NSF Meeting and Recommendations for Research on Enhancing Socially and Behaviorally Modulated Mathematical Models for Human Epidemiology

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Conference Report

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Over the last two centuries, mathematical models have developed as tools in the description, forecasting, and analysis of the spread of infectious diseases. Beginning with the work of William Farr on smallpox (1840), public health researchers have used numbers and modeling to explain and predict the courses of epidemics. An important insight of early epidemiology was that mathematical theory helped scientists understand how the course of infection within a person and transmission to others can explain national and global epidemics. From Farr's auto-regression models and Florence Nightingale's statistical analyses, to Ross-McKendrick compartmental models, to modern agent-based network models, a rich ecosystem of epidemic models can now inform statistical inferences, public policy design, and scientific research.

Because infectious disease epidemics are social processes, all epidemiological models contain behavioral assumptions. However, these assumptions are often implicit, and their relation to the knowledge accumulated in basic behavioral research is not always clear. The current paper summarizes a workshop designed to improve the conceptualization of impact of human behavior in epidemiological models.

The workshop started with seven pre-recorded plenary review presentations (see videos). Each presentation was followed by a plenary panel discussion (see notes attached), and three parallel open discussions in breakout rooms. Five of the seven plenary talks clarified how human behavior is incorporated into extant epidemiological models. The other two talks reviewed recent behavioral research with clear implications to epidemiological models. The meeting agenda and the list of attendees appear in the Appendix. The conference website is here.

Conceptualization of Human Behavior in the Leading Epidemiological Models

The five plenary talks, summarizing extant epidemiological modeling, highlighted five main approaches to the conceptualization of human behavior: (a) classical models, (b) contact structure models, (c) rational choice models, (d) inductive game models, and (e) network and agent-based models.

Classical epidemiological models build on explicit assumptions concerning the spread of an infection and tend to lack explicit assumptions concerning human behavior relevant to transmission. Yet, the leading models include implicit behavioral assumptions. Specifically, they assume that individuals move through different health states. For example, in the basic "Susceptible, Infected, or Recovered" (SIR) model, the states are Susceptible, Infected, or Recovered with immunity (or removed), and the transition between these three states is captured parametrically. The parameters in classic SIR models are transmission and recovery rates. *When these parameters are neither time nor state varying, the resulting models impose strong implicit behavioral assumptions - namely that behavior is invariant to persons, situations, or times.*

Contact structure models extend compartmental models by parametrically capturing mixing rates among exogenous defined types. These models tend to capture non-time varying average behaviors differentiated by predetermined groups such as different ages, genders, or residence locations. *Implicit in this approach is the assumption that people might select their type (e.g., people who use drugs) before the estimation of the groups' parameters but do not change their type after the estimation.*

Rational choice models replace the static behavioral assumptions described above with the rationality assumption. This assumption implies *a decomposition of the underlying behavioral model into three factors: (1) the set of strategies that everyone can use; (2) the information the decision maker perceived and the subjective value (utility) of the feasible outcomes; and (3) the way individuals choose among their strategies.*

Inductive game models generalize rational models by adding specific biases and abstraction of learning. *For example, these models have been used to capture factors like anchoring and groupthink.*

Networks and agent-based models extend the models presented above by incorporating the environment, pre-existing contact patterns, incentives, and strategy of each individual. *Under one cognitive interpretation of this assumption, each agent observes the behavior of its neighbors (and maybe also more removed others) and tends to select the modal choice.*

Examples of Behavioral Models and Questions that Can be Used to Improve Epidemiological Models and Disease Prevention

The two behavioral plenary talks summarized two lines of behavioral research with clear implications to epidemiological models. The first line (Pronsky's talk) focused on basic decision processes. This research suggests that people tend to rely on small samples of past experiences. This tendency implies bimodal reaction to rare risks. Where most people underweight rare risks (like the risk of infection), significant minorities tend to overweight certain rare risks (as in the risk of vaccination side effects).

