**RAISE: IHBEM. Integrating psychological and social dynamics into infectious disease models to anticipate socio-behavioral changes during an evolving pandemic**

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# OVERVIEW

Previous COVID-19 work typically focused on dual relationships among the dynamic interplay between policies, emotions, behaviors, the environment, and transmission. For example, some scholars have investigated how behaviors impact pandemic trends [1,2](https://paperpile.com/c/N5JckZ/xIqeu+4Vned) (infectious disease epidemiology); some scholars have investigated how policies impact behaviors [3,4](https://paperpile.com/c/N5JckZ/uZhTF+mhU4) (behavioral science); some scholars have investigated how pandemic trends impact community psychological states [5](https://paperpile.com/c/N5JckZ/L9bX) (sociology psychology); and others have investigated how pandemic trends impact policies [6–8](https://paperpile.com/c/N5JckZ/1pvVq+sbwAL+3KiEa) (political science). To date, there has not been an attempt to develop a holistic understanding of the complex interrelated feedback loops that give rise to pandemic dynamics. Such understanding would be critical for better anticipating behavioral dynamics and pandemic trends in response to public health policies and interventions. In the present proposal, we aim to move beyond the conventional dual relationships and to model multiple components as one complex system using the extended data generated during the COVID-19 pandemic.

**INTELLECTUAL MERITS**

We propose a series of modeling approaches where infectious disease modelers and social and behavioral scientists collaborate to lay the intellectual groundwork for tackling several fundamental questions. Our proposed work will create a research paradigm grounded in complex systems modeling and integrate perspectives and methods across diverse disciplines: social psychology, social media research, social network analysis, evolutionary biology, mathematical biology, and infectious disease epidemiology.

**BROADER IMPACTS**

The PIs will perform the following activities: (1) encourage post-docs, graduate and undergraduate students to participate in our research; (2) organize workshops and press conferences to disseminate our research results; and (3) freely distribute the software and tools developed from this research. The active commitment of the UT Austin COVID Modeling Consortium as well as the active participation of researchers from multiple institutions (UCLA, UT Austin, The London School of Hygiene & Tropical Medicine (LSHTM), and Nagasaki University) will maximize the impact of the proposed project in both local and global contexts.

**KEYWORDS**

Infectious disease modeling, Social psychology, Health policy, Social mixing survey, and Complex systems.

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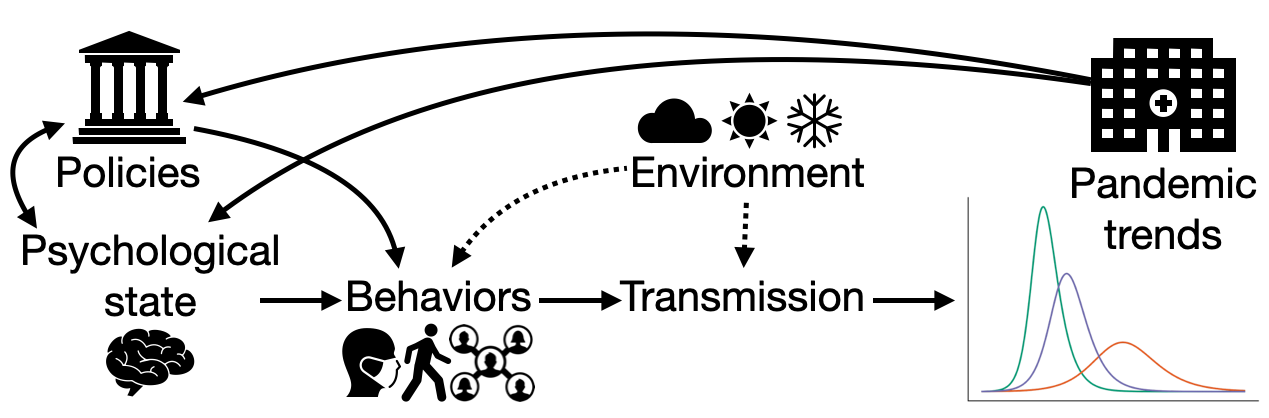
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# 1. INTRODUCTION

From the way people work to the way they socialize, the COVID-19 pandemic has catastrophically altered daily life around the world. Early infectious disease modeling work correctly flagged the risks of the impending pandemic and contributed toward decisions to enact initial lockdowns [9,10](https://paperpile.com/c/N5JckZ/0Htw+X9ga), which likely saved millions [11](https://paperpile.com/c/N5JckZ/hjxW). However, since those initial stay-at-home orders in the United States, fragmented and contradictory responses from elected leaders and public health officials across cities, states, and the country have created confusion about where people should get information and how communities should best respond to the unprecedented disaster. The result of this unclear messaging has been repeated with multiple COVID-19 surges across the country, while a comprehensive explanation for the wave patterns still eludes us.

It is known that historic pandemic waves were influenced by a combination of environmental, behavioral, and political factors [12](https://paperpile.com/c/N5JckZ/S5oC). Therefore, we can assume that similar complex dynamics are currently at play for COVID-19 waves. Community contact rates interacting with environmental factors determine the level of transmission during a pandemic; in addition, public health policies and individual psychological states impact behavioral choices **(Figure 1)**.



**Figure 1. Interrelated dynamic relationships determining the direction of the pandemic.** Arrows indicate the ability of one factor to impact one of the other components. Each of these arrows has been analyzed under the name of different study fields. When the outcome variable (the one getting an arrowhead) is the transmission and pandemic trends such as healthcare capacity, we have called the analysis infectious disease modeling. On the other hand, when the outcome is people’s behavior, we call it behavioral science; when it is emotions, we call it psychology; and when we evaluate policy decision-making, we call it political science. We propose a multifaceted system in which we simultaneously model at least two (and ultimately all) of these components using the wide breadth of data available to us stemming from the COVID-19 pandemic. Dotted arrows indicate relationships not proposed for study as part of this proposal.

Feedback loops between pandemic trends, psychological states, and public health policies add further complexity to anticipating the system. Previous COVID-19 work focused on dual relationships from this diagram, such as the way policies impact behaviors [3,4](https://paperpile.com/c/N5JckZ/uZhTF+mhU4), how behaviors impact pandemic trends [1,2](https://paperpile.com/c/N5JckZ/xIqeu+4Vned), how pandemic trends impact community psychological states [5](https://paperpile.com/c/N5JckZ/L9bX), and how pandemic trends impact policies [6–8](https://paperpile.com/c/N5JckZ/1pvVq+sbwAL+3KiEa). To date, attempts to develop a holistic understanding of the complex interrelated feedback loops that give rise to pandemic dynamics have been limited, which are critical for better anticipating behavioral dynamics and pandemic trends in response to public health policies and interventions. To do so, we will take a step-by-step approach and focus on integrating two understudied socio-behavioral components of the transmission loop into COVID-19 infectious disease models: psychological processing and decision-making **(Thrust 1)** and dynamic and heterogeneous social contact patterns reflecting socio-behavioral factors **(Thrust 2)**.

