Explicit Modelling of Antibody Levels for Infectious Disease Simulations in the Context of SARS-CoV-2

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Summary

Measurable levels of immunoglobulin G antibodies develop after infections with and vaccinations against SARS-CoV-2. These antibodies are temporarily dynamic; due to waning, antibody levels will drop below detection thresholds over time. As a result, epidemiological studies could underestimate population protection, given that antibodies are a marker for protective immunity.

During the COVID-19 pandemic, multiple models predicting infection dynamics were used by policymakers to plan public health policies. Explicitly integrating antibody and waning effects into the models is crucial for reliable calculations of individual infection risk. However, only few approaches have been suggested that explicitly treat these effects.

This paper presents a methodology that explicitly models antibody levels and the resulting protection against infection for individuals within an agent-based model. This approach can be integrated in general frameworks, allowing complex population studies with explicit antibody and waning effects. We demonstrate the usefulness of our model in two use cases.

1 Introduction

Measurable immunoglobulin G (IgG) antibodies to *Severe Acute Respiratory Syndrome Coronavirus 2* (SARS-CoV-2) antigens develop after most infections with and vaccinations against SARS-CoV-2 ([Wel+20]). Although the extent of immunity associated with different antibody titers and other immune responses is not yet fully understood, it is highly likely that an individual's antibody level provides some information about their specific risk and severity of a future infection ([Suh+20; Kra21]). However, SARS-CoV-2 IgG antibody levels are temporally dynamic, and decrease over time if no further immunization event occurs ([Ada+20]). This waning process has been confirmed in multiple studies, showing similar effects regardless whether the immunization happened through vaccination or infection ([Che+22a; Add+22]). It has been consistently shown that the total antibody level starts declining about six weeks after the immunization event and potentially reduces by more than 50% over 10 weeks ([Shr+21; Lon+20; Seo+20]). Hence, waning is important and should be considered explicitly when modelling the antibody level.

During the COVID-19 pandemic, multiple models for projecting and predicting the spread of infections have been developed. In many countries, researchers and policy makers have been using these models to simulate and implement public health policies. From a modelling perspective, explicitly integrating antibody and waning effects into the simulation framework is crucial to allow reliable calculations of the individual risk of infection and severeness estimation. So far, only very few approaches have been suggested that explicitly treat these effects (see Sec. 4.3).

In this paper, we describe how to model antibody levels explicitly on an individual level, such that the population-wide statistics are as close to reality as possible. This approach can be integrated into general frameworks, allowing complex population studies with explicit antibody and waning effects. We demonstrate the usefulness of our model in two use cases: First, we show how to model a population, based on available data, which allows the derivation of time-dependent immunization statistics of the individuals. Second, we describe how the antibody model can be used to calculate protection levels (against infection) from virus variants for the entire population, specific sub-groups or on the individual level.

The contributions of this paper are three-fold:

1. We briefly review the current state-of-the-art literature concerning approaches for modelling individual antibody levels in epidemiological predictive models of COVID-19 (see Sec. 4.3).

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waning for a population or an individual based on available data, such as vaccination and infection statistics.

3. We show how information about the antibody level from our model can be translated into an individual's specific *protection level*. This is done explicitly for various SARS-CoV-2 virus variants (wild-type, Delta, BA.1, BA.2, etc.).

2 Results

The proposed model allows the calculation of an individual's antibody level and, based on that, their protection against COVID-19 infections. By protection, we mean the reduction of the infection probability, as compared to a person without antibodies. In the context of a pandemic, this can, for example, be used to estimate the protection statistics of a country's population. The only data needed for our model are vaccination rates and infection statistics. Both data types can usually be acquired from surveys, other models (e.g. [Mül+21]), or public sources, such as Germany's *Robert Koch Institut* (RKI).

In the following, we show two use cases of our model (details about methods and data can be found in Sec. 4.2). All results refer to the city of Cologne in Germany.

1. We show that the model is able to calculate the number of immunization events of all population members at a given time, even for large populations such as a big city. This is the basis for more complex use cases, such as the following one. Our model is validated by the fact that its outputs closely match the observed data.

2. We show how the model can be used to gain insight into individual population groups and how they are protected against different virus strains. The model can be used as a data basis to develop strategies, such as vaccination campaigns, and can compensate for missing data.

2.1 Use Case 1: Population-wide immunization statistics

The model presented in this paper can be implemented as an extension of our agent-based model (ABM) ([Mül+21]). In this way, we can calculate infection dynamics that are also (but not only) dependent on immune protection. We show in the following section how the model can be used to calculate the number of immunization events (infections and vaccinations) at a given point in time. This allows us to evaluate the model in a real-world scenario by comparing it to available data. Moreover, *number of immunization events* is a relevant parameter because the strategies of policymakers often depend on what share of the population has already acquired some kind of immunity.

In Fig. 1, we show how our model results compares to observed data. Both plots show the number of exposures (vaccinations and infections) that people in different age groups had up to and including Summer 2022. The left plot contains observational data, stemming from antibody level measurements across Germany ([Lan+22]); the right plot shows our simulation results. The age group <18 is not shown because we do not have the observational data to compare it to. When comparing the plots, two things become clear: (1) In our model, more individuals have 4 or more exposures than shown in the observation; this implies that our model's assumption on number of unreported cases is somewhat too high. This deviation may be due to the fact that our model's results refer to Cologne and the data to Germany. In general, however, the deviations are small and the model results structurally fit the collected data. (2) There seem to be two groups of relatively homogeneous profiles in the model (right plot), which are not visible in the data (left plot): 18-59 and 60+. This clustering is due to the fact that the vaccination rate data for adults is only available for these two age groups. In reality, it can be assumed that, e.g., 50-year-olds have a different vaccination rate than 18-year-olds—however, we lack the data here. Although the age groups are less homogeneous in reality, it can be seen that in both the model and the data, the older groups had more frequent contact with the virus than the younger ones.
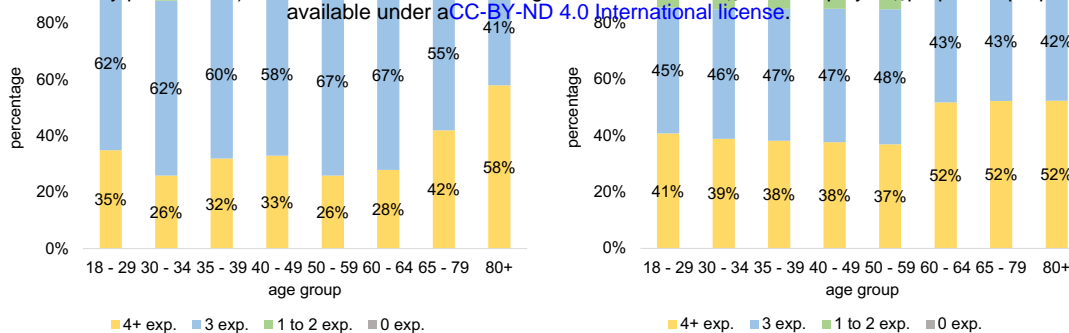
Figure 1: Exposures (vaccinations or infections) by end of July '22. Left: Data from [Lan+22] for Germany. Right: Our model results for the city of Cologne.

In addition to the data shown in Figure 1, there are further surveys ([Bet+22a], [Bet+22b]) that attempted to determine what proportion of the population has had at least one infection. We only found data from summer 2022, but the available studies show results similar to our model: by then, about 35-50% of the German population had been infected with COVID-19 at least once. Since the proportion of vaccinated individuals is higher in the studies than in the general population, this value must be interpreted as a lower limit and can only be used as a rough guide. Our model calculates a value of about 50% for June 2022, which fits well to the aforementioned studies.

2.2 Use Case 2: Variant-specific protection of sub-groups

In general, we assume in our calculations that there is no immune protection at the beginning of the pandemic and that each infection or vaccination increases protection. The exact methodology is explained in Sec. 4.2. In the following, we depict how the population is protected against infection from different virus variants according to the model presented in this paper. Fig. 2 shows the population-wide protection against infection over time averaged over all age groups. The gray area shows that there is a large spread in immune responses; some agents are subsequently very well protected while others have almost no protection. This can partially be explained by the fact that some individuals are unvaccinated (blue dots), while others are vaccinated (red dots) or boostered (more than two vaccinations, green dots). The model results clearly show that vaccinated individuals are better protected than unvaccinated individuals, and missing vaccinations are not compensated for by infections. Thus, unvaccinated individuals do not achieve the same protection through multiple infections as vaccinated individuals.

