



Omicron scenario projections for the Austin-Round Rock MSA

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Overview

The ongoing COVID-19 surge is straining healthcare systems in the Austin-Round Rock Metropolitan area. As of January 21, 2022, COVID-19 hospital admissions have reached record numbers and the total number of COVID-19 patients in hospitals and ICUs continue to rise. To support response efforts and public risk awareness, we used a data-driven mathematical model to simulate the continued spread of the Omicron variant in the Austin-Round Rock MSA area from January 22, 2022 to June 21, 2022 under four plausible scenarios.

Our projections suggest that the 7-day rolling average of reported new cases in the five-county MSA likely peaked on January 9, 2022 at a value 6,109.

In a pessimistic scenario where Omicron is 33% less severe than Delta, 155% more transmissible, and has 42.5%, 32%, and 22% reduced protection against infection, hospitalization, and death, respectively, we project the following:

- The 7-day rolling average of new COVID-19 hospital admissions will reach a peak of 148 (90% CI: 129 - 214) on January 25, 2022 (90% CI: January 19, 2022 - February 01, 2022).
- The 7-day rolling average of COVID-19 patients in ICUs will reach a peak of 236 (90% CI: 190 - 294) on February 7, 2022 (January 25, 2022 - February 15, 2022).

In a more optimistic scenario where Omicron is 33% less severe than Delta, 100% as transmissible, and has 85%, 10%, and 10% reduced protection against infection, hospitalization, and death, respectively, we project the following:

- The 7-day rolling average of new COVID-19 hospital admissions will reach a peak of 140 (90% CI: 129 - 207) on January 25, 2022 (90% CI: January 19, 2022 - January 27, 2022).
- The 7-day rolling average of COVID-19 patients in ICUs will reach a peak of 205 (90% CI: 157 - 265) on February 3, 2022 (90% CI: January 25, 2022 - February 11, 2022).

Epidemiological model

We used a stochastic compartmental model that explicitly tracks the changes in the population immunity acquired from infections and vaccination. We originally developed the model to provide national-scale scenario projections at the request of the US Centers for Disease Control and Prevention (CDC) [1]. The model tracks the changing numbers of individuals who are susceptible, infected, hospitalized, recovered, and deceased, as well as the changing levels of immunity in the population. The projections below make the following assumptions:

- Based on seroprevalence and vaccination data [2,3] we assume that, as of October 22, 2021, 23.1% of the population has immunity from prior infection and 62.44% of the Austin population has been fully vaccinated.
- Between October 22, 2022 and January 21, 2022, we estimate the transmission rate in three week intervals by fitting the model to daily case report data for the Austin - Round Rock MSA area [4]. Between January 22, 2022 and June 20, 2022, we assume that policies and behavior remain constant. We initialize the transmission rate during this period with the value estimated from January 1 to January 21, 2022 and then assume that changes in transmission rate are entirely driven by the emergence of Omicron.
- Hospitalization and mortality rates are fit according to time-dependent polynomial functions that ensure consistency between case, hospitalization, and mortality estimates. The average hospitalization and mortality rates calculated during the fitting are used during the projection period.
- We assume that 25% of all infections are reported as cases prior to the emergence of the Omicron variant.
- Immune waning is assumed to occur an average of eight months following vaccination and twelve months following natural infection.
- Our model incorporates age-specific contact patterns, hospitalization rates, and mortality rates.

Additional details are provided in the Appendix.

Omicron scenarios

We consider four scenarios for the transmission rate and severity of the Omicron variant (Table 1). In all scenarios, we assume that the Omicron infection hospitalization ratio (IHR) is 33% lower than Delta. Vaccine uptake for primary vaccinations and booster doses is assumed to continue at the current rate, until the portion of the population who is eligible and willing to get vaccinated/boosted receive doses. Additional details are provided in the Appendix.

Table 1. Four transmission and severity scenarios for the Omicron variant.

Omicron scenario	Transmission Characteristics		Severity Characteristics	
	Transmissibility relative to Delta	Immune escape relative to Delta (infections)*	Immune escape relative to Delta (hosp)**	Immune escape relative to Delta (deaths)**
A	155%	42.5%	32%	22%
B	100%	85%	32%	22%
C	155%	42.5%	10%	10%
D	100%	85%	10%	10%

* These values indicate the reduction in protection against infection and symptoms for individuals that were previously vaccinated or infected by a non-Omicron variant.

** These values indicate the reduction in protection against hospitalization and death for individuals that were previously vaccinated or infected by a non-Omicron variant.

Rate of Omicron emergence

To estimate the rising proportion of cases caused by Omicron during December of 2021, we fit a logistic function to S-gene target failure (SGTF) data indicative of Omicron prevalence, provided by the Texas Department of State Health Services (DSHS) (Figure 1).