***Thrust 1.*** Psychological processing and decision-making can dramatically alter the shape of epidemic waves, the impact of interventions and responses to public health policies [13–15](https://paperpile.com/c/N5JckZ/G9ar+Hj19+u1fg), and evidence suggests that COVID-19 pandemic trends are dramatically impacting psychological processing [5](https://paperpile.com/c/N5JckZ/L9bX), but few attempts have been made to integrate psychological processes into COVID-19 infectious disease models [16,17](https://paperpile.com/c/N5JckZ/Yzjp4+ozBV).

***Thrust 2.*** Contact patterns are also important for understanding infectious disease dynamics, as they determine the shape of an epidemic, the overall extent of the epidemic, and the effectiveness of interventions [18–21](https://paperpile.com/c/N5JckZ/mXxk+SbnJ+I2gy+lisO). Superspreading events are a well-known phenomenon for COVID-19 [22](https://paperpile.com/c/N5JckZ/7sCc) and such heterogeneous contact patterns led some to believe that the pandemic would be short-lived [23,24](https://paperpile.com/c/N5JckZ/yCwS+fZY5). Surveys to track people’s contact patterns have improved infectious disease model accuracy [25,26](https://paperpile.com/c/N5JckZ/lOxl+48O4), but data from these surveys have not been integrated while accounting for social, economic, psychological, and behavioral factors.

In sum, we propose to continue our COVID-19 research to expand socio-behavioral modeling capabilities for incorporating psychological decision-making processes and dynamic and realistic social contact networks. For both thrusts, we plan to elucidate the role of temporal dynamics over the course of the pandemic, develop novel infectious disease models that more accurately capture the identified trends, apply our models to US contexts, and disseminate our results to social and behavioral scientists to improve pandemic preparedness.

**2. INTELLECTUAL MERITS**

We propose a series of modeling approaches in which infectious disease modelers and social and behavioral scientists can collaborate on three fundamental questions - *How can we use socio-behavioral data, most of which have not yet been used for improving infectious disease modeling in the COVID-19 setting? What kinds of socio-behavioral data directly impact pandemic policies? How can we direct and suggest social and behavioral scientists as well as industry counterparts to collect appropriate social-behavioral data from the infectious disease modeling perspective?* Our proposed work will begin to create a research paradigm grounded in complex systems modeling and integrate perspectives and methods across diverse disciplines: social psychology, social media research, network science, evolutionary biology, mathematical biology, and epidemiology.

**3. BROADER IMPACTS**

Human behaviors and emotions are important to explain the dynamics of infectious diseases, especially directly transmitted ones like COVID-19. The PIs will perform the following activities: encourage post-docs, graduate and undergraduate students to participate in our research; organize workshops and press conferences to disseminate our research results; and freely distribute the software and tools developed from this research. The active commitment of the UT Austin COVID Modeling Consortium as well as the active participation of researchers from multiple institutions (UCLA, UT Austin, The London School of Hygiene & Tropical Medicine (LSHTM), and Nagasaki University) will maximize the impact of the proposed project in both local and global contexts.

# 4. TEAM

**Akihiro Nishi (PI)** is an Assistant Professor of Epidemiology at UCLA. He is a physician-scientist and medical sociologist by training. He has expertise in the evolution of social behavior (e.g. cooperation and inequality aversion) [27,28](https://paperpile.com/c/N5JckZ/j6AM+8lIg), network intervention planning in the COVID-19 context [29,30](https://paperpile.com/c/N5JckZ/XuX4+QbGg), and health policy evaluation [31,32](https://paperpile.com/c/N5JckZ/CYjf+goQj). He is an awardee of a NIH/NIAID K01 award (“Network intervention planning without actual network data using for infectious disease control”) and a Japan Science and Technology Agency PRESTO award (“The evolution of overconfidence and the role of early-warning signals amid pandemics”). He is an external faculty collaborator of the UT COVID-19 Modeling Consortium (UT-CMC).

**Lauren Ancel Meyers (co-PI)** is a Professor of Integrative Biology and Statistics & Data Sciences at UT Austin. She is an expert in network epidemiology and outbreak science [19,33–35](https://paperpile.com/c/N5JckZ/SbnJ+Yoj3+bXa2+DeVo), and is the Executive Director of UT-CMC. She is a mentor for PI Nishi’s NIH career award and is an awardee of an NIH/NIAID R01 award (“Accelerating viral outbreak detection in US cities using mechanistic models, machine learning and diverse geospatial data”) and a CDC/NCIRD U01 award (“Modeling toolkit to evaluate multifaceted control strategies for seasonal and pandemic influenza”). She is also a member of the Santa Fe Institute External Faculty.

**Spencer J. Fox (co-PI)** is a Research Associate at UT Austin (eligible to serve as a co-PI). He is an epidemiologist and data scientist with expertise in infectious disease modeling, forecasting, and digital information transmission [7,36–38](https://paperpile.com/c/N5JckZ/sbwAL+gadW+jugs+8OUH) and is currently Associate Director of UT-CMC. He is an awardee of a CSTE/CDC influenza forecasting contract (“Forecasting influenza hospitalizations with multi-scale curve fitting – a flexible framework integrating healthcare capacity and behavioral change”) and a CSTE/CDC COVID-19 modeling and forecasting contract (“A multi-scale, mechanistic model of COVID-19 healthcare usage in the US for behavior-driven forecasting and the evaluation of layered intervention strategies”).

**James W. Pennebaker (co-PI)** is the Regents Centennial Professor of Liberal Arts and Professor of Psychology at UT Austin. Trained as a social psychologist, his cross-disciplinary research draws on linguistics, cognitive psychology, communications, medicine, and computer science [39–42](https://paperpile.com/c/N5JckZ/v2So+rxxB+qKbY+f8YG). He is an awardee of an NSF/IIS award (“Fine-grained emotion analysis in crises”).

**Akira Endo (collaborator)** is an Assistant Professor at Nagasaki University (Japan) and a Japan Society for the Promotion of Science (JSPS) fellow at the London School of Hygiene & Tropical Medicine (LSHTM). He is a physician-scientist with a research focus on social structure transmission models [43,44](https://paperpile.com/c/N5JckZ/uWOy+0tbS) and public health policy simulation [45,46](https://paperpile.com/c/N5JckZ/sHY9+JeYf). With the current proposal, he may obtain a joint appointment at UCLA and Nagasaki University.

**Kaiming Bi (collaborator, unpaid)** is a fully-funded Postdoctoral Fellow at UT Austin. He is an epidemiological modeler with expertise in infectious disease modeling [47](https://paperpile.com/c/N5JckZ/Lvf1), numerical simulation [48](https://paperpile.com/c/N5JckZ/foN2), and optimal control theory [49,50](https://paperpile.com/c/N5JckZ/Cf1p+n0i8). He is an active member of UT-CMC.