We calculate the protection for the different variants (left to right). Individuals do not have protection against any variants at the beginning of the pandemic and do not acquire significant immunity throughout 2020. This is because only a small fraction of the population was infected in 2020 and vaccinations were not yet available. Relevant immune protection is achieved by mid-2021 because vaccinations became available for the entire adult population. Beginning in July 2021, a significant decline in immune protection through waning is clearly visible. In winter 2021/2022, we see another protection increase when a third round of vaccinations (boosters) was administered to large segments of the population. In addition, the different facets of Fig. 2 show the impact of immune escape variants: in general, protection against infection with Alpha is significantly higher than against Delta, and protection against Delta is significantly higher than against either Omicron variant.
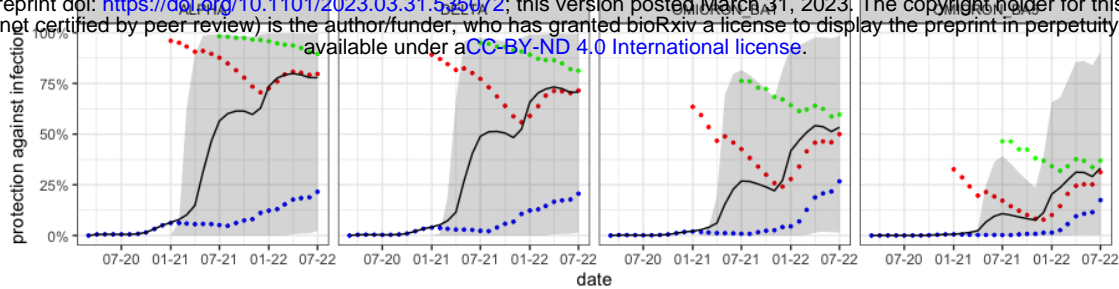
Figure 2: Protection against infection according to the model for different variants. The color coding is as follows: blue: unvaccinated, red: vaccinated, green: boostered, black: mean protection, gray area: 10th to 90th percentile. Reading example: for the Delta variant (2nd plot) it becomes apparent, that unvaccinated (blue) have a significantly lower protection that vaccinated (red) or boostered (green)by July 2022.

Fig. 3 shows how protection varies across age groups. It is clear that the mean protection within the age groups differs significantly. On average, children acquired less protection than adults, which can be explained by low vaccination rates in these age groups. Evidently, according to the model, the lower vaccination rates are not compensated for by infections. According to the officially reported numbers, the group of children under 5 years of age is not vaccinated at all, which results in a low level of immune protection. It also becomes apparent that the different age groups were vaccinated at different times during the vaccination campaign. The elderly over 60 were vaccinated very early, so that immune protection was also built up early. However, due to the early vaccination, there is already a significant decline in vaccination protection in the summer of 2021. In the younger adults, a similar but less pronounced effect is seen; the effect is barely visible for agents under 18. Because vaccinations were no longer administered strictly by age during the winter 2021/2022 booster campaign, it can be speculated that younger individuals had a shorter interval between 2nd and 3rd vaccination than older individuals.
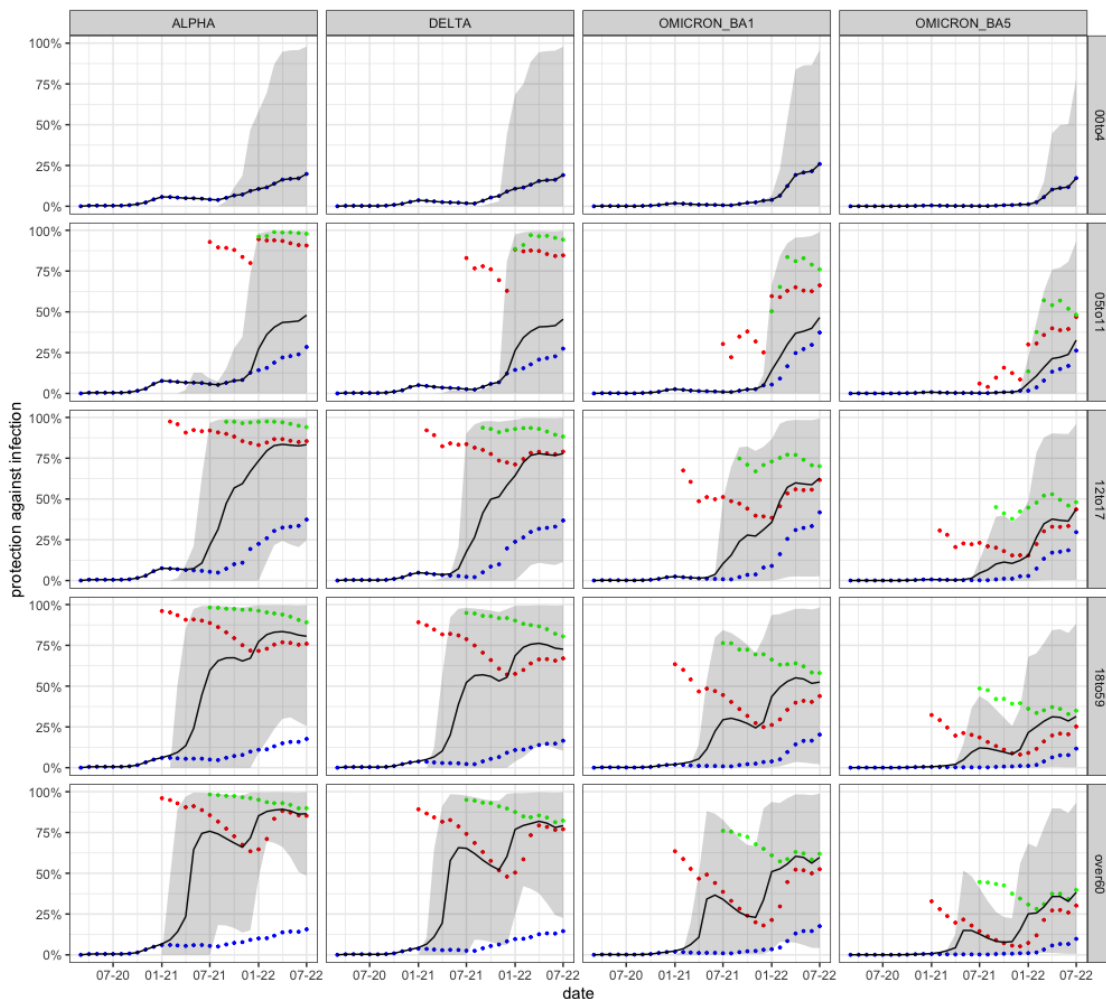

Figure 3: Protection against infection according to model for different variants and age groups. The color coding is as follows: blue: unvaccinated, red: vaccinated, green: boostered.

variant, the time point and the number of administered vaccinations. In particular, there is little protection in young children; hence, according to our model, potential vaccines for this age group could have a significant effect. In addition, it is clear that a vaccine adapted to the new variants would be helpful for all ages, since the mean protection in July of 2022 in all age groups is only about 50% or less.

2.3 Discussion

In the previous sections, we have shown two exemplary use cases that demonstrate the capabilities of our approach to model an individual's antibody level and, based on that, an individual's level of protection against infection. The data needed for our model is usually available from public sources. The presented findings for the study-area of Cologne demonstrate that the model can produce realistic results. In particular, it is possible to derive immune protection of individuals—or the entire population—as a function of time, age, vaccination status and, specifically, virus variant. It should be noted that the model is currently parameterized only for SARS-CoV-2 and its variants. It is possible, however, to adjust the model to be applicable to other infectious diseases, such as influenza.

