

Biocomplexity and AI: A symbiotic relationship

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<https://nssac.github.io/sociotechnicaldigitaltwins>

<https://net.science/home>



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Thanks to Siva, Rajesh, Narahari, Vijay and others at ICTS and IISc and to members of the research team, our students, postdocs, and collaborators at SUNY Albany, CDC, NEU, NIH, DTRA, Georgia Tech, JHU, UMD, Princeton, Stanford, VT, Yale, Argonne, IISc, Pittsburgh and Purdue Supercomputing Centers, Persistent Systems, and others.



 **43** administrative & research staff

 **17-20** graduate students

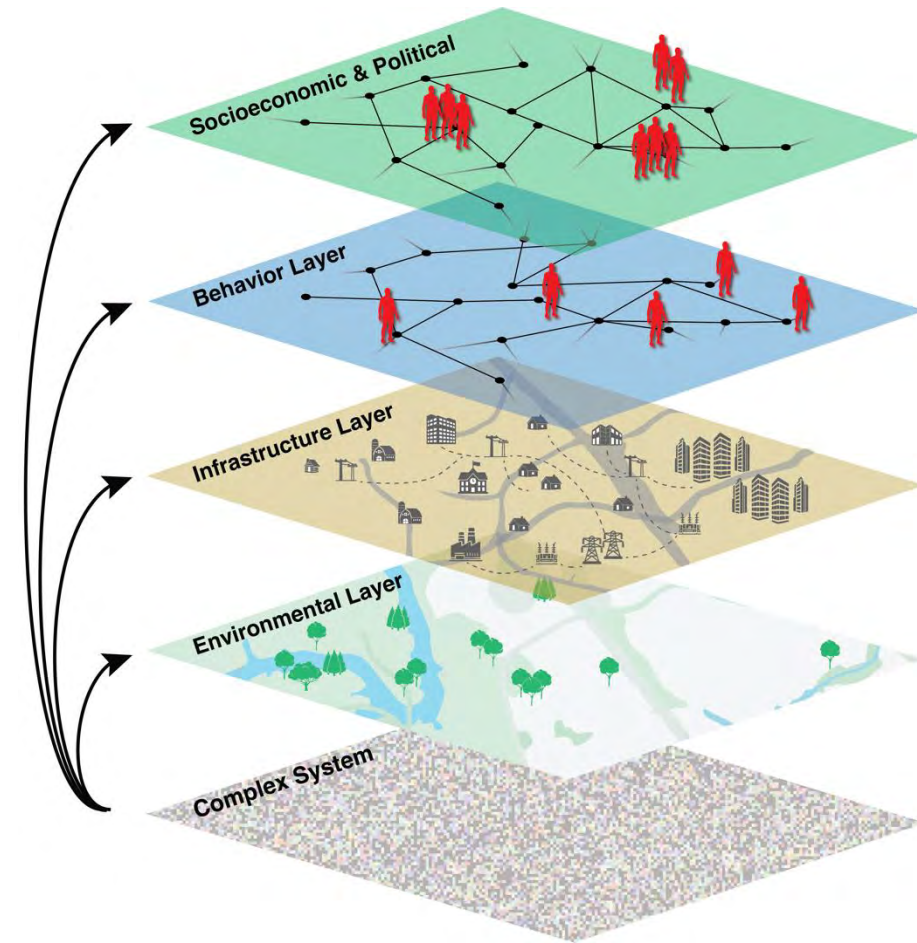
 **6-25** undergraduate students



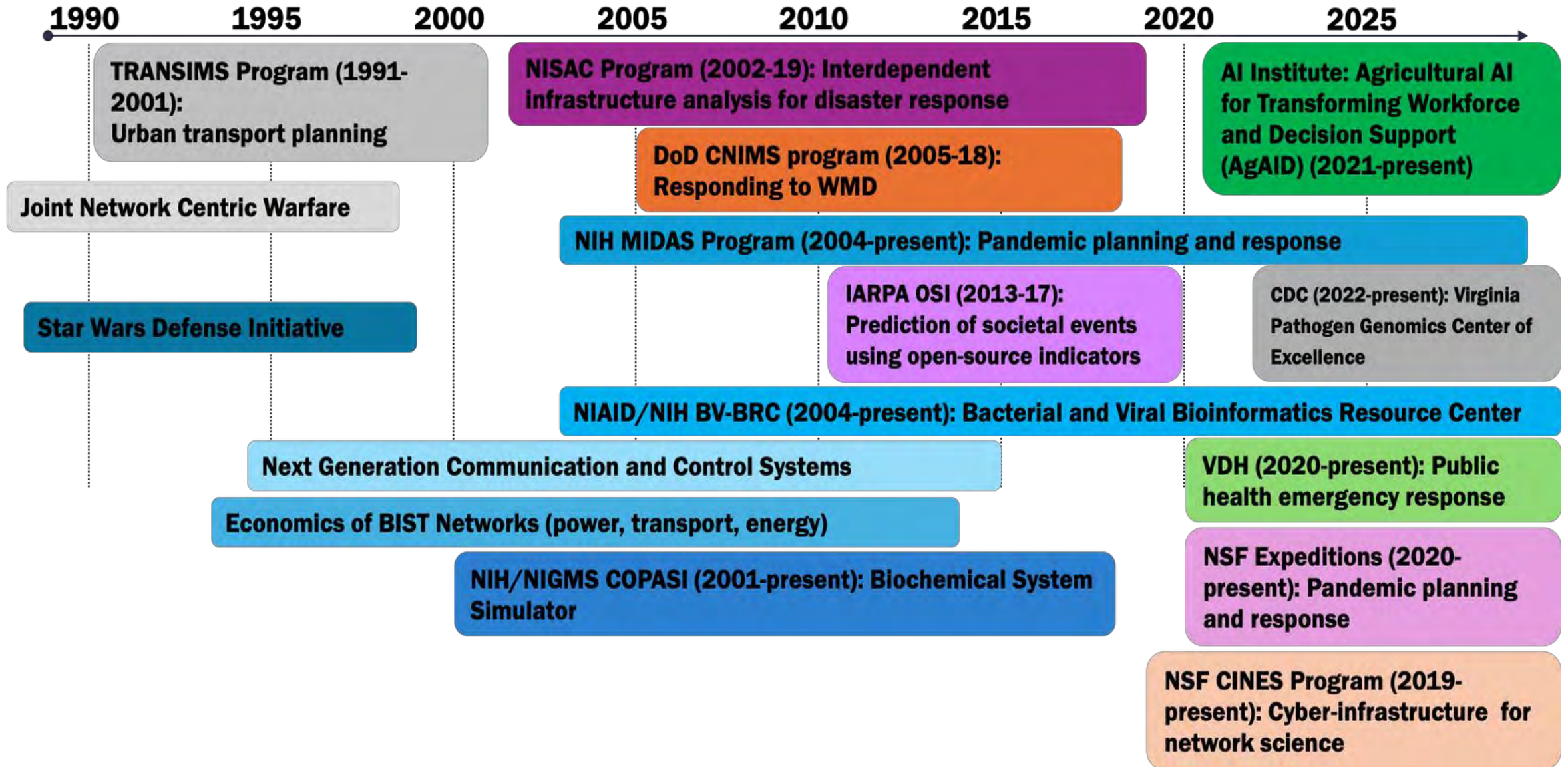
● Biocomplexity Institute

Biocomplexity refers to the interactions of living and non-living agents and ecologies, including humans and their enabling technologies.

- Mission-driven projects that lead to fundamental advances in science and technology
- Problems that cannot be solved by a single faculty member or within the narrow boundaries of a discipline
- Problems that require *sophisticated tools and diverse intellectual resources*
- Tangible societal and scholarly impact (over 350 publications)



● A Brief History



TRANSIMS: Urban Transport Planning Modeling Environment

- TRANSIMS: (1991–2001)
 - Set up to address important national problems
 - Assessing traffic flows during congestion
 - Predicting household behavior when the infrastructure changes
 - Assessing social justice issues in proposed infrastructure changes
 - Predicting environmental impact
- Requirements set by:
 - Government (DOT), regional planning organizations, university researchers & transportation consultants
- Technology developed in collaborations with MPO
 - Developed by team at LANL
 - Case studies with Albuquerque, Dallas, Portland MPOs
- TRANSIMS is currently an open-source system managed by Argonne National Laboratory



Figure 1 – White House Area Street Closures

https://www.ncpc.gov/docs/WHATS_Final_Report.pdf



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National Planning Scenario 1

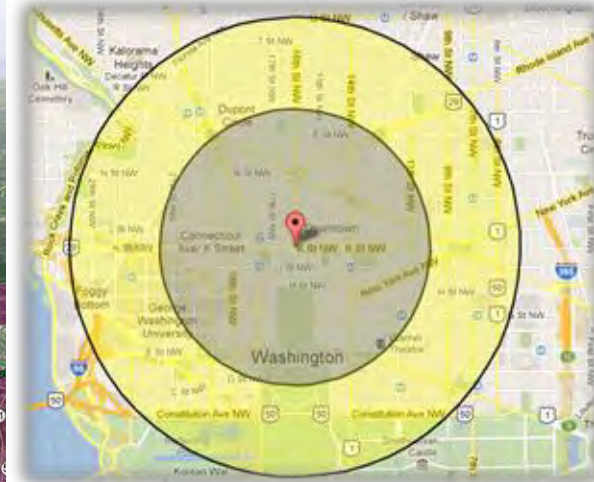
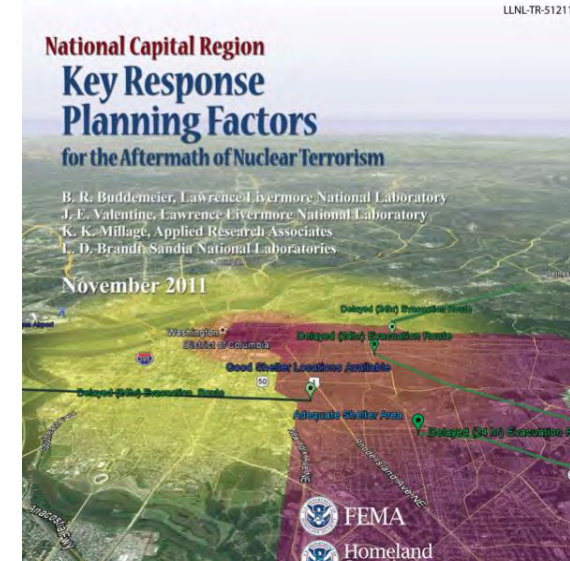
Hypothetical Scenario:

- Unannounced 10 kt detonation of an Improvised Nuclear Device (IND)
- 11:15am May 15th, 2006
- 16th and K Street, Washington DC

Traditional Focus

- Prompt impact on overall health
- Responders and their safety
- Victims as essentially passive
- Cold war scenarios or low-level exposure to radiation

WSC 2015, AAMAS JAAMAS, Mitch Waldrop's articles in Science and PNAS



What did we learn

Even a *partially restored* communication system has disproportionately positive impact on the overall behavior:

- Fewer deaths, better health outcomes & reduction in anxiety
- Policy question: how do we build a self forming comm network?

Large part of power network unlikely to be operational for >2 years

- NO significant cascading failures beyond a small area likely
- Important implications on how the city and its surroundings will be reconstituted

Individual emergent behaviors: personal choices + contextualized dynamic decisions + institutionalized processes and policies

Models: understandable, explainable & computationally efficient

- Individual and collective behavior and behavioral adaptation
- Sensitive to contextual information



Pandemic Modeling and Response: 2000–Present



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COVID-19 resource page: <https://covid19.biocomplexity.virginia.edu/>

COVID work done by NSSAC: <https://nssac.github.io/covid-19/index>

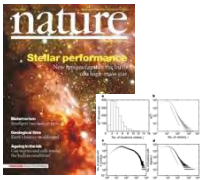
NSF Expeditions Project: <https://computational-epidemiology.org>

NSF PREPARE: Virtual Organization Project: <https://prepare-vo.org>

- Since 2004 BI has supported federal agencies during all major outbreak response efforts

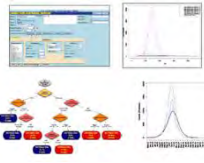
2004

Smallpox



2009

H1N1



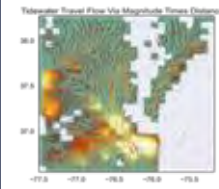
2013

Influenza



2016

Zika



2020

COVID-19



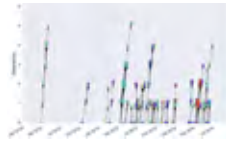
2005

H5N1



2012

MERS



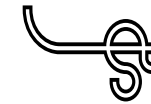
2014

Ebola



2018

Ebola

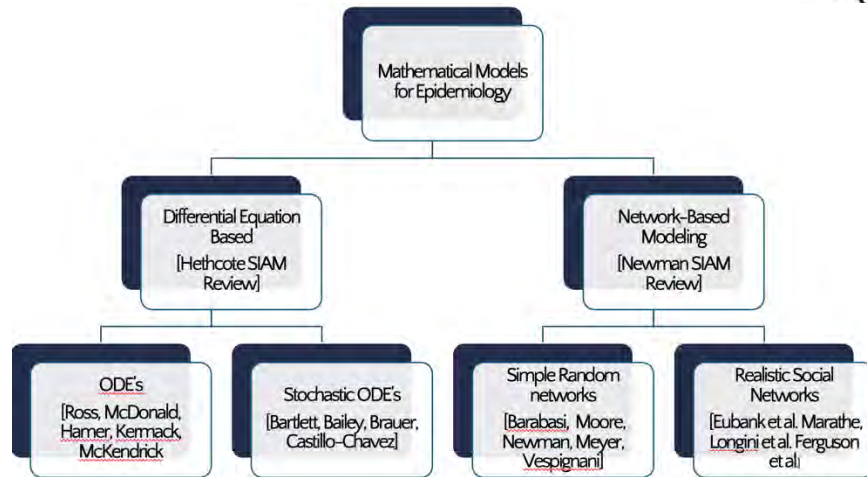
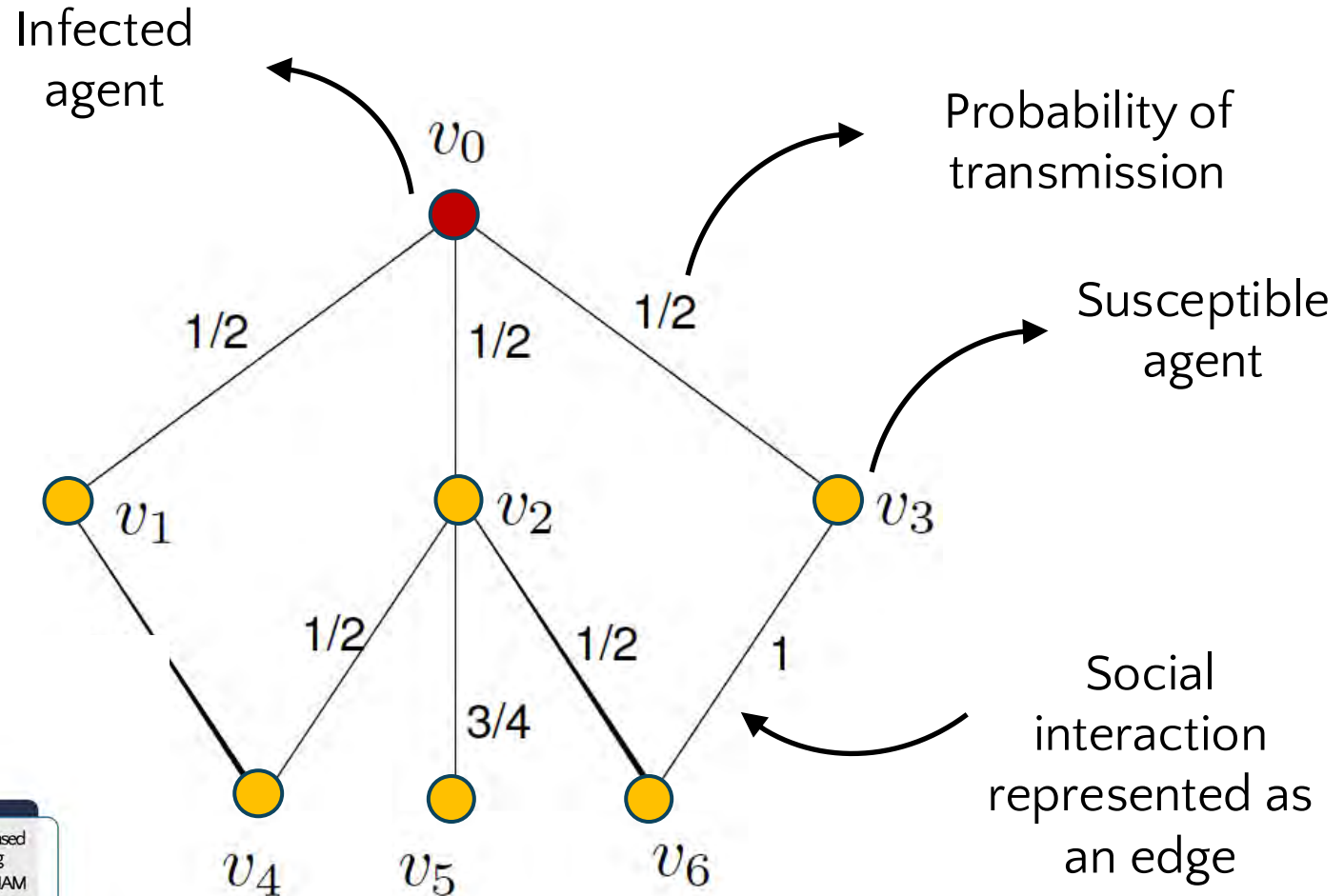
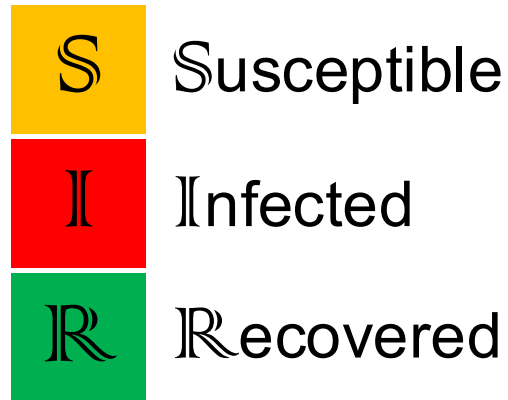


