THE UNIVERSITY OF MELBOURNE

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Modeling Victoria's escape from COVID-19

Some more details about the model we used

Individual agents making up a synthetic population representing the Victorian population were modelled using an agent-based model (ABM) that has been built for multiple COVID-19 modelling tasks. The ABM is calibrated to produce an unmitigated epidemic resulting in approximately 60% infection across the population, consistent with an estimated R0 value of between 2.3 and 2.75 [1,2] (i.e. the R value was used in calibrating the model initially, but not as an input parameter per se).

The objective of the modelling for Vic DHHS was to determine how often a resurgence leading to Stage 3 occurred, and how often Christmas was spent in Stage 1 or 0.

The simulated policy settings allowed movement down and back up through Stages of restriction policies. The step-down rules were as follows. First, all simulations stayed in Stage 4 until 28 September, then stepped down to a stage half-way between 4 and 3 (call it '3.5'; e.g. some students return to classrooms, some workers re-enter the workforce; e.g. mask usage stayed compulsory, strong social distancing remained; described in more detail in the ODD [forthcoming at https://github.com/JTHooker/COVIDModel]). The next step-down from Stage 3.5 to Stage 2 **varied** between the three scenarios shown by Vic DHHS (here), according to these following triggers: an average of 25 cases per day for 14 days; an average of 10 cases per day for 14 days; and an average of 5 cases per day for 14 days. Stage 2 settings included, for example, half of primary school students returning to school, half of the workforce returning to work, and a reduction in requirements in physical distancing (please see detail forthcoming in ODD at https://github.com/JTHooker/COVIDModel). The step down to Stage 1 occurred after 14 days of one case or less per day on average. The final Stage 1 to Stage 0 (pre-COVID-19 settings) step-down occurred after 14 days of zero cases per day on average.

We also include basic retightening's as follows: Stage 0 to Stage 1 if a case is notified; Stage 1 to 2 if there have been an average of 2 or more cases per day for 14 days; and Stage 2 to Stage 3 if there have been an average of 30 or more cases per day for 14 days. Thus, it was possible for 'tight suppression' to occur with cases moving up and down between (say) Stages 1 and 2.

The main outputs for Vic DHHS were: the proportion of simulations resulting in a resurgence of cases that triggered a Stage 3-like lockdown; and the proportion of simulations where Christmas was spent in Stage 1 or 0.

In the ABM, agents move and interact based on stochastic processes and/or in response to policies reflecting exogenous, government-imposed restrictions. Their aggregate behaviour, experiences (e.g., of susceptibility, exposure, infection and recovery) and actions were used to assess the effect of modelled SARS-CoV-2 suppression strategies across a simulated Victorian population. Specifically, we estimated the predicted outcome of the timing and stringency of various social policies related to COVID-19 case suppression as Victoria negotiates declining case numbers

Because the ABM is underpinned by stochastic processes, we conduct 1000 model runs conducted for 120 simulated days, beginning on Sept 1. All programming, documentation, data and details related to the calculations, estimations and assumptions are available for download from the online repository as is a full and detailed description of the model following the principles of the Overview, Design concepts and Details (ODD)[4] standard protocol for ABMs. This is continually being updated as new functionality and evidence comes to hand through the pandemic and will be made available here.

The model has been 'live' in various versions since April 2020. It has been constructed by a multi-disciplinary and international team including epidemiologists, physicians, computer scientists, urban planners, economists and psychologists. Models of this kind are rarely locked down, frozen in time. They evolve as multiple users learn more about the way the world is working and the extent to which the model usefully represents that world. Thus, the process of refining a model over time, is part of the methodology of model development. This model will continue to change as new data becomes available and new users of the model explore its strengths and limitations.

Key generic parameters include population mobility and close contacts, quarantine measures and compliance, transmissibility, age, student status, workforce status (e.g., essential worker status), household structure (including group homes), superspreading events, school closure policies, case fatality rates based on age deciles, mask uptake and mask efficacy, distance, and COVID-Safe tracing application uptake.

