COVID-19 Models: Why Do Projections Differ?

Christopher Jepson – PhD, Research Analyst, Health Technology Assessment
Jonathan R. Treadwell – PhD, Co-Director, Evidence-based Practice Center

Data and models everywhere: what should you believe?

We all want answers to critical questions: How much longer will the SARS-COV-2 pandemic last? Is social distancing working? Are the tests reliable? Do any treatments work? Is reinfection possible? When will a vaccine be available? How will we know when it's safe to reopen society? What will the death toll be?

The world is swimming in SARS-COV-2 scientific data rushed to publication even before peer review. Innumerable data sources are available, each analyzed by a different group of purported "experts," each with its own spin. Several academic groups have created models to try to address some of these questions, and they update the models frequently.

A _New York Times_ article in late April discussed five different models with widely varying estimates of the anticipated deaths. On May 4, one of those models nearly doubled its projected death toll (from 73,000 in mid-April to 135,000). What sense can one make of such drastic changes when deciding what to believe?

Models are math equations using available data and assumptions to predict future events

Simply put, models use data inputs to produce outputs intended to predict events. A model is a way to represent real-world phenomena through a mathematical equation (or set of equations). The equation predicts the value of an outcome variable based on proposed relationships among other variables ("predictors") thought to affect the outcome.

Most of the best-known SARS-COV-2 models are epidemiologic models. That is, their predictors are primarily disease characteristics. For example, Columbia University's model estimates four outcome variables: number of susceptible, exposed, documented infected and undocumented infected individuals over time. Those outcome variables are based on predictors, such as transmission rate, average latent period, and average infection duration. The numeric values of these predictors are based on the best available data. Pandemic data change daily as the pandemic spreads—sometimes hourly. Thus, the values put into models change. The Columbia model also includes a variable representing the disease's spatial spread, based on commuting data maintained by the U.S. Census Bureau. In this model, predictions can be adjusted to reflect the presumed impact of social distancing policies and individual behavior change by adjusting the values of the predictor(s) that represent contact rate between individuals. Thus, the Columbia model makes four sets of projections based on four scenarios: no contact reduction, 20% reduction, 30% reduction, and 40% reduction. The model does not decide which scenario reflects reality; it simply presents them as alternatives. Differing scenarios can yield dramatically differing predictions of death rates.

Another model, frequently cited by government officials, was developed by researchers at the Institute for Health Metrics and Evaluation at the University of Washington. This model contrasts with epidemiologic models in that it is a statistical model that bases its predictions primarily on the observed SARS-COV-2 death rate curves in various locations around the world.

> Early versions of a COVID-19 model cited by some officials assumed social distance/containment stayed in place _until the pandemic ended_. Early May, model assumptions were changed to account for _relaxed measures during the pandemic_: projected deaths nearly doubled.

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The model also includes predictors representing the effect of social distancing measures on death rates. In contrast to the Columbia University model, these predictors are based on the actual observed effects of such measures on SARS-COV-2 death rates in various locations. They take into account both the nature and the timing of these measures.

The model's original version, described in a **March 2020 paper**, considered four kinds of social distancing measures: school closures, nonessential business closures, stay-at-home recommendations, and travel restrictions. The presumed effect of such measures on death rate was based on data from Wuhan, PRC, the only location at that time where a general epidemic of SARS-COV-2 had occurred and was later controlled (according to data submissions from China). The modelers then made model revisions, described in an **April 2020 paper**, by subcategorizing nonessential business closures into partial and complete closures and by adding group gathering restrictions. Thus, the model now considered six measures. Also, modelers estimated the effects of social distancing on death rates based on data from 13 locations where peak deaths had occurred as of April 14. In addition, newly acquired data on the effects of social distancing on mobility in the United States were integrated. These changes led to a reduction in the predicted number of deaths. Importantly, both model versions assumed that social distancing and other containment measures would be maintained *until the epidemic was eradicated* –meaning until the achievement of an infection rate of <1 per million individuals and containment of new cases via widespread testing, contact tracing, isolation, and limiting mass gatherings. On May 4, the model was revised yet again to account for relaxing of the social distancing policies in various parts of the country, and new death count data reflecting the addition of presumptive SARS-COV-2 deaths. These updates led to a sharply increased estimate of the cumulative death rate.