2024

H5N1

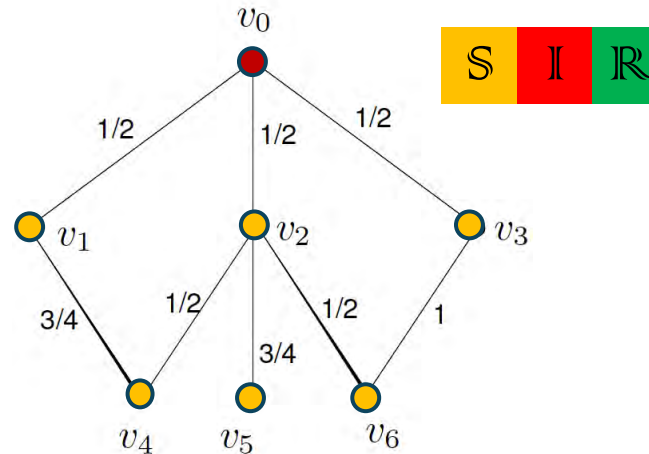


Models based on networks



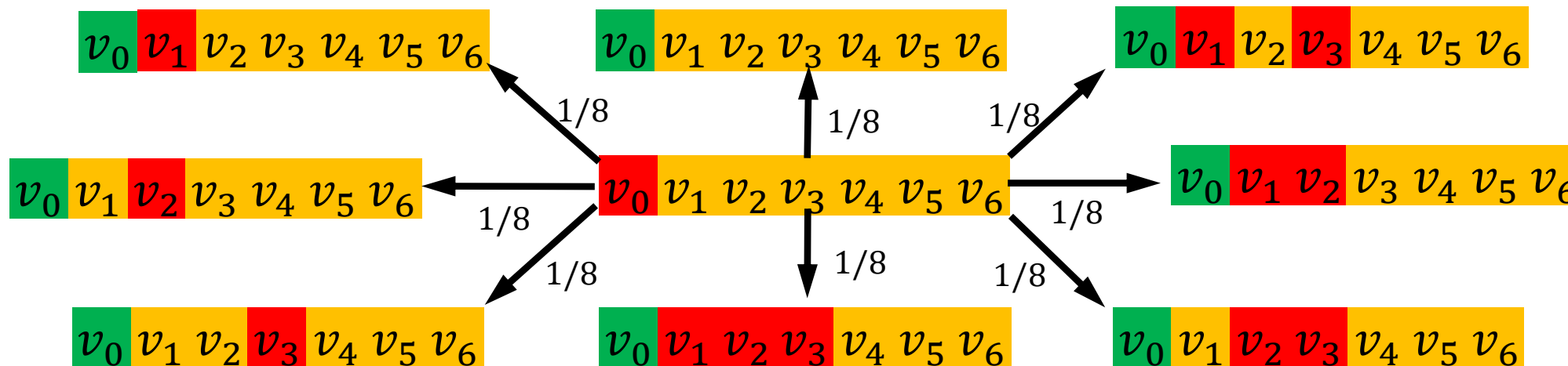
Understanding the dynamics requires the study of exponentially large system

Temporal Dynamics represented by Markov Chain (just a fragment is depicted)



Markov chain (partial) exponentially larger than the network

A social network with n nodes & 3 disease states per nodes yields a chain of size 3^n



● The reachability problem

- Given, time $t = 0$,
 - A fixed network $G(V, E)$ with n vertices and m edges
 - A single infected individual
 - SIR dynamics with infectious and incubation period (more generally we are given a within host disease manifestation function)
 - The transmission probability on edge $\{u, v\}$ is $p_{\{u, v\}}$
- Question:
 - (Reachability) Find the state of the system after t time units
 - **State:** we can consider various functional forms, e.g. the dendrogram, the total number of infections until t , number of active infections at time $t' \leq t$
 - Given that the system is stochastic, each state estimation usually comes with an estimate of the probability associated with that state

- **Computational cost of analyzing SIR dynamics**
- The state assessment problem is **#P**-hard
 - Implies that simulations are needed for understanding the dynamics
 - Even short-term state assessment is hard
 - Result due to stochastic nature of the dynamical process
 - Similar results hold for inference and intervention analysis problems
- *Associated Markov chain size – astronomical in the size of the description*
 - *Network with 10^6 nodes & (3 states: S,I,R), the chain has 3^{10^6} nodes; impossible to do naïve search*

**Simulations are therefore
necessary to solve this problem**

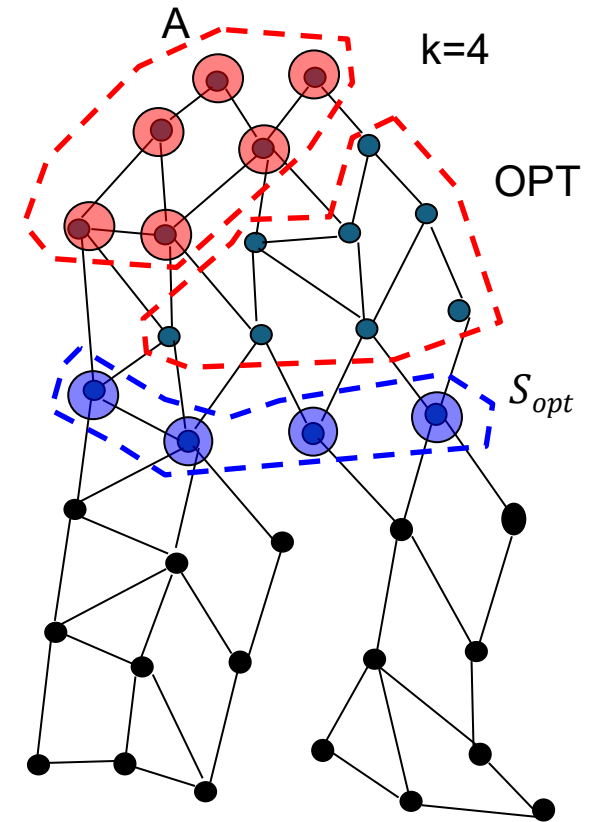
Rosenkrantz DJ, Vullikanti A, Ravi SS, Stearns RE, Levin S, Poor HV, Marathe MV. Fundamental limitations on efficiently forecasting certain epidemic measures in network models. *Proceedings of the National Academy of Sciences*. 2022 Jan 25;119(4):e2109228119.

Control problems: Vaccine allocation

Given: A fixed network $G(V, E)$ with n vertices and m edges. SIR dynamics with infectious and incubation period = 1. The transmission probability on edge $\{u, v\}$ is $p_{\{u,v\}}$. Initial infected set A and budget k for #vaccines

Objective: Select set S (of size k) to vaccinate so that expected #infections is minimized

- Theorem:** $\forall \mu \geq 1$, and $p_{\{u,v\}} = 1$, a polynomial time algorithm that vaccinates $(1 + \mu)k$ nodes & results in $\leq (1 + \frac{1}{\mu})OPT$ infected people. Here OPT denotes the optimal number of infections that when k individuals are vaccinated



COVID-Response



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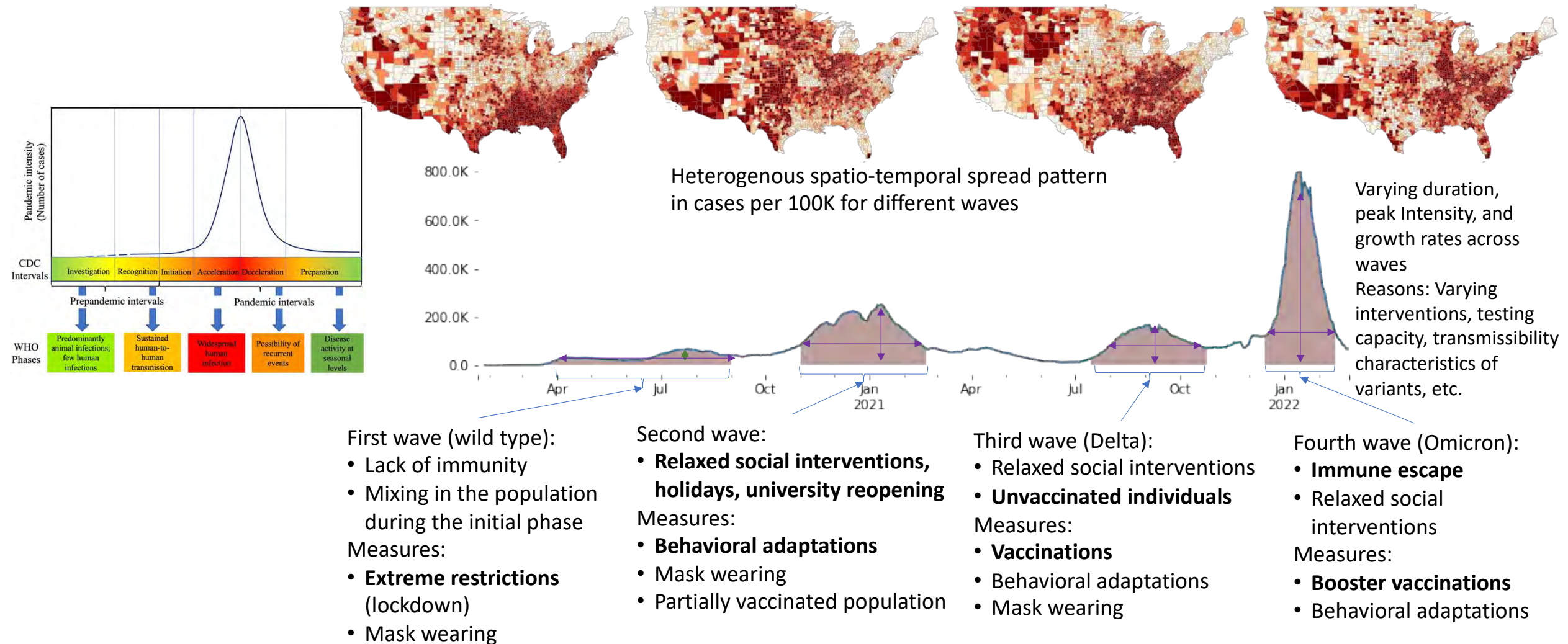
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NSF Expeditions Project: <https://computational-epidemiology.org>

NSF PREPARE: Virtual Organization Project: <https://prepare-vo.org>

● Evolution of COVID-19 pandemic was complicated



● Real-time operational response during a pandemic

- **Real-time:** Strict deadlines drive the time to build, test & complete tasks
- **Operational:** Problems derived from current needs; resulting analysis should be useful to decision makers and need not be perfect every time
- **Evolving:** The pandemic evolves constantly -- pipeline needs constant adaptation
 - Acquire, process, organize and ingest diverse data
 - Vaccine uptake, mobility patterns, interventions, ...
 - Modify, enhance, test and deploy models under strict deadline
 - New situations require new abstractions and models
 - Prepare wide ranging documents, analyses, and presentations for communicating the results (to analysts, decision makers, broad public, press,...)



Harvey V. Fineberg is president of the Institute of Medicine.



Mary Elizabeth Wilson is associate professor of Global Health and Population at the Harvard School of Public Health and associate clinical professor at Harvard Medical School, Boston, MA.

Science
AAAS

Epidemic Science in Real Time

FEW SITUATIONS MORE DRAMATICALLY ILLUSTRATE THE SALIENCE OF SCIENCE TO POLICY THAN AN epidemic. The relevant science takes place rapidly and continually, in the laboratory, clinic, and community. In facing the current swine flu (H1N1 influenza) outbreak, the world has benefited from research investment over many years, as well as from preparedness exercises and planning in many countries. The global public health enterprise has been tempered by the outbreak of severe acute respiratory syndrome (SARS) in 2002–2003, the ongoing threat of highly pathogenic avian flu, and concerns over bioterrorism. Researchers and other experts are now able to make vital contributions in real time. By conducting the right science and communicating expert judgment, scientists can enable policies to be adjusted appropriately as an epidemic scenario unfolds.

In the past, scientists and policy-makers have often failed to take advantage of the opportunity to learn and adjust policy in real time. In 1976, for example, in response to a swine flu outbreak at Fort Dix, New Jersey, a decision was made to mount a nationwide immunization program against this virus because it was deemed similar to that responsible for the 1918–1919 flu pandemic. Immunizations were initiated months later despite the fact that not a single related case of infection had appeared by that time elsewhere in the United States or the world (www.ion.edu/swinefluaffair). Decision-makers failed to take seriously a key question: What additional information could lead to a different course of action? The answer is precisely what should drive a research agenda in real time today.

In the face of a threatened pandemic, policy-makers will want real-time answers in at least five areas where science can help: pandemic risk, vulnerable populations, available interventions, implementation possibilities and pitfalls, and public understanding. Pandemic risk, for example, entails both spread and severity. In the current H1N1 influenza outbreak, the causative virus and its genetic sequence were identified in a matter of days. Within a couple of weeks, an international consortium of investigators developed preliminary assessments of cases and mortality based on epidemic modeling.*

Specific genetic markers on flu viruses have been associated with more severe outbreaks. But virulence is an incompletely understood function of host-pathogen interaction, and the absence of a known marker in the current H1N1 virus does not mean it will remain relatively benign. It may mutate or acquire new genetic material. Thus, ongoing, refined estimates of its pandemic potential will benefit from tracking epidemiological patterns in the field and viral mutations in the laboratory. If epidemic models suggest that more precise estimates on specific elements such as attack rate, case fatality rate, or duration of viral shedding will be pivotal for projecting pandemic potential, then these measurements deserve special attention. Even when more is learned, a degree of uncertainty will persist, and scientists have the responsibility to accurately convey the extent of and change in scientific uncertainty as new information emerges.

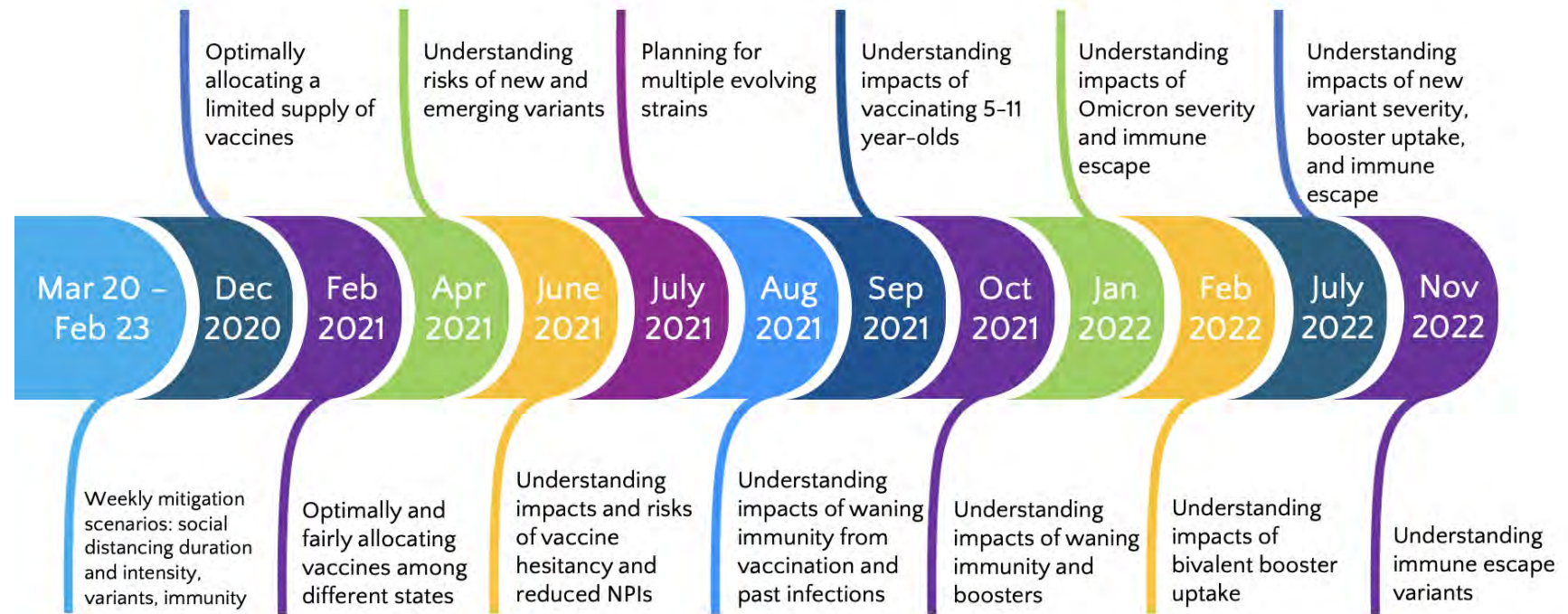
A range of laboratory, epidemiologic, and social science research will similarly be required to provide answers about vulnerable populations; interventions to prevent, treat, and mitigate disease and other consequences of a pandemic; and ways of achieving public understanding that avoid both over- and underreaction. Also, we know from past experience that planning for the implementation of such projects has often been inadequate. For example, if the United States decides to immunize twice the number of people in half the usual time, are the existing channels of vaccine distribution and administration up to the task? On a global scale, making the rapid availability and administration of vaccine possible is an order of magnitude more daunting.

