RESEARCH REPORT

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Effectiveness of Nonpharmaceutical Interventions to Avert the Second COVID-19 Surge in Los Angeles County: A Simulation Study

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16. Abstract

This study used a simulation to examine nonpharmaceutical interventions (NPIs) that could have been implemented early in a COVID-19 surge to avoid a large wave of infections, deaths, and an overwhelmed hospital system. The authors integrated a dynamic agent-based travel model with an infection dynamic model. Both models were developed with and calibrated to local data from Los Angeles County (LAC), resulting in a synthetic population of 10 million agents with detailed socio-economic and activity-based characteristics representative of the County's population. The study focused on the time of the second wave of COVID-19 in LAC (November 1, 2020, to February 10, 2021), before vaccines were introduced. The model accounted for mandated and self-imposed interventions at the time, by incorporating mobile device data providing observed reductions in activity patterns from pre-pandemic norm, and it represented multiple employment categories with literature-informed contact distributions. The combination of NPIs—such as masks, antigen testing, and reduced contact intensity—were the most effective, among the least restrictive, means to reduce infections. The findings may be relevant to public health policy interventions in the community and at the workplace. The study demonstrates that investments in activity-based travel models, including detailed individual-level socio-demographic characteristics and activity behaviors, can facilitate the evaluation of NPIs to reduce infectious disease epidemics, including COVID-19. The framework developed is generalizable across SARS-COV-2 variants, or even other viral infections, with minimal modifications to the modeling infrastructure.

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Glossary

CBG	census block group
CSA	Combined Statistical Area
LAC	Los Angeles County
NAICS	North American Industry Classification System
NPI	nonpharmaceutical interventions
POI	points of interest
RR	relative risk
SCAG	Southern California Association of Government
SOTA	state-of-the-art

Executive Summary

Executive Summary

This study examined the nonpharmaceutical interventions (NPIs) that could be implemented early in a COVID-19 surge to avoid a large wave of infections, deaths, and an overwhelmed hospital system. To simulate the implementation of the NPIs, we integrated a dynamic agent-based travel model with an infection dynamic model. Both models were developed with and calibrated to local data from Los Angeles County (LAC) to simulate a synthetic population of 10 million agents with detailed socio-economic and activity-based characteristics representative of the County's population, including work categories. We focused on the second wave of COVID-19 in LAC from November 1, 2020, to February 10, 2021, before the introduction of vaccines. We accounted for mandated and self-imposed interventions in-place during this time, including mask usage, school closures, and the temporary shutdown of specific activities. To account for these factors, we incorporated (i) mobile device data providing observed reductions in activity patterns from pre-pandemic norms and (ii) evidence-based assumptions regarding mask coverage and closure of specific activities. NPIs evaluated included cloth masks, N95 masks, antigen testing, and reductions in contact intensities, with comparisons made between interventions implemented during all activities vs. only high-risk activities.

Methodological Contributions

The study approach makes several unique contributions to the use of activity-based travel demand and agent-based models to simulate infectious disease dynamics in a population.

First, using highly resolved population attributes and interaction activities improves the accuracy of representing observed infection trends and the specificity of possible public health insights. While state-of-the-art (SOTA) models typically represent work activities in an aggregated single 'work' category, travel and viral infection models represent multiple employment categories. In this case, we model multiple employment categories with employment- dependent contact intensities, informed by public health studies documenting relative risks in COVID-19 infection by occupation.

Second, before modeling intervention scenarios, it is important to ensure that the model represents the baseline 'on-the-ground' reality of modifications made to activities in the focal epidemic period, as they differ from pre-pandemic norms. Such modification would include both mandatory and elective measures from lockdown to physical distancing. While SOTA models have relied on data representing aggregate city-level changes in mobility to reflect observed modifications to activity behaviors, our work incorporates highly resolved mobile device data documenting modifications in specific activities at the level of the spatial census block group.

Third, while SOTA models have represented contact intensity within the home using a fixed measure for all household sizes, we represented heterogeneity in contact intensity within the home as a function of household size. This contribution was motivated by the practical need to account for this mechanism, following research demonstrating the important role of large (5+) and multi-generational household transmission in driving infection dynamics in LAC during the modeled epidemic surge.

Due to this incorporation of fine-grained data and modeling detail, following calibration, the modeling framework we developed was able to reproduce observed infection patterns across age groups and work categories, while accounting for LAC's observed levels of implemented pandemic-motivated reductions in activity behaviors. This detail allowed for realistic inferences into the effect of the evaluated NPIs on the LAC population overall and impact by—and potential disparities across subgroups.

Findings for Public Health Policy

The highly detailed representation of populations and activity types for the LAC population enabled us to derive several findings relevant to public health policy interventions in the community and at the workplace. Overall, we found that combining NPIs is the most effective way to achieve the greatest reductions in infections at the least restrictive levels of intervention. In particular, pairing N95 masks with shutdown and capacity restrictions adopted during the second COVID-19 surge in LAC can be very effective even without increasing the overall masking levels observed during this period (i.e., 65%). For an illustrative example, we found an 80% decrease in cumulative infections by combining a 50% reduction in contact in high-risk work categories with 65% mask compliance, 25% of which being N95s and 45% being cloth. This intervention is also the most 'efficient' combined intervention, meaning that the combination of contact reduction and masking are working most independently from one another to achieve a reduction in overall infections.

We also found that small increases in the proportion of people using N95 masks in the workplace and the general community can effectively reduce spread, even without increasing overall masking levels and, for example, substituting 25% or 50% of the baseline 65% of cloth mask usage during the modeled epidemic period for N95 masks across all workplace and community categories in an almost 60% or more than 85% reduction in cumulative infections.

We also identified the possibility of specific interventions to exacerbate health inequities in specific groups. For example, we found that if interventions such as N95 mask adoption and contact reductions are implemented in high-risk workplace and community activities only, they have a disproportionately lower impact on reducing infections in younger and older populations, who are less likely to be in the workforce and involved in community activities such as shopping, personal care, and other errands. These findings held despite these populations being socially connected with the workforce population and despite the model accounting for school closures impacting younger populations. These findings suggest that workplace-specific interventions must be combined with effective home- and visitation-level interventions targeted toward youth and elderly populations.

Our analysis of possible policy interventions focused on the direct public health impact, i.e., reducing infections, in the LAC overall population and for specific age groups and activity categories. A complete policy analysis before implementation requires an analysis of cost dimensions, political appetite for mandates, and enforceability. A high-level analysis across these dimensions points to the strength of N95-related interventions over other interventions. N95 masks are cost-effective (as low as $1-2/mask), compared with $10/antigen test or untold costs in enforcing contact reduction interventions across communities (including costs on the workplace). While there have been large debates regarding the mandatory use of masks, a shift in those already using cloth masks to upgrade to a more effective N95 respirator could be a less intrusive and, thus, more likely-to-be-adopted policy intervention. We found large effects at levels as low as 25% adoption. This scenario is also significantly less restrictive and thus more politically viable than shutdown or contact reduction interventions, which require more extensive modifications (or even elimination) of behaviors; all the more so because the highest-risk activities are often those most unpopular for shutting down, e.g., restaurants (*Will Nicholas, LACDPH, personal communication*). It is important to note that from a policy perspective, distribution and enforcement of N95 masks would require a strong coordinated effort between local health departments and community-based organizations to ensure that citizens have access to and wear masks when out in the community.

We can also draw some preliminary lessons regarding preparedness for future airborne viral pandemics during pre-vaccine growth stages such as that investigated here, which might similarly apply to future variants of SARS-COV-2 that are immune resistant. Results again point to the value of focusing preparedness for these purposes on N95 masks because, in addition to the reasons above regarding (i) the strength of these interventions above cloth masks, (ii) relative strength in comparison with other interventions considered here, and (iii) palatability of these interventions in implementation, they are likely to be an indiscriminate tool across virus types or variants. Antigen tests must be designed for specific infections and will not be available in the initial growth phases of a new viral pathogen. Given this, pandemic preparedness policy could include stockpiling N95 masks, rather than cloth (or surgical) masks, for future viral pandemics.

Conclusions

Overall, the study introduced several methodological contributions, including integrating employment and activity categories in detail and accounting for category-specific modifications to activity behaviors throughout the epidemic surge. This detailed integration enabled realistic insights into the design and combinations of interventions to best mitigate the spread of future COVID-19 epidemic waves in LAC. In addition, this approach accounts for LAC's unique demographic composition and baseline restrictions, how particular policies focused on specific groups may impact the overall population, and how any given policy may differentially impact specific groups. Indeed, we found that simulated interventions could make a very different impact on overall infection rates if applied to specific work categories only and could exacerbate health inequities in specific age groups, demonstrating the insights into intervention design made possible through the added detail. Future efforts should continue this line of work to incorporate more detail, enabling more model-based representation of the impact of epidemic surges and interventions on subpopulations, particularly those at highest risk.

More generally, these findings demonstrate that investments made in activity-based travel models, including detailed individual-level socio-demographic characteristics and activity behaviors, can facilitate the evaluation of NPIs to reduce infectious disease epidemics, including COVID-19. Furthermore, the framework developed here is generalizable across SARS-COV-2 variants or other viral infections, with minimal modifications to the modeling structure.

Contents

1. Introduction

This study was a simulation to assess the nonpharmaceutical interventions (NPIs) that could be implemented at the early stages of a COVID-19 surge, before the availability of medical interventions, to avoid a large wave of infections, deaths, and an overwhelmed hospital system. We focused on the second wave of COVID-19 in Los Angeles County (LAC) from November 1, 2020, to February 10, 2021, before vaccines were introduced.[1] NPIs evaluated included cloth masks, N95 masks, antigen testing, and reductions in contact intensities. We compared these interventions and possible outcomes when implemented during all vs. only high-risk activities.

To simulate the implementation of the NPIs, we integrated a dynamic agent-based travel model with a viral infection dynamic model. Mueller et al. (2021) initially developed the integrated modeling framework's concept and structure. Their model has been used to advise the German federal government in implementing policy interventions involving reducing activities, using masks, and vaccination throughout the pandemic.[2] The present work adapted and introduced new components to the modeling framework of Muller et al., including a highly-detailed agent-based transport activity model specific to LAC, the LA MATSim model. The LA MATSim model represents highly detailed travel activity patterns for a synthetic population of 10 million agents with detailed socio-economic and activity-based characteristics representative of the County's population. This work represents its first application in an infectious disease modeling context.

This work also introduced several detail-oriented methodological contributions to the original modeling framework from Mueller et al. (2021) and, more generally, to using activity-based travel demand with agent-based models to simulate infectious disease dynamics. All modifications focused on representing population attributes and interaction activities with greater granularity.

First, while state-of-the-art (SOTA) models typically represent work activities in an aggregated single 'work' category, we model multiple employment categories with employment-dependent contact intensities, informed by public health studies documenting relative risks in COVID-19 infection by occupation. This granular articulation of activity and work types was critical to investigating the marginal benefit of expanding the scope of NPI measures and policies to specific work categories, which enabled insights into the differential impact of simulated interventions on overall infection rates if applied to specific work categories only.

Second, before modeling intervention scenarios, it is important to ensure that the model represents the baseline 'on-the-ground' reality of modifying activity behaviors during the pandemic, including mandatory and elective measures, from lockdowns to physical distancing. While SOTA models like that in Mueller et al. have

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[1] The first vaccines were technically administered in mid-December in LAC but were focused exclusively on healthcare workers. Rollout to at-risk populations (65+ years old, immunocompromised) did not begin until mid-January, and then only at a rate of approximately 10,000 doses / week. We furthermore note that vaccine effectiveness for a first dose is lower than for the two-dose series, and both take several weeks before their effectiveness is demonstrated. Therefore, we conclude there was only very minor vaccine coverage in LAC during this time period.

[2] Several reports generated for the German Ministry of Education and Research can be found at https://covid-sim.info.

relied on data representing aggregate city-level changes in mobility to reflect observed modifications to activity behaviors, our work incorporates highly-resolved mobile device data documenting modifications in specific activities at the level of the spatial census block group.

Third, while SOTA models have represented contact intensity within the home using a fixed measure for all household sizes, we represented heterogeneity in contact intensity within the home as a function of household size. This contribution was motivated by the practical need to account for this mechanism, following research demonstrating the important role of transmission in large (5+) and especially multi-generational households in driving infection dynamics in LAC during the modeled epidemic surge (Harris, 2021).

Due to the additional incorporation of fine-grained data and modeling detail, following calibration, this modeling framework could reproduce observed infection patterns for LAC as a whole and across age groups. This detail allowed for realistic insights into the combination and design of interventions to best mitigate the spread of future COVID-19 epidemic waves in LAC, accounting for its unique demographic composition and baseline restrictions. Furthermore, the framework is generalizable across SARS-COV-2 variants or other viral infections, with minimal modifications to the modeling structure.

The report includes a detailed discussion of the models and data used in the research, results from the simulated scenarios, and discussion and conclusions on the simulated scenarios and their results.

2. Methods

2.1. Integrated MATSim and EpiSim Model Overview

We start by providing an overview of the integrated model (Figure 1). In the overall integrated model, an infection dynamic model (EpiSim) uses data output from a dynamic agent-based transport simulation model (LA MATSim Model) that provides the socioeconomic attributes, activity patterns, and interactions by time, location, and activity type (who is mixing with whom and for how long) for a synthetic population of 10 million agents representative of the LAC population. Activity patterns and interactions are modified with Geolocation Mobility Data to reflect time-varying COVID-19-induced changes in behavior following interventions at the geographical resolution of the census block group. The EpiSim model governing equation determines the transmission of infections at the agent level through the synthetic population. When any pair of infectious and susceptible agents come into contact in a specific location (called a "container"), determined by their conducting an activity together in the MATSim model, the infection may be transmitted to the susceptible individual *with some probability* determined by multiple factors including characteristics of the individuals, the space the share and time they share it, and the activity they are conducting. We derive the values of these parameters from the specifics of the activity conducted by agents that involves interaction in the MATSim model, with several parameters also coming from published literature. Monte Carlo-type logic implemented in the EpiSim model determines whether the infection is transmitted between the pair of agents, given the discrete probability value determined by the governing equation. Following exposure, the *progression model* determines an exposed agent's course of illness and infectiousness, perpetuating the infection progression process across the synthetic population. Figure 2 illustrates how the infection process can progress across a population of agents, where each agent is represented by a different icon. When an infected agent (red) comes into contact with a susceptible agent (green), the latter may become exposed (yellow) and, after some time delay, becomes infectious (and later symptomatic, not indicated in color). X_0 shows the chain of infection in the figure where the first infection for the circle agent passed to the diamond agent indicated at the event X_1, and then on to the square agent at X_2 and the triangle at X_3.

Specific EpiSim model parameters include the *intake rate* of the agent and *shedding rate* of their contact, determined by: (i) the masks they are using; (ii) the *contact intensity* of their interaction, determined by features of the space they are sharing, including its size and air flow rate; and (iii) the *duration* of the activity (see Figure 1). The space shared and the duration of the activity, in turn, are determined by the type of activity conducted, e.g., a cashier agent at a grocery store will have a several-minute-long interaction with a customer agent, and the two agents will share the large surrounding of the supermarket as their container. Finally, a meta-parameter is the *calibration* parameter, which takes on a single value determined in the calibration procedure that helps fix the complex integrated model to fit the general trend of the observed infection data. We base all parameters except the *intake* and *shedding rate* on information derived from the LA MATSim model.

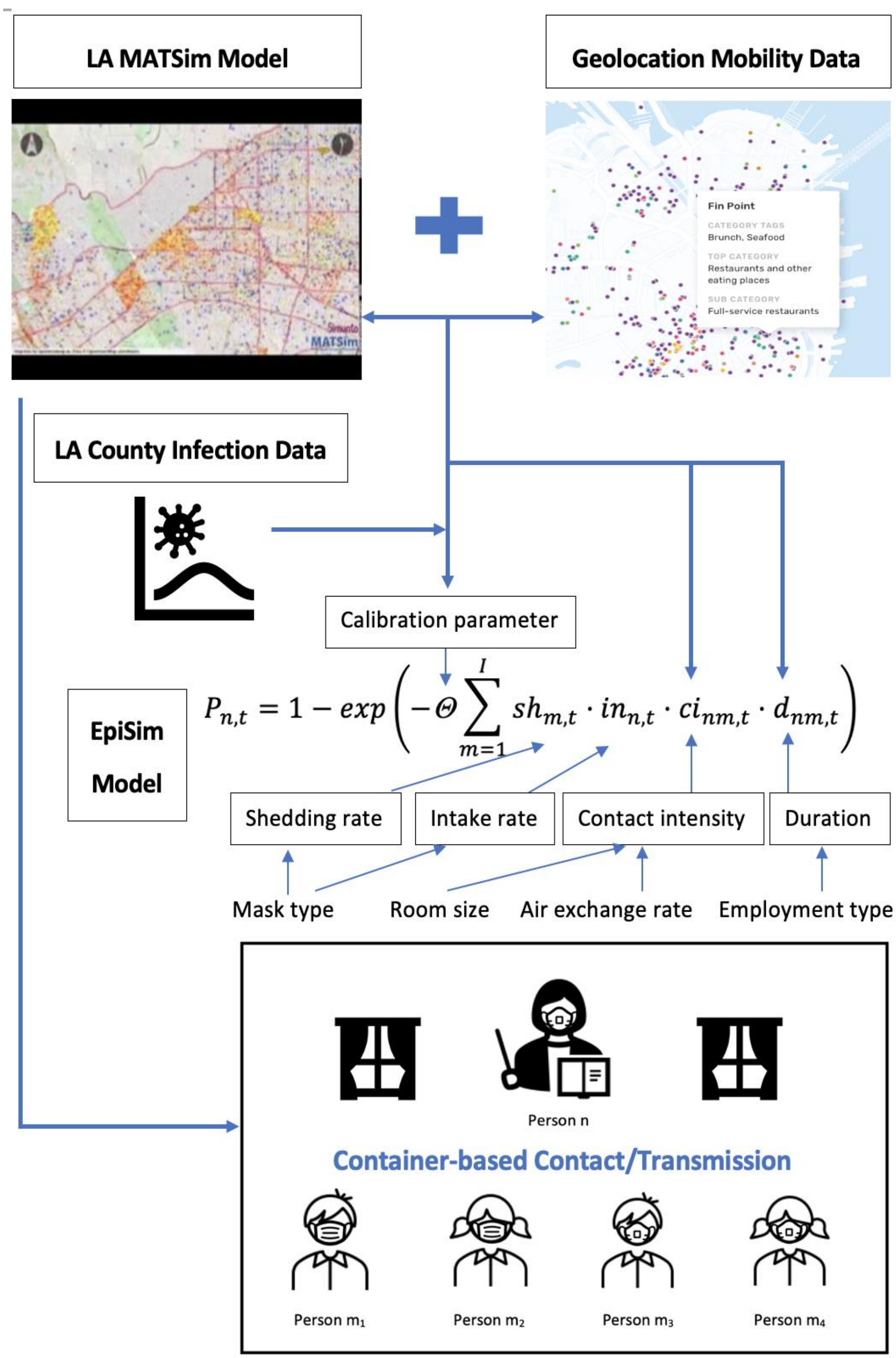

Figure 1. Overview diagram of the integrated Agent Based Transport (LAC MATSim) and Viral Infection Dynamic (EpiSim) models.

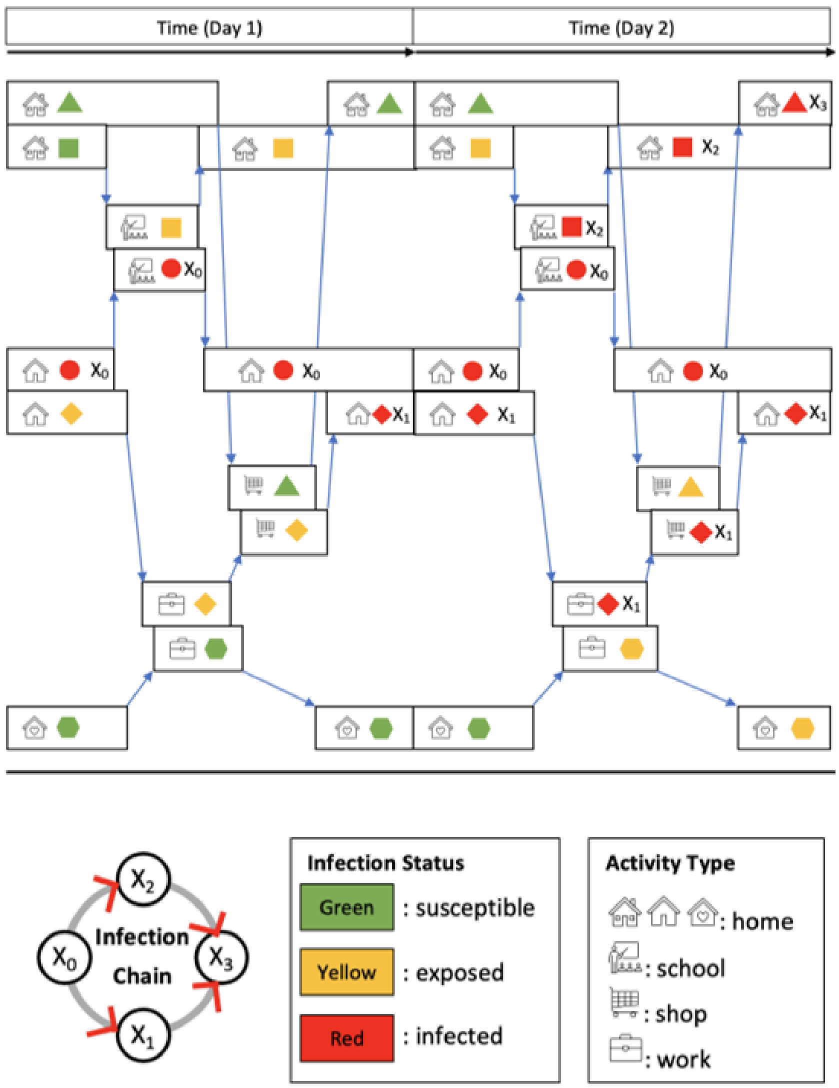

Figure 2. Illustration of diagram of the integrated Agent Based Transport (LAC MATSim) and Viral Infection Dynamic (EpiSim) modelswhere each geometric icon represents a different agent.

