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PEDRO NASCIMENTO DE LIMA

Towards Modeling Infectious Behaviors

November 19th 2021

RAND CORPORATION

Agenda

- **Why** should we consider modeling the coupled dynamics between behaviors and infectious diseases?
- **What** have we done so far?
    1. Reopening California paper: Stress-testing reopening plans including *some* behavioral uncertainty.
    2. Should we Suppress or Mitigate the Next Pandemic?: Modeling decision-making in a hyper-rational society.
    3. Inductive Reasoning Models and the COVID-19 Flu Paths survey.
- **Where** are we headed?
- **How** do you fit? Questions and Answers

Why should you care about Modeling Infectious Behaviors?

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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

https://policyandcomplexsystems.files.wordpress.com/2021/09/modeling-infectious-behaviors.pdf

Which behaviors do we care about?

- **We are interested in behaviors that:**
  - Have a meaningful epidemiological effects, and
  - Are policy-relevant – may change our policy choices.

Mixing Behaviors

Treatment Behaviors

Vaccination Behaviors

"Influence": behavior transmission

Why do we care about those behaviors?

Behaviors can be <u>influenced</u> and <u>constrained</u> by <u>policy</u> (and politics).

- **Social distancing, mask wearing mandates, stay at home orders**

  -> Mixing Behaviors
- **Vaccination Mandates, Vaccine availability**

  -> Vaccination Behaviors
- **Treatment availability, "political sponsorship of specific drugs"**

  -> Treatment behaviors.
- **Misinformation, Mainstream media**

  -> Influence and behavior transmission

Can we pose models that shed light into policy-relevant behavioral mechanisms?

How can behaviors be characterized in infectious disease models?

If behaviors are heterogeneous but static, they can be (and have been) addressed to a certain extent:

- **Mixing Behaviors:**
  - Characterize the heterogeneity of contacts in a network or in population strata with mixing matrices.
  - Fit a time-varying transmission parameter β using your favorite inference method.
  - Use the resulting distribution of parameters for forecasting or policy analysis.

- **Vaccination Behaviors:**
  - Use past data to estimate vaccine uptake by population strata.
  - Assume some people will accept the vaccine and some will not.

Assuming static behaviors or ignoring them can require heroic assumptions

1. **Behavior is persistent**

   People will behave in the future as they behaved in the past.
2. **Behavior is not endogenous**

   People are not adjusting their behavior given new information (e.g., vaccination will not lead you to meet on thanksgiving; people don't wear masks when cases go up as they take umbrella when it is raining.
3. **Behaviors are not infectious**

   There's no network effect, people don't do things just because others are doing those things.

These assumptions may hold when people don't care about infectious diseases.

And they may break precisely when the world is watching our models.

It can be challenging to depart from standard assumptions

1. **Behavior is persistent:** People will behave in the future as they behaved in the past.
    1. **If not persistent, then how is it changing??**
2. **Behavior is not endogenous:** People are not adjusting their behavior given new information (e.g., vaccination will not lead you to meet on thanksgiving).
    1. **If it is endogenous, then what is driving it?? It is even in the model?**
3. **Behaviors are not infectious:** There's no network effect, people don't do things just because others are doing those things. I don't wear masks because everyone else is also wearing a mask.
    1. **How does behavior spread? Spread of behavior could be more stochastic and unpredictable than disease progression.**

Can we formulate credible behavioral models that align with existing evidence and data? Would these models be any better or useful?

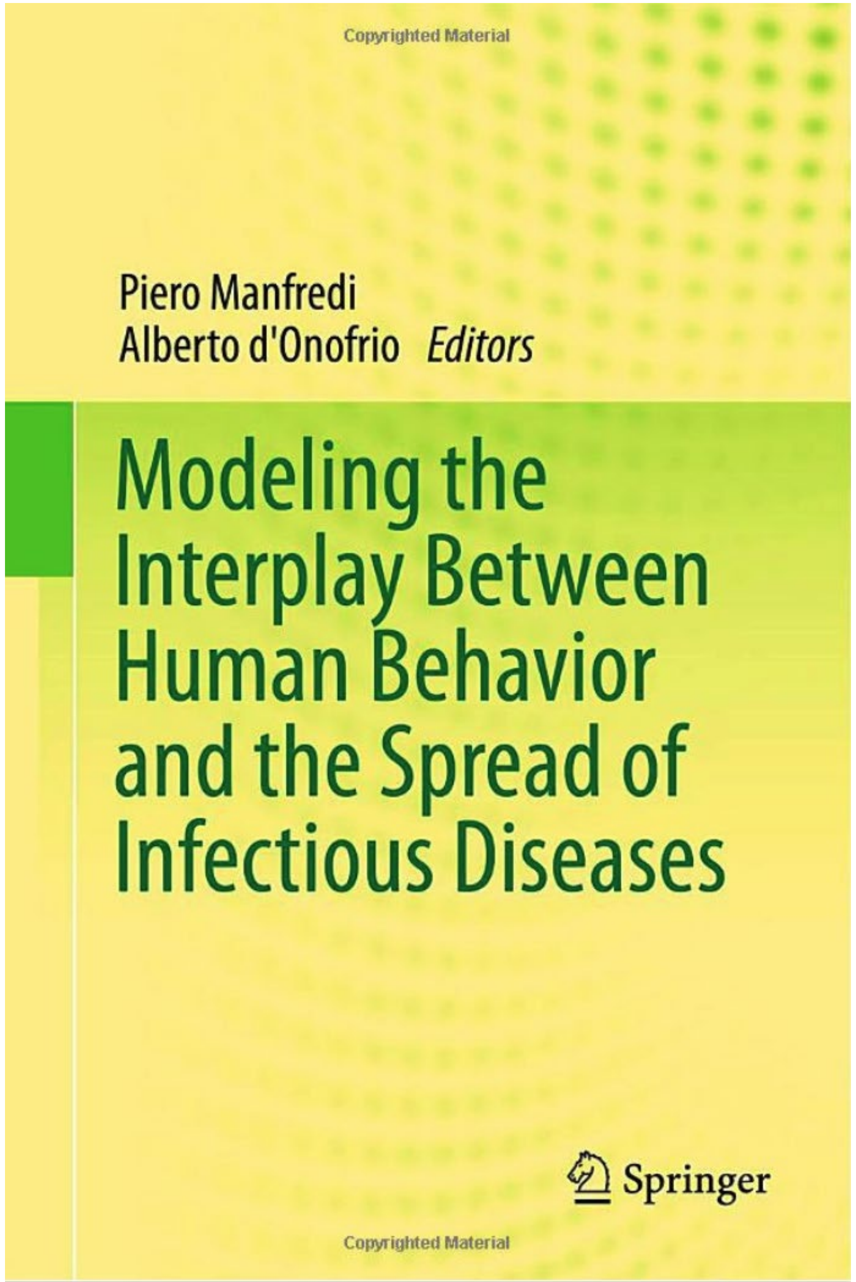
This *is not* a talk about definitive solutions

We do not claim to offer definitive answers to the issues presented above.

But we did made efforts to account for *some* behavioral factors in our work.

We are most interested in **policy-relevant behaviors** – that is, behavioral factors that **could influence policy choices.**

We have also collected **panel data** on Flu vaccination behavior, and we will continue to do so to understand the long-term behavioral dynamics of Flu + COVID-19 vaccination.



We are not the first to care about modeling behaviors

- A growing literature has shown that this can be done for both Population-based and Agent-based models.
- Game Theory has influenced models on vaccination decisions, including models that account for:
  - Forward looking, deductive reasoning individuals that balance risk perceptions and costs.
  - Backward looking, inductive reasoning individuals that adapt to observations and experiences.

Features of Behavioral Models

Feature	Description
Exogenous vs **Endogenous** Behaviors	**Exogenous** behaviors can be specified through time-varying parameters (usually fitted to data). **Endogenous** behaviors emerge as a response to other model inputs, sometimes in non-linear ways.
Reasoning Assumptions	**Deductive** (e.g. utility maximization, rational agents) vs **Inductive** (Heuristics, bounded rationality). Forward vs Backward looking.
Types of behaviors considered	E.g., **Social Distancing**, **Mask warning**, **Hand Washing**, **Vaccination**, **Treatment preferences, rumor spreading**
Time-frame of disease and length of immunity	Does vaccination provide long-lasting immunity, (i.e., a one-time decision) or do individuals need to make **repeated choices**?
Information availability	Source of Information shaping risk perceptions. Is information equally available to all? Personal experience, Local interaction (Social Network) or Global (e.g., Broadcast media)

