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Projection of healthcare demand in Germany and Switzerland urged by Omicron wave (January–March 2022)

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ABSTRACT

In January 2022, after the implementation of broad vaccination programs, the Omicron wave was propagating across Europe. There was an urgent need to understand how population immunity affects the dynamics of the COVID-19 pandemic when the loss of vaccine protection was concurrent with the emergence of a new variant of concern. In particular, assessing the risk of saturation of the healthcare systems was crucial to manage the pandemic and allow a transition towards the endemic course of SARS-CoV-2 by implementing more refined mitigation strategies that shield the most vulnerable groups and protect the healthcare systems. We investigated the epidemic dynamics by means of compartmental models that describe the age-stratified social-mixing and consider vaccination status, type, and waning of the efficacy. In response to the acute situation, our model aimed at (i) providing insight into the plausible scenarios that were likely to occur in Switzerland and Germany in the midst of the Omicron wave, (ii) informing public health authorities, and (iii) helping take informed decisions to minimize negative consequences of the pandemic. Despite the unprecedented numbers of new positive cases, our results suggested that, in all plausible scenarios, the wave was unlikely to create an overwhelming healthcare demand; due to the lower hospitalization rate and the effectiveness of the vaccines in preventing a severe course of the disease. This prediction came true and the healthcare systems in Switzerland and Germany were not pushed to the limit, despite the unprecedentedly large number of infections. By retrospective comparison of the model predictions with the official reported data of the epidemic dynamic, we demonstrate the ability of the model to capture the main features of the epidemic dynamic and the corresponding healthcare demand. In a broader context, our framework can be applied also to endemic scenarios, offering quantitative support for refined public health interventions in response to recurring waves of COVID-19 or other infectious diseases.

1. Introduction

The Omicron variant (B.1.1.529) has become the globally dominant SARS-CoV-2 strain within two months from its identification in South Africa and the designation as a variant-of-concern by the World Health Organization (WHO).[1] Its initial rapid spread across the South African province of Gauteng led to the assessment of a significant transmission advantage over the previously circulating Delta variant (B.1.617.2). Later studies suggested that this transmission advantage may partly be attributed to a strong immunity escape, hence, to the ability to reinfect individuals with prior Delta infection (Viana et al., 2021; Lyngse et al., 2021).

In January 2022, as the surge of Omicron was unfolding in Europe, it was crucial to analyze possible scenarios likely to be seen in the following couple of weeks and determine the potential consequences of Omicron transmission advantage. In that phase of the pandemic, it was of great importance to assess whether the surge in case number would translate into a significant wave of hospitalizations, possibly threatening the healthcare system. While the decoupling between case number and hospitalizations observed in England (Ferguson et al., 2021) and South Africa (Wolter et al., 2021) gave reasons for optimism, the course of the Omicron wave could have been different in countries with a smaller fraction of vaccinated and recovered people, with a

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[1] https://www.who.int/news/item/28-11-2021-update-on-omicron

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different vaccine mix, or with the different age structure. This was the case in central European countries, like Switzerland and Germany, which could turn out more vulnerable as a consequence of a lower vaccination rate and relatively less dramatic previous waves.

We report our work, carried out prior to January 17 2022, that provided an early study on the Omicron wave impact (subvariant BA1), in Switzerland and Germany. For the sake of urgency, results were immediately communicated in an earlier version of the manuscript, made available in public repositories (Gorji et al., 2022). To analyze plausible epidemiological scenarios for Switzerland and Germany we devised specific dynamic compartmental models that were discretized and solved on contact matrices (Towers and Feng, 2012; Prem et al., 2017). Mathematical models are crucial to quantitatively explain the non-obvious concurrent observation of an exceptionally large number of cases and relatively low hospitalization rate that were registered during the Omicron wave. In order to elucidate the mechanisms leading to the epidemiological situation encounter at a given time and reasonably project forward the temporal dynamic of the incidence, our analysis was refined to account for differences across age-groups and their respective social-mixing, as well as for the different level of protection offered by the different types of vaccine. This allowed us to more faithfully describe and anticipate the impact of the Omicron wave on the healthcare system.

Our results turned out to be in line with later studies of the impact on the healthcare system of the Omicron wave and with the successively reported official data (Barnard et al., 2022; Swiss National COVID-19 Science Task Force, 0000; Federal Office of Public Health FOPH, 2021; Robert Koch Institute, 2021a). This is encouraging, as the model still relies on a concise mechanistic structure and, thereby, can be robustly adjusted to cope with different endemic scenarios. In particular, it can be applied to gain further insight into the currently evolving situation, as a result of change in "zero-COVID" policy of China (Dyer, 2023) and emergence of recent sub-variants (Brief, 2023).

2. Epidemiological background

In the summer of 2021, the number of COVID-19 cases, hospitalizations and deaths were contained thanks to the large and effective vaccinations campaigns. In October–November 2021, however, the epidemiological course of SARS-CoV-2 became again unstable both in Switzerland and Germany (Federal Office of Public Health FOPH, 2021; Robert Koch Institute, 2021a). Upon the significant healthcare demand of an intense second wave of Delta, attributed to the waning vaccine efficacy and its high disease severity, the healthcare systems were operating close to their surge limits. Certain public health measures, including wearing masks in public transport and public events, were in place. Besides, only people who were vaccinated, recovered from COVID-19, or tested negative were allowed to attend indoor events or enter indoor restaurants, cultural, sporting and leisure venues.[2,3]

Against this background, the new Omicron variant began circulating in both countries, displaying a much higher effective reproductive number and leading to the resurgence of COVID-19 cases. The question of whether the new situation required further tightening of the measures became critical for public health policy makers. As the consequences of the much higher transmissibility and the relatively milder severity were not clear, there was a large uncertainty on the actual threat posed by the new variant. This led to mounting calls for stricter measures such as allowing only people who received a booster shot to attend indoor events.[4]

[2] https://www.dw.com/en/new-covid-rules-in-germany/a-58970674

[3] https://www.bag.admin.ch/bag/en/home/das-bag/aktuell/medienmitteilungen.msg-id-85035.html