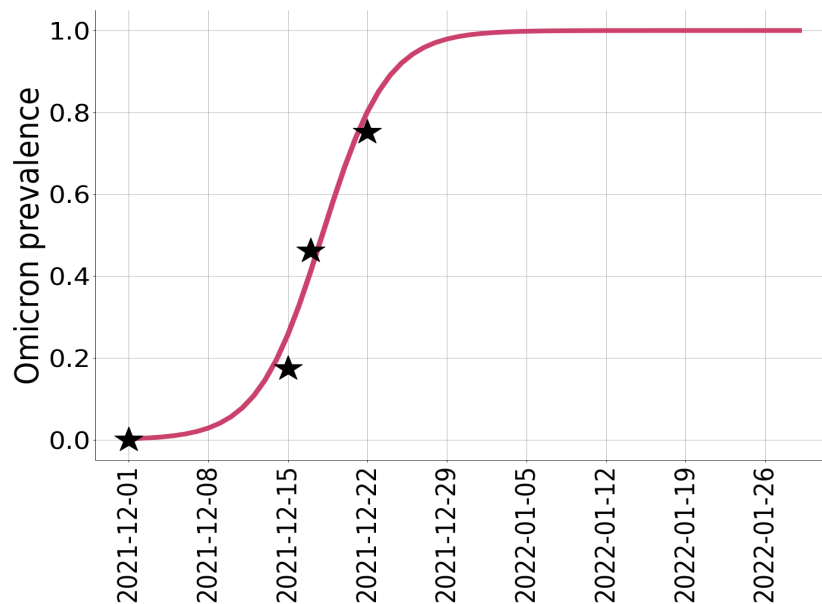


Figure 1: Estimated ascent of the Omicron variant in the Austin area. Values represent the proportion of cases caused by the Omicron variant. Stars represent the reported proportion of SGTF among a sample of COVID-19 tests from Texas; the red line is the fitted logistic curve.

Results

We assume that policies and behavior remain constant from January 22, 2021 through June 20, 2022 and project the number of cases, hospital admissions, and deaths across four scenarios for the emergence and spread of the Omicron variant. Each scenario is defined by the inherent transmissibility and immune evasiveness of Omicron relative to Delta (Table 1). Under all scenarios, our models suggest we have already reached the peak in the 7-day average of reported cases with 90% certainty (6,109 on January 17, 2022). The 7-day average in reported cases is expected to drop below 3,000 by the beginning of February (Figure 2).

In all four scenarios, we expect the 7-day average of COVID-19 hospital admissions to peak by February 1, with a median estimate of January 25 (Figure 3 and Table 2). Under the most pessimistic and optimistic scenarios, we estimate that the 7-day average in COVID-19 hospital admissions will reach a maximum value of 148 (90% CI: 129 - 214) and 140 (90% CI: 129 - 207), respectively.

We project that the 7-day average of COVID-19 patients in ICU's will peak during the first week of February, and could exceed the prior maximum value of 237, which occurred during the August 2021 Delta surge (Figure 4 and Table 3). Under the most pessimistic scenarios, we estimate that the 7-day average COVID-19 ICU patients will reach a maximum value 236 (90% CrI: 190 - 294) and that there is a 48.4% chance it will surpass the August 2021 peak. Under the most optimistic scenarios, we project a peak of 205 (90% CrI: 157 - 265) with a 13.2% chance of exceeding the prior peak.

