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**TITLE PAGE**

**TITLE:** The Importance of an Epidemiologic Team in Advising State-Level Policymakers in Public Health Planning and Response to COVID-19

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**ABSTRACT:**

Due to the global nature of COVID-19, a multitude of COVID-19 models were created. However, these models were not created with the explicit intent to inform policy makers on specific scenarios. Each model has its own advantages and disadvantages depending on the data available and outcomes diseased. Additionally, continuously changing epidemiologic and economic data needs to be considered to appropriately interpret model results. Because of these complexities, state-level policymakers may not be provided adequate training or support to select and interpret models appropriately. We recommend that state-level policymakers, as part of an essential component of their pandemic control efforts, rely on a ‘brain trust’ or technical advisory group as early as possible to navigate the difficult policy decisions by using best available data, evidence, and models. This state-level approach can be modified and applied across international jurisdictions such as municipalities and districts. We highlight major functionalities of various models and the main scenarios encountered by policy makers where modeling could better inform decision making. (164 words)

**KEYWORDS:** pandemic, COVID-19, modeling, epidemiology, economics, public health planning, governance

# Introduction

The toll of global coronavirus disease 2019 (COVID-19) pandemic continues to grow without plateau. In the face of COVID-19’s unrelenting spread, epidemiologic estimates are quickly out of date. As of the week of October 26, 2020, the United States Centers for Disease Control and Prevention reported over 8.9 million total cases and over 220,000 total deaths.1 Because each state has different demographics and needs, state policymakers continue to make significant policy, programmatic, and planning decisions in responding to the multi-dimensional impacts of COVID-19.

In the United States, both policymakers and media alike have latched onto a variety of tools and models to help inform immediate and later-term policy decisions. Specifically, this article is concerned about relevant select models that forecast and make predictions about the spread of COVID-19 and its subsequent health impacts.

The landscape of models can be dizzying. As of the week of October 26, 2020, the CDC listed 47 different models for death forecasts and 12 different models for hospitalization predictions.2,3 Policymakers rarely have a background in infectious disease or epidemiology, so the appropriate use of these models is undoubtedly a challenge. And the availability of these models does not guarantee their appropriate use. This article seeks to advise state-level policymakers who seek to navigate this complex landscape of models, draw from lessons learned from the State of Hawai‘i, and make appropriate evidence-based decisions.

# COVID-19 Policy Demands and Questions

In the face of COVID-19, state policymakers have faced pressing policy, programmatic, and planning questions and decisions that can be grouped into two main categories:

1. **Shutting Down and Healthcare Resource Capacity:** What policy decisions should our state undertake to control and mitigate the impacts of COVID-19, and should our state “shutdown”? Will our healthcare resources (e.g., hospital beds, ventilators, personal protective equipment, medication) be sufficient, or when will they run out?
2. **Reopening:** What policy decisions should our state undertake to reopen while continuing to control and mitigate the impacts of COVID-19? What should be our state’s testing, contact tracing, and quarantine & isolation strategic policy? Does our state have adequate capacity for implementing this testing, tracing, and quarantine policy? What policies and guidance should our state provide on mask wearing and other physical distancing strategies?

# Landscaping Models For State Policymakers

A “model” refers to a mathematical or logical representation of the biology and epidemiology of disease transmission and its associated processes.4 While there are many landscaping models, this article purposely focuses on 4 models: the University of Washington Institute for Health Metrics and Evaluation (IHME) model 5, the Imperial College London model 6, the Epidemic Calculator 7, and the University of Basel model 8. We chose these models to show how models can be used for different purposes. Exhibit 1 summarizes this selection of 4 models landscaped in this article across the following 5 dimensions of (1) model objective, (2) interactivity and local parameter customizability, (3) age distribution, (4) type of model, and (5) open source. These dimensions are not comprehensive, but reflect what we argue to be most relevant for state-level policymakers. We present the case of Hawai‘i to illustrate the application of the use of models for specific policy decisions.