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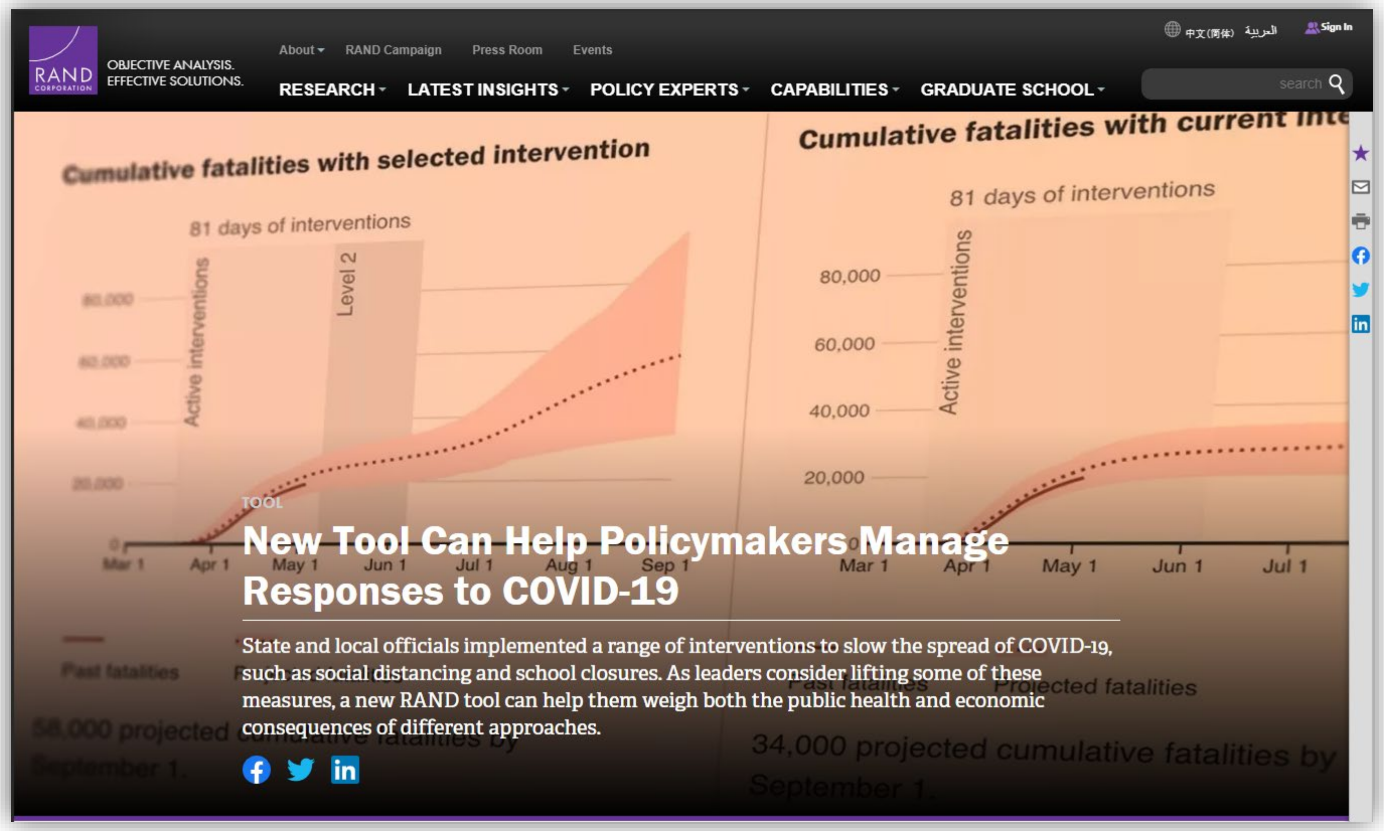
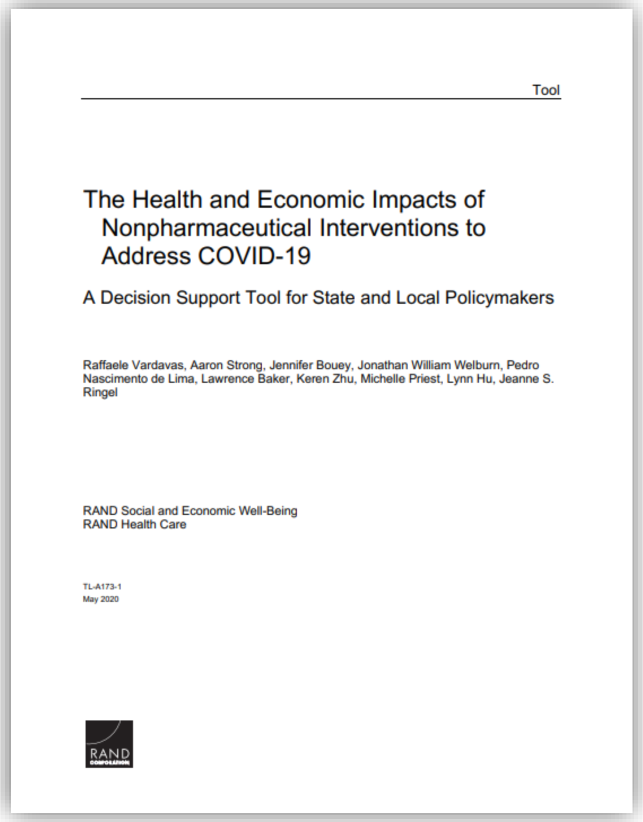
Reopening Under Uncertainty

SEEKING ROBUST REOPENING STRATEGIES DESPITE BEHAVIORAL UNCERTAINTY

Prior Work:

The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19





Tool

The Health and Economic Impacts of Nonpharmaceutical Interventions to Address COVID-19

A Decision Support Tool for State and Local Policymakers

Raffaele Vardavas, Aaron Strong, Jennifer Bouey, Jonathan William Welburn, Pedro Nascimento de Lima, Lawrence Baker, Keren Zhu, Michelle Priest, Lynn Hu, Jeanne S. Ringel

RAND Social and Economic Well-Being
RAND Health Care

TL-A173-1
May 2020

- https://www.rand.org/pubs/tools/TLA173-1.html

Policy Question

How California and other jurisdictions should approach reopening in the wake of vaccination?

WORKING PAPER

Modeling COVID-19 Nonpharmaceutical Interventions

Exploring periodic NPI Strategies

Raffaele Vardavas, Pedro Nascimento de Lima, Lawrence Baker

RAND Social and Economic Well-Being

WR-A1080-1
April 2021

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PLOS ONE

RESEARCH ARTICLE

Reopening California: Seeking robust, non-dominated COVID-19 exit strategies

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Check for updates

Abstract

The COVID-19 pandemic required significant public health interventions from local governments. Although nonpharmaceutical interventions often were implemented as decision rules, few studies evaluated the robustness of those reopening plans under a wide range of uncertainties. This paper uses the Robust Decision Making approach to stress-test 78 alternative reopening strategies, using California as an example. This study uniquely considers a wide range of uncertainties and demonstrates that seemingly sensible reopening plans can lead to both unnecessary COVID-19 deaths and days of interventions. We find that plans using fixed COVID-19 case thresholds might be less effective than strategies with time-varying reopening thresholds. While we use California as an example, our results are particularly relevant for jurisdictions where vaccination roll-out has been slower. The approach used in this paper could also prove useful for other public health policy problems in which policymakers need to make robust decisions in the face of deep uncertainty.

OPEN ACCESS

Citation: Nascimento de Lima P, Lempert R, Vardavas R, Baker L, Ringel J, Rutter CM, et al. (2021) Reopening California: Seeking robust, non-dominated COVID-19 exit strategies. PLoS ONE 16(10): e0259166. https://doi.org/10.1371/journal.pone.0259166

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Data Availability Statement: The code and data underlying the results presented in the study are available from https://github.com/RANDCorporation/covid-19-reopening-california.

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Introduction

The COVID-19 pandemic has wreaked havoc across the US, causing over 37 million confirmed cases and 600,000 deaths, and state-wide shutdowns of all non-essential businesses. As state officials navigate the pandemic, they must manage both health and economic goals. Generally, reopening plans [1–4] have been proposed as phased strategies, in which the state allows economic activity to resume based on meeting COVID-19 incidence targets. However, pandemics often follow oscillatory waves of infection, and many states have already been forced to revise their plans, either shutting down after new outbreaks or adjusting which activities are allowed in each phase. To ensure long-term success in combating the pandemic, local policymakers need to consider the trade-offs underlying reopening decisions, while accounting for deep uncertainties.

Since one-time lockdowns have proven to be insufficient to control the pandemic, a coherent, long-term strategy is needed. Instead of adopting a stable, pre-defined strategy, local policymakers have changed regulations and instated NPIs adaptively, often adopting NPIs based on the decisions of other jurisdictions [5] without necessarily supporting every deliberation

May 2021

Perspective
EXPERT INSIGHTS ON A TIMELY POLICY ISSUE

PEDRO NASCIMENTO DE LIMA, RAFFAELE VARDAVAS, LAWRENCE BAKER, JEANNE S. RINGEL, ROBERT J. LEMPERT, CAROLYN M. RUTTER, JONATHAN OZIK

Reopening Under Uncertainty

Stress-Testing California's COVID-19 Exit Strategy

As administration of the vaccine for coronavirus disease 2019 (COVID-19) has gotten underway in 2021, policymakers across the United States have been navigating how to reopen their local institutions and economies. They must manage multiple objectives, including preserving the health of constituencies, balancing equity, and limiting the economic consequences of COVID-19 nonpharmaceutical interventions. To guide these decisions, many states have adopted decision rules that link reopening to case counts, test positivity, or hospital capacity. Yet uncertainties—such as vaccination uptake, the extent to which vaccinations reduce transmission, and the impact of variant strains—complicate the path to identifying the best path forward.