We first developed and calibrated the MATSim models for LAC with local demographic, travel activity, mobile device, and network data from a LAC-specific activity-based travel demand model. Next, the combined LA MATSim and EpiSim model was calibrated to timeseries data on reported infection cases in LAC, accounting for the estimated large number of unreported infections. The calibration process resulted in the "base case scenario"—the model's most realistic representation of the distribution of infection cases and changes in activity behaviors in LAC during the modeled pandemic period from November 1, 2020, to February 10, 2021. We then developed simulation cases to evaluate the effect of additional or higher levels of the restrictions already in place under the base case. The following sections describe all model components and the calibration process in detail.

The EpiSim framework is open-source JAVA-based software available on GitHub (https://github.com/matsim-org/matsim-episim-libs). A general description of the existing EpiSim framework can be found at https://dx.doi.org/10.14279/depositonce-9835. The LA MATSim model, which is based on MATSim (Multi-Agent transport simulation, www.matsim.org), is also open source and can be accessed via https://github.com/matsim-scenarios/matsim-los-angeles. The application of the EpiSim framework to the Los Angeles model is in the GitHub repository at: https://github.com/matsim-vsp/matsim-episim-la.

2.2. Agent-Based Transport Model

2.2.1. MATSim Framework

We use the agent-based and dynamic transport simulation framework MATSim (Multi-Agent Transport Simulation). See the detailed model documentation in Horni, Nagel, and Axhausen (2016). MATSim is an open-source model programmed in Java and available from GitHub. The model simulates travel for cities and regions using local transportation networks and travel demand. Its framework facilitates large-scale simulations by implementing queue-based network loading rather than car-following behavior in the dynamic routing model. The model uses a co-evolutionary algorithm that allows individuals (or agents) to try new travel choices, which, in addition to route choice, include departure time and mode choice. Agents interact while driving on the roadway network across space and time through an iterative process to optimize their daily travel plan. A "score" measures how a travel plan optimizes activity or trip characteristics, interpreted as economic utility.

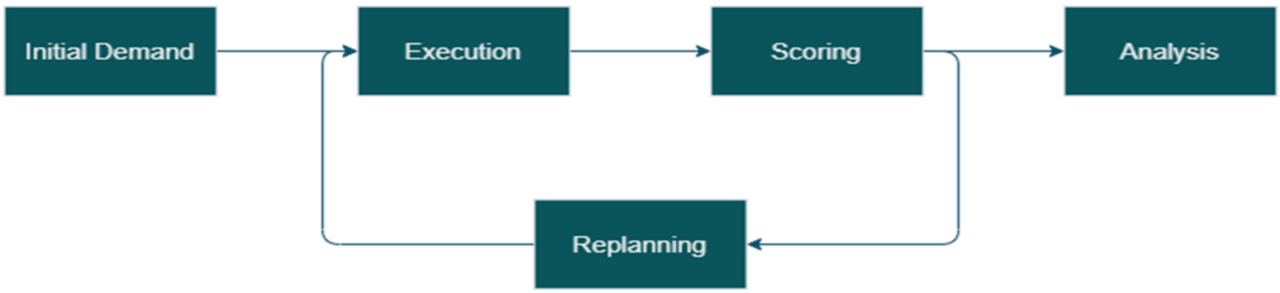

Figure 3. The MATSim framework (reproduced from Horni, Nagel, and Axhausen 2016).

Figure 3 illustrates the generalized modeling process of the MATSim model framework. Initial demand includes all trips a person makes over a typical 24-hour period. Trip information includes departure and arrival times, travel mode, purpose, and origin/destination locations. Person-specific socio-demographic attributes link to travel plans. During the execution step, all individuals and vehicles are loaded onto the transportation system network in second-by-second increments to accomplish their travel plans. The score of an executed plan will decrease when individuals spend more time and money traveling to activities rather than engaging in them. The replanning step allows individuals to modify their plans and improve their scores by changing departure time, mode, and route. The iterative process ends when the average population score stabilizes.

2.2.2. Data and Calibration to LAC

The LAC MATSim model was developed and calibrated in an earlier study (Rodier et al., 2021).[3] As shown in Figure 4 below, we used multiple data sources to develop the LAC MATSim model. The Southern California Association of Governments' (SCAGs') activity-based travel demand model was the source of individual and household attributes and daily activities based on a regional household travel activity survey and census data. SCAG used this data to create the synthetic population for the study area. Attributes for the synthetic population included household characteristics (e.g., size, income, and type) and individual sociodemographic (e.g., age, gender, race/ethnicity, education, worker status, and worker industry) (Table 1) and occupational (Table 2) characteristics. The SCAG model also defines the purpose for each trip (for example, home, work, shop, eat out, and special event), and travel mode (e.g., single-occupant vehicle, high-occupant vehicle, bus, and walk). ***Occupational category and trip purpose were separate and important parameters in defining the simulation of NPIs described in later sections.***

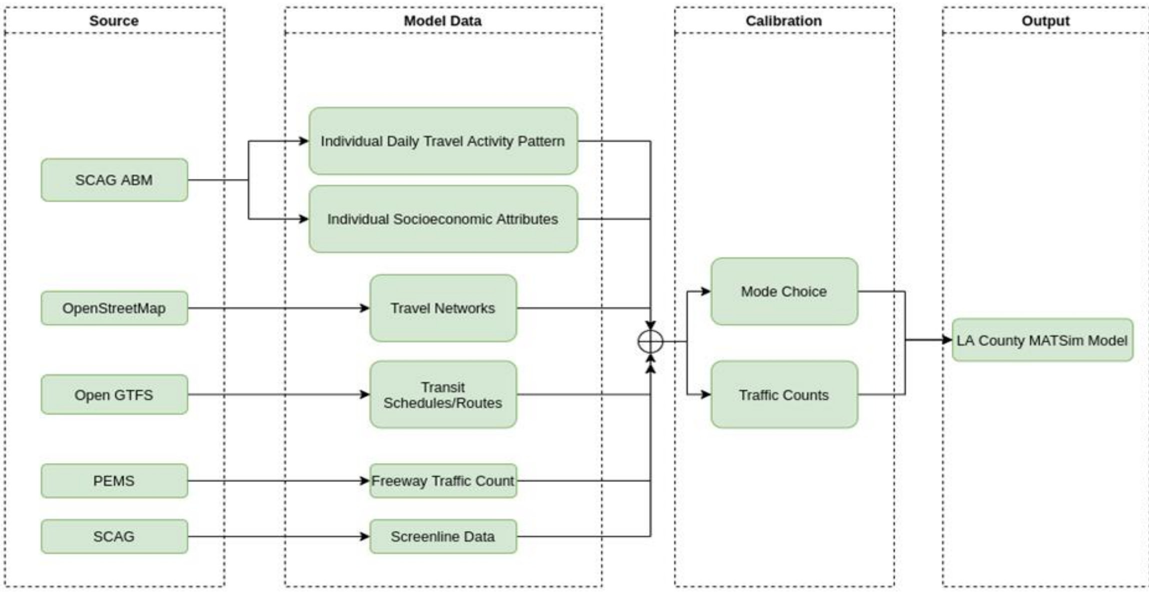

Figure 4. Development and calibration of the LAC MATSim model.

[3] The model can be accessed at https://github.com/matsim-scenarios/matsim-los-angeles.

Table 1. Attributes of household and individual and trip categories for travel purpose and travel mode.

Categories	Variables Included
Household Attributes	size (continuous integer), annual income (continuous integer), housing type (single-detached, single-attached, multifamily, others), housing tenure (own with mortgage/loan, owned, rent), and auto ownership
Individual Attributes	age, gender, race/ethnicity (Non-Hispanic white, black, American Indian, Asian, and other), educational attainment, worker's status, worker's industry, and occupation (see Table 2 below), student grade, work duration, number of jobs, number of days at work, flexibility at work, and compressed workweek
Trip Purpose Categories	home, work, university, school, escort, shop, maintenance (household and personal), eat out (breakfast, lunch, and dinner), visiting, discretionary, special event, at work (business, lunch, other), and business
Trip Travel Mode Categories	single-occupant vehicle, high-occupant vehicle, bus, rail, walk, bike, taxi/ride-hail, and school bus

Table 2. Individual worker's Industry, Occupation, and Location categories.

Categories	Variables Included
Industry (NAICs)	agriculture, farming, forestry, fishing, hunting; mining, quarrying, oil or gas drilling company; utility company, sewage treatment facility, utilities in general; construction; manufacturing; wholesale trade; retail trade; transportation; information; finance and insurance; real estate company, any rental or leasing company; professional scientific or technical services; management of companies and enterprises; administrative support; educational services; health care and social assistance arts, entertainment and recreation; accommodation or food services; other services; and public administration
Occupation	management; business operations specialist; financial specialists; computer and mathematical; architecture and engineering; life, physical, and social science; community and social science; legal; education, training, and library; arts, design, entertainment, sports, and media; healthcare practitioners and technical; healthcare support; protective service; food preparation and serving; building and ground cleaning/ maintenance; personal care and service; sales; office and administrative support; farming, fishing, and forestry; construction trades; extraction workers; installation, maintenance, and repair; production; and transportation and material moving.

We obtained roadway networks from OpenStreetMap and transit networks from GTFS (or the general transit feed specification) provided by the local public transit providers. Finally, we obtained other travel-related cost assumptions from the SCAG model.

We calibrated the base case mode choice in the LAC MATSim model to the mode choice estimates in the SCAG model. In addition, we calibrated the model to base-case traffic count data from two sources (1) the California Department of Transportation's Performance Measurement System (PeMs) and (2) the SCAG model calibration dataset (see Rodier et al., 2021). The points of focus in calibrating the model were examining individual scoring parameters, adjusting parameters, and refining variables. The LAC MATSim model described above represents travel that begins and ends in LAC and from the greater SCAG region that begins, ends, or passes through LAC.

In the LAC MATSim model, the daily activity pattern is the sum of trips made ***within 24 hours on a typical weekday for each individual within each household***, meaning that weekend and holiday behaviors are not represented in the model. An individual's movement from one geographic location (origin) to another geographic location (destination) defines a trip. In addition, each trip includes information on the departure and arrival time (in seconds), purpose, travel mode, and, for vehicle travel, the number of people traveling together and the individual's role within this group (chauffeur, passenger, and driver). Table 1 describes the model's household and individual attributes and trip purpose categories. Table 2 describes individual workers' industry categories (North American Industry Classification System or NAICs) and occupation categories.

2.3. Epidemic Spread Simulation

The EpiSim model incorporates an infection dynamic model and a disease progression model to simulate epidemic spread. The *infection dynamic model* uses information from the LAC MATSim model on the interactions by time, location, and activity type for the synthetic population to determine transmission through the population. The *disease progression model* determines an exposed agent's course of illness and infectiousness.

2.3.1. Infection Model (EpiSim Governing Equation)

The EpiSim framework uses the infection dynamic model initially developed in Smieszek (2009). This model's governing equation determines the *probability* that, given contact with an infected agent *m*, a susceptible agent *n* becomes infected during time step *t* as:

$$P(infection|contact)_{n,t} = 1 - exp\left(-\sum_{m=1}^{I} sh_{m,t} \cdot in_{n,t} \cdot ci_{nm,t} \cdot d_{nm,t}\right) \qquad (1)$$

where I is the total number of infectors, $sh_{m,t}$ is the shedding rate, or microbial load emitted by of infector m at time step t; $in_{n,t}$ is the intake rate, or microbial load taken in by infected n at time step t; $ci_{mn,t}$ is the contact intensity (ci) between the infector m and the susceptible person n at time step t, a relative parameter representing the intensity of viral particles shared between the two agents; and $d_{nm,t}$ is the time individuals n and m interact during time step t. The sources of information for these parameters are described in Section 2.3.2 and summarized in Table 3. The calibration parameter Θ is a meta-parameter that accounts for other contributing factors not directly represented in the model. It takes on a single value process determined by calibrating the model to observed epidemiological data. We describe the calibration process in Section 3.

Table 3. Parameters for Infection Model.

Parameter	Definition	Description	Source
N	individual n	Susceptible individual	LA MATSim model
M	individual m	Infector	LA MATSim model
T	time	Simulation time step	LA MATSim model
Θ	calibration parameter	Accounts for all relevant factors that not explicitly represented, such as the survival probability of the infectious agent.	Derived by fitting simulated infection data to measured epidemiological data, such as epidemic curves
$\mathbf{sh}_{m,t}$	shedding rate for infector m, at time t	Same across ages, depends on mask type	Cloth masks = 0.8 (Konda, Abhiteja, et al., 2020); N95 masks = 0.15 (Asadi et al., 2020)
$\mathbf{in}_{n,t}$	intake rate for susceptible individual n, at time t	Same across ages, depends on mask type	Cloth masks = 0.7 (Konda, Abhiteja, et al., 2020); N95 masks = 0.2 (Asadi et al., 2020)
$\mathbf{ci}_{nm,t}$	contact intensity between the infector m and the susceptible person n, at time t	Depends on the location (container) and the number of people in it	See Section 2.3.2 and Table 4 below
$\mathbf{d}_{nm,t}$	Duration of activity	Time individuals n and m interact during time step t	LA MATSim model

This type of infection model, in which separate parameters represent shedding rate, contact intensity, and duration of contact to quantify various sources of heterogeneity on disease transmission and the success of intervention measures, is common among epidemiological models from microsimulation models (such as this) to network models (e.g., Aleta et al., 2020). It is also common among more traditional population-structured compartmental epidemiological and network models (Del Valle et al., 2013). The specific infection model of Smieszek (2009), used here, leverages the granular data on who, when, where, and for how long individuals interact in every activity represented by the MATSim model.

2.3.2. Infection Model Parameters

This section summarizes the source of information for each EpiSim model parameter, summarized in Table 3.

Intake and Shedding Rate

The mask an agent wears determines the *intake rate* of the agent and the *shedding rate* of their contact. We set the base values for the **shedding** and **intake rate** to 1; we did not parameterize these to be age-specific in this work. If agents are using masks, factor reductions to these parameters are applied. Published studies (Table 3) informed mask-type-specific factor reductions for cloth and N95 masks. The **duration** of contact between agents comes directly from the LAC MATSim model.

Duration of Activity

The properties of an activity in the MATSim model determine its *duration* between two agents. It is important to note that activity trajectories developed in the MATSim model are designed for agents based on their individual and household characteristics.

Contact Intensities

The *contact intensity* of interaction between agents, a relative parameter representing the intensity of viral particles shared by the two agents coming into contact, is determined by features of the space or "container" they are sharing, including its *size* and *air flow rate*; the type of activity conducted determines these parameters, in turn. For example, a cashier agent at a recently-built and ventilation-equipped supermarket will interact with a customer agent, and the two agents will share the large surrounding of the supermarket as their container; this interaction will involve lower viral particles and thus contact intensity than an interaction between a cashier and customer agent at a small, old, poorly ventilated corner store.

The contact intensity parameters are derived from information in the LAC MATSim model while also integrating external information to further characterize features of the location where the activity was conducted, as this is not included. Specifically, we developed the contact intensity parameters by integrating information from the following sources: (i) reviewing the literature on contact surveys generating contact matrices by activity type; (ii) literature-informed assumptions about the average floor size of the space in which the space-activity is conducted, and the average number of people sharing that space; and (iii) estimated COVID-19 exposure or infections rates (or relative risks) by activity type.

Contact intensities were developed first for the general baseline activity categories home[4]; work, business, and errands; schools and preschools; universities; public transport; leisure; and shopping[5]. Then, contact intensities for specific occupational categories conducted during 'work' were developed as intensities relative to the general baseline contact intensity for 'work.' Finally, when simulating scenarios to test the impact of NPIs on distancing interventions, further relative changes were implemented to contact intensities as described in Section 4.

To develop the contact intensities, we adopt the expression developed in Mueller et al. (2021) for parameterizing the contact intensity for a specific space activity based on the fixed spatial location where the

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[4] See https://github.com/matsim-vsp/matsim-episim-la/blob/4c0fa165732434e72a1b93744902933c86165e8a/src/main/java/org/matsim/run/modules/OpenLosAngelesScenario.java#L94.

[5] See https://github.com/matsim-vsp/matsim-episim-la/blob/5d609de52ce60e3db6307535c122f930873e90e6/src/main/java/org/matsim/run/modules/OpenLosAngelesScenario.java#L96.

activity is generally occurring. The expression relies on first developing the contact intensity for a 4-person household living in a home of 'average' dimensions as,

$$Contact\_intensity_{home} = (floor\_area\_pp\ * air\_exchange\ * share\_old\_buildings)_{home}$$

where floor_area_pp represents the floor area dimensions divided by the number of people; air_exchange represents the average air exchange rate for the home, and share_old_buildings represents the share of homes without HVAC systems installed. Then, the contact intensities for space-activity combination k is developed as,

$$Contact_{intensity_{space-activity_k}} = \frac{(floor\_area\_pp\ * air\_exchange\ * share\_old\_buildings)_{home}}{(floor\_area\_pp\ * air\_exchange\ * share\_old\_buildings)_{space-activity\_k}}$$

The parameters for the contact intensity expressions for the baseline activity categories were developed through the following approach, relying on a combination of sources from the literature together with assumptions:

1. We assume a fixed location for each activity category where most of these activities took place (assumption).
2. We obtained references on the average floor size of the space in which the space activity is conducted and the average number of people sharing that space.
3. The air exchange rate was set to 1 for an average home (i.e., for the home activity category). For other activity categories, this was set to a value between (0.5, 10) given an estimate of the ventilation in the space relative to the ventilation in an average home (assumption).
4. The share_old_buildings for homes in LAC was set to 1 (i.e., for the home activity category). For other activity categories, this was set to a value of either 1 or 0.5, given an estimate of the share of physical spaces in this activity category relative to homes (assumption).
5. Home density, for households of sizes different than 4, is a special case. For these households, we modify the intensity as (assumption):

   $$Contact\_intensity_{home\_HHsize} = Maximum\ (1.0, HHsize/4.0)$$

   where *HHsize* is the number of people in the household.
6. Contact intensities for each occupation are developed as relative to the contact intensity for the 'work, business, errands' baseline category of 1.47 (Table 4). This required a different approach because many occupations require moving from room to room or involve travel and transit for which the assumption of a fixed spatial location does not work. We base the relative value for each possibly dynamic occupational activity on estimates of the relative risks (RR) of COVID-19 infection for various employment sectors from published studies (Mutambudzi et al., 2022). This approach assumes that if a certain occupation has a higher rate of observed infection, that was in part caused by workers experiencing a higher viral particle load in their occupational encounters, accounting for any interventions that were commonly put in place to reduce particle load. This approach has limitations and does not account for differences in employment-specific interventions.

The resulting contact intensities for fixed space-activity locations before stratifying by occupational category are shown in Table 4. It is important to note that Step 5, in which contact intensity for a home is determined based on the household size, was a new feature we introduced into the EpiSim model's parameterization and contributed towards the accuracy of the model's calibration to infection data.

Table 4. Contact activities by activity type before stratifying by work categories.