**Core Ph.D. students who will be trained under the proposed grant**

**Tomoka Nakamura (collaborator, unpaid)** is a fully-funded student in the joint LSHTM-Nagasaki University Ph.D. program, who specializes in mathematical modeling and infectious disease epidemiology [51](https://paperpile.com/c/N5JckZ/gRo7). She has been in charge ofthe Japan contact survey data (see section 7.2c) and will help our team analyze available data, while being trained by PI Nishi and collaborator Endo.

**George Dewey (collaborator)** is a third-year Ph.D. student in the UCLA Department of Epidemiology who is supervised by PI Nishi. George was the senior programmer for Nishi et al, 2020, *PNAS* (second author) [29](https://paperpile.com/c/N5JckZ/XuX4) and will be assisting with writing R and Python codes for the data analysis and simulations.

**TBD Ph.D. student at UT Austin (collaborator)** will be one of the first-year doctoral students entering co-PI Meyers’ lab in Fall 2022.

# 5. RESULTS FROM PRIOR NSF SUPPORT

There is no overlap between the present projects proposed here and the past or ongoing research programs funded by NSF and others stated below. **PI Nishi** obtained a grant titled “AI-DCL: Governing bias in AI system with humans in the decision loop” (NSF/EAGER 1927554) as a co-PI with Dr. Kai-Wei Chang (UCLA Computer Science) in 2019. PI Nishi’s Ph.D. student, George Dewey is co-advised by Dr. Chang. The team executing this grant applies natural language processing (NLP) methods and has published several papers exploring socially aware bias measurements (e.g. [52](https://paperpile.com/c/N5JckZ/nuFv) [which is accepted and will be presented at the NAACL 2022 main conference,]). **Co-PI Meyers** has obtained no current NSF support as a PI or co-PI. As a part of her collaborative work under the NSF Beacon Study of Evolution in Action (DBI-0939454), she combined field and model-based epidemiology to investigate how the social networks of non-human primates drive the transmission and evolution of gut bacteria [53–55](https://paperpile.com/c/N5JckZ/I3EIQ+gioll+mVx7R). **Co-PI Fox** has no prior direct NSF support. **Co-PI Pennebaker** has recently been an active Co-PI on one prior NSF project (1344257) and is Co-PI on one ongoing project (2107524). Both projects rely on big data associated with social media. The previously-funded NSF project explored how upheavals affected people’s natural language use over time. For example, in the year surrounding relationship breakup, language use on Reddit showed drops in analytic thinking starting months before the breakup and lasting six months afterwards[56](https://paperpile.com/c/N5JckZ/rFtAa). The methods developed during this project contributed to a COVID-19 study that tracked the social, emotional, and cognitive changes of people in the months before and after the onset of the pandemic. The ongoing emotion grant focuses on ways to detect emotion through similar large language sets. Although the methods developed in these grants will contribute to the current project, the content is independent.

# 6. SCHEDULE AND PLAN

The proposed grant period is 1/1/2023 - 12/31/2026 (three years). co-PIs Fox and Pennebaker as well as collaborator Bi will analyze the data for Thrust 1. Collaborators Endo, Nakamura, Dewey, and PI Nishi will analyze the data and implement the contact survey for Thrust 2. Co-PI Meyers and PI Nishi will jointly supervise the projects undertaken in Thrusts 1 and 2.

For both thrusts, we aim to plan data acquisition and cleaning in Year 1, to develop and iterate on models in Years 1-2, and to write papers and engage in outreach activities in Years 2-3. The contact survey in Thrust 2 is planned to be released in Year 3.

***Outreach activities.*** We plan to reach out to relevant media groups to disseminate our results when we publish papers. We also plan to organize multiple workshops in which the participants (e.g. policy makers, media, and students at UCLA and UT Austin) can experience the models that we will develop interactively (e.g. using R Shiny). Finally, we plan to freely distribute our software and tools developed from this research.

# 7. THRUSTS

## Thrust 1: Explore epidemiological, psychological, and behavioral feedback in the midst of a pandemic to integrate socio-behavioral processes into infectious disease models

### 7.1a. Background and aims. The ongoing COVID-19 pandemic has catastrophically altered daily life around the world. From the beginning of the pandemic, it was clear that there would be unprecedented impacts on community psychological well-being and early warnings and calls to action anticipated an impending mental health crisis following stay-at-home orders [57](https://paperpile.com/c/N5JckZ/JtDX). However, psychological predictions were limited by the unique characteristics of the pandemic. Temporal models for community recovery have focused on short-term traumatic upheavals such as hurricanes, earthquakes, and terrorist attacks [58,59](https://paperpile.com/c/N5JckZ/7UyF+gyFf), but pandemics are disasters that can last months to years with significant uncertainty and continually changing conditions. While wars and political uprisings also can last for extended periods of time, few studies have quantified the prolonged community psychology over that time period. Furthermore, social sharing and communication following a disaster is known to be psychologically beneficial [60,61](https://paperpile.com/c/N5JckZ/zS3G+lwK0), but NPIs (nonpharmaceutical interventions) enacted to mitigate pandemic transmission cause social isolation and prevent communities from coming together for prolonged time periods.

Overall, survey data suggest that communities experienced higher levels of depression and anxiety during the initial phases of the pandemic with higher psychological distress associated with regions closer to pandemic hot spots [62,63](https://paperpile.com/c/N5JckZ/Vy0Z+lYC5). Interestingly, evidence suggests psychological resilience, as reported loneliness is similar to pre-pandemic time estimates [64](https://paperpile.com/c/N5JckZ/YWrB) and psychological impacts declined rapidly following the initial surge [65–67](https://paperpile.com/c/N5JckZ/04qb+KVpW+5KnA) . However, few studies have examined large-scale psychological trends over the entire course of the pandemic through multiple waves. As the pandemic wore on, public health officials discussed pandemic fatigue and the impacts it may have on reducing the effectiveness of mitigative measures [68](https://paperpile.com/c/N5JckZ/sVuS), but evidence of an impact is limited [69,70](https://paperpile.com/c/N5JckZ/DsWG+LeU3).

Improving our understanding of community psychological responses in the midst of a pandemic will help us better anticipate community behavioral responses. Prolonged stress as people navigate uncertainty during the pandemic reduces analytic thinking and may hurt individual decision-making as their thinking switches from logic to relying on cognitive shortcuts [56,71](https://paperpile.com/c/N5JckZ/Q9lwQ+rFtAa). Research suggests that psychological states such as anxiety, fear, and trust are strong predictors of adherence to NPIs and vaccination [72,73](https://paperpile.com/c/N5JckZ/foY3+FNpE) and that increased anxiety in response to COVID-19 trends may slow transmission during a pandemic surge [16](https://paperpile.com/c/N5JckZ/Yzjp4).