[4] https://www.welt.de/politik/deutschland/article235855536/Drosten-Wegen-Omikron-womoeglich-1G-noetig-G-heisst-geboostert.html

Towards the end of November 2021, as the first Omicron case was detected in Switzerland, the country was facing a relatively high hospital occupancy rate besides a constant rise in the intensive care demand (Federal Office of Public Health FOPH, 2021). The share of the population that had been vaccinated (with at least one dose) was around 67%, with almost $2/3$ of the administrated vaccines being mRNA-1273 and the rest mainly BNT162b2 (Federal Office of Public Health FOPH, 2021). A sharp spike of COVID-19 cases a couple of weeks after the detection of the first Omicron case can be seen in Fig. 1(a). Concurrent to the steady growth in the number of hospitalized cases after November, Switzerland experienced a steady increase of ICU occupancy as shown in Fig. 1(b) and (c), respectively.

As of November 27, 2021 Germany detected its first Omicron case (Robert Koch Institute, 2021a). However, it took longer than in Switzerland to observe an increase in case numbers (see Fig. 2(a)), which can be attributed to the significant differences in the geographical scales of the two countries. The vaccine situation was quite similar, although with some nuances. In Germany, 72% of the population was vaccinated with at least one dose. The mix consisted of around 70% BNT162b2, less than 20% ChAdOx1nCov-19, and less than 15% mRNA-1273 (Robert Koch Institute, 2021a). After the high incidence of hospitalized cases in late-November, the demand of intensive care was relatively high by mid-December (see Fig. 2(b) and (c)), but both indicators subsequently showed clear signs of decline.

By mid-January 2022, Germany had around 78% of Omicron share among the new cases (Robert Koch Institute, 2021a), whereas a slightly higher share of 90% was reported for Switzerland (Federal Office of Public Health FOPH, 2021). The rapid take over of the Omicron variant raised the question if the healthcare systems of both countries could withstand the unfolding wave. To support informed public health policy decisions, it was critical to devise robust mathematical models capable of providing quantitative insight into the transmissibility pattern and healthcare burden resulting from the Omicron wave.

3. Model and data

Despite the emerging data on the weakened virulence and reduced mortality of the Omicron variant, the upcoming healthcare burden in both countries was matter of debate. While crude projections of the epidemiological course based on the instantaneous reproductive number could be intuitive, it was of limited use to forecast the healthcare demand. This is due to the fact that the COVID-19 disease progression is strongly stratified by age. Moreover, the significant variability on the vaccination rate among different age-groups undermines the homogenization assumption behind simple exponential extrapolations. On the contrary, highly complex and detailed models of the population dynamics could be prone to the risk of overfitting, compromising the robustness of the results. To provide a sufficiently detailed description of the variability across the population without incurring in the risk of overfitting, we adopted an age-stratified compartmental model, equipped with a contact matrix, which gives us enough flexibility to project different epidemiological scenarios without relying on too many free parameters.

3.1. Model overview

The basic structure of the compartmental model is of the Susceptible–Infected–Removed (SIR) type and comprises susceptible (S), infected (I), hospitalized in general ward (H), hospitalized in ICU (IU) and removed (R) populations. The progress of infection and further disease development among these compartments are illustrated in Fig. 3. Each compartment is stratified per age-group (denoted by superscript i) and refined into vaccinated, unvaccinated, and recently recovered from a separate variant (denoted by subscripts v, u and r, respectively). Notice that the model does not include an exposed compartment as this is not expected to significantly affect the results due to

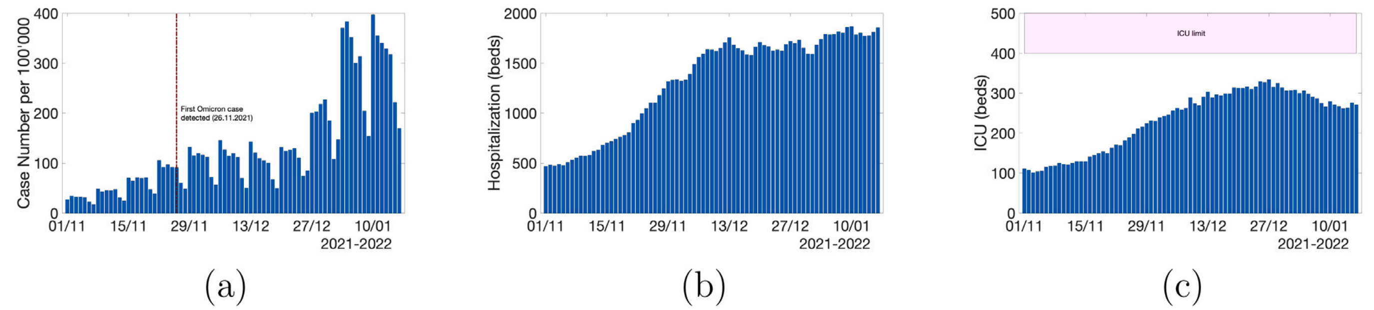

Fig. 1. Epidemiological course of SARS-CoV-2 in Switzerland (November 2021–January 2022) for (a) daily incidence, (b) hospitalization (general ward) and (c) ICU occupancy. Time series data from Federal Office of Public Health FOPH (2021). The operational ICU capacity limit of 400–500 for COVID-19 patients is estimated based on Federal Office of Public Health FOPH (2021).