	Floor Size	Number of People	Floor Area (per Person)	Air Exchange Rate	Share Old Buildings	1/ (floor_pp*airX)	Resulting Contact Intensity	Notes
Home	20	4	5	1	1	0.2	1	Average floor size of dining room in a house in LAC is 20 m^2, assuming 4 people in family
Work, Business, Errands[1]	90	10	9	1	0.5	0.222	1.111	Average m^2 per employee in office space is 9 m^2. [2]
Schools & Kindergarten	60	30	2	0.5	1	1	5	Same assumptions
Universities	60	30	1	0.5	1	1	5	Classes only
Public Transport	30	30	1	1	0.5	2	10	Assumed buses (predominant public transportation in LAC: 1.3 million boardings/weekday vs. 308,653 boardings / weekday for metrorail), nobody standing (29 seats) and 30 m^2. [3]
Leisure	150	200	0.75	2	0.5	1.333	6.667	Average size for a restaurant dining area is 300 m^2 for a capacity of 200[4]
Shop	1500	200	7.5	1	0.5	0.2667	1.333	Average grocery store size is 1500 m^2 with 200 customers

[1]For these occupational activities, we use estimates of the relative risks (RRs) of COVID-19 infection for various employment sectors from published studies to scale the resulting contact intensity; see Table 5.

[2] How much office space do we need. Mike Petrusky. Office+SpaceIQ. November 24, 2020, accessed 5/17/2022. https://www.iofficecorp.com/blog/office-space-per-employee#:~:text=In%20previous%20years%2C%20workplace%20design,2020%20was%20196%20square%20feet.

[3] City|Transit Buses. Dimensions.com, 2021 accessed 5/17/2022. https://www.dimensions.com/element/city-transit-buses

[4] How to Create a Restaurant Floor Plan. Total Food Service. July 25, 2013, accessed 5/17/2022. https://totalfood.com/how-to-create-a-restaurant-floor-plan/

Table 5. Input data for parameterizing contact intensities for employment categories occurring in space-activity combinations that are not fixed in space.

Category - Occupational groups of essential workers	**RR from Mutambudzi et al., 2022**	**LA EpiSim**
Healthcare workers	7.69***[1] (5.58 to 10.60)	8
Social and education workers	1.88**[2] (1.21 to 2.91)	2
Other essential workers (including food workers)	1.15 (0.75 to 1.77)	1.15
Category - Major occupational groups	**RR from Mutambudzi et al., 2022**	**LA EpiSim**
Managers and senior officials (reference)	1	1
Professional occupations	1.53 (0.95 to 2.48)	1.5
Associate professional and technical occupations	2.78*** (1.79 to 4.29)	2.75
Administrative and secretarial occupations	1.24 (0.72 to 2.15)	1.2
Skilled trades occupations	0.50 (0.23 to 1.09)	0.5
Personal service occupations	1.77 (1.00 to 3.13)	2
Sales and customer service occupations	0.90 (0.38 to 2.16)	0.9
Process, plant, and machine operatives	1.26 (0.67 to 2.37)	1.26
Elementary occupations	0.89 (0.44 to 1.79)	0.9

[1] Mutambudzi M, Niedzwiedz C, Macdonald EB, *et al.* Occupation and risk of severe COVID-19: prospective cohort study of 120 075 UK Biobank participants *Occupational and Environmental Medicine* 2021;**78:**307-314 accessed 5/17/2022. https://oem.bmj.com/content/early/2020/12/01/oemed-2020-106731; [2]Assuming that RR of infection varies linearly with contacts.

2.3.3. Disease Progression Model

While the *EpiSim governing equation* in the infection model determines how infection is transmitted between susceptible and infectious agents, the *disease progression model* determines the course of illness and infectiousness for an exposed agent. The progression model used in this study is based on Mueller et al. (2021) and summarized in Figure 5. The model has states *exposed*, in which an agent will become but is not yet infectious; *infectious*, in which an agent can infect others; *showing symptoms*, when an agent is both infectious and symptomatic; *seriously sick*, or hospitalized, *critical*, or in intensive care; and *recovered*. Recovered agents cannot become re-infected in this model and are 'removed' from the transmission chain, i.e., they do not contribute to future spread. There is also a possible transition to fatality from the states *showing symptoms*, and *critical*; these agents are removed from the population. Please see Figure 5 documenting the full disease progression model and the age-dependent probabilities for these hospitalization and fatality states.

There is a delay of a median of 3.5 days between being exposed and becoming infectious, and another delay of a median of 2 days between becoming infectious and showing symptoms; this gap between being infectious vs. symptomatic accounts for the silent spreading characteristic of SARS-COV-2 infection. The entire infectious period is sampled from a log-normal distribution with a median duration of 4 days, implementing the logic that individuals are most infectious during the early stages of their disease, as indicated by the literature (He et al., 2020).

The age-dependent probabilities of transitioning from *showing symptoms* to *seriously sick* and *seriously sick* to *critical* were informed by estimates of these probabilities in the LAC population from Horn et al. (2021) (Table 6). Specifically, Horn et al. used an epidemic model to estimate the probabilities of transitioning from observed infection to hospitalization, and hospitalization to intensive care (ICU), using data on the number of observed infections and patients admitted to hospitals and ICUs overall in LAC. A logistic risk model was then developed to stratify these probabilities across age groups, using observed data on the frequency of each age group in infections, the population-average probabilities from the epidemic model, and data from other studies on the relative risk of hospitalization and ICU admission given infection by age. The severe illness transition probabilities are provided as time-varying in Horn et al. (2021); however, the values do not range widely over time. For this reason, and for simplicity, in this work, we implement these probabilities as the average over all time periods.

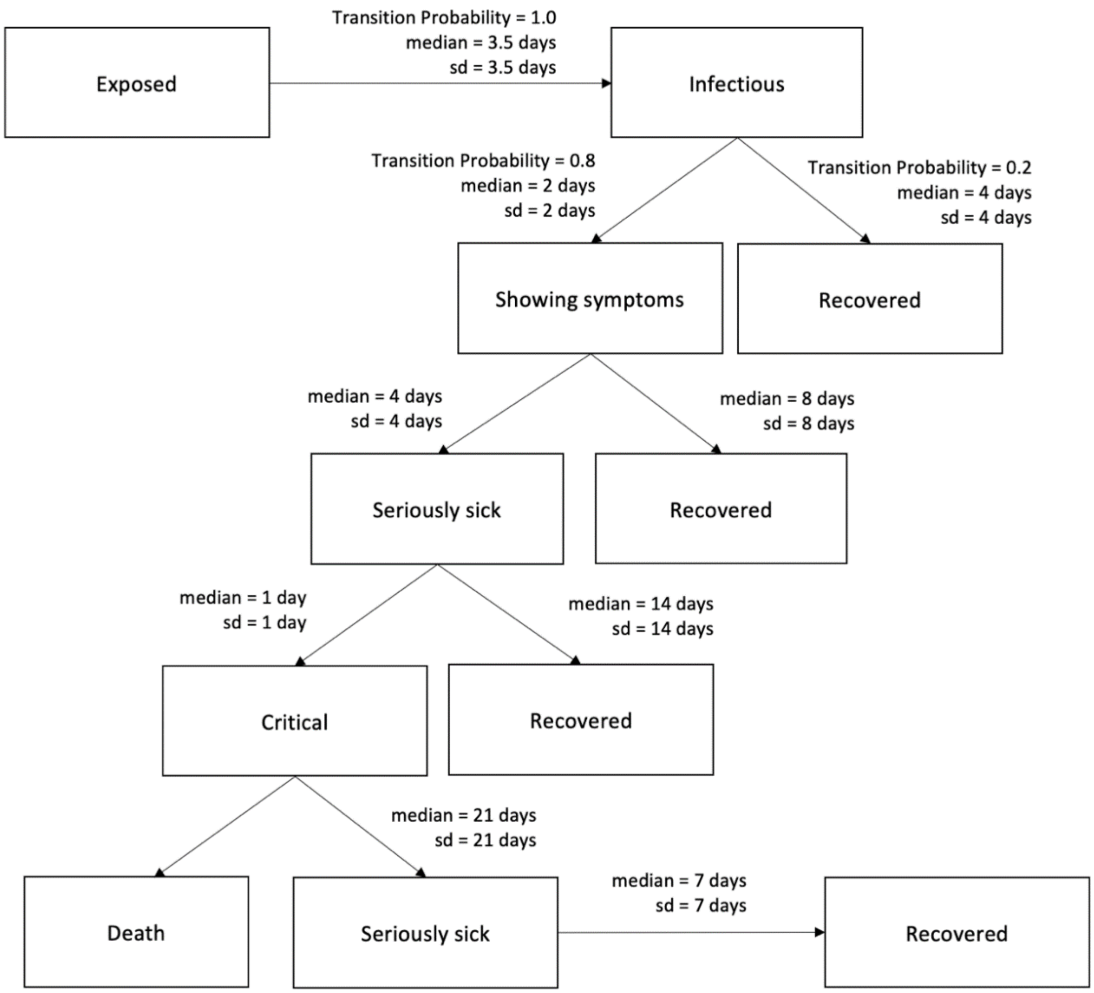


Figure 5. Disease progression model.

Table 6. Age-dependent transition probabilities.

Age-group	Exposed cases becoming symptomatic	Symptomatic cases becoming 'seriously sick' (hospitalized)	'Seriously sick' cases becoming 'critical' (in intensive care)
0 to 19	80%	1.1%	0.9%
20 to 49	80%	9.6%	6.9%
50 to 64	80%	21.8%	15.2%
65 to 79	80%	40.3%	30.4%
80+	80%	62.6%	54%

2.3.4. Simulating the Model

Simulation runs involve advancing the EpiSim model to simulate the process of the infection spreading through the synthetic population, as well as agent infectiousness and recovery (or removal). A simulation run involves the following steps:

- A simulation begins when infected agents are 'seeded' in the synthetic population, chosen at random locations. Because we model the infection period beginning already several months into the epidemic in LAC, we start with a number of seeds equal to a model-based estimate of the number of individuals currently infected at this time from Horn et al. (2021).[6]
- At some point, exposed agents become infectious and can infect others. The EpiSim governing equation is then used to determine the *probability* that they transmit infection to susceptible agents upon contact through their activity patterns determined from the LA MATSim model. Monte Carlo logic in the simulation determines if a contact results in an infection given the probability resulting from the infection model governing equation: (*1*).
- If infection happens, the newly infected agent will go on to infect others in the same process.
- Infected agents will progress from exposed to subsequent disease states as determined by the Disease Progression Model.
- This process is continued for a pre-defined number of days equal to the calendar length of the modeled time period from November 1, 2020, to February 10, 2021.

Due to the computational expensiveness of simulation runs over the 10 million synthetic agents, only one Monte Carlo seed is used for each scenario, including the finalized base case (next section). Previous work has

[6] A model-based estimate was used because the *current* number of infected individuals at any given time cannot be obtained directly from reported epidemiological infection data, which reports *new* and *cumulative* cases.

shown that the model is quite robust across simulation runs using similar parameters for the infection model, producing a narrow prediction interval range (Mueller et al., 2021).

3. Base Case Calibration

3.1. Calibration Procedure

The calibration procedure undertaken for the present project is described in the following sections. Overall, calibration concerns the production of a set of parameter values that represent the model in its "base case," which aims to reflect the observed activity levels and infection dynamics in LAC before any simulated interventions are introduced. The calibration procedure involves two steps: **Step (1): adapt elements and parameters of the EpiSim model to model reductions or changes in contact rates and intensities over time**, due to pandemic-mandated reduction of or changes in activities, peoples' own decisions to modify their behavior, or seasonally-induced changes; and **Step (2): fit the value for the meta-parameter Θ from the infection model governing equation (*1*)** by comparing the infection time series produced by the model against the time series of the number of reported infections in LAC.

3.2. Calibration Step 1: Modeling Changes in Contact Rates and Intensities in LAC

The procedure to model changes in contact rates and intensities in LAC throughout the modeled epidemic period (Step 1) involved first choosing which model elements and parameters to modify in the EpiSim model to best represent the reality of changes implemented, and second identifying data sources that can inform these changes. In the resulting calibrated base case, Step (1) includes the following modifications, noting which modifications were data-driven vs. based on assumptions where observed data was limited:

- **Step 1.1: Model changes in trips and activities** for specific activity categories at the resolved spatial level of census block group, through the integration of observed geolocation mobility data (*data-driven*)
- **Step 1.2: Model seasonally-induced changes in indoor/outdoor activities for leisure activities depending on the temperature**, by defining threshold temperatures (*assumption)*
- **Step 1.3: Model mask usage rates**, using self-reported survey data to determine mask compliance rates (*data* and *assumption)*

3.2.1. Calibration Step 1.1: Modeling Changes in Trips and Activity Levels Using Mobility Data

Throughout the modeled pandemic period in LAC, people modified their trips and activity levels following pandemic-mandates or policies such as lockdowns, specific facility closures, or capacity restrictions; or their own decisions to modify their behavior. Changes in trips and activity levels impact numbers, duration, and intensity of, contacts; and ultimately, the rate of infection spread.

3.2.1.1. Procedure for Modeling Reductions in Activities and Trips from Mobility Data

Reductions in activities and trips were informed by smartphone mobility data providing computed measures representing patterns in trips over time. In previous EpiSim applications, researchers have modeled observed changes in activity levels on highly-aggregated mobility trends on overall reductions in number of trips associated with activities conducted inside vs. outside the home at a *city* level (Muller et al., 2021). This study used a more highly-resolved source of mobility data from the company SafeGraph[7], enabling us to model changes in number of trips associated with multiple activity categories conducted at the smaller spatial level of the census block group. This data source, described in detail in the following section, provides features of the number of trips conducted each week by smartphone users living in a specific census block group (CBG) to specific geolocated facilities, or "points of interest" (POIs) outside the home (e.g., offices, schools, restaurants, clinics, parks). A new module was developed for the EpiSim framework which used these features to inform the reduction in activities and trips. The process is described in detail in Appendix 1, and is summarized below:

1. <u>Calculate aggregate of trips from home CBG to activities conducted in destination CBG</u>: Geolocated POIs in the SafeGraph data are categorized by business purpose (from the NAICS codes) (e.g., office; quick-service restaurant; high school). These categories were mapped to 25 activity categories in the EpiSim model (e.g., work, shop, restaurant). The weekly visit counts from home residence CBG to specific geolocated POI were then used to calculate the aggregate of visits from specific home residence CBG to any POI conducted within an EpiSim activity category in a destination CBG.
2. <u>Calculate weekly reductions in trips by activity category from pre-pandemic times</u>: We assumed the LAC MATSim model was calibrated to a typical week in pre-pandemic times, and we calculated the percentage change in weekly activities conducted from this time. The base week of 3/2/2020 was chosen as typical week (e.g., no holidays); any week after that was considered a scenario week. The *percentage change* in trips by activity category from/to specific CBG from pre-pandemic times was calculated as min(visit counts in the scenario week/visit counts in the base week, 1)*100.
3. <u>Modify EpiSim model to reflect changes in activities conducted from agents living in home CBG going to destination CBG</u>: The *percentage change* in trips by activity category from/to specific CBG from pre-pandemic times was used to inform the deletion of a proportional number of trips conducted by agents living in the home CBG conducting an activity in a specific activity category in the destination CBG. Methodologically, these reductions were implemented at an individual agent level by removing an activity from an individual's schedule and the associated travel to and from the activity. See Mueller et al. (2021) for details.

The consequence of activity and trip removals is that the agent whose activities have been modified no longer interacts with others in the removed activity or in transport to/from the activity, and that agent cannot infect or become infected.

[7] About SafeGraph: https://www.safegraph.com/about

3.2.1.2. Mobility Data Source

The mobility data source used to inform changes in activity level comes from the company SafeGraph, a location intelligence and measurement company that shares aggregated features of human mobility in the U.S. with academics at no cost (https://www.safegraph.com/academics). SafeGraph aggregates geolocated mobility traces from anonymized smartphone users who have opted to provide access to their GPS location to specific applications using location based services through a General Data Protection Regulation and California Consumer Privacy Act compliant framework. Permitting users have selected phone settings to allow location based services to be activated when specific apps are in use. Prior research has used this particular individual-level data resource to model the impact of nonpharmaceutical interventions during the COVID-19 epidemic (Chang et al., 2021; IHME, 2020).

Safegraph data includes a sample of approximately 10% of all mobile devices in the U.S. While Safegraph quantifies sampling bias in its panel and finds that overall it conforms well to census data at national, state, and census block groups across multiple demographic and geographic dimensions,[8] we acknowledge the likelihood for bias in the smartphone user sample. Although smartphone users constituted a large share of the U.S. adult population in 202—85%—there is some uneven representation across socio-demographic groups (e.g., lowest income bracket, 76%; older, 61%; and non-white, 83-85%) (Pew, 2021). This could lead to skewed results in estimating the reductions in specific CBG where users are less represented. The data source is described in detail in Appendix 1.

3.2.2. Calibration Step 1.2: Modeling Seasonally-Induced Changes in Indoor/Outdoor Activities

It is well-established that the probability of contracting COVID is higher for activities conducted indoors vs. outdoors. Activities conducted outdoors have lower contact intensities and thus are less likely to result in infections than are those conducted indoors, since aerosolized viral particles are quickly diffused over more expansive space and do not accumulate as happens indoors. Seasonal changes in temperature and the migration of certain activities from outdoor to indoor when it becomes colder correspondingly impact the rate of infection spread.

To implement changes in infection probabilities resulting from the transition of activities from outdoor to indoor, we make several assumptions. First, as in Mueller et al. (2021), we assume that conducting an encounter outdoors decreases the infection probability by 10 times, i.e., infection probability computed from the EpiSim governing equation is divided by 10.

Second, we assume that only specific categories of *leisure activities* have the opportunity to change from outdoor to indoor with seasonal changes—those in the social visitation, special event, and 'sport activities conducted indoors' categories. We assume that 25% of activities in each of these categories were conducted indoors during the modeled epidemic time period of November 2020–February 2021; thus, the infection

[8] See https://colab.research.google.com/drive/1u15afRytJMsizySFqA2EPlXSh3KTmNTQ#sandboxMode=true&scrollTo=t86CDrDHfi7

probability for 25% of activities in each of these categories coming from the EpiSim model governing equation was increased by an order of 10. This reduction is justified for each activity category as follows below.

- **Visitation and Special Events:** Although the Centers for Disease Control, State of California, and LAC Department of Public Health recommendations urged against it, especially as the infection rate surged in LAC, anecdotes and newspaper articles[9] report that many people had holiday gatherings, large or small. The increase in gathering is reflected in the large increase in infections 1 to 2 weeks following the Thanksgiving, Christmas, and New Year's holidays. In addition, the evening temperatures during this time period are around 50 degrees. While it is common for holiday gatherings to occur in indoor-outdoor mixed settings, we assume that a baseline of 10% of holiday gatherings would be conducted exclusively outdoors in LAC. Because we also assume that some percentage of the population canceled their holiday gatherings or moved them outdoors, we set this percentage at 25%. This assumption implies that a large component of infection spread during the 3rd epidemic period was caused by holiday and holiday-period social gathering behavior.
- **Sport Activities Conducted Indoors** were not allowed during this time period, although personal anecdotes indicate that it is likely some still occurred.

3.2.3. Calibration Step 1.3: Modeling Changes in Mask Usage

When people wear masks, their viral particle shedding and intake rates are reduced, thus reducing the probability of contracting or spreading infection in the EpiSim generating equation (Section 2.3).

Mask usage is implemented in the EpiSim framework by reducing the shedding and intake rate parameters based on published values for specific types of masks used (Table 3). Research (Konda, Abhiteja, et al., 2020) has indicated that on average, wearing a well-fitting cloth mask reduces shedding by 20% and intake by 30%. If both agents wear a cloth mask, we assume that the risk of being infected is reduced by 44% = (1- shedding rate) * (1 - intake rate).

Implementing mask usage in the base case scenario requires determining when, where, and what kinds of masks were worn during this time period. There are limited published data on mask compliance in LAC. A mask mandate for activities conducted outside the home, outdoors and indoors, was in place throughout LAC for the duration of the modeled infection period. However, not everyone followed the mandate at all times, nor did everyone properly wear a mask. We therefore made several assumptions to model mask usage in the LAC population.

[9] A new post-Christmas COVID-19 surge as holidays create 'viral wildfire' by Soumya Karlamangla, Rong-Gong Lin II, and Dakota Smith. The Los Angeles Times. DEC. 27, 2020.