Community characteristics such as mobility levels, mask-wearing behavior, and vaccination rates have been implicated in driving pandemic dynamics [1,11,74,75](https://paperpile.com/c/N5JckZ/qYPO+hjxW+xIqeu+eobH). The psychological underpinnings for these behavioral responses are understudied but understanding them will be necessary to improve our ability to anticipate pandemic dynamics in response to interventions and policy changes moving forward. Although incorporating psychological phenomena in epidemic models has been previously attempted in theoretical studies [13,14](https://paperpile.com/c/N5JckZ/Hj19+G9ar), practical applications to outbreaks with explicit links to psychological states have been limited. To fill this void, we aim to: (1) identify key temporal relationships between community psychological states, behaviors, pandemic trends, and public health policies during the COVID-19 pandemic, and (2) develop infectious disease models that accurately incorporate psychological feedback into the transmission process, and (3) fit the proposed models to COVID-19 data from 24 major metropolitan regions across the United States to estimate key parameters governing socio-behavioral responses to pandemics and identify models that best explain the data.

### 7.1b. Preliminary studies.

### Real-time pandemic surveillance using hospital admissions and mobility data (Fox, …, Meyers, 2022, PNAS [7](https://paperpile.com/c/N5JckZ/sbwAL)). Based on COVID-19 hospital admissions and cell phone mobility data, we established a robust model for forecasting COVID-19 transmission and hospitalizations. The model was developed in partnership with elected leaders, healthcare professionals, and scientific researchers and is an expanded stochastic susceptible-exposed-infectious-recovered (SEIR) model with eight (8) disease progression compartments, including symptomatic, pre-symptomatic, asymptomatic patients, and hospitalization. It includes five age groups, different rates of contact within and between age groups, a high-risk category with each age group, and age- and risk-specific rates of hospitalization. The model successfully predicted healthcare needs in Austin, TX alongside unobserved epidemiological quantities such as the local reproduction number, case detection rates, and the infection prevalence. For over two years, the model has been incorporated into a dashboard providing daily healthcare forecasts that have raised public awareness, guided the city’s staged alert system to prevent unmanageable ICU surges, and triggered the launch of an alternative care site to accommodate hospital overflow. However, we identified that the model had the most trouble predicting healthcare needs immediately before the peak of pandemic surges, a critical inflection point that occurs when behavioral changes slow transmission, a complex phenomenon instigated by individual decision-making and psychology.

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# *7.1c. Data.* We will obtain four different types of data (detailed below) from 24 major metropolitan regions in the United States. These data will be used to both expand on and address the limitations of the preliminary studies described previously.

**Infection data:** Reported COVID-19 cases, hospital admissions, and deaths provided by CDC and HHS [76,77](https://paperpile.com/c/N5JckZ/xR7Ym+2AOkC). The HHS dataset provides facility-level data for hospital utilization for COVID-19 that includes age-specific estimates of hospital admissions. For over two years, we have used variants of these data to produce regional and state COVID-19 forecasts for Texas [78](https://paperpile.com/c/N5JckZ/oOJ2) and the United States as part of the FluSight and COVID-19 forecasting hubs [79,80](https://paperpile.com/c/N5JckZ/zaH4+1fiv).

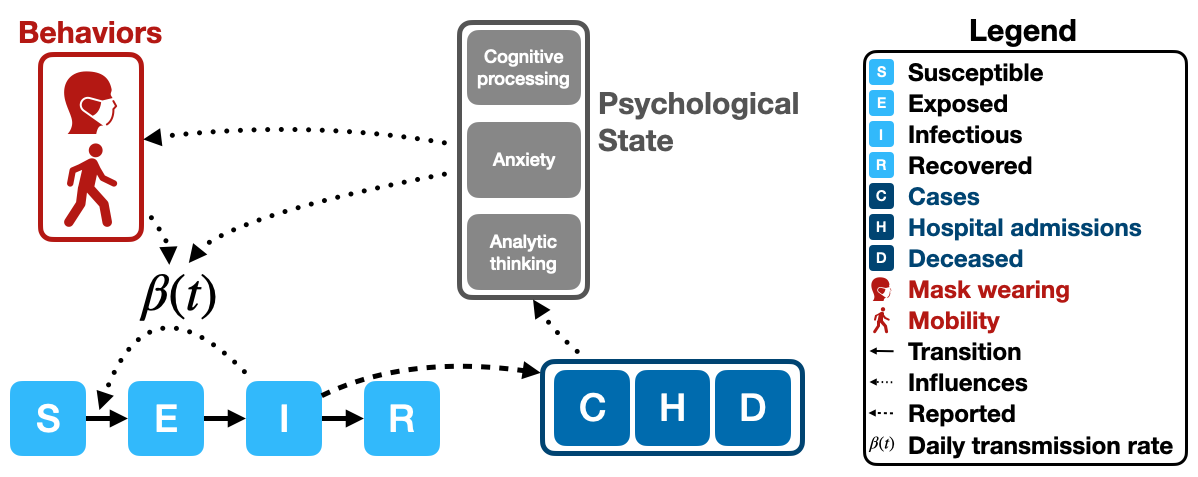
**Policy data**: Implemented public health and governmental policies from the Yale governmental tracker [81](https://paperpile.com/c/N5JckZ/GwQK9). These data quantify the state and county government actions in the U.S. since the spring of 2020 and includes policy restrictions for businesses, elective medical procedures, mass gatherings, employee and resident masking, and nursing home visitors. We have experience working with policy data from our ongoing efforts collecting Texas county-level policy data as part of the Oxford government tracking project [8](https://paperpile.com/c/N5JckZ/3KiEa), and from our work to understand the impact of stay-at-home orders during the first wave of the pandemic [74](https://paperpile.com/c/N5JckZ/qYPO).

**Psychology data:** Community psychological states including emotion, cognition, and social ties obtained through Reddit conversational data and behavioral survey data [5](https://paperpile.com/c/N5JckZ/L9bX). Reddit hosts thousands of active online communities, including city-based communities. Using the Pushshift API, we extracted all comments posted on 18 city-related Reddit communities corresponding to large and representative U.S. cities from January 2018 until May 2020. We now plan to expand the number of cities to 24 and to collect all Reddit data from the city-level participants going back to 2018 and up to the date the grant is funded (if not later). The conversational data have been processed to provide daily estimates for city-level emotional states (anxiety, positivity, sadness, and anger), cognition (analytic thinking and cognitive processing), and social ties (family, friends, and city) using Linguistic Inquiry and Word Count (LIWC) [82](https://paperpile.com/c/N5JckZ/nge0). We rely on a wide array of text analytic methods to identify how people are expressing their internal states (through top-down analyses of function and emotion words) and what the topics they are addressing (through bottom-up topic-modeling methods). A variety of methods are available to compare the unfolding of writing styles and topics across cities and illness surges using BERT, word embeddings, and other methods [83](https://paperpile.com/c/N5JckZ/BOyv). Additionally, we have collected convenience survey samples under the umbrella of the UT Pandemic Project [84](https://paperpile.com/c/N5JckZ/2gSF), where individuals are asked a series of questions about the ways people are thinking and responding to the current coronavirus pandemic. Surveys were collected every two to four weeks from late March 2020 until September 2021. Additional survey collections were made in December 2021, February 2022, and a large (possible) final collection occurred in May 2022.