Uncertainty in the model occurs at two levels – 1) model initialisation, and 2) individual agent actions. Uncertainty at the higher, initialisation level is used in the model's set-up procedures (e.g., the initial stringency of policy settings, health system capacity, and desired restrictions on agent movement) as well as variables that determine cut-off scores for binary classification of agents into groups of importance (e.g., essential workers). These are generally 'normal' distributions.

There is also stochasticity in the lower-level factors attached to variables of importance for each agent. These are more often related to epidemiological factors (e.g., mask efficacy for individuals) or the likelihood of taking actions at each time-step. These are more likely to be either beta distributions (in the case of probabilities between 0 and 1), or log-normal distributions (e.g., distribution of individual incubation and illness durations should the agent become infected).

Example parameters used in the model structure are set out in Table 1.

Table 1. Example parameter estimates and 'agent' characteristics.

Key Parameters	Parameter Estimates (varies under difference stage conditions – example parameter estimates only)
Physical distancing (% of people limiting movement and maintaining a distance of 1.5m in public)¥ [5]	m = 0-90%, sd = +/- 3%
Physical distancing - time (% of time that people successfully maintain a distance of 1.5m)¥[5]	m = 0-90%, sd = +/- 3%
Proportion of essential workers¥	m = 25-100% of working age-people (age 18-70)
Mean incubation period (days, log-normal)[6]	m = 5.1, sd = 1.5
Mean illness period (days, log-normal)[7]	m = 20.8, sd = 2
Mean adherence with isolation of infected cases ¥	m = 93.3% (beta distribution 28, 2; median = 94.3%, sd = 4.5%) †
Likelihood of being traced by the health system per day after initial infection	25% - ~80% of cases traced by day 5/6
Number of days after initial infection that new cases are reported¥*	6*
Date of case simulation initialisation (Day 0)	September 1st, 2020
Asymptomatic cases (% of cases) [3,7]	m = 25%, sd = 3%
Infectiousness of asymptomatic cases vs symptomatic cases (per contact) [8]	m = 33%, sd = 6%
Schools returns policies	True / False
Proportion of people wearing face-masks during interactions outside the home	50-90%
Reduction in transmission risk per contact for people wearing face-masks ¥¥¥	~25% (beta distribution)
Seeded cases for model initialisation based on prior 14 day average	~2400 on day 1 and 90 cases per day for 7 days
COVID-Safe App Uptake	m = 30%, sd = +/- 3%
Agent Characteristics	**Definition**
Infection status	Infected, susceptible, recovered, deceased
Time now	The number of days (integer) since an infected person first became infected with SARS-CoV-2
Age-range	The age-bracket (categorical) of the person, set to Australian census data deciles from 0 to 100. Used in this simulation to capture differences in exposure risk through school closures and workforce status.
Risk of death	The overall risk of death (float) *for* each person based on their age-profile. Purely used in this simulation to remove the agents dying during the 100 day simulation time.
Location	Agents interact in over a 2-dimensional plane with their location recorded at each time-step via an x/y coordinate system (categorical).
Span	The distance the person moves around the environment away from their home location – longer

	distances result in higher likelihood of close contact with novel other people (agents) in the model.
Heading / Distance	The direction and extent of travel of the person at the current time-step. The heading and speed variables combine to create local communities and control interaction between and across communities. At higher lockdown stringency levels, agents are restricted to movement in areas closer to their home location.
Contacts	A count (integer) of contacts the person (agent) had interacted with in the past day as they moved within the model's environment. This is used in estimation of contacts with transmission potential each time-step and calculation of individual reproduction numbers at the end of infectious periods.

¥ Assumed parameter based on expert opinion in conjunctions with available public data sources such as Google COVID-19 mobility reports.
¥¥ 10% of the population potentially transmit infections widely through occasional travel to random locations.
¥¥¥ The source paper reports an adjusted odds ratio of 0.15 for a systematic review of observational studies. Given possible residual confounding, and to be conservative, we used 80% rather than 85%.
*This reports all cases known to the model user on day 6 of their infection. In alternative modes, code also allows for under-reporting under extreme pressure on the track and trace system (e.g., in unmitigated scenarios).
£ % mask wearing is fixed part of scenario, therefore no uncertainty.

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