In a separate working paper (Nascimento de Lima et al., 2021), we evaluate reopening strategies that California can adopt to handle these uncertainties. Our approach uses models to stress-test COVID-19 reopening strategies under a wide variety of scenarios using the Robust Decision Making approach. Although there is a fast-growing literature on strategies to curb the pandemic with

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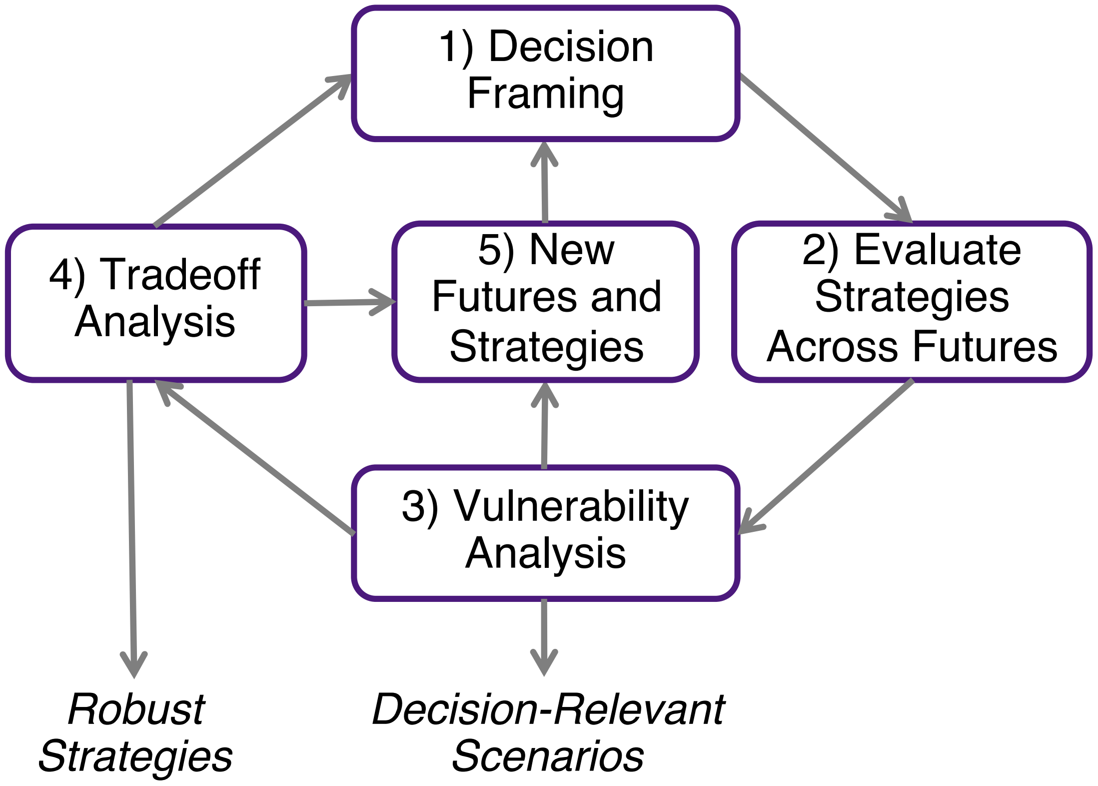
https://www.rand.org/pubs/working_papers/WRA1080-1.html https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0259166 https://www.rand.org/pubs/perspectives/PEA1080-1.html

Robust Decision Making methods can be used to evaluate the robustness of specific policies to behavioral uncertainties

1. RDM provides an ***iterative framework*** for evaluating policies while accounting for *deep uncertainty*
2. Uses *models* to **stress-test policies across wide range of futures**, reflecting uncertainties
3. *Quantitative* ***vulnerability analysis*** **identifies the assumptions that lead policies to be successful and unsuccessful**, and informs development of *adaptive strategies*
4. Tradeoff analysis helps balance across **multiple objectives** and identify *robust* strategies
5. RDM Is part of a family of **Decision making Under Deep Uncertainty (DMDU) methods**.

More information on RDM:
https://www.rand.org/methods/rdmlab.html

Robust Decision Making (RDM)



Decision-framing helps us decide which behaviors we want to include

Failing to consider some of those elements can be misleading:

1. **Not enough levers** -> Results in a **menu of potentially dominated options**.
2. **Not enough uncertainties** -> Plans can be **fragile** and break.
3. **Ignore important metrics** -> Can result in **dominated policies**

1. This approach:
   1. **Doesn't aggregate outcomes**: Look for **non-dominated policies**.
   2. **Doesn't aggregate uncertainties** into a best-guess of the future: **Look for robust policies**.

X - Uncertainties	L - Policy levers

• Vaccine efficacy to prevent transmission
• Loss of immunity
• Behavioral response to vaccination
• Willingness to vaccinate
• Changes in transmissibility (i.e., induced by variant strains)
• Actual vaccination Rate
	• Baseline level of caution x_b
	• NPI strategy $s \in \{C, T, V\}$
	• Time-based strategies $s = T$
	  – Level of caution factor α
	  – Transition date T_α
	• Vaccination-based strategies $s = V$
	  – Vaccination reference point V_{mid}
	  – Relaxation rate k_c

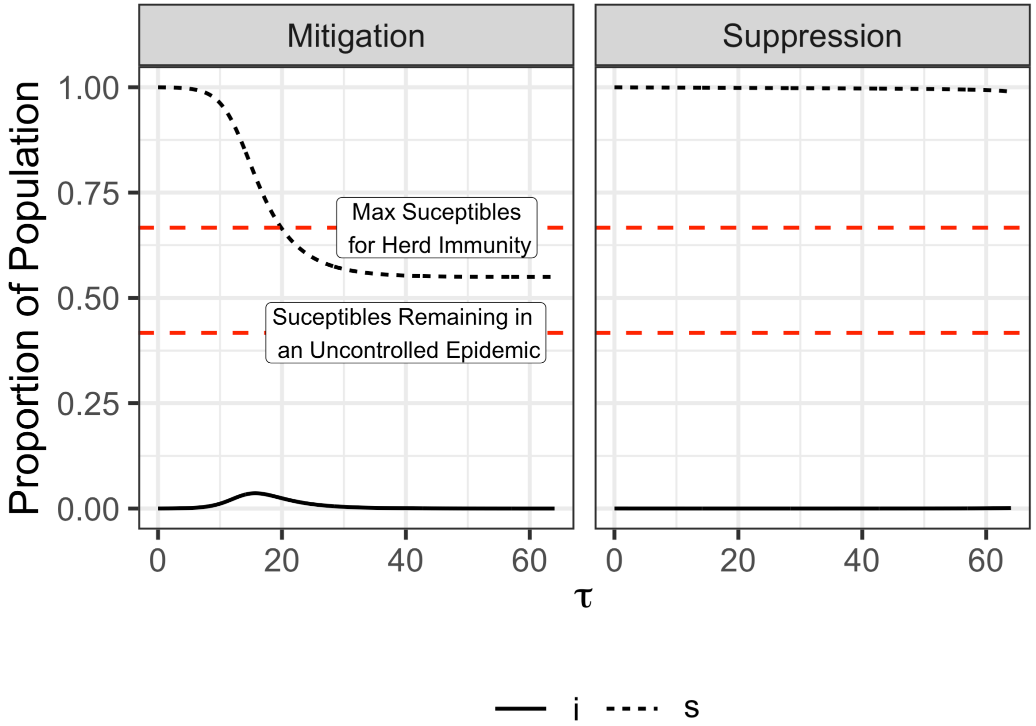
R - Relationships (models)	**M - Metrics**
Meta-population deterministic ODE [10, 33] Computable general equilibrium model [36]	75^{th} Regret percentile of deaths / 100 k people, years of life lost, cases, income loss, and days under NPIs

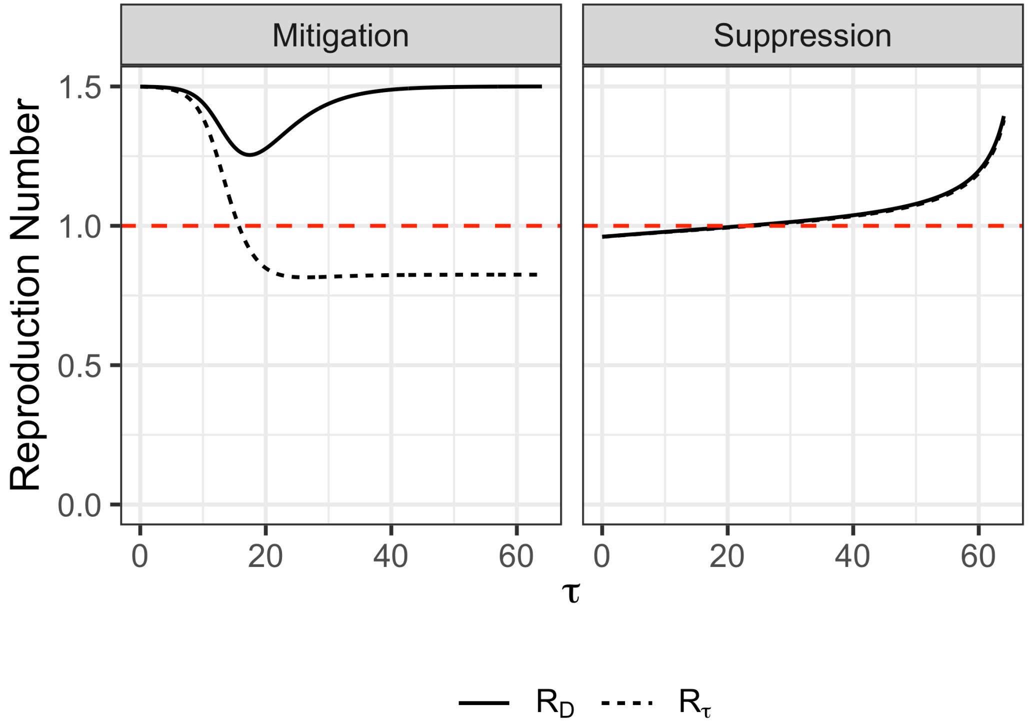
Should we Mitigate or Suppress the Next Pandemic?