**Behavior data:** Community behaviors including anonymized cell-phone mobility metrics provided by SafeGraph, self-reported mask-wearing and vaccine acceptance attitudes provided by the Delphi Group, and documented vaccination estimates provided by the CDC [77,85,86](https://paperpile.com/c/N5JckZ/hvlit+2AOkC+04Yc0). The Delphi Group procures unique data streams that reflect COVID activity from a wide variety of sources and extracts COVID-related signals. We have previously integrated such behavioral data streams into mechanistic infectious disease forecast models and infectious disease models for estimating herd immunity thresholds [7,24](https://paperpile.com/c/N5JckZ/fZY5+sbwAL), and are currently using these data for forecasting influenza and COVID-19 dynamics as part of the COVID-19 Forecast Hub and CDC FluSight [79,80](https://paperpile.com/c/N5JckZ/zaH4+1fiv).

***7.1d. Analytic Plan.*** We will begin by extending our previous analysis to understand the relationships between community psychological phenomena, COVID-19 trends, and public health policies across twenty large and representative cities in the United States (Ashokkumar and Pennebaker, 2021, Science Advances [5](https://paperpile.com/c/N5JckZ/L9bX)). First, we will extend our previous analysis to understand how psychological dimensions fluctuated over the first five major surges during the COVID-19 pandemic with a particular focus on how emotions and cognitive processing changed in response to major events (e.g. the announcement of identifying an efficacious vaccine or the emergence of the Omicron variant). The unprecedented size and length of the sample will give us the first comprehensive view of long-term community responses to a prolonged disaster. We will validate psychological trends observed with our Reddit dataset against estimates from our longitudinal surveys over the course of the pandemic. Following that analysis, we will calculate pairwise cross-correlation metrics across the Reddit, infection, mobility, and policy time series to identify important interactions and lags from March 1, 2020, until May 1, 2022, across all cities, a technique we previously used to identify potential predictors for forecasting purposes [7](https://paperpile.com/c/N5JckZ/sbwAL). Focusing on leading predictors for both pandemic growth trends and psychological states, we will compute daily means for the psychological language dimensions across users in each city subreddit and develop a time-varying mixed effect model to predict psychological states from pandemic trends and vice versa with random effect for cities and users. We will use estimates from the five major pandemic waves in the United States to estimate the feedback loops that exist between socio-behavioral dynamics and pandemic trends, and the time-varying relationships as community risks and sentiments changed.

Second, building off the findings from our previous studies, we will build an infectious disease model that captures the highlighted important psychological and behavioral dimensions to better understand socio-behavioral feedback in the midst of novel pandemics. We will expand our previously validated COVID-19 model to incorporate emotion and cognition processes alongside behavioral characteristics such as mobility and mask-wearing **(Figure 2).** We will include emotion and cognition directly into the model as covariates of the daily transmission rate similar to how we incorporated mobility data into our previous models (Fox, …, Meyers, 2022, *PNAS* [7](https://paperpile.com/c/N5JckZ/sbwAL)). Through this model structure, we will estimate the impact of reported cases, hospital admissions, and deaths on community psychological state over time, and estimate the impact of the socio-behavioral factors on transmission. The modular design will allow for psychological feedback in the transmission process. We will refine the psychological state components of the model structure iteratively alongside psychologists and through testing and validating individual components against the data using best guess parameters from the literature.

**Figure 2. Diagram showcasing integration of psychological state into an epidemiological model.** Compartmental diagram shows connections between epidemiological states and transitions (light blue component), reported COVID-19 burden metrics stemming from those states (dark blue component), the way reported metrics impact psychological states (dark gray component), and the impact psychological states have on behaviors (red components). We will also model five age and two risk groups explicitly, but don’t display those components here for simplicity. Our goal will be to estimate the time-varying reporting and influence relationships between all components.

Third, following model development and initial testing, we will calibrate the full socio-behavioral model to the local reported case, hospitalization, and mortality data using iterated filtering as made available through the R POMP package (an analytic platform for nonlinear stochastic dynamical systems) [87](https://paperpile.com/c/N5JckZ/LKAYz). The result of the statistical inference will be posterior densities for parameters governing the impact of cognition, emotion, mobility, and mask-wearing behaviors on transmission and the reporting process of hospitalization data, and we will assess model statistical convergence through diagnostic plots made available in the POMP package. The method is similar to one we have used for the past two years for fitting complex, nonlinear epidemiological models to healthcare data for forecasting purposes [7](https://paperpile.com/c/N5JckZ/sbwAL). We will simultaneously fit the model to data across all 24 cities to increase our power to detect the impact of the emotion and cognition components of the model. Additionally, we will fit reduced versions of the model that lack these components, and compare AICs and out-of-sample forecast accuracy to optimize model complexity.

### 7.1e. Hypotheses. We hypothesize that anxiety will be closely tied to pandemic dynamics and public health policy changes, but that the relationship may degrade over time as populations become numb to COVID-19 dynamics and pandemic fatigue sets in. We also hypothesize that behavioral changes will be most closely tied to community anxiety levels, with protective behaviors such as reducing mobility, wearing face masks, and vaccine acceptance opinions increasing with increasing anxiety. Finally, we expect there to be a tight relationship between analytic thinking and protective behaviors, with higher analytic thinking promoting higher protective behavior levels.

### Our second and third analyses focus on the development and validation of an infectious disease model that incorporates psychological processes into the transmission process, and we believe that the addition of these components will increase the retrospective fit of the model to historic COVID-19 data by roughly 50% compared to simpler models [88](https://paperpile.com/c/N5JckZ/GNjG). Furthermore, inclusion of these components will increase out-of-sample forecasting accuracy, with inclusion specifically providing a means to accurately predict the peak of a pandemic 2-3 weeks in advance given the delays between information digestion, behavioral change, transmission, and reporting. Finally, we anticipate that the model will also identify statistically significant relationships between COVID-19 burden counts and psychological states, and that these relationships will be highly variable through time as transmission risks varied and communities became numb to pandemic trends.

