services. These services may have included healthcare visits, work, or online classes. Beyond just rural America, a 2014 study found that nearly all of Americans can get access to high-speed Internet, yet only around two-thirds subscribed to that same high-speed Internet at home (Strover, 2014). While most Americans could get access to the Internet, subscribing to it at home was more important due to the COVID-19 pandemic because accessing public areas for Internet access would potentially increase exposure risk to COVID-19. Nationally, price data suggests that people in the U.S. paid more for lower broadband quality than in other industrialized countries and these higher prices amplified the digital divide, especially during the COVID-19 pandemic (Strover, 2014). Higher prices combined with higher Internet usage and remote work caused people who could not afford those prices to lose their jobs or fall behind in their education.

Additionally, to highlight the digital divide during the COVID-19

pandemic, the demographics of poverty contributed to the lack of Internet access and computer access. Vulnerable groups like seniors, the homeless, rural residents, and recent immigrants were the hardest to reach using digital media (Beaunoyer et al., 2020). Their lack of digital media blocked them from accessing up-to-date information about the COVID-19 pandemic, highlighting a consequence of the digital divide (Beaunoyer et al., 2020). This lack of critical COVID-19 information transformed the digital divide into a public health issue because those already vulnerable groups became more at risk for contracting and being harmed by COVID-19.

Moving more specifically to seniors, a 2019 study found that while one-fifth of retirement home residents used the Internet, even they had difficulty using modern computing devices because they lacked the required technological skills (Seifert et al., 2020). This lack of Internet usage and skills created disadvantages for the seniors because proper technical skills were required to attend and access vital healthcare services. Without being able to access important healthcare services online, seniors were more vulnerable to COVID-19 while visiting in person, especially seniors who already belonged to high-risk groups because of serious illnesses. By 2014, several studies of U.S. states, including Texas and California, failed to find or suggest organized solutions and programs to address the digital divide (Strover, 2014). Ironically, these “failed” studies were successful because they opened the door to future

research and studies about the digital divide and allowed researchers to find specialized and smaller grouped solutions to ending the digital divide.

Finally, consider the ethical perspective of the digital divide. Starting from early in the digital divide conversation and research efforts, scholars previously dismissed the divide as a myth because they claimed technology would be prevalent everywhere (Nguyen, 2012). This initial reluctance and dismissal harmed people disadvantaged by the digital divide and benefitted those with access to technology because it allowed those with access to gain benefits while not helping those without technology. Without this hesitation, more people could have been helped and given access to technology earlier. Once the digital divide became a clear issue to scholars and the public, companies started speaking out in support of eliminating the divide.

While these companies, specifically computer companies and Internet providers, spoke out against the digital divide, they did so to gain more customers, not due to any ethical impulse (Moss, 2002). These companies supported eliminating the digital divide because of they intended to increase their profits, which would make their positions ethically questionable (Paul & Elder, 2010). Companies using ethically good statements to drive economic gain while failing to combat the divide with their own resources were taking unethical positions, while companies that were willing to utilize their resources to end the divide were taking ethical

positions. Thus, a company's actions decided whether their statements towards ending the digital divide were ethical or unethical.

Additionally, early claims made by scholars about the digital divide and technology becoming prevalent were not too far-fetched. Newer technology did become prevalent, but their positions did not take into account the harm that disadvantaged groups would suffer in the meantime (Nguyen, 2012). The universal ethical principle should have been to ensure a standard of living for health and well-being, which was violated in the case of disadvantaged groups (Paul & Elder, 2010). During emergency periods, such as during the COVID-19 pandemic, a family's health could have been compromised due to a lack of information about the ongoing pandemic and lack of knowledge of safety precautions. Thus, the principle to have a right to standard living for health and well-being included a right to information, as information could influence one's health and well-being, which was shown during the COVID-19 pandemic.

While there were aspects of the digital divide itself that could be ethically discussed, there were also ethics regarding progress in ending the divide. For example, simply just giving technologies to people was not enough to end the divide, as people needed to be taught and provided resources to allow them to utilize the technology to overcome the divide from within (Busch, 2010). I argue that teaching and providing resources is ethical because

it allows people to share information and resources to solve a societal problem from the ground up (Paul & Elder, 2010). Even beyond just the basic distribution of technology, there were unethical practices that came about when providers pushed low-income people to purchase older and inferior technology for the sake of ending the visible divide, as future technology would make their purchases nearly useless (Moss, 2002). This practice was unethical because it was a refusal by providers to tell the truth about aging technology, creating a cycle of obsolescence for low-income individuals that would force them to buy newer technology to keep accessing to the same systems they had before. Utilizing this practice would not end the divide; it would only delay it.

The concepts of improving situations and adding to the world were important in developing a deeper understanding of the digital divide (Association for Computing Machinery [ACM], 2018). First, improving situations was understood as bringing a more desirable outcome to a situation and bringing it to better conditions than existed before (Dictionary.com, 2021). Working towards ending the digital divide improved a person's situation because it allowed them to access more services and opportunities online and to become more connected to the world. Access to the Internet and computers was also necessary, especially during the COVID-19 pandemic, because it allowed a person to work from their home or attend school at home, protecting them by limiting their exposure to the virus. Ending the digital divide would

end up allowing everyone to be on equal grounds with technology because everyone would have access to the same basic technological necessities as each other, such as online communication. It would also improve the situations of many people situations by simply allowing them to access the same online services and not be left behind in an aspect of life that is becoming more vital.