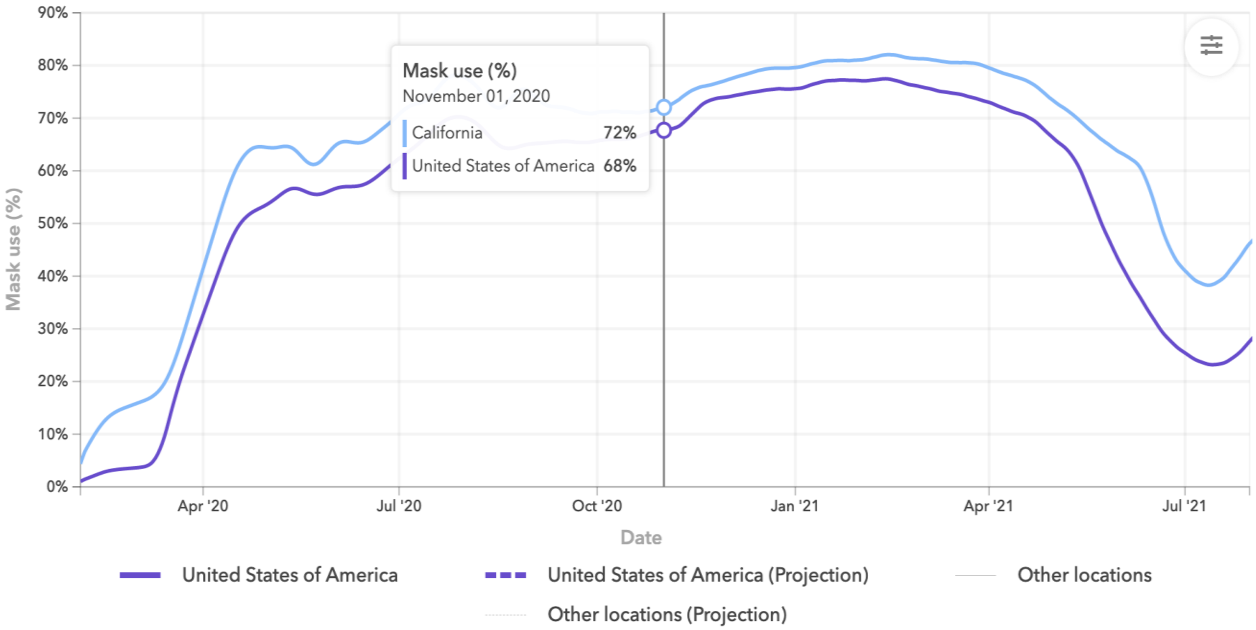
First, we assume that masks are only worn in activities outside of the home. Second, we use reports from several surveys on self-reported mask usage in LAC, California, and in the U.S. to inform mask usage rates in activities outside the home.

- The Understanding America Study Los Angeles County Population Survey ("Understanding America Study" 2020) found that approximately 90-93% of people reported wearing a mask at some point "during the previous 7 days" during the modeled time period, which may be seen as an upper bound on mask wearing as it represents any usage.
- The Delphi Group at Carnegie Mellon University and University of Maryland COVID-19 Trends and Impact Surveys ("Delphi Group.", n.d.) found that 72% respondents reported "wearing a mask" in California and 68% in the U.S. on November 1, 2020; these rates continued at similar levels for the duration of the modeled period through February (Figure 6). Given the ambiguity of "wearing a mask," which does not specify how frequently a mask is used or imply that a mask be used in every single activity, these numbers also likely represent an upper bound on mask compliance across activities.

Considering that these survey self-reported estimates of mask compliance likely represent upper bounds on actual mask compliance levels, we use the lowest rate reported to inform our assumptions. Specifically, we assume a 65% cloth mask compliance for activities outside of the home (including at work) and a 30% mask compliance for visiting activities (visiting friends/family, including social/visit friends/relatives) throughout the modeled period. This means 65% of the population wears cloth masks when they are conducting indoor and outdoor activities.

Third, we assume that all masks used were cloth masks, the lowest level protection masks. The County-wide mask mandate required that only that cloth masks be required.[10] While it was possible to access other types of masks including surgical, KN-95, and N-95, during the modeled time period, these were in shorter supply with priority for these masks reserved for first responders (Iati, 2021); news reports suggest that cloth masks were most commonly used across the U.S. population.

[10] On April 3, 2020, the White House Coronavirus Task Force and CDC announced a new behavioral recommendation to help slow the spread of coronavirus disease 2019 (COVID-19) by encouraging the use of a cloth face covering when out in public.



***Data sources**: Premise (US only); The Delphi Group at Carnegie Mellon University and University of Maryland COVID-19 Trends and Impact Surveys, in partnership with Facebook; Kaiser Family Foundation; YouGov COVID-19 Behaviour Tracker survey.*

Figure 6. Percentage of people wearing masks (last 7 days) in California and the U.S.

3.3. Calibration Step 2: Calibration to Observed Infection Data in LAC

Step 1 modified elements and parameters of the EpiSim model to represent reductions or changes in contact rates and intensities over time due to reductions in activities and trips, seasonal changes, and mask use. Once completed, Step 2 calibrated the reduced model to time series data for new and cumulative infections at the LAC level. This process involved fitting a single value for the calibration parameter Θ in the infection model governing equation (*1*) through visual comparison of the infection time series produced by the model with the time series of the number of infections in LAC during the modeled time period from November 2020 to February 2021. The model calibration was a heuristic process that aimed to choose the value of the calibration parameter Θ for which the overall time trend in modeled cases “best resembled” that of observed cases.

Since many cases of COVID were never detected or reported to public health agencies during the modeled time period, the official count of observed infection cases represents a lower bound in the true total number of people infected, including both reported and unreported cases. Therefore, infection data used to inform calibration included both (i) official counts of observed infections and (ii) estimates of the true infection count accounting for both observed and unobserved infections.

Data on (i), counts of observed and reported infections in LAC, come from the GitHub page of the Los Angeles Times (LA Times) Data and Graphics Department.[11] The LA Times collected and published official public health infection counts for each California county by aggregating reports logged by all public health agencies within each county. In LAC, this includes the Los Angeles, Pasadena, and Long Beach public health agencies.

Several estimates of the true infection count (ii) informed the calibration procedure. Horn et al. (2021) used a dynamic compartmental epidemic model, called the SEIR+ model, to estimate the true number of infections in LAC using the same LA Times data used for calibration in this work. The SEIR+ model included compartments for susceptible, observed infections, unobserved infections, hospitalization, intensive care unit (ICU) admission, death, and recovered populations, producing estimates of the time series of the population numbers in each of these compartments and a 95% confidence interval (CI) around the true total infection curve (Figure 7). Accounting for all other parameters represented in the EpiSim model, we were *not* able to calibrate the LA EpiSim model such that the modeled total infection curve fit within the 95% CI generated from the SEIR+ model. See Figure 7 below, where up_95_I_tot_new is the upper bound of the 95% confidence interval, and low_95_I_tot_new is the lower bound of the 95% confidence interval. This is possibly due to overestimates from the SEIR+ model, or due to misspecifications of the EpiSim model. Thus, the infection timeseries from the SEIR+ model was used as a qualitative benchmark for the true number of infections in LAC.

Other estimates of the numbers of cases that went unreported provided further qualitative benchmarks on the true number of infections. These include a study by Jones et al. (2021) for the LAC population, which found that 2.1 SARS-CoV-2 infections per reported COVID-19 case were estimated to have occurred, and a study by Reese et al. (2021) which estimated that across the U.S. and through the end of September 2020, 1 of every 7.1 non-hospitalized illnesses were reported.

Taking all of these estimates together, in this work we aimed to calibrate the model to an inflation of the estimate of the number of observed infections of at least two times that observed and reported.

[11] See Data LAT, Department G. california-coronavirus-data GitHub; 2021. 845 accessed 5/17/2022 from: https://github.com/datadesk/california-coronavirus-data

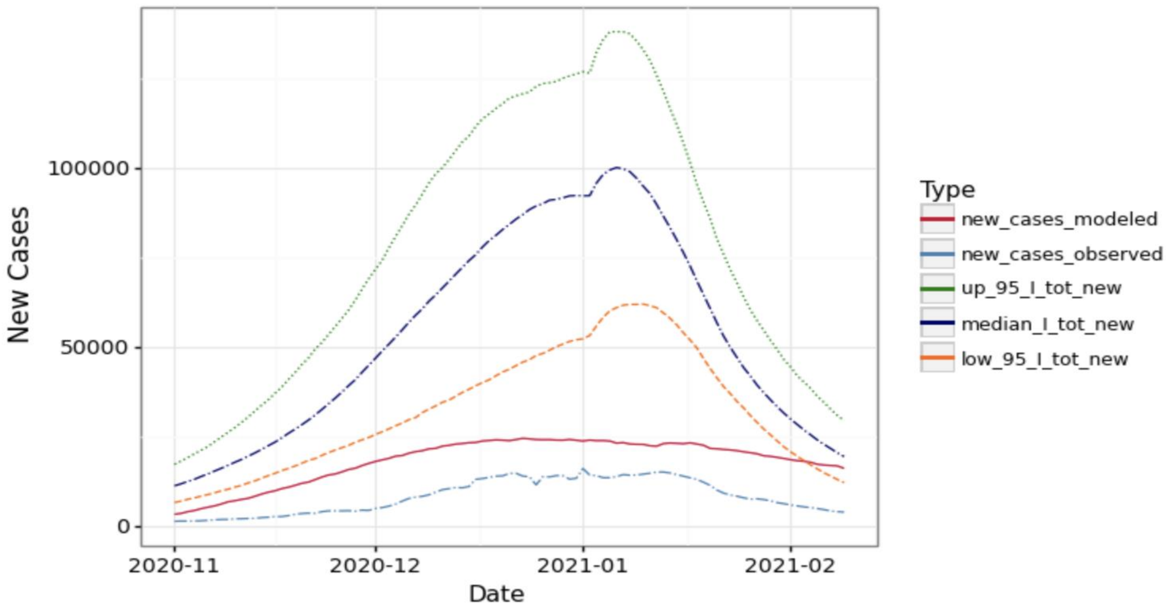


Figure 7. Calibrated EpiSim infection timeseries with data used to inform calibration.

In addition to aiming to calibrate the modeled infections to a multiplier on observed infections, the choice of calibration parameter Θ aimed to replicate several particular aspects of the trend in the observed infections over time. First, we aimed to align the peak of new cases in the observed data on January 1, 2021, with observed and estimated infection data; and second, we aimed to represent a second, smaller peak, which followed shortly after the January 1 peak in the observed and SEIR+ estimated infection trends.

3.3.1. Resulting Calibrated Base Case

The resulting calibrated base case of infections for the overall model, *new_cases_modeled*, is shown in Figure 7 against the observed and SEIR+ estimated trends.

Although not used in the calibration procedure, observed and reported infection rates by age group in LAC were compared to the modeled numbers for these same age groups as a check for the model's goodness of fit to the epidemic trends in LAC. Because the modeled base case represents a higher number of infections than reported, it was not possible to compare modeled and observed cases by age group directly. We therefore compared the proportion of new cases overall in LAC made up by each age group for observed vs. modeled cases (Figure 8), finding a reasonably good fit.

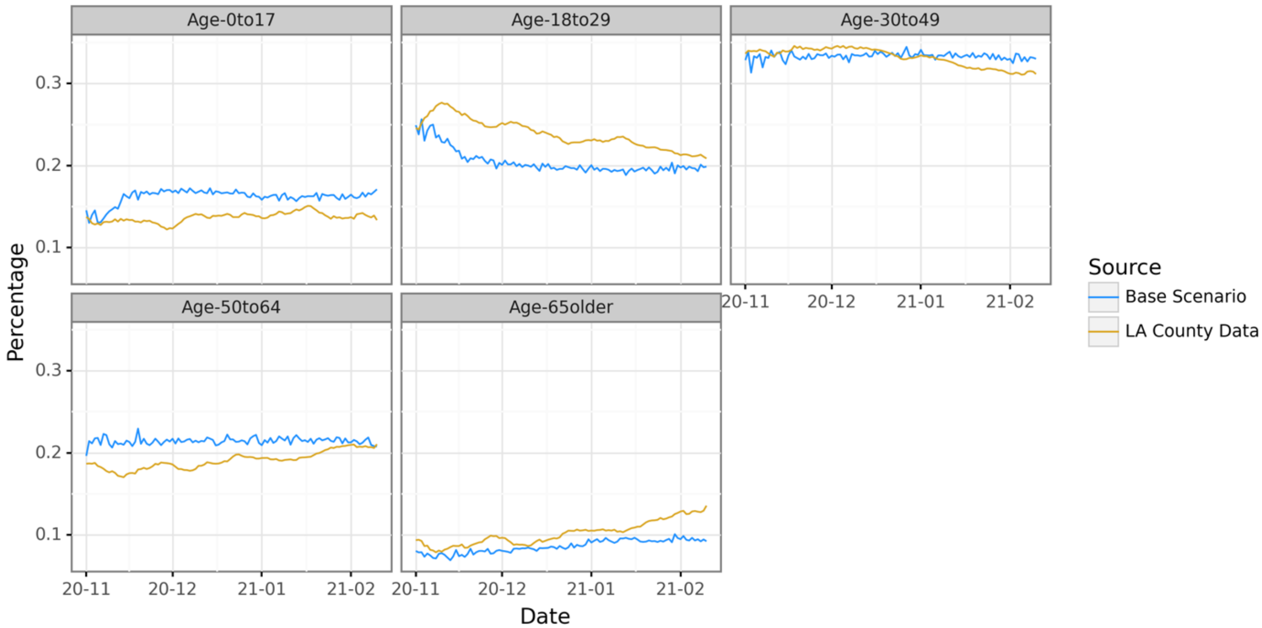


Figure 8. Proportion of new cases by age group over time in the calibrated model base case and LA County data.

4. Scenarios

This study simulated scenarios with different nonpharmaceutical interventions to reduce overall infections and avert new COVID surges. All scenarios build on the model base case, which represents the set of model parameters determined through the model calibration process and accounts for activity reductions determined by the SafeGraph mobility data. Scenarios include cloth mask compliance, N95 mask compliance, contact intensity, and testing frequency. All NPIs are implemented at intervention-specific low to high magnitude levels, allowing comparison between the same NPI at different magnitudes as well as different NPIs at the same magnitude. In the simulation of scenarios, we apply NPIs to all out-of-home activities represented in the model or to a subset of work activities deemed to be of high risk for COVID transmission, including healthcare, retail, transport, foodservice and hospitality, personal care, education, and more; the specific categories and their NAICS codes are summarized in Table 7 below (see Table 1 and Appendix 2 for more detailed descriptions of these activities).

4.1. Activity Classification

For visualization purposes, some related activity types are merged into a larger group of activities. The merged activity types are:

- Household (H.H.) maintenance activities = HHmaintenance and personal maintenance[12]
- Youth Activities = school, university, school escort, and school ridesharing
- Eatout = eatout, eatoutbreakfast, eatoutlunch, and eatoutdinner
- Transportation = non-schoolescort and public transit

We note that youth activities, including school activities, are represented in the base case model as only being moderately reduced during the pandemic period simulated in this study following calibration with the SafeGraph mobility data. This is despite K-12 schools being closed for in-person instruction during this time period. Factors that may explain why we observed only slight decreases in mobility to youth activities in the SafeGraph mobility data from pre-pandemic times include that the MATSim model represents any kind of mixing behavior between children under age 18 as youth activity, including socializing around their homes and university off-campus housing (e.g., frat party infections). Additionally, operationally, schools were still a place visited to pick up lunches, pre-K's were open, and universities were still open for research.

[12] These activities refer to activities to support household maintenance (such as banking, bill paying etc.) and personal maintenance (such as haircut, nail care etc.).

Table 7. High-risk work activities (or industry categories) considered higher risk for COVID transmission.

NAICS	Work Industry
44	Retail Trade, Including Store, Shop, Dealer (e.g., Auto Dealer)
48	Transportation, Bus or Train Company, Airline, Postal Service, Warehouse or Storage
51	Information, Including Publisher, Phone Company, Movie Company, Internet Company, Library, Data Processing, Computer Company
52	Finance and Insurance such as Bank, Insurance Company, Credit Union, Finance Company
53	Real Estate Company, Any Rental or Leasing Company Including Auto or Video Rental
54	Professional Scientific or Technical Services, Including Law, Accounting, Design, Engineering, Consulting or Advertising, Firm or Company, and Veterinary Services, Management of Companies and Enterprises
55	Management of Companies and Enterprises
56	Administrative Support, Including Employment Agency, Travel Agency, Security Guard Company, Waste Management (Trash) Company, Remediation Services
61	Educational Services, Including School, University, Training School
62	Health Care and Social Assistance, Including Hospital, Doctors Office, Assisted Living Home, Day Care Center
71	Arts, Entertainment and Recreation, Including Art Gallery, Museum, Theatre, Bowling Alley, Casino
72	Accommodation or Food Services, Including Hotel, Restaurant
81	Other Services (Except Public Administration) such as Auto Repair, Hair or Nail Salon, Barber Shop, Funeral Home, Labor Union
92	Public Administration, such as Government Agency, City or County Department, Military

4.2. Scenarios

4.2.1. Single-Intervention Scenarios

The following are the single intervention scenarios simulated in this study:

- **Base Case Scenario**: The base case implements the set of model parameter values resulting from the calibration process (see Section 3 for details), which accounts for:

  (1) Changes in trips and activity levels due to pandemic-mandated reductions or individual decisions, determined by the SafeGraph mobility data;

  (2) Seasonally-induced changes in intensity of contacts in specific activity categories when these activities transition from outdoor to indoor due to temperature;

  (3) Mask usage, which implements a 65% cloth mask compliance for activities outside of the home (including at work) and 30% mask compliance for visiting activities (visiting friends/family, including social/visit friends/relatives). This means 65% of the population wears cloth masks when they are conducting outdoor activities.

All subsequent scenarios build off of the base case scenario, meaning that the lower bound for mask compliance is equivalent to the base case values.

- **Cloth Mask Compliance Scenarios**: Scenarios increase the base case cloth mask compliance (65%) to 75%, 85%, 95%, and 100% for all activities except for home and visiting. A compliance rate of 65% means that 65% of the population properly wears their cloth mask at all times (besides home and visiting). Cloth mask compliances are applied to all indoor and outdoor activities or high-risk work activities only.
- **KN95 Mask Compliance Scenarios**: A proper KN95 mask has a filtration efficiency of 80% on average (Plana, D. et al., 2015; Yim, W. et al., 2020), reflecting a 20% intake rate. N95/KN95 respirators reduce outward particle emission rates on average by 90% and 74% during speaking and coughing, respectively, compared to wearing no mask (Asadi et al., 2020). Considering the fact that particle filtration evaluated in a lab setting does not perfectly equate to infection potential, nor account for improper mask use, we apply an overall risk reduction of 85%, meaning the shedding rate in this model is set at 0.15. The intake rate is 0.2 so that if both agents wear N95/KN95 masks, the infection risk is reduced by 1- 0.15*0.2 = 97%. Scenarios simulate 25%, 50%, 75%, and 100% compliance with N95/KN95 masks for either all indoor and outdoor activities, except 30% for visiting; or to high-risk work activities only. The N95 masks are considered as the substitute for cloth masks (65% compliance) in the base case. For instance, when applying N95 masks to all outdoor activities.

Table 8. Shedding rate and intake rate by mask type.

Mask Type	Shedding rate	Intake rate	Reduction in Infection risk	Source
No mask	1	1	0%	
Cloth mask	0.8	0.7	44%	Konda, Abhiteja, et al., 2020
N95 mask	0.15	0.2	97%	Plana, D. et al., 2015; Yim, W. et al., 2020; Asadi et al., 2020

- **Contact reduction and Capacity Scenarios**: This scenario reduces contact intensities for activity types within rooms in buildings. The contact intensities are set per activity type and are constant throughout the simulation. So, we apply percentage reductions to each base-case contact intensity for each activity type. This scenario accounts not only for increasing social distancing and therefore reduced contact intensities but also for other interventions that may effectively reduce viral particle intensity (which is what the contact intensity parameter represents) through improving ventilation (e.g., opening windows, getting fans, and installing HVAC systems for particle filtration, similar to airplanes), moving meetings into bigger conference rooms, and other similar reductions. Scenarios reduce contact intensity values by 25%, 50%, 75%, and 100% and apply to all work activities or high-risk work activities.

- **Testing Frequency Scenarios**: Antigen tests are commonly used in the diagnosis of respiratory pathogens, including influenza viruses and respiratory syncytial viruses. The U.S. Food and Drug Administration (FDA) granted emergency use authorization (EUA) for antigen tests that can identify SARS-CoV-2 and have been evaluated for ancestral, Alpha, and Delta variants. These scenarios assume that everyone in society accepts antigen tests, which are much cheaper, faster, and reliably accurate during the infectious period. A recent study in *Journal of the American Medical Association* (Harmon, A. et al., 2021) analyzed the sensitivity of self-administered antigen tests compared to qRT-PCR (as the gold standard) and broke this down by "day of the infectious period." It found that the at-home antigen test is 96.3% sensitive during days zero to three of symptoms, which are the most contagious days. Overall, from days zero to twelve of symptoms, it was approximately 80% sensitive. This suggests that at-home tests are very good at detecting current contagiousness if used in a timely manner. We modeled testing by truncating the distribution of the number of days an individual can be infected to a number equal to the testing frequency by day plus 1. This is because, assuming a test with 100% accuracy, the maximum number of days an individual can be infected is equal to the testing frequency; the plus 1 corresponds to delays in sharing of a testing result. To see this, take, for example, a testing frequency of seven days, every Monday. If person A becomes infectious on Tuesday, they will be infectious for seven days since they will not be tested again until the following Monday. If they become infectious on Wednesday, the maximum number of days they can be infectious is six, since they will be tested on the following Monday, and so on. Without truncation, each infected agent's infectious period can range from one to twenty days, determined by the log-normal distribution described above. Scenarios modeled the situation where the testing frequency is every 1, 3, 7, and 10 days. Correspondingly, assuming a test with 100% accuracy and a 1-day delay, the maximum number of days of contagiousness is 2, 4, 8, and 11 days.