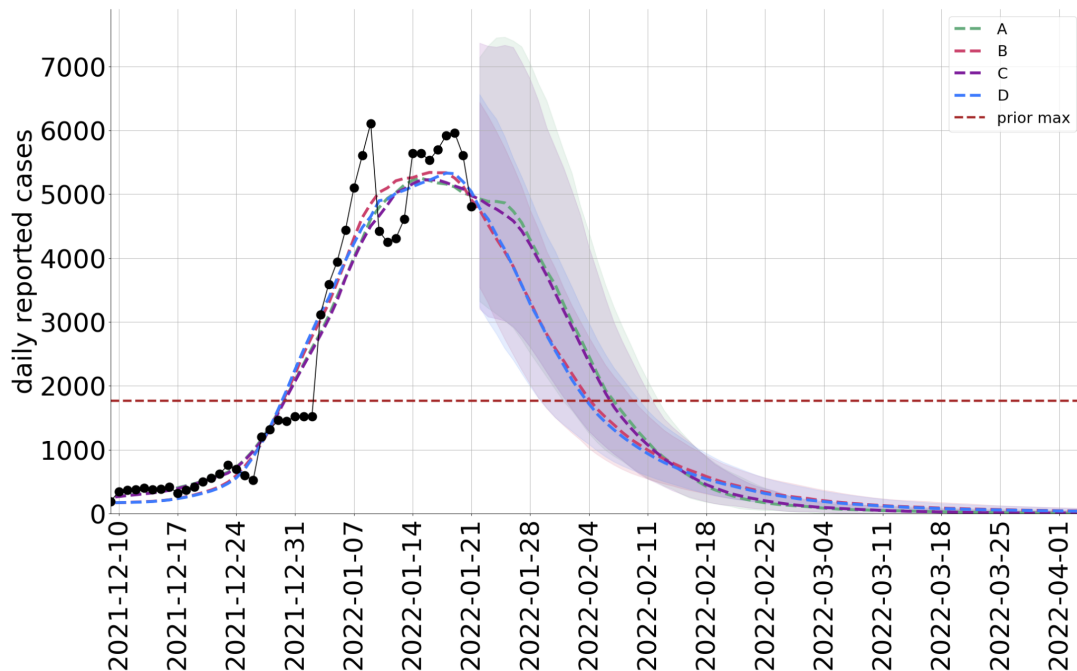


Figure 2: Projected reported COVID-19 cases in the Austin-Round Rock MSA from October 29, 2021 to June 20, 2022, under four different Omicron emergence scenarios. Black dots represent reported 7-day average COVID-19 cases in the Austin-Round Rock MSA [5]. Colored lines represent median projections across the scenarios specified in Table 1, with ribbons indicating 90% projection intervals. The horizontal dashed line indicates the previous maximum 7-day average for reported hospital admissions in the Austin-Round Rock MSA, which occurred in January of 2021.

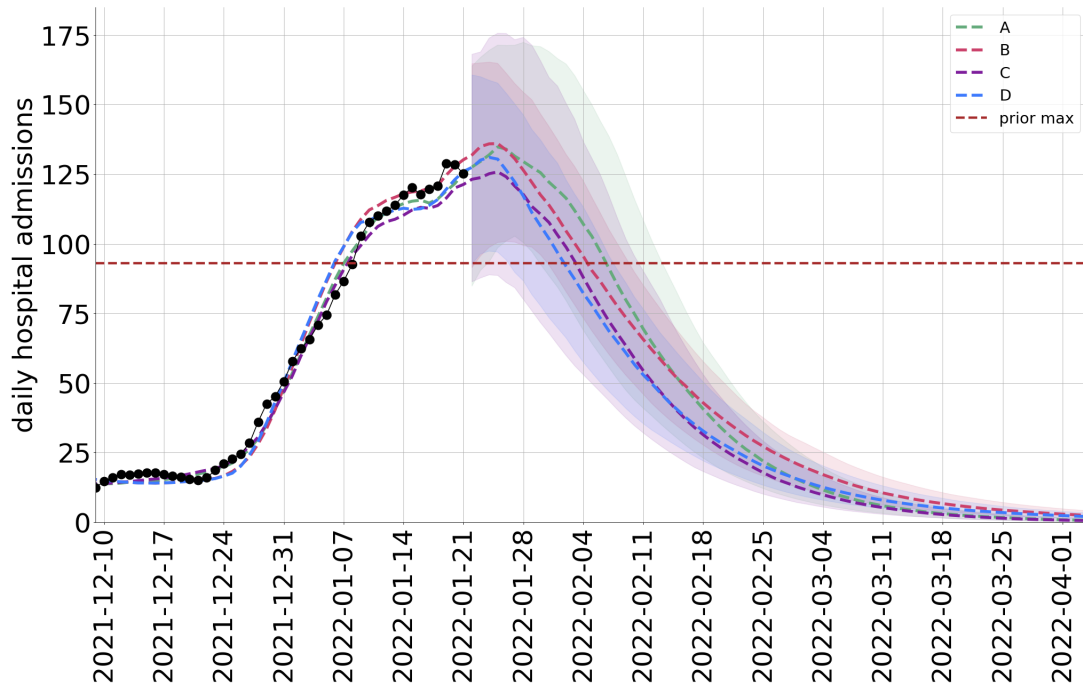


Figure 3: Projected COVID-19 hospital admissions in the Austin-Round Rock MSA from October 29, 2021 to June 20, 2022, under four different Omicron emergence scenarios. Black circles represent reported 7-day average COVID-19 hospital admissions in the Austin-Round Rock MSA [5]. Colored lines represent median projections across the scenarios specified in Table 1, with ribbons indicating 90% projection intervals. The horizontal dashed line indicates the previous maximum 7-day average of hospital admissions in the Austin-Round Rock MSA, which occurred on January 9, 2021.