The presented model is based on certain assumptions and simplifications. We assume, for instance, that there is a direct correlation between antibody levels and protection against infection. Moreover, we currently do not distinguish between the effects of vaccinations and infections, except for the individual's *first* immunization event. In addition, we assume a constant antibody level half-life, regardless of whether the antibodies come from infections or vaccinations (see Sec. 4.2 for details). This can be improved in the future when more bio-medical research on SARS-CoV-2 becomes available.

3 Summary & Conclusion

We have presented an approach on how to model the variant-specific neutralizing effect of antibodies and how to convert it into a protection against infection. The presented use cases demonstrate that the model produces valid results that match the observed historical data in Germany very well. Further, we have shown how this approach can be used within an agent-based modelling framework to allow computation of infection dynamics. In the (current) situation of high population immunity, considering immune protection is essential for achieving realistic simulation results.

Our simulation results show that in summer 2022 there was still a significant difference in immune protection between unvaccinated and vaccinated individuals. According to the model, the lack of vaccination is not fully compensated by infections. This effect also becomes clear when looking at the age groups: according to the model, children have a significantly lower protection against infections than adults. In addition, the model allows quantification of the protection against the immune escape variants. These results suggest that the protection against the Omicron variants is significantly lower than against the original (wild-type) variant. This matches the available data.

The necessary model parameters have either been taken from the available literature or are based on calibration to available data. This process necessarily includes modelling choices. Given the solid agreement between our model results and the available data, we are confident that sensible parameters and fitting parameter values have been identified. This is also confirmed by simulation results that have been achieved by using the presented antibody model in conjunction with our own agent-based model (see, for example, [Mül+22a] and [Mül+22b]). These results demonstrate once more that the agent-based model with the presented antibody-model extension is able to soundly replicate many important parameters, such as case numbers, R-values, and hospitalizations. This is a significant improvement based on the explicit antibody model for each agent.

To the best of our knowledge—and based on the our literature review—no other currently available model allows both (1) the integration of antibody levels as a proxy for protection against infection and (2) the modelling of individual immunization histories. While a small number of models implemented one of these, we haven't encountered any that implement both. In consequence, our approach could help others to integrate any permutation of immunization events, as well as waning, into their COVID-19 models.

3.1 Limitations of the study

The model, as it is, works well for the presented use cases. However, limitations and possible improvements exist, and will be briefly described in the following.

On the technical side, the model is currently designed to be compatible with ABMs, such as ours [Mül+21]. However, adaption to other models types would be straightforward, since the entire source code [Rak+22] and data [Bal+21] is publicly available. From a data perspective, the presented approach is based on the immunization histories of individuals, which we generated based

but other approaches might be chosen for different contexts. Further additional demographic data such as home location, income, or number of household members could be integrated into the model as well. We did not evaluate the effect of this additional information, but we intend to in a future version. The main limitation of our model from a bio-medical standpoint is that not all necessary model parameters can be derived from the literature; the reason is that the studies simply haven't yet published. However, our approach for parameter estimation seems to work well for the presented use cases.

4 STAR Methods

4.1 Resource availability

Lead Contact   Further information and requests for source code and data should be directed to and will be fulfilled by the lead contact, Sebastian Müller (mueller@vsp.tu-berlin.de).

Materials availability   This study did not generate new materials.

4.2 Method Details

In the following, we describe how our model computes antibody levels and how it calculates the ensuing protection against infection with SARS-CoV-2. We explain how the model parameters were chosen using both available data and our own calibration, which was necessary to fill data gaps.

The model is composed of two layers: 1) Modelling the antibody level, based on real-world measurements of antibody titers. 2) Translation of the antibody level into protection against infection, as this is the relevant parameter to calculate the infection probability.

The model is designed as an extension to our agent-based model presented in [Mül+21]. The protection is integrated as an additional parameter into the infection model, described on page 5 of that paper. The principle is simple: the higher the antibody level, the higher the protection. And the higher the protection, the lower the probability of infection, given contact with an infectious agent.

4.2.1 Background

We used the models of [Coh+21] and [Cro+22], with details for the latter in [Kho+21], as starting points for the process of integrating antibodies into our agent-based model. They both postulate a logistic model of type

$$VE = \frac{1}{1 + \exp(-\beta \cdot (\log(N_{ab}) - \log(N_{50})))}$$

for vaccine effectiveness, where N_{ab} is the measured antibody level, N_{50} is the antibody level at which VE is 50%, and β determines the slope at $N_{ab} = N_{50}$. Translated into relative risk, which we here call $immFac$, this can be rearranged to

$$immFac = 1 - VE = \frac{1}{1 + \exp(\beta \cdot (\log(N_{ab}) - \log(N_{50})))} = \frac{1}{1 + (N_{ab}/N_{50})^\beta} = \frac{1}{1 + N^\beta},$$

where N as a strain-specific relative antibody level and is defined as $N := N_{ab}/N_{50}$ (see Sec. 4.2.3 for a detailed explanation). N is unit-less and would need to be multiplied with N_{50} to be expressed in laboratory units. Note that N is time-dependent, as antibodies decrease over time and increase, when an infection or vaccination occurs (see Sec. 4.2.3). The value for β is chosen through calibration (see also Sec. 4.2.4). The equation shows that a relative antibody level of 0 leads to an immunity factor of 1, i.e. a VE of 0%. An antibody level of 1 leads to an immunity factor of 0.5, i.e. a VE of 50%. An antibody level above 1 corresponds to an immunity factor below 0.5, i.e. a VE higher than 50%.

4.2.2 Integration with a dose-response model

Our agent-based model [Mül+21] uses the following well-established dose-response model to calculate the probability of infection ([Wat+10; SC10; Kri+21]):

$$p_{inf} = 1 - \exp(-\Theta \cdot d) \ ,$$

where d is the viral dose, and Θ is a calibration parameter, which depends on the transmissibility of the virus under consideration.

The open question was how to include $immFac$ into the above dose-response infection model; since most simulations use a compartmental approach, they do not need to resolve this issue. A

high antibody levels, even in virus-rich environments, the F2 like. This does not seem plausible given that the virus eventually overcomes the antibodies if the ratio of virus to antibodies is large enough.

As a consequence, we put $immFac$ into the exponent, as such:

$$p_{inf}^{immunized} = 1 - \exp(-\Theta \cdot d \cdot immFac) = 1 - \exp\left(-\Theta \cdot \frac{d}{1 + N^{\beta}}\right) \ . \tag{1}$$

Note that this has the consequence that in a virus-limited environment, where dose d is small, $immFac$ becomes a risk reduction for situations in virus limited environments:

$$\frac{p_{inf}^{immunized}}{p_{inf}^{not-immunized}} = \frac{1 - \exp\left(-immFac \cdot \Theta \cdot d\right)}{1 - \exp\left(-\Theta \cdot d\right)} \approx \frac{immFac \cdot \Theta \cdot d}{\Theta \cdot d} = immFac \ . \tag{2}$$

This linear approximation in a virus-limited environment follows from $1 - exp(-x) \approx x$ when $x \geq 0$ and sufficiently small.

That is, a model that was originally developed for a macroscopic situation is now used at a more microscopic level. The *epidemiological* risk reduction would come out as an average over many exposures with different values of d.

Eq. (1) shows how antibodies reduce the likelihood of becoming infected (reduced susceptibility). However, we also included the fact that agents with antibodies have reduced probability to pass on on the virus (reduced infectivity). Thus, when an unvaccinated agent has contact with a vaccinated agent, the unvaccinated agent indirectly benefits from the vaccinated agent's antibodies because the probability of infection is reduced. If both agents are vaccinated, the probability is further reduced. This is in accordance with findings by [Eyr+22]. In our model, the infectivity is reduced according to the same principle as explained above, but to a lesser extent. The effect of the antibodies on the infectivity is 25% of the effect they have on the susceptibility. Thus, if an agent has a 50% reduced probability of infection due to their antibodies, the probability of transmission is reduced by only 12.5%.