Which questions are most important to answer, and how good are the model's data sources and assumptions?

When reading about disease models, consider the importance of the question modelers are attempting to answer. From a general societal perspective, knowing how many deaths will result from SARS-COV-2 infection is very important to inform near and long-term planning. In the near term, other questions may be just as or even more important, such as: Which social distancing interventions are most effective at reducing transmission?

The next critical question for readers of models to consider is: how good were the data sources that the researchers used in the model? A model's predictions will be only as good as its input data.

Many suspect that SARS-COV-2 deaths have been underreported, partly because some occurred without a SARS-COV-2 diagnosis. Confirming this suspicion, the U.S. Centers for Disease Control and Prevention greatly increased its official count of SARS-COV-2 deaths that occurred between March 8 and April 11. According to *The New York Times*, the update represented almost 9,000 lives, a nearly 50% increase. These observations make one wonder about the data quality modelers had to work with.

Another key question is: how reasonable were the model's assumptions? As described above, the Institute for Health Metrics and Evaluation model, unlike epidemiologic models, attempts to specify the *actual* effect of implementing a given type of social distancing measure, at a given time point, on death rates (as opposed to a range of hypothetical effects). However, this attempt rests on certain assumptions that the epidemiologic models do not have to make. For example, the use of mortality curves from different regions of the world to project a curve in the United States rests on the assumption that effects of social distancing will be the same everywhere. Dropping the original assumption that social distancing and other policies would be maintained until the epidemic was eradicated also dramatically changed the model's projections, as noted earlier.

All models are imperfect, but be wary of models that don't quantify the degree of uncertainty

All models imperfectly represent their targets, and communicating the degree of imperfection is a key aspect of transparency. One should be wary of any model that does not quantify the precision of its projections.

Typically, media reports focus on models' point projections (e.g., cumulative deaths). This can lead to an illusion of precision; these point projections are only guesses. The important thing to keep in mind is how good we think these guesses are. This is particularly crucial in terms of estimates of whether demand for healthcare resources will exceed supply. The difference, for example, between being at 95% capacity or 115% capacity is substantial in terms of avoidable deaths. The former number may only require minor changes, but the latter may require a fundamental reworking. Thus, if the range of model projections is wide enough to require completely different actions by clinicians (and/or policy makers), then the model overall is less useful.

Interpreting the projections that a model yields warrants paying attention to the model's uncertainty bounds as well as the point estimates. Having high-quality data to input typically results in narrower uncertainty bounds. Worth noting, however, is that even the uncertainty bounds must be interpreted with caution. Like point projections, these bounds are only as good as the model's assumptions.

More specifically, the uncertainty bounds represent the range of possible values of the outcome variable that one can expect to occur by chance *if and only if* the model's assumptions are correct. If assumptions are inaccurate – because important predictors are omitted, or the model gets the relationships between predictors and outcome wrong – real outcomes may fall outside the uncertainty bounds.

An important aspect of interpreting models is therefore not to rely exclusively on any one model, but to look at projections made by multiple models and to have some idea of the data those models use and the assumptions they make.

Lastly, keep in mind that some phenomena are just not very predictable, particularly if we expect models to predict at a level of specificity beyond that for which they were designed.

Be a smart consumer of models: Ask these questions

Statistical models are often the only tool we have to project into the future. They can be exciting and informative, but they can also mislead or be out and out wrong. When the next model is published, be a smart consumer. Ask the following questions:

— How important is the question the model is trying to answer?

— Does it take into account all the important inputs to the problem (predictors)?

— Could the input data have quality problems?

— How reasonable are the model's numerical assumptions?

— How wide is the range around the model's projections?

— Have this model's projections changed recently?

— How does this model compare to other models that attempt to address the same question?

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