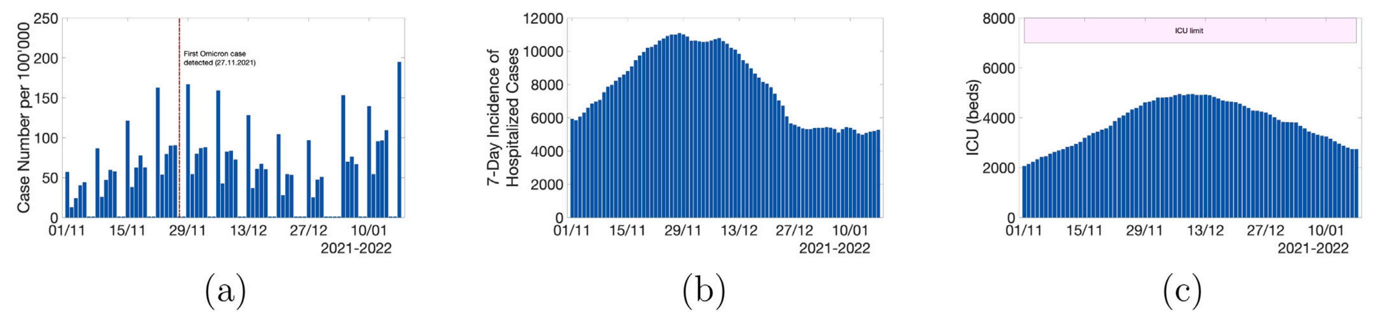

Fig. 2. Epidemiological course of SARS-CoV-2 in Germany (November 2021–January 2022) for (a) daily incidence, (b) 7-day incidence of hospitalized cases (general ward) and (c) ICU occupancy. Time series data from Robert Koch Institute (2021a). The operational ICU capacity limit of 7000–8000 for COVID-19 patients is estimated based on Robert Koch Institute (2021b).

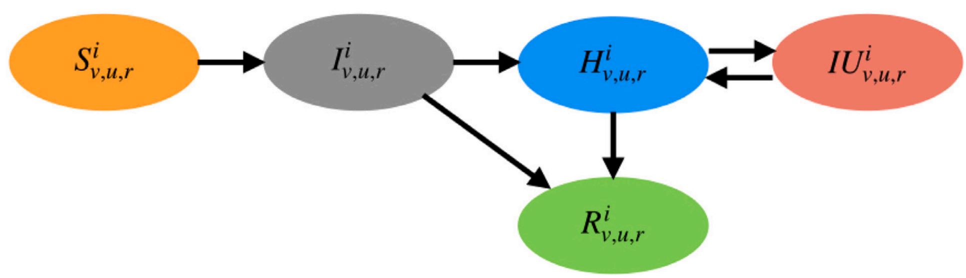

Fig. 3. Graphical depiction of the compartmental model.

the relatively short incubation period of the Omicron variant (around 3 days Jansen, 2021). Also, as the focus is to project the healthcare demand, we do not distinguish between asymptomatic/presymptomatic and symptomatic cases, and we neglect mortality, which hardly impacts the epidemic course in the population and leads to a conservative estimate of the healthcare capacity (overestimating the permanence in hospital bed and ICUs). As a result of these simplifications and the uncertainty on the input parameters, the projections of such model should be considered as plausible scenarios rather than accurate predictions of the future course of the pandemic.

The dynamic of each compartment is governed by the transition rates (see e.g. Diekmann et al., 2010; Balabdaoui and Mohr, 2020; Gorji et al., 2021 as examples of compartmental models). Denoting by $K_{A\to B}$ the transition rate from compartment A to B, we have the following deterministic Ordinary Differential Equations (ODEs),

$$\dot{S}^i_J = -K_{S^i_J\to I^i_J} S^i_J, \tag{1}$$

$$\dot{I}^i_J = K_{S^i_J\to I^i_J} S^i_J - K_{I^i_J\to H^i_J} I^i_J - K_{I^i_J\to R^i_J} I^i_J, \tag{2}$$

$$\dot{H}^i_J = K_{I^i_J\to H^i_J} I^i_J + K_{IU^i_J\to H^i_J} IU^i_J - \left(K_{H^i_J\to R^i_J} + K_{H^i_J\to IU^i_J}\right) H^i_J, \tag{3}$$

$$\dot{IU}^i_J = K_{H^i_J\to IU^i_J} H^i_J - K_{IU^i_J\to H^i_J} IU^i_J \quad \text{and} \tag{4}$$

$$\dot{R}^i_J = K_{I^i_J\to R^i_J} I^i_J + K_{H^i_J\to R^i_J} H^i_J, \tag{5}$$

for each age class i and preexisting protection status $J \in \{u, v, r\}$. The effective reproductive number for the above system can be calculated according to the method of next-generation-matrix (Diekmann et al., 2010) and, following the derivation given in *Supplementary Information*, can be written as

$$\mathcal{R}_e = \rho(\mathcal{T})(1-\kappa)\beta\tau_R, \tag{6}$$

where τ_R is the average recovery time, β is the infection rate, $\kappa \in [0,1]$ is the intensity of measures, $\mathcal{T}$ is the contact matrix adjusted according to the vaccine protection, and $\rho(\mathcal{T})$ is its largest eigenvalue. As we do not know *a priori* the impact of measures, κ is evaluated from the observed value of $\mathcal{R}_e$ by means of Eq. (6).

As discussed in details in *Supplementary Information*, the model allows us to explicitly account for different social-mixing, vaccination and recovery rates across various age-groups. Furthermore, it enables us to implicitly account for the impact of intervention measures on the epidemic dynamics by adjusting the effective reproductive number (which depends on κ). However the model, in its current form, does not describe neither time varying mitigation policies, nor measures that target certain age-groups. These shortcomings can be alleviated though,

Table 1
Hospitalization initial data of Switzerland (as of January 17, 2022) (Federal Office of Public Health FOPH, 2021).

	Estimate used in the model	Corrected value
General ward	1885	1875
ICU	271	267

Table 2
Hospitalization initial data of Germany (as of January 17, 2022) (Robert Koch Institute, 2021a).

	Estimate used in the model	Corrected value
General ward	16,623	NA
ICU	3405	2744

by introducing a more general κ which varies by time and age-group (not considered here).

It is important to note the subtle difference in the model between the number of infected I_J and the daily reported case number: the former accounts for the actual number of infected individuals while the latter is simply the incidence of new cases. The link between the two is given by Eq. (1), as the incidence is given by the decay rate of susceptibles. This should be taken into account to initialize the model based on the reported data. Moreover as the number of active cases I_J depends on the effective reproductive number $\mathcal{R}_e$, the initial value of I_J should be consistent with the considered $\mathcal{R}_e$.

