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The interplay between susceptibility and vaccine effectiveness control the timing and size of an emerging seasonal influenza wave in England

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A B S T R A C T

Relaxing social distancing measures and reduced level of influenza over the last two seasons may lead to a winter 2022 influenza wave in England. We used an established model for influenza transmission and vaccination to evaluate the rolled out influenza immunisation programme over October to December 2022. Specifically, we explored how the interplay between pre-season population susceptibility and influenza vaccine efficacy control the timing and the size of a possible winter influenza wave. Our findings suggest that susceptibility affects the timing and the height of a potential influenza wave, with higher susceptibility leading to an earlier and larger influenza wave while vaccine efficacy controls the size of the peak of the influenza wave. With pre-season susceptibility higher than pre-COVID-19 levels, under the planned vaccine programme an early influenza epidemic wave is possible, its size dependent on vaccine effectiveness against the circulating strain. If pre-season susceptibility is low and similar to pre-COVID levels, the planned influenza vaccine programme with an effective vaccine could largely suppress a winter 2022 influenza outbreak in England.

1. Background

Since early 2020, alongside large-scale vaccination against COVID-19, social distancing measures imposed by governments have been widely used to mitigate the transmission of SARS-CoV-2 and its variants. The reduction of social mixing have also reduced the level of other infectious diseases such as influenza, with reported low levels of influenza worldwide over the 2020–2021 and the 2021–2022 seasons [\(Garza et al.,](#page-6-0) [2022](#page-6-0); [Nazareth et al.,](#page-6-1) [2022;](#page-6-1) [Zipfel et al.,](#page-7-0) [2021](#page-7-0)). Although, influenza subtypes skipping seasons is not uncommon, having two consecutive influenza seasons with very low incidence is rare ([Garza et al.](#page-6-0), [2022](#page-6-0)). While influenza is a common infection and mild for most people, it can be very dangerous for vulnerable people, including older adults, pregnant women and people with underlying health conditions, for whom infection can result in hospitalisations and death. Seasonal influenza can also put winter pressure on the National Health Service (NHS), the extent of which depends on a number of factors including whether there are other circulating viruses such as SARS-CoV-2 and respiratory syncytial virus (RSV) which can induce increased hospitalisations, the state of the backlog of elective surgeries following the pandemic years, increased demand for General Practitioners (GP) consultations and hospitalisations and intensive care bed

admissions. Even in the absence of other high prevalence circulating viruses, influenza can put constrains on the NHS; in the winter of 2017– 2018, influenza levels were high and this led to deferral of all elective inpatient and outpatient NHS care in England throughout January 2018 [\(NHS](#page-6-2), [2018;](#page-6-2) [Pebody et al.](#page-6-3), [2018](#page-6-3)).

Social distancing measures relaxing, either fully or partly, and possible increased susceptibility to influenza viruses this year, may lead to an increased influenza season in 2022. Australia's season is often examined as a portent for northern hemisphere activity. Over April-July 2022, Australia experienced an early influenza season. This is likely to reflect factors such as national COVID-19 control circumstances and influenza vaccination coverage, but indicates the potential for disrupted seasonality in England in the autumn 2022.

1.1. Planned vaccination strategy for 2022–2023 season in England

Vaccination against the circulating influenza strain is the most effective way to prevent influenza surge in the population, and England has a well-established annual influenza immunisation programme rolled out from September each year. The annual influenza immunisation

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programme is delivered to protect people at risk from influenza and is the most important public health intervention to mitigate influenza resurgence, reduce morbidity and mortality and winter pressure on the NHS. An annual vaccination programme against influenza is necessary as influenza evolves from year to year and the influenza vaccine needs to be updated to protect against the evolving virus.

In England, eligible cohorts, i.e. individuals eligible for vaccination, and vaccine types, to be rolled out, are decided yearly based on scientific advice from the Joint Committee on Vaccination and Immunisation (JCVI). In 2022–2023, the agreed cohorts were children age 2 or 3 year old on 31 August 2022, primary school aged children (4–11 years old) and secondary school children to Year 9 (11–13 years old) with some older children also included, those aged 6 months to under 65 years in clinical risk groups, and those aged 50 years and over. This is an increase in eligible cohorts compared to the pre-pandemic (2019–2020) influenza immunisation programme, which did not include healthy children 11–13 years old nor healthy adults between 50 and 64 years old.