Table 2. Projected peak number and date of peak in COVID-19 hospital admissions in the Austin-Round Rock MSA between October 1, 2021 and June 15, 2022, under 4 scenarios for the emergence of the Omicron variant. Values are median and 90% confidence intervals based on 250 stochastic simulations.

	Maximum hospital admissions (7-day average)	Date of peak
Scenario A	148 (129 - 214)	Jan 25 (Jan 19 - Feb 1)
Scenario B	147 (129 - 214)	Jan 25 (Jan 19 - Jan 28)
Scenario C	140 (129 - 196)	Jan 25 (Jan 19 - Jan 31)
Scenario D	140 (129 - 207)	Jan 25 (Jan 19 - Jan 27)

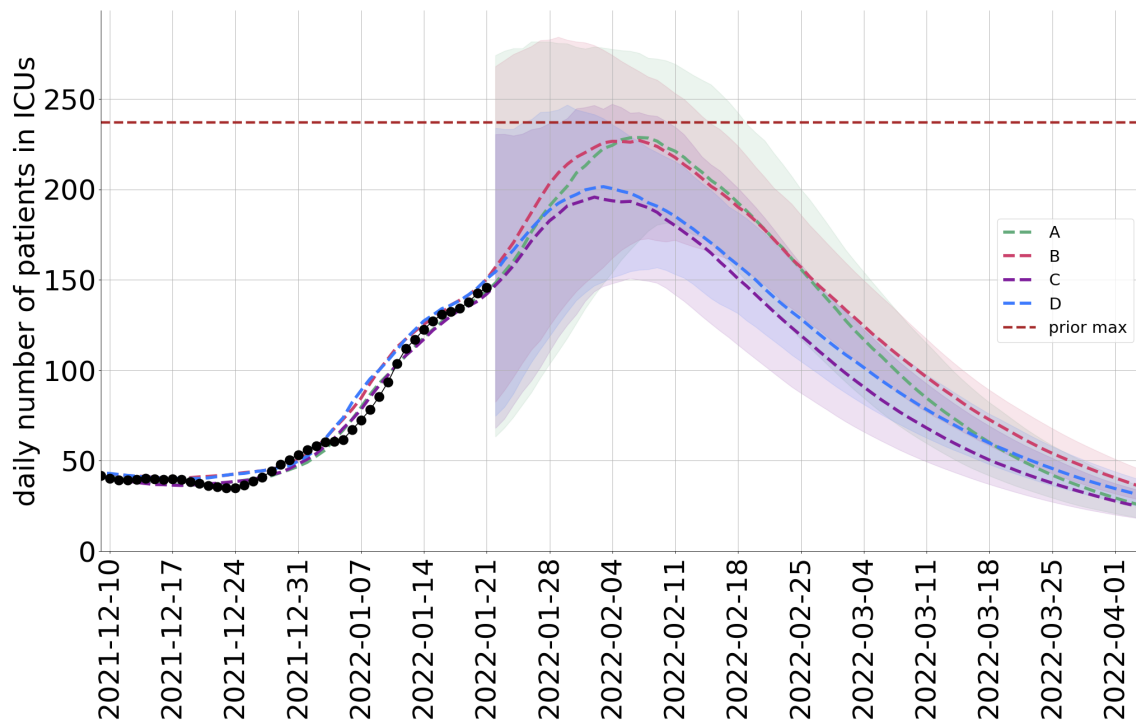


Figure 4: Projected COVID-19 patients in ICUs in the Austin-Round Rock MSA from October 29, 2021 to June 20, 2022, under four different Omicron emergence scenarios. Black circles represent the reported 7-day average COVID-19 ICU census in the Austin-Round Rock MSA [5]. Colored lines represent median projections across the scenarios specified in Table 1, with ribbons indicating 90% projection intervals. The horizontal dashed line indicates the previous maximum 7-day average number of COVID-19 patients in ICUs in the Austin-Round Rock MSA, which occurred on August 22, 2021.

Table 3. Projected peak number and date of peak in COVID-19 ICU patients in the Austin-Round Rock MSA between October 1, 2021 and June 15, 2022, under 4 scenarios for the emergence of the Omicron variant. Values in the second and third columns are median and 90% confidence intervals based on 250 stochastic simulations. The fourth column indicates the proportion of simulations in which the peak surpassed the maximum ICU census of 237 reached during the August 2021 Delta surge.