3.2. Data overview

The transition rates depend on the intrinsic properties of the virus, the statistics of the population, and the efficacy of the vaccine. In *Supplementary Information*, we review the main parameters that govern the transition rates. To close the model and project different scenarios, we inferred the parameters and the initial conditions from literature data, official reports, and our own estimates. Key surveillance indicators of COVID-19 were provided by the Federal Office of Public Health (FOPH) in Switzerland and the Robert Koch Institute (RKI) in Germany. Furthermore, to facilitate our computations, we relied on open-access monitoring dashboards provided by Our World in Data[5] and The Swiss National COVID-19 Science Task Force.[6]

However, not all details of the initial conditions were available when simulations were performed (i.e., prior to January 17, 2022). Below we discuss the initial conditions employed for each country.

- For Switzerland, we had access to the daily case numbers as well as to the hospital occupancy (both in general ward and ICU) until January 16, 2022. To adjust for weekly fluctuations in reported case numbers, in the model we used the 7-day average as the initial condition for case numbers. In Table 1 we summarize the input data of hospitalization, and the retrospectively corrected values. The differences between the two is be below 2%.
- Similarly, for Germany we had access to the daily case numbers, and we applied the 7-day average to infer the initial condition of the number of infected individuals based on case numbers. However, RKI does not publish data on actual occupancy of hospital beds. We estimated the hospital occupancy in general ward based on the incidence of hospitalized cases. Furthermore, we used the most recent updated weekly average of ICU occupancy as the estimate for January 17, 2021. The actual value turned out to be almost 20% lower, as shown in Table 2.

For both countries, we assumed the share of Omicron cases to be 90%. Later data reported by FOPH and RKI showed that the share of Omicron at that time was 90% and 78% in Switzerland and Germany, respectively (Federal Office of Public Health FOPH, 2021; Robert Koch Institute, 2021a). For the recovered populations, we conservatively assumed that 30% of unvaccinated individuals had recovered from Delta and 10% from Omicron. While there is no comprehensive seroprevalence data to confirm assumptions, they can be supported by two observations. First, seroprevalence of 29.9% was observed among non-vaccinated individuals in Geneva (Switzerland) after the initial Delta wave (Stringhini et al., 2021), which suggests that our estimate could be considered a lower bound. Second, by cumulative sum of the number of individuals reported to be infected by Omicron, we can obtain a lower bound of 10% for the immunity against Omicron at the time of the analysis. Note that a less optimistic scenario regarding the prior immunity is considered in the sensitivity analysis. Finally, data on vaccination rate and corresponding vaccine mix, stratified by age-groups, were used based on the reports provided by FOPH and RKI (Federal Office of Public Health FOPH, 2021; Robert Koch Institute, 2021a) (see *Supplementary Information* for details of vaccination implementation).

4. Results

To project the situation observed in mid-January 2022 into the following weeks and investigate the consequences of the Omicron wave in terms of case number, hospitalization, and ICU bed occupancy in Switzerland and Germany, we considered three scenarios that are characterized by different effective reproductive numbers (i.e., 1.3, 1.5 and 1.8). These scenarios should be contrasted with the epidemiological course around mid-January 2022, in which we observed reproductive numbers between 1 and 1.2 in both countries. For a given target value of $\mathcal{R}_e$, we computed the corresponding measure impact κ. Since different scenarios were initialized with an identical incidence rate, yet different effective reproductive numbers, different number of active cases were expected (see *Model Overview*). This resulted in an initially higher number of active cases in a scenario governed by a lower reproductive number as more infected individuals are necessary to achieve the same incidence.

For the base scenario, we fed the compartmental model with the central estimates of the involved parameters (listed in Table 3–10 in the *Supplementary Information*). Then, we conducted a sensitivity analysis with respect to the severity of the disease and the vaccine protection (see Figures 9–18 in the *Supplementary Information*) and found that our results were robust as long as the considered parameters remained in a plausible range. It is worth noticing, however, that many of the adopted parameters were subject to significant uncertainties. For instance, the severity of Omicron, the protection offered by the vaccines against this variant, and their waning efficacy were not sufficiently studied nor well characterized at that time. Also, nothing was known about possible long-term consequences of the Omicron infection.

The projection of daily case numbers, COVID-19 occupied hospital beds, and intensive-care requirement are shown in Figs. 4 and 5 for Switzerland and Germany, respectively. We observe a significant increase of the case numbers in the worst case scenario of $\mathcal{R}_e = 1.8$. Our projection showed that the case number per 100,000 inhabitants at the peak were 20% higher in Germany than in Switzerland. This is mainly due to differences in the matrices that describe the contacts among different age-groups in the two countries: in general, more heterogeneous contact patterns, as those observed in Switzerland, yield markedly lower attack rates in epidemics (Fumanelli et al., 2012). Besides, the average protection against Omicron infection offered by the different mix of administrated vaccine types was estimated (see *Supplementary Information*) to be 20% higher in Switzerland (approximately 0.5) than in Germany (approximately 0.4).

The number of severe cases, especially those requiring hospitalization in ICUs, were expected to remain lower than the peak levels

[5] https://ourworldindata.org/
[6] https://sciencetaskforce.ch/en/current-situation/