The rolled out annual vaccine in England is based on the strains of the virus that are most likely to be circulating. In the case of 2022–2023 season, at the time of modelling, in November 2022, A(H3N2) subtype was detected more frequently than A(H1N1)pdm09 in sentinel laboratories in England. Some samples have tested positive for B [\(UKHSA](#page-7-1), [2022c](#page-7-1)) but B-type influenza historically appears later in the season. For the season 2022–23 in England, the recommended influenza vaccine was a quadrivalent vaccination with protection against AH1N1, AH3N2 and two B influenza strains.

In this paper, we evaluate whether this planned vaccination strategy will be able to mitigate an influenza epidemic wave over the autumn and winter 2022 in England, using an established epidemiological model for influenza transmission and vaccination ([Baguelin et al.](#page-6-4), [2013](#page-6-4); [van Leeuwen et al.,](#page-7-2) [2017;](#page-7-2) [Wenzel et al.,](#page-7-3) [2021\)](#page-7-3).

2. Methods

We use an established epidemiological models to quantify the timing and the size of an influenza epidemic wave peak under different population susceptibility and vaccine efficacy scenarios. In the next few sections we outline the model, data and different scenarios we will explore.

2.1. Transmission model

We are using an age-stratified dynamic-transmission compartmental model to simulate seasonal influenza transmission. The model is based on an established mathematical model of Susceptible–Exposed– Infected–Recovered compartments ([Baguelin et al.](#page-6-4), [2013;](#page-6-4) [van Leeuwen](#page-7-2) [et al.,](#page-7-2) [2017;](#page-7-2) [Sandmann et al.](#page-7-4), [2022](#page-7-4)) that has been previously used to evaluate different vaccination strategies ([Sandmann et al.](#page-7-4), [2022](#page-7-4)). The specific parameters and references we used in this model are given in Table S1.

The model was previously calibrated to the age-specific number of influenza-like-illness (ILI) primary care consultations and virological confirmation of influenza virus infection for each year from 1995–1996 until 2017–2018 [\(Baguelin et al.](#page-6-4), [2013](#page-6-4); [Sandmann et al.,](#page-7-4) [2022](#page-7-4)) For the purposes of this analysis we re-calibrated the model for the 2017– 2018 season, using updated vaccine effectiveness parameters as per and from [Pebody et al.](#page-7-5) ([2020\)](#page-7-5) (See panel A in [Fig.](#page-3-0) [3\)](#page-3-0). The calibration used a Bayesian evidence synthesis approach, which captures uncertainty in the model parameters and is able to generate a distribution of model outcomes consistent with available data. Specifically, the model uses an adaptive Markov chain Monte Carlo (MCMC) approach to infer the expected number of infections by age group, risk group, and influenza virus subtype across different scenarios. Additionally, the model captures the dynamics of A/H1N1, A/H3N2, and B strains separately. The plots of the calibrated model over the period 2017–2018 against ILI

consultations and stratified per influenza subtypes A/H1N1, A/H3N2 and B are shown in supplementary information. From the calibrated model, we can use the posterior parameter values, to model the impact of the updated vaccination programme under different scenarios for vaccine effectiveness and population susceptibility.

2.2. Hospitalisations model

Since the paper concerns evaluation of the impact from influenza transmission and infection on hospital admissions in England, the key model outcome from the calibrated model is the number of hospitalisations with different influenza subtypes. Hence, for the purpose of this analysis we extended the existing model with a hospitalisations model rather than just transferring the ILIs from the model via hospitalisations ratios. Specifically, instead of using a single parameter to transfer ILI to hospitalisations, our hospitalisations model assumes that infections result in hospitalisations with an age group dependent rate α_i , and also captures a possibility of a delay between being infected and hospitalisations at rate γ . This is modelled by including two delay states in the compartmental model $(\Delta i, j)$, resulting in gamma distributed delay times for hospitalisations:

$$
\frac{d\Delta_{i,1}(t)}{dt} = \frac{dI_i(t)}{dt} - \gamma \Delta_{i,1}
$$

$$
\frac{d\Delta_{i,2}(t)}{dt} = \gamma \Delta_{i,1} - \gamma \Delta_{i,2}
$$

$$
\frac{dH_i(t)}{dt} = \alpha_i \gamma \Delta_{i,2}
$$

The data we are fitting the model against are the weekly number of hospitalisations $(k_{i,t})$ by age group and the size of the monitored population $(n_{i,j})$. The latter can change dependent on the number of hospitals that report their cases by week. The likelihood function is then defined below, noting that we calculate the modelled number of hospitalisations by integrating over the previous week, resulting in the total number of hospitalisations for that week.