The second behavioral plenary talk (Albarracin's talk) addressed the impact of communications and behavioral interventions, centered first around the paradox that even though nobody doubts the impact of information on behavior and health behavior specifically, the actual impact of an informational message is close to 0. Therefore, we need to understand the conditions under which information has an influence, the temporal lag of this influence, and interactions with human behavior over time. In addition, we need to explicate and understand the impact of other interventions, including those that have the potential to impact behavior directly. This understanding must also be contextualized within the historic course of an epidemic and how to best match interventions to the stage of an epidemic.

Open Questions, and Suggested Directions for Future Research

The panels and breakout rooms discussions highlight four main obstacles to effective accumulation of knowledge between epidemiological modelers and behavioral scientists. First, the large volume of the behavioral literature, and the situation-specific nature of many of the hypotheses, imply that it is difficult for epidemiological modelers to identify the behavioral research that can help them improve their assumptions. Second, the technical nature of the leading epidemiological models, and the implicit nature of the behavioral assumptions, imply that it is difficult for behavioral scientists to propose refinements of the leading models. Third, the absence of a general model of behavioral prediction and change limits progress by a multiplication of studies of the same constructs with different names and frequent reinvention of the wheel due to disciplinary silos. Fourth, although the epidemiological data for some epidemics are available in real-time, large-scale efforts to collect behavioral data longitudinally are nonexistent.

We believe that NSF can help address this obstacle by encouraging the submission of proposals that explicitly present and compare alternative refinements of the leading epidemiological models and advance behavioral, social, and economic research that can contribute to those refinements. This report summarizes research ideas that emerge from the discussion in the breakout rooms. Those relevant to the Division of Mathematical Sciences appear below. Other ideas potentially relevant to other divisions (e.g., SBE) appear in the Appendix.

I. **Problem of epidemiological-modeling language.** An obstacle that the conference identified concerns the language of epidemiological models. Thus, one recommendation is to fund projects that translate epidemiological models into a language that social, behavioral, and economic scientists can understand and help refine. Projects that, for example, create new nomenclature that exists in the social, behavioral, and economic scientists will help to then refine the incorporation of behavior into the models. Another example involves the addition of "behavioral sensitivity analysis" to epidemiological analyses. Although we see the value of starting with the simplest model that captures the results (even if its behavioral assumptions are inconsistent with basic behavioral research), it is important to know if the predictions are sensitive to the replacement of the simplified assumptions with the assumptions suggested by the relevant behavioral literature.

II. **Problem of limiting, unrealistic assumptions within epidemiological modeling.** Another problem is that the assumptions of epidemiological models lack realism and precision. For example, SRI models often treat behavior as classes of individuals, such as people who use drugs, without more explicit recognition that people vary in the extent to which they perform a behavior as a function of contextual variables such as space, time, and interpersonal contexts. Therefore, future multi-disciplinary projects could review model assumptions more explicitly and investigate how to make improvements in these assumptions to make them consistent with reality. For example, research could tackle a particular limitation, seek a relevant theory, and test model improvements to offset the problem. Projects that uncover limitations and rigidity in modeling assumptions would also be worthwhile. For example, researchers could systematically evaluate whether models closely reflect reality through a combination of inductive and deductive methods, systematic review, and/or analyses of how models perform with data from different diseases, periods, or populations. This problem is complex and includes the different facets described below.

a) **Absence of a comprehensive, agreed-upon formulation of human behavior to incorporate into epidemiological modeling**. A problem that plagues the behavioral, economic, and social sciences is the lack of a comprehensive formulation of behavior that is shared across scientists and disciplines. Therefore, it seems desirable to encourage multi-disciplinary projects that select or build a broad, bold approach to explain behavior and health outcomes during a pandemic.
b) **Insufficient attention to basic behavioral, social, and economic research to build epidemiological models**. Another limitation is that there is no clear pipeline to ensure rapid, mutual influences between basic research in behavioral, social, and economic sciences, and epidemiological modeling. Studies testing specific basic processes to develop novel questions for epidemiological modeling seem worthwhile.
c) **Insufficient incorporation of model of policy decisions**. Although epidemiological models often present the outcome of different policy scenarios, how decisions are made is rarely modeled even though this aspect is key from an explanatory and intervention perspective. Thus, it would be useful to promote research on the factors that influence decisions and information use by policymakers and integration of these factors into epidemiological models.
d) **Inadequate incorporation of complex interactions between individual and cultural differences**. Another limitation is that individual behavior varies as a function of attitudes, norms, risk perceptions, and other motivational and cognitive factors that can interact with group differences, including culture. Thus, projects that model how the salience of cultural aspects (e.g., from race-targeted PSAs or neighborhoods with different demographic compositions) changes people use of internal representations (e.g., norms versus perceptions of risk) should be investigated. Research that compares performance of alternative

epidemiological methods to model these questions should be particularly encouraged.