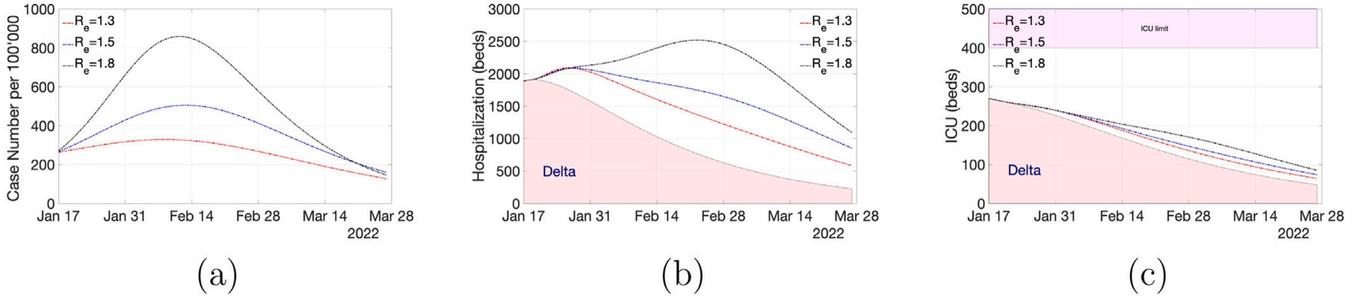

Fig. 4. Projection of scenarios in Switzerland for (a) daily incidence (Omicron cases), (b) hospitalization (general ward) and (c) ICU occupancy. Three scenarios of $\mathcal{R}_e \in \{1.3, 1.5, 1.8\}$ are considered for Omicron, whereas $\mathcal{R}_e$ of 0.9 is assumed for Delta. The red shaded areas in (b) and (c) account for the occupancy due to Delta. The operational ICU capacity limit of 400–500 for COVID-19 patients is estimated based on Federal Office of Public Health FOPH (2021). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

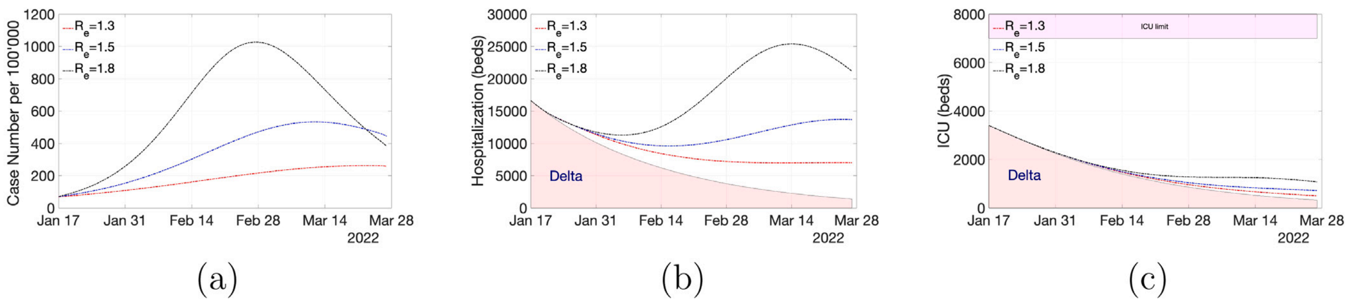

Fig. 5. Projection of scenarios in Germany for (a) daily incidence (Omicron cases), (b) hospitalization (general ward) and (c) ICU occupancy. Three scenarios of $\mathcal{R}_e \in \{1.3, 1.5, 1.8\}$ are considered for Omicron, whereas $\mathcal{R}_e$ of 0.9 is assumed for Delta. The red shaded areas in (b) and (c) account for the occupancy due to Delta. The operational ICU capacity limit of 7000–8000 for COVID-19 patients is estimated based on Robert Koch Institute (2021b). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

attained during previous waves. This favorable outcome, observed despite the huge case numbers, was due to the lower intrinsic severity of Omicron as well as to the protection from the severe course offered by the vaccines (and refreshed by booster shots administrated in the previous months for the vulnerable population). We estimated the overall efficacy of the vaccine mix administered in Germany and Switzerland against hospitalization to be approximately 0.6 and 0.65, respectively (see *Supplementary Information*). Our results suggested that case numbers would have likely continued to rise within a short time as a result of the high transmissivity of the Omicron variant. It was expected that up to 10% of the population may have been infected in a week at the peak of the least favorable scenario (i.e., $\mathcal{R}_e = 1.8$, which corresponded to a less restricted circulation of the virus than what was observed at the time of the projection). While by itself this was not expected to directly translate into a health-system crisis, the abrupt increase in the number of infected individuals could have interrupted the presence of workforce, with significant consequences also on the healthcare system (depending on the applicable quarantine and isolation rules that would have been introduced for healthcare workers). Furthermore, the SARS-CoV-2 diagnostic capacity would have become inadequate to test such a large number of infected individuals, leading to a heavy underestimation of the real number of cases, even among the symptomatic ones.

All modeled scenarios suggested that, despite the impressive increase in the number of infections, neither in Switzerland nor in Germany the Omicron wave could have led to a significant pressure on the healthcare system in terms of shortage of hospital beds. Indeed, even the least favorable scenarios displayed hospital occupancy lower than the peaks attained during previous waves. In particular, as long as the reproductive number would have remained below 2, the ICU bed occupancy would have not reached the critical thresholds, which were estimated at 400–500 and 7000–8000 beds occupied by COVID-19 patients for Switzerland and Germany, respectively (Federal Office of Public Health FOPH, 2021; Robert Koch Institute, 2021b). This can be attributed to the intrinsically lower hospitalization rate caused by the Omicron variant as well as by the effectiveness of the vaccines in protecting from a severe course of the disease. While Germany had a slightly higher vaccination rate, we estimated that the protection was stronger in Switzerland where a vaccine type with a slightly longer term efficacy was administered to the majority of the population.

5. Model evaluation and limitations

The described age-stratified compartmental model was developed towards the end of 2021 with the aim of providing a tool to delineate possible scenarios of the development of the Omicron wave, and help assess and anticipate possible critical issues for the healthcare systems in the two countries. The results described above were obtained prior to January 17, 2022 and rapidly communicated in Gorji et al. (2022), leaving more comprehensive validation of the model with extended data-sets and more updated parameters to follow-up studies. We remark that here we stick to the evaluation of the model results obtained by January 17, 2022 (given in Figs. 4–5), and that no information posterior to that date has been included. We emphasize that, given all the assumptions and uncertainties in parameters, model, and data, these results should not be treated as absolute figures, but rather for scenario analysis. A posteriori, however, we can assess the relevance of the delineated scenarios by comparison with the data reported by FOPH and RKI (for Switzerland and Germany, respectively) in the months that followed.