***7.1f. Metrics of success.*** We will evaluate our work as successful if we: (i) identify time-varying relationships between community psychological states, behaviors, pandemic trends, and public health policies, and are able to quantify the optimal lags and effect sizes for their relationships; and (ii) find that incorporating the behavioral impact of emotion and cognition into infectious disease models improves the model fit to COVID-19 burden data across 24 major metropolitan regions in the U.S, and provides accurate forecasts of pandemic peaks.

***7.1g. Limitations and future directions.*** Our proposed work has the following limitations: (i) our estimates for community psychology are derived from publicly available Reddit conversations and convenience-sampled online survey data, which may have biases that make them not representative of the whole population [89](https://paperpile.com/c/N5JckZ/xYPA); and (ii) we exclude the impact of environmental factors on COVID-19 transmission, as previous work suggests that these factors will not be as important during the initial pandemic emergence phase [90](https://paperpile.com/c/N5JckZ/GOvny). Seasonal dynamics have been observed during the COVID-19 pandemic, but may be due to behavioral characteristics rather than environmental ones [91](https://paperpile.com/c/N5JckZ/aGab).

Next steps following successful completion of the proposed project would include: (i) further validation of the representativeness of the Reddit conversational dataset across other psychological dimensions, alongside the design of a fully representative digital online survey; and (ii) incorporation of climatic variables such as relative humidity and temperature alongside the evolution of the SARS-CoV-2 virus alongside the psychological components for improving model fits to COVID-19 burden estimates.

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### 7.1h. Backup plans. A key risk from the proposed analyses is the potential to be unable to disentangle the feedback relationships between socio-behavioral factors, policies, and pandemic trends altogether in a single model (Figure 1). We believe we have minimized the risk, but we propose that in such a scenario we will instead independently quantify the dual relationships between psychological states and reported behaviors, pandemic trends, and policies. Specifically, we will estimate independent time-varying regression coefficients for each socio-behavioral and epidemiological interaction and fix values in the epidemiological model to those values. We will then fit the resulting model to COVID-19 burden data to estimate the remaining epidemiological parameters, circumventing the need for simultaneous estimation of all parameters.

## Thrust 2. Incorporating detailed dynamic contact patterns in epidemic models

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### 7.2a. Background and aims. Directly transmitted infectious diseases spread from person-to-person, and individuals face different exposure risks based on the number of contacts they have [34](https://paperpile.com/c/N5JckZ/bXa2). However, epidemiological models often use a simplifying assumption called compartmental models where individual contact patterns are homogeneous within a population [92](https://paperpile.com/c/N5JckZ/MGDg). Empirically-collected population contact data suggest that there is high heterogeneity in individual contact patterns, and network epidemiological models show how these heterogeneous patterns can dramatically impact infectious disease dynamics such as the speed, shape, and magnitude of epidemic waves, individual risks, and the efficacy of interventions [18–20,25,93–97](https://paperpile.com/c/N5JckZ/Hybe+iKvm+lOxl+dIRQ+SbnJ+mXxk+I2gy+qkT0+DHkj). However, to date, individual contact patterns have not been fully incorporated into epidemiological models for COVID-19, except for understanding superspreading events [22,98,99](https://paperpile.com/c/N5JckZ/7sCc+PahP+xYZI) and differentiating age-dependent contact patterns for policy decisions (e.g., determining priority age for vaccination and guiding school closure and reopening policies) [100–102](https://paperpile.com/c/N5JckZ/Kvff+r4z3+gwB8).

It is known that people’s social interactions are selective rather than random and that social networks tend to form a cluster of individuals with similar characteristics, e.g., risk behavior and perception (“homophily” in sociology terms) [103](https://paperpile.com/c/N5JckZ/pvyC), which impacts transmission dynamics [104,105](https://paperpile.com/c/N5JckZ/yeJ4+N7rf). The role of social, economic, psychological, and behavioral factors (“sociobehavioral factors”) has been studied in the context of disease dynamics; however, these early studies [106](https://paperpile.com/c/N5JckZ/vUJM) were mostly on a theoretical or descriptive basis unfortunately, primarily due to the limited availability of contact data encompassing detailed sociobehavioral factors. Individual contact patterns based on socioeconomic, psychological, and behavioral characteristics other than age have been understudied [107](https://paperpile.com/c/N5JckZ/QdNP). Moreover, individual risk perception and adherence to policies shape their contact patterns and may drastically change over time [26,108](https://paperpile.com/c/N5JckZ/rH7V+48O4). As discussed in Thrust 1, people can experience quarantine fatigue and rebound their behavior during extended policy restrictions, which introduces dynamic patterns in people’s adherence to restrictive policies. Although extensive literature on the impacts of these characteristics on social mixing has been accumulated in the field of social and behavioral sciences [103,109–114](https://paperpile.com/c/N5JckZ/Nk5B+pvyC+7k7R+tvaB+rJTD+WLrK+P15M), there is still a crucial knowledge gap in empirically supported understanding of the role of dynamic sociobehavioral factors in people’s contact patterns, network structures, and how these dynamics impact pandemic transmission dynamics.

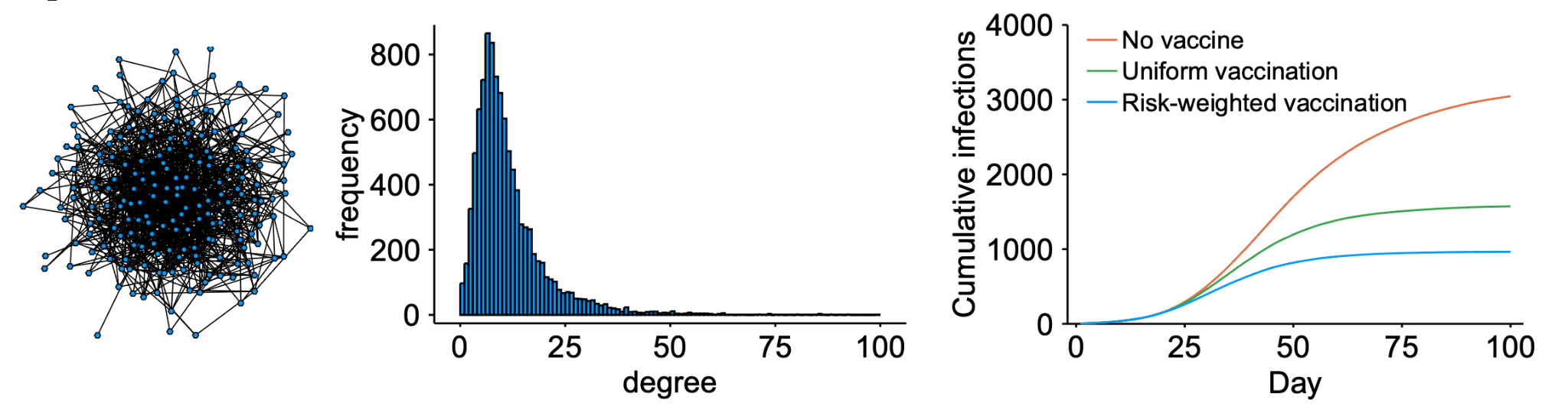
In this Thrust, we aim to explore causal relationships between psychological states, policies, behaviors and transmission through the lens of fine-scale empirically-derived dynamic contact patterns and networks. In more concrete terms, we will use longitudinal contact survey data during the COVID-19 pandemic from multi-country sources [26](https://paperpile.com/c/N5JckZ/48O4) and aim to (1) quantify the magnitude of heterogeneity in and correlations between social, psychological, and behavioral variables and contact patterns, as well as their temporal changes over the course of the pandemic, (2) construct a mathematical model using a heterogeneous contact network and assess by simulation the degree of improvement in estimation and prediction by incorporating contact data along with socio-behavioral factors, and (3) propose a study design for effective real-time collection of socio-behavioral factors and contact patterns specifically for improving modeling for future pandemics.