**Model** **Objective.** Each model had a different objective. The IHME model intended to estimate COVID-19 hospital impacts, whereas the Imperial College London model sought to illustrate how public health measures such as physical distancing and protecting vulnerable populations affected the spread of COVID-19. Understanding the objective of the model is an important but incomplete aspect to its appropriate use.

**Local Parameter Customizability.** Some models allowed for interactivity and customizability of the model parameters. The Epidemic Calculator had sliders to allow for a user to modify parameters driving the transmission and clinical dynamics underpinning the model (e.g. the population size and the basic reproduction number R0) and to add an intervention to decrease transmission by a specified amount from a given day. The Basel model allowed for the user to modify various model parameters, age-group-specific parameters, and isolation measures, as well as to add multiple interventions to reduce transmission. In contrast, the IHME model had limited local parameter customizability. Although it generated state-specific estimates, it did not allow for state-specific parameters to be incorporated. Moreover, although the IHME model used a wide variety of data sources, not all states had their data reflected in its model. In the case of Hawai‘i, the IHME model did not utilize data from Hawai‘i but instead utilized average estimates of time from hospitalization to death from other states despite widely different demographic, epidemiologic, and socioeconomic considerations.

**Age Distribution.** Age is well documented as one of the largest and most significant risk factors for COVID-19, with older adults at increased risk of being hospitalized and dying due to COVID-19.9,10 Each state has different age distributions and demographic structure, and so it is important for models to account for age to project the case, hospitalization, and fatality numbers more accurately. The University of Basel model is one of the only Susceptible Infected Recovered / Susceptible Exposed Infected Recovered (SIR/SEIR) compartment-based models that accounts for age, allowing for the user to adjust the age distribution and age-group-specific parameters to reflect the population of interest.

**Type of Model.** Models can be broadly categorized into two types – mechanistic and statistical. Mechanistic models make assumptions about how the actual process of COVID-19 disease transmission occurs and include the SIR/SEIR compartmental models and their modified variants. In contrast, statistical models fit curves using existing data, the main example being the IHME model which early on used the existing data from China and Italy to predict what would happen in the United States and elsewhere. This means that while statistical models can forecast what will happen in the near future, mechanistic models can make assumptions on the transmission dynamics of COVID-19 and forecast longer-term scenarios based on different interventions and policy changes.11

**Open Source.** Models that are open source, defined as having the source code made publicly available for use and modification, are models that enable users to “open up the hood of the car” or “look into the sausage-making machine” or “black box”. This transparency in model assumptions and limitations should have appropriate interpretation by an epidemiologist to policymakers to ensure appropriate planning. Most importantly, open source incurs little to no cost and offers support states with limited technical and epidemiologic capacity. In Hawai‘i, the Hawai‘i Data Collaborative in partnership with local hospitals and the Hawai‘i Pandemic Applied Modeling (HiPAM) Work Group built on and modified the open source Epidemic Calculator model to show how policy measures on reopening and resuming travel could impact the spread of COVID-19.

In contrast, the IHME model is not open source which makes it very challenging to assess even basic assumptions such as how it incorporates age-specific distributions. Policymakers should take model interpretations with a grain of salt and not make over assumptions of the data.

## Application of Models to State Policy Decisions: Case of Hawai‘i

Because these models require a firm grasp of epidemiologic concepts, policymakers should involve public health epidemiologists as early as possible to translate modeled outcomes into actionable context. In Hawai‘i, the Hawai‘i Emergency Management Agency (HI-EMA) sought help from a lead epidemiologic adviser to make sense of the numerous models available.

As a case study, we next describe how one state (Hawai‘i) has used different models for informing policy decisions on (1) shutting down and hospital capacity and (2) reopening.