AN EXAMPLE OF A DEDUCTIVE REASONING APPROACH

Time-Horizons: Mitigate or Suppress

We consider a simple SIR model and a population of hyper-rational agents all with the same perceived final time horizon and cost of infection and social distancing – how do they behave?





Should We Mitigate or Suppress the Next Pandemic? Time-Horizons and Costs Shape Optimal Social Distancing Strategies
Sarah A Nowak, Pedro Nascimento de Lima, Raffaele Vardavas medRxiv 2021.11.14.21266322; doi: https://doi.org/10.1101/2021.11.14.21266322
bit.ly/infectiousbehaviors

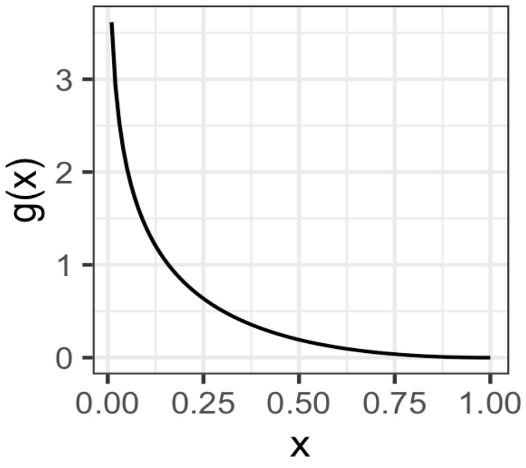
Fixed Time-Horizon Variational Method

$$R_D(t) = \beta(t)\tau_{i\to r}$$
$$\frac{R_D(t)}{R_0} = \frac{\beta(t)}{\beta_0}$$
$$R_\tau(t) = sR_D(t)$$

$$\frac{d}{d\tau}s = -R_D si,$$
$$\frac{d}{d\tau}i = R_D si - i,$$
$$\frac{d}{d\tau}r = i.$$

$$c = C\tau_{i\to r}/D$$
$$h(s,i,R_D) = R_D si + cg(R_D/R_0)$$

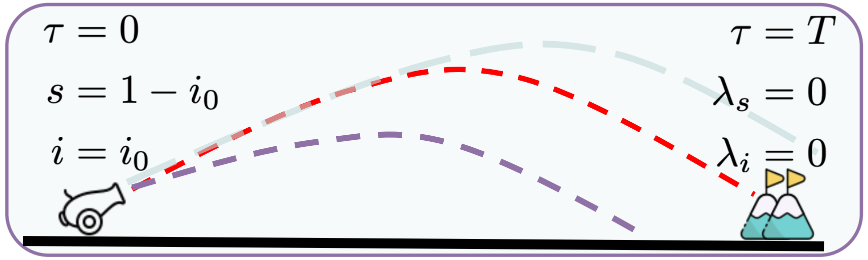
$$g(x) = -\ln(x) + x - 1$$



$$\begin{aligned}\mathcal{L}(s,i,R_D) = h(s,i,R_D)+ \\ \lambda_s\left(s' + R_D si\right) + \\ \lambda_i\left(i' - R_D si + i\right)\end{aligned}$$

Parameter	Description
$\tau_{i\to r}$	Duration of infectiousness ~ 14 days
$\beta(t)$	Transmissibility at time *t*.
$R_D(t)$	Reproductive number at time *t*.
$R_\tau(t)$	Effective reproductive number.
C	cost of social distancing per unit time.
D	cost of infection.

$$\frac{\partial\mathcal{L}}{\partial y_i} - \frac{d}{d\tau}\left(\frac{\partial\mathcal{L}}{\partial y_i'}\right) = 0.$$



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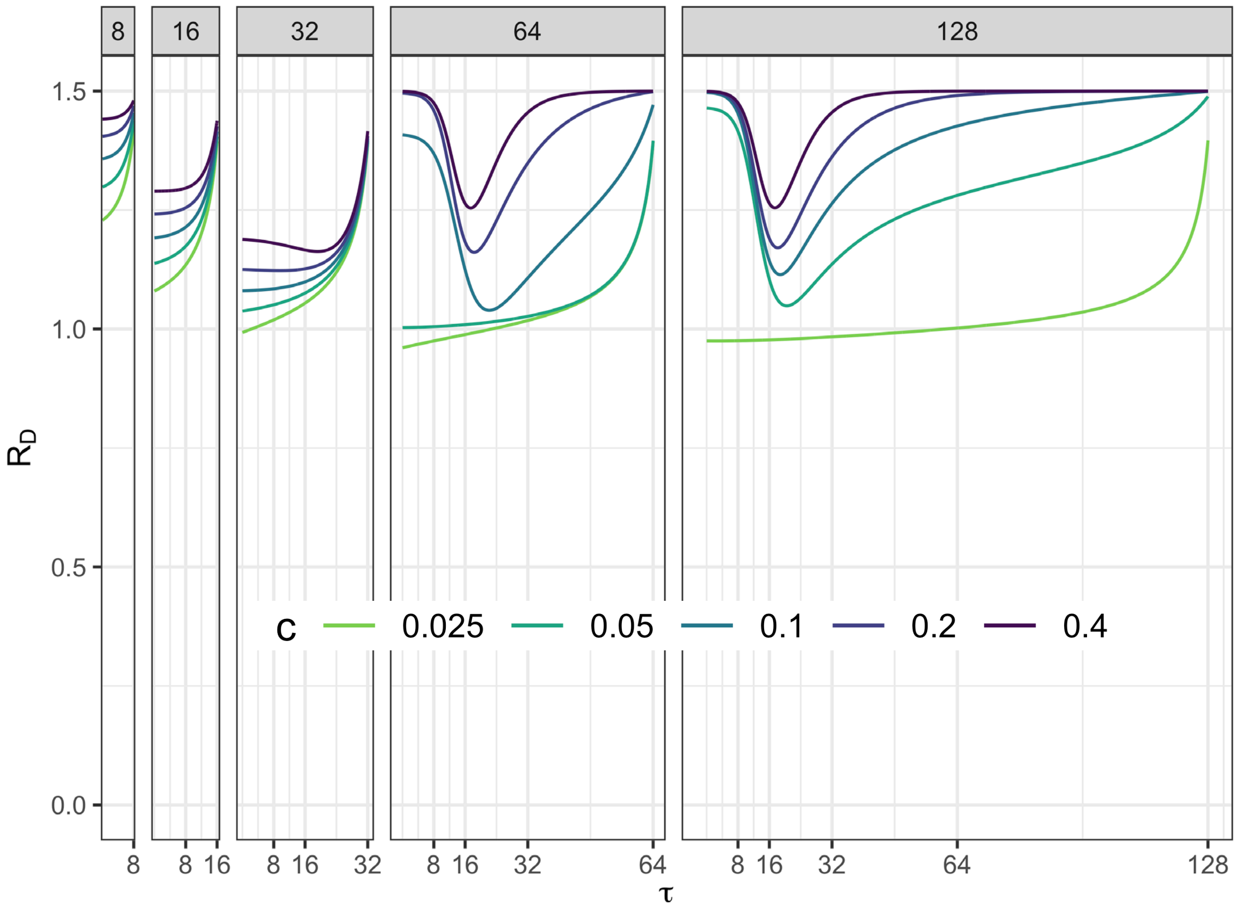
bit.ly/infectiousbehaviors

Example Dynamics

Inputs:

Parameter	Value/Range	Description
R_0	1.5	Basic Reproductive Number
$i(0)$	10^{-4}	Initial number of infectious
$\tau_{i\to r}$	1	Rescaled time. 14 days
T	$8,16,\ldots,128$	4 to 60 months
c	2.5×10^{-2} to 0.4	Threshold duration of distancing: 1 month to 2 years.

$$(C/D)\times\ 2\ \text{years}\ \sim 2.5\times10^{-2}$$
$$(C/D)\times\ 1\ \text{month}\ \sim 0.4$$