$$
\mathcal{L} = B\left(k_{i,t}; n_{i,t}, \int_{t-7}^t \frac{\mathrm{d}H_i(t)}{\mathrm{dt}} \mathrm{d}t\right)
$$

We note that the original infection model results produced posterior estimates for the weekly number of infections. For the hospitalisations model we therefore assume that during that week the number of new infections is constant over time. Inference of the parameters for the hospitalisations model is done by fitting the above model separately to a subsample of the posterior samples using a MCMC algorithm. This results in a number of posterior samples for the hospitalisations model, of which we store one (i.e. each posterior sample of the infection model results in a corresponding sample for the hospitalisations model). We note that while this approach does not result in a proper posterior sample, because it does not account for the fact that some of the posterior samples of the infection model are more likely given the hospitalisations data, we feel that it is sufficient for the purpose of this work as it gives a conservative approximation of the posterior parameters of the calibrated model given the hospitalisations data.

3. Modelling scenarios

Using the calibrated model, we quantified the timing and the size of an influenza epidemic wave peak under different susceptibility and vaccine efficacy scenarios. Specifically, we simulate two scenarios of pre-season population susceptibility (low and similar to pre-COVID levels versus high due to non-exposure to/low prevalence of influenza over last two years) and two scenarios of vaccine efficacy (low and high; with details in [Fig.](#page-3-1) [2A](#page-3-1)). We summarise these scenarios in the next two sections. We also assume vaccine uptake to be based on the 2021–2022 uptake ([UKHSA,](#page-7-6) [2022b](#page-7-6)[,a](#page-7-7)) [\(Fig.](#page-3-1) [2](#page-3-1)B and Fig. S5).

Fig. 1. Historic rate of influenza hospitalisations (all levels of care) by week of admission and season, all ages, using sentinel data from acute NHS trusts in England. The rates are based on the catchment population of responding trusts in the sentinel surveillance scheme. In 2017–2018 both AH3N2 and B were circulating in significant numbers, 2018–19 was dominated by AH1N1pdm09, while 2019–20 was again dominated by AH3N2.

3.1. Population susceptibility scenarios

We simulate two scenarios of pre-season population susceptibility: low and similar to pre-COVID levels versus high due to non-exposure to/low prevalence of influenza over last two years. To get an indication of the difference in susceptibility in the 2017–18 season and the current susceptibility we used serological data, by calculating the total percentage of samples with a titre of 40 or over for the most relevant strains over the 2017–18 season. We used the inferred parameter values from model fitted to the 2017–18 season for the low susceptibility scenario. These are shown in the top panels of Figs. S2 and S4 in the supplementary material, respectively for AH2N3 and B strains. For the high susceptibility scenario, we then multiplied these values by 1.1 times based on our results from the serological data. See Section [4](#page-2-0) in the supplementary materials for more details.

3.2. Vaccine effectiveness scenarios

We model the vaccine efficacy and uptake to be based on the 2021–2022 uptake for the influenza programme [\(UKHSA,](#page-7-6) [2022b](#page-7-6)[,a](#page-7-7)). The efficacy of the vaccine values against subtypes A/H3N2 and B are shown in [Fig.](#page-3-1) [2](#page-3-1)A stratified per age and also contained in Table S1 of the supplementary material. The uptake of the vaccine is shown in [Fig.](#page-3-1) [2B](#page-3-1) and Fig. S5.

3.3. Model outcomes

Across the two susceptibility and vaccine efficacy scenarios, we projected the weekly hospitalisations rate related to AH3N2 and B influenza strains.

4. Results

4.1. The influenza burden over the pandemic years

During the 2020–2022 pandemic years, influenza levels in England declined dramatically ([Fig.](#page-2-1) [1\)](#page-2-1). The peak rate of influenza hospitalisations was 5.3 and 6.9 times lower in 2021–2022 compared to

Table 1

Historical peak hospitalisations per 100,000, the timing of the peak (in iso weeks) and the timing of the peak compared to our reference season (2017/18). Note that the COVID-19 seasons (2020–21 and 2021–22) show a low peak number of hospitalisations compared to earlier seasons. In the 2020-21 season the highest number of hospitalisations was actually measured in iso week 39, which is the final week of the season and a full 37 weeks later than in 2017–18.