Scientists and other flu experts in the United States and around the world have much to occupy their attention. Time and resources are limited, however, and leaders in government agencies will need to ensure that the most consequential scientific questions are answered. In the meantime, scientists can discourage irrational policies, such as the banning of pork imports, and in the face of a threatened pandemic, energetically pursue science in real time.

— Harvey V. Fineberg and Mary Elizabeth Wilson

**J. Am. Med. Assoc.*, Science 14 May 2009 (10.1126/science.1171662).

Supporting COVID Response: 2020-2025



International & Federal agencies



Commonwealth of Virginia

Primary modeling for planning and response efforts



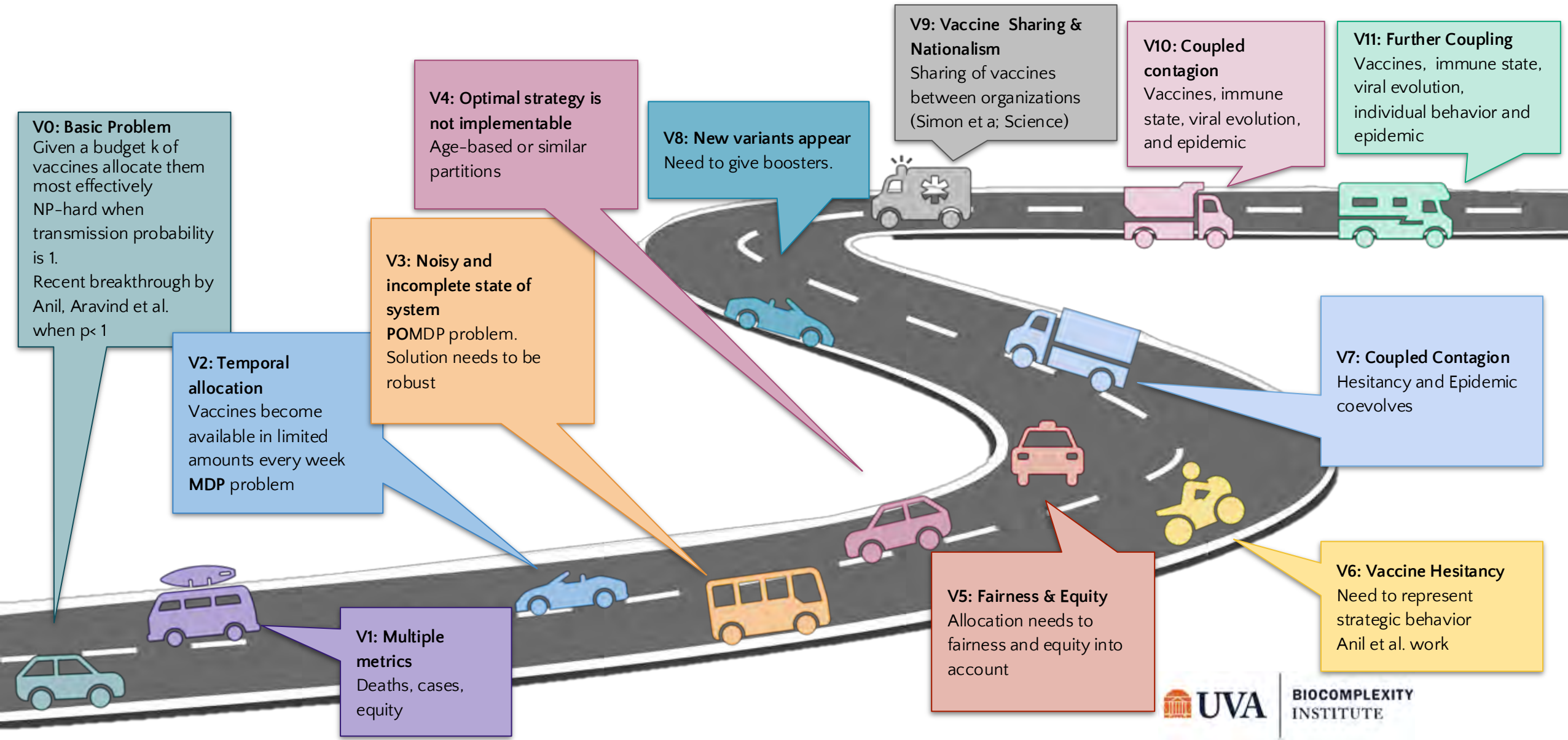
Local agencies

Virginia Hospital and Healthcare Association (comprised of 27-member health systems and 110 community and specialty hospitals)



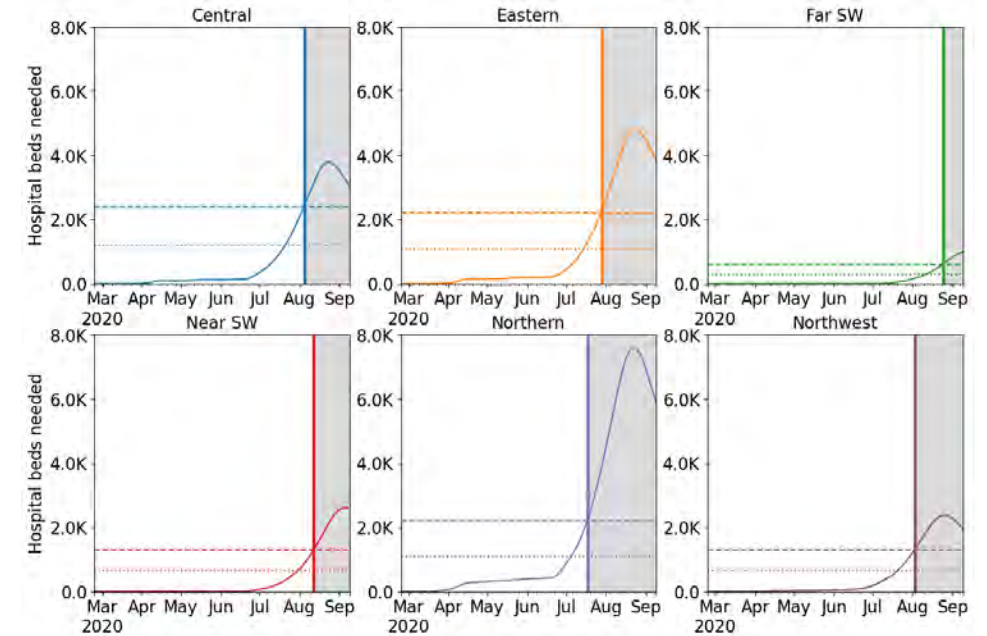
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Motivated new fundamental questions – Vaccine allocation: from simple to complex



● Guidance on field hospitals

As of April 13, 2020, model estimated at least 3 months of lag before hitting hospital capacity under the "Pause" scenario



April 13, 2020

April 17, 2020

April 21, 2020

May 7, 2020

HEALTH & MEDICINE

U.Va.'s coronavirus model projects Virginia will have enough hospital capacity in next few months

By Peter Cozzitelli and Gary A. Hahn
The Virginian-Pilot on Apr. 13, 2020 at 11:02 AM



Gov. Ralph Northam, left, speaks, accompanied by state Secretary of Health and Human Resources Dr. Daniel Carney, right, during a news conference on the state's preparedness for the coronavirus at the Capitol in Richmond, Va., on Wednesday, Mar. 4, 2020. (AP Photo/Steve Heller) (Steve Heller/AP)

Virginia is 'pivoting away' from field hospitals

Dr. Danny Avula of Richmond/Henrico health departments says hospitals likely can handle coming surge.

PUBLISHED APRIL 17, 2020 BY KATE ANDREWS

virginia
BUSINESS

Virginia is "pivoting away" from needing field hospitals to handle patient overflow because health systems believe they'll be able to manage any surge in COVID-19 cases, said Dr. Danny Avula, the director of Richmond and Henrico County's health departments, Friday evening.

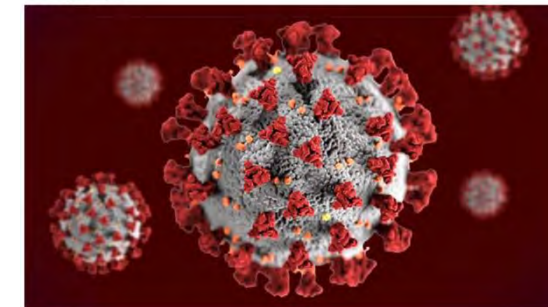
"We have not seen any significant increase in hospitalization [and] ventilator use is under 25%," Avula said during a news briefing. "It feels like the calm before the storm, and hopefully the storm will never come."



Dr. Danny Avula, director of Richmond and Henrico County health departments, at his April 17 news conference

Examining the [University of Virginia's COVID-19 forecasting model](#), Avula said, Virginia seems

Virginia hits pause on plans for 3 large field hospitals



COVID-19 (AP)
Updated: Apr. 21, 2020 at 5:52 PM EDT

U.S. Field Hospitals Stand Down, Most Without Treating Any COVID-19 Patients

May 7, 2020 - 1:15 PM ET
Reported by: Ali Thomas, Contributor

JOEL ROSE



Construction at the COVID-19 field hospital at McCormick Place in Chicago on April 16. The city opened back space for a 3,000-bed temporary hospital as the nation's largest convention center as infection numbers decreased.

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● Tools to support decision makers in real-time



[Best Paper Award for SIG KDD 2021](#)

Mobility-based policy analysis tool

Interactive tool to analyze the impact on future cases based on altering mobility to different types of locations



<https://nssac.bii.virginia.edu/covid-19/dashboard/>

Global COVID-19 cases

Provides interactive resource for monitoring and analyzing COVID-19 health statistics from around the world



<https://nssac.bii.virginia.edu/covid-19/vmrddash/>

Medical Resource Dashboard

Provides interactive resource for monitoring current and future projected hospitalization burden



<https://nssac.bii.virginia.edu/covid-19/vaxstatdashboard/>

Vaccination Statistics Dashboard

Provides predictive modeling and multiple reports assessing vaccination coverage

Contributing to CDC supported scenario modeling hub (SMH) for public health policy and decision making

<https://covid19scenariomodelinghub.org/index.html>

NPI decisions
after primary
vaccination
(MMWR May
2021)



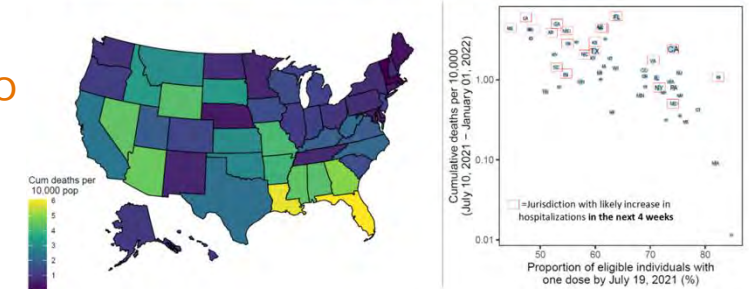
Modeling of Future COVID-19 Cases, Hospitalizations, and Deaths, by Vaccination Rates and Nonpharmaceutical Intervention Scenarios — United States, April–September 2021

Rebecca K. Borchering, PhD^{1,2}; Cécile Viboud, PhD^{2,3}; Emily Howerton¹; Claire P. Smith¹; Shaun Trudove, PhD³; Michael C. Runge, PhD⁴; Nicholas G. Reich, PhD⁵; Lucie Contamin, MS⁶; John Leventer⁶; Jessica Salerno, MPH⁶; Wilbert van Boven, PhD⁷; Matt Kinney, PhD⁷; Kate Tallacron, MS⁷; R. Freddy Obenhe, PhD⁷; Laura Asher, MS⁷; Cath Costello, MS⁷; Michael Kelbaugh⁷; Shelby Wilson, PhD⁷; Lauren Shin⁷; Molly E. Gallagher, PhD⁷; Luke C. Mullany, PhD⁷; Karlin Rainwater-Lovett, PhD⁷; Joseph C. Lemaitre, MS⁸; Juan Dent, SM⁹; Kyra H. Grant⁹; Joshua Kaminsky, MS⁹; Stephen A. Lauer, PhD⁹; Elizabeth C. Lee, PhD⁹; Hannah R. Mendillo, PhD⁹; Javier Perez-Saez, PhD⁹; Lindsay T. Keegan, PhD⁹; Dean Karlen, PhD⁹; Matteo Chinazzi, PhD¹⁰; Jessica T. Davis¹¹; Kumpeng Mu¹¹; Xinyue Xiong, MS¹²; Ana Pastore y Piontti, PhD¹³; Alessandro Vespignani, PhD¹⁴; Ajitesh Srivastava, PhD¹⁵; Przemyslaw Forecki, PhD¹⁶; Srinivasan Venkatesan, PhD¹⁷; Aniruddha Adiga, PhD¹⁸; Bryan Lewis, PhD¹⁹; Brian Kohn, MS²⁰; Joseph Outton²¹; James Schlot, PhD²²; Patrick Corbett²³; Payam Alexander Teloni, PhD²⁴; Lijun Wang, MS²⁵; Akhil Sai Peddibadri²⁶; Benjamin Hunt, MS²⁷; Jinghui Chen, PhD²⁸; Anil Vallikanti, PhD²⁹; Madhav Marathe, PhD³⁰; Jessica M. Healy, PhD³¹; Rachel B. Slayton, PhD³²; Matthew Biggerstaff, ScD³³; Michael A. Johansson, PhD³⁴; Katrina Shea, PhD³⁵; Justin Lessler, PhD³⁶

¹The Pennsylvania State University, State College, Pennsylvania; ²Fogarty International Center, National Institutes of Health, Bethesda, Maryland; ³Johns Hopkins Bloomberg School of Public Health, Baltimore, Maryland; ⁴U.S. Geological Survey, Laurel, Maryland; ⁵University of Massachusetts Amherst, Amherst, Massachusetts; ⁶University of Pittsburgh, Pittsburgh, Pennsylvania; ⁷Johns Hopkins University Applied Physics Laboratories, Laurel, Maryland; ⁸Ecole polytechnique fédérale de Lausanne, Lausanne, Switzerland; ⁹University of Utah, Salt Lake City, Utah; ¹⁰University of Victoria, Victoria, British Columbia;

Expansion of
vaccine eligibility to
5–11-year-olds
(Sep 2021)
Lancet Regional
Health

Projected cumulative deaths, Jul 4, 2021–Jan 1, 2022, low vaccine/high transmissibility scenario



Slide courtesy: Matt Biggerstaff, CDC

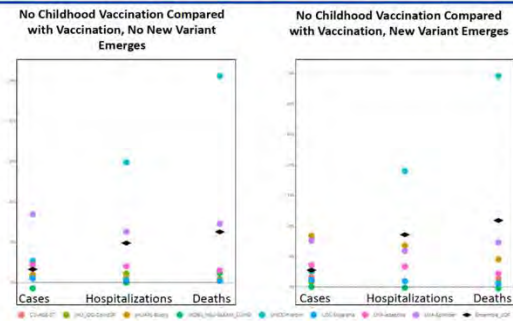
Projected outcomes averted with childhood vaccination (September 2021–March 2022)

"No New Variant" Scenarios

- Vaccination of 5–11-year-olds was projected to reduce cases, hospitalizations, and deaths between 3 and 13% (point estimates over entire projection period)
- Wide variability between individual projections and working to visualize uncertainty

"New Variant" scenarios

- Estimated reductions due to vaccination greater than when compared to the "No Variant" Scenario



Slide courtesy: Matt Biggerstaff, CDC

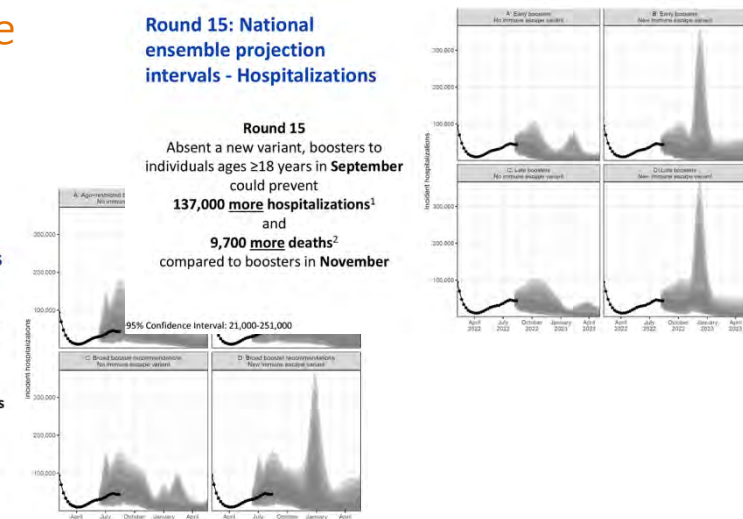
Role in bivalent dose
recommendation
(Sep 2022)

Round 14: National ensemble projection intervals - Hospitalizations

Round 14
Regardless of presence of a new variant, flu-like vaccine uptake in individuals ages ≥18 years would lead to a
>20% reduction in hospitalizations
and
>15% reduction in deaths
versus a recommendation for individuals ages ≥50 years only

Round 15: National ensemble projection intervals - Hospitalizations

Round 15
Absent a new variant, boosters to individuals ages ≥18 years in **September** could prevent
137,000 more hospitalizations¹
and
9,700 more deaths²
compared to boosters in **November**