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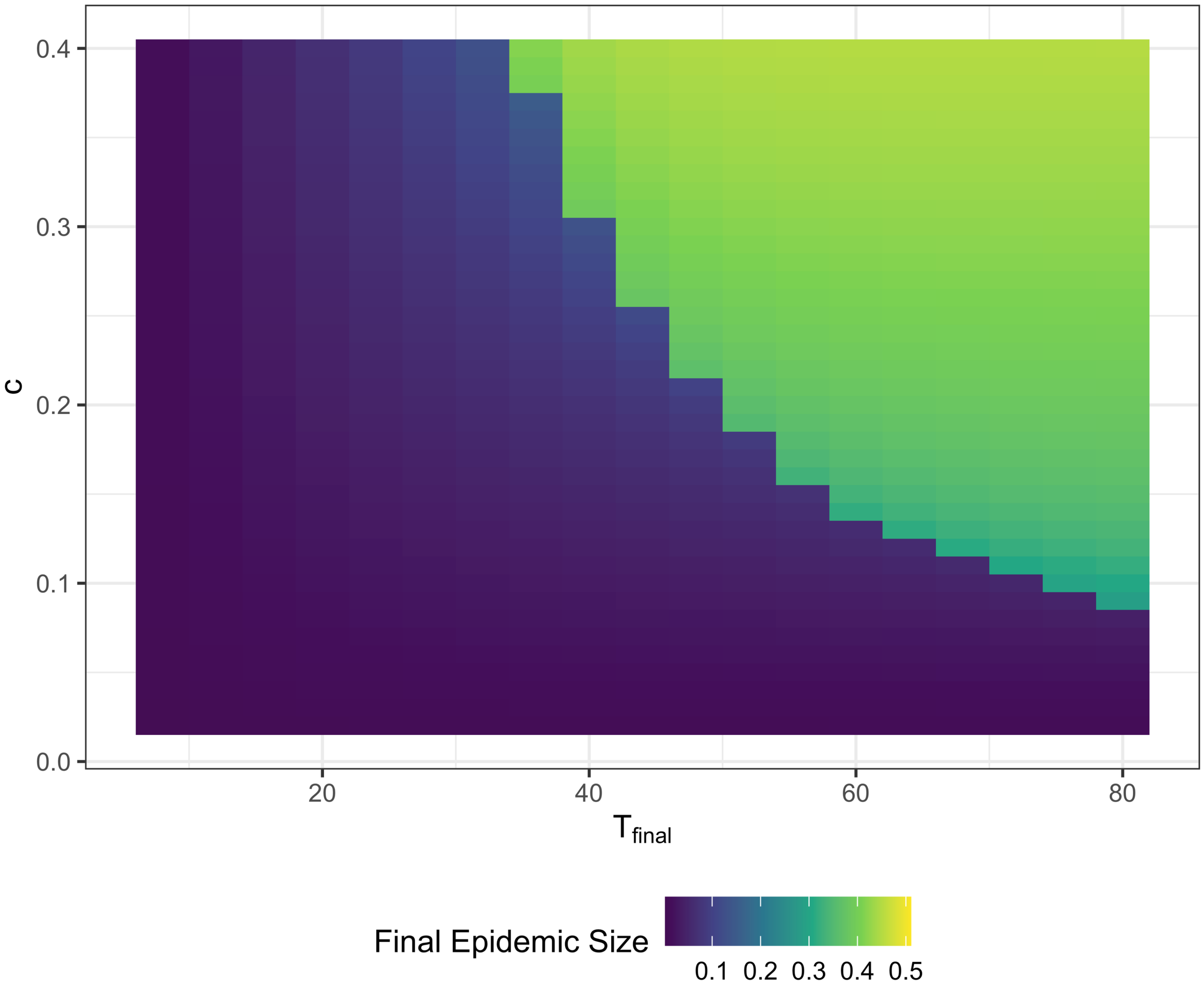


Time-Frame and relative Costs shaped optimal policy

- We used the epidemic size by time T to indicate which policy was would be preferred.

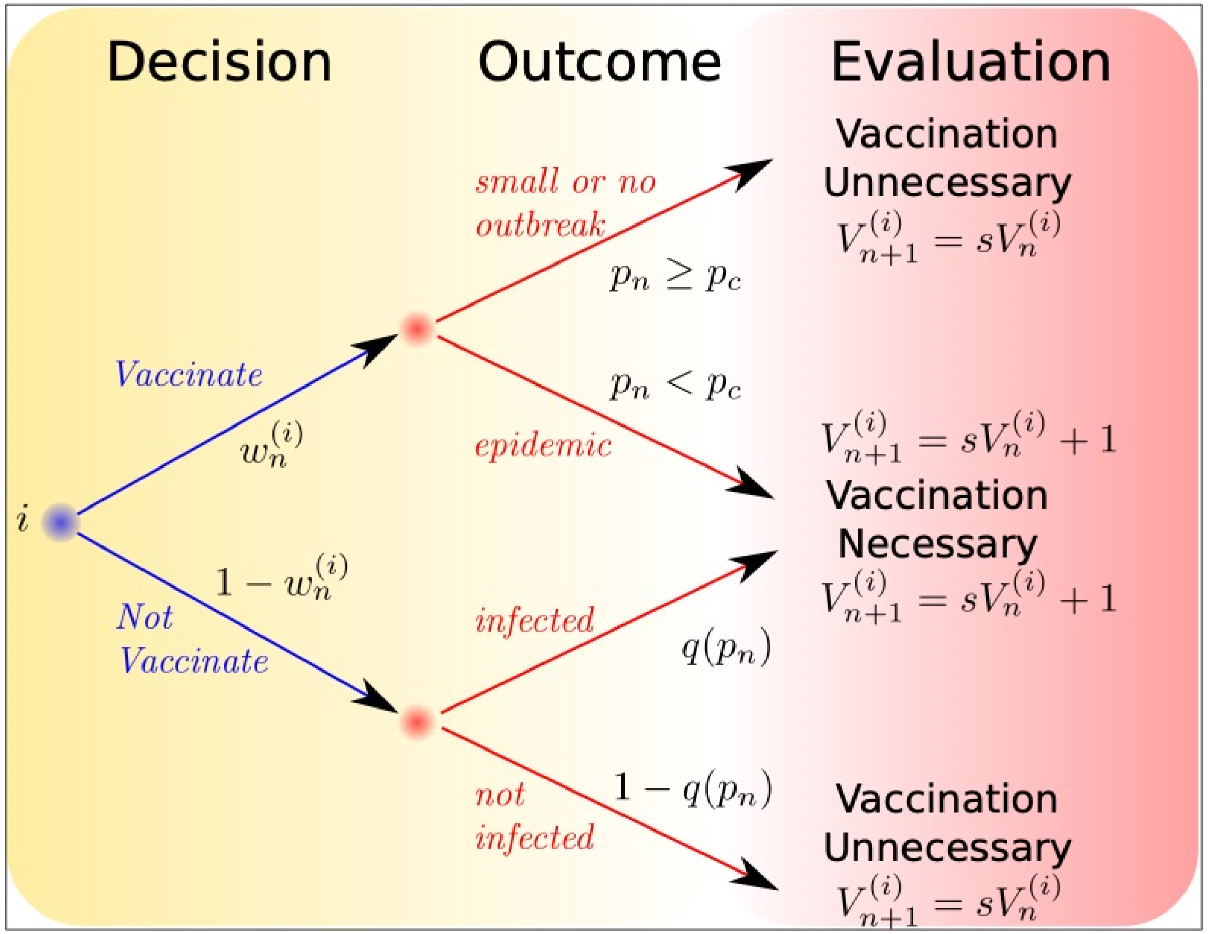
Strategy	Conditions
Suppression	Short T and/or low c
Mitigation	Long T and/or high c

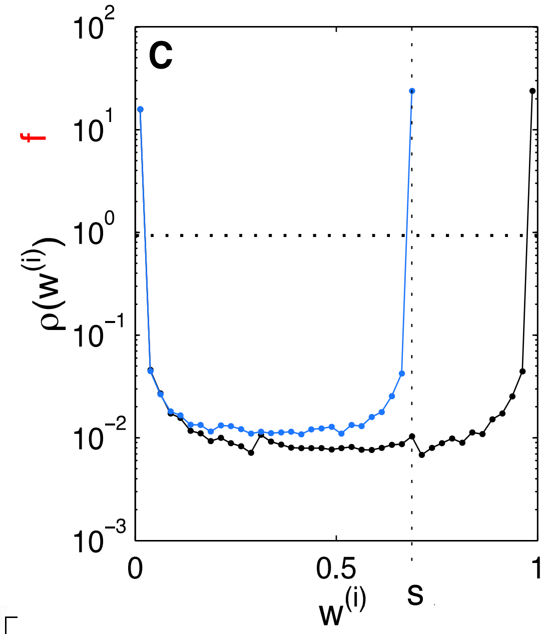
- Interestingly the change between strategies is very abrupt.

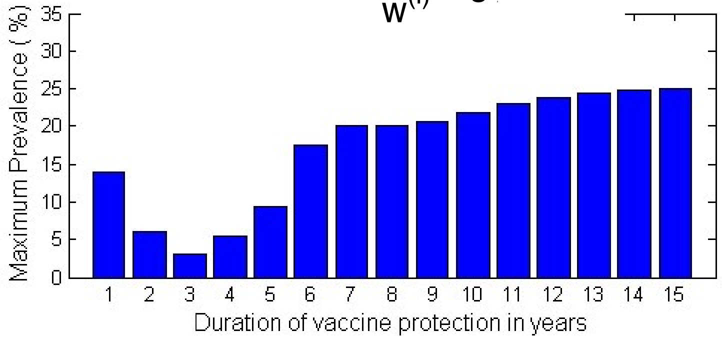
Can Influenza Epidemics be prevented from voluntary vaccination?

AN EXAMPLE OF THE INDUCTIVE REASONING APPROACH

Voluntary vaccination alone cannot prevent influenza epidemics.