Season	Peak size	Peak week	Compared to 2017-18 season
$2017 - 18$	7.8993349		0
2018-19	6.0699368	6	
2019-20	6.4238420	51	-3
$2020 - 21$	0.0887145	39	37
$2021 - 22$	1.1485631	14	12

2018–2019 and 2017–2018 respectively and close to zero (0.089) in 2020–2021 ([Fig.](#page-2-1) [1](#page-2-1) and [Table](#page-2-2) [1](#page-2-2)). Furthermore, the peak week was very different in seasons 2020–21 and 2021–22 than earlier season, occurring 37 and 12 weeks later than in 2017–18 [\(Table](#page-2-2) [1\)](#page-2-2). In comparison, 2018–19 and 2019–20 seasons occurred closer to the 2017–18 season (respectively 4 weeks later and 3 weeks earlier; [Table](#page-2-2) [1\)](#page-2-2).

4.2. Emerging timing and size of winter influenza waves depends on population susceptibility and vaccine efficacy

Using an established epidemiological model for influenza transmission and vaccination combined with data for England [1], we explored how the interplay between population susceptibility and influenza vaccine efficacy impact the timing and the size of a possible winter influenza wave over the 2022–2023 season.

Our results suggest that the combination of relaxing the COVID-19 social distancing measures and two previous low incidence influenza seasons in England could lead to a large influenza epidemic wave in late 2022 ([Fig.](#page-3-0) [3\)](#page-3-0). The size and the timing of such an influenza epidemic wave in late 2022 in England are highly dependent on the population susceptibility, vaccine uptake and vaccine efficacy ([Fig.](#page-3-1) [2A](#page-3-1)–C).

Population susceptibility affects the timing and the size of a potential influenza wave, with higher susceptibility leading to an earlier

Fig. 2. Vaccination assumptions used in the scenarios. (A) High efficacy assumptions for AH3N2 are based on 2021–2022 results, while for subtype B we use the results from a meta-analysis ([Belongia et al.](#page-6-5), [2016\)](#page-6-5). Low values are half the estimated efficacy in the 2017-2018 season (shown in grey for reference; ([Pebody et al.](#page-6-6), [2019\)](#page-6-6). (B) Vaccine uptake is based on 2021–2022 uptake, which includes uptake in the additional eligible cohorts. (C) Available serological data at the start of both seasons. The lines represent the probability that a sample has the given titre value (x-axis) or higher. Higher values correspond with a higher proportion of the population having antibodies against influenza. The dashed line shows the titre of 40. Generally, it is assumed that 50 percent of individuals with a titre value of 40 or above are immune to infection. (D) The fitted hospitalisations rates for both H3N2 and B. The red points show the data in 2017-2018. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

Fig. 3. Inferred weekly hospitalisations by age group per 100,000 individuals. The colour labels refer respectively to the different scenarios. All the scenarios assume the projected vaccine uptake, with either, high susceptibility (blue) or low susceptibility (orange). Vaccine efficacy is assumed to be low (lighter colours) or high (darker colours). Each trace represents a simulation (total of a 100 simulations per scenario). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

influenza wave (comparing the two blue curves with the two orange curves in [Figs.](#page-3-0) [3](#page-3-0)). The efficacy of the rolled out vaccine affects the magnitude of the peak of the influenza wave, with more effective vaccine able to flatten the epidemic curve substantially (comparing

Table 2

Peak hospitalisations per 100,000, the relative timing of the peak (in weeks) compared to the base case (2017/18) and the total hospitalisations per 100,000 for the different scenarios. The values represent the rounded median value and the total range of results (square brackets). Lower bounds were rounded down, while upper bounds were rounded up.