Potential impact
of Delta wave
across states
Elife, Jul 2022)

● Supporting CDC Forecasting Hub

Challenge: Support multiple agencies with weekly forecasts and analysis – US Forecast Hub, EU Forecast Hub, VDH, and DTRA; work closely with IISc for Indian forecasts

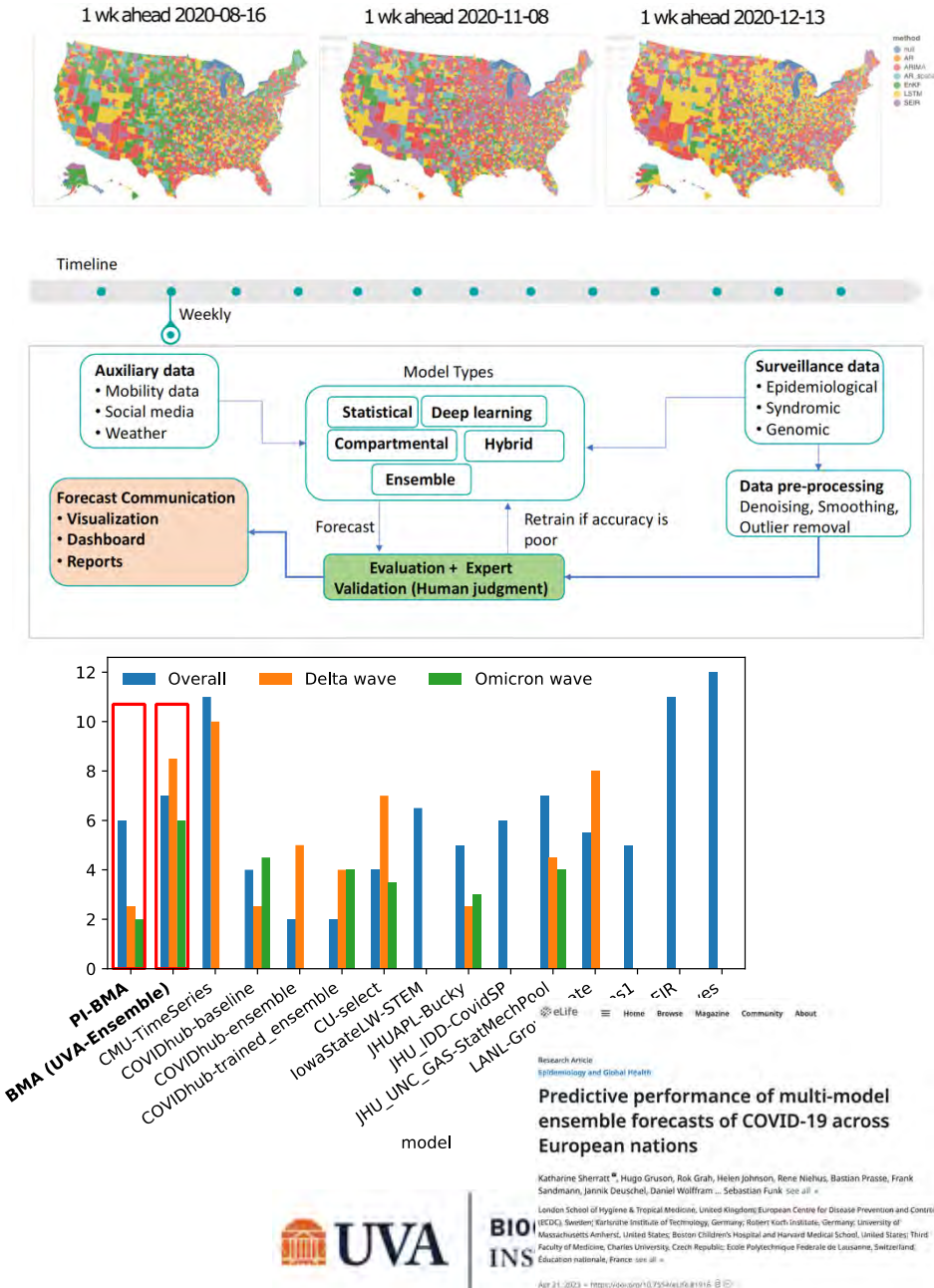
Multiple forecasts targets and resolution – 1–4 weeks ahead cases for 3000 US counties, 50 states, and EU countries and daily hospitalizations 1–28 days ahead for US states

Computational advances:

- Multi-model data driven for weekly national forecasting
- Phase driven forecasting
- Bayesian ensembling methods

Social and Policy Impacts: Forecasting Hub forecasts are provided on the CDC data portal and are incorporated in federal government decision making. Provided the CDC with weekly updates for this county-level ensemble of statistical, machine learning, and mechanistic models since August 2020.

KDD 2021, IAAI 2022, Nature SD, Elife 2022



How do we approach these problems?



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• Three simple steps that combine network science, AI and high-performance computing



Synthesize a digital similar of a city/country

- Combines data and ML to create digital similar
- Yields a multi-scale, relational social contact network
- Has desirable statistical properties



Build AI-enabled agent-based simulations

- Scalable to high-performance computing systems
- Rich representation of policies
- Works with irregular and time-varying networks



Develop AI + Simulation-driven workflows and apps

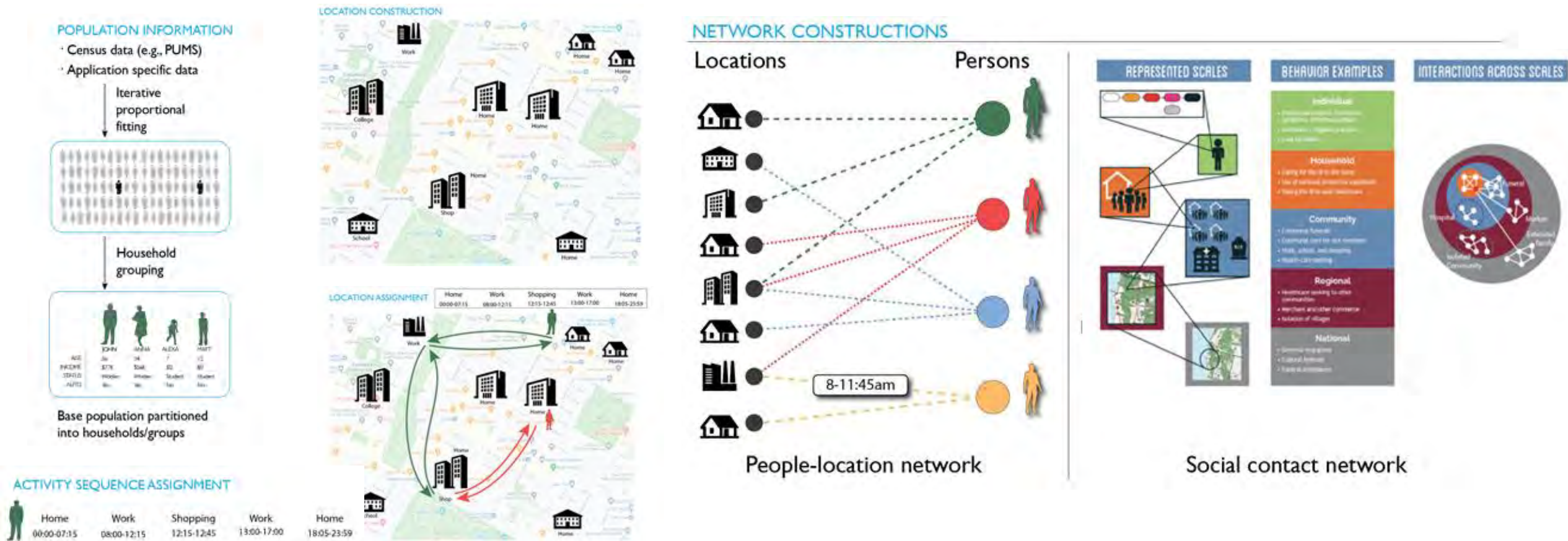
- Calibration
- Forecasting
- Explanation
- Planning and what-if scenario analysis
- Resource allocation
- Inference



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● Digital Similar (Twins) of US social contact network



Digital twin captures heterogeneous spatially explicit, multi-scale, multi-theory, multi-level social contact network representations

● Why Digital Similars?



Provides a spatially and individually resolved data structure

- Fusing of diverse information in a statistically consistent manner, e.g. (demographic + energy + cell phone) data
- Agents have nominal (age, income), declarative (activities they take) and procedural (e.g. how to drive) data
- Enables information privacy and attribution

A social coordinate system for incorporating new (intra- and inter) agentic information



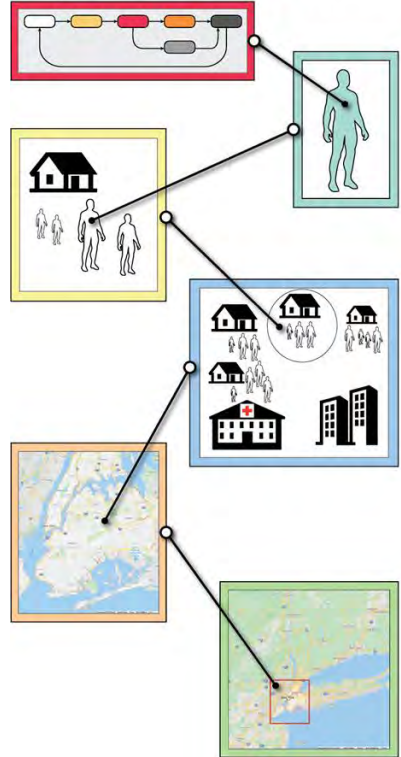
Agentic representations enable causal interaction-based models & data integration

- Putting procedural, social and behavioral theories in motion, e.g. contagion theories of Granovetter, Macy, Schelling, et al.
- Explicitly represent interactions as networks
- Model outputs can then be aggregated to any desired level

Supports next generation modeling and analytics at-scale

• What it Captures: Multiple Scales and Theories

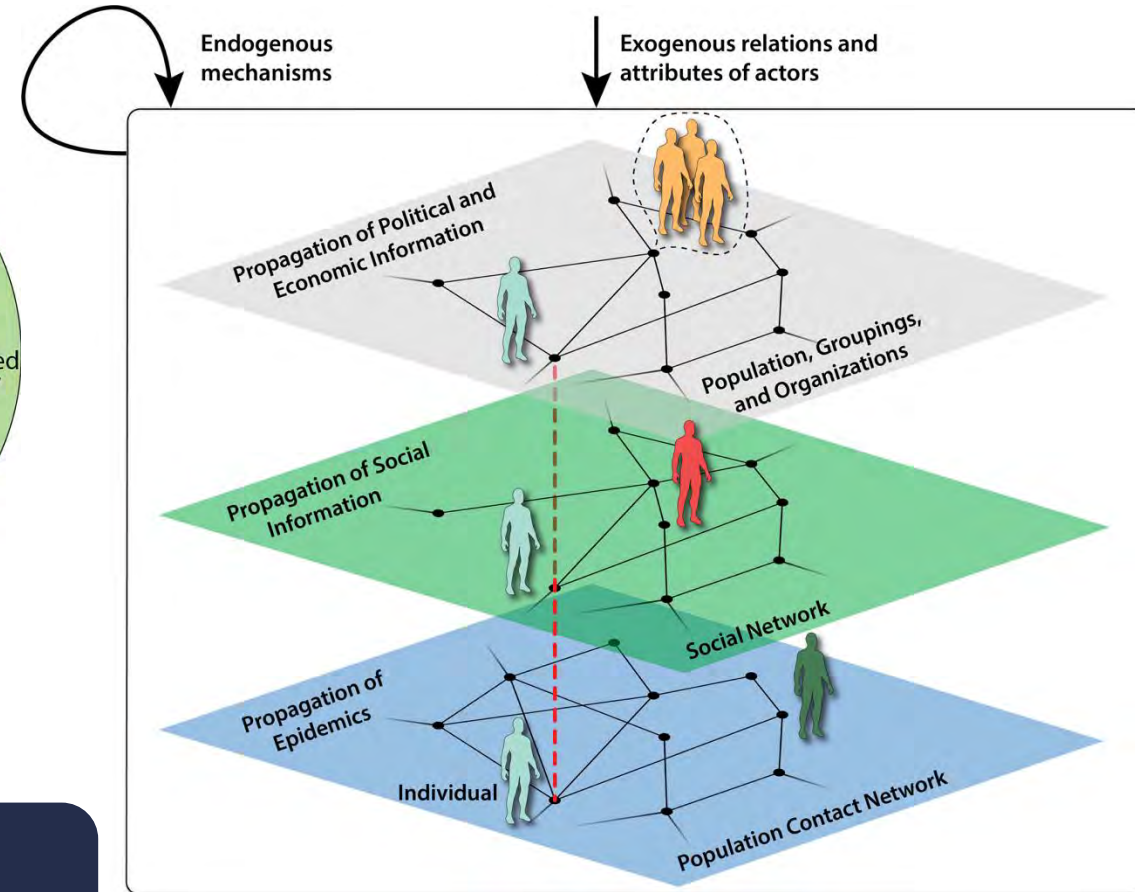
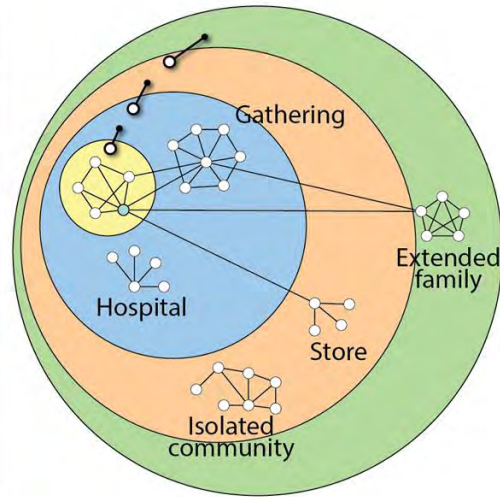
Represented Scales



Behavior Examples

- Individual**
 - Disease parameters; incubation, symptoms, infectious periods
 - Sanitation/Hygiene practices
 - Care for others
- Household**
 - Caring for the ill in the home
 - Use of PPE
 - Taking the ill to seek healthcare
- Community**
 - Communal events/gatherings
 - Communal care for sick members
 - Health-care seeking
- Regional**
 - Healthcare seeking to other communities
 - Merchant and other commerce
 - Isolations of towns
- National**
 - Seasonal migrations
 - Cultural festivals
 - Conferences

Interactions across Scales



Digital twins capture heterogeneous spatially explicit, multi-scale, multi-theory, multi-level social contact network representations

● Scale & Size

US Population Digital Twin



People & households



Activity sequence



Activity locations



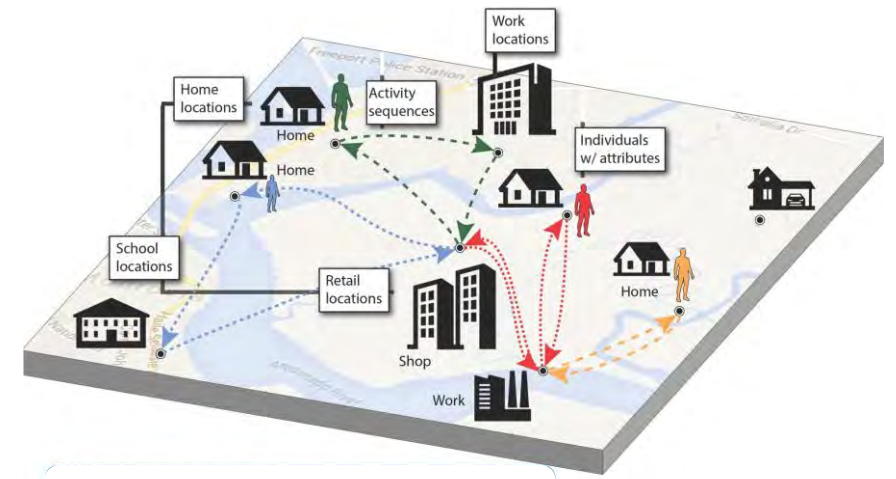
Individual locations



Contact network

AIIA Digital Twin Model: (Only one of its kind)

- Covers 48 contiguous US states
- 2.5 Terabytes of data! 12Hours on Rivanna
- Protects privacy – no personally identifiable data