	Maximum ICU Census (7-day averages)	Date of peak	Chance of exceeding prior maximum (237)
Scenario A	236 (190 - 294)	Feb 7 (Jan 25 - Feb 15)	48.4%
Scenario B	232 (174 - 288)	Feb 6 (Jan 25 - Feb 13)	43.2%
Scenario C	205 (160 - 264)	Feb 4 (Jan 25 - Feb 11)	16.8%
Scenario D	205 (157 - 265)	Feb 3 (Jan 25 - Feb 11)	13.2%

Appendix

Epidemiological model

We use an age-structured COVID-19 SEIRS compartment model that tracks changes in the level of protection acquired from past infection and vaccination (Figure A1). We describe the changes in population-wide immunity resulting from three sources: Delta infections, Omicron infections, and vaccination. The level of each source of protection is explicitly modeled through a state variable. Natural infections increase the infection-acquired protection variables and primary and booster vaccines increase the vaccine-acquired protection variable. The levels of immunity wane at different speeds that are based on published estimates. The variables are used to reduce disease susceptibility and severity by inhibiting infections, symptomatic disease, hospitalizations, and deaths. The efficacy of each form of immunity depends on the relative prevalence of the circulating variants.

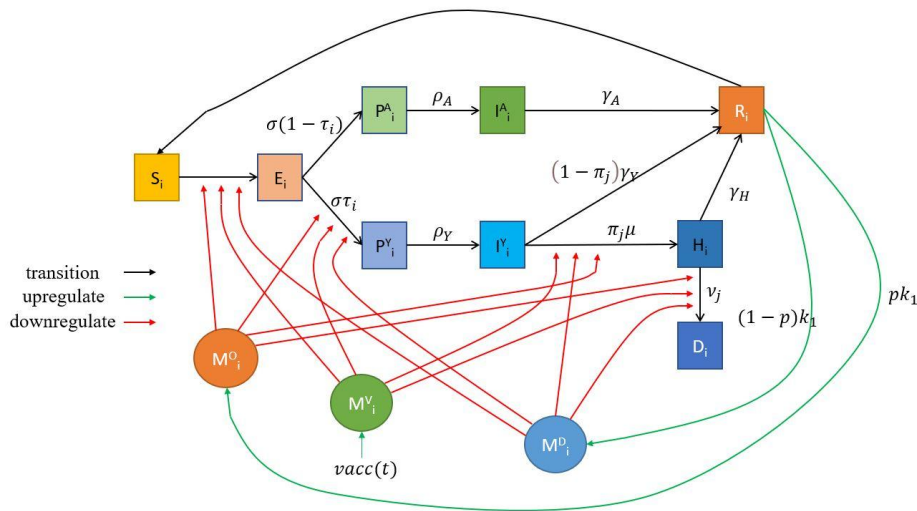


Figure A1. Schematic representation of the mathematical model of SARS-CoV-2 transmission and vaccination. Each subgroup (defined by age) is modeled by a separate set of compartments. Upon infection, susceptible individuals (S) progress to the exposed state (E). Exposed individuals either transition into the pre-symptomatic (P^Y) or the pre-asymptomatic (P^A) compartment. Pre-asymptomatic cases first transition to the infectious asymptomatic compartment (I^A) and then to the recovered compartment (R) where they are fully immune to reinfection. Pre-symptomatic individuals first move to the symptomatic compartment (I^Y); a fraction of individuals move directly to the recovered compartment, while the remaining transition to the hospitalized compartment (H). Hospitalized cases will either move to the recovered compartment (R) or go to ICUs (IH). Patients in ICUs either recover or die and move to the compartment (D). Recovered individuals eventually become partially susceptible again and move into the susceptible compartment (S). At the same time, we describe the changes in population-immunity acquired from Omicron (M_O), Delta (M_D), vaccination and other variants (M_V). These immunities increase through natural infections and vaccination. Each of these immunities downregulates infection rates, symptomatic disease, hospitalization, and death with efficacies that depend on the circulating virus.

Changes in immunity are captured through specific non-dimensional state variables. We begin by describing the changes in the population-level immunity acquired from Delta infections:

$$\frac{dM_D^I}{dt} = \frac{k_1(1-p)R_l}{N_l(1 + K_{s,1}M_D^i + K_{s,1}M_V^I + (1 - (1-p)\epsilon)K_{s,1}M_O^I)} - \omega_1 M^D,$$

where the first term on the right-hand side of the equation describes the development of immunity upon recovery from Delta infections. R_l is the number of recovered individuals among the age group l , and p denotes the relative prevalence of Omicron to Delta. Saturation of immunity reduces its upregulation because most of the people who get infected while having antibodies do not generate as many antibodies as during primary infections. The second term represents the waning of immunity. Next, we describe the changes in the population-immunity acquired through vaccination:

$$\frac{dM_V^I}{dt} = k_2 \frac{Vacc(t)}{N_l(1 + K_{s,2}M_V^I)} - \omega_2 M_V^I,$$

where $Vacc(t)$ is a time-dependent function that describes the daily administered dose two weeks before during the vaccination program. The model does not make a distinction between doses administered as primary series or as third doses. The effect of each dose on immunity is considered two weeks after their administration. The last term on the right-hand side of the equation describes the waning of immunity acquired from vaccination and all variants except Delta and Omicron. After that, we describe the evolution of the immunity acquired from Omicron infections as follows:

$$\frac{dM_O^I}{dt} = k_1 p \frac{R_l}{N_l(1 + (1-p\epsilon)K_{s,1}(M_D^i + M_V^I) + K_{s,1}M_O^I)} - \omega_1 M_O^I.$$