**Using Models to Plan for Shutting Down and Hospital Capacity**

In many states that did not have an established epidemic/pandemic modeling response plan for COVID-19, the most pressing question was how quickly COVID-19 would spread in their state or community. As such, the IHME model was utilized because it provided early state-specific estimates. It gave a hard deadline by which a state’s bed surge capacity might be reached because of the speed by which COVID-19 spreads, and leads to hospitalization. The IHME model arguably helped policymakers and emergency management leaders act quickly to make hard decisions about imposing public health measures to stop COVID-19 spread (e.g., through closing business and halting travel).

The models also helped policymakers to plan for ensuring adequate bed capacity and to decide whether to stand-up additional acute care facilities. In Hawai‘i, policymakers pondered challenging decisions of whether to retrofit existing hotel rooms or outfit a convention center. Either option would require collaboration with the U.S. Army Corps of Engineers with an expensive price tag. This policy decision required COVID-19 case and hospitalization projections specific for Hawai‘i. In the beginning of the pandemic, with no other available guidance or tools as well as limited or no epidemiologic advisors, policymakers turned to the web-accessible IHME model for guidance on when Hawai‘i would be hit with a “surge” of cases.

At the onset of COVID-19 in the US, many states had yet to fully understand how the virus was spreading through their individual communities and how measures such as requiring face mask use in public would affect the spread.12 Through the month of March and early April, many states did not yet have a high case count and fatality count to get a sense of the trend of COVID-19 within their state. The IHME model used the hospitalization to death ratio from seven locations within the US with the most cases to create a weighted average for their ratio and applied it to states with fewer than five fatalities, which included Hawai‘i. This resulted in Hawai‘i expecting to see a surge in cases and hospitalizations that was projected to overwhelm the local healthcare system.

However, when a team of Hawai‘i epidemiologists and researchers in HI-EMA sat down and utilized a basic SEIR model with Hawai‘i specific parameters, no surge was estimated within the same time frame that IHME was predicting. The modeling team in Hawai‘i understood that Hawai‘i’s unique geography and early mitigation efforts drastically reduced the Rt below the value of 2.2 that was used by most models. The public health team stated all the limitations and assumptions of their early model to the decision makers. Based on the recommendation of state specific data, and use of a more appropriate epidemiologic model by HI-EMA, the decision was made to not retrofit the Hawai‘i Convention Center into an acute care facility at that time, and to re-evaluate at a future date. Looking back, Hawai‘i was never hit with a surge at the level predicted by the IHME model. Due to the intervention of epidemiologists, the state of Hawai‘i avoided millions of dollars in unnecessary costs better spent on other COVID-19 efforts.

Allocation, logistics, and utilization of personal protective equipment (PPE) during the initial response to COVID-19 is another use of COVID-19 models by policymakers. Hospital administrators and policymakers need to accurately account for burn rates of PPE (e.g., masks, surgical gowns, facemasks) to request appropriate funding from their funding sources. Hawai‘i used the University of Basel model for informing PPE. In regard to stockpiling respirators, appropriate estimations of need were essential to decreasing inappropriate over-stocking which may dimmish the supply in other areas of need, or may under-stock respirators which would have had an equally devastating consequences.

**Using Models to Plan for Reopening**

In the US, the use of epidemiologic models for the initial response and planning was aided by the experiences and lessons of other countries and jurisdictions such as China, South Korea, Italy, and Taiwan, whose information and data helped inform some of the models. However, as American policymakers begin to plan and implement the reopening of their states, the need for geographically specific models informed by local context is even greater.