Table 9. Summary of single-intervention scenarios.

Scenario Name	Intervention	Low Level	Medium Level	High Level	Upper-bound Level
Cloth mask, all	Increases cloth mask compliance for all activities from .65 base rate	0.75	0.85	0.95	1.0
Cloth mask, high-risk work	Increases cloth mask compliance for high-risk work activities from .65 base rate	0.75	0.85	0.95	1.0
N95 mask, all	Share of N95 masks for all activities	0.25 N95 / 0.40 Cloth	0.5 N95 / 0.15 Cloth	0.75 N95	N95
N95 mask, high-risk work	Share of N95 masks for high-risk work activities	0.25 N95 / 0.40 Cloth	0.5 N95 / 0.15 Cloth	0.75 N95	1.0 N95
Contact reduction, all work	Reduce contact intensities for all work activities	0.25	0.5	0.75	1.0
Contact reduction, high-risk work	Reduce contact intensities for high-risk work activities	0.25	0.5	0.75	1.0
Testing Frequency (days)	Testing Frequency for all activities	10	7	3	1

4.2.2. Combined-Intervention Scenarios

Table 10 summarizes the combined-intervention scenarios. All combinations consist of two single interventions at two intervention levels. Therefore, each combination scenario modeled includes four simulations. For the combination of cloth mask compliance and N95 mask compliance, if the cloth mask compliance for all default activities is 75% and the N95 mask compliance for high-risk work activities is 25%, the portion of the high-risk work activities wearing cloth masks will be 50%.

Table 10. Combined-intervention scenarios.

	Cloth mask compliance, all default activities	Cloth mask compliance, high-risk work activities	N95 mask compliance, all default activities	N95 mask compliance, high-risk work activities
N95 mask compliance, high-risk work activities	-N95 mask, high-risk work: 0.25, 0.5 -Cloth mask, all (beyond those with N95's): 0.75, 0.85			
Contact reduction, all work activities	-Contact reduction, all work: 0.5, 0.75 -Cloth mask, all: 0.75, 0.85	-Contact reduction, all: 0.5, 0.75 -Cloth mask, high-risk work: 0.75, 0.85	-Contact reduction, all: 0.5, 0.75 -N95 mask, all: 0.25, 0.5	-Contact reduction, all: 0.5, 0.75 -N95 mask, high-risk work: 0.25, 0.5
Contact reduction, high-risk work activities	-Contact reduction, high-risk work: 0.5, 0.75 -Cloth mask, all: 0.75, 0.85	-Contact reduction, high-risk work: 0.5, 0.75 -Cloth mask, high-risk work: 0.75, 0.85	-Contact reduction, high-risk work: 0.5, 0.75 -N95 mask, all: 0.25, 0.5	-Contact reduction, high-risk work: 0.5, 0.75 -N95 mask, high-risk work: 0.25, 0.5

5. Results

5.1. Overall Scenario Performance

This study assesses the nonpharmaceutical interventions (NPIs) that could be implemented at the early stages of a COVID-19 surge to avoid a large wave of infections, deaths, and an overwhelmed hospital system. Our case study is the LAC COVID-19 surge from November 2020 to February 2021, before vaccines had any impact (see footnote 10). Modeled scenarios are compared to the base case representing the model's version of the epidemic in LAC during this time period, accounting for reductions in activity levels and trips, and associated contact rates and intensities during this time period.

Figure 9 shows the impact of single NPIs implemented at low to high magnitude levels (see Table 9 and Section 4 for descriptions of these scenarios). Figure 9a shows the results for cloth masks, N95 masks, and distance or contact intensity policies for all activities and high-risk work activities. Figure 9b shows the results for COVID-19 testing, because it has a different base case, as discussed in Section 4 and Table 9. Figure 10 shows the percentage change in cumulative cases during the simulated COVID-19 wave from November 2020 to February 2021.

The largest reductions in new cases was achieved with universal N95 masking policy, eliminating almost all (100%) of infections. Figure 9a and Figure 10 depict results for cloth mask vs. N95 mask scenarios, showing the relative ineffectiveness of cloth mask policies and the effectiveness of N95 mask interventions for all activities and selected activities. The N95 scenario is ten percentage points (75%) above the calibrated base cloth mask compliance rate (65%). If only 25% and 50% of the 65% base cloth mask compliance rate are substituted for N95 masks across all activities, then cumulative reductions are 59% and 87%. When N95 masks interventions are applied only to selective work activities, they are less impactful, with percentage reductions from 18% to 67%. In comparison, increases in compliance with cloth masks at the low compliance level (75%) reduce the percentage of cumulative cases by 13% for all activities and 3% for high-risk work.

Compared to the N95 mask scenarios, the distance and contact intensity scenarios apply to all work activities and high-risk work activities (see Figure 9a and Figure 10). The contact intensity reduction scenarios (at .25, .5, .75, and 1 level), when applied to all work activities, reduced cumulative cases from 26% to 86%, and, when applied to high-risk work activities, decreased cases from 19% to 82%. These results show that applying distance or contact intensity interventions to all work activities rather than high-risk work activities only marginally increases reductions in infections. These results indicate that further reducing contact intensities in high contact intensity work environments reduces infections over and above what was possible during the COVID-19 wave examined in this study. Moreover, broad applications of distance or contact intensity policies to all work activities may not be the most effective use of enforcement budgets.

Finally, the antigen testing scenarios are shown in Figure 9b and Figure 10. These scenarios require that the entire population be tested every 10, 7, 3, and 1 day(s). At the higher end of testing frequency (every 1 day and 3 days), the COVID-19 surge is almost eliminated. However, the more realistic scenario levels (7 and 10 days) show percentage reductions in cumulative cases of 59% and 26%, respectively.

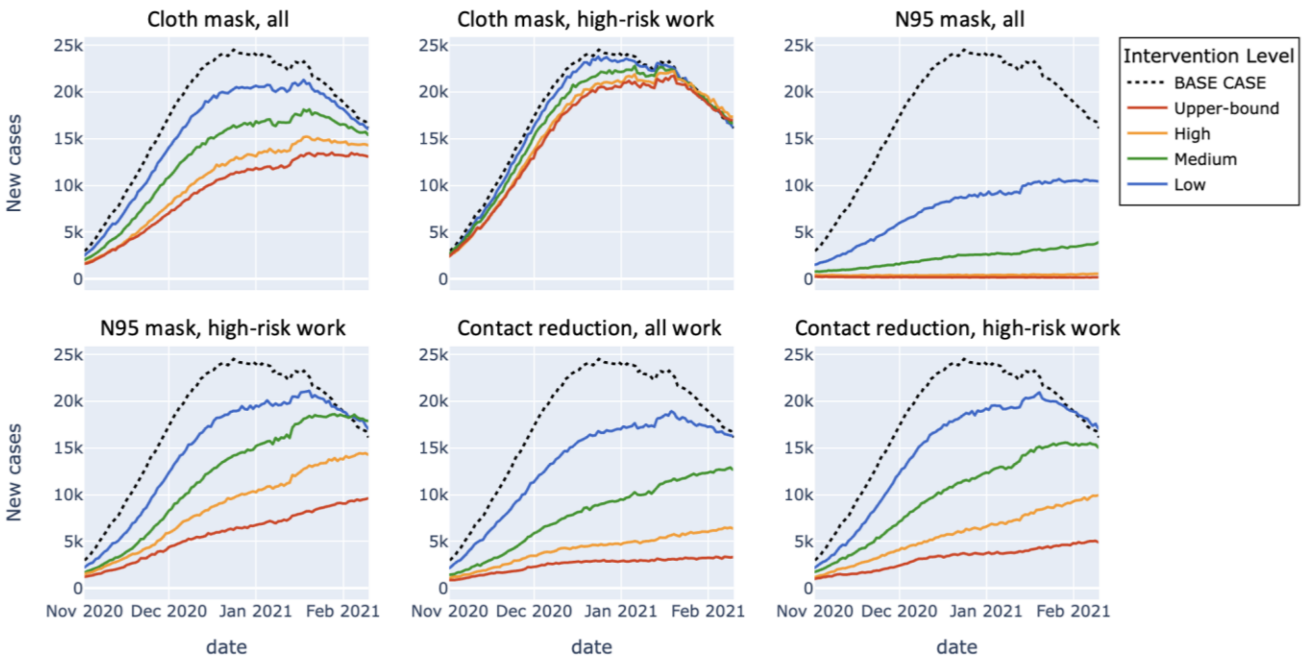


Figure 9a. Mask compliance scenarios and contact reduction scenarios

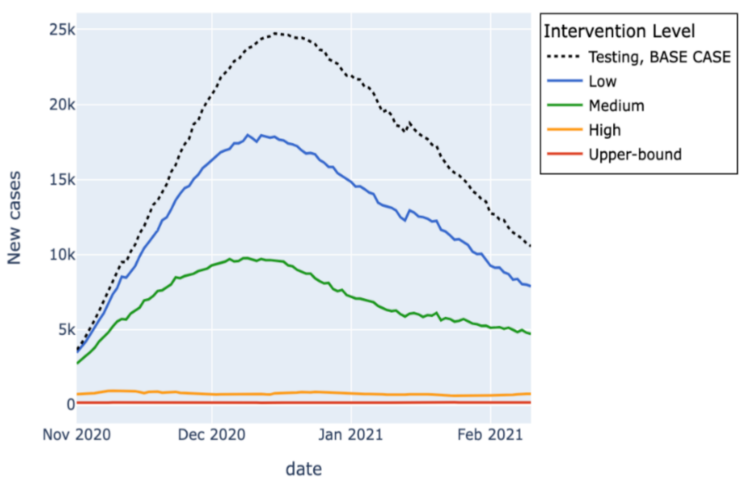


Figure 9b. Testing frequency scenarios

Figure 9. New cases over time with different single intervention levels by scenario.

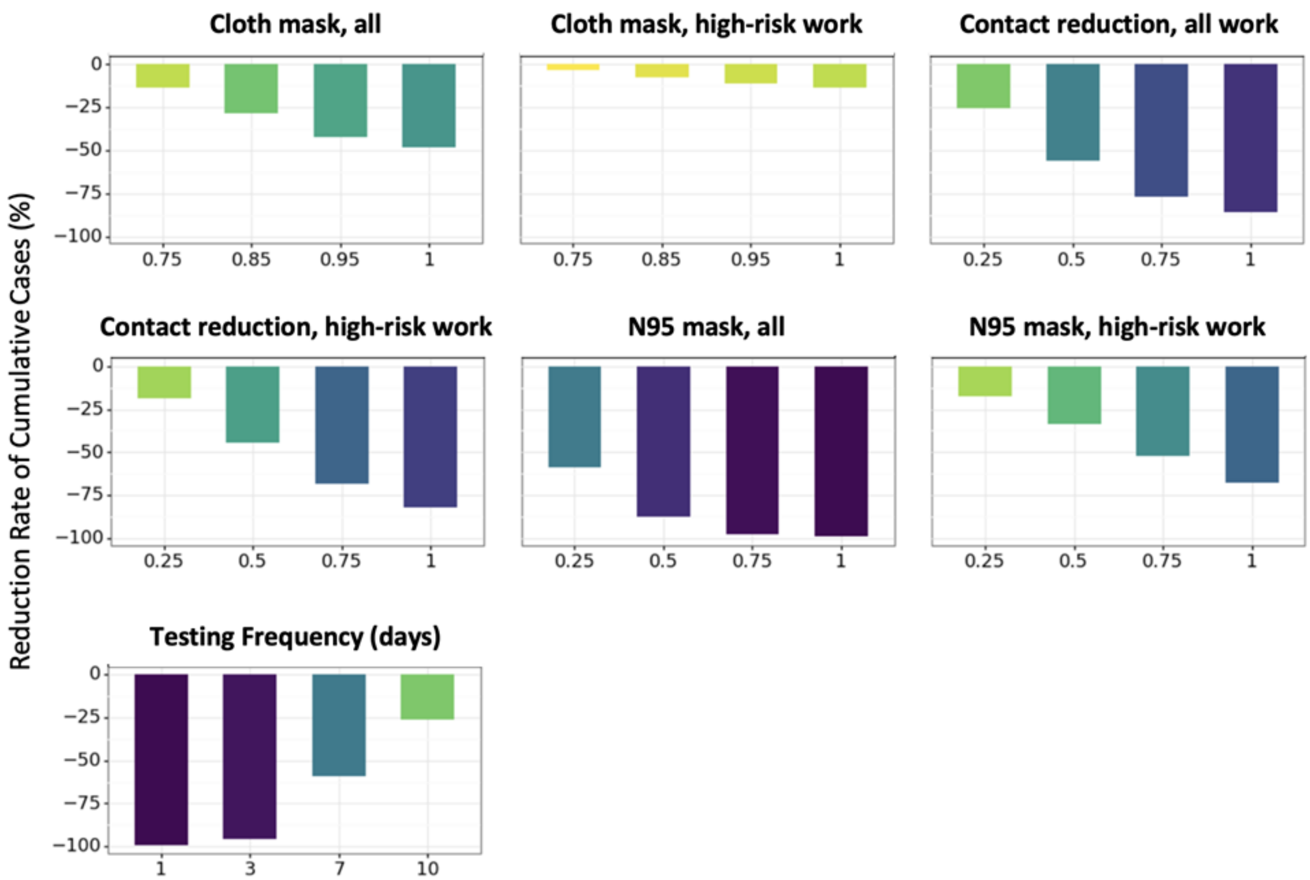


Figure 10. Reduction of cumulative cases for single-intervention scenarios.

The combined-intervention scenarios are displayed in Figure 11 for new cases over time, and Figure 12 is a heatmap that shows the percentage reduction in cumulative cases over the study timeline at the following intervention levels:

- Cloth mask compliance: low 0.75 and high 0.85
- N95 mask compliance: low 0.25 and high 0.5 (substituted shares of 0.65 base case compliance)
- Contact reduction (reduced contact intensity: low 0.5 and high 0.75)

In general, we see synergistic results in the combined-intervention scenarios. In other words, these scenarios reduce COVID-19 infection more than adding the reductions from the same individual scenarios. In the combined-intervention scenarios, this works through two mechanisms. First, fewer initial cases dampen the spread of infections and reduce cumulative inflections to a greater degree than adding the cumulative reductions from two single scenarios. Second, since the interventions work through different mechanisms, they may combine to address multiple aspects of transmission and more effectively reduce initial transmission and thus overall infection than scaling up single interventions.

In the combined-intervention scenarios, we again see a smaller marginal benefit of (1) increasing cloth mask compliance versus substituting N95 masks for cloth masks at existing levels of cloth mask use and (2) applying distance or contact intensity restrictions to all work activities versus selected high-intensity work activities. Conversely, the marginal benefit of applying N95 mask policies to all work activities is larger than applying it to high contact work activities. The most effective and least restrictive combination intervention applied is a 0.5 decrease in contact intensity and 0.25 N95 mask compliance to only selective work activities. The percentage reduction in cumulative reductions for this scenario is 53%. When N95 masks are applied to all activities instead of just selected activities in this scenario, the reduction in cumulative infections increases to 82%. If N95 mask compliance increases from 0.25 to 0.5 for all activities, then the reduction in inflections increases to 95%. Compared to the single scenarios described, the N95 mask compliance for all the 0.25 and 0.50 levels reduced cumulative infections by about 60% and 80%, respectively.

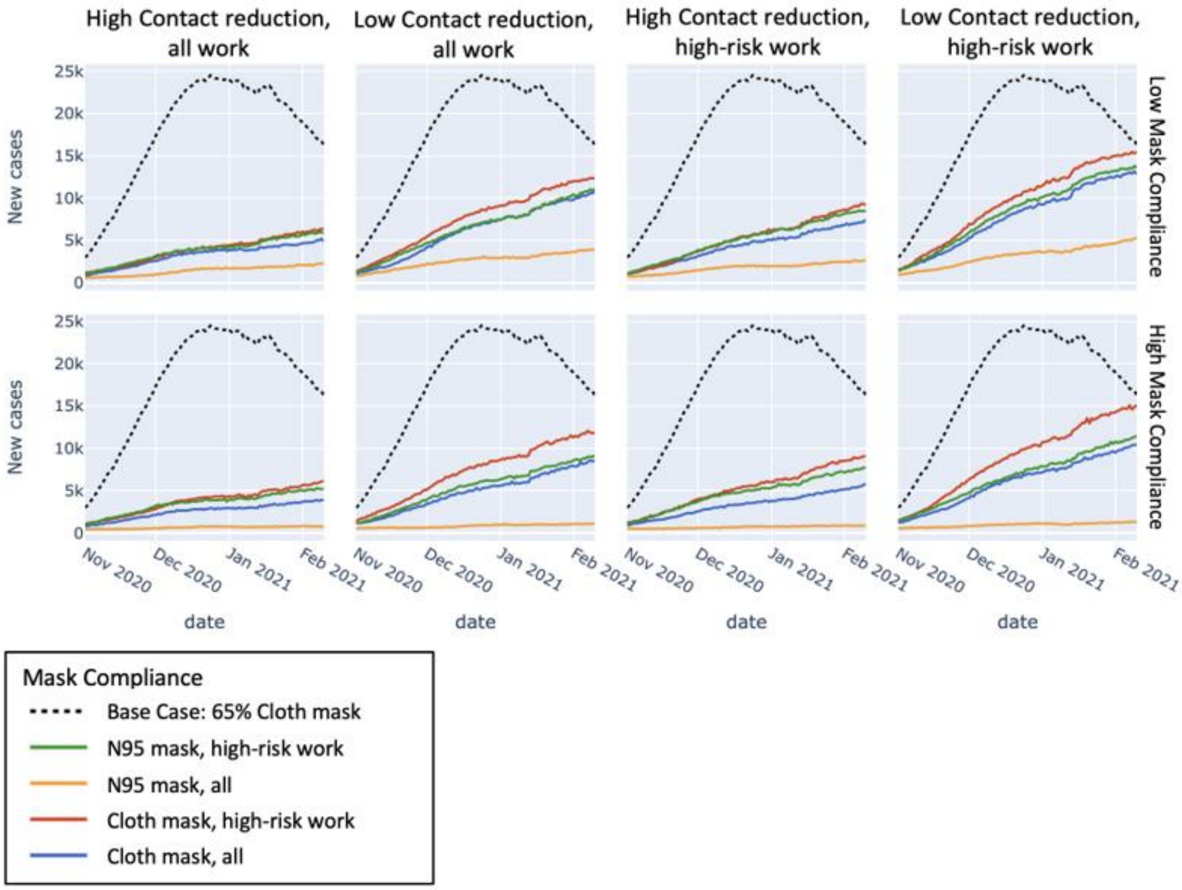


Figure 11a. Combined interventions of contact reduction and mask compliance

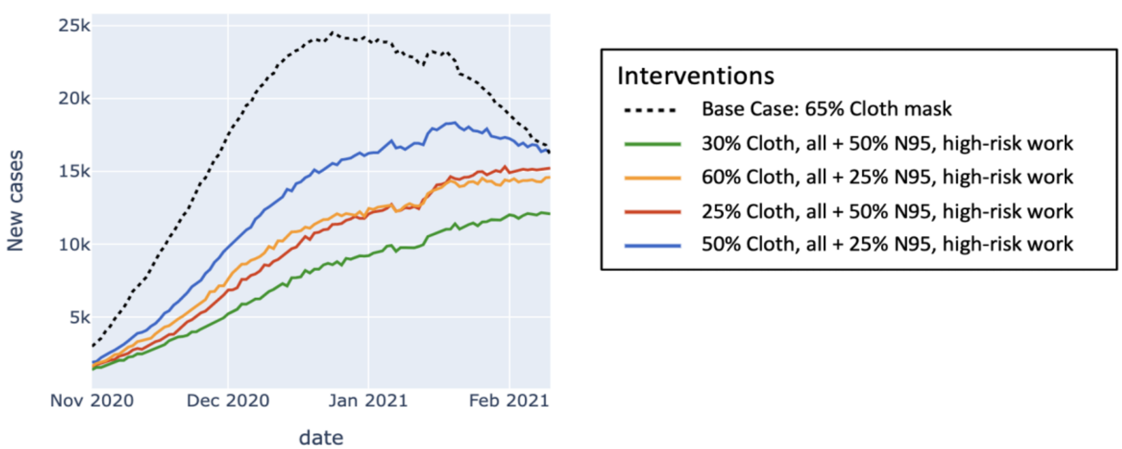


Figure 11b. Combined interventions of cloth and N95 mask compliance

Figure 11. New cases over time for combined intervention scenarios by intervention level.