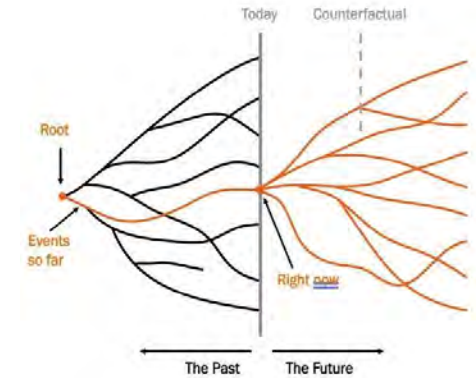
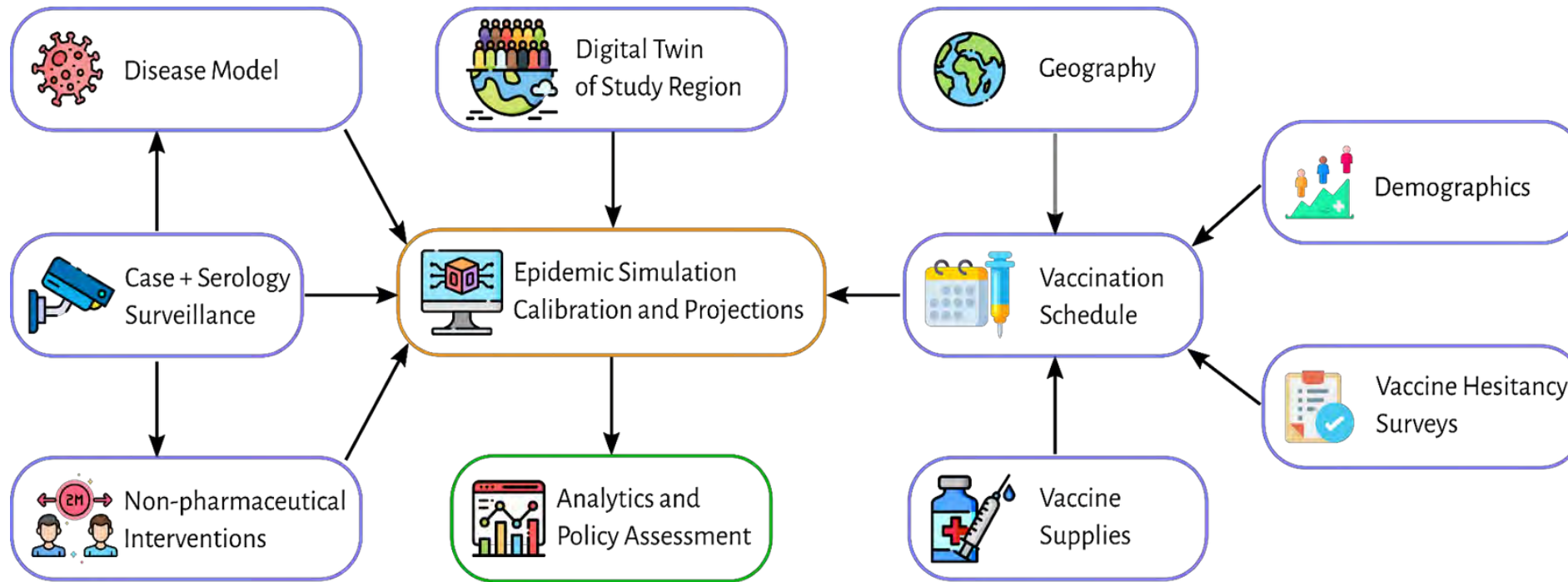


Data Sets

- US Census demographic distributions at block group resolution
- American Community Survey (ACS) commuting flow data
- ACS Public Use Micro Sample data 2013–2017
- US Census National, State, and County Housing Unit Totals
- National Household Travel Survey 2017 and 2001
- Bureau of Labor Statistics employment data
- National Center for Education Statistics data
- Microsoft Building Footprint data
- Building Footprint USA (now Lightbox)
- HERE location and Points of Interest data
- Black Knight geographical parcel data

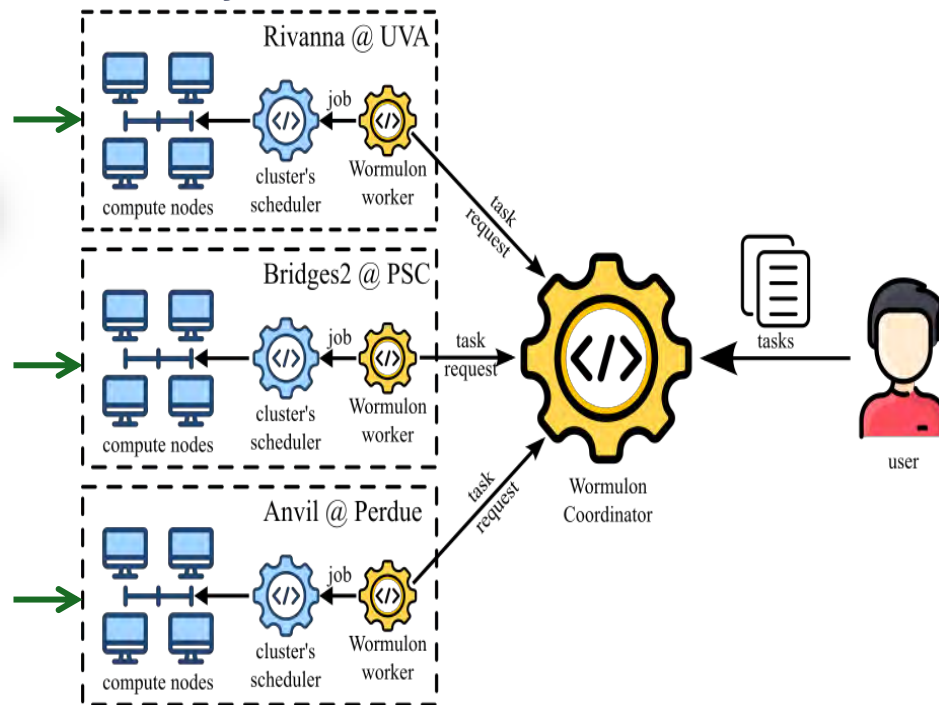
● Live Digital Twins for real-time response

Incorporates multiple new datasets updated as the pandemic evolves



Bringing the Digital Twin to life:
contextualize the DT with current ground conditions

Parallel socio-epidemic simulators and analytics engine



2550 simulation instances
calibration

~10200 simulation instances
projections

3100 US counties
500 days
confirmed case count data

~20GB synthetic population
person, household, location, and activities data

~1.5B entries, ~4GB
aggregate output data
250 days, 200 health states, 3 counts

~4TB individual-level
output data
*multi--million state transitions
= multi-billion entries*

The Hybrid HPC pipeline for national pandemic planning and response can run: 400 replicates of **national (US) individualized multi-agent socio-epidemic simulations** (300M nodes & 12B edge networks yielding over 1Trillion interactions over 200 simulated days) in **33 hours** on **9K cores** spread over two (and more recently three) machines

Examples of scientific questions we address



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● Example 1: Tradeoffs across temporal scales

PNAS

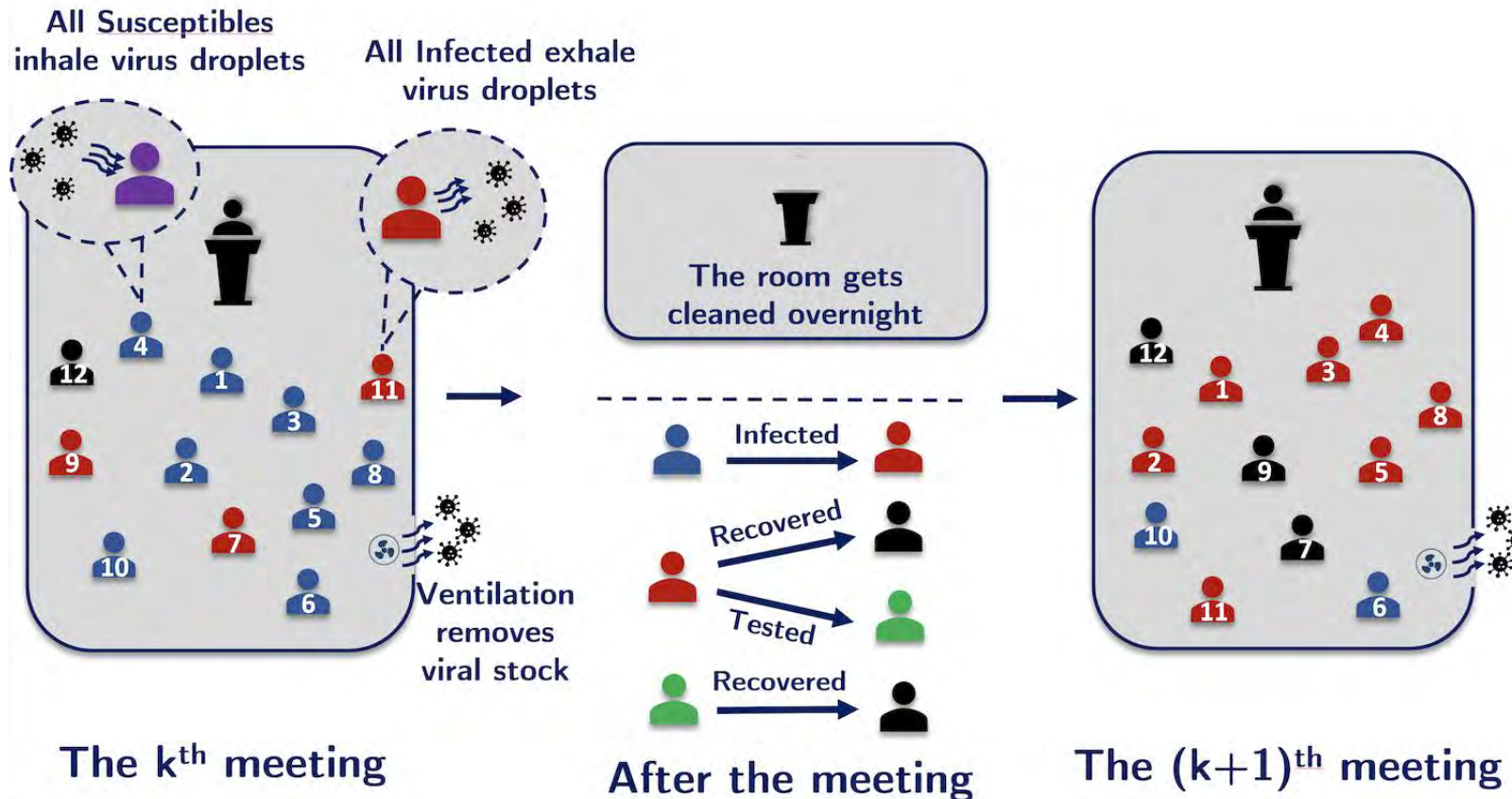
RESEARCH ARTICLE

BIOPHYSICS AND COMPUTATIONAL BIOLOGY

OPEN ACCESS

Airborne disease transmission during indoor gatherings over multiple time scales: Modeling framework and policy implications

Avinash K. Dixit^{a,1}, Baltazar Espinoza^b, Zirou Qiu^{b,c}, Anil Vullikanti^{b,c}, and Madhav V. Marathe^{b,c,1}



Robert H. MacArthur award lecture. *Ecology*, 1992.
The Problem of Pattern and Scale in Ecology
Simon A. Levin

Individual incentive drives epidemics

Collective behavior modulates individual incentive

EPIDEMIOLOGY

Social Factors in Epidemiology

Chris T. Bauch¹ and Alison P. Galvani^{1,2}

The coupling of social and biological contagion in human populations can have positive or negative outcomes.



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● Scenarios, control variables and policy insights

Scenario	Description	Control variables	Policy insights	Dynamic components
Short time-scale	Single meeting at a single day.	<i>a, b, c, d</i>	For short meetings, ventilation and masking have similar effects. For long meetings, ventilation has a greater impact than masking.	Viral load
Medium short time-scale	Multiple meetings at a single day.	<i>a, b, c, d, e</i>	For short meetings, break times of 10–15 min have a similar impact than 50% mask compliance. For long meetings, break times of 20–25 min have a similar impact than 50% mask compliance.	Viral load
Medium-long time-scale	Single meeting at multiple days.	<i>a, b, c, d, f</i>	For short meetings, masking and testing shows that a trade-off follows a 2:1 For long meetings, masking and testing shows a trade-off of 1:1.	Viral load Infectious individuals
Long time scale	multiple meetings at multiple days.	<i>a, b, c, d, e, f</i>	For short meetings, a 60% testing reduction is balanced by around 20-min breaks. For long meetings, a 40% testing reduction is balanced by around 20-min breaks.	Viral load Infectious individuals

a. Group size b. Air mass (room size) c. Mask compliance d. Ventilation e. Break times f. Testing

● BRAVE: Revolutionizing Indoor Air Safety

- BRAVE: \$40M ARPA-H grant to develop a smart building system to detect and respond to airborne health threats
- BRAVE: Led by Linsey Marr at Virginia Tech with collaborators from BI@UVA, WashU, UC Davis, Michigan, Yale, Penn State, Emory, Signature Sc. and industry partners
- Goal:
 - Will develop enhanced biosensors + modeling to detect pathogens and trigger HVAC interventions (ventilation, filtration, UV)
 - Reduce respiratory illnesses by 25% and improve public health in communal spaces
- Biocomplexity Institute (UVA) leads modeling and simulation efforts and develop multi-scale AI-enabled decision support systems

BREATHE research teams kick off efforts to enhance indoor air quality to improve health, advance the future of smart buildings

Teams will seek to develop systems that reduce harmful pathogens and allergens in buildings across the country, ensuring indoor air quality is always safe and healthy.

The Advanced Research Projects Agency for Health (ARPA-H), an agency within the U.S. Department of Health and Human Services (HHS), today announced the research and development teams receiving awards from the Building Resilient Environments for Air and Total Health (BREATHE) program. BREATHE intends to advance the next generation of smart and healthy buildings by developing integrated systems that will provide continual measurement and risk assessment of indoor air quality and deploy real-time interventions, like extra ventilation or disinfection, to reduce airborne threats to human health.

Poor indoor air quality exacerbates chronic diseases like asthma and allergies and is a leading cause of preventable respiratory illnesses like the flu. Airborne pathogens and allergens can have a significant effect on people's health, especially children, the elderly, and those living with chronic illnesses. Even though Americans spend 90% of their lives indoors, we do more to monitor and reduce outdoor air threats than those inside our homes, schools, and workplaces. Rather than only treating illness after it occurs, BREATHE aims to create healthier indoor environments that prevent disease, improve productivity, and enhance quality of life for everyone.

"BREATHE will revolutionize public health by greatly advancing our ability to detect and address indoor air quality threats like never before," said [Jason Ross, Ph.D., ARPA-H Acting Director](#). "ARPA-H's investment has the potential to bring about the next-generation of smart buildings, making sure indoor air is always clean and healthy."

The agency's initial total commitment to these teams is up to \$156 million over 5 years, to establish this groundbreaking approach. [Other Transactions Agreements](#) (not procurement contracts, grants, or cooperative agreements) vary in funding amount per awardee and are contingent upon each team meeting aggressive and accelerated milestones.

● Example 2: Dueling dynamics over multiple networks

PNAS

RESEARCH ARTICLE

ENVIRONMENTAL SCIENCES

Understanding the coevolution of mask wearing and epidemics: A network perspective

Zirou Qiu^{a,b,1}, Baltazar Espinoza^b, Vitor V. Vasconcelos^{c,d,e,f}, Chen Chen^b, Sara M. Constantino^{g,h,i}, Stefani A. Crabtree^{j,k}, LuoJun Yang^l, Anil Vullikanti^{a,b}, Jiangzhuo Chen^b, Jörgen Weibull^m, Kaushik Basu^{n,o}, Avinash Dixit^p, Simon A. Levin^{l,1}, and Madhav V. Marathe^{q,a,b,1}

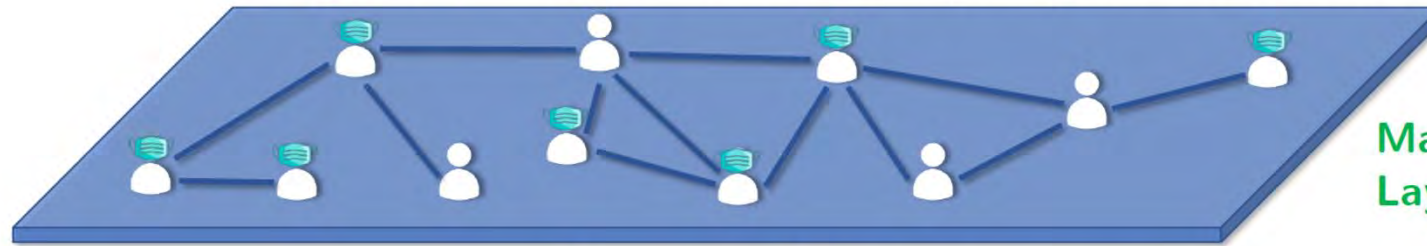
Behavior is modeled by a set of threshold conditions