e) **Lack of nuance and absence of recognition that the outcome of a behavior can affect performance of that behavior in the future**. Traditional epidemiological models fail to provide nuanced depictions of behavior, especially when behaviors are correlated with outcomes. Therefore, it would be beneficial for researchers to work on projects that rely on social, behavioral, or economic theory to model recursive relations by which behavior affects outcomes but outcomes also affect behavior, sometimes in combination with policy interventions.

III. **Lack of theory for population level phenomena.** Human behavior models are quite sophisticated in individual behavior but naive in many other ways, including the population level kind of predictions. This problem may be ameliorated with research on the processes leading to different outcomes at the aggregate versus the individual levels and determining the effect of those processes on epidemiological models.

IV. **Absence of systematic methods to define epidemiological models**. Another area for improvement identified during the conference concerns the lack of systematic, agreed-upon methods to define epidemiological models. For example, a project may tackle parameter selection and establish possible ways of balancing data-driven and theory-based approaches. Whereas data-driven approaches have limitations such as data completeness, bias, and sensitivity, adding complexity to the model increases computational burden. Tests of systematic methods to select parameters for epidemiological prediction are therefore desirable.

APPENDIX

Other Research Ideas about SBE Research Relevant to Epidemics

1. Studies that clarify the co-existence of insufficient sensitivity to the risk of pandemics, and oversensitivity to the risk of vaccination. These studies should examine the relationship of this pattern to basic research in decisions from experience.
2. Studies that use machine learning to predict vaccination rates.
3. Research on the failure to understand expert evaluation and its relation to the tendency to trust fake news.
4. Studies that integrate basic decision-making research that focuses on deviations from rational choice into epidemiological modeling.
5. Studies of the effect of experience on the way people treat objective data and expert's evaluation of data.
6. Studies of the best enforcement policies for different regulations and clarification of the feasibility of enforcing different regulations.
7. Studies of the impact of enforcement and incentives on vaccination.
8. Studies of the way people learn from the experience of others in the context of pandemics.
9. Exploration of the conditions under which beliefs persist and the role of social pressure.
10. Studies that clarify the difference between predictions of short term and long-term epidemiological outcomes.
11. Implementation science projects in which a research group teams up with a government jurisdiction (e.g., a state or county) to design a policy test and then implement and study the policy.
12. Projects that study vaccination by integrating economic factors such as good distribution and incentivization and psychological variables that constitute immediate determinants of behavior.
13. Projects that integrate insights from behavioral prediction models into social network theory and research.
14. Research that collects longitudinal data to compare the impact of various behavioral, social, and economic variables at different points of a pandemic or at different phases of a given policy implementation (e.g., vaccination).
15. Research that combines longitudinal and experimental methods to develop a necessary and sufficient account for the role of behavior in epidemics, comparing different infections of varying characteristics (e.g., airborne versus sexual transmission).
16. Research using meta-analysis including individual-level synthesis to understand the impact of different interventions to control epidemics, particularly projects that compare cultures, nations, or demographic groups and seek to understand mechanisms of change.
17. Research on business and government processes related to privacy and information sharing to determine what improves data access and how actors make decisions about data sharing.
18. Projects that seek to understand variability in the social and/or economic impact of different diseases, particularly in combination with social health disparities.