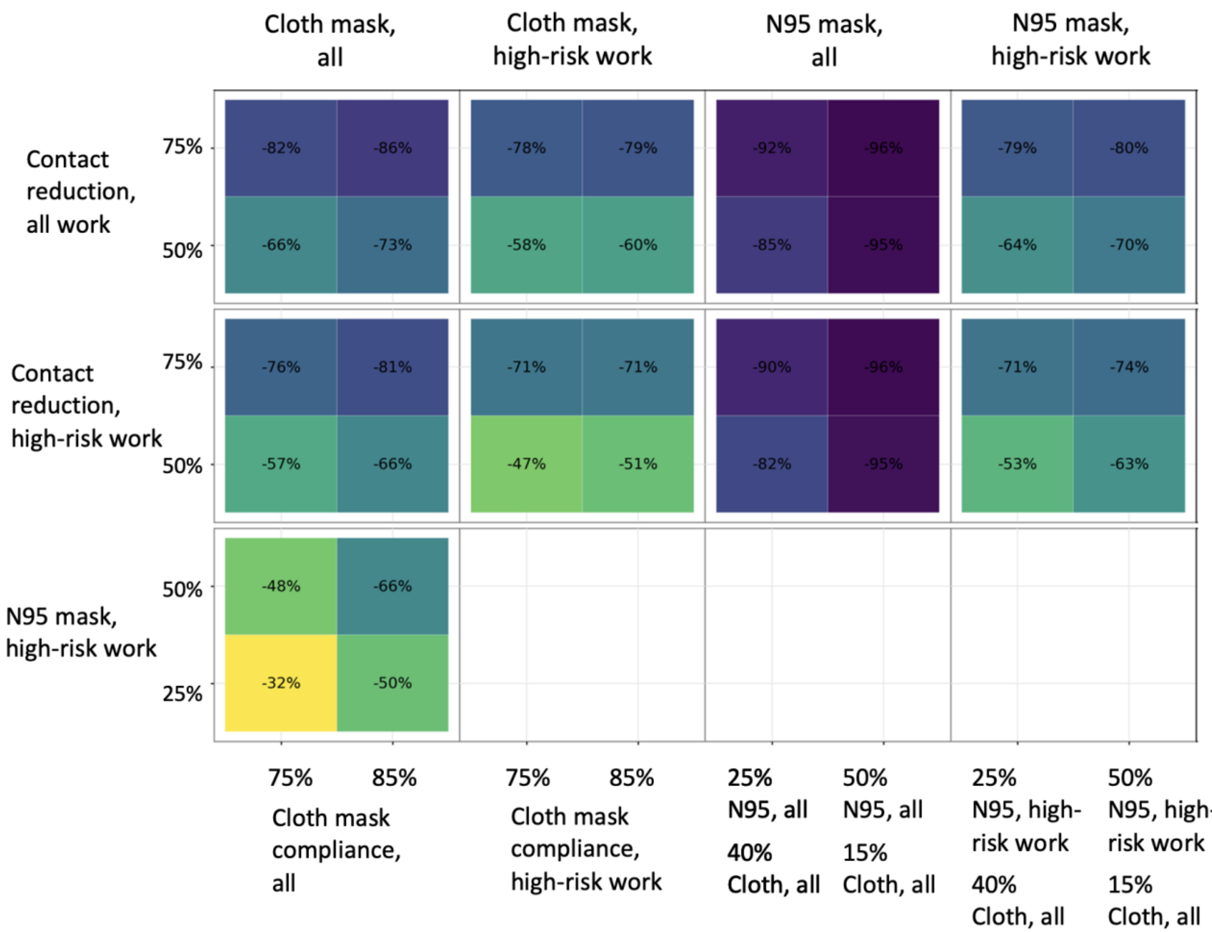


Figure 12. Reduction of cumulative cases for combined-intervention scenarios.

Table 11 analyzes the efficiency of combined interventions, that is, the extent to which the total effect of two interventions implemented simultaneously is comparable to the sum of the effects of the two interventions if implemented individually. The last column of the table, *Combined Intervention A&B efficiency*, shows the ratio between the effect of the combined intervention on reducing infections (%) over the sum of the effects of each individual intervention A and B. This indicates how much unique value each intervention is contributing to reducing infections in the combined intervention. We can see that there are several interventions with uniqueness of 81% or higher (highlighted in yellow), indicating the combined interventions that are working most independently from one another to achieve a reduction in overall infections, and thus doubling up on the same effort. Combined interventions with low uniqueness and thus high overlap are less efficient at reducing infections. **The combined intervention that jointly maximizes both the efficiency/uniqueness of each of the individual interventions (80% in the last column) and overall effectiveness in reducing infections (82% second to last column) involves 50% contact reduction in high-risk work categories only, combined with 25% of the population using N95 masks in all activity categories and 40% of the population using cloth masks (second row, highlighted in green).**

Table 11. Synergistic effects and efficiency of combined interventions.

Intervention A (Contact reductions)	Intervention A Reduction (%)	Intervention B (Mask usage)	Intervention B Reduction (%)	Sum of Intervention A and B Reduction %'s	Combined Intervention A&B Reduction (%)	Combined intervention A&B efficiency (A&B/A+B)
75% Contact reduction, high-risk work	68%	25% N95 mask, all + 40% Cloth mask, all	59%	127%	90%	70%
50% Contact reduction, high-risk work	44%	25% N95 mask, all + 40% Cloth mask, all	59%	103%	82%	80%
75% Contact reduction, high-risk work	68%	50% N95 mask, all + 15% Cloth mask, all	87%	156%	96%	61%
50% Contact reduction, high-risk work	44%	50% N95 mask, all + 15% Cloth mask, all	87%	132%	95%	72%
75% Contact reduction, high-risk work	68%	25% N95 mask, high-risk work + 40% Cloth mask, all	18%	86%	71%	82%
50% Contact reduction, high-risk work	44%	25% N95 mask, high-risk work + 40% Cloth mask, all	18%	62%	53%	85%

Intervention A (Contact reductions)	Intervention A Reduction (%)	Intervention B (Mask usage)	Intervention B Reduction (%)	Sum of Intervention A and B Reduction %'s	Combined Intervention A&B Reduction (%)	Combined intervention A&B efficiency (A&B/A+B)
75% Contact reduction, high-risk work	68%	50% N95 mask, high-risk work + 15% Cloth mask, all	34%	102%	74%	72%
50% Contact reduction, high-risk work	44%	50% N95 mask, high-risk work + 15% Cloth mask, all	34%	78%	63%	81%

* Green highlight indicates most effective and efficient scenario; yellow highlights the only the most efficient scenarios

5.2. Scenario Performance by Age Groups

Figure 13 explores how these interventions influence different age groups. The reduction rate does not differ significantly among age groups for interventions applied to all activities. However, for interventions applied to high-risk work activities, the reduction rates in school-aged children (age 0 to 17) and slightly in those aged 18 to 29 are lower than in the other groups. The reason is that children and university students are not employed and thus are not impacted by the implementation of high-risk work activities. The model does not simulate scenarios designed specifically for these groups because schools were closed during the study period, and thus, it is hard to implement the restrictions on students. On the other hand, 30–65-year-old people are most likely employed and are affected equivalently by each intervention.

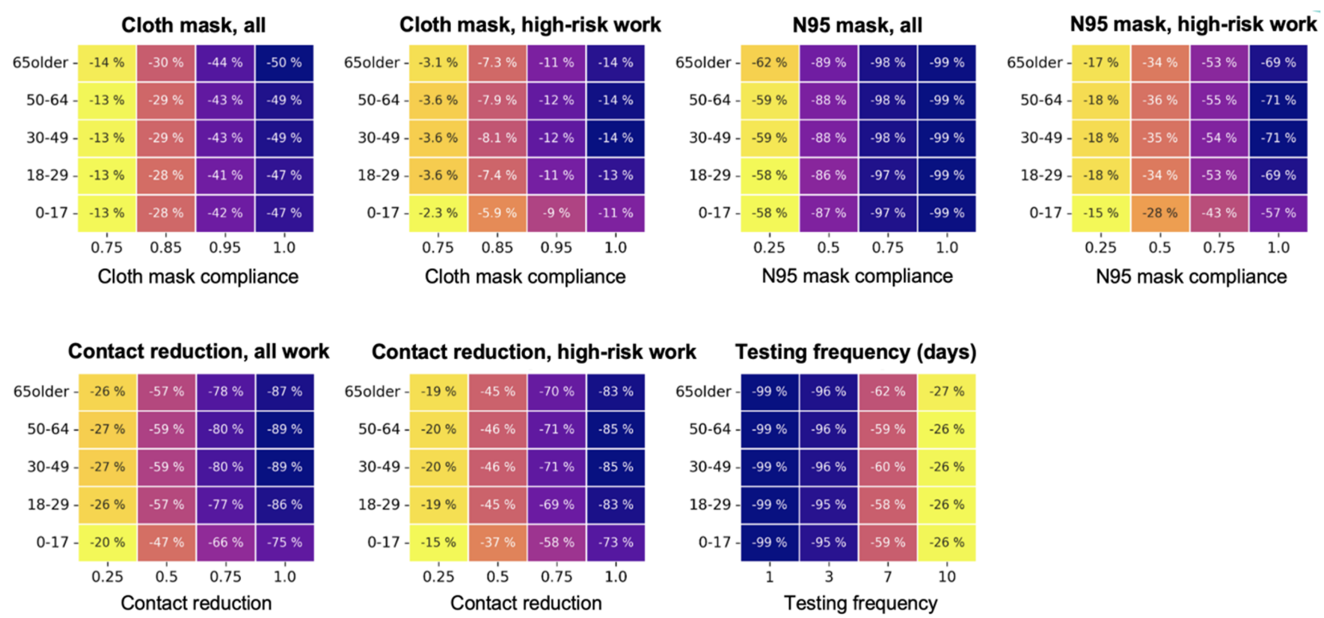
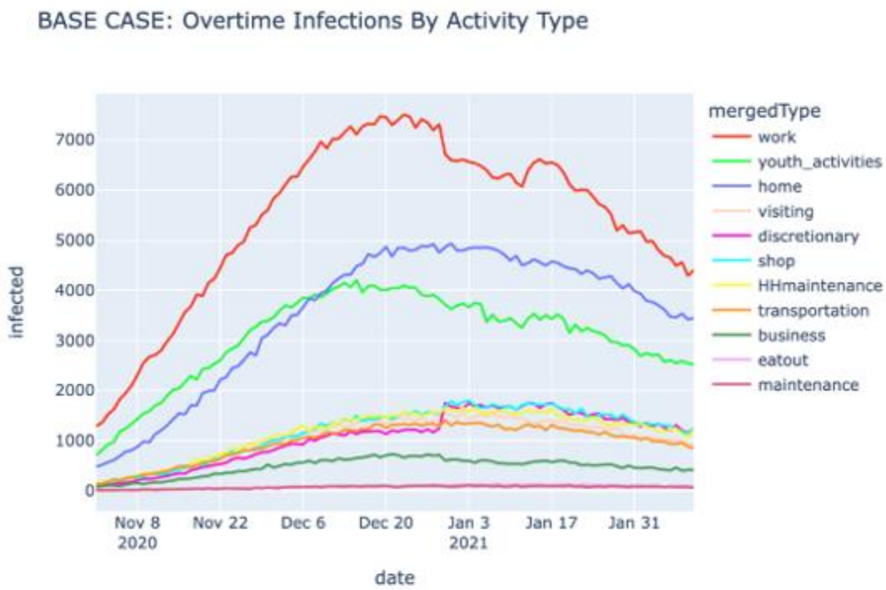


Figure 13. Reduction of cumulative cases by age group.

5.3. Scenario Performance by Activity Types

Figure 14 shows infections over time by activity type in the base case scenario. Most infections come from work and home activities. Over time, infections shift from work locations to home. Youth activities also account for a large proportion of infections.



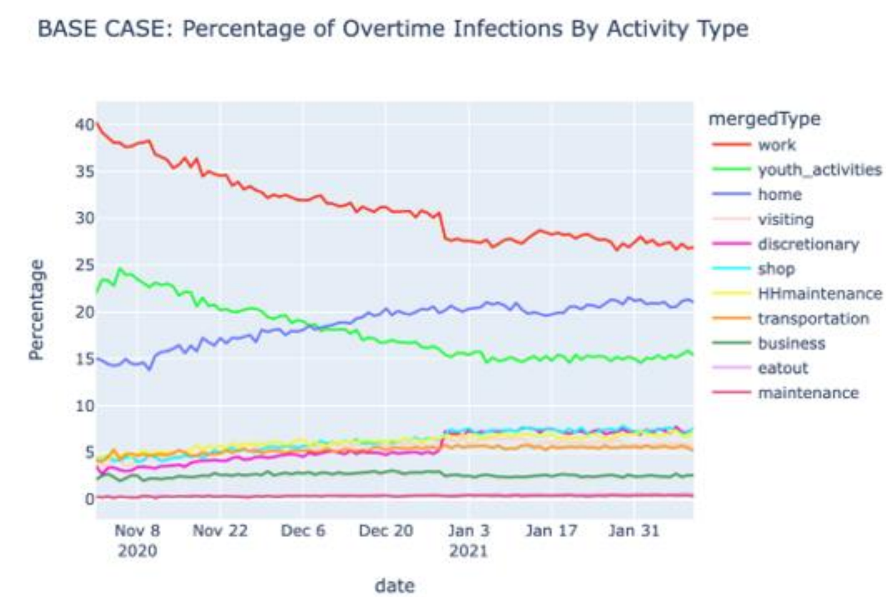


Figure 14. Base case: infections over time by merged activity type.

We explored infections over time by merged activity types for each scenario and found that most scenarios have the same pattern as the base case results, which means the interventions have the same degree of impact on all merged activity types. However, some scenarios show different patterns—for instance, Figure 15 displays infections over time by merged activity type for N95 mask compliance scenarios. Applying N95 mask compliance to all activities has an equivalent effect on all merged activity types, and it is a potent intervention for reducing infections. As for N95 mask compliance for high-risk work activities, there is a notable decrease in infections from work activities. Again, youth activities are less affected because youth are not employed and therefore not affected directly by this intervention. The distance scenarios in Figure 16 also show the same pattern as N95 mask compliance scenarios because distance interventions apply to only work activities.

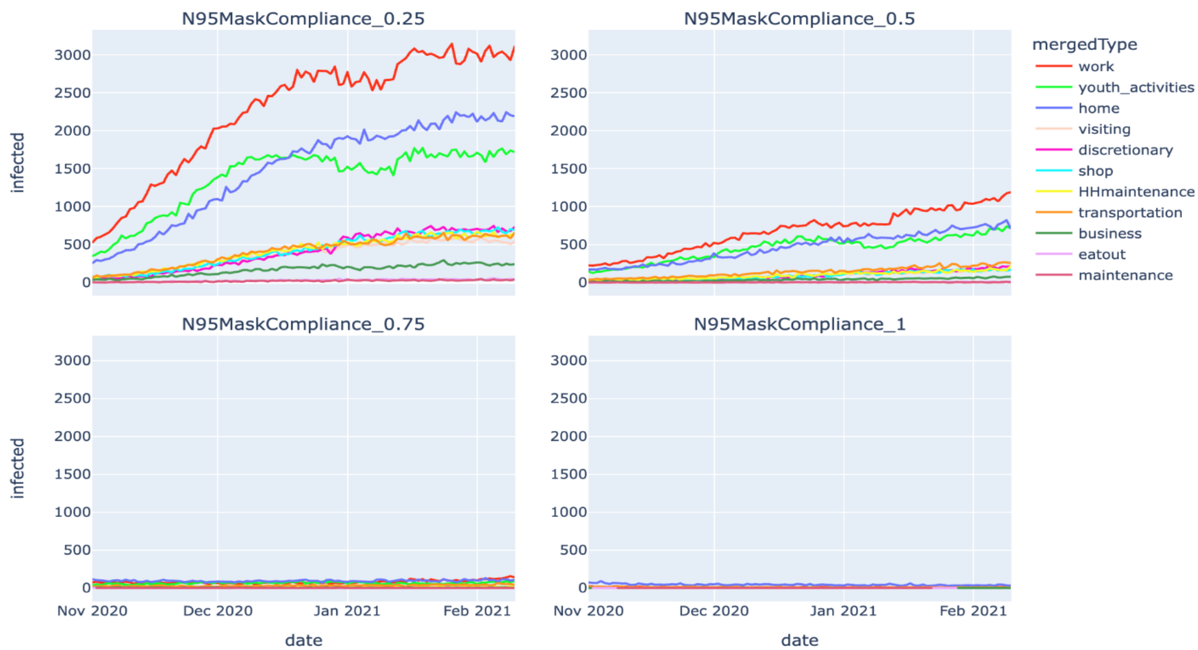


Figure 15a. N95 mask, all

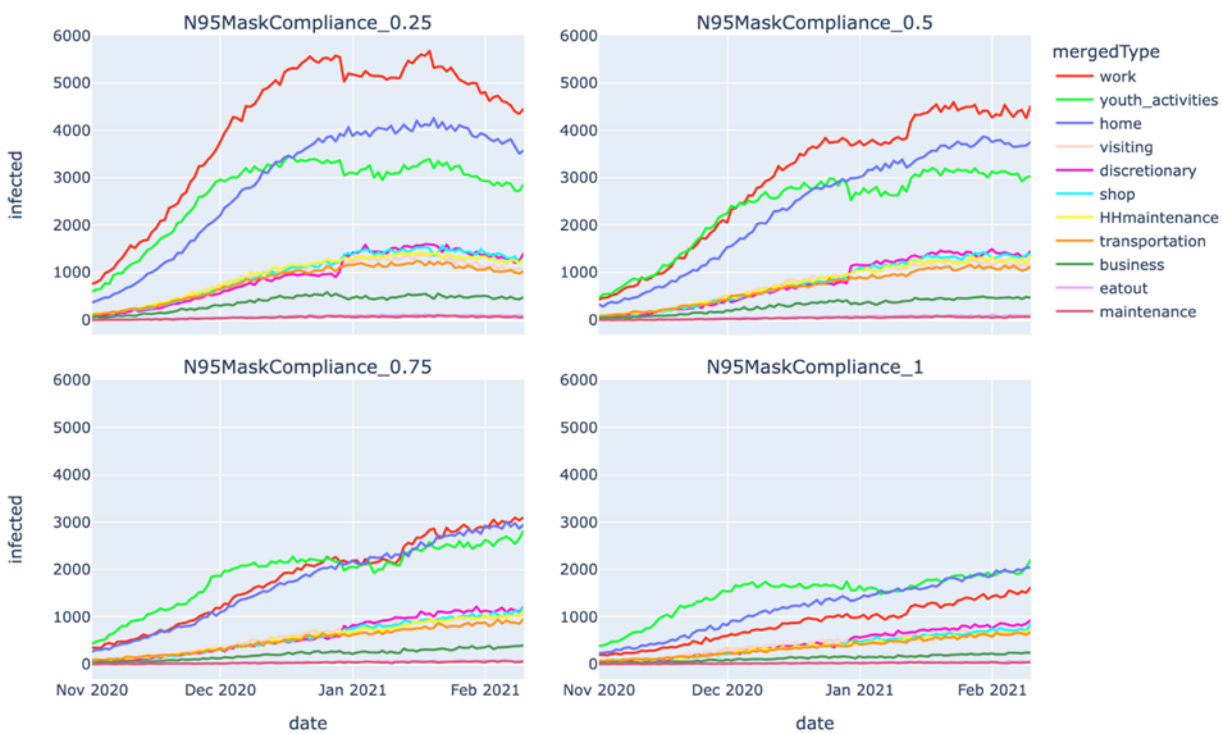


Figure 15b. N95 mask, high-risk work

Figure 15. N95 mask scenarios: Infections over time by merged activity type.