Mechanisms: Peer pressure, fear, pro-sociality

Response: Use or not face mask

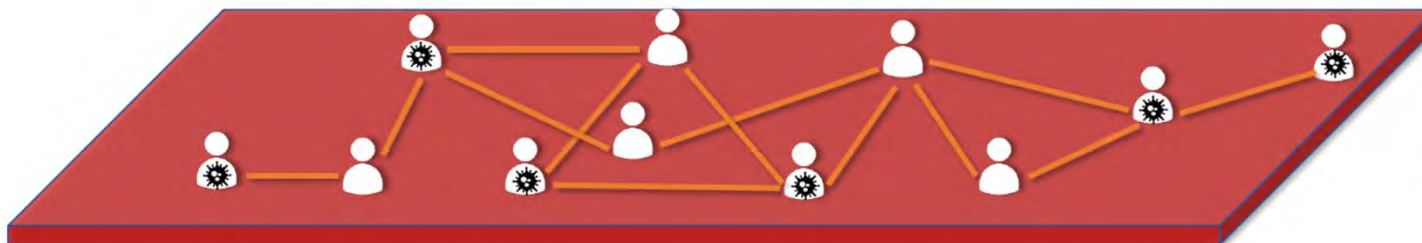
Social Interaction layer

Peer pressure - wears a mask if many neighbors wear masks



Fear - wears a mask if there are many infections

Mask effectiveness - decreases the transmission probability



Proximity Contacts layer

Mask-wearing Layer

Share the same population

Disease Layer

Collective human behavior drives epidemics

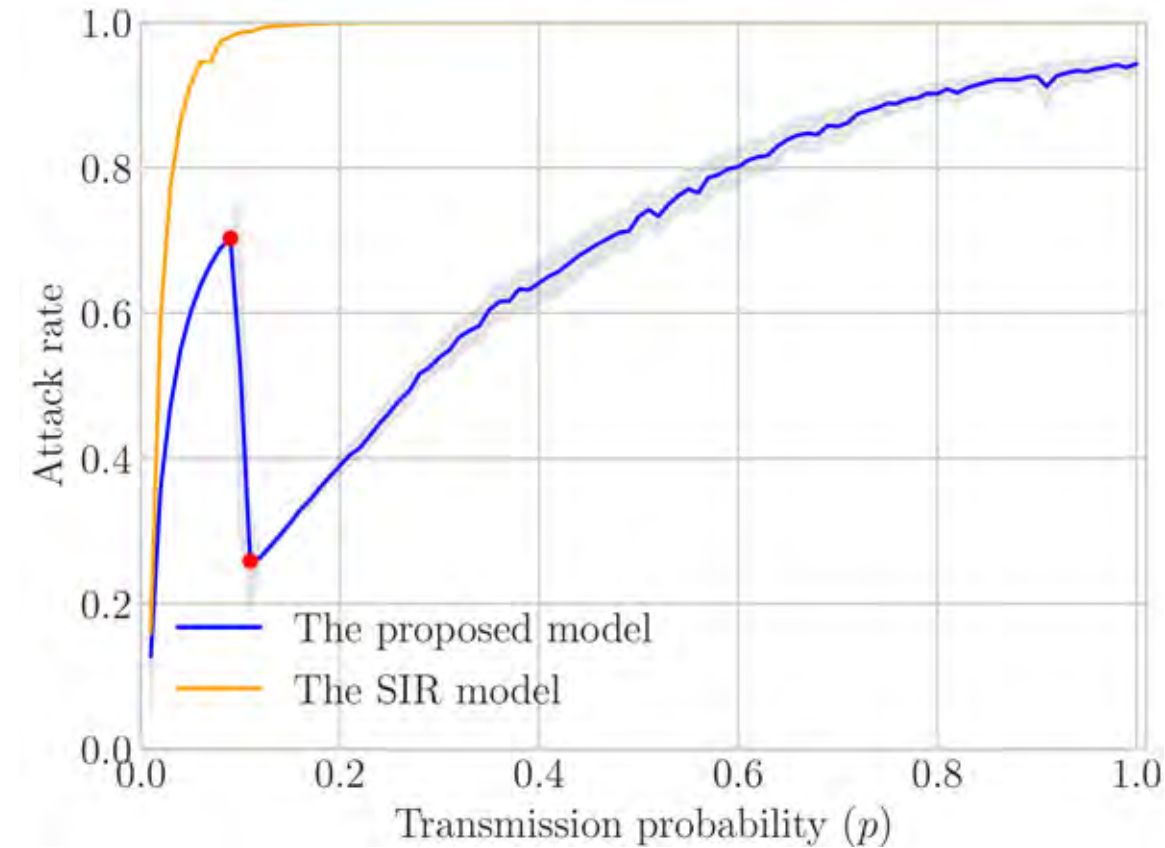
Epidemics drive collective human behavior



UVA

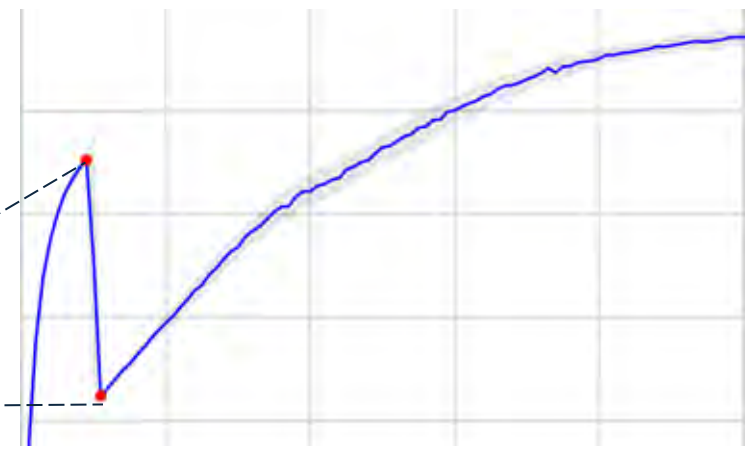
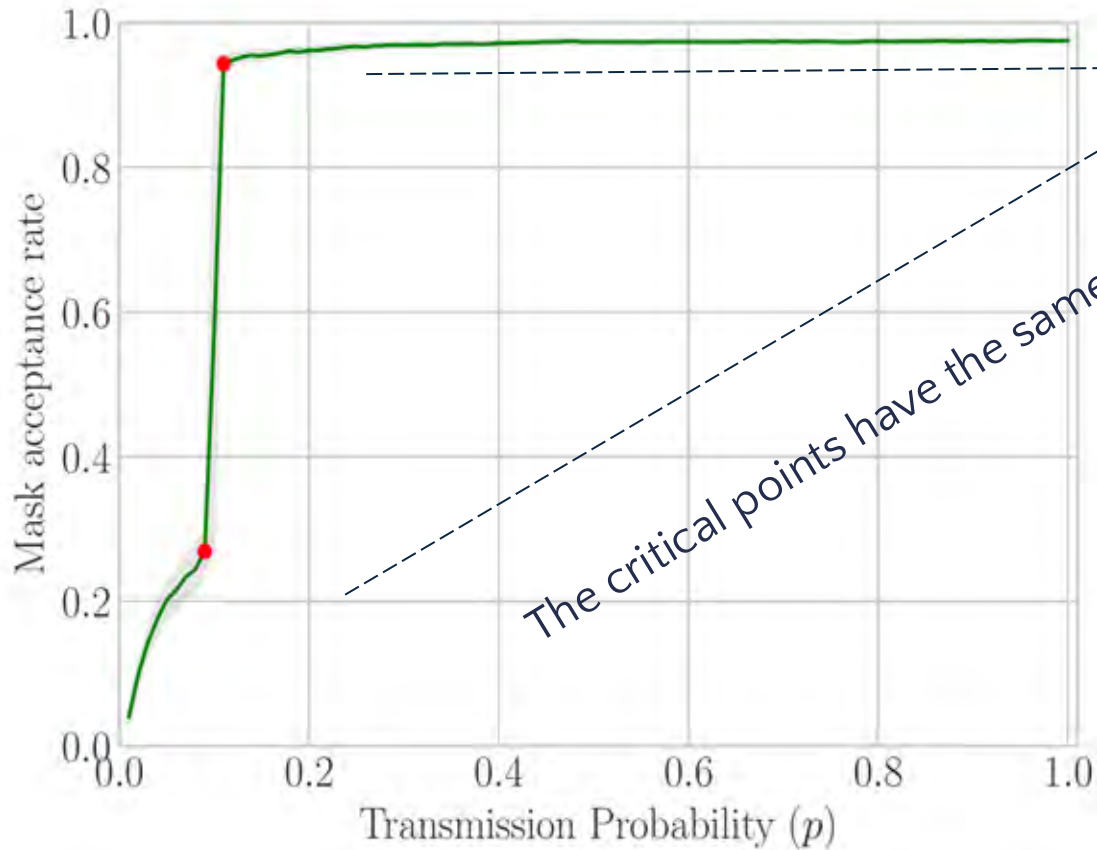
BIOCOMPLEXITY
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● A phase transition of dueling dynamics



- A **monotonic increase** of the attack rate under the SIR model as the disease becomes more infectious
- The disease dynamic for the behavior model exhibits a **phase transition**, characterized by two **critical points**
- Studied sensitivity of the model w.r.t:
 - Initial condition
 - Randomness of the network
- Observed a low variance

● A phase transition of the social dynamic

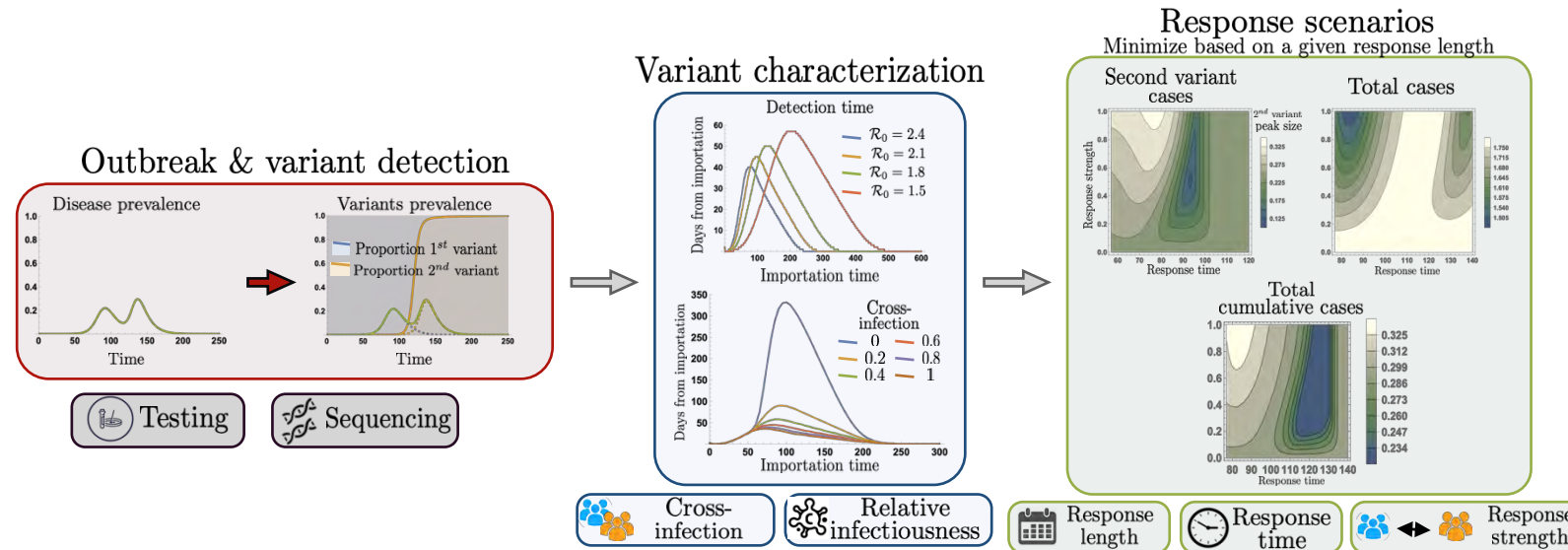


- The mask acceptance rate increases gradually as p increases, up to the first critical point
- Then mask acceptance rate rises drastically as p continues to increase to the second tipping point
- The social dynamic enters a saturation stage after the second critical point

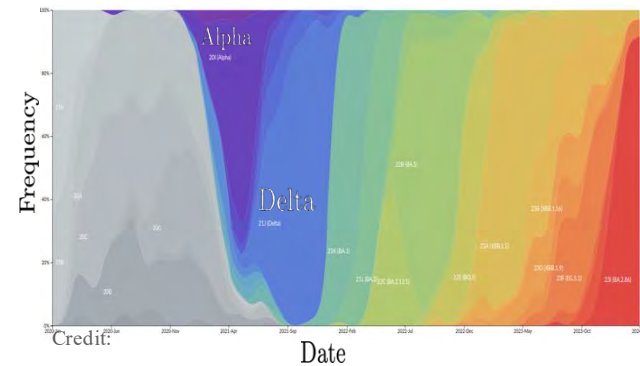
The two critical points can be captured with a finer granularity where the system exhibits a **sharp phase transition**.

Example 3: Genomic epidemiology and biosurveillance

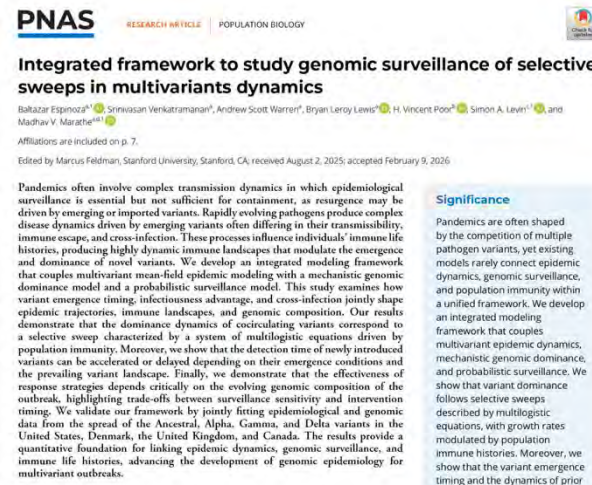
- Variant dominance time in the US*
 - Delta – within 7–13 weeks after detection
 - Omicron – within 4–6 weeks after detection
- How do different variant's importation conditions shape epi-genomic dynamics?
- How fast can we detect an outbreak? A novel variant?
- How do intervention effects depend on the variant's competing dynamics?



COVID-19 variants in North America

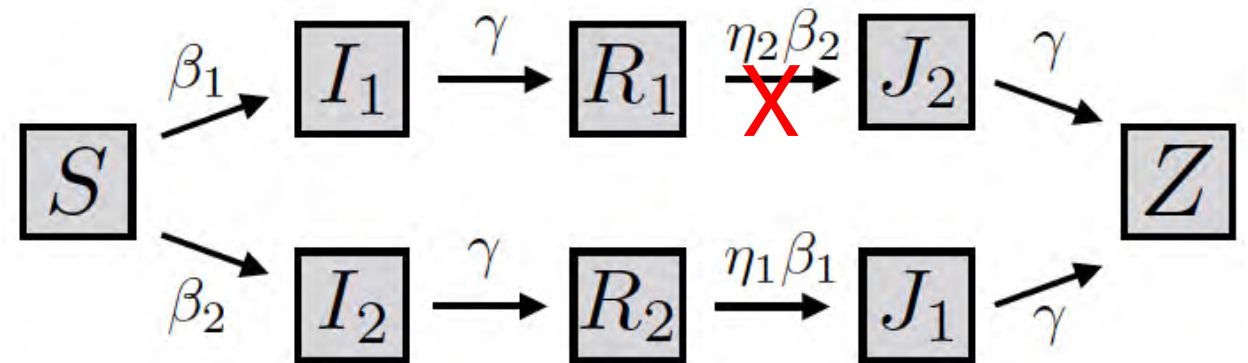
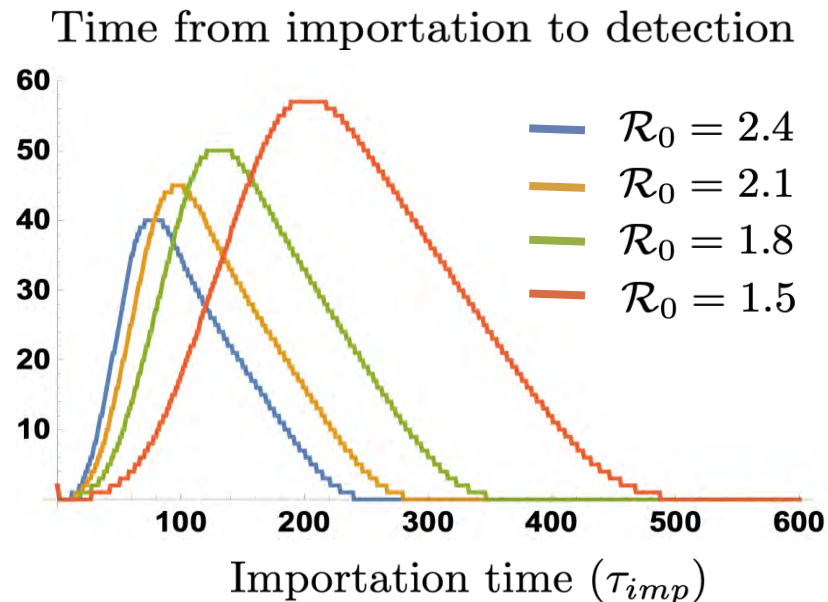
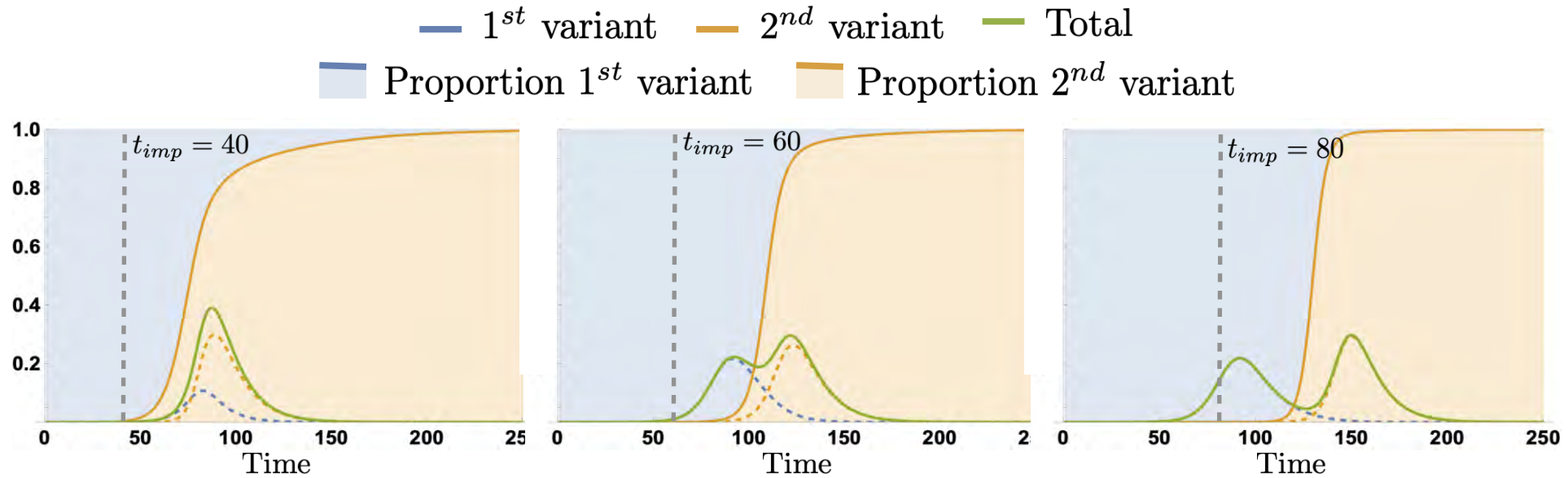


nextstrain.org



*Chan Y, Irvine MA, Prystajecky N, Sbihi H, Taylor M, Joffres Y, et al. Emergence of SARS-CoV-2 Delta Variant and Effect of Nonpharmaceutical Interventions, British Columbia, Canada. Emerg Infect Dis. 2023;29(10):1999–2007. <https://doi.org/10.3201/eid2910.230055>