### 7.2b. Preliminary studies.

**Longitudinal contact survey along with socio-behavioral factors in Japan, 2021–2022 (Nakamura et al, working paper).** Our team at Nagasaki University conducted longitudinal social contact surveys in Fukuoka and Osaka prefectures, Japan from 2021 to 2022. We recruited individuals living in Fukuoka and Osaka into online-based questionnaire surveys at eight different time points over the COVID-19 outbreak. The eight time points are: February 2021 when the national state of emergency was issued shortly after the New Year holidays, March 2021 after the state of emergency was lifted, May 2021 shortly after the Golden Week holidays (consecutive national holidays that span for over a week in May), which coincided with the onset of the wave of the Delta variant, November and December 2021, shortly after the wave of the Delta variant subsided, and finally in January, February and March 2022 during the start and peak of the Omicron variant.

Participants reported the contacts (either physical or conversational) they experienced on a survey day. They also provided their COVID-19 vaccination status, frequency of precautionary behaviors including facial mask wearing, hand washing, teleworking, and testing, and their perceptions and views on COVID-19 infection and vaccination risks. Each survey recruited around 1,500 participants (approximately evenly distributed between Osaka and Fukuoka), most of whom participated in multiple or all the eight time points, allowing for analysis of dynamic changes in perceptions and behaviors.

**Simulating heterogeneous contact patterns that affect the effect of interventions (Endo, Fox, Meyers and Nishi, working paper).** We conducted a simple simulation study to explore how contact network structures and heterogeneous compliance to prevention measures (vaccination) can modify the impact of interventions. We employed a Barabasi-Albert (BA) network of 10,000 individuals and simulated outbreaks under different vaccination scenarios **(Figure 3)**. A BA network is constructed through a so-called “preferential attachment” process, where individuals are more likely to make a new network tie to those who already have many ties, resulting in those “popular” individuals even more popular [115](https://paperpile.com/c/N5JckZ/733I). The degree distribution of a BA network typically shows a heavy-tailed pattern, as is often observed in real-world social contact patterns [93](https://paperpile.com/c/N5JckZ/Hybe). In our “risk-weighted vaccination” scenario, we assumed that individuals with many network ties are aware of their heightened risk of exposure to infection and thus have a higher chance of getting vaccinated. Combined with the property of the BA network, this means that vaccinated and socially active individuals are clustered together on the social contact network. The total number of infections in this scenario was about 40% smaller than that in the “uniform vaccination” scenario where all individuals are evenly vaccinated, even though the population vaccination rate (1% per day) and final coverage (50%) are identical between the two vaccination scenarios. This preliminary analysis highlights the importance of incorporating population heterogeneity and network structure in epidemic models to accurately predict the impact of interventions.



**Figure 3. The impact of vaccination in a clustered network. Left panel: Graph of a BA network; Middle panel: Degree distribution of a BA network; Right panel: Cumulative incidence of simulated outbreaks with and without vaccination.** In the two vaccination scenarios, 1% of the population is vaccinated per day until the coverage reaches 50%, which reduces infection risk by 95%. Individuals either have an equal chance to be vaccinated (the uniform scenario) or have a chance proportional to their number of neighbors (the risk-weighted scenario).

### 7.2c. Data.

**Japan contact survey data.** Please see the first preliminary study (Nakamura et al, working paper).

**CoMix contact survey data.** The CoMix contact survey is an online longitudinal questionnaire collected in the U.K. from March 2020 to March 2022 [94](https://paperpile.com/c/N5JckZ/iKvm). Two cohorts responded to a survey every two weeks in parallel, providing weekly longitudinal data from alternating participants (500–800 participants per cohort). The dataset is collected by a research team at LSHTM and has been made publicly available. As in the Japan contact survey data, survey questions include a variety of sociobehavioral factors: the recent history of symptoms/testing/isolation in households, COVID-related risk perception (e.g., the perceived chance of catching COVID-19 infection, developing severe illness and spreading it to vulnerable others), preventive measures (e.g., vaccine status, compliance to mask wearing or hand hygiene), attendance at events during the lockdown, and the details of their contacts (e.g., age, setting, duration, and if contact with the same person was repeated regularly). In addition to these factors, the relative reduction in the number of contacts during lockdown periods can be used as an indicator of compliance to social restriction policies.

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### 7.2d. Analytic Plan. First, we will analyze empirical contact survey data to examine the relationship between socio-behavioral factors, contact rates, and their temporal dynamics. We use longitudinal contact survey datasets collected during the COVID-19 outbreaks in the U.K. and Japan (see section 7.2c). We will study individual-level heterogeneities in the sociobehavioral factor variables and the correlation between them. We will also perform cluster analysis [116](https://paperpile.com/c/N5JckZ/Cqbv) to identify multiple classes of individuals who show distinct socio-behavioral factors and contact patterns, e.g., “risk-aware and precaution-compliant people” or “workers whose responsibility involves high contact rates”. In addition, we will compare the characteristics of the U.K. and Japan datasets to test if there are country-specific features that we need to take into account when designing a similar contact survey for the U.S. population.