One major question facing policymakers seeking to reopen is how and when travel volumes, both domestic and international, can increase. Some of the early mechanistic models only accounted for a population where the total size stayed the same as well as for how COVID-19 would progress under certain mitigation efforts scenarios pre-programmed into the model. Moreover, there continues to be tremendous uncertainty and evolving understanding about the basic scientific facts and assumptions of COVID-19 (e.g., extent of screening for asymptomatic transmission 13 and the infection fatality rate 14), making policy decisions difficult. As travel volumes return to higher levels, models that factor in imports of new cases can provide more accurate estimates of travel impacts on overall disease spread. Epidemiologists can estimate these metrics for different travel volume scenarios and demonstrate how the range of new cases is dependent on how many imported cases are brought into their community. Going forward, epidemiologists will have to consider the level of inter-state travel, which is not well captured in these models. There is a risk that inappropriate model use will likely lead to an underestimate of total severity.

There are many assumptions built into the various COVID-19 models, such as whether symptomatic travelers will restrict themselves from traveling and whether they will be identified at the port of departure. Arguably, one of the largest considerations for developing travel scenarios is that of asymptomatic and presymptomatic cases – how assumptions about these parameters are incorporated into a given model, the distribution of COVID-19 cases which are asymptomatic or pre-symptomatic, and the rate of spread from these cases.15–17 Reopening strategies based on one or multiple tests have been suggested without any numerical estimations of possible infected travelers slipping through. Modeling can provide policymakers with an educated guess when comparing reopening strategies based on frequency and type of tests.

Testing, contact tracing, and quarantine & isolation represents the major public health tool for policymakers responding to COVID-19. States can consider how tests such as body temperature and symptom screens as well as standard polymerase chain reaction (PCR) tests can be linked to travel policies, and use models to help estimate the potential impacts and consequences of different testing strategies.

Most models at present do not account for non-COVID-19 health impacts such as those pertaining to mental health, reductions in use of other essential health services, or long-term care facilities or other congregate settings. Mental health and substance use, already an important public health issue prior to COVID-19, has become exacerbated by secondary and tertiary impacts due to COVID-19.18

COVID-19 will continue to directly impact communities through 2021 and indirectly for decades to come. Policymakers will need to shift from use of models that focus on hospital capacity and reopening, to models identifying long-run health and economic impacts of COVID-19, such as mental health, access to non-COVID-19 health care services, education, and other dimensions of the social determinants of health. Most of the COVID-19 models used at present have not directly incorporated these long-run impacts. Use of Bayesian modeling and synthetic population models can and have begun to be used to examine these longer-term health impacts and policy implications, as this type of modeling accounts for additional differences in a population such as economic status and race.

# Discussion and Conclusion

Epidemiologic models used for COVID-19 are numerous and complex, requiring content experts to appropriate utilize data and interpret results. The 4 selected models summarized in this article demonstrate how even with accurate date, utilization of an inappropriate model and/or considerations may lead to inappropriate interpretation of results. COVID-19 models vary by their designed intent and understanding these differences, including their differences in geographic application and their application to specific policy decisions, is necessary for policymakers to better utilize them in making decisions.

One of the most valuable lessons learned from epidemiologic COVID-19 modeling in Hawai‘i’s was the incorporation of state specific data which directly resulted in cost savings from decreased unnecessary spending. This model incorporated two of the most important factors that assist local leaders in modeling local issues, age distribution and customization that was specific to Hawai‘i.9,10

Because of the complexity of models and the potential for misinterpretation, some have argued that these models do more harm than good. Rather than dismiss the use of models because of their complexity, policymakers should incorporate into their response team a ‘brain trust’ or technical advisory group as early as possible to navigate the difficult policy decisions that can have positive impacts on their constituents and communities. A brain trust is a diverse team which provides input from various areas of expertise (e.g., epidemiology, data science, and math).

Going forward, we recommend that states utilize a brain trust, bringing in planning and logistics experts to put modeling into operational context. In Taiwan, for example, one critical component of their multi-faceted and comprehensive response was the use of a technical advisory board, chaired by a leading infectious disease physician and epidemiologist, who convened regularly to review the current evidence and scientific base to make recommendations to Taiwan’s Minister of Health.