Then, we describe the transition among the different compartment for each specific age group l as follows:

$$\begin{aligned} \frac{dS_l}{dt} &= -S_l \cdot \sum_{i \in A} \frac{\beta_i \phi_{l,i}(I_l^Y + I_l^A \omega^A + P_l^Y + P_l^A \omega^A)}{N_i(1 + K_1^1 M_D^I + K_1^2 M_V^I + K_1^3 M_O^I)} + \eta R \\ \frac{dE_l}{dt} &= S_l \cdot \sum_{i \in A} \frac{\beta_i \phi_{l,i}(I_l^Y + I_l^A \omega^A + P_l^Y + P_l^A \omega^A)}{N_i(1 + K_3^1 M_D^I + K_3^2 M_V^I + K_3^3 M_O^I)} - \sigma E_l \\ \frac{dP_l^A}{dt} &= (1 - \tau_l + K_2^1 M_D^I + K_2^2 M_V^I + K_2^3 M_O^I) \sigma E_l - \rho^A P_l^A \\ \frac{dP_l^Y}{dt} &= (\tau_l - K_2^1 M_D^I - K_2^2 M_V^I - K_2^3 M_O^I) \sigma E_l - \rho^Y P_l^Y \\ \frac{dI_l^A}{dt} &= \rho^A P_l^A - \gamma^A I_l^A \\ \frac{dI_l^Y}{dt} &= \rho^Y P_l^Y - (1 - \pi_m) \gamma^Y I_l^Y - \frac{\pi_m \mu I_l^Y}{1 + K_3 M_l^H} \\ \frac{dH_l}{dt} &= \frac{\pi_m \mu I_l^Y}{1 + K_3^1 M_D^I + K_3^2 M_V^I + K_3^3 M_O^I} - \gamma_H H_l - \nu_m H_l \\ \frac{dR_l}{dt} &= \gamma^A I_l^A + (1 - \pi_m) \gamma^Y I_l^Y + \gamma_H H_l + \gamma^{IH} H I_l - \eta R_l \\ \frac{dH I_l}{dt} &= \nu_m H_l - \frac{\nu_D H I_l}{1 + K_4^1 M_D^I + K_4^2 M_V^I + K_4^3 M_O^I} - \gamma^{IH} H I_l, \end{aligned}$$

where A , are all possible age groups, ω^A is the relative infectiousness of the infectious

compartments I^A , I^{PA} , β is the transmission rate, $\phi_{a,i}$ is the mixing rate between age group a , $i \in A$, and γ^A , γ^Y , γ^H are the recovery rates for the I^A , I^Y , H compartments, respectively, σ is the exposed rate, ρ^A , ρ^Y are the pre-(a)symptomatic rates, τ is the symptomatic ratio, π is the proportion of symptomatic individuals requiring hospitalization, μ is the rate at which hospitalized cases enter the hospital following symptom onset, ν is the rate of ICU admission for hospitalized cases, and η is the rate at which recovered individuals become susceptible again, K^j with i in $[1, 2, 3, 4]$ and j in $[1, 2, 3]$ are positive constants that describe the efficacy of immunity in reducing the rates of infection, symptomatic disease, hospitalization, and death, p describes the relative prevalence of Omicron to Delta. Numerical values of the epidemiological parameters are provided in Table A1 and values of immunological parameters are presented in Table A2.

Model parameters

Table A1: list of epidemiological parameter values used in the numerical simulations.

Parameters	Value	Source
γ^A : recovery rate on asymptomatic compartment	Equal to γ^Y	Assumption
γ^Y : recovery rate on symptomatic non-treated compartment	0.25	[6]
τ : symptomatic proportion (%)	0.35	Adjusted to have 1 symptomatic case out of 4 in the steady-state for Delta
σ : exposed rate	1/1.5	increased from 1/2.9 to 1/1.5 because of Delta [3]
ρ^A : pre-asymptomatic rate	Equal to ρ^Y	
ρ^Y : pre-symptomatic rate	$\frac{1}{2.3}$	[6]
ω^A : relative infectiousness of infectious individuals in compartment I^A	$\frac{2}{3}$	[7]
IFR : infected fatality ratio, age specific (%)	Low risk: [0.0009, 0.0022, 0.0022, 0.0339, 0.2520, 0.6440]	Age adjusted from Verity et al. [8]
YFR : symptomatic fatality ratio, age specific (%)	Low risk: [0.001608, 0.003823, 0.003823, 0.05943, 0.4420, 1.130]	$YFR = \frac{IFR}{\tau}$
γ^{IH} : recovery rate of ICU patients	Fitted between 1/2 and 1/5	Should be lower than the hospital length of stay