Second, we will use simulations to assess estimation and predictive performance of epidemic models that incorporate socio-behavioral factors and the homophilic network structure stemming from these factors. Simulations will be either compartmental or agent-based depending on the assumed contact pattern input and Markov-chain Monte Carlo (MCMC), particle-MCMC [117](https://paperpile.com/c/N5JckZ/pQih) or approximate Bayesian computation [118](https://paperpile.com/c/N5JckZ/jb8L) will be used as the estimation approaches. Based on the empirical findings in the first data analysis above, we will first construct a virtual social network where individuals have heterogeneous sociobehavioral characteristics studied in the first data analysis above. Traditional contact surveys (including the datasets we plan to use) provide key summary statistics of the social network such as degree distribution but not full network information. Therefore, additional assumptions on the social network structure, specifically the degree of assortativity and clustering [104](https://paperpile.com/c/N5JckZ/yeJ4), need to be made. We will vary these parameters drawing from relevant (or surrogate) estimates from social science literature [119–122](https://paperpile.com/c/N5JckZ/VuJs+Vqa0+D6F8+Iaqt) and synthesize a virtual population embedded in a social contact network consistent with both the assumed parameters and empirical data obtained in the first data analysis above. We will then simulate outbreaks over this virtual network with time-varying interventions to generate hypothetical epidemic and contact pattern datasets. Finally, we will apply epidemic models using different types of contact pattern inputs (i.e., traditional homogeneous or age-dependent contact patterns, contact patterns combined with socio-behavioral data, and dynamic contact patterns) to the hypothetical datasets and compare their performances based on the following criteria: (i) accuracy of estimates of the time-varying reproduction number (*R*t) and the efficacy of intervention; (ii) prediction performance of the impact of future interventions; and (iii) computational and data collection costs.

Third, we will design a contact survey that will assist epidemic models that incorporate sociobehavioral factors. As contact surveys are generally a very resource-intensive research method, they should aim for the lowest possible complexity and scale that will still sufficiently improve model performance. Indeed, the contact surveys for the Japan and U.K. surveys described previously were very intensive and included many questions to capture as many factors as possible that could be associated with contact patterns. More efficient survey designs with selected key questions should be developed for future pandemics. Using results from the first and second data analyses above, we propose an optimal design for future contact surveys; key decisions in such a study design should include: (a) a minimum but sufficient set of survey questions on socio-behavioral factors, which will be informed by defining characteristics of clusters of individuals identified in cluster analysis (a part of the first data analysis); (b) whether and how network information of survey participants should be (at least partially) collected, e.g., via partial network design [123](https://paperpile.com/c/N5JckZ/6xqp); and (c) what sample size to target and how to recruit representative participants. We will collaborate with social scientists to further refine the survey details, e.g., wording, the order of questions, and recruiting and weighting participants.

Finally, we will also conduct a pilot contact survey to examine if the designed contact survey works well in the US setting. We aim to recruit 300 participants from Prolific, a crowdsourcing platform that allows us to obtain nationally representative samples of the U.S. (with a potential oversampling of specific minority groups). Participants will be invited to our contact survey form and will be asked to fill in the survey every month over the 5-month survey period (a total of 1,500 responses are expected). As a final output, we will aim to publish a template for ideal dynamic contact surveys to be used in epidemic models incorporating socio-behavioral factors.

***7.2e. Hypotheses.*** We hypothesize that certain key demographic, socioeconomic, and perceptual characteristics are associated with contact patterns and social network structure and can be used as good predictors of people’s contact behavior and responses to interventions as well as the resulting transmission dynamics in the population. Furthermore, we expect that there are multiple classes of individuals with distinctive socio-behavioral and epidemiological properties that can be identified by cluster analysis. We also hypothesize that the models of transmission dynamics can achieve a substantial improvement in their estimation and prediction performance when we consider people’s socio-behavioral characteristics as well as (potentially dynamic) contact network data over the course of an outbreak.

### 7.2f. Metrics of success. We will evaluate our work as a success if we (i) prove that demographic, socioeconomic and perceptual variables can be used to better predict contact rates of individuals (measured by Kullback-Leibler divergence [124](https://paperpile.com/c/N5JckZ/ytdz)), (ii) quantify the degree of improvement in the estimation and prediction performance of epidemic models incorporating socio-behavioral characteristics and contact network structure compared with traditional homogeneous or age-dependent models (measured by interval forecast scores [125](https://paperpile.com/c/N5JckZ/wkMx)), and (iii) establish a template for future contact surveys incorporating socio-behavioral factors.

***7.2g. Limitations and future directions.*** Our proposed work has several limitations. First, the contact survey data that we plan to use only include contact data after the COVID-19 pandemic started and a comparison with existing pre-pandemic contact data brings limitations (e.g. the well-known POLYMOD study [93](https://paperpile.com/c/N5JckZ/Hybe) is now 15 years old and may not reflect recent changes in contact patterns in the population). Therefore, our analysis of temporal changes in contact patterns during an outbreak relative to the baseline (non-pandemic) periods may be subject to biases. Second, our model simulation will be limited to variables that are included in the empirical dataset available and therefore certain potentially important variables that have an impact on epidemic progression may be excluded from consideration.

Next steps following successful completion of the proposed project would include: (i) conducting regular contact surveys (e.g. every 5 years) to identify long-term trends in contact patterns and assess if they are predictable from available data, e.g. national census data, so that the baseline pre-pandemic contact pattern data would always be available when a new pandemic started; and (ii) considering other socio-behavioral variables not included in the current contact surveys referring to social science literature that are potentially related to contact behaviors and collect empirical contact and epidemic data for validation.

***7.2h. Backup plans.*** First, we may fail to identify key variables that determine people’s contact patterns and precautionary behaviors from the available data. In such an instance, we will try to understand heterogeneity in our datasets as random effects and test if such handling is still more useful than traditional models in our further analytic plans (second and third data analyses). Second, our simulation may show that incorporating socio-behavioral factors in epidemic modeling does not significantly improve the performance because their impact on behavior is small. While this would still be an important finding to report, we will move the main focus of our analytic plan (the third one) to contact surveys for reconstructing the population network structure to aid epidemic models, which are not primarily related to other socio-behavioral factors.

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| **Appropriateness to the Three RAISE Guidelines**  **1) Scientific advances lie in great part outside the scope of a single program or discipline, such that substantial funding support from more than one program or discipline is necessary.**  We (the team of social and behavioral scientists [PI Nishi and co-PI Pennebaker] and infectious disease modelers [co-PIs Meyers and Fox as well as Collaborator Endo]) propose to integrate sociobehavioral processes into infectious disease models to learn about psychological and behavioral responses in the midst of a pandemic and capture important epidemiological dynamics. Our work will promote pandemic preparedness through not only the integrated models, but also suggested designs for social survey and data collection systems from the epidemiological perspective that will allow for rapid integration with infectious disease models in future pandemics. Therefore, scientific advances from the proposed project lie in the scopes of multiple NSF disciplines.  **2) Lines of research promise transformational advances.**  Thus far, there have been few attempts to accurately model sociobehavioral processes due to a dearth in data. Through explicit modeling of these processes, incorporation into infectious disease models, and validation with large empirical data sets, our proposed project will produce transformative approaches for bridging multiple fields that will improve our ability to respond to current and future epidemics and pandemics.  **3) Prospective discoveries reside at the interfaces of disciplinary boundaries that may not be recognized through traditional review or co-review.**  Survey designs have been established in social and behavioral sciences, while behavioral and epidemic models have been developed in mathematical biology (“traditional views”). Our prospective discoveries will enhance non-traditional communication loops between social and natural scientists that have not previously been prioritized. |

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