Subtype	Susceptibility	Efficacy	Peak	Peak time	Total	
AH3N2	High	High Low	4.1 $[3.4 - 4.8]$ 10.6 [10.1-12]	-9 [$-10-7$] -10 [$-10-9$]	35 [29-40] 64 [59-88]	
	Low	High Low	0.2 [0-0.5] 3.1 [2.6-3.6]	10 [$-7-15$] 0 [-1-0]	6 [1-12] 35 [33-37]	
B	High	High Low	2.9 [$2.2 - 3.8$] 15.4 [14.6-16.4]	-5 [$-6-4$] -7 [$-8-7$]	25 [21-28] 75 [70-83]	
	Low	High Low	0.1 [0-0.3] 5.7 [4.9-6.2]	16 [$-7-23$] 0 [-1-0]	$3 [0 - 7]$ 46 [43-48]	

the two blue curves with each other and the two orange curves with each other in [Fig.](#page-3-0) [3](#page-3-0) and comparing scenarios in [Table](#page-4-0) [2\)](#page-4-0). For example, when we consider high susceptibility scenario (blue curves in [Fig.](#page-3-0) [3\)](#page-3-0) the median peak height changes from 4.1 [3.4–4.8] to 10.6 [10.1–12] when vaccine efficacy decreases in the case of AH3N2 strain. The impact is even more when we consider the B subtype — at high susceptibility, the median peak increases from 2.9 [2.2–3.8] to 15.4 [14.6–16.4] with decrease in vaccine efficacy. The trend also remains when we model low population susceptibility (orange curves in [Fig.](#page-3-0) [3](#page-3-0) and results in [Table](#page-4-0) [2](#page-4-0)). Similarly, the peak of the potential epidemic can be much earlier under scenarios of high susceptibility than low susceptibility. In the case of the AH3N2 strain, under high/low vaccine efficacy it can occur around 9–10 weeks earlier, while in the case of B stain it is only 5–7 weeks earlier. The differences are even more notable under low susceptibility scenarios with an AH3N2 peak predicted to occur delayed by around 10 weeks, while a B-type peak can be up to 16 weeks delayed ([Table](#page-2-2) [1](#page-2-2)).

We show that if the population susceptibility is similar to that in 2017–2018 season i.e. pre-COVID-19, the extended planned influenza immunisation programme for 2022–2023 with an effective vaccine has the potential to prevent an influenza resurgence over September– December 2022 (light orange curve in [Fig.](#page-3-0) [3](#page-3-0) and [Table](#page-4-0) [2\)](#page-4-0). Overall, increased susceptibility can lead to an earlier influenza wave (blue shaded curves in [Fig.](#page-3-0) [3](#page-3-0) also see [Table](#page-4-0) [2\)](#page-4-0) while vaccine efficacy controls the size of the peak of the influenza wave (light shaded peaks in [Fig.](#page-3-0) [3](#page-3-0).)

5. Discussion

We use an established model for transmission and vaccination against influenza in England, to evaluate whether the rolled out influenza immunisation strategy can prevent a large epidemic wave over the 2022–2023 season. Pre-COVID-19 i.e pre the 2020–2021 influenza season, our model has been routinely used to explore the impact of different mixing patterns and the planned immunisation programme on the yearly upcoming influenza wave, with our results shared with the with public health stakeholders across the UK.

Aiming to evaluate the impact of the planned influenza vaccine in England, we explore how the interplay between pre-season population susceptibility and influenza vaccine efficacy affect the timing and the size of a possible winter influenza wave in England over October– December 2022. Our findings suggest that susceptibility affects the timing and the height of a potential influenza wave, with higher susceptibility leading to an earlier and higher influenza wave while vaccine efficacy controls the size of the peak of the influenza wave. We observed that influenza activity substantially declined during the 2020– 2021 and the 2021–2022 seasons and during the COVID-19 pandemic in England. As a consequence, our findings highlight that an extensive annual influenza immunisation programme can substantially mitigate the impact of an influenza epidemic in a season where the underlying population immunity is reduced.