Overall, the epidemiological course of SARS-CoV-2 turned out to be consistent with the conclusions that we could draw from the simulated scenarios, which robustly described a trend of concurrent high case number but uncritical healthcare demand. Yet the emergence of the new sub-variant BA2 by mid-February (Swiss national SARS-CoV-2 genomic and variants surveillance program, 0000; Sievers et al., 2022), with substantial immunity escape, should be taken into account when evaluating the model results. Indeed, the model was blind to this new situation (as well as to other possible changes in epidemiological conditions), hence, the consequences on the epidemiological course could obviously not be detected in our results.

In comparing the reported epidemiological course of the two countries, we observe a later peak in Germany than in Switzerland, with slightly higher value of 588 on 21/03/2022, compared to 555 on 24/01/2022, per 100,000. Given the higher test positivity ratio at peak of 56% in Germany than 41% in Switzerland, we expect that the epidemic wave had a noticeably higher peak in Germany. Both these observations are consistent with our scenario forecasts.

In Switzerland, we observed the first peak of case number in the second half of January 2022. The peak came slightly earlier than our scenarios predicted with lower $\mathcal{R}_e$ values (Fig. 6(b) and (d)). It is important to note that in Switzerland the test positivity ratio increased from around 35%, in mid-January 2022, to 40% by end of the month. Therefore, it is possible that the actual peak was reached a bit later than what reported in the official reports, and that it was overlooked due to under-reporting (as hinted by the increase in the test positivity ratio). There was also the second peak due to BA2 in mid-March 2022, as shown in Fig. 6(b) and (d), which is absent in our analysis. Remarkably good agreements between reported data and our simulated scenarios with $\mathcal{R}_e \in \{1.3, 1.5\}$ can be seen for hospitalization, shown in Fig. 6(f), and ICU occupancy, shown in Fig. 6(h). The impact of BA2 can be further seen in the hospitalization and ICU occupancy, which displayed a second spike that was again absent in the results of our simulations. Furthermore, data reported over a longer period of time (till June 2022) supports the predicted trends of declining case number and occupancy of hospital beds, both in general ward and ICU (Fig. 6(a), (c), (e), and (g)).

In Germany, the situation described by the officially reported data is in a less detailed agreement with our scenarios. While the main peak comes by mid-March, which is consistent with our scenarios predicted for the lower reproductive numbers (Fig. 7(b) and (d)), a (slightly smaller) peak by early-February was observed, which is completely absent in our scenario simulations. It is possible that Delta cases still contributed to the first peak, as later data showed that Germany had a lower share of Omicron (around 80%) as of January 17 2022 than what we assumed in our simulations (90%). This hints to the importance of near real-time genomic surveillance to monitor the impact of different variants. For ICU occupancy, the model anticipated an earlier decay than what observed in the reported data, as shown in Fig. 7(f), although the later trend (in the data reported from the beginning of April and shown in Fig. 7(e)) was similar to our results. The more persisting occupancy of ICUs could again be linked to an underestimation of the Delta cases assumed at the beginning of our predictions, as those cases had a higher probability of ICU admission. We could not compare the result of the hospital occupancy in general ward due to the lack of such data in the RKI situation reports.

In interpreting the reported data, we need to take note of two issues. Both countries experienced an unprecedented spike in case numbers, during considered period, with astronomical test positivity ratios in the range of 40%–50%. Therefore, it is plausible that a large fraction of infections remained unobserved and that the official reports heavily underestimated the incidence. Moreover, the high virus prevalence in the populations inevitably gave rise to SARS-CoV-2 positive cases that were hospitalized for other reasons than COVID-19. Therefore, the reported data might have suffered from a significant bias towards smaller values in the case number, in contrast to a bias towards larger values in the hospitalization (both in general ward and ICUs). These biases might partially explain why the reported case numbers and hospitalizations, in both countries, are systematically lower and higher than in the predicted scenarios, respectively.

Besides the uncertainty in virus parameters, population statistics, epidemiological model, and reported data, the assumption of treating Germany uniformly might have also contributed to the deviations between the simulated scenarios and reported data. Especially because the proportions of co-circulating variants (Delta, Omicron BA1, and Omicron BA2) were significantly different across different regions of Germany, it might be impossible to account for different stages of the epidemic dynamics without resolving fine-scale geographical differences. As the underlying coarse-graining assumption, employed by our model, omits different stages of the epidemics among different subregions of Germany, it is highly plausible that the model performed better in the case of Switzerland thanks to its more homogeneous and compact epidemic dynamics. More refined treatment of the spatial variability should be pursued, in future, in order to improve performance of the model on larger geographical scales.

6. Discussion

The impressive resurgence of COVID-19 infections in Europe occurred while the healthcare demand generated by the most recent Delta wave was already high. In such a context, a reliable analysis of the epidemiological situation was critical to help secure the necessary healthcare resources for anticipated COVID-19 patients. An important characteristic of our modeling framework is to account for different age-groups and their specific social-mixing, as well as for their vaccination status, administrated vaccine type, and protection waning. This was essential to depict reliable scenarios because a strong stratification of the hospitalization risk with the age-group has been observed throughout the entire COVID-19 pandemic, and because the vaccination rate is biased towards elderly individuals.

In summary, the simulated scenarios allowed us to promptly provide several important messages for the healthcare systems. (i) A significant further increase in ICU patients was not be expected. (ii) The sharp and rapid increase of infected cases would have been followed by a likewise sharp and rapid decline of the case numbers, with the exception of prolonged hospitalizations of ICU patients as it was also observed during previous waves. (iii) The sharp increase in the overall number of infections could have also led to a high infection rate among medical and nursing staff in hospitals and nursing homes. (iv) The demand for normal care beds for COVID-19 patients could have still risen within a short period of time depending on the effective reproductive number. In addition to the patients hospitalized for COVID-19, the large prevalence among the population could have led to an increased number of patient hospitalized and treated for other reasons but co-infected with SARS-CoV-2. This presented a new challenge, putting an additional burden on the hospital systems.