19. Projects that study media impact on policy and citizens' reactions, including research on social media, during an epidemic.
20. Research on the reasons for population noncompliance during an epidemic.
21. Research that separates different reasons for vaccination hesitancy and investigates ways of addressing it using a combination of experimental and modeling methods.
22. Projects designed to estimate and understand the impact of communication, both positive messages as well as misinformation/disinformation, on health behavior during a pandemic.
23. Research that uses computer science advances to better create or disseminate messages during a pandemic.
24. Projects that test different methods of tailoring information to individuals, including projects that use computational methods.
25. Research that uses experimental methods to identify the best interventions to increase vaccination.
26. Research that studies fatigue and passive responses in the population and how these vary with the stage of a pandemic.
27. Research on fear appeals and reactions to fear during a pandemic.
28. Studies of trust in information and how the public health system makes communication decisions, particularly in interaction with government factors and ideas about the democratic process.
29. Research on how changes in scientific information are communicated and the best methods of revising beliefs in response to such changes.
30. Research that tests theories of how different messages mix within a network or over time to produce positive or negative attitudes during a pandemic.
31. Studying how different government agencies interact to make decisions and the impact of those interactions and processes on the pandemic.
32. Research that innovatively integrates multiple data sources (e.g., social media, geolocation, survey) to test theories about interaction in networks.
33. Research that investigates the role of opposing forces in the decision to vaccinate (free ride vs. network peer effects) and integrates these forces into epidemiological models.
34. Research projects that use natural experiments and propose methods to address limitations such as the lack of a valid control group (i.e., everyone is being treated in natural experiments during epidemic/pandemic).
35. Research projects that investigate how to overcome data limitation. In particular, research that addresses lack of micro level data about behavior is necessary. A lot of modeling groups use publicly available data which is aggregated. But if behavior changes in an epidemic, this changes the dynamics even if the mean is constant.
36. Multi-disciplinary projects that investigate inconsistencies across disciplines in the definitions such as "rationality".
37. Research projects that investigate how to deal with intertemporal forecasting in models with a rational decision maker and the model endogenously changes throughout time.
38. Research projects that investigate what should be included in utility function when the objective is maximizing utility. For example, should we have altruism in the case of COVID, when people are voluntarily social distancing?
39. Research projects that study the rules or aggregation for different psychological and behavioral variables. If you're deciding individually or as a family or a group, they're probably clear on differences between emotion and how that will transfer to the group.

And something like deciding on a math problem, which is self-evidence. So, with one individual proposing that, that becomes the solution for the group.

40. Research projects that investigate how to use current agent-based models to add cognitive models that have value in them.

SUPPLEMENT

Agenda Summary

Thursday, May 6

EDT	**CDT**	**Event**
11:00 AM	10:00 AM	Introduction (*Moderator*: Albarracin)
11:20 AM	10:20 AM	Epidemic modeling and behavior (*Plenary*: Eubanks; *Panelists*: Auld, Dangerfield, Sheeran; *Moderator*: Reluga)
12:56 PM	11:56 AM	Behavioral phenomena and their connection to epidemics (*Plenary*: Plonsky; *Panelists*: D'Onofrio, Finnoff, Gonzalez-Vallejo; *Moderator*: Erev)
2:32 PM	1:32 PM	Measuring response to policy changes and pathogen risks (*Plenary*: Murray; *Panelists*: Anderson, Bayham, Holtgrave; *Moderator*: Fenichel)
4:08 PM	3:08 PM	Network structure in epidemic models with behavior (*Plenary*: Fefferman; *Panelists*: Miller, Ognyanova; Vullikanti; *Moderator*: Reluga)

Friday, May 7

EDT	**CDT**	**Event**
11:00 AM	10:00 AM	Introduction
11:08 AM	10:08 AM	Rational epidemic theory and game theoretic models (*Plenary*: Toxvaerd; *Panelists*: Gonzalez. Reluga, Werning; *Moderator*: Fenichel)
12:44 PM	11:44 AM	Connecting epidemic modelling to society (*Plenary*: Fenichel; Panelists: Sattenspiel, Tan, Tertilt; *Moderator*: Erev)
2:20 PM	1:20 PM	How communication and information lead to learning and behavior (*Plenary*: Albarracin; Panelists: Bauch; Palacios; Peters; *Moderator*: Erev)
3:46 PM	2:46 PM	Mini-Pitch Session

EDT = Eastern Daylight Time; CDT = Central Daylight Time

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