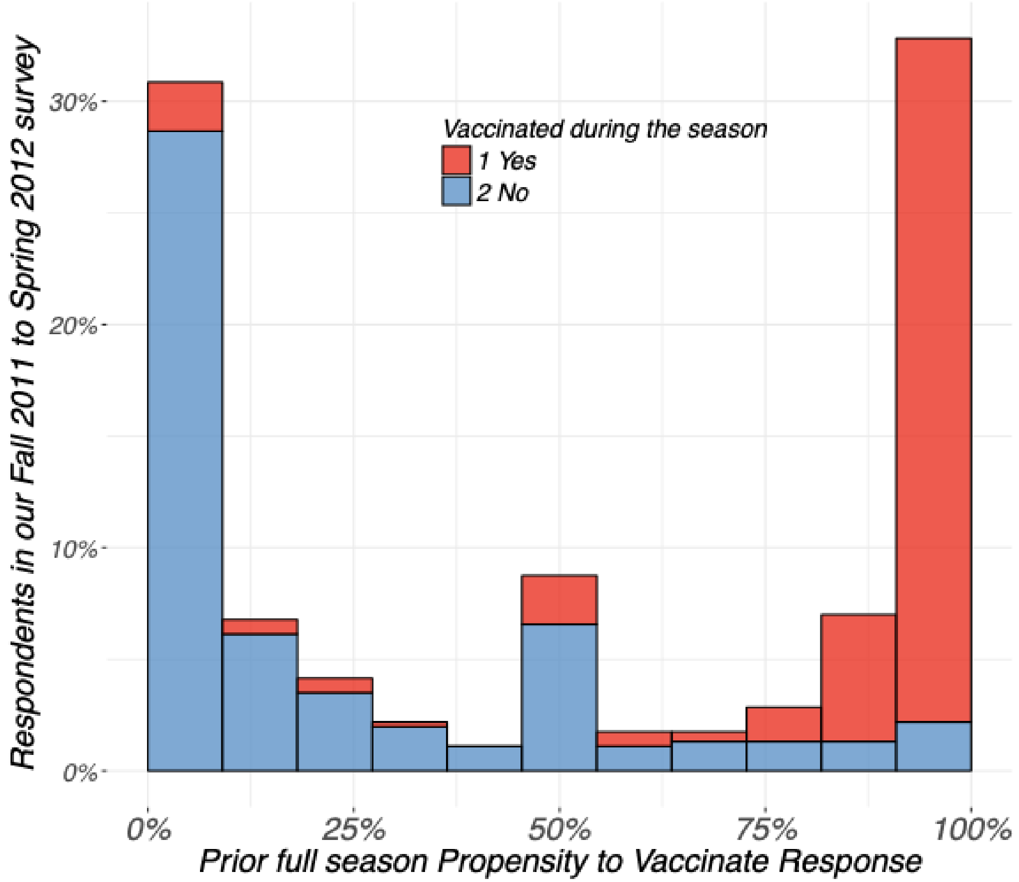


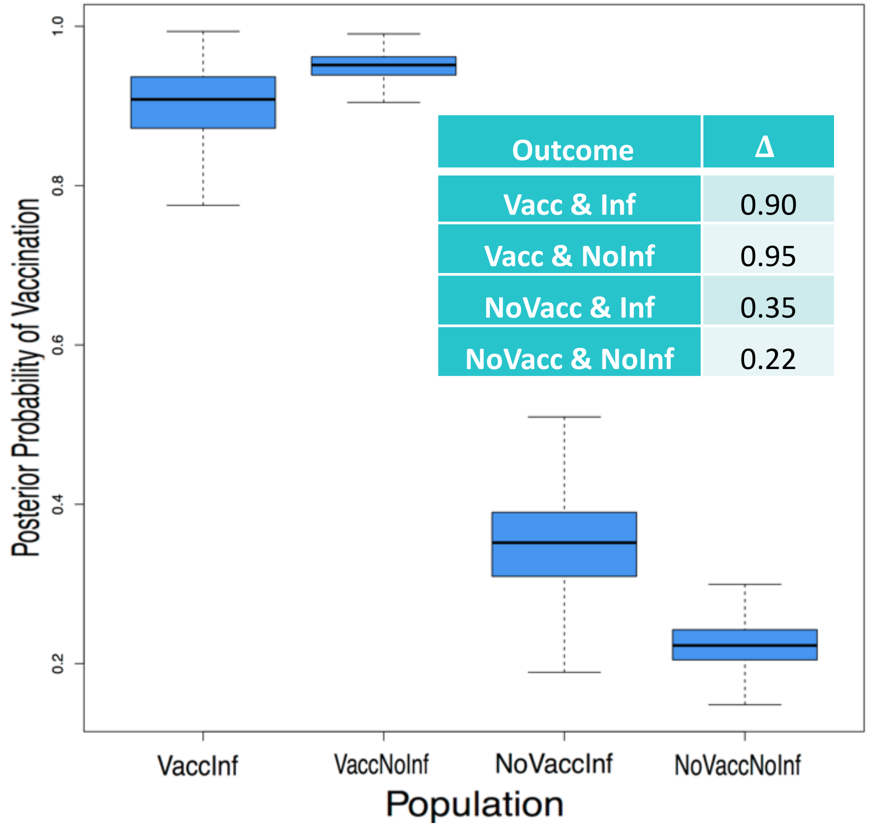




Vardavas R, Breban R, Blower S. Can influenza epidemics be prevented by voluntary vaccination? PLoS Comput Biol. 2007

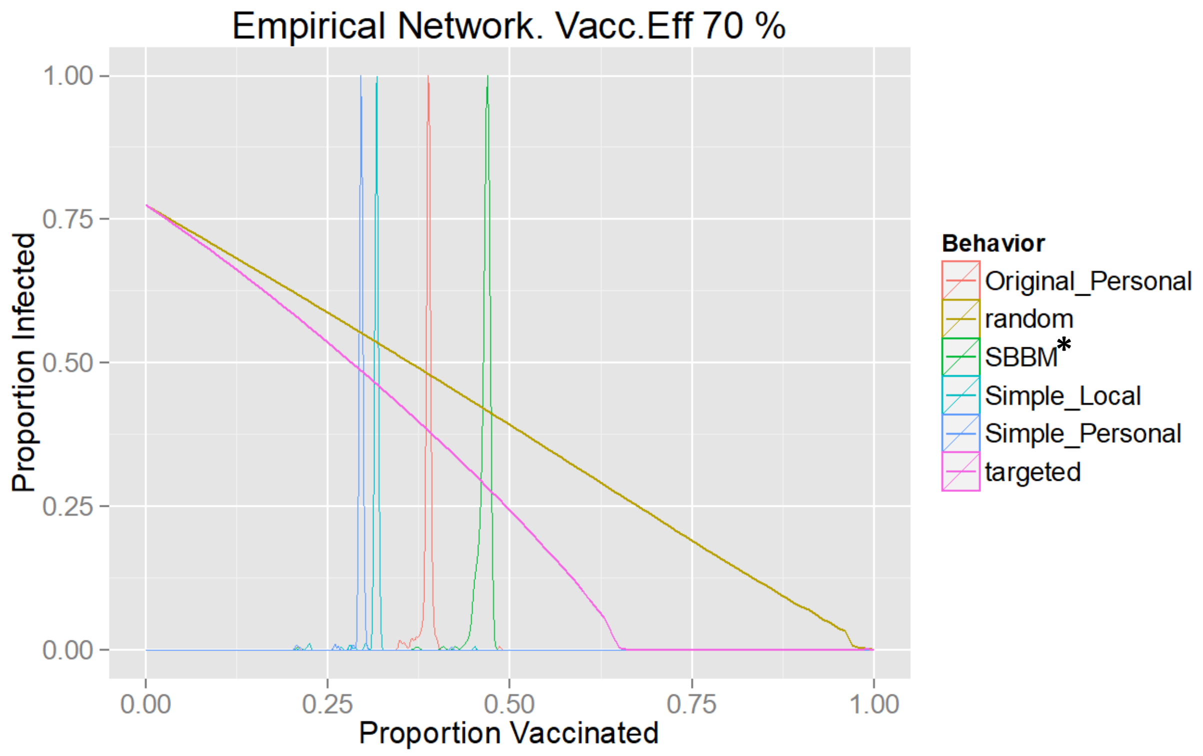
Initial ALP survey on influenza vaccination behaviors started in 2011