4.2.3 Modelling the antibody level

In the next step, the relative antibody levels (N in Eq. (1)) are modelled. For every simulated day and agent, the model updates the agent's relative antibody level with respect to each SARS-CoV-2 strain. A relative antibody level of 0 corresponds to no protection, while a relative antibody level of 1 corresponds to 50% protection (see Sec. 4.2.1 for details). At the beginning of the simulation, all agents are initialised with a relative antibody level of 0. Immunization events (vaccinations and infections) increase an agent's relative antibodies. On days on which no immunization event occurs, the antibody levels follow an exponential decay curve, as shown in Eq. (3):

$$N(t) = N_0 \cdot 2^{-t/t_{0.5}}, \tag{3}$$

where $N(t)$ is the antibody level on day t after the most recent immunization event, N_0 is the antibody level immediately after the most recent immunization event and $t_{0.5}$ is the half-life, which is 60 days in this case. The value of 60 days is rather on the lower end of what can be found in the literature ([Cro+22], [Yam+22], [Gil+22]). However, the value is the result of our calibration: at 60 days, our model best matches the literature in terms of the declining level of protection against infection acquired through vaccination (due to waning antibody levels). See also Sec. 4.2.4 for more details.

The general principle of the model is shown as an example in Fig. 4. The left figure shows how the antibody level of an example agent develops over time. The spikes in relative antibodies correspond, in this illustrative example case, to a SARS-CoV-2 infection, an mRNA vaccination, and an infection with the Delta variant. On days without an immunization event, the waning becomes apparent. In addition, it becomes clear that we distinguish between the different virus variants. As a result, this means that agents are less protected against the immune escape variants after vaccination. The right plot shows how we translate the antibodies into protection. See Sec. 4.2.1 and Sec. 4.2.2 for details.
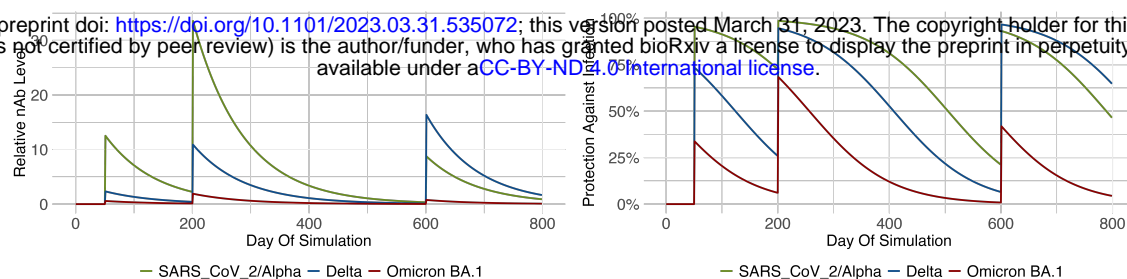
Figure 4: Exemplary immunization history. The agent gets infected with the wild-type on day 50, receives the mRNA vaccine on day 200 and gets infected with the Delta variant on day 600. Left: Neutralizing antibody levels, Right: Resulting protection against infection (Protection is computed as follows: $1 - immFac = VE$).

Initial Immunization: As noted above, we assume that initially (at the beginning of the pandemic) all agents have an antibody level of 0. The first immunization event generates a strain-dependent initial antibody level, which is shown in Tab. 1. The agent's antibodies have varying neutralizing effects against different SARS-CoV-2 strains. Thus, we model that an agent has a different relative antibody level per strain. As shown in Tab. 1, an infection with Delta provides more relative antibodies against a reinfection with Delta than against an infection with an Omicron variant. Similarly, the vaccinations were designed to protect against the wild-type and Alpha variants; thus, the vaccinations provide more relative antibodies against these strains than for later variants.

Tab. 1 is based on studies that examined protection against (symptomatic) infection and on various studies that measured antibody titers after vaccination or infection ([Rös+22b], [Rös+22a]). Here, protection obtained through vaccination with the mRNA vaccines developed by Moderna (mRNA-1273), and by BioNTech-Pfizer (BNT162b2) are summarized under 'mRNA', while the vector vaccines developed by AstraZeneca (ChAdOx1-S) and Johnson & Johnson (Ad26.COV2.S) are summarized under 'vector'. In consequence, we do not distinguish between vaccine brands, but only between vaccine types.

The starting point for Tab. 1 was protection after vaccination with an mRNA vaccine against the wild-type, the Alpha, the Delta and the Omicron BA.1 variant (marked with ⋆ in Tab. 1). For these cases, studies that assess vaccine effectiveness over time are available ([NBN22], [And+22; UKH22a; UKH22b; Che+22b]). To match these studies, the corresponding initial antibody values in Tab. 1 were calibrated. In the same step, the half-life of 60 days from Eq. (3) was estimated (for the calibration process see Sec. 4.2.4 and for the conversion between vaccine effectiveness and neutralizing antibodies see Eq. (4)).

In the next step, we used measurements from [Rös+22b] and [Rös+22a] to populate the other entries. For example, the second row of Tab. 1 represents the relative antibodies versus various strains resulting from a vector vaccination. For Alpha, [Rös+22b] measure a neutralizing effect of approximately 700 after mRNA vaccination and approximately 210 after vector vaccination (we obtained these values from Figure 1 in [Rös+22b]). We used this ratio to calculate the relative antibodies against Alpha after vector vaccination: $29.2 \cdot 210/700 = 8.76$. The remaining entries in the table were filled following the same logic.

The measurements by [Rös+22b; Rös+22a] and others show that there is virtually no neutralizing effect if the initial immunization event is an Omicron infection, so we assume a very low value (0.01) here. We do not use 0, as it is to be expected that at least a small protection is present in the case of repeated infections.

For Omicron BA.2 and BA.5 we did not have accurate measurements at the time of the study, so we calibrated the immune escape by using our agent-based model. Here, we take the values for BA.1 from Tab. 1 and divide them by a factor. The factor was calibrated so that our model correctly replicates the infection dynamics, in particular the initial growth of BA.2 and BA.5, respectively.

immunization event	SARS_CoV_2	Alpha	Delta	BA.1
mRNA	29.20*	29.20*	10.90*	1.90*
vector	8.76	8.76	5.45	0.38
SARS_CoV_2	12.5	12.5	2.33	0.57
Alpha	12.5	12.5	2.33	0.57
Delta	8.76	8.76	16.4	0.76
BA.1	0.01	0.01	0.03	0.21

Table 1: Initial relative antibodies per variant after certain immunization events. Based on calibration ($\star$, see Sec. 4.2.4 for details) and [Rös+22b; Rös+22a]. 'mRNA' means a vaccination with an mRNA vaccine (either mRNA-1273 or BNT162b2), 'vector' means a vaccination with a vector vaccine (either ChAdOx1-S or Ad26.COV2.S), and 'SARS_CoV_2/Alpha/Delta/BA.1' means an infection with the 'SARS_CoV_2/Alpha/Delta/Omicron BA.1' variant.

Agent heterogeneity: To account for the fact that immune response towards vaccinations or infections varies across the population, we assign an *immuneResponseMultiplier* to each agent. The lowest possible *immuneResponseMultiplier* is 0.1, which is an attempt to adequately depict the immunocompromised population; the maximum multiplier is 10.0. Tab. 1 presents the initial antibodies for an individual with an average response to immunization events (*immuneResponse-Multiplier* = 1.0); for low and high responders, the antibodies shown in the table are multiplied by an agent's *immuneResponseMultiplier* to calculate the antibodies gained in response to an immunization event. A log-normal distribution of *immuneResponseMultiplier* with a median of 1.0 is applied to the population.

Subsequent Immunizations: If the agent is subject to an additional immunization event, their antibody levels will be multiplied by a factor of 15 across the board for vaccinations and infections ([Atm+22]). The maximum antibody level that an agent can have is 150 (which corresponds to a protection of nearly 100%). If multiplication by 15 still leads to a lower protection than indicated in Tab. 1, then the value from Tab. 1 is used. This means that, at minimum, the initial antibody level from Tab. 1 is always reached.