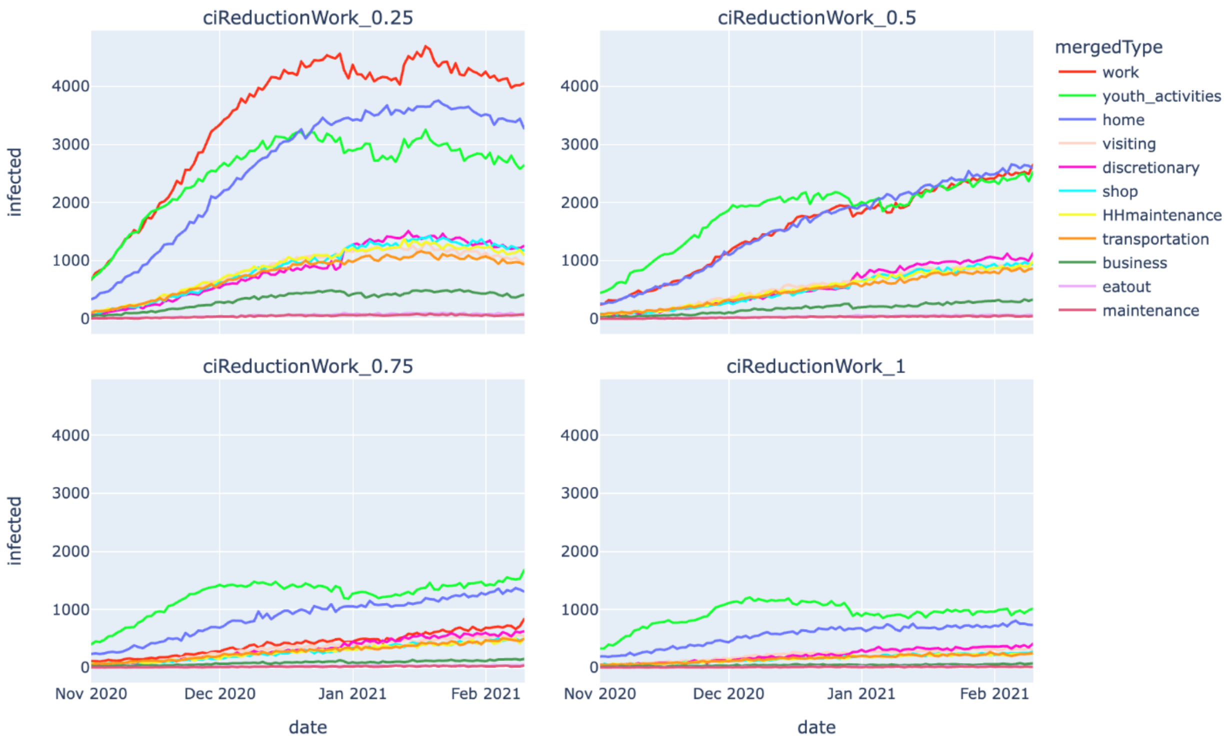


Figure 16. Contact reduction scenarios: Infections over time by merged activity type.

The percentage of infections for work is impacted strongly by the distance or contact intensity scenarios at all intervention levels. This is because the interventions are implemented directly on all or selected employed populations by reducing contact intensities for each work category. In contrast, distance interventions do not affect youth activities because youth are not included in the employed groups.

Applying high-level N95 mask compliance to all activities can effectively reduce infections from all activities except home, because masks are not typically worn at home.

6. Conclusions

This study was a simulation to assess nonpharmaceutical interventions (NPIs) that could be implemented at the early stages of a COVID-19 surge to avoid a large wave of infections, deaths, and an overwhelmed hospital system. To simulate the implementation of the NPIs, we integrated a dynamic agent-based travel model with an infection dynamic model. Both models were developed with and calibrated to local data from LAC, resulting in a synthetic population of 10 million agents with detailed socio-economic and activity-based characteristics representative of the County's population, including work categories. We focused on the time period of the second wave of COVID-19 in LAC from November 1, 2020, to February 10, 2021, before vaccines were in use[13]. We accounted for mandated and self-imposed interventions in-place during this time period, including mask usage, school closures, and temporary shutdown of specific activities. We did this by incorporating (i) mobile device data providing observed reductions in activity patterns from a pre-pandemic norm, (ii) assumptions about which activities were conducted indoors vs. outdoors, and (iii) evidence-based assumptions regarding mask coverage and closure of specific activities. NPIs evaluated included cloth masks, N95 masks, antigen testing, and reductions in contact intensities, with comparisons made between interventions implemented for all vs. only high-risk activities.

6.1. Study Findings

The highly-detailed representation of populations and activity types for the LAC population enabled this study to derive several findings relevant to public health policy interventions in the community and at the workplace. Here we summarize the key results across all **individual** NPIs evaluated. The findings from this study suggest that:

(1) **Reasonable substitutions of N95 masks for cloth masks at baseline use levels significantly reduced cumulative infections.** If only 25% and 50% of the baseline 65% of the population using cloth masks substituted N95 masks across all activities, then cumulative reductions are approximately 60% and 85%.

(2) **N95 mask interventions are substantially less impactful when applied to high-risk activities only**, with percentage reductions from approximately 20% reduction for 25% usage (vs. 60% reduction for all categories) to 65% reduction for 50% usage (vs. 85% reduction for all categories).

(3) **Contact reduction interventions, on the other hand, are similarly impactful when applied to all work types or high contact intensity work types only**. A contact intensity reduction of 25% and

[13] The first vaccines were technically administered in mid-December in LAC but were focused exclusively on healthcare workers. Rollout to at-risk populations (65+ years old, immunocompromised) did not begin until mid-January, and then only at a rate of approximately 10,000 doses / week. We furthermore note that vaccine effectiveness for a first dose is lower than for the two-dose series, and both take several weeks before their effectiveness is demonstrated. Therefore, we conclude there was only very minor vaccine coverage in LAC during this time period.

75% applied to all work activities reduced cumulative cases by approximately 25% and 75% when applied to all work categories, and by approximately 20% and 70% when focused on high-risk work categories.

(4) **N95 masks applied to all categories were substantially more impactful than contact reduction interventions to all work categories**, however, when N95 masks are applied in only high-risk work categories, they are less impactful than contact reductions to high-risk categories.

(5) **Antigen testing is also very effective at reducing cumulative infections, at frequencies higher than once a week**. At the higher end of testing frequency (every day and 3 days), the COVID-19 surge is almost eliminated. However, the more realistic scenario levels (everyone testing every seven and ten days) show percentage reductions in cumulative cases of approximately 60% and 25%, respectively.

(6) An approximately **50% reduction in cumulative infections** is achieved by each of the following: **25% of the population wearing N95 masks across all work activities**; 75% of the population wearing N95 masks only when engaged in high-risk work activities; **100% of the population wearing cloth masks across all work activities**; approximately 50% of the population implementing contact reductions in all or high-risk work categories; or **the entire population testing once a week**.

The modeling framework used in this study allowed the representation of potential synergistic effects of combining intervention scenarios. The results across **combination** scenarios suggest:

(7) The most effective and least restrictive scenario included a 50% contact reduction and 25% N95 mask compliance, both to only high-risk work activities; this reduced cumulative infections by approximately 50%.

(8) When a 50% contact reduction is combined with 25% N95 mask compliance in all activities instead of only high-risk activities, the reduction in cumulative infections increases to over 80%.

(9) When a 50% contact reduction is combined with N95 mask compliance at 50% for all activities, then the reduction in inflections increases to 95%.

(10) Compared to these scenarios combining N95 and contact reduction interventions, scenarios involving only N95 masks at 25% or 50% compliance in all activity categories reduced cumulative infections by about 60% and 80%, respectively.

(11) An 80% decrease in cumulative infections is achieved by combining 50% reduction in contact in high-risk work categories with 25% N95 mask compliance in all work categories (similar results for a 50% contact reduction in all work and not only high-risk work categories), or 75% contact reduction in all work categories with 75% adoption of cloth masks in only high-risk work categories.

(12) The most efficient combined intervention (that is, the combination where each component works most independently from one the other to achieve a reduction in overall infections and not doubling up on the same effort) **with the largest impact on reducing overall infections is: 50% contact**

reduction in high-risk work categories only, combined with 25% of the population using N95 masks in all activity categories, and 40% of the population using cloth masks.

6.2. Public Health Takeaways

We now synthesize the evidence across all quantitative findings from the effect of interventions on reducing infections for public health practice. Overall, we found that combining NPIs is the most effective way to achieve reductions in infections at the least restrictive levels of intervention. In particular, when N95 masks are paired with shutdown and capacity restrictions adopted during the second COVID-19 surge in LAC, they can be very effective even without increasing the overall masking levels observed during this time period (i.e., 65%). These results suggest that great gains can be achieved in reducing infection rates at more 'tenable' NPI implementation and compliance levels.

We also observed that small increases in the proportion of people using N95 masks in the workplace and general community can be very effective in reducing spread, again even without even increasing overall masking levels. For example, substituting 25% of the observed 65% of cloth mask usage for N95 masks across all, not just high-risk, workplace and community categories results in an almost 60% reduction in cumulative infections.

We also identified the possibility for specific interventions to exacerbate health inequities in specific groups. In practice, NPIs are often mandated, enforced, and adopted at different levels in different activities; for example, some workplaces will require a higher level of intervention than mandated by public health authorities, while others will not monitor or enforce the adoption of these mandates; certain high-risk activities are shut down first during phased lockdowns, while others are allowed to remain open. Our study findings indicate that these types of selective interventions can result in unequal impact across populations. In particular, we found that when interventions such as N95 mask adoption and contact reductions are adopted in only high-risk workplace and community activities, they have a disproportionately lower impact on reducing infections in younger and older populations. These groups are not or are less likely to be, respectively, in the workforce and involved in community activities such as shopping, personal care, and other errands. These results held true despite these populations being socially connected (i.e., having contact) with the workforce population and despite the model accounting for school closures impacting younger populations. A tentative conclusion from these findings is that workplace-specific interventions must be combined with effective home- and visitation-level interventions that are targeted towards youth and elderly populations.

6.3. Recommendations

Our analysis of possible policy interventions focused on the direct public health impact, i.e., reducing infections, in the LAC population overall and for specific age groups and activity categories. A complete policy analysis prior to implementation requires analyzing dimensions of cost, political appetite for mandates, and enforceability (Reddy et al., 2021; see also Persad & Pandya, 2022). A very high-level analysis across these dimensions points to the strength of N95-related interventions over other interventions. N95 masks are cost-effective (as low as $1-2/mask), compared with $10/antigen test or untold costs in enforcement of contact reduction interventions across communities (including costs on the workplace). While there have been large debates regarding the mandatory use of masks, a shift in those already using cloth masks to upgrade to a more effective N95 respirator could be a less intrusive and thus more likely adopted policy intervention; large effects are seen at levels as low as 25% adoption. This scenario is also significantly less restrictive and thus more politically viable than shutdown or contact reduction interventions, which require more extensive modifications (or even elimination) of behaviors. These advantages of upgrading mask quality compared to more extensive changes especially apply to the highest-risk activities, which are often those most unpopular for shutting down, e.g., restaurants (*Will Nicholas, LACDPH, personal communication*). It is important to note that from a policy perspective distribution and enforcement of N95 masks would require a strong network of action between local health departments and community-based organizations to ensure that citizens have access to and wear masks when out in the community. Still, enforcement of the other NPI considered here, contact reduction interventions, is likely to be significantly more difficult; this requires a combination of policies around restrictions and paid leave for workers, especially essential workers, to enable individuals to appropriately implement interventions (e.g., workers are provided support for paid time off or sheltering away from family members, in a culturally appropriate way). To the best of our understanding, these types of measures have not been successfully implemented at scale across LAC during the previous epidemic surges. Thus, weighing all of these considerations, adoption of N95 masks may be the most impactful, feasible, and politically viable intervention to require at scale across LAC. In a crisis period at the beginning of an epidemic surge, public health and local government policies might consider distributing these masks, just as they are currently distributing free testing kits, and focusing on their enforcement.

We can also draw some preliminary takeaways regarding preparedness for future viral pandemics in stages before vaccines become available and when there is epidemic growth, such as that investigated here. This might similarly apply to strongly immunity-evading variants of SARS-COV-2. Results again point to the value of focusing preparedness for these purposes on N95 masks, because in addition to the reasons above regarding (i) the strength of these interventions above cloth masks, (ii) relative strength in comparison with other interventions considered here, and (iii) palatability of these interventions in implementation, they are likely to be an indiscriminate tool across virus types or variants. Antigen tests must be designed for specific infections and will not be available in the initial growth phases of a new viral pathogen. Given this, pandemic preparedness policy arsenal could include stockpiling N95 masks, rather than cloth (or surgical) masks, for future viral pandemics.

6.4. Methodological Contributions

This study makes several unique methodological contributions in the area of using activity-based travel demand and agent-based models to simulate infectious disease dynamics in a population.

First, the accuracy (to represent observed infection trends) and specificity of public health insights possible with combined infection dynamic and activity-based travel models is improved by the representation of highly-resolved population attributes and interaction activities. Yet, state-of-the-art modeling approaches typically represent work activities in an aggregated single 'work' category. In this study, we represented multiple employment categories with employment-dependent contact intensities informed by public health studies documenting relative risks in COVID-19 infection for workers in these categories. This granular articulation of activity and work types was critical to investigating the marginal benefit of expanding the scope of NPI measures and policies to specific work categories. Overall, we found that simulated measures could make a very different impact on overall infection rates if applied to specific work categories only, demonstrating the insights to intervention design made possible through these added methods.

Second, for appropriate calibration of the agent based model simulation to infectious disease dynamics (i.e., infection data) for a specific epidemic context, it is important that the simulation model represents the baseline 'on-the-ground' reality of modifications to activity behaviors from pre-pandemic norms, including both mandatory and elective measures from lockdown to physical distancing. Previous work has relied on data representing aggregate city-level changes in mobility to reflect observed modifications to activity behaviors, such as that in Muller et al., 2021. In this work, we used mobility data highly resolved by spatial location and activity type to represent the diversity of time-varying reductions in contact rates throughout all of LAC. This enabled us to complement the highly resolved details of the synthetic population, parameterized with features such as work category, with similarly highly resolved and time-varying changes in baseline activity behaviors throughout the modeled period.

An additional methodological development was motivated by an observed trend in the infection dynamics in LAC. Research has demonstrated that increased infection rates within large (5+) and in particular multi-generational households played a large role in driving infection numbers and dynamics during epidemic waves in LAC (Harris, 2021). Previous transport-based simulation modeling frameworks have represented contact intensity within the home using a fixed measure for all household sizes. The approach we developed represents contacts within the home as a function of household size. We note that we did not explore differences in household density (number of people per spatial area) because we were not able to find appropriate data to base these estimates on.

Due to the incorporation of fine-grained data and modeling detail including these noted contributions, following calibration, the modeling framework we developed was able to reproduce observed infection patterns across age groups and work categories, while accounting for LAC's observed levels of implemented reductions in activity behaviors. This detail allowed for realistic inferences into the effect of the evaluated NPIs on the LAC population overall, as well as impact on—and potential disparities across—subgroups. Overall, the framework enables evaluation into how combinations of interventions can be designed to best mitigate the spread of future COVID-19 epidemic waves in LAC, accounting for its unique demographic composition and baseline restrictions. The framework is furthermore generalizable across SARS-COV-2 variants, or even other viral infections, with minimal modifications to the modeling structure.

6.5. Limitations and Future Work

Future work should improve the modeling and simulation approach used here by addressing the following key areas:

- **Capturing heterogeneities in infection by socio-demographics and employment category.** Because these were not integrated into the calibration process, we were not able to representatively reflect infection rates in these groups, nor report meaningful findings across these groups. Integrating infection data stratified by these populations within LAC was not possible given the sparsity of valid infection data for strata such as by race/ethnicity, income, or employment groups; the only indicator for which data is available is by race/ethnicity group, and this data is unreliable due to the large underreporting of race/ethnicity information by infected individuals at point-of-test. However, infection rates are published by Census Statistical Area (CSA), of which there are approximately 300 spatial units within LAC. Future work could explore the feasibility of imputing socio-demographic inferences about infection numbers on the basis of census population distribution residing in these CSAs and integrating imputed numbers into the model calibration process.
- **Addressing area density and area deprivation, which both have been shown in other research to contribute to increased exposure to COVID-19** (Chang et al., 2021). These aspects were not addressed by our modeling approach, despite the inclusion of the finely spatially resolved SCAG data the LA MATSim model runs on. Future work should integrate infection data by the spatial CSA level noted above into the model calibration process, to appropriately represent infection rates by this geographic unit of analysis. In addition, additional indicators representing area density and baseline area-specific contact intensities within specific types of activity destinations could be brought into the underlying MATSim model to help better represent disparities in contact rates across LAC. For example, previous work has shown that in lower income and predominantly Latino neighborhoods in LAC, the points of interest that people conduct activities in, such as grocery stores, are smaller and population clustering is denser than in higher income neighborhoods (Chang et al., 2021). These insights could be brought into the MATSim model mechanistically.
- **Addressing holiday behavior, which covered Thanksgiving, Christmas, and New Year’s holidays, and weekend behavior, but was not addressed by the activity model.** The MATSim activity model represents trajectories of each agent on an average workday and does not account for holiday or weekend activities. However, previous research has demonstrated that the intensity of indoor, unmasked, visitation-type contact during holiday activities had a large impact on driving the winter 2020-2021 epidemic surge that our analysis focused on (Horn et al., 2021; see also Harris, 2021). The

impact of these holidays on the infection time series is evident through the trendline demonstrating two peaks following Christmas and after New Year's. The realism of modeling results could be improved by incorporating holiday and weekend dynamics by modifying the MATSim model to incorporate increased intensity of visitation behaviors during these periods. Both higher frequencies of these types of activities and higher numbers of contacts per activity should be accounted for. Mobile device data might be a resource to inform weekend vs. weekday activity differences, but it would not appropriately represent personal (within home) mixing behavior and thus could not inform differences in party-type visitation activities. Future work will have to investigate other sources of data or models to inform these dynamics.

- **Quantifying the uncertainty of results.** Due to computational limitations, the model was simulated once under a single set of conditions for each scenario evaluated. Future work should explore running the model under perturbations of conditions to produce 'prediction intervals' or for extensive sensitivity analyses exploring a range of possible impact of various conditions.
- **Investigating further intervention scenarios, including less 'invasive' combinations of interventions.** This study did not investigate all possible NPIs. A notable intervention which should be investigated in future work is contact tracing, and the implications this intervention has on continued infection in workplace and home-based transmission. It is also important to note that all the interventions evaluated in this study were implemented *on top of existing interventions 'observed' during the modeled time period of the second epidemic surge in LAC*, that is, the set of distancing and restrictions estimated through the combination of input data (mobile device data indicating observed reductions in contact patterns), evidence-based assumptions (65% cloth mask adoption in the community and workplace) and model parameters determined through the calibration process. Thus, the scenarios implemented accounted for in-place interventions including shutdown and capacity restrictions in specific high-risk activity categories such as closure of K-12 schools and temporary closure of restaurants and personal care locations (beginning one month into the modeled period). These types of interventions are likely to be among the most costly scenarios due to labor costs (and losses) and enforcement costs, in addition to being unpopular as noted in Section 6.3. Results would look different if we were evaluating interventions on completely unrestricted behavior and activity patterns (i.e., pre-pandemic behaviors). Future work could consider investigating combinations of less 'invasive' interventions that could be implemented to achieve similar results as those evaluated here, including contact tracing.
- **Calibrating home-based transmission rates to observed data on secondary transmission within households.** Multiple studies informing these parameters exist and could be brought in to better parameterize the EpiSim model's representation of the probability of transmission within the household as a function of the household size.
- **Using the model in creative ways to better understand transmission dynamics in specific settings and between specific groups.** The model could be used to examine, for example, the impact of

workplace-based policy on transmission in the home, or the impact of specific capacity limitations (e.g., number of people in a room) on the decreased effect on transmission dynamics.

We close by noting that in spite of these methodological limitations, the methodological contributions introduced in this study, including integrating employment and activity categories in detail and accounting for category specific modifications to activity behaviors throughout the epidemic surge, allowed novel insights into the impact both *overall for LAC* and *for specific groups* of interventions that could target specific groups. This detailed integration enabled realistic insights into how combinations of interventions can be designed to best mitigate the spread of future COVID-19 epidemic waves in LAC, accounting for its unique demographic composition and baseline restrictions, and how particular policies focused on specific groups may impact the overall population, and how any given policy may differentially impact specific groups. Indeed, we found that simulated interventions could make a very different impact on overall infection rates if applied to only specific work categories, and could exacerbate health inequities in specific age groups, demonstrating the insights to intervention design made possible through the added detail. Future efforts should continue this line of work to incorporate more detail, enabling more model-based representation of the impact of epidemic surges and interventions on subpopulations, in particular those of highest risk.

More generally, these findings demonstrate that investments made in activity-based travel models, including detailed individual-level socio-demographic characteristics and activity behaviors, can facilitate the evaluation of NPIs to reduce infectious disease epidemics, including COVID-19. The framework developed here is generalizable across SARS-COV-2 variants, or even other viral infections, with minimal modifications to the modeling structure.