With tremendous uncertainty about a novel disease, the need for thoughtful application of scientific knowledge is ever more pressing. In the face of numerous models, each with different assumptions and limitations, policymakers should incorporate into their epidemic/pandemic response team a brain trust to appropriately use these models to make better informed policy decisions in controlling and mitigating the spread of COVID-19 and other communicable diseases.

**Conflict of Interest**

None Declared.

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**Ethics approval**

Not required.

# References

1. Centers for Disease Control and Prevention. CDC COVID Data Tracker. https://www.cdc.gov/covid-data-tracker/index.html. Accessed October 30, 2020.

2. Centers for Disease Control and Prevention. COVID-19 Forecasts: Cumulative Deaths. https://www.cdc.gov/coronavirus/2019-ncov/covid-data/forecasting-us.html. Accessed October 30, 2020.

3. Centers for Disease Control and Prevention. COVID-19 Forecasts: New Hospitalizations. https://www.cdc.gov/coronavirus/2019-ncov/cases-updates/hospitalizations-forecasts.html. Accessed October 30, 2020.

4. Dubé C, Garner G, Stevenson M, et al. The use of epidemiological models for the management of animal diseases. *Conf OIE*. 2007:13-23.

5. Team IC-19 health service utilization forecasting, Murray CJ. Forecasting the impact of the first wave of the COVID-19 pandemic on hospital demand and deaths for the USA and European Economic Area countries. *medRxiv*. April 2020:2020.04.21.20074732. doi:10.1101/2020.04.21.20074732

6. Ferguson N, Laydon D, Nedjati Gilani G, et al. Impact of non-pharmaceutical interventions (NPIs) to reduce COVID19 mortality and healthcare demand. March 2020. doi:10.25561/77482

7. Goh G. Epidemic Calculator. https://gabgoh.github.io/COVID/index.html. Published 2020. Accessed June 9, 2020.

8. Noll NB, Aksamentov I, Druelle V, et al. COVID-19 Scenarios: an interactive tool to explore the spread and associated morbidity and mortality of SARS-CoV-2. *medRxiv*. May 2020:2020.05.05.20091363. doi:10.1101/2020.05.05.20091363

9. Bialek S, Boundy E, Bowen V, et al. Severe Outcomes Among Patients with Coronavirus Disease 2019 (COVID-19) — United States, February 12–March 16, 2020. *MMWR Morb Mortal Wkly Rep*. 2020;69(12):343-346. doi:10.15585/mmwr.mm6912e2

10. Garg S, Kim L, Whitaker M, et al. Hospitalization Rates and Characteristics of Patients Hospitalized with Laboratory-Confirmed Coronavirus Disease 2019 — COVID-NET, 14 States, March 1–30, 2020. *MMWR Morb Mortal Wkly Rep*. 2020;69. doi:10.15585/mmwr.mm6915e3

11. Holmdahl I, Buckee C. Wrong but Useful — What Covid-19 Epidemiologic Models Can and Cannot Tell Us. *N Engl J Med*. May 2020. doi:10.1056/NEJMp2016822

12. Lyu W, Wehby GL. Community Use Of Face Masks And COVID-19: Evidence From A Natural Experiment Of State Mandates In The US. *Health Aff (Millwood)*. June 2020:10.1377/hlthaff.2020.00818. doi:10.1377/hlthaff.2020.00818

13. Park M, Cook AR, Lim JT, et al. A Systematic Review of COVID-19 Epidemiology Based on Current Evidence. *J Clin Med*. 2020;9(4):967. doi:10.3390/jcm9040967

14. Basu A. Estimating The Infection Fatality Rate Among Symptomatic COVID-19 Cases In The United States. *Health Aff (Millwood)*. May 2020:10.1377/hlthaff.2020.00455. doi:10.1377/hlthaff.2020.00455

15. Gandhi M, Yokoe DS, Havlir DV. Asymptomatic Transmission, the Achilles’ Heel of Current Strategies to Control Covid-19. *N Engl J Med*. 2020;382(22):2158-2160. doi:10.1056/NEJMe2009758