Age-specific contact patterns

Contact matrices for the US were used to describe mixing rates between age groups in the Austin - Round Rock MSA [9]. We use three matrices to describe the contact patterns in all locations, schools and workplaces to describe the reduction in mobility during holidays and weekends. We consider that schools close during weekends and from December 18 to January 02, and also during the months of June, July and August. We also consider that workplaces are closed during the weekends. Then, the overall contact matrix is taken as follows:

$$CM = CM_{all} - \alpha_s(t)CM_s - \alpha_w(t)CM_w,$$

where CM_{all} , CM_s , CM_w , are the contact matrices for all locations, schools, and workplaces, respectively. $\alpha_s(t)$ and $\alpha_w(t)$ are time-dependent functions that describe the opening or closure of schools and workplaces, they take the value of 0 if the corresponding location is opened and 1 if it is closed. The three considered contact matrices are as follows:

$$CM_{all} = \begin{bmatrix} 2.598237 & 1.600682 & 0.1895988 & 4.1198752 & 0.912514 & 0.112739 \\ 0.640235268 & 8.428533343 & 0.400015072 & 4.028603965 & 0.709643468 & 0.103204179 \\ 0.173684 & 2.0999574 & 6.663684 & 8.710766 & 0.5601588 & 0.0327582 \\ 0.490443671 & 1.516968944 & 0.759891199 & 10.27014274 & 1.714438659 & 0.095919246 \\ 0.431143971 & 1.339346998 & 0.592373724 & 6.379632659 & 3.196133287 & 0.188612431 \\ 0.204998347 & 0.718001781 & 0.182731115 & 2.136319698 & 1.558267141 & 0.602532372 \end{bmatrix},$$

$$CM_s = \begin{bmatrix} 1.196597632 & 0.269627261 & 0.03173379 & 0.38262616 & 0.049755762 & 0 \\ 0.139739606 & 3.973684579 & 0.051319078 & 0.369792419 & 0.075075384 & 0.000263253 \\ 0.016961126 & 0.903246574 & 3.427856164 & 2.582830513 & 0.060321191 & 0 \\ 0.058180033 & 0.331477088 & 0.188215674 & 0.461408137 & 0.042344186 & 0.000352703 \\ 0.093904827 & 0.568170143 & 0.243358213 & 0.35953993 & 0.073783363 & 0.0005338 \\ 0.000729122 & 0.021954765 & 0.006167126 & 0.029787663 & 0.03474166 & 0.011651215 \end{bmatrix},$$

$$CM_w = \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 1.20585 \times 10^{-05} \\ 0 & 0.039768604 & 0.005775822 & 0.091897952 & 0.006139445 & 0 \\ 0 & 0.020170591 & 0.386451333 & 1.666005478 & 0.136647372 & 0 \\ 0 & 0.056904943 & 0.171469933 & 4.893999929 & 0.792456512 & 0 \\ 0 & 0.069619305 & 0.071928236 & 2.526315884 & 0.70871039 & 0 \\ 0 & 0 & 0 & 0.00026916 & 8.88673 \times 10^{-05} & 2.02847 \times 10^{-05} \end{bmatrix}.$$

Validating the estimated immunity in model

The model dynamics were inspired by the numerical simulations of an agent-based within- and between-host model. This multiscale model has revealed that population immunity reduces disease susceptibility and severity. The parameters for immunity development and saturation (k_1 , k_2 , $K_{s,1}$) were estimated by fitting the results of the multiscale model.

Initializing the epidemiological model

Age-specific patterns for immunity history were assumed to match the data for seroprevalence [2,10]. We start accounting for vaccination dose allocation on October 07, 2021. The first date for vaccination is considered to be two weeks before the beginning of

the simulation. This is because we consider that each allocated dose upregulates vaccine-acquired immunity two weeks of its administration. Vaccine-induced immunity was initiated by considering the vaccination coverages, in terms of administered doses per age group, until this date. We assume that all individuals who received vaccine shots until October 06 2021, did not lose their immunity because the considered half-life time for vaccine-acquired immunity waning is 8 months. Then, vaccination acquired from Delta infections is computed as the remaining immunity, such that 70% are immunized either through vaccination or natural infection [10]. Thus, we obtain the following initial age-specific values for Delta-induced and vaccine-induced immunities:

$$M_{D0} = [0.22, 0.42, 0.86, 0.61, 0.39, 0.26], \quad M_{V0} = [0, 0.0017, 0.4997, 0.6628, 0.6040, 0.8739].$$

Table A2: list of immunological parameter values used in the numerical simulations.