4.2.4   Calibration

As not all necessary parameters were available in the literature when we built this model, some had to be estimated. These estimations were based on studies on vaccine effectiveness and Eq. (1). The relative risk of an immunized individual vs. a non-immunized individual given dose d is $\frac{p_{inf}^{immunized}}{p_{inf}^{not-immunized}}$. Vaccine effectiveness is defined as one minus this relative risk:

$$VE = 1 - \frac{p_{inf}^{immunized}}{p_{inf}^{not-immunized}} = 1 - \frac{1 - \exp\left(-\Theta \cdot \frac{d}{1+N^\beta}\right)}{1 - \exp(-\Theta \cdot d)} \ .$$

This depends on the dose d; for example, for $d \to 0$ one obtains $VE \to 1 - \frac{1}{1+N^\beta}$, while for $d \to \infty$ one obtains $VE \to 0$. That is, according to the model, immunity can be overcome by a sufficiently high dose. This is similar to the distinction between virus-rich and virus-limited environments, where protection measures such as masks only make a difference in virus-limited environments [Che+21].

We performed the calibration for the exemplary value of $\Theta \cdot d = 0.001$. We also tested the calibration for values other than 0.001 and obtained very similar results, so that the value can be understood as a placeholder. In the model of [Mül+21], a value of 0.001 corresponds to contact with a contagious person for about 1000 sec without protection (e.g, masks) in a room of 20 m^2.[1]

From the above, one obtains the following equation that can be used to convert $immFac$ (and therefore the antibody level) to vaccine effectiveness against infection and vice versa:

$$VE(t) = 1 - \frac{1 - \exp(-0.001 \cdot immFac(t))}{1 - \exp(-0.001)}. \tag{4}$$

By use of the above equation we performed parameter estimations for:

- $t_{0.5}$ in Eq. (3)

- Entries marked with $\star$ in Tab. 1

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[1]A typical value for Θ in the model of [Mül+21] is of the order of 10^{-5}. At the same time, without protection (e.g. masks) $d = \tau/(rs \cdot ae)$, where τ is the time of exposure in seconds, rs is room size in m^2, and ae is the air exchange rate per hour. Assume $rs = 20m^2$ and $ae = 0.5/h$, typical values for a two-person office or a smallish living room, and $\tau = 1000sec$ of exposure time. These values result in $\Theta \cdot d = 0.001$.

To this end, for the wild-type/Alpha, the Delta, and the Omicron BA.1 variants, Eq. (4) was fitted to data points taken from studies ([NBN22; And+22; Che+22b; UKH22a; UKH22b]) by minimizing the mean squared error. For this, we used R (version 4.1.1) and the optim function from the stats package ([R C21]). Optim can be used for general purpose optimization as it is based on Nelder–Mead, quasi-Newton and conjugate-gradient algorithms. The results can be seen in Fig. 5, where the dots are values taken from the studies mentioned above, and the lines show the vaccine effectiveness $VE(t)$ in our model when using the calibrated values. The increased vaccine protection after 210 days is related to booster vaccinations.
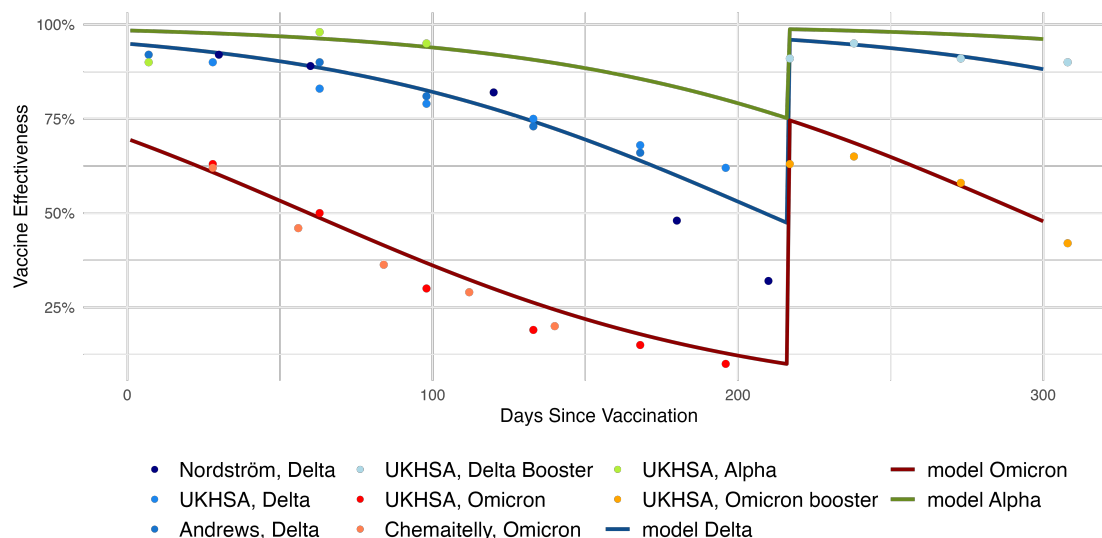

Figure 5: Calibration results. Dots were taken from the literature, lines are the fitted curves. On day 210 the agent receive a booster dose, which increases their level of protection.

4.3 Antibody Models for Epidemiological Predictive Modelling of COVID-19: A Literature Search

The previous section described our approach for modelling antibody levels in an epidemiological context. In this section, we present an overview of similar approaches that exist in the literature, as of July 2022. We compiled a list of all models that have been listed in one of the following resources: (a) the *Covid-19 Forecast Hub*[2] ([Cra+21]), (b) the *European Covid-19 Forecast Hub*[3] ([She+22a; She+22b]), and (c) the *European Covid-19 Scenario Hub*[4] ([Eur22]). The final list contains 90 models. Additionally to the 86 models from the three resources, we also included four more models that we found through a PubMed literature search. The full list can be found in Appendix A. To get the relevant information for the individual models, we went to the respective websites, and analyzed connected publications and available source codes (e.g. from GitHub). We were in particular interested in models that either (1) related antibodies and protection against infection and integrated this into their model or (2) acknowledged and integrated into their model the waning of protection against infection (after vaccination and/or infection).

From this literature review, we conclude that, apart from Covasim ([Ker+21; Coh+21]), whose influence on our model has been discussed in Sec. 4.2.1 and which can be found as model #1 in Appendix A), none of the reviewed models explicitly integrate antibody levels as part of their infection sub-model. This is also due to the fact that many models focused on the prediction of hospitalization numbers and thus do not need to explicitly model individual antibody levels. However, some approaches seem to have integrated some kind of vaccination or antibody sub-model, but no detailed description is available. This includes (see table for details): IHME, UC3M-EpiGraph, ECDC-CM_ONE, and SIMID-SCM.

5 Data and code availability

The data used in this study are all available from public resources that have been appropriately cited within the manuscript. Any additional information required to run the model is available from the lead contact upon request.

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[2]From the community sub-section, as of 07/21/22.
[3]From the community sub-section, as of 07/21/22.
[4]From the models sub-section, as of 08/31/22.

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Author contribution

S.M., K.N., T.C. conceptualized the idea; S.M., S.P., J.R. curated the data; S.M., S.P., J.R. performed the experiments and S.M. did the formal analysis. S.P. did the literature review and S.M., S.P., J.R., K.N., T.C. wrote the original draft. All authors read, reviewed and approved the manuscript.

Declaration of interests

The authors declare no competing interests.

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Appendices

A Appendix

A.1 Literature Review

EMI: (YES, NO, N/A) Explicit Modelling of immunisation events (distinguish between infection, immunisation etc.) AND/OR of waning AND/OR of a relation between antibodies and protection against infection. If the model description solely mentions any of the criterion above, but provides no details, we still set EMI = N/A. If the same model was, under a slightly different name, part of multiple of our sources, we put down all names separated by a "/".