The subsequent official reports on the epidemiological situations turned out to support the described short-term predictions formulated on the basis of the simulated realistic scenarios; thereby the model forecasts were in general consistent with the actual development of the pandemic, which confirmed the ability of our model to describe the essential features of the epidemic dynamics. Yet, certain limitations will have to be addressed in future extension of the model. For instance, the current model does not account for spatial heterogeneity nor for the corresponding mobility (Arino and Van den Driessche, 2003; Riley et al., 2015). This can be crucial for the epidemic dynamics at large geographical scales. Furthermore, it will be necessary to equip the model with tolls that will enable uncertainty quantification, including Bayesian inference, to better assess the probability of different scenarios as well as the uncertainty of the predicted results (Li et al., 2021). This is especially important at the early stage of epidemic waves, when the central rate parameters typically bear significant uncertainties due to lack of information about epidemiological and virological parameters. Such improvements will allow us to provide a probabilistic description to better quantify the impact of under-reporting and other data uncertainties on the model forecasts.

Given the adequate performance of our projected risk and healthcare demand in the Omicron wave in early 2022, the model can be further used to refine the measures to be implemented to manage the SARS-CoV-2 endemic phase, with special focus on the healthcare

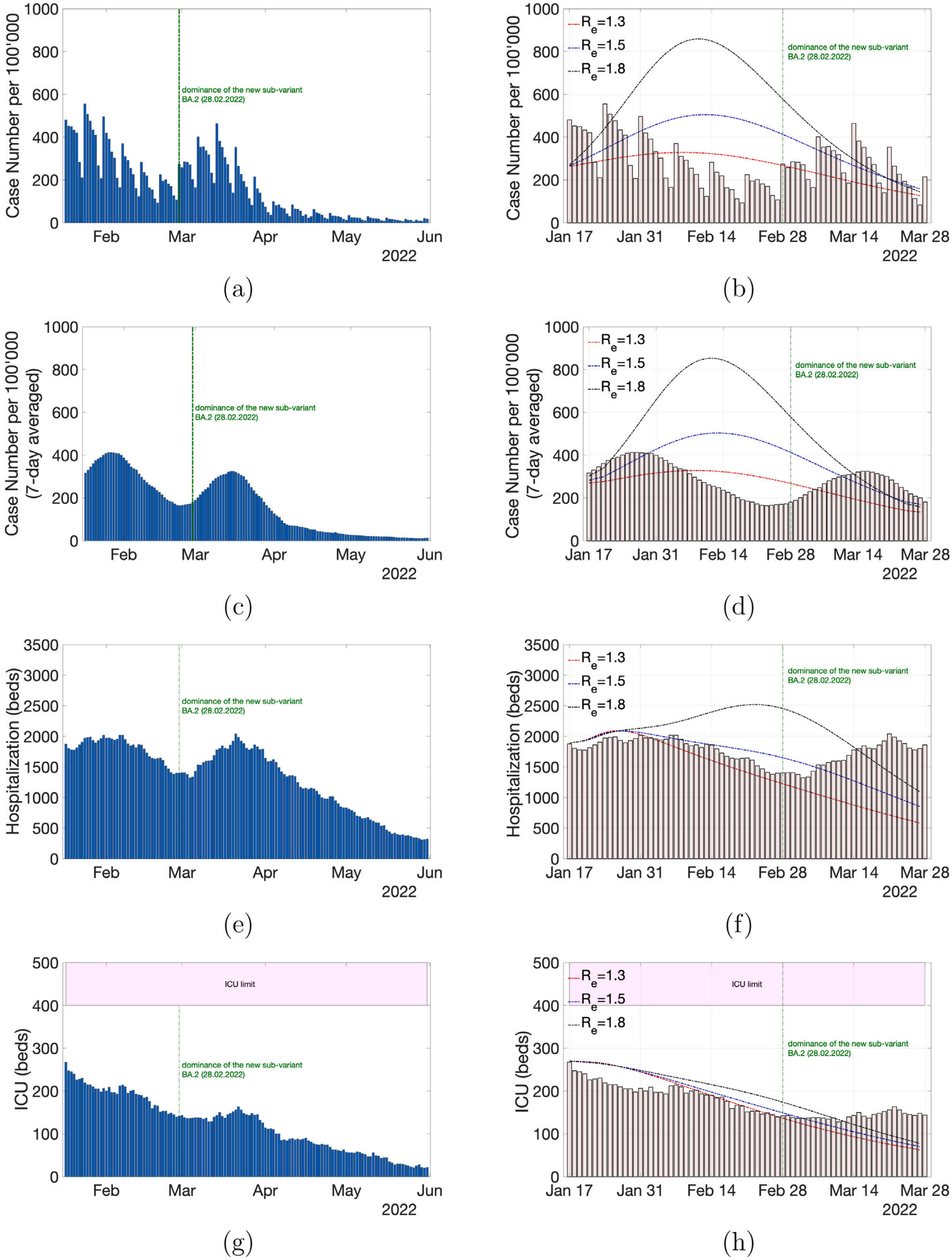

Fig. 6. Evaluation of projected Omicron scenarios in Switzerland for (b) daily incidence, (d) 7-day averaged incidence (f) hospitalization (general ward), and (h) ICU occupancy. The official reported data (Federal Office of Public Health FOPH, 2021) are indicated by bars. They are also shown over a longer period of time for (a) daily incidence, (c) 7-day averaged incidence, (e) hospitalization (general ward), and (g) ICU occupancy. The operational ICU capacity limit of 400–500 for COVID-19 patients is estimated based on Federal Office of Public Health FOPH (2021).