Variant detection and intervention implementation

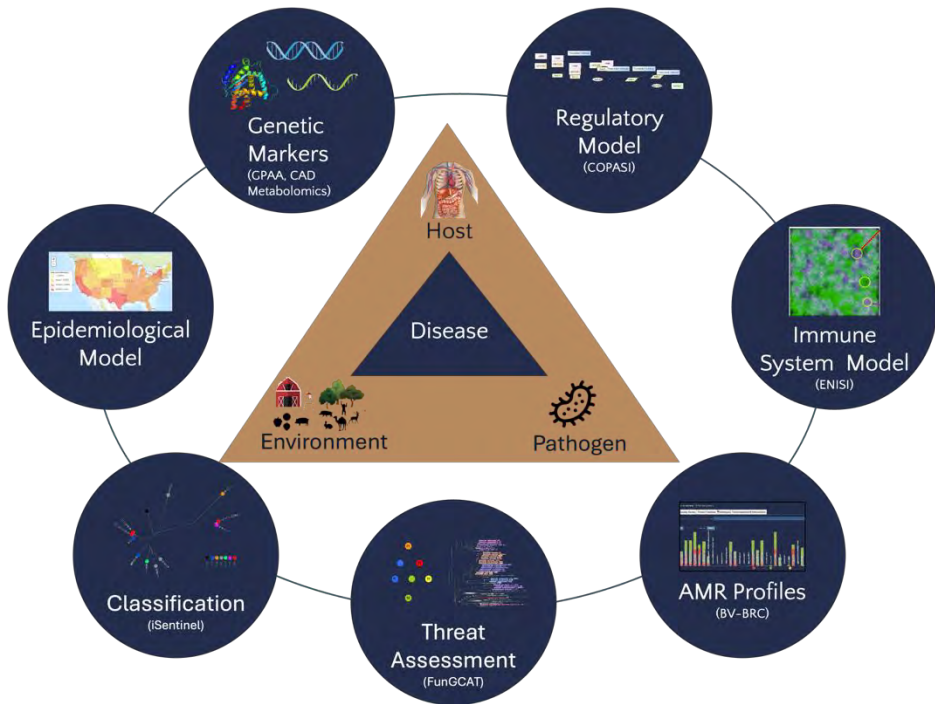


Competing variant dynamics impact the detection time of novel variants

Developing computational and data
infrastructures for health sciences for
over 25 years



Long standing expertise in building Cyber-infrastructures and Cores



2022



2018

EXCEADS

2004



2004



2004

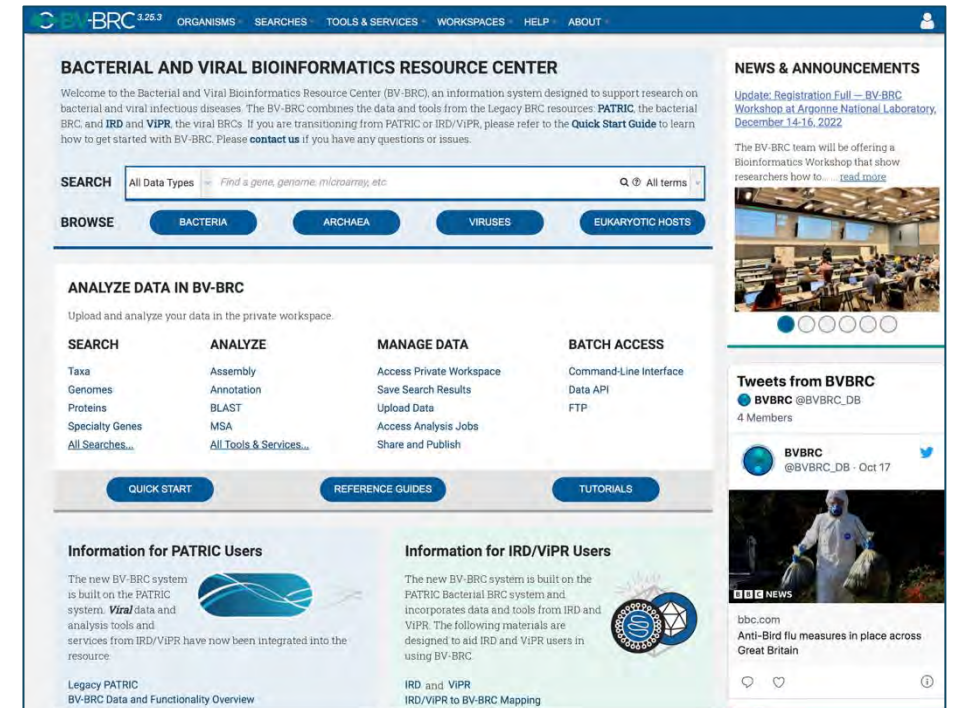


2003

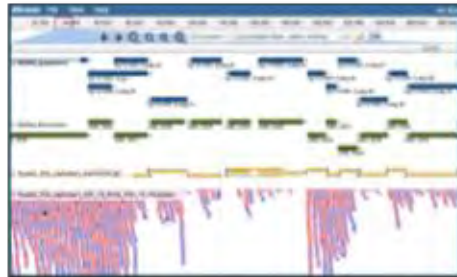


● Bacterial & Viral Bioinformatics Resource Center (BV-BRC)

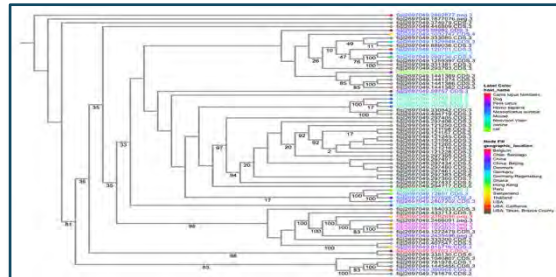
- 22+ years continuous funding (\$130M total, \$65M BI)
- 77K+ registered users
- 3M+ pageviews/year
- 30K citations
- 1.3M+ bacterial genomes; 15M+ viral genomes
- 1M+ user analysis jobs; 820TB user workspace
- 100+ workshops/webinars with over 4K participants
- <https://www.bv-brc.org>



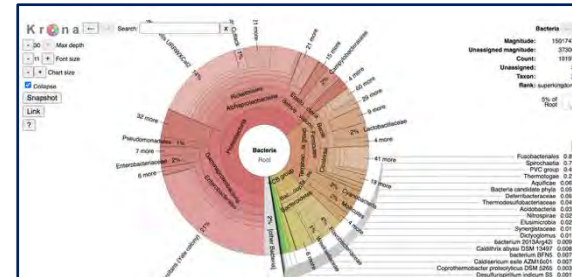
Genome Browser



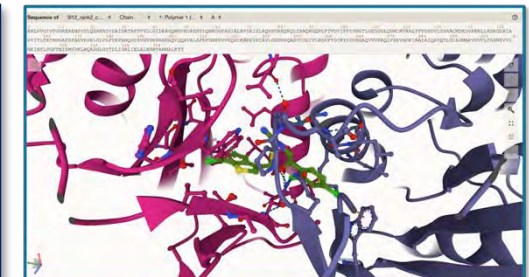
Phylogenetic Tree Analysis



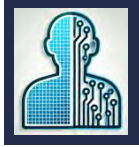
Metagenomic Analysis



Protein Structure Viewer



Pathogen Genomic Center of Excellence – VA



Data Products

- Multi-layer digital similars
- Integrated genomic information to enhance situational awareness
- Sampling frame based on population characteristics



Scalable Software Infrastructure

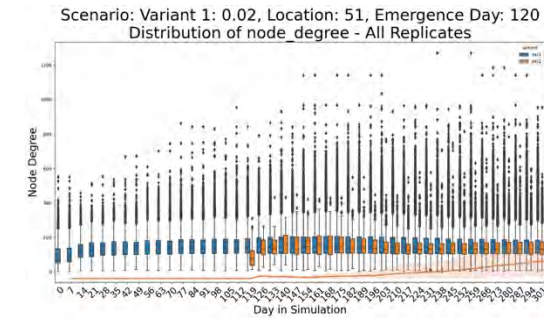
- Create tools for PH
- Enable new functionality
- Lower barrier to entry



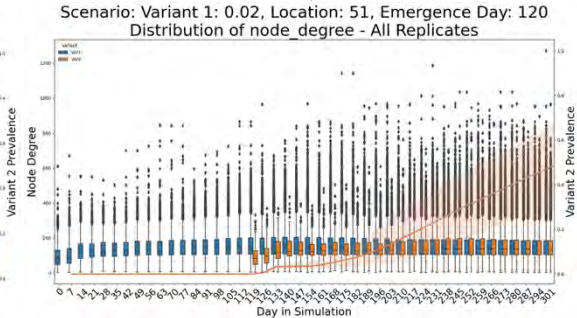
Analysis Techniques & Publications

- Quantify impact of strategies
- Understand spread based on genomic information
- Benchmarking bioinformatics and phylodynamics

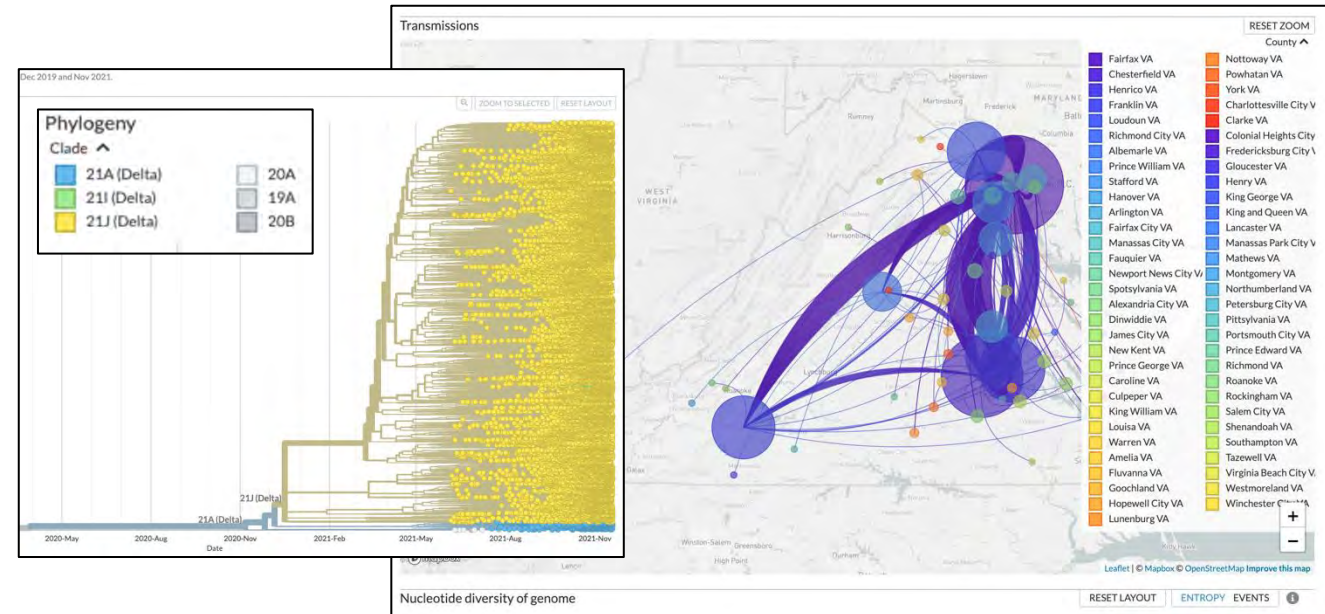
Impact of importation scenarios on variant sampling



Household Importation



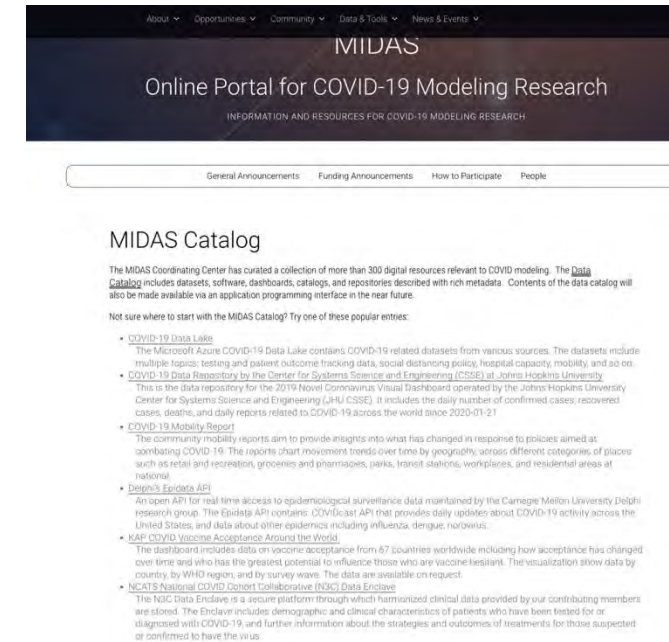
Distributed Importation



Detailed geographic and demographic case movement and resource allocation

● MIDAS

- **Global Modeling Network:** MIDAS unites experts advancing computational, statistical, and mathematical models of infectious disease dynamics.
- **Modeling & Data Infrastructure:** MCC develops and maintains US Scenario Modeling Hub infrastructure, including standardized GitHub repositories, pipelines, and interactive dissemination portals.
- **Methodological Innovation:** Active R&D in ensembling, data harmonization, benchmarking, and epidemiological reasoning, leveraging ML/AI to modernize outbreak modeling.
- **Technical Community Leadership:** Coordinates sustained collaboration through seminars, shared resources, and the annual MIDAS meeting to accelerate rigor, reuse, and impact.
- <https://midasnetwork.us/covid-19/>



Reducing antibiotic resistant infections using hospital digital twins

Surveillance and control of the spread of hospital acquired infections (e.g., MRSA)

- Prediction of MRSA can help clinicians in choosing antibiotic treatment
 - Testing is limited and incurs delays
- Optimize infection control policies, especially for seniors and at nursing homes



Representative results

- Effective prediction tools for clinicians using Electronic Health Record (EHR) data from UVA hospital
 - Supports antimicrobial stewardship
- Optimal policies for discontinuation of isolation precautions at UVA hospital (currently in use)
- Estimating source of infection during outbreak investigations
- Ongoing: estimation of MRSA risk at Long Term Care Facilities

Cui et al., NPJ Digital Medicine 2025

Kamruzzaman et al., Improving Risk Prediction of Methicillin-Resistant Staphylococcus aureus Using Machine Learning Methods With Network

Features: Retrospective Development Study, [JMIR AI](#) 2024

Cui et al., Modeling relaxed policies for discontinuation of methicillin-resistant Staphylococcus aureus contact precautions, [ICHE](#) 2024

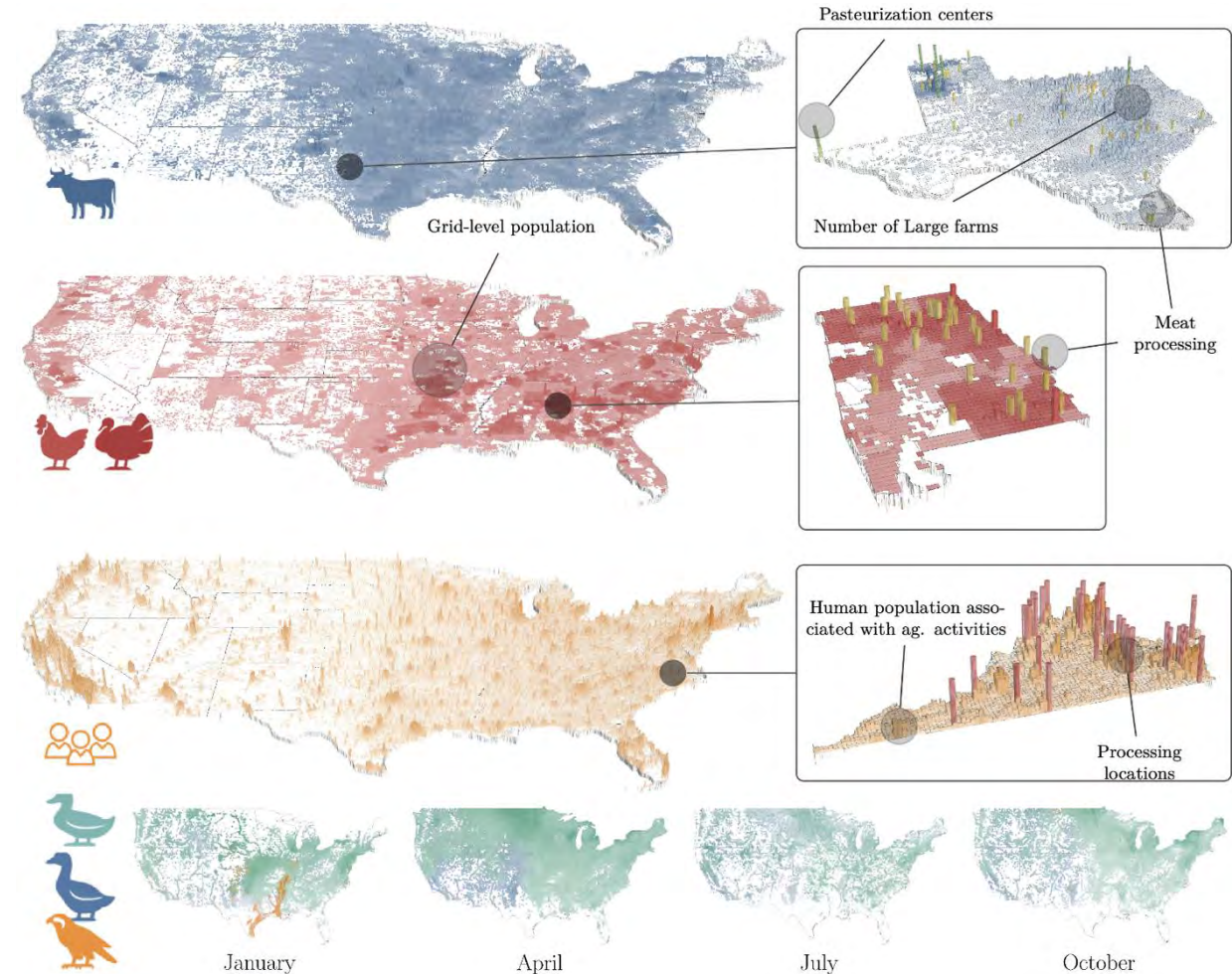
Jang et al., Detecting Sources of Healthcare Associated Infections, [AAAI](#) 2023