#	Model	EMI	Source	Model description
1	Covasim	YES	Lit. Search	Agent-based model that simulates the transmission of COVID-19. Individual may pass through the following infection stages: susceptible, exposed, infectious, and recovered (SEIR). The associated GitHub repository has last been committed to in January 2022 and their paper [Ker+21], which was published in July 2021 mentions that they will incorporate waning efficacy, but no more recent information or model description could be found. Their additional methods preprint [Coh+21], which does not explicitly mention Covasim but is noted on their project website, served as the basis for our antibody model and has been discussed in Sec. 4.2.1.
2	CovidSim	N/A	Lit. Search	Agent-based model developed by MRC Centre for Global Infectious Disease Analysis hosted at Imperial College, London. Model documentation, as part of the associated GitHub repository ([Cen]), has last been updated in February 2021. No mentions of vaccines, waning or antibodies.
3	CoSim	N/A	Lit. Search	Expanded SEIR model containing 27 compartments (as of December 2021) ([Leh]). COVID-19 related metrics are computed on German federal state level. Checking both the model description on their website as well as the FAQs for their simulator (which have last been updated in December 2021), no information on waning or antibodies could be acquired.
4	OpenCOVID	YES	Lit. Search	A stochastic, discrete-time, individual-based transmission model of infections and disease dynamics. In their paper ([Sha+22]), dating from December 2021, the authors note that they did not consider waning immunity in this study. But, in the supplementary material, they model the probability of transmission as $p(transmission) = \beta \cdot \nu_i(\tau) \cdot \phi_1 \cdot \sigma(t) \cdot (1 - \mu_s)$, where $\nu_1(t) \in [0,1]$ denotes the viral load of the infectious individual and τ denotes they days following infection. ϕ_1 denotes the infectivity factor of the SARS-CoV-2 variant with which the infectious individual is infected, $\sigma(t)$ denotes the season factor at date t and μ_s denotes the immunity of the susceptible individual. Here, $\mu_s = 83\%$ for recovered individuals (independent of disease severity, risk group or age) and $\mu_s = 80\%$ for vaccinated individuals. GitHub repository has last been committed to in January 2022. Hence, we could not determine whether or not they are still continuing their work and if they have by now integrated waning immunity into their model.
5	KITmetriclab	NO	Covid-19 Forecast Hub	Models from the COVID-19 Forecast hub are ranked according to their performance over the previous four weeks and then ensembled and weighted iteratively to achieve a combined forecast.
6	CovidAnalytics at MIT/MIT_CovidAnalytics-DELPHI	N/A	Covid-19 Forecast Hub, European Covid-19 Forecast Hub	Expanded SEIR model. Their technical report ([Li+20]) was published in July 2020 and consequently does not contain vaccinations, waning or antibodies.
7	UMass-Amherst	N/A	Covid-19 Forecast Hub	Model is based on the 'HHS Protect daily Covid-19 hospital' admission data. Creating a set of simple time-series baseline models, which are then combined into a single ensemble forecast of hospitalizations. No documentation provided.

8	Johns Hopkins University Applied Physics Lab – Bucky	NO	Covid-19 Forecast Hub	Age-stratified SEIR model to estimate mid-term case loads and provide additional outputs relating to the associated healthcare burden on county level. No mention of waning immunity and antibodies could be found.
9	MOBS Lab at Northeastern	NO	Covid-19 Forecast Hub	Usage of the Global Epidemic and Mobility (GLEAM) model, an individual-based, stochastic, and spatial epidemic model. Four week forecast of weekly hospitalizations and deaths and US state and national level. Projections have not been updated since April 2022, no mention of waning or antibodies.
10	Masaryk University/MUNI-ARIMA/MUNI-LaggedRegARGIMA/ MUNI-Var	N/A	Covid-19 Forecast Hub, European Covid-19 Forecast Hub	Newest forecasts on their website are for late 2021/early 2022. They claim that methods of statistical time series analysis are used, but no further explanation is provided.
11	GT	NO	Covid-19 Forecast Hub	Deep learning model that is data-driven and learns the dependence of hospitalization and mortality rate based on a variety of syndromic, demographic, mobility and clinical data. Their preprint ([Rod+21]) from March 2021 presents their model in detail, but does not mention vaccinations, waning immunity or antibodies.
12	COVID-19 Forecast Hub	N/A	Covid-19 Forecast Hub	Baseline predictive model to forecast number of cases. No documentation provided on website or associated GitHub repository.
13	HKUST	NO	Covid-19 Forecast Hub	Deep neural networks to forecast cumulative deaths on the US state level. Here, deaths, cases and hospitalization data are taken into account.
14	QJHong	NO	Covid-19 Forecast Hub	"Encounter Density" (which is based on cell phone data) is used to predict the future reproduction number and confirmed cases.
15	Predictive Science Inc	N/A	Covid-19 Forecast Hub	Associated GitHub repository provides no documentation. Hence, no information about the model could be acquired.
16	IDSS COVID-19 Collaboration (Isolat) at MIT	NO	Covid-19 Forecast Hub	Curve-fitting model to make short-term (for the following two weeks) predictions on number of cases and deaths in the US, on state and federal level. Based on the assumption that the metric of interest (i.e. the number of deaths) can be explained by the sum of a set of Gaussian curves.
17	Steve McConnell	N/A	Covid-19 Forecast Hub	Forecasts deaths in the US, work is submitted to CDC to integrate into their ensemble model. No description of model provided.
18	Robert Walraven/RobertWalraven-ESG	NO	Covid-19 Forecast Hub, European Covid-19 Forecast Hub	Website has not been updated since 2021. According to the author, no epidemiological parameters are used. Contrarily, he uses a skewed Gaussian distribution to fit the available case data and a second skewed Gaussian distribution to fit the available deaths data.
19	Carnegie Mellon Delphi Group (COVID-cast)	NO	Covid-19 Forecast Hub	Creation and evaluation of an ensemble forecast.

20	Predictive Science	N/A	Covid-19 Forecast Hub	The associated GitHub repository states that this is a "R package for modeling and forecasting direct-contact and vector-borne infectious diseases". No further documentation provided.
21	UT	N/A	Covid-19 Forecast Hub	Consortiuum, which both surveils and forecasts the infection dynamics of covid. In their paper from February 2022 they present their age- and risk-structured SEIR model and note the necessity for forecasting models to integrate dynamics of infection-acquired and vaccine-acquired immunity. At the time of our screning, no publications nor documentation on the website which included acquired immunities, vaccines or antibodies could be found.
22	LUcompUncertLab	N/A	Covid-19 Forecast Hub	Associated GitHub repository states that they forecast infectious disease dynamics by combining forecasts of computational models and human judgement. No documentation provided.
23	UCSD_NEU	NO	Covid-19 Forecast Hub	A hybrid mechanistic and deep learning model for short-term (up to 4 weeks ahead) predictions of deaths on US state level.
24	University of Virginia, Biocomplexity COVID-19 Response Team/UVA-Ensemble/UVA-EpiHiper	N/A	Covid-19 Forecast Hub, European Covid-19 Forecast Hub, European Covid-19 Scenario Hub	Multi-method model (integrating multiple statistical, machine learning and mechanistic methods) forecasting the new confirmed cases on US state, county and national level. These model forecasts are combined using Bayesian model averaging [Adi+21]. In the publication from August 2021, neither antibodies nor waning are mentioned.
25	MIT-Cassandra	N/A	Covid-19 Forecast Hub	Associated GitHub states that this is a Markov Decision Process inference model to capture the dynamics of the growth rates of cases and deaths. No documentation provided.
26	University of Central Florida	N/A	Covid-19 Forecast Hub	The associated GitHub repository contains a variety of CSV files, but no documentation. Hence, no information on the model could be gathered.
27	Columbia University	N/A	Covid-19 Forecast Hub	Use a metapopulation SEIR model to forecast for the upcoming 42 days of daily new cases, infections and hospitalized individuals on US state, county and national level. The model documentation, which we scanned, dates from 2020 and hence does not mention antibodies or waning. No more recent documentation was found.
28	Hussain Lab at Texas Tech University	N/A	Covid-19 Forecast Hub	Associated GitHub repository states that this is an SIR-based compartmental model, which takes into account the possible immunity loss for recovered individuals. No documentation provided and linked preprint is from July 2020. Hence, this does not contain any valuable information for this study.
29	CU Boulder	NO	Covid-19 Forecast Hub	Associated GitHub repository states that they predict COVID-19 cases at the county-level in the US using a stacked long short-term memory model (LSTM). In their paper ([LVK22]), neither antibody levels or waning are mentioned as a necessity for their model. Same group as in 'CUB_PopCouncil' below.