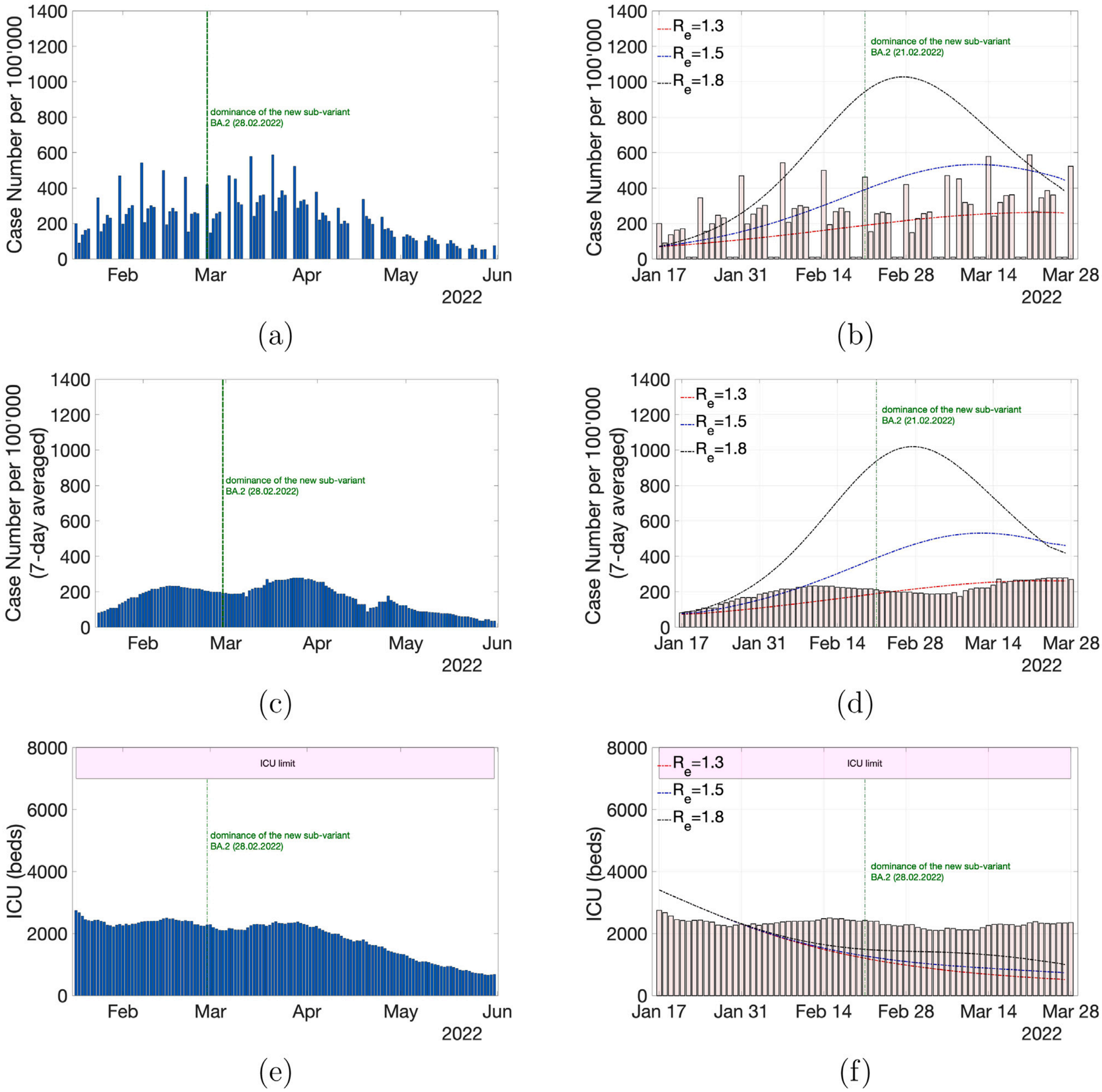

Fig. 7. Evaluation of projected Omicron scenarios in Germany for (b) daily incidence, (d) 7-day averaged incidence, and (f) ICU occupancy. The official reported data (Robert Koch Institute, 2021a) are indicated by bars. They are also shown over a longer period of time for (a) daily incidence, (c) 7-day averaged incidence, and (e) ICU occupancy. The operational ICU capacity limit of 7000–8000 for COVID-19 patients is estimated based on Robert Koch Institute (2021b). Note that the hospital occupancy in general ward could not be investigated due to the lack of such data in the RKI situation reports.

demand. The detailed description of the different age-groups and vaccines allows us to more faithfully project the dynamic of outbreaks and support more targeted intervention strategies (e.g., adapted to the specific risk of hospitalization of different population groups).

Moreover, the proposed modeling framework can be adapted to the future epidemiological conditions, e.g., by modifying the compartments to describe newly emerging variants of concern (or new viruses) and adjusting the model parameters as soon as new knowledge becomes available. Notice that this presupposes access to (near) real-time genomic surveillance data, along with conventional epidemiological indicators, to properly account for the different proportions of circulating variants. In perspective, the model can also be adapted to investigate endemic scenarios and to estimate the long-term vaccination rates necessary to maintain a certain immunity level of the population at risk during future outbreaks.

7. Computation and datasets

The dynamic model was implemented with MATLAB and the Statistics Toolbox Release 2020b. The vaccine efficacies were implemented with R. The codes are available upon request from the corresponding author. All datasets used in this study are publicly available. The current epidemiological state of Switzerland and Germany are set according to the official data of Federal Office of Public Health (FOPH) and the Robert-Koch-Institute (RKI), respectively. We used contact matrices estimated by Prem et al. (2017).

CRediT authorship contribution statement

Hossein Gorji: Study design, Conceptualized method, analysis and presentation, Performed simulations and analysis, Visualization, Writing – original draft, Writing – review & editing. **Noé Stauffer:** Conceptualized method, analysis and presentation, Performed simulations and analysis, Visualization, Writing – review & editing. **Ivan Lunati:** Study design, Conceptualized method, analysis and presentation, Allocated the resources, Administered the project, Writing – review & editing. **Alexa Caduff:** Study design, Writing – review & editing. **Martin Bühler:** Study design, Writing – review & editing. **Doortje Engel:** Study design. **Ho Ryun Chung:** Study design, Conceptualized method, analysis and presentation, Writing – review & editing. **Orestis Loukas:** Conceptualized method, analysis and presentation, Writing – review & editing. **Harald Renz:** Study design, Conceptualized method, analysis and presentation, Allocated the resources, Administered the project, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.epidem.2023.100680.

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