At the time of writing the original submission, in November 2022, in England, there have been indications of an early onset of the 2022– 2023 influenza season, with the hospital admission rate for confirmed cases of influenza in mid-October being greater in 2022 than seen in preceding years within norms for influenza seasonality [\(UKHSA](#page-7-1), [2022c](#page-7-1)). At this point, the AH3N2 strain of influenza was in circulation, which was also the dominating A-type strain earlier in the year in the southern hemisphere. B-type cases are often seen later in the season, with some also circulating earlier in the year in the southern hemisphere. Based on these observations, at the onset of our modelling work, we set out to model the AH3N2 and B influenza cases and omitted AH1N1 cases which were not circulating in England at the time and we did not expect to start circulating based on the southern hemisphere trends. By the time our paper had gone through the revision process at the journal, in April 2023, the influenza epidemic in England had happened. The dominating strains over the 2022–2023 season in England were the A-type viruses AH1N1 and AH3N2 with around two thirds of the infections caused by the AH3N2 strain and the number of cases due to B type strains negligible. In [Fig.](#page-5-0) [4](#page-5-0), we show the subtyped AH3N2 infections compared to our predictions. We can see that the AH3N2 2022–2023 wave seems to resemble one of the largest epidemic scenarios i.e. one with high population susceptibility and low vaccine efficacy. In terms of the B-strain epidemics, since negligible number of cases of it were reported over the 2022–2023 season, this is aligned with our best-case scenario i.e. one with low population susceptibility and high vaccine efficacy.

[Fig.](#page-5-0) [4](#page-5-0) shows that looking retrospectively, at the data from 2022– 2023 season the AH3N2 peak was very close to the predicted worst-case scenario, although the wave was much shorter than the worst-case scenario, resulting in lower total hospitalisations. The B epidemic was negligible and hence comparable to our best-case scenario. We also note that peak in the worst case (high susceptibility and low vaccine efficacy) scenario we modelled is around 10, which is more than twice as high than the AH3N2 peak seen in 2017–2018 as expected with higher susceptibility. The combined B and AH3N2 peak in that season is almost as high though $(Fig. 1)$ $(Fig. 1)$ $(Fig. 1)$ $(Fig. 1)$, so there is historical precedent for an outbreak of this size. The increase is due to assumed larger susceptibility than in 2017–2018 season, and hence we do not think this is an infeasible outcome in a very bad flu season.

Looking ahead at the start of the season, our modelling showed that there was high uncertainty as to the size of the winter influenza epidemic wave over the 2022–2023 season. The importance and novelty of our work is that we show, under different scenarios, a spectrum of possible winter pressures scenarios from influenza over this season: from a very small influenza epidemic wave with highly effective vaccines and low population susceptibility to a very large epidemic wave with low effectiveness vaccines and high population susceptibility. This uncertainty has also been shown in other modelling studies. For example, analysis by [Ali et al.](#page-6-7) ([2022](#page-6-7)) suggests that there is a possibility of large upcoming influenza seasons worldwide, while [Garza et al.](#page-6-0) ([2022\)](#page-6-0) suggest that future seasonal influenza virus epidemics will likely be similar to the previous one and would not have an increased burden. Such a broad spectrum of results and uncertainty is an important aspect of scenario modelling and often a consequence of different modelling assumptions and methods used.

The uniqueness of our study is that we show that the uncertainty of the timing and height of a possible influenza epidemic wave can emerge from the interplay between pre-season population susceptibility and the rolled-out vaccine effectiveness. Bearing in mind that we do not know the vaccine effectiveness for the season until the end of the influenza season, our modelling remains a crucial tool for pre-season winter pressure planning.

Using modelling to explore and forecast influenza epidemic trajectories is regularly used in the UK to inform policy decision makers ([Birrell](#page-6-8) [et al.,](#page-6-8) [2020\)](#page-6-8). For the 2017–2018 season, which was one of the largest influenza epidemics over the last three decades, a set of mechanistic

Fig. 4. Predicted number of hospitalisations, compared to measured number of hospitalisations (red dots).

models, similar in structure but with some technical differences and also fitting to a variety of data, were used individually and also combined to project future epidemic trajectories. Modelling and analytical methods to inform public health decision-making are also used by the United States Centres for Disease Control and Prevention (CDC) via the Flu Scenario Modelling Hub ([Flu scenario model hub,](#page-6-9) [2023\)](#page-6-9). Such ensemble scenario modelling hubs allow the outcomes from models to be combined to generate medium-term projections that are useful for policy decision makers. Another type of predictive modelling is the forecasting modelling. CDC have also developed such modelling hub, via organising seasonal influenza forecasting challenges since the 2013– 2014 season. In the 2017–2018 season, 22 teams participated and this challenge was later the base for the development of the FluSight — the CDC influenza forecasting hub ([Reich et al.](#page-7-8), [2019\)](#page-7-8). Such forecasting hubs often comprise data-driven non-mechanistic models that use the available data to infer possible influenza futures over short upcoming periods (normally 2–3 weeks). While the UK does not yet have such a modelling hub, there are plans to in future develop one lead by senior modellers in UKHSA.