30	'Swiss Data Science Center/University of Geneva'/SDSC_ISG-TrendModel	NO	Covid-19 Forecast Hub, European forecast hub	Short-term (1 week ahead) predictions of cases and deaths, very little documentation provided on website. In their preprint, they clarify that they implemented a piecewise trend estimation method based on the robust Seasonal Trend decomposition procedure based on LOESS (STL).
31	Karlen Working Group	N/A	Covid-19 Forecast Hub, European Covid-19 Forecast Hub	Usage of discrete-time difference equations with long periods of constant transmission rate. Their model description from July 2020 does not mention waning or immunity, but they provide some presentation slides, which mention the integration of waning into their model. No further documentation is provided and antibodies are not mentioned.
32	University of Southern California/USC-SlkJalpha/USC-SlkJalpha_update	N/A	Covid-19 Forecast Hub, European Covid-19 Forecast Hub, European Covid-19 Scenario Hub'	Usage of their own SIkJα model to forecast cumulative cases on US state, county and national level as well as internationally. Their preprint ([SXP20]) dating from July 2020 does not mention antibodies or waning, but their website notes that they are accounting for vaccines and all current variants. Here, no further documentation could be found.
33	CUB_PopCouncil	NO	Covid-19 Forecast Hub	Associated GitHub repository provides very little documentation According to the repository, this is code for predicting COVID-19 hospitalizations at the state-level in the US. Hereby, a stacked long short-term memory model (LSTM) is used.
34	John Hopkins ID Dynamics COVID-19 Working Group	N/A	Covid-19 Forecast Hub	SEIR model incorporating the uncertainty in the effectiveness of NPIs to project different possible epidemic trajectories and healthcare impacts. Associated GitHub repository has last been updated in September 2020 and paper ([Lem+21]) dates from April 2021. Paper does not yet consider vaccines and mentions neither waning nor antibodies. No more recent documentation could be acquired.
35	BPagano	N/A	Covid-19 Forecast Hub	Death-based SIR model to project cumulative confirmed cases, confirmed cases per day, cumulative deaths, deaths per day and some additional metrics for a variety of individual countries and on US state and county level. Neither antibodies nor waning immunity are mentioned in the model description.

36	Institute for Health Metric and Evaluation (IHME)	YES	Covid-19 Forecast Hub	(0) Blog post dating from December 2021 [Rei21], which describes their model update in detail. Their new model is a system of integro-differential equations. (1) Individuals are placed in different compartments based on variant by which they were more recently infected and round of vaccination they most recently got → One compartment for each combination of vaccinations and infections (at the time of the blog post they are considering 24 compartments); (2) Time since last vaccination and/or infection is tracked; (3) Protection from infection and vaccine interact multiplicatively. In other words, if ε is the protection (against a variant) acquired from vaccination and ϕ is the protection acquired from infection, then a person's risk of infection is $(1-\varepsilon)(1-\phi)$ times the risk of a naive individual. Hence, an individual's risk of infection depends on the variant and time of their last infection, the brand and time of their last vaccination and the variant they're currently confronted with. They estimate the average protection in a particular susceptible compartment to a specific variant. This is then integrated into their integro-differential equations which describe the transitions between compartments. In the appendix of their recent publication [RCM22] it is noted that to estimate waning protection against infection following vaccination they used Bayesian meta-regression with a monotonically decreasing spline on time since second dose. Waning curves are estimated by vaccine and a lower bound of a 10% efficacy is introduced.
37	BIOCOMSC-Gompertz	N/A	European Covid-19 Forecast Hub	Description of their (early) empirical model can be found in their report from March 2020. Hence, no mention of partial (immunity), antibodies or waning. Unfortunately, large parts of the website are in Catalan, so they were not considered in this review.
38	bisop-seirfilter	NO	European Covid-19 Forecast Hub	Unfortunately, their website is only available in Czech. However, in their preprint ([Šmı+21]) from February 2021 they describe their SEIR compartmental model. Neither immune waning, nor antibodies are mentioned.
39	bisop-seirfilterlite	NO	European Covid-19 Forecast Hub	Same people as for 'bisop-seirfilter'.
40	CovidMetrics-epiBATS	N/A	European Covid-19 Forecast Hub	Short-term (for the following 10 days) predictions of cases for Germany and its federal states. Apart from that, visualizations of different metrics, no documentation provided.
41	DirkBeckmann-Gompertz	N/A	European Covid-19 Forecast Hub	Accessed the associated GitHub repository, which did not provide any documentation. Hence, no documentation about the model could be acquired.
42	DSMPG-bayes	N/A	European Covid-19 Forecast Hub	Bayesian inference and forecast of different COVID-19 related metrics like the effective growth rate, daily new reported cases and the total of reported cases.
43	ECDC-hosp_model	N/A	European Covid-19 Forecast Hub	Ensemble model forecasts by the European COVID-19 forecast hub predict the numbers of cases, hospital admissions and deaths to be reported for the upcoming two weeks for every EU country. ECDC's forecasts of ICU admissions are currently not displayed, as the model is undergoing adjustments. Apart from description of data sources, no documentation could be found.

44	epiforecasts-arimareg	NO	European Covid-19 Forecast Hub	Estimate and forecast effective reproduction number and confirmed cases based on case and death notifications while accounting for reporting delays.
45	epiforecasts-caseconv	NO	European Covid-19 Forecast Hub	Leads to the same website as 'epiforecasts-arimareg'.
46	epiforecasts-EpiExpert_direct	NO	European Covid-19 Forecast Hub	Leads to the same website as 'epiforecasts-arimareg'.
47	epiforecasts-EpiExpert_Rt	NO	European Covid-19 Forecast Hub	Leads to the same website as 'epiforecasts-arimareg'.
48	epiforecasts-EpiExpert	NO	European Covid-19 Forecast Hub	Leads to the same website as 'epiforecasts-arimareg'.
49	epiforecasts-EpiNow2	NO	European Covid-19 Forecast Hub	Package to estimate the effective reproduction number, growth rate and doubling time.
50	epiforecasts-tsensemble	NO	European Covid-19 Forecast Hub	Leads to the same website as 'epiforecasts-arimareg'.
51	epiforecasts-weeklygrowth	N/A	European Covid-19 Forecast Hub	Leads to the personal website of Sam Abott, who is also involved in the models mentioned above. No model documentation could be acquired.
52	epiMOX-SUIHTER	N/A	European Covid-19 Forecast Hub	Depicts data of the COVID-19 pandemic at the national Italian as well as on a regional (20 Italian regions) level. Their paper ([Par+21]) from July 2021 neither mentions antibodies nor immune waning, but rather evaluates the ability of their dashboard to provide fast and in-depth analyses of the past trends of the pandemic in Italy and supply predictions on its evolution based on their compartmental model, named SUIHTER.
53	EuroCOVIDhub-baseline	N/A	European Covid-19 Forecast Hub	Forecasts and reports can be found on the European Covid-19 Forecast Hub website, but no documentation could be found.
54	EuroCOVIDhub-ensemble	N/A	European Covid-19 Forecast Hub	Same as above.

55	FIAS_FZJ.Epi1Ger	N/A	European Covid-19 Forecast Hub	Broken URL, no information could be acquired.
56	fohm-c19inbel	N/A	European Covid-19 Forecast Hub	Broken URL, no information could be acquired.
57	HZI-AgeExtendedSEIR	N/A	European Covid-19 Forecast Hub	They are currently conducting a multi-local and serial cross-sectional prevalence study on antibodies in Germany, but no model (description) on infection dynamics could be found on their website.
58	ICM-agentModel	N/A	European Covid-19 Forecast Hub, European Covid-19 Scenario Hub	Predict confirmed cases, occupied hospital beds and critical cases for the following two months in Poland. Agent based model, but hardly any model documentation provided on website. Their preprint ([Zie+21]) from September 2021 does neither mention antibodies nor waning, describes their agent based model (not mentioning the influence of multiple vaccine jabs/infections) and focuses on finding an optimal lockdown strategy for Poland. In said preprint, they define they probability of infection as $p_{infection} = 1 - exp(-\alpha I)$. Here, α is the transmission coefficient and I is the total infectivity defined via $I = \sum_c w_c I_c$, where the sum is over the different infection contexts (household, workplace, preschool, school, university, large university, street, and travel), w_c is the time dependent contact rate of context c and I_c is the time dependent context infectivity depending the number of (a)symptomatic and all agents at context c, the fraction of symptomatic agents who don't self-isolate and a curbing parameter for the infectivity of the asymptomatic agents. Consequently, no protection acquired from infection/vaccination is included.
59	IEM-Health-CovidProject	N/A	European Covid-19 Forecast Hub	AI based disease model to predict the number of new cases during the following seven days in the USA. Dashboard has not been updated since April 2021, no model description available.
60	ILM-EKF	N/A	European Covid-19 Forecast Hub	Leads to a GitHub user page on which no documentation is provided. Unable to acquire information.
61	Imperial-DeCa	NO	European Covid-19 Forecast Hub	Short-term forecasts of COVID-19 deaths in multiple countries. Produce ensemble forecasts from the output of three different models.
62	Imperial-Rtl0	NO	European Covid-19 Forecast Hub	Leads to same website as 'Imperial-DeCa'.
63	Imperial-sbkp	NO	European Covid-19 Forecast Hub	Leads to same website as 'Imperial-DeCa'.