16. He X, Lau EHY, Wu P, et al. Temporal dynamics in viral shedding and transmissibility of COVID-19. *Nat Med*. April 2020:1-4. doi:10.1038/s41591-020-0869-5

17. Oran DP, Topol EJ. Prevalence of Asymptomatic SARS-CoV-2 Infection. *Ann Intern Med*. June 2020. doi:10.7326/M20-3012

18. Hartnett KP, Kite-Powell A, DeVies J, et al. Impact of the COVID-19 Pandemic on Emergency Department Visits — United States, January 1, 2019–May 30, 2020. *MMWR Morb Mortal Wkly Rep*. 2020;69. doi:10.15585/mmwr.mm6923e1

# LIST OF EXHIBITS

EXHIBIT 1 (table)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Objective of model** | **Localized Customizability** | **Local Age Distribution** | **Type of Model** | **Open Source** |
| IHME 5 | Estimate hospital impacts | No | Unknowna | Statistical | No |
| Imperial College 6 | Assess public health measures on spread | Nob | Nob | Mechanistic | Nob |
| University of Basel 8 | Planning tool with features such as imported cases and age groups | Yes | Yes | Mechanistic | Yes |
| Epidemic Calculator 7 | Estimate change in epi curve after reduction in transmission | Yes | No | Mechanistic | Yes |

TITLE: Landscape of Selected Models for Informing COVID-19 Control and Mitigation

SOURCE: Authors

NOTES: aThe IHME model is closed source so it is unknown how local age distribution is taken into account.

bThe source code was not available when the original Report 9 was released. The updated source code was eventually made available much later with no support and minimal documentation, making local use of the model difficult.

EXHIBIT 2 (table)

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Key Assumption #1: Asymptomatic vs Symptomatic** | **Underestimate or Overestimate on Total Severity (cases, deaths)** | **Key Assumption #2: Age Distribution** | **Underestimate or Overestimate on Total Severity (cases, deaths)** | **Other Assumptions** |
| IHME 5 | As the model is not open source, it is unapparent to what extent asymptomatic vs symptomatic is taken into account | As the model is not open source, it is unapparent to what extent asymptomatic vs symptomatic is considered | Uses actual data and are based on results for specific age distributions (for China and Italy) applied and adapted to other populations | As the model is not open source, it is unapparent how the age-specific distributions are incorporated and applied |  |
| Imperial College 6 | Does not appear to distinguish between asymptomatic and non-hospitalized symptomatic individuals | Same as for Epidemic Calculator (see below) | Agent based model has individuals that reflect the population’s age distribution | n.a. | Assumes changes in transmission are reflected through mobility of the population |
| University of Basel 8 | Does not appear to distinguish between asymptomatic and non-hospitalized symptomatic individuals | Same as for Epidemic Calculator (see below) | Divides population into age groups with age-group-specific parameters (such as how severe, critical, and fatal the infection is) | Depends on whether the user correctly selects the age distribution and age-group-specific parameters of geographic location of interest | Puts imported cases into the Exposed compartment, which can be interpreted as the cases coming from outside are all incubating/recently infected and not symptomatic |
| Epidemic Calculator 7 | Does not appear to distinguish between asymptomatic and non-hospitalized symptomatic individuals | May underestimate total severity as asymptomatic individuals are more likely to spread COVID-19 as they are unaware they are infected and/or infectious | Does not take age or age distributions into account and unclear the reference population or data used to benchmark (e.g. China) | May overestimate hospitalizations and fatalities if population is younger, as increased age significantly increases riska |  |

TITLE: Selected Model Assumptions for Informing COVID-19 Control and Mitigation

SOURCE: Authors

NOTES: aUnited States has a younger age distribution compared to China, so models that use aggregate estimates of mortality for China may overestimate mortality for US unless age-specific mortality distributions are accounted for.