As with any modelling work, our study has some limitations. Firstly, we note that the modelling is based on the assumption that social contacts rates will return to pre-COVID-19 levels for this winter. Current data suggest that contact rates are still lower than they used to be prepandemic (especially in adults). If this continues throughout the season,

then that could reduce influenza transmission, especially in the adults age groups. Secondly, we note that we assume that the majority of the vaccine doses will be distributed before any influenza outbreak. In case of a very early peak, the planned immunisation programme could be much less effective, because it arrives after the start of the outbreak.

Thirdly, we have limited serological data available, making it difficult to compare the two seasons. For example, the 2017 data was based on opportunistic serological samples, while the 2021 data is based on samples collected through the Royal College of General Practitioners Research and Surveillance Centre (RCGP RSC) which provides clinical surveillance data and collects virological specimens from a representative national sample of 100 general practices ([Pebody et al.,](#page-6-6) [2019](#page-6-6); [Whitaker et al.,](#page-7-9) [in preparation\)](#page-7-9). Furthermore, for the 2017 data we did not have their vaccination status available, while for the 2021 season we do not have data for the younger age groups. Future work to collect, process and make timely available serological data for modelling is necessary for better influenza surveillance.

Fourthly, as highlighted in the methods, the inference for the hospitalisations model used a simplified method, due to time constraints. Related to that the uncertainty in the outcomes for each scenario is likely to be an underestimate of the full uncertainty given the data. Note though that any uncertainty within the scenarios is much lower than the differences between the scenarios. This means that for scenario modelling the impact of using a simplified model will be minimal, as the goal of the modelling is to capture the range of outcomes under different scenarios and the impact of uncertainty (or lack thereof) within the scenarios is limited.

Next, as we transition from the pandemic COVID-19 era, there is still uncertainty around changes to seasonal activity of many respiratory infections, including any timescales over which these might reestablish conventional seasonality. Further work is needed across surveillance and modelling, including accounting for any increases in microbiological testing.

Finally, an aspect we need to get better understanding of is crossimmunity between different influenza strains. In this modelling work we have fitted the data on two strains independently as the data does not contain cases of co-infection. Hence we could not model crossimmunity and cross-infection here, but this is something that we plan to explore more in future.

Modelling using epidemiological and statistical models has been a crucial aspect of the informed advice for policy decision making over the COVID-19 epidemic in the UK. As we move to the ''living with COVID-19 era'', expanding existing models, developing new ones and combining them with data remains an important tool for providing quantitative evidence for the outcome of possible interventions, including vaccination, to improve public health.

6. Conclusions

Using existing epidemiological model combined with influenza data from England, we determine that if susceptibility in the population is largely unchanged post COVID-19 and the rolled out influenza vaccine is effective, then the planned vaccine programme could suppress any emerging influenza outbreaks in the period October to December 2022. If susceptibility to influenza is higher than previous years, then an influenza epidemic is possible over this period. Its timing depends on the susceptibility level, and its peak value depends on the effectiveness of the vaccine; this wave could be significantly worse than historic waves under cases of high susceptibility and poorly matches to the strain variant or could be negligible if susceptibility is the same as pre-COVID and the vaccine is well-matched to the circulating influenza strain.

CRediT authorship contribution statement

E. van Leeuwen: Conceived the study, Developed and undertook the modelling with input, Contributed to designing modelled scenarios based on conversations within UK Health Security Agency (UKHSA), Writing – orginal draft. **J. Panovska-Griffiths:** Contributed to modelling, Contributed to designing modelled scenarios based on conversations within UK Health Security Agency (UKHSA), Writing – orginal draft. **S. Elgohari:** Contributed to designing modelled scenarios based on conversations within UK Health Security Agency (UKHSA). **A. Charlett:** Contributed to designing the modelled scenarios based on conversations within UK Health Security Agency (UKHSA), Conceived the study, Writting – Editing original draft. **C. Watson:** Contributed to designing modelled scenarios based on conversations within UK Health Security Agency (UKHSA), Conceived the study.

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.

Data availability

Data will be made available on request.

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Code availability

The code is included as a supplementary file, and will be publicly available on GitHub upon publication of the article.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at [https://doi.org/10.1016/j.epidem.2023.100709.](https://doi.org/10.1016/j.epidem.2023.100709)

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