64	itwm-dSEIR	N/A	European Covid-19 Forecast Hub	Link provided on the European COVID-19 Forecast Hub leads to the general website of Fraunhofer-Institut für Techno- und Wirtschaftsmathematik ITWM. There, no information on any sort of COVID-19 related model could be acquired.
65	ITWW-county_repro	N/A	European Covid-19 Forecast Hub	Leads to same GitHub user page as 'ILM-EKF'.
66	JBUD-HMXK	N/A	European Covid-19 Forecast Hub, European Covid-19 Scenario Hub	Projections for various scenarios and countries. "News" subpage has not been updated since December 2021, no documentation provided. Associated GitHub repository has last been updated in April 2022, but does not provide documentation either.
67	KITmetricslab-bivar_branching	N/A	European Covid-19 Forecast Hub	GitHub repository simply states that this is a simple model of a branching process for delta and non-delta cases in Germany. No additional documentation available.
68	LANL-GrowthRate	NO	European Covid-19 Forecast Hub	Their model description (dating from October 2020) introduces their model COFFEE, which is a probabilistic model that forecasts daily reported cases and deaths. Additionally, the top of their website states that they made their last real-time forecast in September 2021. Hence, we assume that they discontinued their work. No mention of antibodies or waning.
69	LeipzigIMISE-SECIR	N/A	European Covid-19 Forecast Hub	Forward to a GitHub repo which does not provide any documentation and has last been committed to in April 21.
70	MIMUW-StochSEIR	N/A	European Covid-19 Forecast Hub	Unfortunately, their website is only available in Polish and has last been updated in July 2021. Hence, no information could be acquired.
71	MOCOS-agent1	N/A	European Covid-19 Forecast Hub, European Covid-19 Scenario Hub	Short-term forecasts (up to one month) of cases and deaths in Poland. Both their reports and linked papers are from 2020. No model documentation in English could be found.
72	MUNI_DMS_SEIAR	N/A	European Covid-19 Forecast Hub	Unfortunately, their website is only available in Czech. Hence, no information could be acquired.

73	PL_GRedlarski-DistrictsSum	N/A	European Covid-19 Forecast Hub	Unfortunately, their website is only available in Polish. No information could be acquired.
74	prolix-euclidean	NO	European Covid-19 Forecast Hub	Unfortunately, the website is mostly in French and has last been updated in May 2022. Their preprint ([Pot21]), dating from April 2021, states that the forecast the number of ICU patients in France. No mention of waning or antibodies.
75	Statgroup19-richards	NO	European Covid-19 Forecast Hub	Unfortunately, website is only available in Italian. Associated blog is in English, but has not been updated since September 2021. Their paper ([Ala+21]) was published in July 2021 and introduces their parametric regression model, which is motivated by incidence indicators such as the number of hospitalized, deceased, recovered and isolated cases. No mention of (partial) immunity, waning or antibodies.
76	Statgroup19-spatialrichards	NO	European Covid-19 Forecast Hub	Leads to same website as Statgroup19-richards above.
77	UB-BSLCoV	N/A	European Covid-19 Forecast Hub	Broken URL, no information could be acquired.
78	UC3M-EpiGraph	N/A	European Covid-19 Forecast Hub, European Covid-19 Scenario Hub	Agent-based model, whose infection model is a SEIR++ model with 17 different compartments. A different R-value is associated with every compartment. The compartments for the different stages of infection differentiate between vaccinated and unvaccinated individuals. Additionally, their vaccination model considers a decrease in protection as well as an age-dependent efficacy and the risk of vaccine failure. How these properties are incorporated is not described.
79	LZF-SEIRC19SI	N/A	European Covid-19 Forecast Hub	Unfortunately, their website is solely available in Slovenian. Hence, no information could be acquired.
80	UMass-MechBayes	N/A	European Covid-19 Forecast Hub	GitHub repository has not been updated since July 2021. Apart from the repository, there is no documentation available.
81	UMass-SemiMech	N/A	European Covid-19 Forecast Hub	Same repository as for 'UMass-MechBayes' is provided.
82	UNED-PreCoV2	N/A	European Covid-19 Forecast Hub	Unfortunately, the website is only available in Spanish. They note that in late March 2022 a new strategy for the surveillance and control of COVID-19 as implemented. As a consequence, the daily data that feeds into their model is no longer available and they discontinued their work. Due to the language barrier, no model documentation could be acquired.

83	UNIPV-BayesINGARCHX	NO	European Covid-19 Forecast Hub	Developed the 'COVID Atlas', which provides visual analytics on several aspects of the pandemic. Here, health (i.e. data regarding the pandemic progression), socio-economic and socio-political data are integrated. The atlas lets the user visualize data on multiple layers, but does not contain its own disease digression model.
84	UpgUmibUsi-MultiBayes	NO	European Covid-19 Forecast Hub	GitHub repository has not been updated since January 2021. In their paper ([BPM21]) from August 2021, their Bayesian multinomial and Dirichlet-multinomial autoregressive models are proposed. Here, time series of numbers of patients in exclusive categories (for example hospitalized in regular wards, in ICU units, deceased) are estimated. No mention of (partial) immunity, antibodies or waning.
85	USyd-OneModelMan	N/A	European Covid-19 Forecast Hub	GitHub repository has last been comitted to in April 21. Use global linear models to reproduce forecasts on COVID-19 daily cases. No documentation provided.
86	ECDC-CM_ONE	N/A	European Covid-19 Scenario Hub	From the GitHub repository of the Scenario Hub we learned that they integrate that protection against infection wanes based on decaying antibody titers. No detailed model description or publications associated with this model were found. Hence, we are unable to discuss the antibody integration in this model
87	MODUS_Covid-episim	YES	European Covid-19 Scenario Hub	Our own project.
88	RIVM-vacamole	NO	European Covid-19 Scenario Hub	GitHub repository states that this determinisitc, age-structured, and extended (severe disease outcomes, vaccinations) SEIR model was developed to investigate different vaccination strategies. No mention of antibodies or waning in documentation.
89	SIMID-SCM	N/A	European Covid-19 Scenario Hub	Their paper from June 2021 [Abr+21] introduces their stochastic age-structured discrete time compartmental model to describe the transmission of COVID-19 in Belgium. In their technical report from September 2022 [Con22] the SIMID consortium notes a constant waning rate of 1/240d based on the assumptions of the European Scenario Hub. No additional information is provided, antibodies are not mentioned.
90	TUWien-AustrianCoVABM	NO	European Covid-19 Scenario Hub	Their paper from May 2021 ([Bic+21]) introduces their stochastic agent–based model, which evaluates contact tracing policies in 2020. Hence, (partial) immunity is of no concern and neither waning nor antibodies are mentioned.

Table 2: Models, which were discovered through (a) the Covid-19 Forecast Hub, (b) the European Covid-19 Forecast Hub, (c) the European Covid-19 Scenario Hub, or (d) a literature search. (a) and (b) were accessed on 07/21/22, while (c) was accessed on 08/31/22.