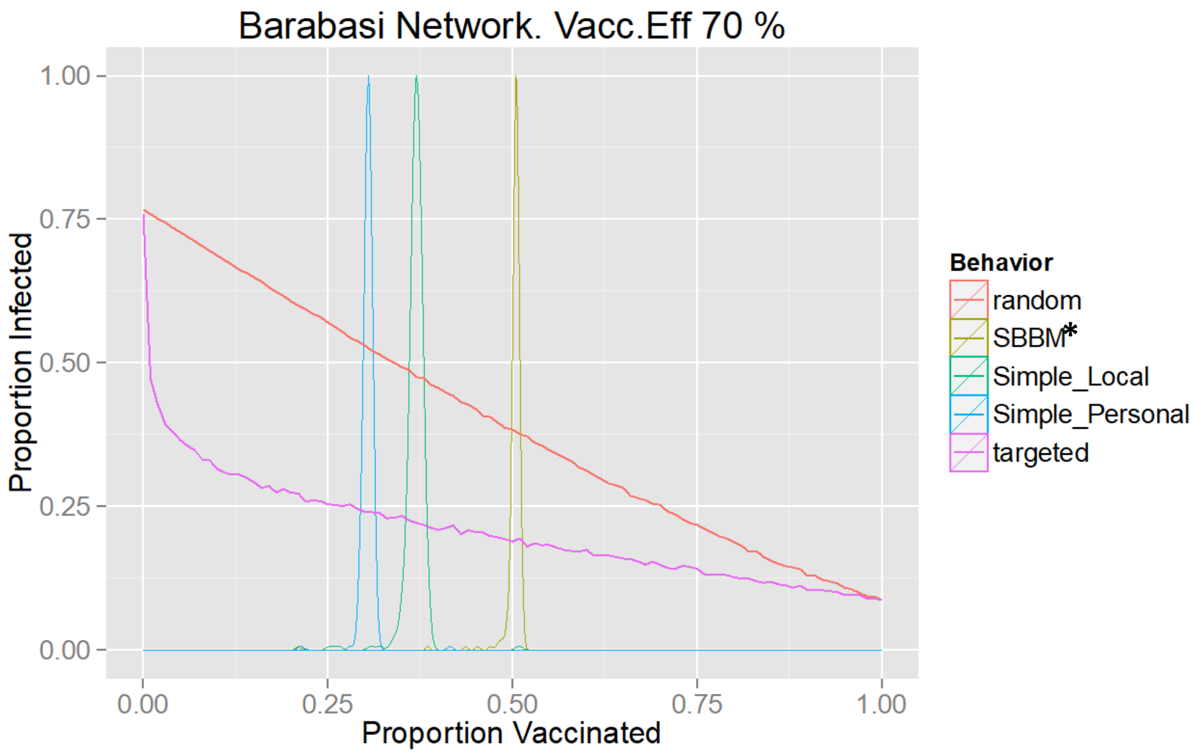




Outcome	Δ
Vacc & Inf	0.90
Vacc & NoInf	0.95
NoVacc & Inf	0.35
NoVacc & NoInf	0.22

Behaviors and network structure can shape epidemic outcomes





***SBBM: Survey-Based Behavioral Model**

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Longitudinal Surveys can help inform Behavioral Models

FluPaths Study

A 4-year, 8-wave longitudinal survey fielded from Fall 2016 to Spring 2020.

Spring 2020 wave included question on COVID-19

	Sample Size
Influenza Season	Ego
Fall 2015 to Spring 2016	2,173
Fall 2016 to Spring 2017	1,935
Fall 2017 to Spring 2018	1,888
Fall 2018 to Spring 2019	1,740
Fall 2019 to Spring 2020	1,642

FALL waves example questions

Pre-Season Question	Description
Vaccination Expectation	Chances that to get the flu vaccine this flu season.
Never Sometimes Always	View themselves as never sometimes always for influenza vaccination.
Recommendation	Whether they received a recommendation to vaccinate by a health care professional
Flu Expectations	Risk perceptions of catching the flu with and without vaccination.
Social Distancing	Chance of staying home if they have the flu. Chance that others would remain at home.

SPRING waves example questions

Post-Season Question	Description
Vaccinated Flu	Did they vaccinate for the flu and was it in response to a provider recommendation
Had Flu	Did they think they caught the flu; was it confirmed by a healthcare provider
Severe	How severe was it including symptoms and hospitalization.
Antiviral	If they caught the flu, were they prescribed an antiviral. Would they take them again.
News	What they heard on the news about the flu and its influence on vaccination.

Additional non-longitudinal example questions

General Question	Description
Job Requirement	Does their employer require them to vaccinate.
Importance	Importance of factors affecting vaccination decisions: Cost, convenience, needles etc.
Norms	How many people generally vaccinate for influenza and how many catch the flu.
Beliefs	Beliefs on how serious influenza is, the efficacy of the vaccine and other measures.
Social Media Use	Do they use SM, how often, how frequently posts on vaccination appear in their feeds.

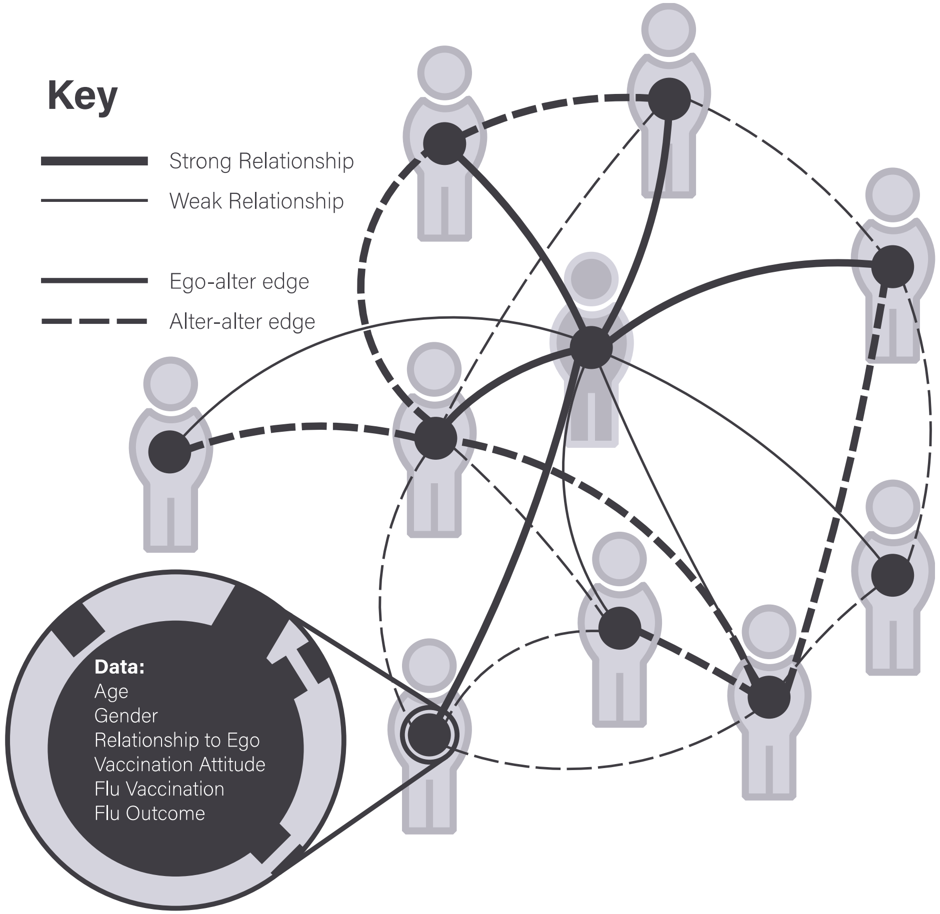
RAND's ALP: https://www.rand.org/research/data/alp.html. Surveys 460, 476, 488, 502, 512, 527, 532, 540, 552

FluPaths’ Ego-centric Network Data

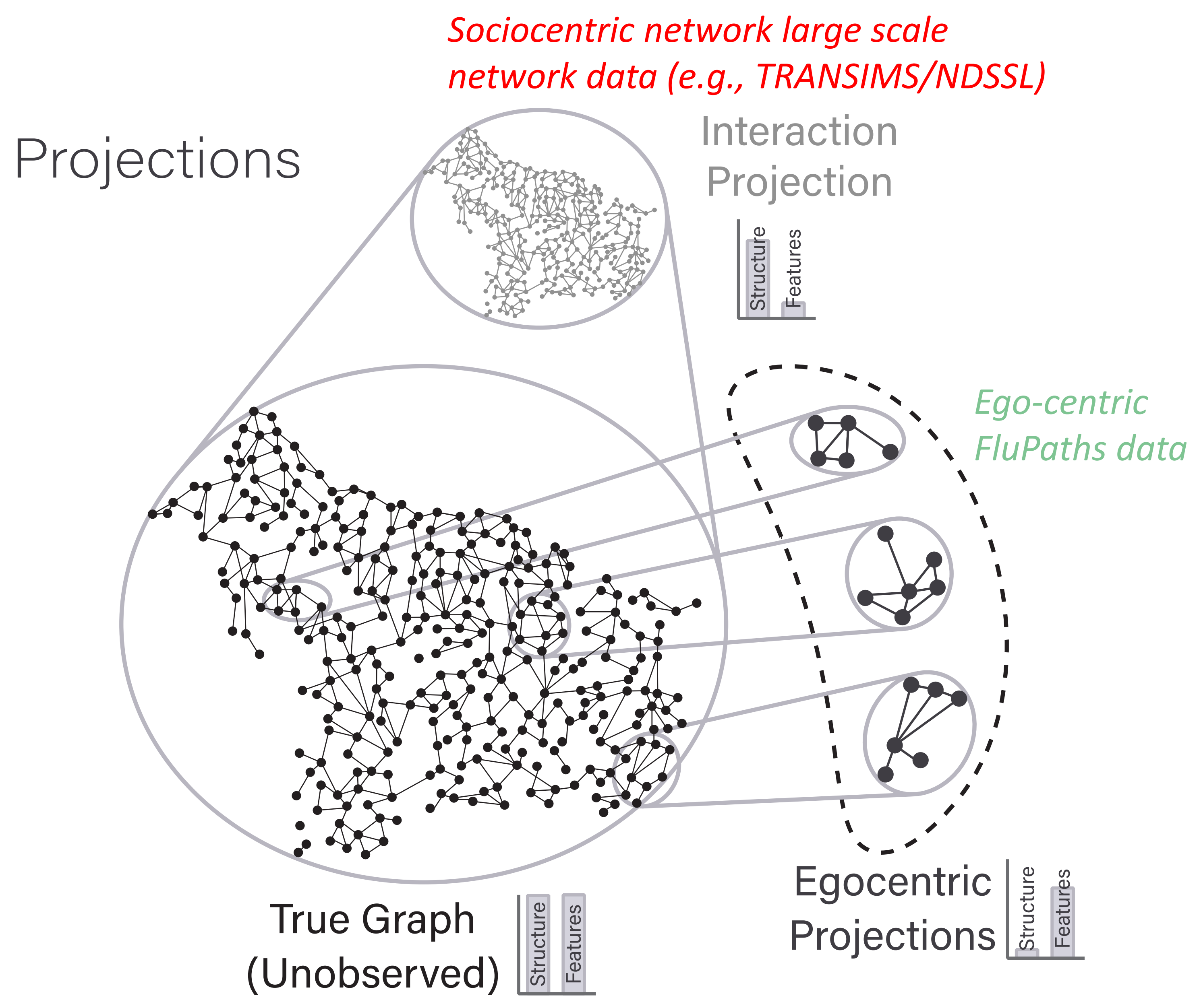
Survey collected information on each respondent's social network structure to assess local network influence over time.