Ongoing work

● Livestock Digital Similar

A US-scale multi-layered high-resolution digital representation of:

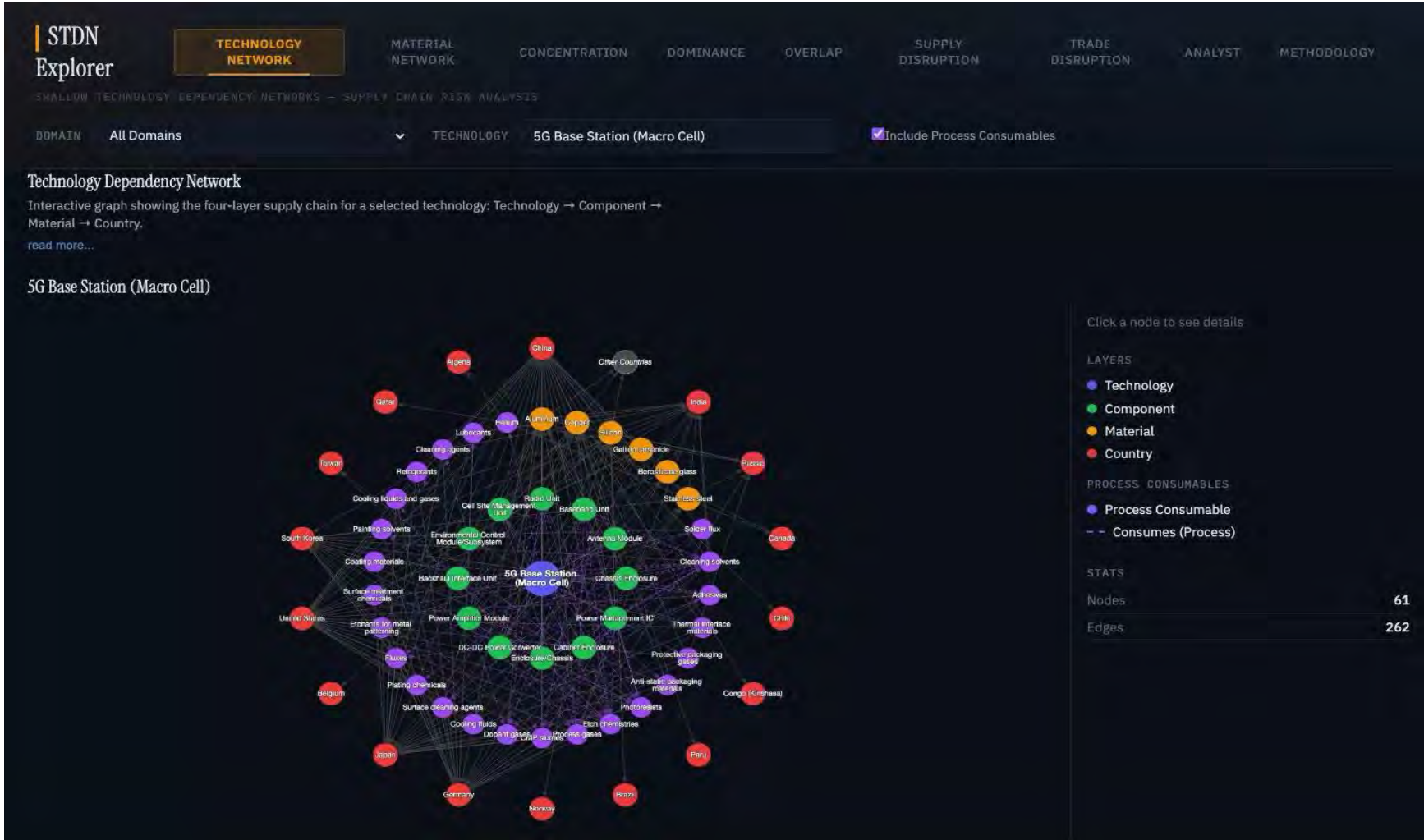
- **Livestock:** Multiple farm-level livestock populations modelled from Census of Agriculture and Gridded Livestock of the World datasets
- **Processing centers:** Milk, meat, eggs and poultry
- **Human population:** By size and occupation type based on our US v2.4.0 digital similar
- **Wild birds:** Multiple species of migratory birds from eBirds Avian Abundance data



- More about this in preprint: <https://arxiv.org/abs/2411.01386>
- Data visualization and downloads at <https://ditto.bii.virginia.edu>

- **CMAP: Critical Materials Supply Chain Analytical Platform**

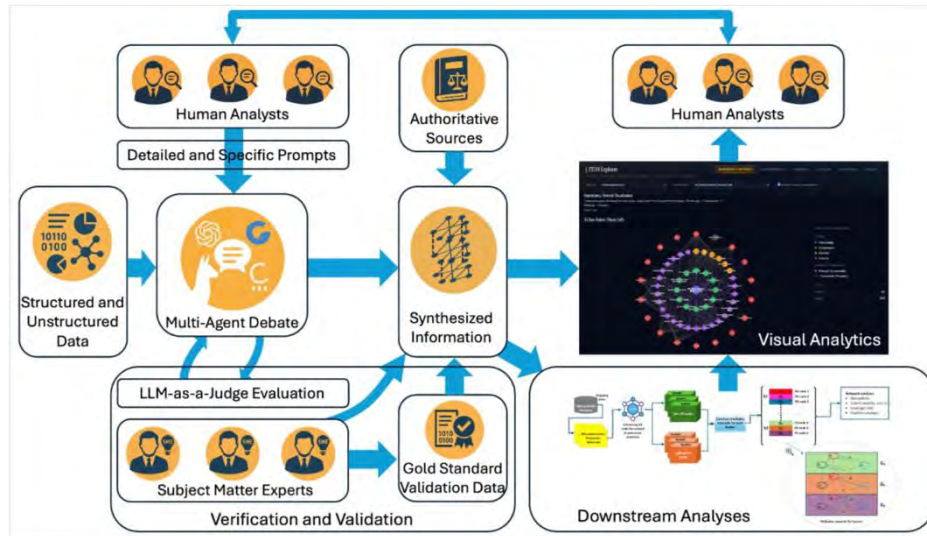
**Supply chain
disruptions and
foreign dependencies
are no longer
theoretical risks, but
active concerns
shaping federal
investment, industrial
policy,
and defense
readiness planning**



Helium Case: A 40% Cut to Qatar's Production

What the analytical stack reveals — and what it changes

WHAT THE DATA SHOWS



Multi-method pipeline: agent debate, validation, and visual analytics produce evidence-backed dependency data.

15.5%

GLOBAL SUPPLY REMOVED
at a 40% Qatar production cut

152/180

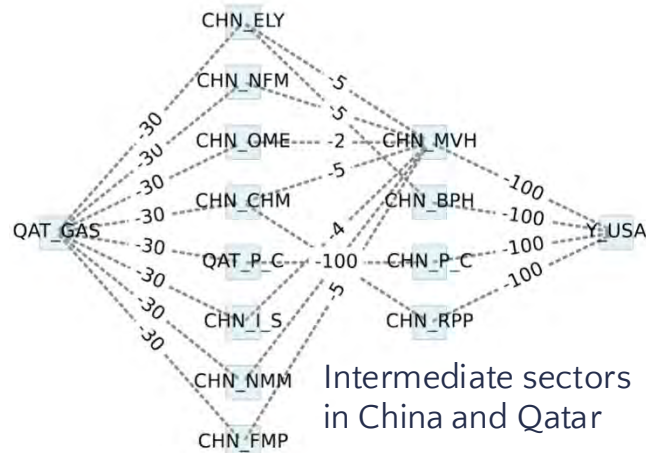
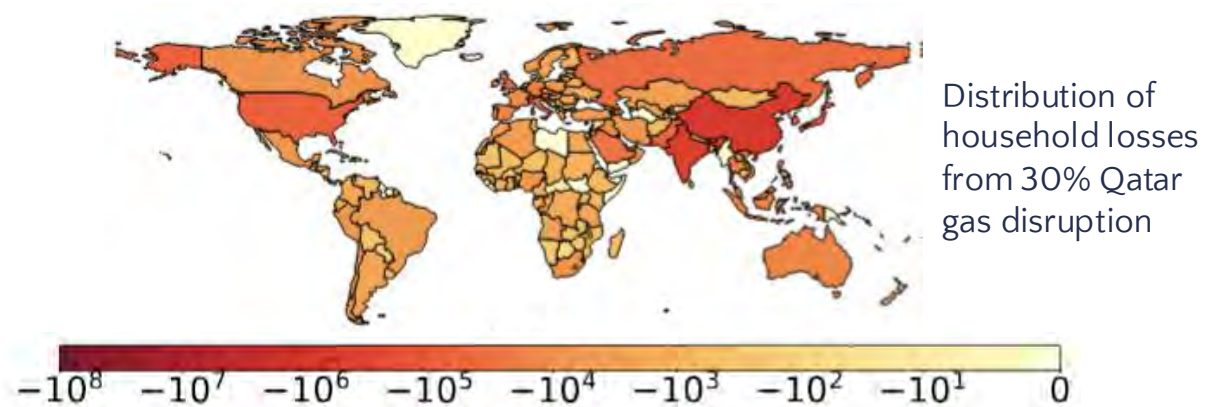
SYSTEM TECHNOLOGIES EXPOSED
across microelectronics, biotech, pharma

- Concentration: HHI 2,815; Qatar 38.8% + US 35.3% = 95% of global production from just 6 countries
- Qatar's profile: "narrow but deep" — leads in only 1 material, yet hits 60 of 60 microelectronics technologies (36.2% avg share)
- US direct exposure has pivoted: Qatar dominated imports through 2021; Canada has supplied ~97% since 2022
- Locked in: only 2 countries have held the top US supplier position across 9 years — no meaningful substitution

Policy Implications

- Price-shock risk (global supply) and US import-exposure risk are now distinct questions with distinct answers
- Process consumables like helium sit outside existing critical-minerals frameworks
- The 2024 Federal Helium Reserve wind-down left no stockpile buffer for a commodity with HHI 2,815 and no substitution channel

● Cascading impact of Qatar gas disruptions



WHAT THE DATA AND MODELS SHOW

- Qatar gas disruptions lead to significant losses for multiple sectors in Asia and Europe, with the largest aggregate impacts observed in India, China, and South Korea
- Expansion of production capacity among major gas-producing countries improves supply conditions and leads to broader output gains
- However, benefits remain concentrated in a few large economies

WHAT IT MEANS FOR POLICY

- US households are also impacted, even though US is a big gas producer, and doesn't import directly from Qatar
- Adaptive mechanisms such as trade reallocation and production expansion can alleviate the effects of supply shocks but their effectiveness is limited and heterogeneous

17%

QATAR LNG SUPPLY REMOVED
Likely for over 3 years

24%

HELIUM DISRUPTION
From Qatar Ras Laffan facility

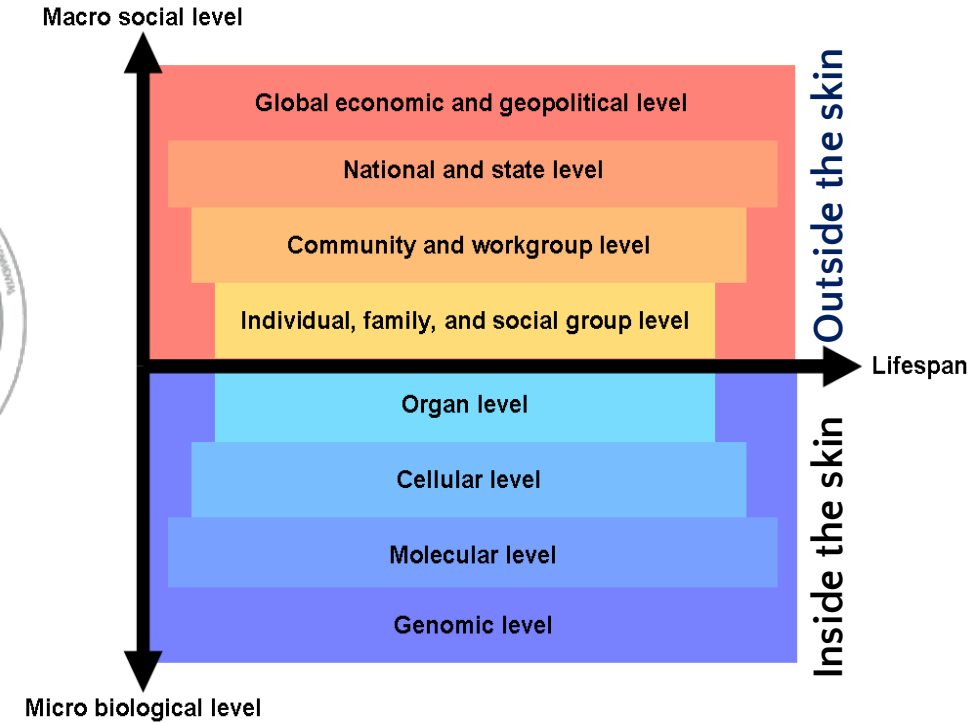
6%

SULPHUR DISRUPTION
From Qatar Ras Laffan facility

Where we are heading



● A Grand challenge: From Genomics to Populomics to “Sociomics”: Digital Twins for Human Ecology



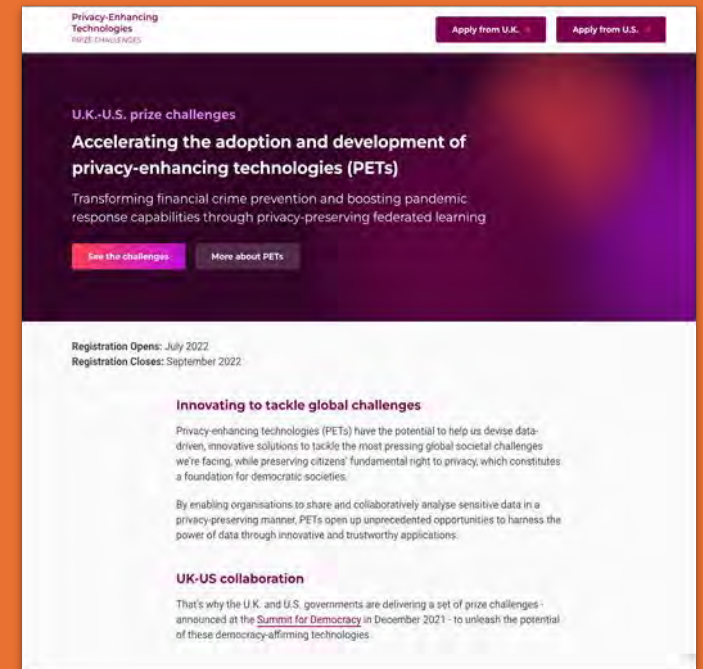
Develop the computing and data infrastructure to represent synthetic humans, synthetic populations and ultimately synthetic societies to facilitate advancing translation of cellular and molecular data into clinical decision-making

Unifying scientific foundation: Science of Networks and Interactions

● Pervasive, Personalized and Precision (P³) decision-making & analytics for biocomplex networks

- **Pervasive:** Enable decision maker to make decisions at any place, anytime, and on any device
- **Personalized:** Enable decision maker to get personalized information that reflects her context
- **Precise:** Provide decision maker with precise information in space, time, and context

US-UK Prize Challenge: Privacy Enhancing Technologies



<https://petsprizechallenges.com/>



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● Key Takeaways

- The notion of agents and interaction are two central concepts in AI and Biocomplexity
- Advances in AI are proving to be force multipliers in the study of Biocomplex systems
 - Neurosymbolic methods for developing surrogate models for planning and control problems in pandemic science
 - Agentic methods for creating more efficient workflows and decision support systems
 - Digital twins of human body for personalized medicine and care
- Concepts from biocomplex systems can prove useful in understanding next generation AI systems
 - Ideas in cognition, social cognition for designing future generation AI systems
 - Ideas from Immunology to develop secure AI systems
 - Ideas from Ecology