Parameter	Value	Source
Rate of population immunization from natural infections (k_1)	153.55	Fitted to multiscale model results
Rate of population immunization from vaccination (k_2)	0.112	Fitted to data
Constant of saturation from natural infection ($K_{s,1}$)	100	Fitted to multiscale model results
Constant of saturation from vaccination ($K_{s,2}$)	10	Fitted to data
M_D and M_O immune waning rate (ω_1)	$1/(12 \times 30)$	Immunity acquired from infection is considered to last longer than vaccine-induced one [11]
M_D and M_O immune waning rate (ω_2)	$1/(8 \times 30)$	[11]

Fitting the epidemiological model to Austin data

In the absence of immune escape, we consider the values for the rate of immunity efficacy in blocking infections, symptoms, hospitalizations, and deaths summarized in Table A3.

Estimating the effect of immune escape

The model considers that immune escape reduces the efficacy of a type of immunity in reducing susceptibility and severity of another immunity type. Omicron escape to immunity acquired through vaccines and other variants is simulated by reducing the efficacy of Omicron as follows:

$$K_1^i(p) = 4(1 - p\epsilon), \quad K_2^i(p) = 0.15(1 - p\epsilon), \\ K_3^i(p) = 19(1 - p\epsilon_2), \quad K_4^i(p) = 38(1 - p\epsilon_2),$$

where i can be either 1 or 2, p is the relative prevalence of Omicron to Delta, ϵ_1 and ϵ_2 represent the levels of Omicron immune escape to infection/symptoms and to severe

disease, respectively. We assume that Delta has the same chances to escape immunity acquired through Omicron infections.

Table A3. Efficacy levels against the same variant in the absence of immune escape.

	Value	Efficacy against infection for the fully immunized
K_1^1, K_1^3	4	80%
K_1^2	3 for under 65 and 1.33 for over 65	75% for under 65 and 57% for over 65
K_2^1, K_2^3	0.15	90%
K_2^2	0.15	90%
K_3^1, K_3^3	19	90%
K_3^2	19 for under 65 and 9 for over 65	90% for under 65 and 90% for over 65
K_4^1, K_4^3	38	97.5%
K_4^2	38 for under 65 and 19 for over 65	97.5% for under 65 and 90% for over 65

Estimating the prevalence of the Omicron variant

We fit a logistic curve to the relative frequency of Omicron among sequenced SARS-CoV-2 specimens in Texas (Figure 1).

Estimating age-specific vaccination rates

Vaccination is modeled by considering the daily number of allocated doses. These doses can be either administered during primary series or as additional shots. We assume that each administered dose upregulates the age-specific immunity M_V two weeks after its administration. The number of administered doses per age group is aggregated for the five counties from the CDC dataset [3]. Then, the rollout of daily administered doses for each age group during the future period is assumed to remain the same. Booster dose rollout is also kept the same until 70% of the fully vaccinated individuals received a third dose. The administration of primary doses stops as soon as it reaches the age-specific levels of vaccine hesitancy summarized in Table A4. Hesitancy among children is assumed to be higher than among adults.

The model is parameterized using the Austin data for immunity and vaccination history. Next, it is fitted to the latest trends in COVID-19 cases until January 21, 2022. Omicron is introduced to the system starting from December 2021 according to a growth function fitted to prevalence estimates of Omicron in Texas.

Table A4. Assumed SARS-CoV-2 vaccine hesitancy levels for each age group.

Age group (years)	Proportion hesitant
[0-4]	-
[5-11]	30 %
[12-18]	26 %
[19-49]	24.9 % [12]
[50-64]	12 % [13]
[65+]	7 % [13]

Making projections

The model is fitted using Austin data for cases, hospitalization, and mortality ([4], [5]) for the period from 10/21/2021 to 01/21/2022. Then, projections are made for the period between 01/21/2022 and 06/20/2022. Microstochasticities are introduced using the Euler-Maruyama Method. Furthermore, the daily transmission rate is sampled from the distribution $N(\beta_F, \sigma_\beta)$, where β_F is the transmission rate for the period between 22/10/2021 and 01/21/2022 fitted using Austin data, σ_β describes the difference between the 90% confidence interval and the median for the fitted transmission rates values during the fitting period.

For each scenario projection, we made 250 simulation runs and computed the 7-day rolling averages. Then, the 0.05, 0.50, 0.95 quantities are computed for each day.

References

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