Adding to the world is also critical to gaining a deeper understanding of an issue (ACM, 2018). Adding to the world is understood as benefitting society and the environment surrounding it (ACM, 2018). Ending the digital divide is adding to the world because individual people in society benefit from gaining access to the Internet and computers, allowing for more opportunities and a better life. The environment can also be improved by ending the digital divide because as more people are connected worldwide via the Internet, more solutions to problems of today's world can be solved. More great minds working together can result in more solutions to problems like the changing climate or environmental issues. Additionally, parts of society that have been historically left behind could prosper more because they could be able to access opportunities previously not obtainable. Overall, setting people on a more equal playing field with technology could allow the world to advance quicker and allow more people to succeed in life more easily.

## Conclusion

The COVID-19 pandemic amplified the digital divide in a negative way for society because of the shift society had taken to function virtually. Society moved online, yet those without access to computers and the Internet had a barrier form between them and work, school, online health-care systems, and other online connections. The digital divide already affected certain communities more than others so, with the addition of the COVID-19 pandemic, their divide became more apparent. Information and resources became harder to acquire in a time where information and resources were more important than ever.

If the digital divide does not end up being resolved soon, disadvantaged communities will remain behind in our current technology and will continue

to be behind when newer technology arises. This is not an issue that will be solved when the technology currently defining the divide becomes outdated, it will instead change to be defined by the technology that people also use in the future. Another significant point is the fact that when the COVID-19 pandemic is over, the digital divide will not disappear. As current technology defines the digital divide and the COVID-19 pandemic amplifies it, an absence of the pandemic will not bring an absence of the digital divide. We will go back to a more normal society that includes the digital divide and its disadvantages. If the digital divide is not tackled now, generations of families and individuals will continue to live with unnecessary and solvable problems based only on the fact that they do not own an essential piece of technology.

## References

Association for Computing Machinery. (2018). *Code of Ethics and Professional Conduct*. Retrieved from <https://www.acm.org/code-of-ethics>.

Beaunoyer, E., Dupéré, S., & Guitton, M. J. (2020). COVID-19 and digital inequalities: Reciprocal impacts and mitigation strategies. *Computers in Human Behavior, 111*, 106424. <https://doi.org/10.1016/j.chb.2020.106424>

Busch, T. (2010). Capabilities in, capabilities out: Overcoming digital divides by promoting corporate citizenship and fair ICT. *Ethics and Information Technology, 13*(4), 339–353. <https://doi.org/10.1007/s10676-010-9261-3>

Elder, L., Paul, R., & Foundation for Critical Thinking. (2010). *The Thinker's Guide to Analytic Thinking*. Foundation for Critical Thinking.

Improve. (n.d.). In *Dictionary.com*. Retrieved April 2, 2021, from <https://www.dic>

[tionary.com/browse/improve](https://dictionary.com/browse/improve)

Lai, J., & Widmar, N. O. (2020). Revisiting the digital divide in the COVID-19 era. *Applied Economic Perspectives and Policy*. <https://doi.org/10.1002/aepp.13104>

Moss, J. (2002). Power and the digital divide. *Ethics and Information Technology*, 4(2), 159–165. <https://doi.org/10.1023/a:1019983909305>

Nguyen, A. (2012). The digital divide versus the ‘digital delay’: Implications from a forecasting model of online news adoption and use. *International Journal of Media & Cultural Politics*, 8(2), 251–268. [https://doi.org/10.1386/macp.8.2-3.251\\_1](https://doi.org/10.1386/macp.8.2-3.251_1)

Perrin, A. (2019, May 31). *Digital gap between rural and nonrural America persists*. Pew Research Center. <https://www.pewresearch.org/fact-tank/2019/05/31/digital-gap-between-rural-and-nonrural-america-persists/>

Ramsetty, A., & Adams, C. (2020). Impact of the digital divide in the age of COVID-19. *Journal of the American Medical Informatics Association*, 27(7), 1147–1148. <https://doi.org/10.1093/jamia/ocaa078>

Rogers, S. E. (2016). Bridging the 21st century digital divide. *TechTrends*, 60(3), 197–199. <https://doi.org/10.1007/s11528-016-0057-0>

Schweitzer, E. J. (2014). *Digital divide*. Encyclopedia Britannica. <https://www.britannica.com/topic/digital-divide>

Seifert, A., Batsis, J. A., & Smith, A. C. (2020). Telemedicine in long-term care facilities during and beyond COVID-19: Challenges caused by the digital divide. *Frontiers in Public Health*, 8, 601595. <https://doi.org/10.3389/fpubh.2020.601595>

Strover, S. (2014). The US digital divide: A call for a new philosophy. *Critical Studies in Media Communication*, 31(2), 114–122. <https://doi.org/10.1080/15295036.2014.922207>

van Dijk, J. A. G. M. (2006). Digital divide research, achievements and shortcomings. *Poetics*, 34(4–5), 221–235. <https://doi.org/10.1016/j.poetic.2006.05.004>