Alter data type	Description
Demographic Attributes	Age, Gender, work in the medical field
Behavioral Attributes	Vaccinate for Influenza, Caught Influenza, are Never, Sometimes or Always
Relationship	Relationship to the Ego, frequency of both face-to-face and remote interactions

Season Ending	Percentage Vaccinate		Percentage Influenza	
	Ego	Alter	Ego	Alter
2016	48.2%	64.0%	14.7%	33.5%
2017	52.4%	59.1%	7.3%	19.3%
2018	55.5%	64.8%	9.4%	20.8%
2019	56.7%	67.5%	5.8%	19.8%
2020	59.3%	68.3%	7.4%	17.9%



Empirical Behavioral Synthetic Networks



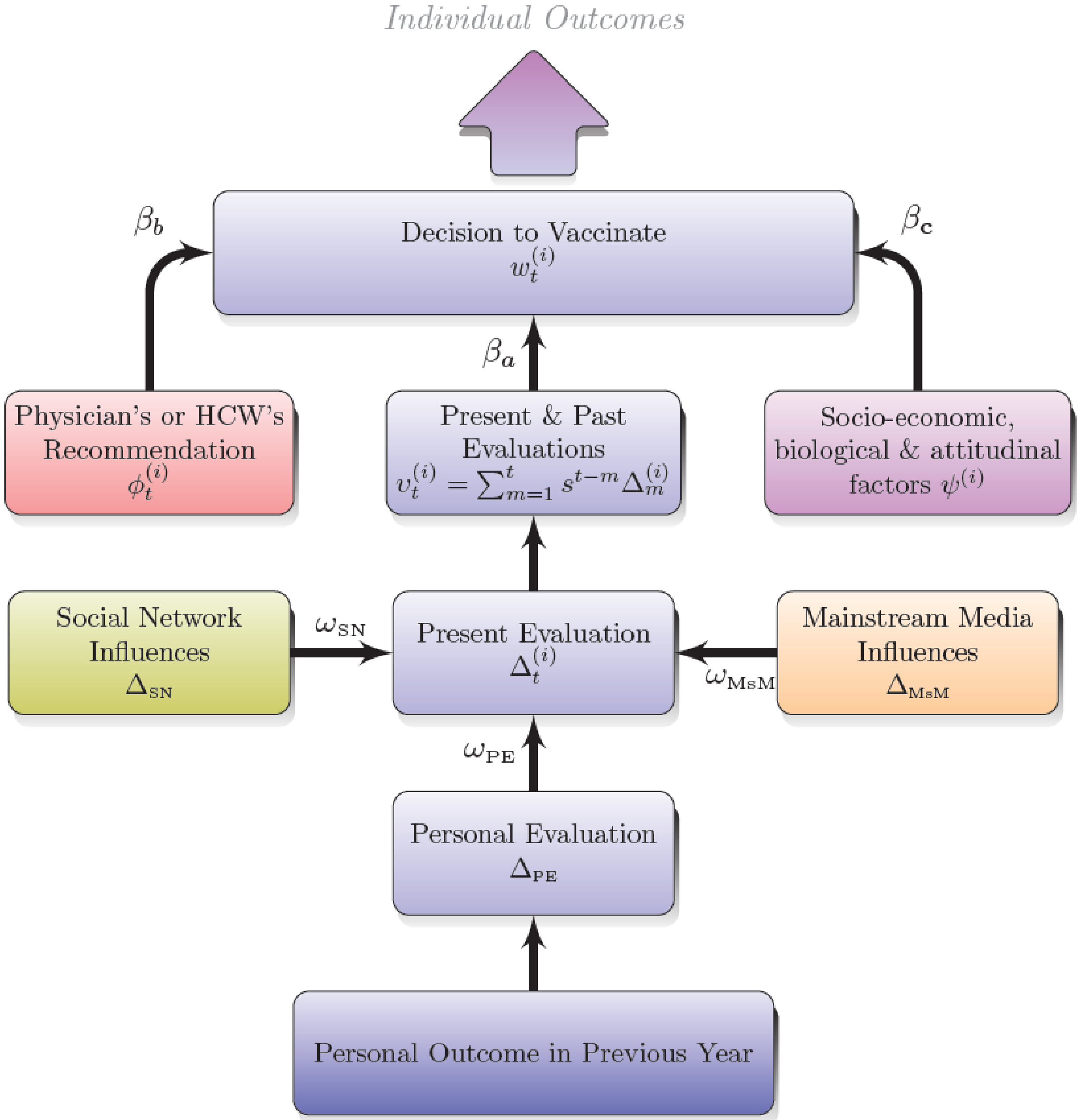
- ❑ Need to merge the network influenza vaccination attitudes from *FluPaths* to a large scale-network.
- ❑ Methods used include
  - ❑ Matching methods
  - ❑ Exponential Random Graph Models
  - ❑ Graph Convolutional Neural Networks
- ❑ It is used to create Input Synthetic Networks to Agent-Based Models.

Hartnett, Gavin S., et al. Deep Generative Modeling in Network Science with Applications to Public Policy Research. Santa Monica, CA: RAND Corporation, 2020. https://www.rand.org/pubs/working_papers/WRA843-1.html

Adaptive Behavioral model for Influenza Vaccination

Adaptive Components
Personal past experiences with influenza and its vaccine.
Local observations and influences in one's social network.
Global effects such as media

Fixed and External Factors
Provider Recommendation
Socio-Economic Factors.



ACT-R Models from Cognitive Psychology also help model behavior

- Our adaptive model design is consistent with computational models developed in the fields of experimental and cognitive psychology.
- **Adaptive Control of Thought—Rational (ACT-R)** is a cognitive architecture consistent with existing theories of attitude and behavior change in response to personal experiences, social network experiences, and information sources.
  - ACT-R uses activation-based theory of declarative memory accounting for the acquisition and retention of knowledge and experiences. Information stored in declarative memory is used to make decisions.
- We extracted ACT-R model parameters from the survey data and verified by simulation that they statistically reproduce the observed vaccination decision trajectories.
- These have helped inform the simulation Behavioral Model.

Next Steps

- We have received NIH funding to continue our Flu work and extend it to COVID-19.
- Starting this Fall, we will be fielding eight more Surveys over the next 4 years.
- We will have 1600 FluPaths respondents + 400 new respondents.
- We will have data for 4 years pre- and 4 years post-pandemic.
- Data will continue to have Egocentric network data and have State and time stamp data information.

Flu+ COVID Paths Study

We will share our survey data with the MIDAS community network and aim for our surveys to be informative our new ABMs on influenza and COVID-19 (not just ours).

Example COVID Paths Questions

- Our First Survey is being coded.
- We plan to field between Thanksgiving and the New Year's Eve.
- Please reach out to suggest new questions for future surveys.

Flu+ COVID Paths Study

Question	Description: COVID and COVID vaccine experiences
Vaccinated COVID	Did they vaccinate for COVID-19
Had COVID	Did they think they caught COVID-19 – was it confirmed.
Policies	Which Vaccination, Mask wearing, Social Distancing local polices affect them.
Never Sometimes Always	Never Sometimes Always in Mask Wearing and avoiding Social Indoor gatherings

Question	Description: Risk perceptions and expectations
Vaccination Expectation	Chances of getting the COVID-19 vaccine by April 2022
Never Sometimes Always	View themselves as never sometimes always for influenza vaccination.
COVID Expectations	Risk perceptions of catching the COVID-19 with and without vaccination by April 2022
COVID Hospitalization	Risk perceptions of hospitalization if infected and with and without vaccination.
COVID Death	Risk perceptions of death if hospitalized given current treatments.

Question	Description: Norms and Prevalence
Vaccination Norm	Estimate the percentage of adults in their state that received at least one dose.
COVID Norm	Out of 10^5 adults in their state estimate how many caught COVID in the last month

Question	Description: Other Constructs
Child Vaccinate	If a Parent of a 5–11-year-old, do they plan to vaccinate their child by February 2022.
Child Mask	How often do they make their child wear a mask outside the house or around people.
Child Mixing	How often do they limit their child from interacting in-doors at venues with other people.
Household Mixing	Do they live in a intergenerational household with children, elderly

Contacts & Acknowledgements

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