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Appendix 1: Adjustment of Post Pandemic Activities

SafeGraph Data

SafeGraph's datasets include over 7 million consumer Points-of-Interest (POI) in the U.S. and Canada, which includes business listing information (like phone number, business category, open hours) and POI location info (lat/long, physical address, and building footprint). Researchers used three primary SafeGraph datasets[14] to adjust the activity or trip data in the EpiSim framework:

1. **"Places** include base information such as location name, address, category, and brand association for points of interest (POIs) where people spend time or money. This data is available for about ~8.4 million POI, including permanently closed POIs" (Places | SafeGraph Docs, 2022).
2. **"Patterns** include place traffic and demographic aggregations that answer: how often people visit, how long they stay, where they come from, where they go, and more. This data is available for about 4.5 million POI. Associated summary files include home_panel_summary.csv, which describes a number of distinct devices observed with a primary nighttime location in the specified census block group" (Patterns | SafeGraph Docs, 2022).
3. **"Home Panel Summary** includes those devices whose homes are eligible to be counted" (December-2020 Release Notes, 2020), which can be considered the Safegraph data sample size.
4. **"Open Census Data** includes the United States Census Bureau's American Community Survey 5-year Estimates (5-year ACS), reported at the Census Block Group level" (Open Census Data | SafeGraph Docs, 2022).

Researchers compared SafeGraph data before and after COVID-19 to estimate the activity reductions caused by the COVID-19. Based on different time periods, the following datasets are collected: Core_us_2020_to_present; Core_us_pre_2020: Weekly Places Patterns v2 (until 2020-06-15); Weekly Places Patterns (for data from 2020-06-15 to 2020-11-30): Weekly Places Patterns (for data from 2020-11-30 to Present). The data was downloaded using aws cli tool: aws s3 sync s3://sg-c19-response/core-places-delivery/ ./myLocalDirectory/ --profile safegraphws --endpoint https://s3.wasabisys.com.

[14] The documentation for SafeGraph datasets can be accessed at: https://docs.safegraph.com/docs/places.

Data Processing

Researchers processed the SafeGraph data by implementing the following steps.

1. Extracting Los Angeles County Data: The original datasets cover places all over the U.S. and Canada, but the EpiSim model simulates L.A. County only. To extract data for L.A. County, we used the unique FIPS code for L.A. County (06037) to filter patterns datasets, home panel summary data, and census data.
2. Calculating the Weekly Visit Counts by Activity Purpose. The SafeGraph Core Places dataset contains the "sub_category" of each POI, which is associated with the 6 digits of the POI's NAICS category. In EpiSim, activities are categorized by 25 "activity_purpose" labels such as "work", "shop", and "maintenance." To apply SafeGraph data to the model, a correspondence table was created by mapping "sub_category" to "activity_purpose." See Appendix 2 for documentation of the correspondence table. Afterward, the weekly visit counts by activity purposes were calculated as described directly below.
    - Add "activity_purpose" to Core Places dataset using the correspondence table;
    - Join Core Places dataset and Weekly Patterns dataset by the key column 'safegraph_place_id';
    - Split the raw visit counts in each place by workers and non-workers. Assume a threshold of 120 minutes as general work hours, the visits to each place are divided into work-related activities and non-work-related activities. For instance, if the "bucketed_dwell_times" > 120, the visit is counted as a "work" activity; and
    - Sum up the visits according to activity purpose.
3. Adjust Visit Counts Based on the Sample Size: It is critical to consider the underlying changes in data collection (e.g., sample size) across time because the SafeGraph Patterns dataset is collected from a dynamic panel across time. For example, the sample size can increase between months because more devices are added to the device panel. Consequently, adjustments need to be made to the visit counts as described below.
    - Sample Size: In "home_panel_summary.csv", the "number_devices_residing" (number of distinct devices observed with a primary nighttime location) is considered the sample size. The total sample size for L.A. County is the sum of all census block groups' sample sizes.
    - Total Population: From Open Census Data, derive the total population in L.A. County by summing up the population in each census block group.
    - Scaling Factor: Define the scaling factor as: Total Population / Sample Size.
    - Adjusted Visits: Scale visits data by multiplying the scaling factor.
4. Clean Data: In this step, we combine all the weekly visits into one table with the date as a parameter. In addition, we filled the N/A data with 0, and the cells that had values equal to infinity or greater than 1 with 1.

Calculate Weekly Activity Reductions by Activity Purpose: A typical week (e.g., no holidays) before the early beginning of the pandemic was selected as a base week. Any week after that was considered a scenario week. We used the base week of 3/2/2020 The activity level is the percentage of activities by type that still occur under the pandemic restrictions, which is equal to min(visit counts in the scenario week/visit counts in the base week, 1)*100.

Appendix 2: Correspondence Between Travel Activity Purposes and SafeGraph Place Categories

The correspondence table's function converts SafeGraph place categories into activity purposes applied in the EpiSim model. Afterward, the weekly visit counts from SafeGraph data can be used to calculate the activity reductions for different activity purposes.

SafeGraph Place Categories

The SafeGraph Core Places dataset contains the "sub_category" of each point-of-interest (POI), associated with the 4 digits of the POI's NAICS category. The North American Industry Classification System (NAICS) is the standard used by Federal statistical agencies in classifying business establishments to collect, analyze, and publish statistical data related to the U.S. business economy. Table 2-1 shows examples of 4-digit NAICS codes and descriptions.

Table 2-1. 4-digit NAICS codes and descriptions for SafeGraph data.

4-digit naics_code	sub_category	Description
5416	Management, Scientific, and Technical Consulting Services	This industry group comprises establishments primarily engaged in providing advice and assistance to businesses and other organizations on management, environmental, scientific, and technical issues.
5418	Advertising, Public Relations, and Related Services	This industry group comprises establishments primarily engaged in advertising, public relations, and related services, such as media buying, independent media representation, outdoor advertising, direct mail advertising, advertising material distribution services, and other services related to advertising.

EpiSim Model Activities

As listed in Table 2-2, in the EpiSim model, activities are categorized differently from SafeGraph data, with 25 activity purposes such as "work," "shop," and "maintenance." These model activity purposes are classified from survey trip purposes, as described in Table 2-4. Take “Work” as an instance, Table 2-2 shows the corresponding Survey Activity/Trip Purpose number is “9, 16”, which can be related to the same numbers in Table 2-4, and we can know “work” activity includes “9 = Work/Job Duties” and “16 = All Other Work-Related Activities at My Work”. The EpiSim model also provided the NAICS code for the work industries, which subdivides the “work” activity into 20 groups based on the first 2 digits of the NAICS code. Table 2-3 shows the categories of “work” activity in the EpiSim Model.

Table 2-2. Activity purposes in EpiSim model.

Index	Activity Purpose Label	Survey Activity/Trip Purpose #	SCAG ABM Activity Purpose #
1	Home	1-8, 21	0
2	work	9, 16	1
3	university	17-18	2
4	School	17-18	2
5	Escort	22	4
6	schoolescort	22	4
7	schoolpureescort	22	4
8	schoolridesharing	22	4
9	non-schoolescort	22	4
10	Shop	27,28	5
11	maintenance	23-24	6
12	HHmaintenance	29,32,26	6
13	personalmaintenance	30	6
14	Eatout	31	11
15	eatoutbreakfast	31	11
16	eatoutlunch	31	11
17	eatoutdinner	31	11
18	visiting	37	9
19	discretionary	33-35, 13, 15, 20	7
20	specialevent	14, 19, 36,38	10
21	atwork	11	11
22	atworkbusiness	25, 10	12
23	atworklunch	12	13
24	atworkother	38	13
25	business		7

Table 2-3. 2-digit NAICS codes and descriptions for EpiSim model work activities.

2-Digit NAICS CODE	DESCRIPTIONS
11	11=Agriculture, Farming, Forestry, Fishing, Hunting
21	21=Mining, Quarrying, Oil or Gas Drilling Company
22	22=Utility Company, Sewage Treatment Facility, Utilities in General
23	23=Construction
31	31=Manufacturing, Including Bakery, Food Processor, Mill, Manufacturer, Machine Shop, Medical Biotechnology
42	42=Wholesale Trade
44	44=Retail Trade, Including Store, Shop, Dealer (e.g., Auto Dealer)
48	48=Transportation, Bus or Train Company, Airline, Postal Service, Warehouse or Storage
51	51=Information, Including Publisher, Phone Company, Movie Company, Internet Company, Library, Data Processing, Computer Company
52	52=Finance and Insurance such as Bank, Insurance Company, Credit Union, Finance Company
53	53=Real Estate Company, Any Rental or Leasing Company Including Auto or Video Rental
54	54=Professional Scientific or Technical Services, Including Law, Accounting, Design, Engineering, Consulting or Advertising, Firm or Company, and Veterinary Services
55	55=MANAGEMENT OF COMPANIES AND ENTERPRISES
56	56=Administrative Support, Including Employment Agency, Travel Agency, Security Guard Company, Waste Management (Trash) Company, Remediation Services
61	61=Educational Services, Including School, University, Training School
62	62=Health Care and Social Assistance, Including Hospital, Doctors Office, Assisted Living Home, Day Care Center
71	71=Arts, Entertainment and Recreation, Including Art Gallery, Museum, Theatre, Bowling Alley, Casino
72	72=Accommodation or Food Services, Including Hotel, Restaurant
81	81=Other Services (Except Public Administration) such as Auto Repair, Hair or Nail Salon, Barber Shop, Funeral Home, Labor Union
92	92=Public Administration, such as Government Agency, City or County Department, Military

Table 2-4. Activity purpose classification.

Survey Activity/Trip Purpose		SCAG ABM Activity Purpose	
#	**Description**	**#**	**Description**
1	Personal Activities (Sleeping, Personal Care, Leisure, Chores)	0	
2	Preparing Meals/Eating	0	
3	Hosting Visitors/Entertaining Guests	0	
4	Exercise (With or Without Equipment)/Playing Sports	0	
5	Study / Schoolwork	0	
6	Work for Pay at Home Using Telecommunications Equipment	0	
7	Using Computer/Telephone/Cell or Smart Phone or Other Communications Device for Personal Activities	0	
8	All Other Activities at my Home	0	
9	Work/Job Duties	1	Work
10	Training	12	Work/Business
11	Meals at Work	1	Work
12	Work-Sponsored Social Activities (Holiday or Birthday Celebrations, etc.)	12	Work/Business
13	Non-Work Related Activities (Social Clubs, etc.)	7	Discretionary
14	Exercise/Sports	10	Discretionary
15	Volunteer Work/Activities	7	Discretionary
16	All Other Work-Related Activities at My Work	1	Work
17	In School/Classroom/Laboratory	2	School / University
18	Meals at School/College	2	School / University
19	After School or Non-Class-Related Sports/Physical Activity	10	Discretionary
20	All Other After School or Non-Class Related Activities (Library, Band Rehearsal, Clubs, etc.)	7	Discretionary
21	Change Type of Transportation/Transfer (Walk to Bus, Walk To/From Parked Car)	0	
22	Pickup/Drop Off Passenger(S)	4	Escorting
23	Drive Through Meals (Snacks, Coffee, etc.)	6	Maintenance
24	Drive Through Other (ATM, Bank)	6	Maintenance
25	Work-Related (Meeting, Sales Call, Delivery)	12	Work-related

Survey Activity/Trip Purpose		SCAG ABM Activity Purpose	
#	**Description**	**#**	**Description**
26	Service Private Vehicle (Gas, Oil, Lube, Repairs)	6	Maintenance
27	Routine Shopping (Groceries, Clothing, Convenience Store, Household Maintenance)	5	Shopping
28	Shopping for Major Purchases or Specialty Items (Appliance, Electronics, New Vehicle, Major Household Repairs)	5	Shopping
29	Household Errands (Bank, Dry Cleaning, etc.)	6	Maintenance
30	Personal Business (Visit Government Office, Attorney, Accountant)	6	Maintenance
31	Eat Meal at Restaurant/Diner	11	Eat-out
32	Health Care (Doctor, Dentist, Eye Care, Chiropractor, Veterinarian)	6	Maintenance
33	Civic/Religious Activities	7	Discretionary
34	Outdoor Exercise (Playing Sports/Jogging, Bicycling, Walking, Walking the Dog, etc.)	10	Discretionary
35	Indoor Exercise (Gym, Yoga, etc.)	10	Discretionary
36	Entertainment (Movies, Watch Sports, etc.)	8	Discretionary
37	Social/Visit Friends/Relatives	9	Visiting Friends/Family
38	Other (Specify)	13	Discretionary
39	Loop Trip (For Interviewer Only-Not Listed on Diary)	0	
97	No Additional Activities	0	
99	Don’t Know/Refused	0	

Some activity purposes are subdivided into more detailed categories. For example, "escort" is subdivided into "schoolescort," "schoolpureescort," "schoolridesharing," and "non-schoolescort." Not all of them can be mapped with SafeGraph subcategories. As a result, only 12 activity types are used to calculate the activity level change after the COVID-19, as shown in Table 2-5.

Table 2-5. Activities used to calculate activity level.

Index	Activity Purpose Label
1	home
2	work
3	university
4	school
5	escort
6	schoolescort
7	schoolpureescort
8	schoolridesharing
9	non-schoolescort
10	shop
11	maintenance
12	HHmaintenance
13	personalmaintenance
14	eatout
15	eatoutbreakfast
16	eatoutlunch
17	eatoutdinner
18	visiting
19	discretionary
20	specialevent
21	atwork
22	atworkbusiness
23	atworklunch
24	atworkother
25	business

*labels in red are not matched with SafeGraph categories

Correspondence Table

A correspondence table maps "sub_category" in the Safegraph data to "Activity_Purpose" in the EpiSim model. For each SafeGraph POI, people who are visiting can be either workers or non-workers. Therefore, some POI will be associated with two activity purposes – one is work, and the other is the primary trip purpose of the visits other than work.

For work visits to the SafeGraph POI, we matched the first 2-digit NAICS code for POI and the 2-digit NAICS code for EpiSim work categories. For example, if the subcategory of the SafeGraph POI is " Management, Scientific, and Technical Consulting Services " with a NAICS code = 5416, we label all work visits to this place as "work_54". The NAICS codes used in the LA EpiSim model is a little different from the SafeGraph NAICS codes. The EpiSim model combined NAICS code 32 and 33 together with 31. Consequently, all SafeGraph POI belonging to NAICS code 32 and 33 are classified into "work_31". For activities other than work visits, the mapping is based on the descriptions of SafeGraph subcategory and the descriptions of model activity purpose (Table 2-4).

Table 2-6. Example of final SafeGraph and EpiSim category correspondence table.

naics_code (SafeGraph)	sub_category (SafeGraph)	Description	Activity_Purpose (EpiSim Model)
3399	Other Miscellaneous Manufacturing	This industry group comprises establishments primarily engaged in miscellaneous manufacturing, such as jewelry and silverware manufacturing, sporting and athletic goods manufacturing, doll, toy, and game manufacturing, office supplies (except paper) manufacturing, sign manufacturing, and all other miscellaneous manufacturing.	work_31
5416	Management, Scientific, and Technical Consulting Services	This industry group comprises establishments primarily engaged in providing advice and assistance to businesses and other organizations on management, environmental, scientific, and technical issues.	work_54
5418	Advertising, Public Relations, and Related Services	This industry group comprises establishments primarily engaged in advertising, public relations, and related services, such as media buying, independent media representation, outdoor advertising, direct mail advertising, advertising material distribution services, and other services related to advertising.	work_54
5617	Services to Buildings and DwellingsT	This industry group comprises establishments primarily engaged in one of the following: (1) exterminating and pest control services; (2) janitorial services; (3) landscaping services; (4) carpet and upholstery cleaning services; or (5) other services to buildings and dwellings.	work_56/HHmaintenance

naics_code (SafeGraph)	sub_category (SafeGraph)	Description	Activity_Purpose (EpiSim Model)
6233	Continuing Care Retirement Communities and Assisted Living Facilities for the Elderly	NULL	work_62/visiting

Appendix 3: Disease Progression Model

In this project, the default age-dependent progression model in EpiSim was developed with available German data (see Mueller et al., 2021). We replaced this default age-progression model with a new progression model using Los Angeles statistics (see Table 3-1). The age-dependent probabilities of transitioning from infection to "seriously sick" and "seriously sick" to "critical" were informed by estimates for the Los Angeles County population in Horn et al. (2021). Specifically, Horn et al. used an epidemic model to estimate the probabilities of transitioning from observed infection to hospitalization, and hospitalization to intensive care (ICU), using data on the number of observed infections and patients admitted to hospital and ICU overall in L.A. County. A logistic risk model was then developed to stratify these probabilities across age groups, using observed data on the frequency of each age group in infections, the population-average probabilities from the epidemic model, and data from other studies on the relative risk of hospitalization and ICU admission given infection by age. The severe illness transition probabilities are provided as time-varying in Horn at el.; however, the values do not range widely over time. For this reason, and for simplicity, in this work, we implement these probabilities as the average over all time periods. The new age-dependent progression model is included in the L.A. EpiSim model code.[15]

[15] See https://github.com/matsim-vsp/matsim-episim-la/blob/5d609de52ce60e3db6307535c122f930873e90e6/src/main/java/org/matsim/run/modules/OpenLosAngelesScenario.java#L422

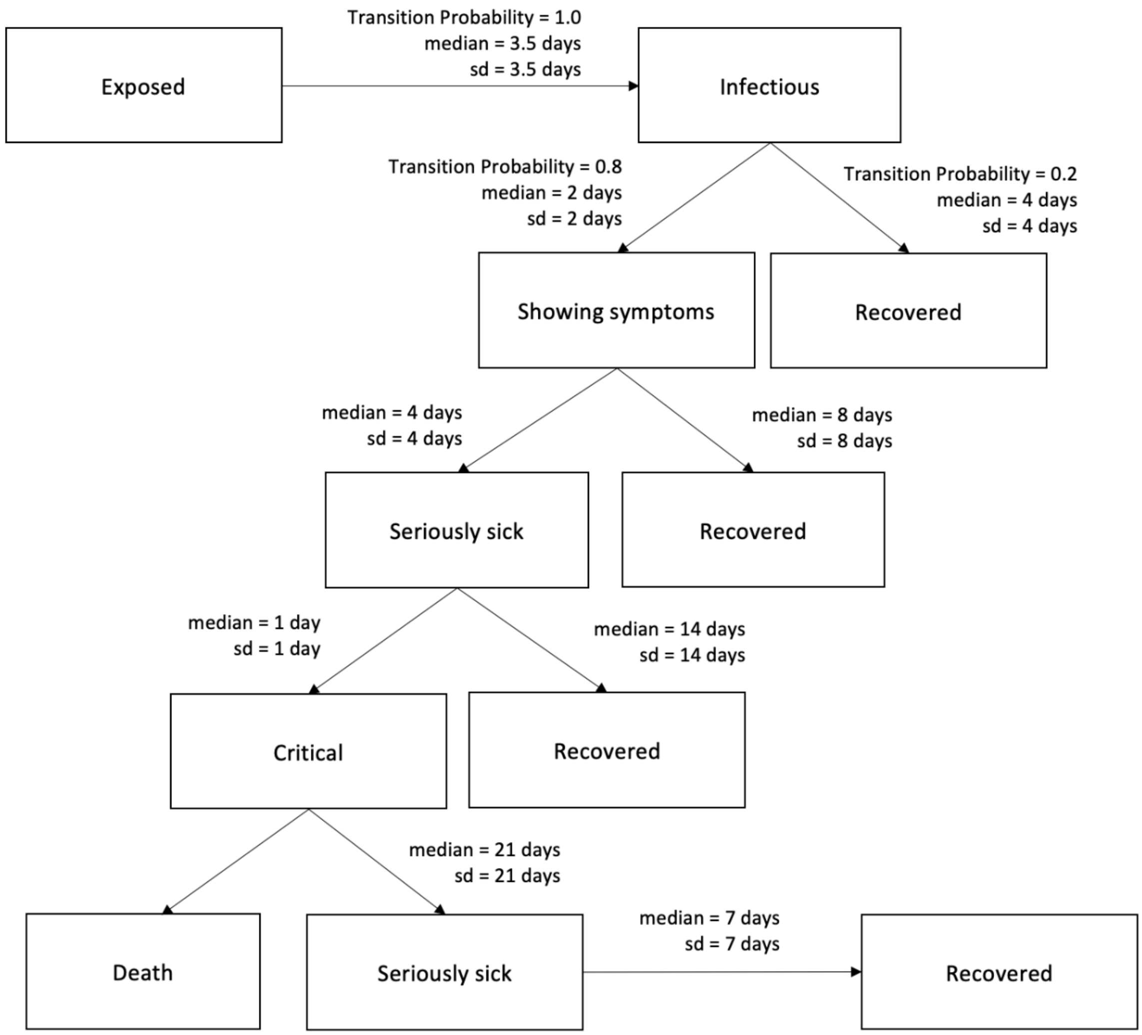

Figure 3-1. Disease Progression Model in the LA EpiSim model.

Table 3-1. Age-dependent transition probabilities.

Age-group	Exposed cases becoming symptomatic	Symptomatic cases becoming 'seriously sick' (hospitalized)	'Seriously sick' cases becoming 'critical' (in intensive care)
0 to 19	80%	1.1%	0.9%
20 to 49	80%	9.6%	6.9%
50 to 64	80%	21.8%	15.2%
65 to 79	80%	40.3%	30.4%
80+	80%	62.6%	54%